Accounting for Trends

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Relevance, Explanatory and Predictive Power of the Framework of Triple-Entry Bookkeeping and Momentum Accounting of Yuji Ijiri

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PROEFSCHRIFT

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1

Introduction

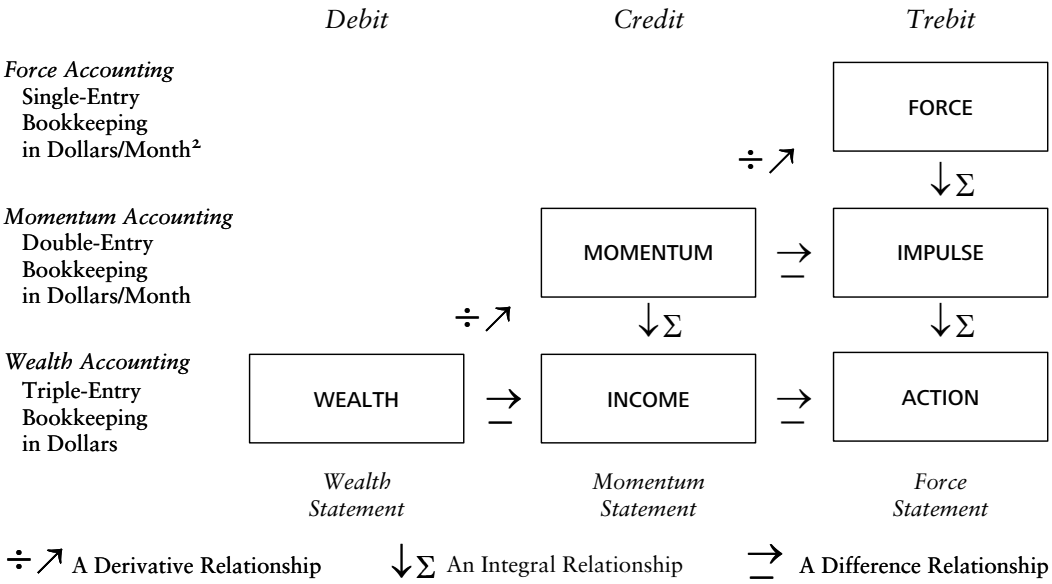

Figure 1 A framework for triple-entry and momentum accounting (after Ijiri, 1986).

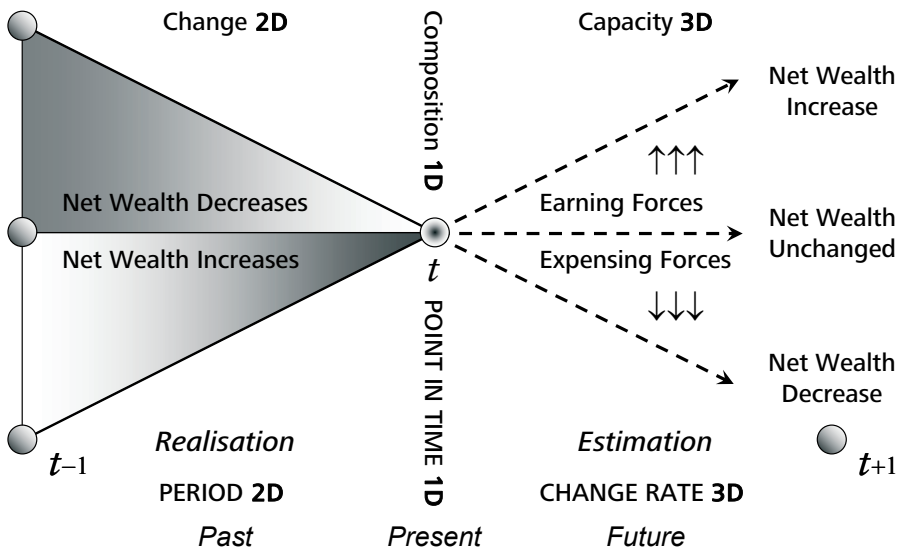

Figure 2 The arrow of time in the framework of triple-entry and momentum accounting (TEMA).

1 Abstract

The ever-increasing pace of the economy incites the need to disclose trends at the microeconomic level of a company. Recent developments related to corporate governance give new imputes to search for the answer to the question if we can improve the reliability and effectiveness of accounting in general and financial statements in particular as a source of information. The findings of this study show that the framework for triple-entry bookkeeping, also known as momentum accounting, has much to offer to users of financial accounting information. In this chapter the TEMA *framework and momentum accounting theory of Ijiri are presented. Relevant literature related to momentum accounting is discussed as well as the opposition raised against it. The research hypotheses, objective, motivation and its contribution are offered. Finally, the structure of the thesis is described.*

1.1 Introduction

Accounting has a history of deliberation with its scope, purpose and objective (Chambers 1998, Vatter 1963, Peasnell 1978, Zeff 1982). Recently, leading academics concluded that the '…foundational questions in accounting are far from settled' (Demski *et al.* 2002, 166). In October 2004, a Joint Project was launched by the IASB and FASB 'to develop an improved and common conceptual framework that is based on and builds on their existing frameworks' (IASB 2004, 4). This thesis strives to make only a very small contribution to accounting theory. My subject is forward-looking analysis of a firm's performance based on financial statements data, the balance sheet in particular. This work is framed in the momentum accounting theory of Yuji Ijiri (Levin *et al.* 1998). He followed a long line of investigation into the mathematical foundation of financial accounting from a system perspective (Ijiri 1965A-B, 1966, 1967, 1975, 1981).[1] Ijiri proposes to administer accounting measurements with three dimensions: force, momentum and wealth (Ijiri 1982, 1986, 1987, 1989). He developed the so-called framework of Triple-Entry/Momentum Accounting, or TEMA in short, that is composed of these three dimensions (FIGURE 1). Firstly, wealth accounts measure the magnitude and composition of capital sources and uses. Secondly, momentum accounts measure the change of wealth, or value realized. Thirdly, force accounts measure the change of the capacity to acquire new wealth, or value creation to be realized, and this includes various internal and external business and economic forces. Ijiri's objective is to account for existing and new momentum created by management during the reporting period in between the opening and closing balance sheet. Management incentive plans, in his opinion, could be based on action taken by management to maintain and increase momentum. But, Ijiri admitted that '…by no means [it is] an easy task to develop momentum accounting…' as '…managers' and accountants' *sensitivity* to momenta and impulses…' has to develop. Objections were raised by critics of the TEMA framework. In particular the required effort to implement triple-entry bookkeeping and the increase in the number of accounting variables to administer, compile and report is viewed to be rather daunting and possibly superfluous. More fundamental, doubts were raised about the TEMA framework itself and momentum accounting as a new source of information for financial statement analysis and decision making. For example, Fraser (1994) does not see it as a viable alternative for current accounting methods, which might be one explanation for its lackluster performance so far. As long as some evidence is not put forward that the TEMA framework has explanatory

[1] See Tippett (1978) for a review of Ijiri's early work on the axioms of accounting.

and predictive power, I expect that its advancement will be mired. For that reason, the primary goal of this study is to empirically test the viability of the TEMA framework by econometric modeling methods and to determine if my research findings could advance its practical application.

Organization of this chapter

The chapter is organized as follows. Section 1.2 continues the introduction with a more detailed discussion of the background and objective of the TEMA framework. Although I expect from the reader certain background knowledge about the methodology, instruments and organizational procedures of accounting, most specialized terminology is defined and explained by some example.[2] Section 1.3 describes three dimensional accounting, its measurement and application for various purposes. Analogies with physics are also discussed. Section 1.4 evaluates the advancement of TEMA. This section includes a review of previous and later literature about TEMA and related subjects and applications. In section 1.5 TEMA is discussed from the perspective of value creation, measurement and management. In Section 1.6, criticisms are discussed that were raised in opposition against TEMA. The research objective is presented in Section 1.7. The research hypotheses and considerations behind them are presented in Section 1.8. The research motivation is offered in Section 1.9. The research contribution is discussed in Section 1.10. Section 1.11, finally, describes the structure of the dissertation and explains how the following chapters are organized.

1.2 Accounting for disclosure, analysis or decision?

Financial statements supposedly depict the current condition of a company completely and accurately (McEnroe & Martens 2004, Haskins & Sack 2006).[3] Aside unwittingly made mistakes, technical flaws or fraud, accounting information is by definition 'historic' and therefore 'reliable' because financial statements are compiled from facts, past facts (ex post facto).[4] At times we may find in the notes to the financial statements information about the expectations management has for the future (Hutton *et al.* 2003). Obviously past results cannot offer any

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[2] There is available a plethora of textbooks on accounting, one of which was particularly useful to this author: Weygandt *et al.* (2003).

[3] There are four main *financial statements* (or *financial reports*) in use. They are formal records of a business' financial activities when audited to ascertain the validity and reliability of information. The *audit* is performed by competent, independent and objective individuals, who are known as the *external auditors* or *accountants*. First, the *balance sheet* is referred to as the 'statement of financial condition' and reports on the magnitude and composition of a company's assets, liabilities and equity for a given point in time. Second, the *income statement* is also referred to as the 'profit or loss statement' and reports on a company's results of operations over a period of time, i.e. in between two balance sheets. Third, the *cash flow statement* breaks up the sources of cash generation into three sections: cash flows from operating, investing and financing activities. This breakdown allows the company to determine where its money is coming from, and how it is being spent. Fourth, but not always produced, the *statement of retained earnings* explains the changes in a company's retained earnings over the reporting period. To these four statements, Ijiri adds a whole new set of financial statements to enable reporting on the then current rates of change of accounts, the *momentum statement*, changes in net momenta in the *impulse statement*, and the *action statement*, which classifies income by its causes. (This note was written using Weygandt *et al.* (2003) and Wikipedia articles.)

[4] Misrepresentation of facts in financial statements is a subject that in this study is not discussed further but nonetheless it is an important and problematic issue (e.g. Rezaee 2005, Stalebrink & Sacco 2007). However, I think that momentum accounting increases transparancy and, as a result, it is expected to reduce the risk of misrepresentation of facts (see also Blommaert 1994A, 230).

guarantee for results in the future, such notes are indications only for better or worse. I see the TEMA framework as an initiative to innovate financial accounting so that management or the auditor are better facilitated to disclose trends that have future bearings. The objective of the TEMA framework is to add a dynamic perspective to the financial accounting system for the purpose of additional disclosure, analysis and decision making. It explicitly requires attention for the causal links in the business model and administers business economic facts outside the scope of traditional bookkeeping, for example with revenue accounting (Glover & Ijiri 2002). This is an ambitious effort that, certainly in the eyes of the critics of TEMA, strains the boundary between financial and management accounting (Fraser 1994, Salvary 1985, Vaassen 2002, 33, Wagensveld 1995 1996).

1.2.1 Points past

However complete and accurate financial statements may be, the information they contain is exclusively 'historical' for the simple reason that the accounts contain data pertaining to facts that can be proven to have happened. This, of course, is a gross simplification because not only does the balance sheet include data from the past but also data that points to the future (Glover *et al.* 2002, 2005, Levine & Ijiri 2004). The obvious example is debtors that record the amount of money owed by customers to the firm. From the standpoint of the accountant that data is a historical fact but for the treasury department only a marking of future cash in hand. More important, we can characterize all balance sheet data as point measurements, i.e. a record of the source and use of wealth at a given date and as such, it is a static or 'non-moving' representation of economic information (FIGURE 2). To account for the business dynamics in between two such point measurements we account for income and expenses, hopefully the first being the larger sum than the second and then report a profit. This profit increases owners' equity, or net wealth, and is equal to the wealth increase between the balance sheet total at two succeeding dates, excluding equity raised or retired. Likewise, a loss is then equal to the decrease of total wealth. Consequently, the income accounts are period related. Conceptually, they constitute the second dimension of the TEMA framework and explain the change of magnitude of the first dimension: wealth.

1.2.2 Management by momentum

Yuji Ijiri proposes a system of accounting with three dimensions. Besides *wealth* and *income*, he proposes *force* as a more reliable and relevant alternative to our current 'point-and-period' measurement to meet managerial demand for more forward-looking information about business dynamics. The fundamental notion is to account for the *income capacity* of a firm in terms of levels rather than differences. Ijiri seeks to report the growth level instead of (only) explaining the growth of net wealth as the lump sum difference from the previous point at any particular point in time. He calls this the *momentum* by which net wealth changes or the growth rate per month, week or day. By comparison with car driving, he wants to measure the speed at which the car travels instead of only measuring the distance traveled so far (Ijiri 1988A, 160). His car driving metaphor can be extended and deepened to further explain the measurements of the TEMA framework as well as its managerial use. The two principal meters in any dashboard are the odometer that measures the mileage driven during the cars' life time and the speedometer. Most, if not all, dashboards also have an odometer that counts the mileage driven per day and cycles its measurement from 0 to 999 miles or kilometers. While the odometers count the *state* of the cars mileage, the speedometer reports the *rate of change* of the car – its

speed. The importance of the difference between these two meters becomes very clear when we match them against the balance sheet and the income statement for their explanation of wealth magnitude, composition and its change:

- odometer continuous — balance sheet, wealth magnitude & composition as of 'now,'
- odometer period — income statement, wealth change explained by its 'how,'
- speedometer — ?, the change of wealth change explained by its 'why.'

The fundamental notion we have to grasp is that it is impossible to read from any financial statement the rate of change by which new wealth is created, or the change of any financial variable for that matter.[5] We should compare the user of financial statements with a driver in a car with his or her attention focused solely on the revolving number wheels of the odometer. Indeed, it is possible to see wealth increase and conclude that the company is in business, but without any other reference against which we can perceive speed, it is impossible to tell by which speed wealth is increasing.[6] In other words, the financial accounting dashboard is lacking speedometers: a pretty uncomfortable position to be in.[7]

However, we cannot stretch the metaphor too far. Neither financial analysts nor investors are the 'drivers' of the company, therefore, should we be bothered with the missing speedometer on the financial dashboard? Ijiri feels that we should expect from management that they are able to 'see' at which speed their business is 'moving.' How else can they intervene when momentum is dissipating? Actually, it is not uncommon for managers to think in terms of impulses and momentum when they discuss the state of the economy and their business. Lord Simon, director of Unilever, whilst commenting on the U.K. Government continued delay to decide on the Euro introduction: 'I think the most important issue now is looking forward, to having a more consistent momentum ....'[8] The term *momentum* is busied daily in opinions of analysts and other decision makers to indicate both direction and thrust of economic or market dynamics.[9] The challenge really is to move away from momentum being determined by personal intuition and have it reported in a consistent manner instead. Moreover, measurement of momentum in the framework of Ijiri can be objectified and thus be audited so that we can ascertain the validity and reliability of the information.

The foundational notion Ijiri puts forward is that the double-entry accounting framework does not exclude the possibility to include 'speed' measurements. He thinks it is feasible to extend the double-entry bookkeeping framework with a third dimension so that we can ac-

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5 That is, the rate of change per time unit *smaller* than the time period in between two financial statements. As will become clear when the research methodology is discussed in the next chapter, we can count the rate of change per year or quarter with the currently available financial statements of firms.

6 Or decreasing; whereas the mileage of a car cannot be reduced (something which is illegal to do) wealth can decrease during the lifetime of the firm when capital is retired or dividend is paid out.

7 To be honest, the items on the cash flow statement can be viewed as 'speedometers' when we set the rate of change equal to one year or one quarter. However, Ijiri's vision is to provide much more detailed information with a much shorter time rate of change.

8 *BBC News*, Business, 'Unilever chief warns of Euro "indecision",' June 12, 2001.

9 As any search using an Internet browser will confirm. E.g. the following statement in reference to the 'Stellar growth in banking, legal services, recruitment agencies and accounting fuelled a strong British economy between April and June [2007] ... Vicky Redwood of Capital Economics said the data suggested "there is plenty of *momentum* in the real economy to help it deal with any fallout from the financial market crisis"' (italics supplied). In: 'Economy driven by growth in business services,' by Chris Giles, economics editor of the *Financial Times*, Monday August 27, 2007, published on www.ft.com.

count for the 'rate of change' of a firm's business. He wants to apply the same methodological and procedural rigor to the administration of facts pertaining to the future as is expected from the administration of transactions past (Blommaert 1994A).

1.3 Three dimensional accounting

Yuji Ijiri proposes to extend the present framework of double entry bookkeeping with a third entry to account for the forces that are responsible for the change of the momentum by which new wealth is acquired (Ijiri 1971A, 1982, 1984, 1986, 1987, 1988A-B-C, 1989 & 1993). Single-entry is based on the *stock* or *wealth accounts* of a business that are found on the balance sheet and decomposed into two categories: assets and liabilities with owners' equity or net wealth. Single-entry accounting was extended with a second or double-entry to be able to account for the change of the stock accounts and is identified with *flow* or *momentum accounts*. These are represented by revenue or wealth increasing accounts and expense or wealth decreasing accounts (Ijiri 1986). Changes in a balance sheet account are reconciled to changes in income, which is an aggregate of the revenues and the expenses.[10] The extension of double-entry to triple-entry bookkeeping suggests that it is possible to include in the accounting system a new dimension that looks at the change of the flow accounts. Ijiri introduces to this purpose the *force accounts* that measure the *rate* at which the *flow* or *momentum accounts* change (FIGURE 1).

1.3.1 Quantitas materiae

To explain the dimensional relationship of the accounts, Ijiri borrows a metaphor from physics.[11] In classical mechanics, we define the velocity of an object in a friction free environment as the product of its speed and mass. Acceleration then is the change of velocity. In analogy the definition of mass by Sir Isaac Newton as *quantitas materiae* (Cohen & Smith 2002), Ijiri proposes to define the wealth of a firm as an economic 'mass' that has a certain velocity or momentum to create value.[12] Ijiri posits that firms can reach a certain level of stability and continuity as profit making entities given the presence of a certain mass that maintains a certain speed. Dull (1997, 23) suggests that this matches with the physical concept of *inertia*, defined from the physical perspective as '...the property of an object to remain at constant velocity unless acted upon by an outside force...' and is most commonly defined using Sir Isaac Newton's First Law of Motion, which states:

> The *vis insita*, or innate force of matter is a power of resisting, by which every body as much as in it lies, continues in its present state, whether it be of rest, or of moving uniformly forwards in a right line.[13]

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[10] As reported in the statement of cash flows.

[11] Ijiri uses the analogy with Newtonian mechanics only to obtain some insights into how the triple-entry bookkeeping framework should be developed. He cautions against '...a wholesale translation without regard to its applicability to accounting...' (Ijiri 1986, note 11, 748).

[12] This assumption is not eccentric. E.g. in macro-economic theory a similar metaphor is used: the so-called *gravity model* (Baier & Bergstrand 2001, 3). In this model, which originally was developed by the Nobel price winner Jan Tinbergen (1964, 262-293), international trade flows are formulated as a function of national income, the population, geographical distance and proximity. In this model, national income functions as 'mass.'

[13] From the article *inertia* of http://en.wikipedia.org.

Inertia, according to Dull, is the state of a firm that essentially seeks to maintain the status quo and opposes strategic renewal. This is not to say that a firm's wealth is not growing when it is inert. It very well could be growing because the rate of growth is stable and follows a linear function (and be very predictable!). Any increase or decrease in the rate of growth would result in fluctuations and become a subject of interest to management for controlling purposes as well as for outside analysts of company performance. In agreement with Dull's interpretation, the '...traditional view of a start-up company...' is that at its conception it has no wealth (Dull 1997, 25). Forces are 'gathered' to provide funding at the foundation of the new company, its first impulse, and we can account for this new company's wealth for the first time. Compared with the concepts of the motion of matter in classical physics, wealth is similar to the physical concept of *position*. Physicists consider any change of position over time using the first derivative of position, a transformation that yields the *velocity* or speed of the object.[14] The second derivative of wealth renders *acceleration*, which is the application of force to an object such that its velocity or rate of change is changed. The parallel drawn by Ijiri is that of *impulse* and *force* (FIGURE 1) with which we account for the growth potential of a firm's wealth.

Triple-entry accounting research thus builds upon, in the words of Dull (1997, 25), the '...relationships between organizational concepts and their corresponding physical science components, and it applies the visualizations used to aid in understanding the physical science components to their momentum accounting counterparts.' The question that will be answered in the next subsection is how we can measure the components of the TEMA framework as business economist, financial or management accountant, or auditor?

1.3.2 Dimensions of accounting measurement

The accounting dimensions are temporally determined *sources of information* and concern the substance of information and not its form (Wagensveld 1995, 3). FIGURE 2 depicts the purpose of each dimension as wealth measurements in time. Through the accounts it should be possible at any point in time to explain the *composition* of wealth (1D), i.e. how it was acquired (liabilities and equity) and used (assets). Next, it should be possible to determine for a given period between points if an increase of wealth was realized (2D). To this two-dimensional system of accounts, Ijiri adds the ability to account for the capacity to acquire new wealth in the future (3D) by means of administration of cost and income forces, data collection and analysis; not necessarily within the bookkeeping system. A framework of three dimensions is proposed by Ijiri (1986, FIGURE 1):

1. *Wealth* — the first dimension for the administration of the *magnitude of wealth* and *wealth composition*, with accounting variables that are set apart as net wealth (equity) and liabilities (sources of capital), or as assets (uses of capital). Accounts of this dimension are on the balance sheet.
2. *Momentum* — the second dimension for the administration of the *change in magnitude of wealth* (the first dimension), with accounting variables that are set apart as cost (outflows) and income (inflows). Accounts of this dimension are on momentum statements that include the income statement.
3. *Force* — the third dimension for the administration of the *change of capacity to acquire new wealth* (the second dimension), with accounting variables that are set apart to administer internal and external forces. Accounts of this dimension are on force statements that also include impulse and action.

[14] The same is explained more formally in Chapter 2 when relevant equations are introduced.

FIGURE 1 shows the relations between the three accounting dimensions in Ijiri's framework for triple-entry bookkeeping. We should not think of each dimension as one axis of a geometrically determined three dimensional Cartesian system of three axes (x, y and z) and with time as the fourth dimension.[15] In Ijiri's system we do not measure or project the spatial 'location' of an economic fact or business transaction as a vector in geometric space. Instead, we measure the temporal aspect of business transactions. The three accounting dimensions should be viewed as temporally determined information sources (Wagensveld 1995, 2, note 6).[16]

FIGURE 1 is the framework of accounting measurements that can be compiled in each of the three dimensions. We find at the left bottom *wealth* as a point measurement. These accounts are used to compile the balance sheet. To the right, there is *income* and these are accounts used for the income statement. They are a period measurement and as the framework shows, income has a derivative relationship with (net) wealth. This means that the difference between two (net) wealth measurements should be equal to income realized during the period in between the two points in time (FIGURE 1). We can see that the inverse is also true. When income is added to the (net) wealth measurement at the previous point in time we get (net) wealth at the current point in time. Hence, the *difference relationships* between the accounting dimensions can be inversed to *integral relationships* or vice versa.

So far, my discussion of the TEMA framework involves only two dimensions, wealth and income, and it is identical to the model of double-entry bookkeeping. But, Ijiri introduces a new set of financial variables he calls *momentum* accounts that are in the same vertical column of the framework as income. Although they are also period related, they have a different temporal position because they explain the rate of (new) income and their values aggregate dynamically into income in the same manner as income aggregates into wealth. Suppose a firm realizes net income at a rate of $12 per month, its 'level' of income momentum. Assuming nothing else changes, income realized after one year should be: $144 (Ijiri 1987, 27). At that time, income is reported as $144 while income momentum is reported as $12/month. The information added to the income statement is that we now know the rate by which new income is expected to be created, namely $12 per month. Assuming that this is the firm's first year of business, recalling the car driving metaphor discussed before, the odometer is now at $144 and the speedometer is at $12.

1.3.3 *Force accounting & the controller*

Wealth momentum is likely to change during the year and to be able to distinguish between changes for better or worse, as well as to identify the causes of such changes, Ijiri proposes a

[15] Among the many alternative representations of the accounting system, e.g. as an *events based* model (Johnson 1970, Lieberman & Whinston 1975), as an *entity relationship* model (Dunn & McCarthy 1997, Geerts & McCarthy 1997, 1999, 2002, McCarthy 1979, 1982), as a *composition of equations* (Vousten-Sweere & Groenendaal 1999), as a *formal logic* model (DePree 1989), as *transaction logic* model (Eaves 1966), as a *network* model (Mattessich 1958), as a *vector* model (Deguchi & Nakano 1986), as a *mechanical physics* model (Fischer & Braun 2003), as a *set theoretical* model (Mattessich & Balzar 2000), as a *stock & flow* model (Burstein 1982, Correa 1977, Patterson & Stephenson 1988) and as an *input-output* model (Richards 1960). It is the *matrix* model that suggests a two-dimensional geometric structure (Charnes *et al.* 1972, Faux 1966, Mattessich 1978). The accounting matrix can easily be made three dimensional with the introduction of a third axis to get a cubic suite of matrices (Ijiri 1988c). However, the matrix lay out itself, whether two or three dimensional, does not imply the introduction of accounting dimensions as such. Dull (1997) studied a three dimensional graphic solution to visualize momentum accounting.

[16] This is discussed in more detail in subsection 1.6.1, page 25.

third dimension of accounting measurements: *force*. In the rightmost column in FIGURE 1, we find successively from the top row of the framework: force, impulse and action. These measurements also aggregate vertically in the same manner as momentum does to income. The objective of these accounts is to measure the causes of any change of the earning power of the business model. Forces aggregate into an impulse at a single measurement of the period change (that could be a year, quarter month, week or day). *Forces* are either internal or external and when these add up to a net wealth increase, then the earning forces are obviously greater then the expensing forces (FIGURE 2). The converse leads naturally to a decrease of net wealth and when the forces balance net wealth will remain unchanged.

Given Ijiri's examples, in force accounting we should include any new information that determines the economic value added by the business model (Ijiri 1986, 758). For *internal forces*: investment, divestment, research & development, labor, production, marketing, financing; for *external forces*, competition, economic, government, international, natural, and, finally, *residual forces*. Force accounting stretches the scope of accounting widely into the domains of management accounting and strategic control. We should consider here also the changing role of the management accountant or controller as a facilitator of managerial decision making processes (Birkett 1998, Bots 2006, Otley 2003, Pierce & O'Dea 2003, Riedijk *et. al* 2002, Parker 2001, Ross 1997, Vaassen 2003). Force accounting might deliver, with more rigor, business information required by the controller in that changed role and possibly enable its standardization.[17]

1.3.4 Impulse & action accounting

It is the *impulse* that changes net income momentum and hence it aggregates horizontally in the TEMA framework into *momentum* (FIGURE 1). For example, when we launch a new product and then, as a result, for a certain period new income will be realized. We measure this as force times duration when the force is stable and aggregate it as an impulse together with all other forces that are recognized at that time. The impulse we add to the existing momentum. In the TEMA framework, impulses are aggregated vertically into *action* during a reporting period. Management is then able to separate income realized by existing momentum from the part that is realized by new momentum created during the current reporting period. Ijiri wants to reward management differently for maintaining existing momentum and for any action that they undertook to create momentum anew. In his view it is less difficult to realize income from existing momentum then from new momentum. For example, TEMA excludes variations in the return on investment due to writing down investments. Therefore, a managerial reward system should reflect the difference with existing momentum realized and encourage management to make best effort to create new momentum in their business. The ambition should be to overcome organizational inertia and accelerate the firm instead.

1.3.5 Illustration

Our explanation of the third accounting dimension is possibly somewhat enigmatic. The following example may help to understand. Let us assume that a firm signs a lease-contract with

[17] Nowadays the comparability of internal measurements between companies is limited due to the lack of any form of standardization. This is not to say that management accounting systems cannot be standardized. Certainly between companies of the same group this is regularly the case, but between companies such data can seldom be compared for lack of standardization. Force and momentum accounting derived from financial variables might offer a first opportunity to strive for such comparability.

monthly installments for a period of two years. Ijiri (1987) would recognize this economic event and account for it. In his view we should account that the 'expense momentum' has been increased monthly for the next two years due to the occurrence of this new 'expense force.' This way of thinking is comparable with the amortization of the asset investment.[18] The reasoning of Ijiri is that a 'historic' obligation to expense is as much a fact as is the 'historic' expense itself (once invoiced or paid).[19]

1.3.6 Other accounting analogies with physics

Nelson (1953) proposed the Momentum Theory of Goodwill in an article on the accounting for purchased goodwill. Nelson discusses 'commercial goodwill' that constitutes '...customer lists, organization costs, costs of development, trade names, secret processes, patents, copyrights, licenses, franchises, superior earning power, and going value.' In short, '...*goodwill*, ... refers to favorable attitudes toward an enterprise ... is about as fickle as the human nature of which it is an aspect ... it is hard to build up.' Therefore, '...the buyer of a [going] concern will often pay a large sum of money for ... he wants this starting "push" in his new enterprise.' Then, Nelson defines the Momentum Theory with '...the hypothesis that a businessman purchases a promotional push instead of an annuity and that the "push" dissipates like momentum.' But, momentum '...is not a continual, everlasting one, but ... a running start.' Momentum has to be '...fed in new energy to keep from slowing to a standstill. Thus arises the Momentum Theory which, it is hoped, will be distinguished from the Annuity Theory.'

Accounting for this '...superior earning power,' this momentum, Nelson recommends '...that the investment ought to be charged against income over the estimated life of the momentum, the period during which it will be contributing its "push" or benefit.' Hence, '...the amortization, ..., would be over a life of two to ten years' in contrast to 'the Annuity Theory [which] would call for a shorter life then [sic] the Momentum Theory hypothetically, since excess earnings would cease before all the "push" was dissipated.' In other words, according to Nelson, goodwill momentum related investments should not be written off by a charge directly to retained earnings nor by a charge to capital surplus because he sees them more as an asset that has earning power.[20] Nelson certainly premeditates Ijiri (1988, 164) with his position on the depreciation of momentum dissipation. Nelson is also aware of the subjectivity involved in estimating '...the life of the purchased momentum' because '...there could be no reliance on a table stating past experience on useful life.'[21] Another worrying issue for Nelson is how to account for discrepancies at the end of the estimated life of momentum.[22] Nelson's opinion is

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[18] This is very much like the *permanence* principle that is well known in double-entry bookkeeping and is closely associated with the idea behind *force* and *momentum accounting*. I am indebted to D. van der Kouwe AA who pointed this out to me.

[19] For the purpose of explaining the principles behind three-dimensional bookkeeping and momentum accounting I do not discuss issues related to financing and taxation. Unsurprisingly, these aspects do influence the capacity to increase or decrease net wealth. We focus here on aspects related to the operation of the company (and, hence, we will model operating income to explain net wealth momentum).

[20] Accounting for intangible assets, of which goodwill is an example, has become a field of its own in accounting research during the last decade of the previous century. This is driven by the recognition that the earning power of modern companies come mote from their intangible assets than their tangible assets. For more on the subject consult: Lev 1999, or in Dutch: Goldman & Hoogenboom 1998.

[21] Vaassen (2002, 33) is most concerned about this aspect of triple-entry bookkeeping and momentum accounting.

[22] Ijiri (1987, 32) is well aware of this problem and proposes to mitigate it with '...momentum reconcilia-

that '…the buyer's estimate of the life should be controlling, according to the Momentum Theory.' Nelson's Theory of Momentum is in agreement with similar considerations of Ijiri. Clearly, Nelson's theory is limited only to the issue of goodwill accounting and of little relevance for the accounting framework as a whole. As far as this author could determine Ijiri was not aware of Nelson's theory. However, the similarity in thinking between Ijiri and Nelson is cunning. Both strive to account for 'superior earning power' as a 'push' that 'dissipates' like 'momentum,' which requires '…new energy to keep from slowing to a standstill. (Id.)' Both construct theory from a dynamic forward-looking perspective based on mechanical physics in contrast with the conventional rear view perspective of accounting.

Salvary (1985, 22-23) draws, like Ijiri, an analogy with physics in his discussion of the accounting measurement unit. He sets:

- 'Miles Traveled = X(miles/hour) times Y hours,' equal to:
- 'Money Exchanged = X(Dollars/Commodity) times Y Commodities,' equal to:
- 'Value = Price times Physical Quantity.'

His imperative is: '…to recognize that **within a money economy** accounting is a valuation discipline that focuses on a money flow and not a physical flow, although the physical flow underlies the money flow' (Salvary 1985, 25). According to him: '…**the concept of distance** (a uni-dimension measure) as a measurable operation **is the measurement concept** underlying the monetary unit in accounting' (Id. 24). His conclusion is that, as goods and services are exchanged, the accounts administer their nominal value and as such become dimensionless as they account the product or service at market prices times physical volumes. The likeness between Salvary's approach and that of Ijiri's is that 'value' is set equal to the product of a rate times the amount of time passed.

Recently, a physics model of double-entry bookkeeping was proposed by Fischer & Braun (2003). They analyze bookkeeping from a mechanical viewpoint and compare money with momentum. They translate the accounting system '…to the physicist vocabulary of momentum, energy and force.' Fischer & Braun translate 'asset currency units' to positive momentum of particles in Feynman-diagrams.[23] Likewise, liabilities have negative momentum. There is some likeness between the approach of Fischer & Braun and that of Ijiri given the fact that they draw a parallel between the administration of financial transactions and the phenomena of particle physics. Noteworthy is their conclusion: 'We therefore see that the income statement is the time derivative of assets and liabilities.' Their work does underpin that accounting as an 'adaptive mechanism,' in the words of Salvary (1985, 1), is inspirational even for physicists to be modeled in their paradigm.[24] Fellingham & Schroeder (2006) demonstrate that double entry infor-

tion.' For more on such bookkeeping particulars consult, in Dutch: Blommaert (1994A).

[23] Feynman-diagrams are graphs to perform scattering calculations in quantum field theory invented by American physicist Richard Feynman without a concept of position, space or time aside from the distinction between incoming and outgoing lines.

[24] According to Kuhn (1970) such a cross-over between scientific disciplines can lead to a revolutionary change in our scientific view of the world we live in. See also Sterling & Bentz (1971) or Peasnell (1978) for a thorough discussion of Kuhn's ideas on the development of science and the state of accounting as a (pre-)scientific discipline. Hunton (2002) recommends such synergistic efforts: '…researchers in accounting information systems (AIS) and other areas of accounting, such as financial, auditing, tax and managerial, should work together on projects … such teamwork hold great potential to yield high-quality research results… .'

mation processing emerges naturally when interference is combined with quantum correlation or entanglement to produce a reduced set of potential performance measures. Their objective is to employ the same information signal as a performance for the two agents involved in the communication of financial information.

1.4 Advancement of TEMA

The methodology, accounting rules and procedures required to implement TEMA have been developed further through the research of Blommaert (1994A-B, 1995B), Blommaert & Blommaert (1990), Blommaert *et. al.* (1997) and Olders (1995). These publications describe in more detail the methodology of triple-entry bookkeeping; in particular Blommaert (1994A). Dull (1997) investigated in a laboratory experiment the relationship between visual representations of the output of a momentum accounting system and subjects' ability to make predictions (Dull & Tegarden 1999). Momentum data was simulated and graphics were rendered in various formats. Subjects made prediction decisions based on the graphics produced for four companies that were stratified based on size (high or low) and growth patterns (high or low). The subjects using the three-dimensional data that could be rotated were found to provide the most accurate predictions.[25]

Naturally, whenever time determined variables are under investigation, momentum accounting can be extended to any other accounting, economic or business application area. Momentum accounting has been applied by Ijiri and his co-researchers for brand accounting (Farquhar *et al.* 1992A, B) and brand management (Farquhar & Ijiri 1993). Erdem *et al.* (1999) also extend momentum accounting to brand equity measurement. Larreche (2008) demonstrates business cases of profitable growth and presents a comprehensive investagtion of the driving phenomena he calls the *momentum effect* in marketing and business strategy. The momentum effect is, under specific conditions, the '...self-fueling characteristic of growth ... that leads us to call it *momentum growth* and to use the word *exceptional*...' (Id. XXI, 282). Although he is not aware of Ijiri's theory there are several parallels in his reasoning. Like Ijiri, his focus is on *value creation* and takes an 'entire process' perspective, very similar to Ijiri's force analysis (1986, 758). Furthermore, Larreche argues that '...the notion of "momentum" has permeated all spheres of society ...' and '... is defined as the mass of an object multiplied by its velocity ... adopted in common language to convey the idea of an intangible force that boosts performance and leads to repeated successes...' (Id. 281). Larreche points at the need to design a product or service so appealing to the market that it can create momentum (an internal force in Ijiri's view) almost all by itself. This he calls *momentum design* that has carefully to be managed by *momentum execution* to be realized. Interestingly, Larreche also takes stock of financial, functional, emotional and intangible *equity*, economic value or *wealth*, in Ijiri's terminology. But he fails to incorporate his framework and concepts into a structured measurement system like the TEMA framework of Ijiri.

Another example of the advancement of the momentum concept by Ijiri himself is for revenue accounting in an e-business setting (Glover & Ijiri 2002). Preiss & Ray (2000A-B) applied triple-entry accounting to money velocity accounting in time-based costing as a tool for

[25] The axes of this experiments' visualization measured wealth, momentum and impulse by time (x) against value (y) in two-dimensional graphs. The three-dimensional graphs had momentum added as the z-axis and its lines color coded by the impulse of each point in time.

operational and strategic decision making in a dynamic business environment. Recently, Ijiri & Lin (2006) proposed a symmetric accounting equation with two new types of information elements: present and (expected) future *goods* and *bads*, respectively resources that are of positive value or detrimental, to firms. Another line of investigation is the balance sheet of *facts* and *forecasts* to disclose the level of certainty of contained in accounting information (Levine & Ijiri 2004).

Financial analysts frequently think in terms of *momentum*, i.e. positive auto correlation, and about how earnings momentum and price momentum are related (e.g. Asness 1997, Chan *et al.*2004, Chordia & Shivakumar 2006, Griffin *et al.* 2003, Grundy & Martin 2001, Ivanova & Wille 2002, Lui *et al.* 1999), as do analysts in insurance companies (e.g. Lane & Beckwith 2003, 71). Besides financial disciplines, the notion of momentum is also used in marketing (De Moranges & van Riel 2003, 524), sociology (Kopponen 2002), human resource management and organizational development (e.g. Jansen 2004, Kelly & Amburgey 1991, Nevin 2002, Pollitt 2002). From this, I conclude that momentum as a concept of business dynamics is well accepted in organizational, financial and economic theory.

1.5 Value creation, measurement & management

In this section Ijiri's theory is discussed from the perspective of value creation, measurement and management. Value-creation models and value-based management systems have grasped the attention of basically each and every professional in the financial disciplines since the late 1980s (Ashton 2007). It involves the search for alternative metrics, models and systems for management accounting, financial management and compensation—usually phrased as value-based management or VBM in short (Black *et al.* 1998, Martin & Petty 2000, Peterson & Peterson 1996, Prahalad 1993, Rappaport 1986, Young & O'Byrne 2001). Although the scope of VBM reaches beyond this thesis, it is appropriate to compare it with the TEMA framework because they have a similar objective: advancement in performance measurement. Also, in the economic value literature some research findings pertain to the methodological approach of this thesis. TEMA offers a multi-period ex ante perspective on performance measurement. On the other hand, VBM measurements, notably Economic Value Added, or EVA in short, are single-period and ex post. TEMA measurements of the change of value drivers—called *forces*—enable dynamic econometric models, such as presented in this thesis. Another important distinction is that with TEMA we can determine the *expected change* in EVA or any other economic value variable. Therefore, I think of TEMA as a forward-looking performance measurement system.

1.5.1 Relevance lost

Accounting-based performance measures are used in different formats for financial management and management accounting purposes like the valuation of acquisitions or capital projects, setting performance targets and their measurement, as well as the determination of bonuses for management (Hanlon & Peasnell 1998). Nevertheless, inconsistent accounting standards, goals and terminology have resulted in procedures that were heavily criticized by many for a lack of relevance of accounting information, in particular financial statements (e.g. Ashton 2007, 17, Rappaport 1986, 44). Empirical evidence against this position was provided (e.g. Collins *et al.* 1997) whereas other studies confirm the decrease of value relevance (e.g. Lev & Zarowin 1999. For earnings, see: Goodwin & Ahmed 2006).

The publication of *Relevance lost. The rise and fall of management accounting* was cata-

clysmic for the status of management accounting systems as Johnson & Kaplan argued that these are designed primarily to compile costs for periodic financial statements instead of (strategic) control levers for value creation (Johnson & Kaplan 1987, 255). They also observed, that the role of short-term financial performance measurement itself was in general being '...undermined by the rapid changes in technology, shortened product life cycles, and innovations in the organization of production operations.' As a consequence, they argued that '...short-term financial measures have become invalid indicators of the recent performance of the enterprise.' Moreover, they advocated that the financial accounting system alone is no longer a sufficient source of information for the management of daily operations and thus also cannot facilitate strategic or financial management decisions. The alternative they offered at that time was to identify, measure, manage and report a variety of *non-financial indicators* that should '...be based on the company's strategy and include key measures of manufacturing, marketing and R&D success' and disclose value added' (Id. 187). This was further developed into a performance measurement system that became known as the 'Balanced Scorecard' (e.g. Kaplan & Norton 1996, 2001A-B).

1.5.2 Relevance recovered

Since then, many have researched the 'informational relevance' of both financial and non-financial performance measurements and several alternative models were proposed. Ashton (2007, 25) distinguishes between them: measurement and valuation approaches. In the *measurement approach* the focus is on the 'underlying dimensions of performance' which allows measurements to have a variety of units (like currency, scores, rates, percentages, time, etc.). Examples of these, among others, discussed by Ashton (Ib.) are: Deming's Chain Reaction, the Baldridge Performance Excellence Model, Heskett's Service-Profit Chain, as well as Kaplan & Norton's Balanced Scorecard and Strategy Map. The disaggregated measurements of these models should enable the determination of causal chains that link fundamental value drivers with financial outcomes. In the *valuation approach* the focus is on aggregated financial outcomes restricted to measurements in a monetary unit. Much of the debate here centers on the question how to value the *intangibles* or *intellectual capital* of firm, i.e. capital that is not accounted for with the balance sheet. The objective of *fundamental analysis* is the study of a firm's current activities and future prospects to estimate its *market value* incorporating the *book value* of assets and the *present value of expected profit*.[26]

1.5.3 Value drivers

The most critical issue of any value-creation model for management purposes, in the opinion of Ashton (2007, 27), is: '... the extent to which it embodies chains of cause-and-effect relationships that link measures of intangible value drivers to each other and, ultimately, to financial outcomes such as profit, cash and share return.' The Skandia Business Navigator, which shows a strong resemblance with the Balanced Scorecard, has a related framework of a chain of leading and lagging indicators of economic success, which includes both financial and non-financial capital (Figure 3). The Balanced Scorecard has four perspectives that are causally linked from the Learning and Growth Perspective, to the Internal Perspective and the Customer Perspective,

[26] For the combination of earnings and book value accounting information in equity valuation models and fundamental analysis see: Feltham & Ohlson 1995, Morton & Neill 2001, Penman 1998 and Ohlson 2001. See: Amir *et al.* 2003, Hurwitz *et al.* 2002, Aboody & Lev 1998 and Gu & Wang 2005 for intangibles in such approaches. For an economic view on the subject see: Goldfinger 1997.

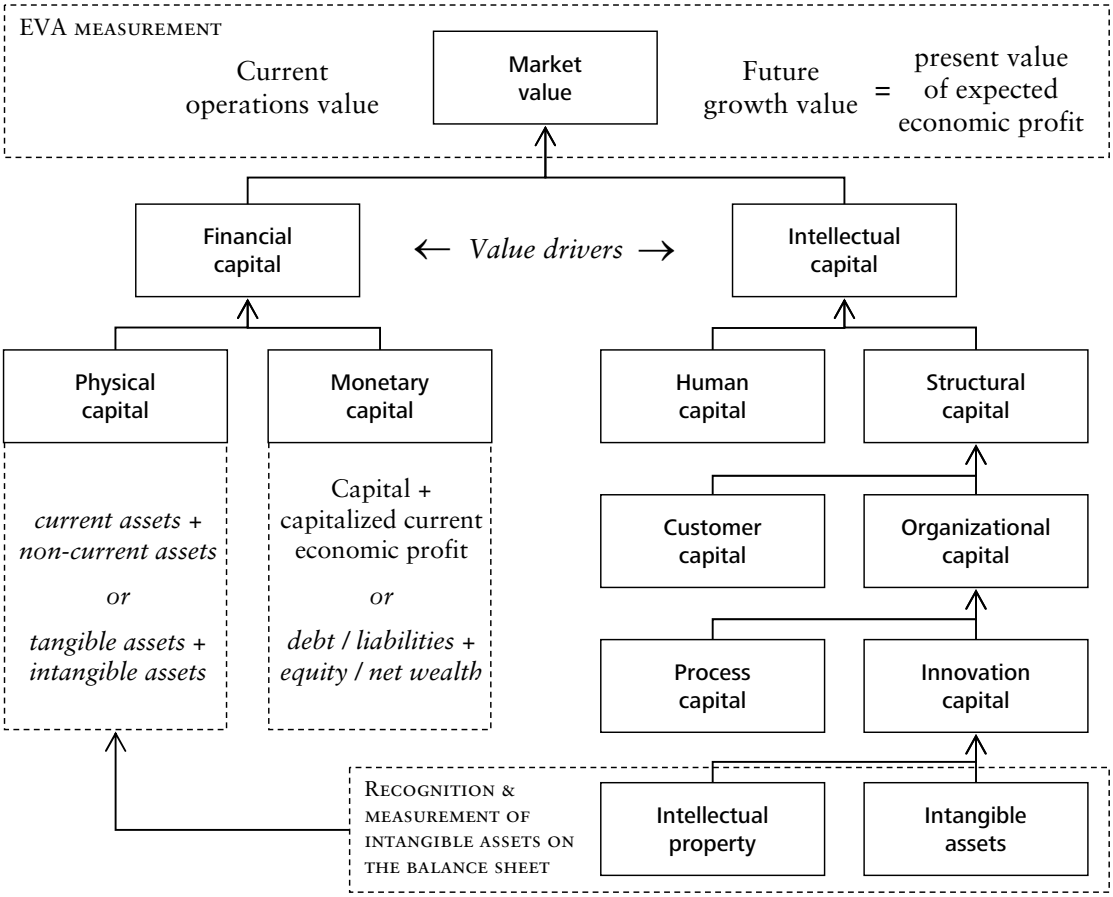

Figure 3 Skandia Value Scheme with the measurement of EVA and intangible assets indicated.
Source: Adapted from Ashton (2007) & Edvinsson (1997).

which in their turn link, finally, to the Financial Perspective. The Skandia Business Navigator incorporates in its center a 5th perspective: human focus.[27] At the top of the model we find the *market value* of a public firm (i.e. listed on a stock exchange). Ashton (2007, 17) reports that the original goal of Skandia was to communicate to the outside world, i.e. the capital markets, the 'hidden value' of the firm by creating metrics on intellectual capital .[28] The *value drivers* embody the conceptual overlap of the measurement and the valuation approach, indicated in Figure 3 in between *financial capital* and *intellectual capital*, or financial wealth and intellectual wealth as Ijiri would call it. Financial capital branches out to the two sides of the balance sheet: *physical capital* and *monetary capital*, or assets and debt with equity (or net wealth as Ijiri would call it). Since long, many have noted that the balance sheet does not reflect the *current value* of a firm. To explain the market value of a public firm, an informed opinion has to be made of the value of its intellectual capital that itself branches out into *human capital* and *structural capital* (i.e. internal to the firm: processes, procedures, databases; and external to the firm: supply chains, partnerships & alliances, etc.). In its turn, structural capital branches out into *customer capital* and *organizational capital*, which is made up of *process capital* and *innovation capital*. Finally, at the lowest breakdown level, we find *intellectual property* and

[27] Note that these perspectives developed over time and went to various versions with different classifications of subject categories and key roles of value creating processes (Ashton 2007, 17-24).

[28] The Skandia annual financial statements included from 1994 to 1998 intellectual capital supplements on various aspects of their framework and can be downloaded from: http://www.skandia.com.

intangible assets in the skandia value scheme.

The conceptual distinction between the value drivers financial and intellectual capital of the original skandia Business Navigator is these days not so clear anymore. The growing interest in the accountability of intangible assets has resulted in various efforts to include on the balance sheet intellectual property and other intangible assets (Eckstein 2004, Lev 1999, 2001, 2002). The capitalization of these hitherto unrecognized assets is indicated at the bottom of FIGURE 3 by a dashed box and line to *physical capital* (assets). Based on empirical research, Kanodia *et al.* (2004, 216) argue that intangibles should only be measured '...when their relative importance in constituting the firm's capital stock is high and when they can be measured with sufficiently high precision.'[29] On the other hand, Gu & Wang (2005) report that financial analysts' forecast errors tend to increase for firm's *intangible intensity* that deviates from the industry norm and are even greater for firms with diverse and innovative technologies. Such errors are smaller with firms that are subject to intangibles-related regulation like biotechnology, pharmaceutical and medical equipment firms.

Using their so-called *value-based management accounting framework*, Ittner & Larcker (2001) reviewed existing empirical research in managerial accounting of six basic steps they see fundamental to increase shareholder value.[30] They observed '...the lack of integration between financial and managerial accounting research. With the possible exception of compensation studies, accounting researchers have treated these fields as independent, even though it is likely that these choices do not stand alone' (Ib. 402). Furthermore, they emphasize that '...the value-based management literature argues that the value driver analysis should not only influence the choice of action plans and the design of control systems, but should also affect external disclosure requirements...' (e.g. Black *et al.* 1998). Moreover, they conclude that '...without greater integration of financial and managerial accounting research, our understanding of the choice and performance implications of internal and external accounting and control systems is far from complete.' It is remarkable that, after all the effort to mitigate the limitations of financial accounting based performance measurements for management accounting purposes, the alternative system that Ittner & Larcker (2001) recommend should entail both fields.

1.5.4 A dynamic view

How should the integrated accounting model serve both internal and external purposes as well as provide data for the fundamental analysis of firm value? Ashton (2007, 27) sees that the principal goal of value-creation models is '...to support management activities aimed at long-run shareholder value creation.' This is accomplished:

1. '... through guiding the identification and measurement of tangible and intangible value drivers,' which to some extent depends on how
2. '... these value-creation models take a dynamic, or whole-system, view of value creation,'
3. and '...whether multiple value drivers should be explicitly weighted and combined to form a "value index".'

[29] The analysis of the balance sheet of 3M, in Chapter 6 of this study, shows the structural change and persistence due to the inclusion of intangible's in 'deposits & other assets' from the year 2000.

[30] Abbreviated, respectively: (1) identification of organizational objectives, (2) develop strategies & select organizational design, (3) identify value drivers, (4) development of action plans, measures selection & target setting, (5) performance evaluation, and (6) assessment of the ongoing validity of (1)-(5) and their modification (Ittner & Larcker 2001, 353).

He discusses these three issues at some length and points out that to resolve the first issue: '...causal relationships could be estimated statistically ... or could be estimated subjectively based on careful reasoning by knowledgeable managers and others.' To circumvent the risk of oversimplification that a *static view* of the process of value-creation tends to have, he recommends resolving the second issue by exploring the patterns that a *dynamic view* might disclose. Multiple causes could produce multiple effects '...via sets of causal relationships in which effects feed back to influence causes ... [to] affect other causes in an ongoing process.' Ittner & Larcker (2001, 401) think that the designated methodology to deal with the fabric of such a network of linkages and dynamics is offered by System Dynamics, originally proposed by Forrester (1961, see also: Richardson 1991, 1996, Roberts 1978, and Sterman 2000). Indeed, it is possible to simulate the financial accounting system with a System Dynamics model (Melse 2006). It is the third issue that still poses the largest challenge in Ashton's eyes (2007, 33): '...explicitly weighting and combining ... measures into a single metric—whether monetary as in Economic Value Added, or non-monetary as in the Intellectual Capital Index—would likely result in the kinds of criticisms leveled at *traditional* [sic] composite metrics, for example, earnings per share.'[31]

1.5.5 The measurement of economic value

The purpose of VBM is to provide an integrated management strategy and financial control system designed to mitigate agency conflicts between shareholders and managers of the public firm and to increase shareholder value (Ryan & Trahan, 2007). This is accomplished by providing managers '...with a set of decision-making tools (metrics) that, at least in theory, identify which alternatives create or destroy value (Id. 113)' Four variations of VBM metrics of single-period measurements of performance are usually identified that take into account return of invested capital and the cost of capital (Ryan & Trahan 1999, 2007, 113-4):

1. Discounted cash flow—DCF in short.
   Expresses value as expected future cash flows discounted to the present time at the cost of capital of the firm (see: Rappaport 1986, 1998).
2. Cash flow return on investment—CFROI in short.
   Expresses value as an estimate of a firm's single-period cash flow as a percentage of total investment (see: Black *et al.* 1998, 56-68, Madden 1999).
3. Return on invested capital—ROIC in short.
   Expresses value as the ratio of net operating profits less adjusted taxes (NOPLAT) to invested capital (see: Koller *et al.* 2005).
4. Residual income—RI in short.
   Expresses value as the excess earnings over a capital charge based on investment opportunities of similar risk (see: Wallace 1997).
   Also known under the market name of Economic Value Added—EVA in short.

Malmi & Ikäheimo (2003) discuss various applications of VBM for capital budgeting, valuation, management control and incentive compensation. Richardson & Tinaikar (2004) survey empirical evidence on RI models to explain or forecast firm value. Ryan & Trahan (2007, 136) report that residual income improves considerably following the adoption of VBM. However, they also report that '...no one component of residual income (after tax operating profit, invested capital or cost of capital) drives the result' of their analysis of 84 adoptions of

[31] In Chapter 3, I compare the informational value of return on equity (ROE), return on total assets (ROTA) and net wealth momentum with the common size ratio of net wealth momentum.

VBM systems '...but rather all three components appear to be working together.' The growing application of value-based concepts is also reported in other fields, like operations and maintenance performance management (e.g. Liyanage & Kumar 2003). For an integrated approach through EVA to manage human capital, customer capital and supplier capital, like the skandia Business Navigator, see: Strack & Villis (2002).

Much of the VBM literature is devoted to residual-income-based performance measures, like EVA that is discussed below, for compensation purposes (e.g. O'Byrne & Young 2005, 2006A-B, Ryan & Trahan 1999, Wallace 1997). These might be based on only one of the four variations of value-based management metrics but incentive plans usually involve both financial and non-financial measures (Ashton 2007, 39-49). Although VBM metrics are designed to measure 'value added' objectively, bonus schemes based solely on profits or other financial accounting numbers have been criticized because managers tend to sacrifice long-term performance to improve short-term financial results in an effort to maximize their enumeration (Ittner *et al.* 2003). Moers (2005) studied the effect of subjectivity in the weighting of multiple performance measures at one firm for one year and observed that '...performance measure diversity leads to more lenient performance ratings and less differentiation among employees.' The implication is that when 'balanced' value-based management metrics are used, performance evaluation tends to become more biased if the superior has discretion in weighting these measures, according to Moers (2005, 79).

1.5.6 EVA®

In this section, I discuss the corporate financial management system that is known as Economic value Added — EVA in short. EVA was developed and trademarked by the New York consulting firm Stern Stewart & Co. (Bouwens & Lent 2003, Stern *et al.* 1995, Stewart 1991, 1994).[32] The EVA system is designed to provide a single value-based measure which can be used to value acquisitions, to evaluate business strategies and capital projects, but also to set managerial performance targets, measure performance and determine management bonuses (Blij & Dekker 1999, O'Hanlon & Peasnell 1998). Both EVA and TEMA share the objective of fair performance evaluation (O'Byrne & Young 2005, 2006A-B). Ijiri (1988A, 162) states that '...managerial goals have been overwhelmingly centered on income as evidenced by numerous income-based incentive compensation plans ... in the form of bonuses, promotions and salary raises...' Management incentive plans, in his opinion, should be based on action taken by management to maintain and increase momentum. But the use of financial accounting information to this purpose, as already discussed, no longer suffices in the opinion of many. Stewart (1991, 32), in a section titled 'Burn the Books' phrases it as follows:

> *'In the economic model, the value of a company is an ever unfolding journey for its cash, not one-night stands that voyeuristic accountants can take snapshots of. The book value of assets simply is not an accurate picture of the value of a business, and it should not be construed to that purpose. A company's book value should be used only to measure its capital, which, simply put, is the cash deposited in a company over its life, much like a savings account.'*

Stewart's Götterdämmerung of 'voyeuristic accountants' originates from his idea that '...a company's balance sheet can at best be a measure of "capital"—that is, the amount of cash deposited by (debt as well as equity) investors in the company (Id.).' Stewart's problem with

[32] See: http://www.sternstewart.com, EVA® is registered trademark of Stern Stewart & Co.

that is that it is in his opinion not possible to determine from financial accounts '...whether such capital translates into value (Id.).' It depends on '...management's success in earning a high enough discounted cash flow rate of return on that capital...' and it is left to the judgment of the *stock market* whether that is the case or not.

Stern concludes in the preface of Stewart (1991, XIX) that the principal implication for firm valuation is that '...a firm's value is based on the timing and risk of future cash receipts and disbursements...' and '...for the purpose of valuation there really are no such things as a balance sheet and an income statement.'[33] Stern is '...thoroughly convinced [that this] means ... that bookkeeping entries that have no effect on cash have no effect on value.' He then continues with some examples to underpin that the financial accounting system can distort the true value of a firm. He argues that some of the '...most important assets are ... recorded as liabilities...' and provides some examples: unearned income items, magazine subscriptions payable and advanced billings net. He mentions two firms, Time-Warner and Pitney Bowes, that are able to semi permanently finance their operation on related cash receipts to the amount of hundreds of millions of dollars.[34] Stern concludes that, for as long as the backlog of business does not shrink in size, such 'liabilities' continue indefinitely as a cash resource. In contrast, the accounting model '...records these cash benefits as revenues only sometime in the future as taxable income' and thus this practice makes no sense if free cash flow is the measure of value. Stern Stewart & Co. went about to make over 120 changes of conventional Generally Accepted Accounting Principles (GAAP) to arrive at a proper EVA calculation (O'Hanlon & Peasnell 1998, 429).[35] However, these were not all published whereas typically only about ten of them are sufficient for most companies. The adjustments are intended to ensure that book capital reflects the full cost of investment in operating assets.[36]

1.5.7 TEMA, VBM & EVA®

The effort of Ijiri, in contrast to EVA, is to devise an accounting measurement system that discloses the long-run firm benefits of management actions and that are as reliable as income figures (Ijiri 1988A, 163). Rather then to 'burn the books' his focus is on the structural design of the accounting system as a whole. Instead of discarding bookkeeping, or 'tweaking' GAAP, he proposes an *extension* of the accounting system with a third dimension: force. His TEMA framework is consistent with GAAP although new rules are required for triple-entry bookkeeping (Blommaert 1994A). Neither VBM nor EVA conflict with the financial accounting system. On the contrary, the objective of VBM or EVA could very well be furnished by the TEMA framework because, in principle, it can administer most of the future earning and expensing forces that determine momentum of income or earning power.[37] Such 'facts' are accounted *today* but

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[33] While discussing Miller & Modigliani (1961).

[34] Amazon is known to have financed its growth with credit card receipts from its customers while purchased goods where still in the delivery process and thus not yet paid for by Amazon.

[35] GAAP is the standard framework of guidelines for financial accounting, mainly used in the United States of America. It includes the standards, conventions, and rules accountants follow in recording and summarizing transactions, and in the preparation of financial statements (http://en.wikipedia.org). Other literature refers to more than 160 changes (e.g. Bouwens & Lent 2003, 11-13).

[36] In the next section where criticisms of momentum accounting are discussed it is mentioned that the required administrative effort is a serious limitation. It should be noted that the EVA based financial management certainly requires a comparible effort both conceptually as in administration.

[37] I discussed in section 1.3 that the TEMA framework, like VBM, seeks to administers facts that are

expected *tomorrow*. We can establish the *expected change* in any accounting variable. To which extent such administration is worthwhile and sufficiently reliable very much depends on a cost-benefit analysis in each case.

Value creation as defined by VBM is factually the realisation of a change of income momentum during a certain period. With VBM or EVA this is disclosed *ex post* and we speak of value creation when income momentum has increased. With TEMA, in contrast, we measure continuously and this implies that any change of income momentum is observed instantaneously and we can administer it *ex ante*. In a 'perfect world' both measurement systems should give the same result for a given period. TEMA and EVA have a similar vision and approach. I think of TEMA as a *real-time* forward-looking performance measurement system. But, to summarize with the words of Stewart (1991, 1), '...nothing less than a revolution in thinking is called for...' to have such an accounting information system implemented.

1.5.8 EVA® *calculation*

In basic terms, EVA is the excess return of the cost of capital, EVA improvement and the changes in investor expectations of future EVA improvement (O'Byrne 1997, Bouwens & Lent 2003). O'Hanlon & Peasnell (1998) discuss in depth the formal features of the calculation of EVA. The focus of EVA calculation is on the value equivalence of accounting and cash flow measurements to arrive at the accounting profit P_t for period t, computed on a 'comprehensive income,' 'clean surplus' or 'abnormal earnings' basis. This implies that all adjustments in book value during period t are included, except for transactions with owners:

(1) $$\mathsf{P}_t = \mathsf{C}_t + (\mathsf{A}_t - \mathsf{A}_{t-1}) \qquad \text{with } t=1, \ldots, T,$$

where C_t is the cash paid to (net of contributions by) owners for period t and A_t is the accounting book value of net assets at time t. According to O'Hanlon & Peasnell, EQUATION (1) is sufficiently general to calculate the proprietary concept of profit, viewed from the equity shareholders' perspective, and the entity concept of profit as defined by Stern Stewart. They continue with the definition of residual income (RI) as the accounting profit for period t, denoted as X_t, minus a capital charge based on the net assets employed with:

(2) RI, $$\mathsf{X}_t = \mathsf{P}_t - k\mathsf{A}_{t-1} \qquad \text{with } t=1, \ldots, T,$$

where k is assumed to be the constant cost of capital during the period.[38] Next, they define the expression of the economic value of an entity with a finite life when it is liquidated at time $t+T$, denoted as V_t, from the first book value and the sum of RI of each period as:

(3) $$\mathsf{V}_t = \mathsf{A}_t + \left(\sum_{\tau=1}^{\tau=\infty} ((\mathsf{X}_{t+\tau})/(1+k)^{\tau})\right) \qquad \text{with } t=1, \ldots, T.$$

O'Hanlon & Peasnell (Id. 424) note that EQUATION (3) holds for any accounting procedure that follows the clean surplus relationship. Bernard (1995, 745) refers to Feltham & Ohlson (1995) and concludes that the clean surplus equation is identical to EVA. Accounting conservatism (against which Stern Stewart raised their objections) adjusts the relative magnitudes of the two terms on the right hand side of EQUATION (3) by under estimating book value at time t and over estimating subsequent RI's (O'Hanlon & Peasnell, Id. 424). Also, different methods of

'known' and have effects on firm value in the future. Therefore, like VBM or EVA, momentum accounting implies an integrated perspective on information and, therefore, to distinguish between 'management' and 'financial' accounting becomes much less relevant.

[38] O'Hanlon & Peasnell (1998) note that this is not essential but it simplifies the equation.

accounting give different periodic measures of book value and earnings (Barker 2001, 185, Peterson & Peterson 1996, 17). Earnings might differ across periods as a result of the accounting method used, even though the sum of present values of earnings remains the same. Thus, Stern Stewart's approach to the valuation issue involves the adjustment of A_t and relabels X_t (RI) into EVA (for an extensive discussion see also: Biddle *et al.* 1997, 307). Consequently, EQUATION (3) becomes:

(4) EVA, $$V_t = A_t + (\sum_{\tau=1}^{\tau=\infty}((\text{EVA}_{t+\tau})/(1+k)^{\tau}) \quad \text{with } t=1, \ldots, T.$$

According to O'Hanlon & Peasnell (Id. 425) '...the crucial difference between economic value and book value is in the timing of the recognition of gains and losses...' and they point out that '...the excess of economic value over book value is commonly referred to as the entity's unrecorded goodwill.' EQUATION (4) provides a formal statement of that unrecorded goodwill as the present value of the future EVA's. Finally, Stern Stewart see the market as the arbiter of business success and this implies that '...the creation of economic value by business units must ultimately result in higher market values for the equity and debt claims on the business as a whole' (Id.). Stern Stewart call the difference between the market value of a firm over invested capital Market Value Added — MVA in short — and is formalized as:

(5) $$\text{MVA}_t = V_t - A_t = (\sum_{\tau=1}^{\tau=\infty}((\text{EVA}_{t+\tau})/(1+k)^{\tau}) \quad \text{with } t=1, \ldots, T.$$

The EVA model facilitates the necessary adjustments to reported financial statements data to create a '...superior measure of abnormal earnings...' (Id.). Barker (2001, 185) points out that '...the method of accounting underpinning EVA must give greater economic meaning to annual book values and earnings than would otherwise be the case...' and '...the EVA model must generate a measure of return on equity that can be more meaningfully compared with the cost of capital.' He continues by stating '...this possibility is of considerable practical importance ... because historic performance is used as a basis from which to forecast future performance, and forecasts for the near future feed directly into estimates of terminal value' (Id. 185-6). In this study, I approach financial statements data in the same manner but, instead, I develop dynamic TEMA models to forecast future net wealth positions of the component companies of the DOW and the AEX stock index.

1.5.9 EVA® *& valuation*

Barker (2001, 186-7) underpins the importance of MVA and EVA for firm valuation. MVA is used to mean goodwill in the special case where abnormal earnings is defined using the EVA model. Therefore, MVA is the sum of the present values of EVA. It includes all future cash flows since EVA is calculated using capitalized costs with book value measuring invested capital. But note that EVA does not measure changes in MVA like accounting earnings do not measure changes in goodwill. Barker concludes that both EVA and accounting earnings are historic measurements that record realized performance. In his opinion, EVA is not really a measure of economic value-added at all but he thinks also that '...this is probably a good thing, because EVA is attempting to measure economic performance in the period it occurred, rather than anticipating future performance.' Barker believes that this is more useful to analysts because they use '...historic performance measures to, first understand the accuracy of forecasts for the period and, second, to extrapolate this performance into future periods.' It is exactly that what this study strives to accomplish but with dynamic TEMA models not of EVA but of operating income and total wealth. This study seeks to find evidence with examples that the TEMA

framework facilitates the disclosure of the earning power of a firm as its primary measure of business success. The growth rate of net wealth is what Ijiri wants to measure. Wealth and operating income are used here to test empirically whether or not the TEMA framework yields superior measures of economic performance.

1.5.10 The explanatory power of EVA®

In the literature substantial attention was given to the explanatory power of EVA and shareholder return, or EVA and market value (e.g. Barker 2001, Malmi & Ikäheimo 2003). Biddle *et al.* (1997) tested the relationship between share prices and several earnings calculations like residual income and cash flow from operations as well as EVA and its decomposed components. Across a range of statistical tests, to determine the relative and incremental information content of the various measurements, they find that *changes* in share prices (a momentum measurement) and *absolute levels* of share prices (a wealth measurement) both are marginally better explained by earnings than by other variables, including EVA. Biddle *et al.* (1997, 302) thus are highly critical of EVA and in particular the claim of Stewart (1994, 75) that '...EVA is almost 50% better than its closest accounting-based competitor in explaining changes in shareholder wealth.' They conclude that '...although for some firms EVA may be an effective tool for internal decision making, performance measurement and incentive compensation, it does not dominate earnings in its association with stock market returns' for the sample' of 6,174 firm-year observations during 1983-1994, for 773 firms of the Stern Stewart & Co. database (Biddle *et al.* 1997, 311).[39]

Peterson & Peterson (1996, 45) found in their study for the years 1988-1992 of, on average 269 NYSE listed firms, that market-value-added rankings are biased toward large firms: '...adding 1$ million in value is easier for large firms than for small firms' even when adjustments are made to reduce this bias. They argue that market-value-added measurements do not provide information above that offered by stock returns (Id. 47). Those '...do not depend on accounting book values of capital...' and '...can be calculated for any interval of time and do not rely on the use of accounting values, which are made available at specific intervals of time (e.g. quarterly).'[40] Moreover, they are concerned that when market-value-added is calculated using values from all sources of capital this will be sensitive to changes in yields of firm capital. To focus on '...the market value of equity, and hence on stock returns' does not solve the problem completely as 'stock prices are also affected by market yields.' Still, Peterson & Peterson (Id.) have the opinion that '...if the objective of the management of a firm is to maximize the value of equity, then stock returns, adjusted for market movements and risk, are superior to market-value-added measures in evaluating a firm's overall performance.'

O'Byrne (1997) is a response to the criticisms raised by these authors against EVA and a third critical empirical study: Olson (1996). All report poor statistical relationships of EVA and shareholder return of market value. O'Byrne's reaction is primarily methodological. To circumvent size bias he applies log normal transformation of the capital term. Next, he distinguishes in his EVA models two terms: one for positive EVA (increases) and one for negative EVA (decrea-

[39] Biddle *et al.* (1997) mention the difficulties involved with testing the explanatory power of EVA due to the fact that it requires data at a level of detail only available to Stern Stewart on the individual adjustments required for the calculation of EVA. See also: Peterson & Peterson (1996, 25).

[40] The subject of disclosure intervals and time in force and momentum models is discussed in section 1.9.4, page 38.

ses). Thus O'Byrne applies *directional change analysis* which is also a methodology to study the association between the change dynamics of momentum and force variables.[41] Next, O'Byrne calculates EVA and market value changes as a *fraction* of beginning values to arrive at '...equal percentage errors rather than equal dollar errors' (Id. 51).[42] Again, this is a method well suited to study the change dynamics of momentum and force variables.[43] O'Byrne posits that EVA-*changes* explain significantly more of the variation in market value changes than NOPAT changes do (reporting variance explained (R^2) of 55% over 24% for a five years period). The explanation that O'Byrne offers for his result is that investors put a much higher multiple on positive EVA then on negative EVA and hence EVA models explain better when these two directional variables are incorporated.[44]

Peterson & Peterson (1996, 47) in their 'EVA-critical' study also found that force measurements have explanatory power: '...the change in market value added is correlated with stock returns.' However, they are not convinced that '...from the perspective of an analyst ... value-added measures add value...' for reasons already discussed above. Nevertheless, the fact that both O'Byrne (1997) and Peterson & Peterson (1996) report the presence of explanatory power in their models with *force* variables, i.e. the *change of momentum*, is of interest to this study. It indicates that models with differenced financial accounting variables might be superior to those with undifferenced variables. Indeed, such variables enable dynamic econometric models, as presented in various chapters of this thesis.

1.5.11 EVA® *& the* TEMA *framework*

The principle logic of valuation with MVA and EVA applies in a similar fashion to Ijiri's proposed three-dimensional accounting system. For example, when a multi-period contract is signed with future earnings (and regular payments) this will be accounted in the TEMA framework (Blommaert 1994A). Although traditional business accounting systems ignore such transactions, when the news of these 'events' is released through an ad-hoc or press release, capital markets could (and usually do) respond to this change in expected future wealth. A firm's stock may go up or down, that is then a matter of market judgment. Consequently, the company's market value will differ from its book value. The reconciliation between book and market values in momentum accounting was discussed by Ijiri (1981, 1987). In a momentum accounting information system all of such forces with future bearings are known and accounted using the TEMA framework. It should then be possible to determine and account all the future (residual) earnings and arrive at the expected (market) value of the firm (Dull 1997, 19). Where analysts currently strive to 'guestimate' the *market value* of a firm through fundamental analysis, TEMA accounting could seriously simplify that effort with the additional disclosure of all known (and auditable) facts pertaining to the growth of future value (Blommaert 1994A). Having said that, the question can be raised why Ijiri's TEMA accounting information system is not commonly used. There are indeed criticisms and these are discussed in the next section 1.6.

Methodological similarities were identified in this section between the TEMA framework

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[41] Directional change analysis is applied in Chapter 5, 7 and 8 of this thesis.

[42] This has the statistical advantage that such errors are much closer to a normal distribution.

[43] In this thesis it is applied to develop the common size momentum ratio in Chapter 3.

[44] Directional variables are useful in a static regression model. For time series analysis it suffices to use only the momentum or the force variable (that have directional data). In a dynamic regression model these variables incorporate directional changes over time. More on this subject in the following chapter.

and the EVA metrics framework. More specific, EVA is a momentum calculation because it employs period measurements but these are used only for static 'single-period' metrics that can be extrapolated to forecast economic performance. The TEMA framework, in contrast, enables dynamic multi-period models and this thesis will show that these have explanatory as well as predictive power for that reason. I will make forecasts for several quarters at the company level and of an aggregated market value index: the DOW. Value-based metrics, therefore, need not be limited to a single-period measurement but dynamic multi-period models with variables from the TEMA framework could be incorporated as well.

1.6 Criticisms

Although Ijiri is widely acknowledged for his work on Triple-Entry/Momentum Accounting, it also received various criticisms. In this section some of these criticisms are discussed; in particular those that are addressed by the current study.

1.6.1 Dimensional analysis & Ijiri's framework

Dimensions are the units in which a quantity or magnitude is measured and its analysis aids in examining the validity of equations.[45] Three basic dimensions can be distinguished with which economic quantities can be characterized: time, money and realia (Jong 1967). Rigorous equations should have the same dimension at both sides (Wagensveld 1994A-B).[46] Karman & Wagensveld (1994) and Genderen *et al.* (1996) argue that dimensional analysis leads to the conclusion that the TEMA framework is one or unidimensional. In their view there are no accounting 'dimensions' in the strict sense of the mathematical definition of what supposedly a dimension is. However, Olders (1995) disagrees with that position.

Ijiri is well aware of the dimensional aspect of accounting measurements but takes a very different perspective, namely that the temporal relations are foundational and as such determine the dimensions of the TEMA framework (Ijiri 1981, 32-33, 1982, 11). It should be noted that he actually counts in the TEMA framework columnwise six dimensions but categorises them as three: debit, credit and trebit, so it is a triple-entry accounting system (Ijiri 1986, 751). Time seems to grow in importance in accounting research and management science as a quantitative or qualitative aspect of the business environment (Ancona *et al.* 2001A-B, Baert 2000, George & Jones 2000, Glover *et al.* 2002, Kavanagh & Araujo 1995, Lee & Liebenau 2000, Mitchell & James 2001, Mosakowski & Earley 2000, Mouritsen 1999, Preiss & Ray 2000A-B, Petranker 2005, Purser & Petranker 2005, Takatera 2000 and Zaheer *et al.* 1999).

Whether or not we can call each information perspective of the TEMA framework a 'dimension' will certainly be subject of further debate. Here, I subscribe to the notion that Ijiri's framework has three 'dimensions' or 'temporal perspectives' to discipline my modeling effort and the analysis of my empirical results with the selected examples. The implication is that financial variables of one dimension will not be 'mixed' in the dynamic models with those of another dimension in the TEMA framework.[47]

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[45] For an example, in Dutch, see: Vernooij (1993A-B), discussed by Karman & Wagensveld (1994).

[46] For more on dimensional analysis consult: Becker (1976), Jong (1967), Langhaar (1980), Massey (1986), Quade (1967) and Szirtes (1998).

[47] Something which is actually a common thing to do with the calculation of financial ratios. This subject is further discussed in Chapter 3.

1.6.2 Administration or confusion?

Vaassen (2000, 33) sees more disadvantages than opportunities with the implementation of triple-entry bookkeeping. For one, the administrative effort will simply be too costly to outweigh the possible benefits. Moreover, Vaassen feels that the bookkeeper-analyst will be forced to make value judgments when confronted with evidence '...that may not even pertain to a transaction...' which would be eligible for administration under the rules of triple-entry bookkeeping. Vaassen objects to the implication of triple-entry bookkeeping that non-financial facts, e.g. a drop in the market interest rate, are translated by the bookkeeper into financial facts to account for its (possible) effect in earning power. Fraser (1993, 156) agrees with Vaassen: 'The underlying forces making for changes in wealth, ..., when we progress to considering them, there is a distinct shift from "hard" to "soft" measures.' And '...it is impossible to visualize the forces behind each particular gain or loss in an accounting period being identified so easily.' Fraser continues with an example of how to attribute '...sales to continuing customers, a good example of forward-looking information eligible to be administered as wealth increasing force to be added to the current momentum:

1. 'increased advertising on the company's part in the current year;
2. the demise of a competitor in the current year;
3. diversification on the company's part into a new and increase range of products;
4. unavailability of competitor's products.

The problem of identifying the relevant forces is a significant one.' Thus, Vaassen argues, the position of the bookkeeper moves away from objectivity to subjectivity, something neither he nor Fraser recommend: '...triple-entry is likely to engender endless potential for dispute and argument; such a lack of credibility might well affect not just the additional third dimension but the existing double-entry framework.'[48] Clearly, Fraser is but just one step away from declaring Ijiri's TEMA framework a danger to the existing practice of double-entry bookkeeping.[49]

Both Fraser and Vaassen seem to have missed the fundamental notion that Ijiri's theory puts forward: TEMA strives to improve performance measurement with the systemized accounting of transactions as well as events that have future bearing. It is in the interest of managers and not bookkeepers, accountants or auditors to have such additional disclosure (Blommaert 1995A). Indeed, Ijiri wants to account all internal and external forces, the *performance drivers* in the terminology of Kaplan & Norton (1996), because that should improve the disclosure of the future earning capacity of the firm. Once such information is on the table it is expected to improve the decision making ability of management. Ijiri himself recognizes that the implementation of the TEMA framework in the bookkeeping system as well as its acceptance as an internal or external performance measurement system will require a lot of effort. The first and probably most difficult barrier to overcome is that of managerial disinterest for causal relations

[48] In defence of Ijiri, which one of the four momentum accounts proposed by Fraser should be used in his example really depends on the judgement which one is the most relevant. In any case, such an effort is obligatory for any management team that strives to develop a 'balanced view' of the causal network of relations in their business model (see: Kaplan & Norton 1996, 2001A-B). The inherent complexity of the business model or the difficulties one might encounter describing it should not discourage anyone from trying to determine it, in the future such knowledge might be the only differentiator left that competitors cannot copy.

[49] Such heated debate is not uncommon when opposing world views confront each other (Kuhn 1970).

in their business, let alone to have forward-looking data be administered. It is also correct that Ijiri only published by example the necessary guidelines for the administration under the rules of triple-entry bookkeeping (Ijiri 1986, 1988A, 1989). Blommaert (1994, 171-220) developed with great detail the accounting rules that triple-entry bookkeeping requires. At this point, I know of only one example of the implementation of triple-entry bookkeeping in software.[50] Nonetheless, it cannot be denied that the development and implementation of the TEMA framework into the bookkeeping system will be a time consuming and costly effort. On the other hand, the collection and analysis of all required information is done anyway by managers and controllers for the purpose of budgeting and business planning. This issue will not be addressed further in this thesis for my objective is to test the viability of the TEMA framework and to determine its merit ato provide informational measures. According to Ijiri (1989, 9.1), such effort can be undertaken on a statement-basis instead of a record-basis '...because of its significantly lower implementation cost.' This also addresses to some point the subjectivity criticism raised by Vaassen against momentum accounting because I will not undertake any subjective translation of non-financial facts into financial facts.

1.6.3 A general relationship?

Fraser (1993, 155), criticized the TEMA framework mainly with the contention that: '...it may be difficult to sustain the argument that there is a *general* relationship between income, wealth and momentum since that relationship will be dependent upon the model of income and value measurement adopted (e.g. historical cost, economic income, etc.) and upon the level of distributions in each accounting period.' In other words, although Fraser, citing Ijiri (1986, 22), thinks that it is '...reasonable to argue that "force changes income which, in turn, changes wealth"...' many objections can be raised against that proposition (1993, 154). One argument is that '...particular definitions of income and of wealth selected ... have both usefulness and logical implications for triple-entry bookkeeping systems.' For example, value measurements of past transactions based on historical cost might have to be 'mixed' with those based on market value, i.e. the forward-looking force measurements. Fraser's main objection is that it is doubtful that force measurements '...will have the same effect on income as income has on momentum; income, for instance, may be fully distributed each period by way of dividend *or* retained to greater or lesser extents in order to finance growth.' That observation is correct but Ijiri's response to it will be that we should measure force and momentum as (new) wealth generating components separately from their distribution once realized. In recent articles, Glover *et al.* (2002, 2005) and Levine & Ijiri (2004) addressed the issue of consolidating data that are facts or forecasts in financial statements. All the same, Fraser has a point here in the sense that whether or not the general relationship of accounts holds in the TEMA framework has yet to be tested empirically.

1.6.4 Information by accident?

Fraser (1993, 156) believes that Ijiri underestimates how many practical problems have to be resolved before the TEMA framework can be considered a meaningful and useful accounting system. Wagensveld (1995, 13) acknowledges the potential advantages of triple-entry account-

[50] Two software tools: PSUM[sm] (for portable, scalable, usable, maintainable) and Report Accounts (RA[sm]) facilitate TEMA. The databases supported are DB2 & Informix (IBM), Ingres (Computer Associates), ORACLE, SQL Server (Microsoft), and Sybase. RA[sm] is based on single logic table technology and supports double- and triple-entry bookkeeping. Browse: http://www.cec-services.com.

ing but believes it is better to delay its implementation because it has no (yet) been scientifically established that it provides any meaningful new information. He agrees with Fraser (1993, 157) that: '...useful information is likely to result by accident, rather than by design...' and '...there is no substantial reason for believing that a triple-entry bookkeeping system would provide an increase in useful information.' Without empirical tests with results that confirm structural linkages between the three accounting dimensions these authors think that it is unwise to recommend the implementation of triple-entry accounting as a system for performance measurement and management control. This study aims to investigate the possible occurrences of structural links in the cases of component companies of the Dutch stock exchange index, the AEX, and the DOW.[51]

1.6.5 Corroboration or contradiction?

Fraser (1993, 153) holds the opinion that it is not possible to express a '...contemporary commercial reality...' with the financial accounting system. As long as we operate under the convention of historical cost accounting, which underlies financial statements, measurement of momentum or force is superficial. Hence, according to Fraser, it is also impossible to test the viability of the TEMA framework. His reasoning is that two-dimensional (double-entry) bookkeeping does not predict nor explain but solely describes the material effect of past market transactions (Fraser 1993, 155, 157). Nevertheless, information concerning the past and the present is the only 'firm data' available for forecasting purposes. Therefore, the information in financial statements, derived by conventional accounting, should, in my opinion, not be discarded too readily. The basis of my arguement is rather simple: published financial statements are usually the only as well as most extensive source of financial information available to outside observers (see also: Lev 1999 and McEnroe & Martens 2004). To mitigate the criticism raised by Fraser against triple-entry bookkeeping and the limitations to test its feasibility, we must pass by his position that it is impossible to either predict or explain using financial accounting data. Indeed, before that is accomplished, any other effort involving triple-entry bookkeeping and momentum accounting is, in the words of Fraser, '...merely the generation of intellectual artifacts...' (1993, 153).

1.7 Research objective

Fraser, for all his criticism, does offer us one possibility to research the feasibility of momentum accounting (1993, 157): 'As far as the *future* dimension is concerned, the focus of interest is likely to be on *aggregation* rather than on individual transactions, and to disaggregate budgets into individual transactions is to clothe the budgeting process with a precision that is both counterfeit and unnecessary.' Whether or not the budgeting process can benefit from triple-entry bookkeeping is a subject not explored in this thesis. Blommaert provided some evidence in his research experiment that it does. He used a sample of 36 Dutch controllers to test the decision relevance of a triple-entry and momentum accounting system (Blommaert 1994A). Also the findings of Dull (1997) and Dull & Tegarden (1999) are supportive of the idea of using output of a momentum accounting system for decision making, in particular through the generation and use of 3D representations of accounting information.

[51] Many accounting researchers doubt whether empirical research methods can be applied on financial accounting data. For discussions of this subject: Salvary (2007), Suzuki (2003) and Thomsen (1998B).

The purpose of the TEMA framework of interlocking accounts is to measure the capacity to create new wealth during the accounting period.[52] In other words, we can search for the cause and duration of wealth creating business dynamics as these are supposedly reflected in the financial accounts. This we can administer on a record-basis or on a statement-basis. Ijiri (1989, 9.1) recommends the latter approach '...because of its significantly lower implementation cost...' and thus addresses one of the criticisms raised against the difficulty of implementing momentum accounting (Fraser 1993, 156, Vaassen 2000, 33). In this study aggregated accounts are used for the analysis of financial statements because I do not have full disclosure in each accounting dimension of the example companies that are used.[53] Consequently, the research objective of this study is *to test if the generality assumption of the* TEMA *framework holds in the investigated cases by econometric modeling methods and to determine if the research findings support the practical application of* TEMA.

1.8 Research hypotheses

In this thesis, I follow the line of research into the TEMA framework using aggregated data. Ijiri (1989, 9.1) suggested a statement-basis approach as an alternative for the implementation of momentum accounting on a record-basis approach at its most detailed level. This study addresses with several hypotheses the essential research question: do econometric TEMA models of selected cases explain *ex post* and predict *ex ante* the trend of net wealth and thus render support for the generality assumption that underpins the TEMA framework? Central in my effort is the association I expect between financial accounting variables both over time and between different levels of aggregation in the TEMA framework. In this section the research hypotheses are presented and considerations behind them are discussed. FIGURE 4, on page 48, is a directed graph showing the line of reasoning from one hypothesis to the other and serves to illustrate the connectedness of the various studies of this research.

1.8.1 A general relationship between wealth, momentum & force

The basis of financial accounting is a system model (Blommaert & Blommaert 1990-1, 48, Churchman 1971, Correa 1976 & 1977, Kefford 1995, Mattessich 1978, Thomsen 1998). The accounts that are reported on the balance sheet and income statement are part of a coupled 'whole'; an all encompassing or holistic system. If indeed we accept this notion of a holistic system as a mathematical construct then it should be possible to explain its structure from a coherent accounting theory that pertains to the information it provides (Arya *et al.* 2000 & 2004, Butterworth 1972 and Vousten-Sweere & Groenendaal 1999). In the literature, however, there is less agreement about this issue, see for example Mattessich (1995A). As an example, it is illustrated in Chapter 3 that financial ratios based on income statement and balance sheet variables are not necessarily unambiguous in their signal. With the TEMA framework in mind, this could be explained as a conflict between dimensions.

[52] Dull (1997, 3, note 2) points at the fact that '...currently decision-makers are focused on earnings and therefore tend to "manage" earnings...' and thinks that '...decisions that manipulate earnings would have reduced significance...' when '...the focus is on wealth.'

[53] It would be most welcome if a company would grant access to its information systems to analyse the association between financial and non financial variables with shorter time periods, like a month, week or day.

De Groot *et al.* (2004, 36) points at the importance of recognizing that certain foundational principles have to be understood and that a proper understanding of basic business dynamics is required to determine a company's position and to be able to develop scenario's for corporate control.[54] In Penman's (2003A, 90-91) view the accounting system captures the dynamics of a company operating in its business environment. Therefore, the assumption is that the financial accounting variables that measure wealth can be differentiated to measure their change, i.e. their momentum, and the change of the rate of growth itself, i.e. their force. Moreover, I expect that the momentum and force measurements can also be applied to the composition of wealth accounts, not just the magnitude or trend of net wealth.[55] In other words, the magnitude of each account can be differenced according to the TEMA framework. The cascade of measurements and their aggregation (*concatenation* in logical-mathematical terminology) within the accounting process is expected to reflect dynamic and temporal relations that follow from business decisions that were made about financing, cash flow management, investments, process management, logistics, and the like. In fact, this is a familiar position in accounting theory (Butterworth 1972, Salvary 1985, 54). I expect that such information will disclose more than '...just ... the "aggregation" of market transactions of their historical cost price...' as Fraser (1993, 157) puts it.[56]

Ijiri (1986) assumes implicit and explicit linkages in the accounts when firms adhere to accounting rules. Possibly these are not self-evident and it is perhaps also impossible to test if these are valid for certain market segments. Notwithstanding all the limitations of financial statements, I assume that the presence of the general relationship can be tested between wealth, momentum and force accounts. If this is indeed found in the studied cases, it should also be possible to develop models within the TEMA framework that explain *ex post* and predict *ex ante* the dynamics of net wealth (equity). My objective is to test if these features have structural and temporal properties and if this confirms in the selected cases the general relationship between wealth, momentum and force of the TEMA framework. Thus, my first and foremost hypothesis (stated in the alternative) is:

H 1_a Accounting variables in the dimensions of the TEMA framework exhibit dynamics in agreement with the general relationship assumption.

Should the null of this hypothesis, H 1_o, be valid, this then indicates that the general relationship between accounting variables of TEMA framework is not found to be present in the selected cases. The null implies that no relationship exists between accounting variables of the different dimensions of the TEMA framework. In contrast, what I expect is that *association* between financial accounting variables can be found for two features: *time* and *composition*. The notion is that the dynamics of a firm are expressed in the vast number of financial transactions that are administered through the accounting system. Financial accounting condenses the dynamics of the business environment, although limited to the companies included in this

[54] The boundary between financial accounting and management accounting becomes a somewhat problematic subject with the discussion of the use of financial statements data for predictive purposes.

[55] The chart of accounts then needs not to be changed in the course of time and this would entertain ex post force and momentum analysis. Decomposition analysis will involve the study of the TEMA framework at various levels of integration. This implies the use of multiple component accounts at a lower level that aggegrate into a single account at a higher level.

[56] See also Ijiri 1981 and Berry & Waring 1995 on this subject.

research (Penman 2003A, 90-91).[57] This follows from the measurement of market transactions on each day (even under the historical cost convention) and the accounting per period through the income statement, after which the result is aggregated as new wealth (e.g. added to the reserves). Furthermore, the balance sheet reports important shifts in the composition of assets and liabilities together with owners' equity or net wealth.

Lim (1966) provides us with mathematical underpinning of how to determine if a general relationship exists between wealth, momentum & force. In his theory of accounting measurement '...the level of generality refers to the scope of the monetary property required to be measured...' and '...thus if the level of generality is determined to be the "unique transaction," no two items may be related because no two transactions possess perfectly identical properties...' (Lim 1966, 645-6). But, as soon as the 'unique transactions' are aggregated, grouped, the '...level of generality has been increased (made more general).' For example, '...if items of plant, equipment, and other fixed assets are to be interrelated, the level of generality must be increased to "fixed assets."' Consequently, '...if items of the various financial statements are to be interrelated, the level of generality must be increased to "financial statements."' The implication for this study is that in the TEMA framework there are two criteria of necessary and sufficient generality that must be fulfilled. The first criterion is the generality assumption of 'wealth' that incorporates 'momentum,' which, in turn, incorporates 'force' measurements. The second criterion is the generality assumption that in the TEMA framework in each dimension the same level of disaggregation of accounts is sufficiently specific. In other words, when the same categories of accounts are chosen in each dimension. I should also be able to distinguish the same phenomena, structural or temporal.

Thus, one feature to study here is how dynamics cascade upwards through the aggregation of individual transactions into accounts, as well as through accounts that aggregate upwards to summary accounts, and finally to a single figure of total company wealth. The other feature to study here is how dynamics sequentially cascade; like a line of dominoes ready to collapse. Thus, my first hypothesis is separated (stated in the alternative) into two:

H 2_a Accounting variables in the dimensions of the TEMA framework exhibit dynamics by compository association in agreement with the general relationship assumption.

H 3_a Accounting variables in the dimensions of the TEMA framework exhibit dynamics by temporal association in agreement with the general relationship assumption.

Combined with the reasoning that the TEMA framework enables the structural and the temporal analysis of accounts with different dimensions, I will test these two hypotheses with *decomposition analysis* and *econometric modeling*.

Fraser (1993, 155) expects on formal grounds that H 1_a, H 2_a and H 3_a will be rejected. On the other hand, the works of Theil (1967, 1969), Bostwick (1968), Caspari (1968) and Lev (1968, 1969, 1970, 1971, 1973 and 1974) on *informational measures* in economics and accounting suggest the opposite. In decomposition analysis, financial statements are seen as numerical decompositions of certain total sums, i.e. as 'parts' of a 'whole' like total assets or

[57] Recently, it has been empirically confirmed that a firms' business dynamics can have predictive power even for a macro economic variable (De Groot *et al.* 2004, De Groot 2006). In his example, weekly staffing services obtained from Randstad Company, is a single explanatory variable of the quarterly growth trend of the Dutch GROSS DOMESTIC PRODUCT (GDP). Note that this does not imply that staffing services causally determine the Dutch GDP! The implication is that variations in the Dutch GDP are observed earlier by those of Randstad Company weekly staffing services.

total sales.[58] Thus, the change of proportion between financial accounts can be measured to determine if dynamics at a lower level warrant further investigation. Within the TEMA framework, the decomposition measures developed by Lev are compared in this study with the disaggregation measure of Ijiri (1995). *Color coding of informational measures* will be used to facilitate their interpretation. Furthermore, spectramap *decomposition* and *visualization* will be applied to the same time series (Lewi 1976, 1982, 1989, 1995). This should expose the structural or long running association between wealth variables, their momentum and force. Furthermore, *color coding of factor scores* will be used to add an additional layer of information to the spectramap decomposition and visualization to search for more subtle associations between variables and time points in the decomposed system of balance sheet variables.[59]

1.8.2 Explanatory power

For this thesis, financial accounting data are used to develop econometric models of the component companies of two stock market indices, the Amsterdam stock exchange–AEX in short, and of the Dow Jones Industrial Average index–DOW in short. These models are used to test the explanatory power of independent financial accounting variables. To this purpose, operating income serves as a proxy for business dynamics reflected by variation of income statement data. In addition, dynamics of the structural composition of the balance sheet as a whole is expected to be associated with the growth trend of net wealth (equity). Moreover, their combined association will be tested vis-à-vis net wealth. Net wealth is used as the dependent variable because it is the accounting variable of primary interest for TEMA. Only the association is researched here between operating income and that of total wealth with net wealth.[60] Thus, the temporal or long running association should be exposed between net wealth growth and that of business success reflected in the operating income time series and the total wealth time series. Thus, my fourth, fifth and sixth hypothesis are as follows (stated in the alternative):

H 4_a Operating income is associated with net wealth.

H 5_a Total wealth is associated with net wealth.

H 6_a Force and momentum time series are stationary or trend-stationary.

The rejection of these hypotheses would indicate that support for the presence of the general relationship between wealth, momentum & force variables cannot be found to be present in the selected examples of this study. The null's, H 4_o and H 5_o, suggest that the accounting variables in these cases does not trend together in any sensible manner. Any effort to try to model them to explain the dynamics of one with the other is then ineffective. That result would confirm the principal criticism of Fraser (1993, 157) that '...there is no substantial reason for believing that a triple-entry bookkeeping system would provide an increase in useful information...' for the simple reason that its variables are not associated. Note that H 6_a is conditional to the modeling of time series. It would make it much more difficult to employ them as variables in econometric models when the time series are not stationary or trend-stationary.[61] The null of the sixth hypothesis, H 6_o, implies that momentum and force variables have a unit root

[58] This is discussed further in Chapter 4.

[59] This is discussed further in Sections 2.4 Visual analytics and 2.5 Color coding, pages 71-76.

[60] This a research limitation and certainly not a conceptual limitation.

[61] But not completely impossible when tests indicate that the trending variables cointegrate. The particulars of econometric time series analysis are discussed with some detail in Chapter 2.

and tend to trend. If that is the case, further differencing would be required until the time series are stationary or trend-stationary. That might suffice for econometric modeling but the economic reasoning behind the TEMA framework would be lost if triple or quadriple differencing is required of balance sheet or income statement accounts.

With *directional change analysis* I can study if and in which direction the independent and dependent variables move (De Mortanges & Van Riel, 2003). Using that result I determine if directional change occurs parallel (either ++ or −−) or if directional change is opposite (either +− or −+). Certainly on the basis of the TEMA framework, I expect a certain degree of association between the change dynamics of momentum and force of total wealth or operating income and that of net wealth (equity).

Econometric analysis of the aforementioned force and momentum variables is employed by me to test their explanatory power dynamically through time series modeling. My assumption is that when the complexities of a firms' dynamics can be replicated by relatively simple econometric models this will offer support Ijiri's TEMA framework. Ijiri (1989, 10.5) suggested that '...ARIMA models ... may be considered in momentum measurement...' as an alternative for the measurement of forces and their aggregation into momentum variables.[62] An additional benefit is that such models should also enable the prediction of future values of the dependent variable. For example, Silhan (1989) applied ARIMA analysis to forecast corporate earnings using quarterly sales and margins as explanatory variables. In any case, econometric analysis provides me with the tools to test the viability of the TEMA framework.

1.8.3 Predictive power

There is a considerable amount of literature that suggests that financial accounting variables have some degree of predictive power. Most effort in this area has been focused on the prediction of corporate earnings (e.g. Foster 1977, Keil *et al.* 2004, Richardson *et al.* 1995, and Silhan 1989) and stock valuation (Atiase & Tse 1986, Barniv & Myring 2006, Bird *et al.* 2001, Lee 1999, Ou & Penman 1989 and Richardson & Tinaikar 2004). In this study, therefore, I expect that accounting variables within the TEMA framework, or their ratios, exhibit dynamics in agreement with the assumed general relationship. When I find that the econometric TEMA models of the selected example firms indeed have explanatory power, it is also likely that these will have predictive power to some degree. Therefore, the seventh hypothesis (stated in the alternative) is as follows:

H 7_a Operating income and total wealth can predict net wealth.

The confirmation of the null of this hypothesis, H 7_o, implies that it is less likely that the TEMA framework can be used for decision making purposes as it fails to predict in the selected cases. It implies that any possible trend behavior of variables does not contain any form of consistency between them with future bearings in these models. The TEMA framework would offer in this case little theoretical foundation for further empirical research into (causal) relationships of the selected firms' business model. That result would suggest that financial accounting variables indeed are only lagging indicators of company performance (Kaplan & Norton 1996). Their usability would further diminish for strategic control (Brouthers & Roozen 1999, Roslender & Hart 2003 and Ross 1997) or investment analysis (Atiase & Tse 1986,

[62] ARIMA modeling is introduced in section 2.3 about Time series analysis, page 52.

Barniv & Myring 2006, Penman 2003B and SEC 2001). Should that be case, then no support will be offered by the result of this study for the idea, put forward by Dull (1997, 78), to use the TEMA framework in the effort to modernize Accounting Information Systems (Haskins & Sack 2006, Tillema 2003 and Vosselman 1997).

1.8.4 Forecasting with factors

Stowe *et al.* (1980) provided through canonical correlation analysis statistical support for the explicit and implicit linkages in the balance sheet that reflect the not unimportant shifts in its composition. The decomposition of multivariate financial accounting variables could deliver factors with explanatory power for regression analysis (Masters 1995, 16, Seiler 2003, 165). In this study, I will use spectral mapping to obtain factors from TEMA time series that will be used as the independent variables of econometric TEMA models to explain and predict balance sheet dynamics and stock exchange index dynamics (Lewi 1976, 1982, 1989, and 1995). The eighth and ninth hypotheses (stated in the alternative) are as follows:

H 8_a Decomposed accounting variables from the TEMA framework of a single company can model balance sheet dynamics.

H 9_a Decomposed accounting variables from the TEMA framework of component companies can model stock exchange index dynamics.

The null of the eight hypothesis would lead to the conclusion that the dynamics of balance sheet composition do not exhibit trend like behavior because any explanatory and predictive power is absent in the example studied here. Acceptance of the null of the ninth hypothesis would lead to the conclusion that the dynamics of multiple companies' (panel) financial variables neither exhibit trend like behavior nor that a common trend can be decomposed from them. Thus, any collective explanatory and predictive power would then be absent in the case studied here. The confirmation of the null of these hypotheses, H 8_o and H 9_o, would indicate that it is less likely that the TEMA framework can be used for any type of decision making purposes as it does not facilitate models used here to predict individual firm or panel dynamics.

1.9 Research motivation

There are several contemporary economic and technological developments that have an impact on the business world at the beginning of the 21st century. In this section, those developments that are important for the motivation of this research are discussed.

1.9.1 The 'new economy' – is it real-time?

Whether or not the 'new economy' is a 'real economy' is still a subject of debate (Heertje 2006, Shepard 1997). What is a very real phenomenon in the economy, new or old, is that the pace of change is relentlessly increasing and that the stewards of business are faced with an ever growing volume of data (Lewi 2004). The capacity of information and communication technology (ICT) is so great that data can be presented 'any moment – any time' on a computer screen or hand-held device. It is this capacity that guarantees that the disparity dissolves between the moment a fact occurs, the moment it is measured and the moment such fact can be presented to 'whoever it may concern.' Obviously, this puts pressure on anyone responsible for the business process that is measured – there is less room for evasive maneuvers when each and every movement can be monitored – and the persons who measure and report, and those that have to manage the firm or its capital.

These challenges did not go unnoticed in the accounting and auditing field (Hunton 2002, Sutton & Hampton 2003, Vaassen 2002 and Vergauwen & Vandemaele 2001). The FASB issued a Special Report on business and financial reporting in which the 'Challenges from the New Economy' are discussed (Upton 2001). The report reviews the '...perceived disconnect between the new economy and existing business and financial reporting practices...' and '...proposals for prospective reporting paradigms that report on the entity's balances and flows, using monetary measures, but in ways that depart from traditional financial statements.' Issues that are central to the 'prospective reporting paradigms' are related to the measurement of a firm's plans and prospects, recognition and measurement of internally generated intangible assets and their possible accounting book value (see: Lev 1999, 2001).

The *Economist* concluded in a recent survey of the 'real-time economy' that real-time technology not only will '...take much of the slack out of supply chains, it is also bound to improve firms' ability to plan their financial affairs...' (*Economist* 2002A). Except that, '...many firms revise their forecasts and budgets only once a quarter, often on the basis of old data...' and '...new information, such as a sudden drop in demand for a particular product, may be known to the salespeople, but not to the chief financial officer.' The *Economist* cites the vision of Katherine Jones, an analyst with Aberdeen Group, an ICT consultancy, of how a chief financial officer in control and his or her team operates:

> 'This way financial planning becomes a continuous collaborative process, rather than the periodic and mostly top-down exercise that it is today. Moreover, it will not only give chief financial officers a better view of the road ahead, but also allow them to play with scenarios based on current information and make more confident earnings estimates.'

This vision describes exactly what Ijiri strives to accomplish: to shorten the cycle from measuring business events that have an impact on the (future) bottom-line, to aggregate them and report to the decision maker and improve the ability to evaluate and respond. Having said that, the *Economist* (2002B) also cautions that '...the real-time enterprise is not simply about speeding up information flow. It is also ... about being able to monitor a business continuously and react when conditions change.'

The motivation that derives from this development to this research is that the TEMA framework includes forward-looking measures. Whether that is compiled on the basis of detailed records or with aggregated data is a matter of confidence as well as a cost-benefit assessment. That subject is not researched in this study because the research objective is to first determine if the TEMA framework by design can disclose forward-looking information.

1.9.2 Accounting Information Systems

Can accounting provide a workable alternative? During the last two decades, Accounting Information Systems (AIS) evolved from a systems environment used primarily for bookkeeping into flexible and integrated systems that provide information to management for planning and decision-making (Dull 1997, Hunton 2002 and Vaassen 2002). The financial department has progressively changed its role from the gatekeeper of administrative organization, internal control, and accounting into a more proactive role as one of the pathfinders of future business success. For the Netherlands, Oude Vrielink & Verbeeten (2004), report that the implementation of an Enterprise Resource System (ERP) frees time for such decision-support related activities. Performance measurement as a system of business organization is gradually developing into a performance management system.

In spite of these technological and organizational advances, accounting theory has not fully absorbed all of these innovations (Vasarhelyi & Greenstein 2003, Sutton 2006). Faster accounting does not necessarily bring better accounting. It is gradually becoming clear to many that accounting should not only provide convincing explanations that reveal basic causes but could (should?) also disclose the forward-looking information. I accept that any kind of accounting system can only report data 'after the fact' for that is where today the border is drawn. But that does not necessarily imply that with such data it is impossible to draw inferences of current influences on future results. Simply put, whenever a manager looks at his or her reporting 'traffic lights' it can already be too late: just hitting the breaks then might not be very helpful. The reason is that managers have to deal with the momentum that is *now* present in their business. A window must be available to be opened with a view on possible futures. The minimum we should expect is that management prepares how to respond to anticipated developments (Stout 1998). In the real world, nowadays, markets respond ever faster on any company action (or lack of it!). For that reason it is necessary that managers not only have instantaneous access to performance reports of their business but also have to be able to ascertain the most likely path their business will take (Bertsche *et al.* 1996, Draman *et al.* 2002, Larsen & Lomi 1999, Nersesian 1990, Petranker 2005, Purser & Petranker 2005, Pidd 1985, Richardson 1996, Stout 1998 and Van der Heijden 1996).

A separate but important line of AIS research involves the sociological and behavioral phenomena of the decision making process of managers and auditors (Brouthers *et al.* 2000, Bonner 1999, Bouwens & Abernethy 2000, David *et al.* 1999, McEwen & Hunton 1999, Purser & Petranker 2005 and Wheeler *et al.* 2004). Every manager must make decisions to keep on the organizational path of agreed upon actions. Given the volatility of today's economy and the interconnectedness between economic sectors, the near and long term impact of such decision-making can drop on our head like a stone. Almost half a century ago, Simon (1997) argued that opposite to the rational 'economic man,' who supposedly maximizes by selecting the best alternative from many available options, we find the 'administrator' who recognizes that the perceived world is a dramatically simplified model of the real world.[63] He or she '...treats situations as only loosely connected...' and thus just takes a small number of the factors of the situation into account, namely those that are perceived as most relevant or crucial. Simon sees people *satisfice* when they make decisions and take action. That is, we look for a course of action that is satisfactory or 'good enough' in our personal opinion. However, recent case study based research indicates that bargaining as well as analytical quantitative approaches are powerful and successful tactics to get a decision adopted and implemented fast (Nutt 1998). It is only when considerable effort is made to improve team decision-making that better outcomes can be claimed. Most interesting for my research is the finding that '...a quantitative assessment of data from systems, pilots, and simulations were used far more often than previously reported.'

How can we know with certainty which factors sufficiently represent reality in an economic model to support decision-making? Eisner (1989) concludes, from four decades of econometric research, that we have failed to corroborate even the most fundamental assumptions of micro or macro economic theory. For example, it cannot be proven if the 'law of demand' that lower prices will increase quantities demanded, is valid since it is most likely associated with expectations of the public that still lower prices are expected in the near future.

[63] We can interpret this administrator to be a manager, controller, accountant or auditor.

Thus, some of the key variables in mathematical functions of economic models are uncertain values expressing expectations anyway, or probability distributions of future variables. The best recommendation Eisner is able to give firms is that they '...should invest if they expect the future demand for output to be high, if they expect the cost of capital to be higher in the future than now, and if they look to higher future profits as a consequence of current investment, but little if any at all in response to current or past values of these variables.' Even if that is the case and sufficient to decide – the framing problem confronts management as well (Tversky & Kahneman 1986). We have to concede that when it concerns the use of models, economic man has to succumb to some degree of satisficing behavior, if it is not for the manner in which a personal or team decision is made, then it will be for the impact of how questions are formulated (Flood 1995).

The motivation that derives from these technological, sociological and behavioral advances is that Accounting Information Systems seem to have developed to a point where the collection and presentation of *ex post* data no longer suffices. The automation of bookkeeping systems has brought us to a point where the information needs of business for more *ex ante* data can be met conceptually and technically. This research investigates if the advancement of the TEMA framework to that purpose can be substantiated by acceptable forecasts made with it, and if this could be relevant for decision makers. If that is indeed the case for the selected firms is also a matter of confidence and a cost-benefit assessment. Both technological, sociological and behavioral considerations can only be made when users are more confident with TEMA based models. I research this subject here with regression based econometric models because my objective is to first determine if financial variables within the TEMA framework have explanatory and predictive power in the models of the example firms.[64]

1.9.3 The REA *framework*

The advent of computers in business was certainly not discouraged by accountants or financial analysts (Barron 1984). From the earliest years that computers were used their impact on bookkeeping and budgeting was recognized (Mattessich 1961, Mattessich *et al.* 1964). Possibly the most consistent line of research about an alternative model for bookkeeping inspired by the availability of computer technology is the Resource-Event-Agent framework, or REA in short, developed by McCarthy (1979, 1982, 2003). REA accounting can be understood as an object-oriented framework based on the entity relation ship model (Dunn & McCarthy 1997, Geerts & McCarthy 1997, 1999, 2002, Gerard 2005). It bears some resemblance with the framework of the Natural Language Information Analysis Method, or NIAM in short, developed by Nijssen (Wintraecken 1987). The three types of object of the REA framework are (Vaassen 2002, 33):

1. the acquired and used resources (R),
2. the events in which the firm is involved (E),
3. and the people, or agents, who are related to these events (A).

Vaassen discusses REA based accounting as an alternative for triple-entry accounting. An advantage of REA accounting he advocates over double-, or triple-entry accounting is that it enables the financial as well as the non-financial administration of facts pertaining to business processes. The link between financial accounting and management accounting methodologies is

[64] An alternative modeling methodology is System Dynamics. During this research such a financial accounting simulator was also developed (Melse 2006).

therefore easier to make (Geerts & McCarthy 2006, Church & Smith 2007). In this thesis the REA framework is not discussed further nor compared to the TEMA framework in any detail. However, one recent extension of the REA framework proposed by Verdaasdonk (2003) has to be discussed. Verdaasdonk argues that accounting models such as the REA model focus on the modeling of static accounting phenomena and '...are not able to provide relevant *ex ante* accounting data for operations decisions ... [which] require dynamic descriptions of the consequences of alternative future courses of actions and the resulting events.' Verdaasdonk proposes an extension of the REA framework to include '...new static aspects as "recipes," "potential contracts," and "reservations," together with behavioral aspects expressed as theoretical scripts for the retrieval of relevant accounting data.' With this proposition, Verdaasdonk certainly moves beyond the outermost boundary of the accounting paradigm because he administers behavioral aspects in an accounting model. His objective is to capture '...cash flow consequences of operating management decisions relating to *future* events...' (Verdaasdonk 2003, 57). Clearly, the vision of Verdaasdonk is that of a momentum accounting system.

The motivation for this research that derives from this development is that alternative extensions of the traditional double-entry bookkeeping system are still researched. The TEMA framework could possibly be supportive to that effort as well as benefit from more advanced object oriented implementations, like the REA model, when it is demonstrated in this study that it could facilitate decisions relating to future events.

1.9.4 Virtual close, XBRL *& the continuous audit*

It was already recognized about fifty years ago that the timing of disclosure might become an issue for the accounting profession (Nichols & Grawoig 1968). The widespread use of computers and integrated software for production management, added to the increased communication capability between information systems and their users, enables the instantaneous administration of business transactions. This development has also had its impact on the use of accounting systems and the (interim) financial statements they can generate on a quarterly, monthly, weekly and often daily basis. The integration between the organizations' information system and the accounting system can be so timely that financial statements can be compiled (unaudited) virtually after a day ends, hence the name *virtual close*.

The phenomenal expansion of available data sources and system functionality made available on the Internet has also had a serious impact on accounting information systems, company disclosure on its web site as well as on auditing (Beattie & Pratt 2003, Ettredge *et al.* 2001, Lymer 1999, Locke & Lowe 2007, Lymer & Debreceny 2003, Poon *et al.* 2003). Lymer *et al.* (1999) investigated for International Accounting Standards Committee (IASC in short) the impact of the Internet on business reporting.[65] After a detailed analysis of the websites of the 30 largest companies in 22 countries, it calls for new codes of conduct to be applied to Internet based publication of business and financial information. Recently, Jones & Xiao (2004) did a Delphi study into corporate financial reporting by 2010. Twenty U.K. experts in accounting and the Internet participated in the study representing academics, auditors, regulators, reporting companies and users. The main conclusion was that '...the financial reporting package would evolve into a core of general purpose, standardized information (in both the hard copy and Internet version) together with a non-core of general purpose and customized information.'

[65] In 2001 the responsibilities of the IASC were transferred to the International Accounting Standards Board (IASB), from: http://www.iasb.org.

Also '…auditors will be reactive and cautious, and regulators will adopt a minimalist approach.' Thus, in their view, '…the fundamental dilemma of financial reporting in the Internet environment will be between standardization and customization.' Considering that last point, of special interest is the effort to standardize the data elements of financial statements to be disclosed via the Internet with web page coding language called extended Business Reporting Language, or XBRL in short (Hannon 2004, Higgins & Harrell 2003). While XBRL comprises an XML-based standard for external financial reporting, the related XBRL GL specification is aimed at internal accounting systems at the transaction level (Murthy & Groomer 2004, 144).[66] The research of Ashbaugh *et al.* (1999) on Internet Financial Reporting (IFR in short) concluded that '…consumers who demand financial information can access firms' web sites to obtain financial information more timely than that provided by traditional paper-based reporting and in some cases, obtain more financial and non-financial data than that provided via traditional reporting methods.' They also warn that '…the increasing supply and demand for electronically disseminated financial information may increase the demand for attestation services provided by accounting professionals.'

A new phrase was coined to signify that an instantaneous financial reporting ability enabled by the virtual close of the bookkeeping system (and its disclosure enabled through XBRL) also requires a *continuous auditing* or *continuous assurance* facility (Gibbins & Pomeroy 2007, Kogan 1999, Rezaee *et al.* 2001, 2002, Uday *et al.* 2004 and Vasarhelyi & Halper 1991). The technology driven decrease of the time required in between the moments that business controls (Alles *et al.* 2006), or financial statements are compiled, audited and published must have serious implications for the way such reports are used by their internal and external users (Blokdijk 1991, Dull *et al.* 2003, Dull & Tegarden 2004). Vasarhelyi *et al.* (2002) believe that continuous auditing would be helpful in detecting fraudilous accounting like the unreported related-party partnerships that caused the downfall of Enron and its accountancy firm Arthur Andersen. Cordeiro (2007) has the opinion that continuous auditing can provide nothing more than mere signals that will be as hard to diagnose as those of an electrocardiogram (ECG).

Again, the question can be raised if the purpose of financial statements is to (only) disclose and facilitate financial statements' analysis, or if it also might be used to forecast business performance. McSweeney (2000) argues that current financial statements are 'in eliminable' filled with '…a plural unity of temporality together with an chronological sense of time' and have an '…[entangled] triple present (the present of the past, the present of the present, the present of the future). Also Lundholm (1999) and Glover *et al.* (2002, 2005) discussed the entanglement of facts and forecasts in financial statements. The answer surely does not depend on the length of the period in between reports but on the model I envisage the data should fit. However, a recent survey indicated that it is not so much technology that is a barrier to the decrease of time required to audit but the availability of staff (Behn *et al.* 2006). The implication of the ever shortening lapses of time in between disclosures is that the pressure for more relevant forward looking information is expected to increase because more reporting moments will also trigger ever more questions about the outlook of business (Flowerday *et al.* 2006). A

[66] XML is the abbreviation of Extensible Markup Language. It is a general-purpose markup language and a fee-free open standard. It is classified as an extensible language because it allows its users to define their own tags. Its primary purpose is to facilitate the sharing of structured data across different information systems, in particular via the Internet. It is recommended by the World Wide Web Consortium. (Based on an article from http://en.wikipedia.org.)

better understanding of the model that drives business, described by the TEMA framework, will then possibly be helpful.

These disclosure related developments are interconnected because the technology involved is the same while informational needs are also similar (Woodroof & Searcy 2001). This motivates the present research for three reasons. Firstly, shorter reporting cycles will generate more measurements due to the increased availability of financial statements data. That enables models with smaller time increments. Secondly, due to XBRL-based standardization and Internet enabled access, more financial statements data of a greater number of companies can be researched. This will result in a growing number of comparable data sets. Thirdly, continuous audit should increase the reliability of interim financial statements data which will increase confidence in firm analysis and models. Likewise, Debreceny (2007), while indicating future directions for research, has the opinion that multidimensional accounting information must be facilitated by the XBRL standard and cites for inspiration: Ijiri (1982, 1987), Ijiri & Kelly (1980) and Mattesich (1964). Furthermore, Debreceny (2007, 9) observes that following this approach '...there is much XBRL can do to allow financial reporting to move beyond the iron grip of paper-based publication paradigms.'

1.9.5 Corporate governance: disclosure & transparency

The importance of corporate governance was made very clear by the negative experience of the accounting scandals of recent years that raised concerns about the efficacy of incentive alignment and control systems (Donoher *et. al.* 2007, Lev 2002, Scharff 2005 and Vasarhelyi *et al.* 2002). Recently, a SEC Task Force, concluded (SEC 2001):

> '... improvements in company disclosure would help investors assess the value of dynamic, high-growth companies. Since value is driven by a company's expected future profits and cash flow, investors are interested primarily in information that will help them project both, such as intangible assets, operating performance measures, business model descriptions, market information and forward looking data. ... The current reporting system, comprised of Generally Accepted Accounting Principles (GAAP) and SEC -mandated disclosures, focuses primarily on historical financial transactions. This system provides limited guidance about the other information that investors need.'

This SEC Task Force made two recommendations. First, academics, the accounting firms and institutional organizations should undertake an attempt to '...create an environment that encourages *innovation in disclosures*' (italics supplied). Second, an effort is required to '...create a *new framework* for supplemental reporting of intangible assets and operating performance measures ... in order to move forward with a framework *for voluntary supplemental reporting* ... that would help investors assess a company's *future performance*...' (italics supplied). It seems that new imputes is appropriate to search for the answer to the question if we can improve the reliability and effectiveness of accounting and financial statements to meet these demands. In short, for investment decisions, to control the firm and to determine corporate compensation, more information on its future financial position is longed-for. This is of interest to the business community in the U.S.A., Europe, or any place, because it drives home the message that we have to improve current accounting and management practices and disclosure to meet the challenges of a more dynamic and demanding future.

The *corporate governance framework* should ensure that timely and accurate disclosure is made on all material matters regarding the corporation, including the financial situation, per-

formance, ownership, and governance of the company. A strong disclosure regime that promotes real transparency is a pivotal feature of market-based monitoring of companies and is central to shareholders' ability to exercise their ownership rights on an informed basis. In the section about what should be included in company's disclosures, two out of seven subjects that are listed pertain to forward-looking information (OECD 2004, 50):

> '*The financial and operating results of the company*
> Investors are particularly interested in information that may shed light on the future performance of the enterprise.
> *Foreseeable risk factors*
> Users of financial information and market participants need information on reasonably foreseeable material risks that may include: risks that are specific to the industry or the geographical areas in which the company operates; dependence on commodities; financial market risks including interest rate or currency risk; risk related to derivatives and off-balance sheet transactions; and risks related to environmental liabilities.'

Furthermore, regarding disclosure and transparency the OECD has the opinion that 'A strong disclosure regime that promotes real transparency is a pivotal feature of market-based monitoring of companies and is central to shareholders' ability to exercise their ownership rights on an informed basis…' (OECD 2004, 49).

The American standards authority, Financial Accounting Standards Board (FASB), initiated the Business Reporting Research Project and published a report on the '…disconnect between information provided in financial statements and the information needs of investors and creditors…' and what to do about this problem (Upton 2001, III, XI). In their view '…improved business and financial reporting of the "new economy"…' will require attention to:

- Recognition of internally generated intangible assets in financial statements and improved measures of those assets.
- Expanded and systematic use of nonfinancial performance metrics.
- Expanded use of forward-looking information.'

To that purpose, the report examined two approaches that report on a firm's '…balances and flows, using monetary measures, but in ways that depart from traditional financial statements…' (Id. 21). The first is the so called CICA Total Value Creation™ (TVC©) system, a new reporting model aimed at describing a firm's value-creating activities, which the proponents distinguish from value-realizing activities. The fundamental premise behind the system is that managers and boards of directors are expected to get a better insight into *pre-transactional value creation* (Id. 22). Thus its scope and objective is very similar to that of TEMA. The second approach discussed by the FASB is known as Accounting For The Future, or AFTF in short, and uses a system of projected future cash flows to present a corporation's activities in financial terms (Nash 1998). The opinion on these approaches is that they have a certain appeal but '…several conceptual and practical problems with developing a new reporting paradigm…' are identified (Upton 2001, 25). First, the FASB sees that '…the cost of implementing a prospective accounting model in a complex organization would be considerable … it essentially requires a second management information system…' and '…any attempt to do variance analysis would require that the prospective system be integrated with traditional bookkeeping systems.' This sounds very familiar to the criticisms raised against TEMA. It looks as if any proposal to innovate existing accounting and reporting practices first has to overcome the angst of implementation costs and the effort required for procedural, organizational and institutional change.

FASB members and staff interviewed 56 individuals who are users of financial statements, to determine the extent to which the basic financial statements (balance sheet, income and cash flow statements, and the statement of shareholders' equity) currently provide sufficient information for analyses and forecasts (FASB 2002). The first principal finding listed in the report is: 'Users have a *strong interest in greater disclosure of information with predictive value that could be provided in financial statements* but there is no widespread dissatisfaction with or demand for sweeping change in financial statement display…' (italics supplied). But the report is less than enthusiastic about the possibility that with a single financial measure we can assess financial performance and instead recommends to judge future prospects in a broader context (FASB 2002, 5-6):

> 'The many concerns raised during the course of our interviews provide a clear and strong reminder about the characteristics and *limitations* of the kind of information that financial statements can provide … and the shortcomings of present GAAP and financial reporting. This suggests that the FASB not prematurely raise expectations that it might be possible, in our present environment, to assess a company's financial performance through a single financial measure or financial statement. Certainly, financial statements provide useful information for purposes of assessing a company's performance, but judgments about past performance as well as future prospects are best made in context with the environment in which a company operates and in relation to its peer group.'

However, I suggest that financial performance measurement and evaluation by firm, segment or peer group requires appropriate accounting theory and practical solutions.

In April 2004, the IASB and FASB '…discussed and expressed support for a staff proposal to undertake a joint project that would have as its objective the development of a common conceptual framework—a single framework in which the existing frameworks of the two boards converge and which improves upon them…' (IASB 2004, 4). It is reported that, during meetings in April and May 2007, the IASB and FASB Boards made a number of decisions of which the following relate to this study (IASB 2007, italics supplied):

- 'Verifiability should be separated from faithful representation and identified as a separate qualitative characteristic.
- *Relevance* and faithful representation should be distinguished as necessary qualitative characteristics.
- Whether the qualitative characteristic of *relevance* should be described as "capable of making a difference."
- Whether faithful representation should replace reliability as a qualitative characteristic.
- Whether verifiability should be a component of faithful representation or a separate qualitative characteristic.'

And the subjects in the section about Asset Definition:

- *Likelihood*—Some people misinterpret the terms 'expected' in the IASB definition and 'probable' in the FASB definition to mean a high likelihood of future economic benefits for the definition to be met, thus excluding from the definition of asset items with a low likelihood of future economic benefits.
- *Future economic benefits*—Existing definitions focus on identifying the future flow of economic benefits, instead of focusing on the item that presently exists, an economic resource.

- *Past transaction or event*—Undue emphasis is being placed on identifying the past transaction or other event that gave rise to the asset, instead of focusing on whether the economic resource and the entity's access to it exist at the balance sheet date.
- *Contractual promises*—It is unclear how the definition applies to contractual promises.

Clearly, all four issues about the definition of assets on the balance sheet are about the forward-looking informational content of the reported figures. Moreover, the above mentioned IASB and FASB boards' decisions reflect the need for (more) relevant information on the one hand but with the possibility to substantiate its qualitative characteristics. Again, this is why Ijiri developed TEMA as an extension of the existing double-entry bookkeeping system. It is his ambition to administer which procedures are used such that also the qualitative characteristic, i.e. the subjective interpretation, of forces (economic resources) can be substantiated. Actually, the IASB—FASB provide a good definition for the administration of such forces, economic resources or assets (italics supplied):

- An asset is a present economic resource to which the entity has a present right or other privileged access.
- Present means that both the economic resource and the right or other privileged access to it exist on the date of the financial statements.
- An economic resource is something that has positive economic value. It is scarce and capable of being used to carry out economic activities such as production and exchange … [and] … include non-conditional *contractual promises* that others make to the entity, such as promises to pay cash, deliver goods, or render services.

A more concise definition of momentum cannot be given than that of the definition of future economic benefits in the section about Liability Definition (italics supplied):

- *Future economic benefits*—Existing definitions focus on identifying the future outflow of economic benefits, instead of *focusing on the item that presently exists*, an economic burden.

The motivation for this research that derives from this development is that I argue that the TEMA framework can be supportive to any effort for additional disclosure of forward-looking information to the benefit of shareholders.

1.9.6 Strategic accounting & auditing

The interest in the dynamics of strategy is certainly growing (Day & Reibstein 1997, De Groot *et al.* 2004, Roslender & Hart 2003, Van der Heijden 1996 and Van Eenennaam 2006). Force accounting in the TEMA framework stretches the scope of analysis of the causal network of relations from mere financial accounting, to management accounting, if not strategic accounting (Brouthers & Roozen 1999, Roslender & Hart 2003). With Ijiri's TEMA framework, a methodology could be developed to expand the accounting information system to help management to exercise both better strategic and operational control. Ijiri did not mention the Balanced Scorecard of Kaplan & Norton (1996, 2001A-B) himself as a method with a similar objective as momentum accounting in his later publications (Glover & Ijiri 2002, Glover *et. al.* 2002, 2005). Nevertheless, TEMA strives to integrate financial accounting with management accounting and control in a manner similar to Kaplan & Nortons' approach. Both have a holistic view of the firm. It does not seem unreasonable to assume that the TEMA framework can contribute to the development of strategy with its disclosure of more forward-looking information.

Another line of strategy related research from within the auditing profession has been put forward under the title of 'strategic-systems auditing' (e.g. Bell & Solomon 2002). Bell *et al.* (1997, v) recognize that:

> '...information technology has brought dramatic changes to business processes, to business organization, and even to auditing. These changes require major consideration of what we know about financial-statement audit technology.' But '...business viability and profitability assessments are essential elements of financial statement auditing today and for the twenty-first century ... the viability of the whole of a business is more than the sum of its parts. The individual financial-statement elements can be valid yet the entity as a whole not be viable because of the complex interdependencies comprising business viability ... focuses on analyses of business strategy, business processes to achieve strategy, key indicators necessary to monitor performance of business processes in achieving strategy, and risks faced by the entity.'

The TEMA framework not only can provide the '...key indicators necessary to monitor performance of business processes in achieving strategy...,' it also provides all the necessary instruments to enable their audit! Of course, this all depends on the implementation of triple-entry bookkeeping so that '...the complex interdependencies comprising business viability ... focuses on analyses of business strategy...' are substantiated by evidence (Blommaert 1994A, 171-220). Bell *et al.* (1997, 18) are looking for a 'strategic systems lens' so that auditors are able to study the dynamics and strategic position of the whole system:

> 'To gain the appropriate level of understanding of a client's business and industry for the purpose of conducting a financial-statement audit, we believe that today's auditor should direct his attention to the client's systems dynamics – its strategic positioning within its environment; its emergent behaviors that impact its attained level of performance; the strength of its connections, or structural couplings, to outside economic agents; the nature and impact of any symbiotic alliances; the specific interrelationships and internal process interactions that dominate its performance; and potential changes in other reaches of the vast economic web that might threaten the viability of the client's strategies and niches. These systemic properties determine the strategic competencies and capabilities that enhance the value of the organization and that promote changes in that value over time.'

The hypotheses of this thesis were developed from the contention that the basis of financial accounting is a system model (Correa 1976, 1977, Kefford 1995, Mattessich 1978, Thomsen 1998). Therefore, it is interesting to observe the sense of urgency in the Bell *et al.* (1997) study for the fact that logic dictates that the whole business 'system' is already captured by the accounting system. What is lacking is the disclosure of business dynamics as rates of change in momentum accounting statements as well as with models using econometric or System Dynamics' models (Sterman 2000). Theory and technology is abundant to discipline the accounting and auditing process to facilitate business strategy, both its formulation and its deployment (Brouthers & Roozen 1999, Coyne & Subramaniam 1996, Day & Reibstein 1997, Draman *et al.* 2002, Hutton 2004 and Roslender & Hart 2003).

The motivation for this research that derives from this development is that I expect that the TEMA framework might be supportive to any effort to administer the complex interdependencies between variables and models that might disclose business viability. As such, TEMA could be helpful to articulate as well as to realize business strategy and its auditing process.

1.10 Research contribution

When this study confirms the general relationship assumption for TEMA framework with the firms selected, it will contribute to the foundation of the momentum accounting theory of Yuji Ijiri (1982, 1986, 1987 and 1988A). Firstly, the study involves the *relevance* of TEMA by:

- Comparing a performance ratio to a momentum ratio and to establish if the latter is more informative than the former by means of scatter plots.
- Establishing if measurements of wealth, momentum and force disclose changes in balance sheet composition by comparing the informational measures of 3M Company.
- Testing the generality assumption by Spectramap decomposition analysis and visualization of balance sheets of 3M Company.

Relevance concerns the nature and materiality of the information disclosed. Color coding is applied here for the analysis of informational measures and data structures (TABLE 1).

Secondly, the study involves testing the general relationship assumption by econometric time series analysis for TEMA framework. This should be accomplished by the development of ARIMA models of force accounting variables, as suggested by Ijiri (1989, 10.5). The verification of the *ex post* trend of net wealth through explanatory models would provide some evidence for the general relationship assumption of the TEMA framework. The possible contribution of TEMA will be more relevant if I can show that it is possible to also forecast the trend of net wealth *ex ante* with ARIMA models. Furthermore, if forecasting of the trend of net wealth has an acceptable success rate, TEMA might aid analysts and investors with their assessment of a firm's market performance. This could also have repercussions for existing accounting theory, especially in the domain of management accounting and strategic control for the reason that financial variables are to date perceived to be lagging indicators of business performance and not leading indicators (Kaplan & Norton 1996, 2001A-B).

TEMA might also aid analysts and investors with their assessment of a firm's market performance. To study this, econometric models of decomposed TEMA variables of the Dow Jones component companies will be tested. With a study of the balance sheet composition of one firm, the explanatory and predictive power is tested of decomposed variables. With any luck, this discloses the dynamic relationships between variables of the TEMA framework.

1.11 Structure of the dissertation

The findings of this research are presented in eight chapters which are structured into two parts (TABLE 1). Chapters 3 to 6 are the first part that addresses the informational relevance of the TEMA framework with data analysis. In Chapter 3, I compare performance ratios with a new TEMA ratio while discussing the firm Robert Half International Inc.: the common size format momentum or force ratio. In Chapter 4, I apply decomposition analysis to study the structural change of the balance sheet of 3M Company. The decomposition measure of Baruch Lev is compared with the disaggregation measure of Yuji Ijiri for wealth, momentum and force measures. In Chapter 5, I propose a new approach for the decomposition analysis of financial statements using Spectral Map Analysis for multivariate data analysis and visualization. Chapter 6 concludes the first part of the thesis with Spectramap biplot visualization and color coding to expose the 'data structure' change of ten-years of quarterly balance sheets.

Chapters 7 to 10 are the second part of this thesis in which time series modeling and simulation is applied. The explanatory and predictive power of accounting variables of the TEMA framework is tested with dynamic econometric TEMA models of the component companies of the Amsterdam Exchange index in Chapter 7 and the Dow Jones Industrial Average in Chapter 8. In Chapter 9, a new approach is proposed for the study of dynamic change of the balance sheet with a TEMA model, in this case of 3M Company. In Chapter 10, finally, the potential relevance of the theory of momentum accounting is empirically investigated for market index explanation and prediction, in this case the Dow.

Chapter 11 contains the summary and conclusion. Chapter 12, finally, provides a summary in Dutch. The Appendix contains the references of this thesis, the authors' curriculum vitae, papers & posters presented during this study and the color figures of Chapter 4 and 6.

Part I – Data Analysis	*Part II – Time Series Analysis*	
Informational Relevance	Explanatory Power of TEMA variables	Predictive Power of TEMA variables
Informational signals & data structures	TEMA *models ex post regression*	TEMA *models ex ante forecast*
Chapters 3-6	Chapters 7-10	

Table 1 Structure of the dissertation.

2

Research Methodology

	Part I – Data Analysis	*Part II – Time Series Analysis*		
	Relevance	Explanatory Power		Predictive Power
	momentum ratio	*net wealth ex post*		*net wealth ex ante*
3	Robert Half Int.	AEX firms Dow firms	7 8	AEX firms Dow firms
	information	*wealth ex post*		*wealth ex ante*
4	3M Company	3M Company	9	3M Company
	decomposition	*index ex post*		*index ex ante*
5 6	3M Company	Dow models	10	Dow models

Table 2 Research matrix (chapter numbers in bold type).

1. There is a general relationship between variables in the TEMA framework.
2. There is a general relationship between TEMA variables by compository association.
3. There is a general relationship between TEMA variables by temporal association.
4. Operating income is associated with net wealth.
5. Total wealth is associated with net wealth.
6. Force and momentum time series are stationary or trend-stationary.
7. Operating income and total wealth can explain and predict net wealth.
8. Decomposed TEMA variables of a company model balance sheet dynamics.
9. Decomposed TEMA variables of component companies model index dynamics.

Table 3 Research hypotheses summarized.

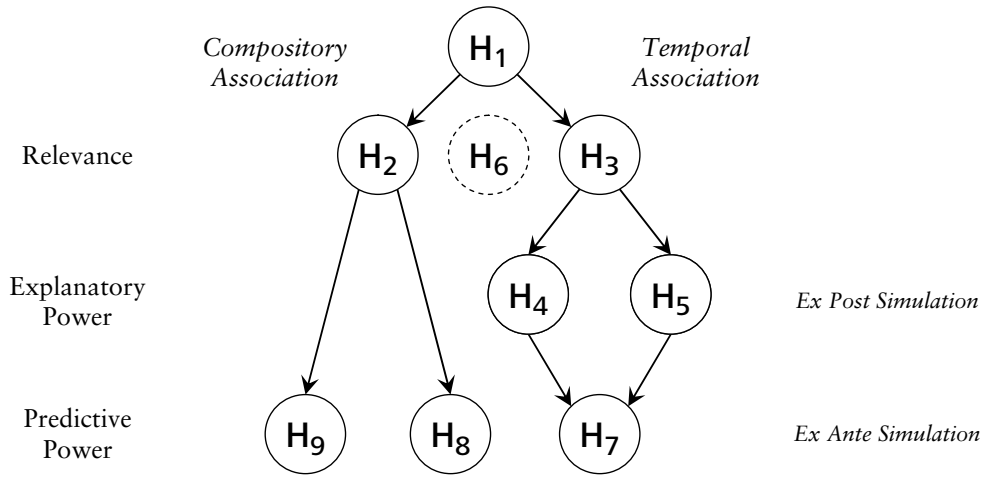


Figure 4 Directed graph of the research hypotheses.

	Part I – Data Analysis	*Part II – Time Series Analysis*		
	Relevance	Explanatory Power		Predictive Power
	momentum ratio	*net wealth ex post*		*net wealth ex ante*
3	H1	H3 H4 H5	7 8	H7
	information	*wealth ex post*		*wealth ex ante*
4	H1 H2	H6	9	H8
	decomposition	*index ex post*		*index ex ante*
5 6	H1 H2	H6	10	H9

Table 4 Hypotheses positioned on the research matrix (chapter numbers in bold type).

2 Abstract

This study investigates phenomena of financial statements, in particular the balance sheet, in an effort to acquire new knowledge about the validity of the TEMA *framework and to integrate it with previously developed financial statement analysis methods. It is based on measurable evidence using archival data of publicly available financial statements compiled with double-entry accounting. The hypotheses of this thesis are tested through the decomposition of data structures in the three dimensions of the* TEMA *framework and the formulation and simulation of dynamic econometric models. In this chapter, I explain the methodology that is applied to develop the time series models with a fully developed example. Through* ARIMA *time series modeling the research hypothesis of this study will be tested using* TEMA *variables. Furthermore, a brief explanation is given of the visual analytics methodology used in several studies presented in this thesis of multivariate data analysis with spectral mapping. Lastly, a new color coding methodology is introduced that is applied in informational analysis and decomposition analysis of balance sheet data by means of spectramap biplots.*

2.1 Introduction

In the four following chapters of this thesis, which discusses the research of the relevance of the TEMA framework, the static structure of balance sheet data is analyzed and visualized by means of ratio analysis, informational measures, color coding and decomposition by Spectral Map Analysis. In the four chapters thereafter, the research into the explanatory and predictive power of TEMA models is discussed and a time series modeling methodology for dynamic simulation is applied. In this chapter all these research methodologies are introduced but mostly rather brief because more in depth explanations are available in the literature. The section about time series analysis explains the applied methodology. It also contains a detailed analysis of one of the 30 component companies of the DOW: 3M Company. This example of econometric model development, simulation and testing of time series statistics is part of the research material of Chapter 8, where the empirical study is discussed of all 30 DOW component companies. Those readers who are familiar with ARIMA modeling can browse through the time series section of this chapter and read about the example with closer consideration. The example of 3M Company is included in this chapter to provide an in depth discussion and to illustrate the particulars of ARIMA time series modeling and analysis to those who are unfamiliar with it. I refrain from more detailed explanations of individual models in the other research chapters where instead I will concentrate on the findings and discussion of the limitations and implications.

Organization of this chapter

Section 2.2 presents the material researched in this study. A research matrix provides an overview of the next chapters and data sources used in the analysis. Section 2.3 is a concise introduction of time series analysis, methods and tests relevant to this thesis. I discuss the regression models that I use to find evidence that the generality assumption holds for TEMA. An in depth discussion of an example analysis of 3M company is presented as an illustration of the econometric methodology used. Section 2.4 introduces the Spectral Map Analysis methodology used to facilitate visual analytics and econometric modeling. A new methodology for the color coding of data is discussed in section 2.5. In this thesis informational measures and spectral mapping decomposition data (loadings and scores) are color coded to reveal additional insight into the association between balance sheet items. The conclusion is presented in section 2.6.

2.2 Research material

This section continues with a discussion of the material used to study the static structure of accounting data and the dynamic simulation of TEMA models. To this purpose a research matrix is used. Next, a brief description of the various studies and how they are connected to the research hypotheses and the reasoning behind the directed line of research hypotheses. Data samples are described as well as the time granularity of the financial statements data studied.

2.2.1 The research matrix

TABLE 2 is the research matrix in which the studies of this thesis are arranged vertically by research focus and horizontally by research topic. Left from each study, the related chapter number that presents the study, is printed in bold type in TABLE 2. The research hypotheses are summarized in TABLE 3 and discussed in relation to the research matrix in TABLE 4.

The first part of this thesis research, *data analysis*, presents three topics: a TEMA ratio, informational measures and balance sheet decomposition. With the informational relevance of the TEMA framework I investigate, along the lines of the definition discussed by the (IASB 2007), the qualitative characteristic of accounting information as being '...capable of making a difference.'[1] Chapter 3 discusses a *common size format momentum and force ratio* by example of Robert Half International. Chapter 4 discusses the *informational measures* of Lev and Ijiri by example of 3M Company. Chapter 5 discusses *decomposition analysis* of quarterly balance sheets of 3M Company in each dimension of the TEMA framework. Chapter 6 extends the analysis with the decomposition by spectral mapping of the balance sheet at a lower level of disaggregation. Color coding is employed to add more information to the static structure of the first three SMA factors. By decomposition analysis with spectral mapping I seek to find support for research hypothesis H 2_a and thus provide also some support for the more general hypothesis H 1_a. However, my research to this point is limited to *compository association* of variables from the TEMA framework. It will only expose that an association between variables holds with static data. This is of interest when exploring whether such association exits, but it is still rather weak evidence since the true nature of financial accounting time series is dynamic (Cooke & Tippett 2000).

The second part of this thesis, *time series analysis*, branches out into two subparts, respectively, *explanatory power* and *predictive power* of the econometric models created with variables from the TEMA framework. Both subparts are covered in Chapters 7 to 10 and not by separate chapters. The reason is that in each study I first try to determine that it is possible to make an explanatory model with TEMA variables for the selected example firms. The time series data of the dependent variable is then calculated using a model that is created with independent variables on the basis of the original data, i.e. these are *ex post simulations* of the base period time series. In a manner of speaking, such models are 'self-explanatory' and they show that an association between variables holds dynamically over time. When the model is created with independent and dependent variables following the dimensionality of the TEMA framework I can conclude that it has explanatory power for the selected cases. This in itself would give some support for several of my research hypotheses, namely H 3_a, H 4_a and H 5_a. However, more support for the general hypothesis H 1_a will be given by H 7_a when it is in this study possible, within acceptable limits, to predict hold-out sample data with these TEMA models, i.e.

[1] Section 6.2.2, Relevance of balance sheet information, page 139, discusses this with more detail.

with *ex ante simulations* or *forecasts*. Together with the possible disclosure of explanatory power, it will then be shown that these econometric TEMA models have predictive power for the selected cases. The result put forward in this thesis is based on simulation of the component companies of the AEX stock exchange in Chapter 7 and the DOW in Chapter 8.

In Chapters 9 and 10, the same is done but with factors derived from the decomposition analysis by Spectral mapping of, respectively, the balance sheet of 3M Company and TEMA variables of all component companies of the DOW. The hypothesis to be tested by the first study is if SMA factor variables can model and simulate balance sheet dynamics (H 8_a). The hypothesis to be tested by the second study is if it is possible to predict the DOW index with the SMA factor variables of all its component companies (H 9_a).

Of course, statistical tests are required to reduce the risk of spurious regression between TEMA variables, or heteroskedasticity and autoregression in the equation residuals. Another important constraint that must be met is that the modeled time series are not trending and thus do not contain a unit root. In that case the TEMA variables are stationary, or trend-stationary, and my conditional research hypothesis H 6_a is met. The time series methodology is explained in some detail in section 2.3 together with the applied test statistics.

2.2.2 *Connectedness of the hypotheses in the research studies*

Depending on the constraint set by the conditional hypothesis H 6_a, any success of the ex post and ex ante simulations of this study would imply that the evidence is consistent with TEMA theory and the general hypothesis H 1_a. FIGURE 4 is a directed graph to show the line of reasoning from one hypothesis to the other and serves to illustrate the connectedness with the various studies of this research. As mentioned above, TABLE 4 is the research matrix of this thesis but now with the hypotheses superimposed. It further illustrates the connectedness of the hypotheses within the research studies. Part I of this thesis, which is focused on the *informational relevance* of the TEMA framework seeks to find evidence to support H 1_a, H 2_a and H 3_a. Part II of this thesis, which is focused on the econometric modeling of time series, as explained in the previous subsection, has two sub-parts. One part is about the *ex post simulations* that seek to find evidence for the explanatory power of the TEMA framework. Taken together, the various studies seek to find support for hypotheses H 7_a, H 4_a and H 5_a. The *ex ante simulations* seek to find support for hypothesis H 7_a. Assuming that hypothesis H 6_a also holds for the factor time series of the decomposed balance sheet and the accounting variables of the DOW component companies, evidence of the last two studies will support H 8_a and H 9_a. Hopefully, the results of the various studies, taken together, support the general hypothesis H 1_a. When the research objective is met for the selected cases then the generality assumption of the TEMA framework holds for this study.

2.2.3 *Data samples & time granularity*

Any evidence to be provided by this study to support the research hypotheses depends on the data used and on the number of measurements. There is a lower limit of the number of time points measured under which dynamic time series analysis renders unreliable results. Rule of thumb is that a time series length should not be less than 20 measurements. It is also the question whether the selected sample of measurements will contain the desired 'information' that will resonate with the assumptions of this study (Lewi 1999). Whether or not this will be the case is a matter of theory, sample, tests, taste and debate. In this study the data samples of the various studies are financial statements data of the component companies of two stock ex-

changes and of Robert Half International. In the first study of component companies, yearly data of Dutch companies are used that are part of a stock market index, traded on Euronext Amsterdam (excluding financials), formerly known as the Amsterdam Stock Exchange, or AEX in short. The second study uses quarterly data of all component companies of the Dow Jones Industrial Average index, or DOW in short. The data is used 'as published' and not corrected for possible seasonal trends or changes in accounting regimes. The reason is that I take the position that analysts, investors or managers, when they assess firm performance are not likely to do the same. However, this induces the likelihood that the association I seek to test is weakened or disturbed by unwanted effects. On the other hand, should I find evidence of associations between variables from the TEMA framework I can conclude that the generality assumption holds in the selected cases, even with data that might be contaminated with other unwanted information. Should the findings mostly be on the border of what is statistically acceptable then I have to fear for the reliability of this study. If this is not the case, I expect that repeating my analysis with data sets that are controlled for possible interfering disturbances will only confirm and improve the findings of this research.

2.3 Time series analysis

In this section I elaborate on the econometric methodology used to construct dynamic models in accordance with the TEMA framework. I employ econometric time series analysis to test its validity. Econometric models are used as a vehicle to let the 'data demonstrate itself' whether or not TEMA has any explanatory and predictive power in the selected cases.

The following subsections present a concise definition and comprehensive discussion of the applied econometric methodology. Most of the subject matter is discussed while using 3M Company as a modeling and simulation example. This, so I hope, offers an opportunity to grasp the essentials of econometric modeling from the perspective of its application to the analysis of accounting information. Those familiar with econometric methodology can browse through this section rather quickly, but are encouraged to read about the example, and continue with the following chapters.

2.3.1 Accounting measurement of change

This study researches evidence of the association between financial accounting variables within the TEMA framework of Yuji Ijiri of force, momentum and wealth accounting. Yuji Ijiri draws an analogy between his momentum accounting theory and mechanics when he introduces the concepts of *momentum* and *force* in financial accounts (Glover & Ijiri 2002, Ijiri 1986, and Blommaert 1994). Ijiri postulates force in the accounting interpretation as an investment times acceleration (rate of change):

$$\$10/\text{mo}^2 = \$10{,}000 * 0.1\%/\text{mo}^2.$$

Momentum, stated as a fraction per month, increases by 0.1%/mo for each month's duration. Ijiri draws his system of accounts for triple-entry bookkeeping as an interlocking framework of derivative, integral and difference relationships (FIGURE 1, page 2). This is extended to incorporate the rate of change of wealth accounts (FIGURE 5). The TEMA framework is used to obtain econometric models that estimate the association between the independent TEMA variables — force accounts — and a dependent TEMA variable (FIGURE 6).

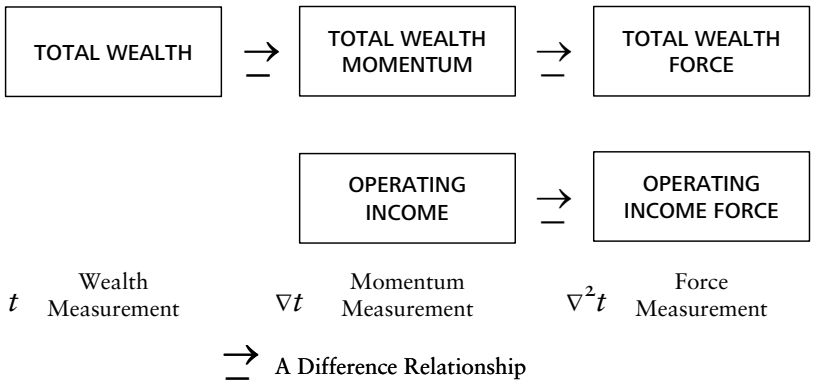


Figure 5 Determination of momentum & force variables from double-entry accounting time series.

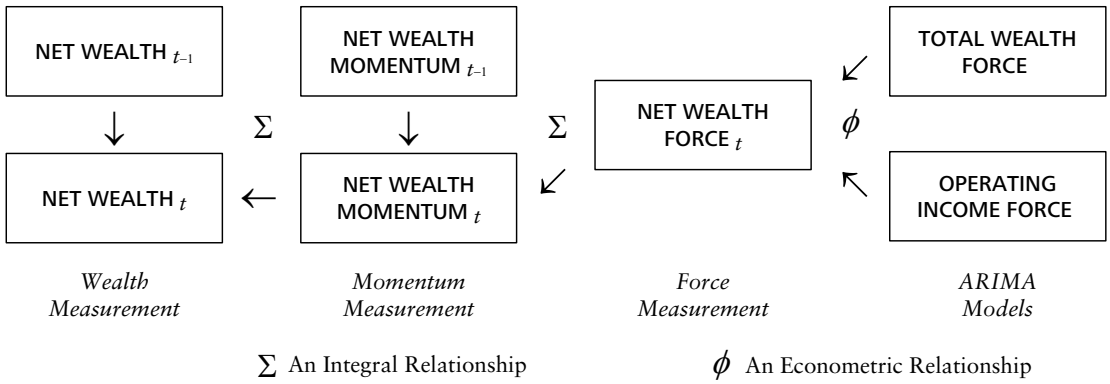


Figure 6 Aggregation of data from ARIMA models in the TEMA framework.

Over time (t), net wealth force is added to the previous value of net wealth momentum whilst that is added up to the previous value of net wealth. Ijiri formulates momentum (M) in monetary units per period through the derivative relationship of wealth accounts (W):

$$\mathsf{M}_t = \Delta \mathsf{W}_t / \Delta t. \tag{6}$$

Similarly, force (F) is formulated in monetary units per period through the derivative relationship of momentum accounts:

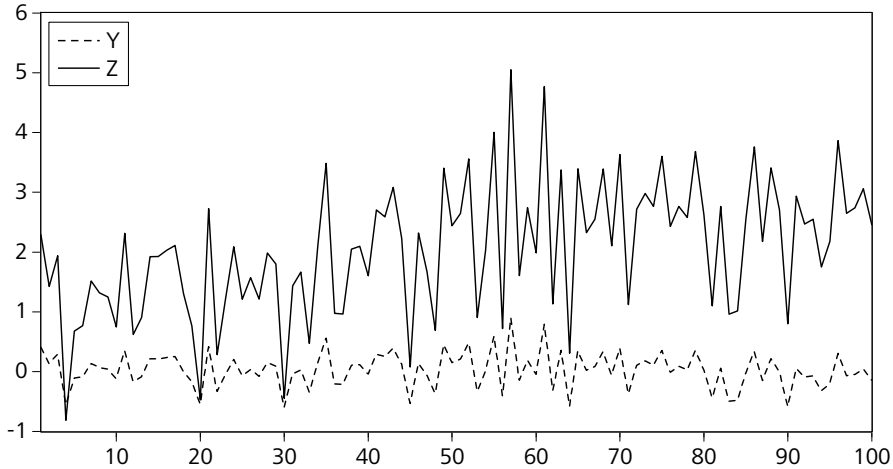
$$\mathsf{F}_t = \Delta \mathsf{M}_t / \Delta t = \Delta^2 \mathsf{W}_t / \Delta t^2. \tag{7}$$

For lack of time series data with a smaller time step difference than one year or one quarter the incremental time period in the momentum and force models is kept constant in this study at either one year or one quarter. Therefore, the measurement of momentum or force by means of wealth (or income) accounts is calculated with the unit period at hand—either a year or a quarter ($\Delta t = 1$ and, therefore, $\Delta t^2 = 1$). For that reason, the econometric models have a yearly or quarterly change rate or change of change rate, ∇t or ∇t^2. This leads to the replacement of Equations (6) and (7) by:

$$\mathsf{M}_t = \mathsf{W}_t - \mathsf{W}_{t-1} = \nabla \mathsf{W}_t \qquad \text{with } t=1, \ldots, T, \tag{8}$$

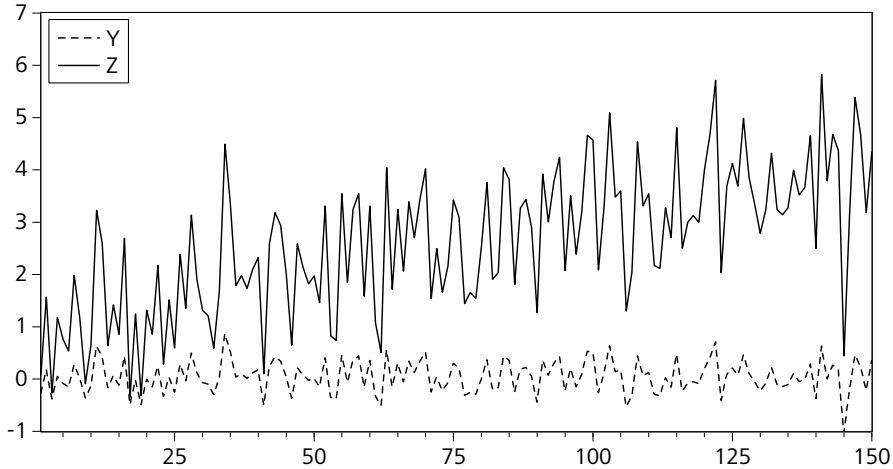
$$\mathsf{F}_t = \mathsf{M}_t - \mathsf{M}_{t-1} = \nabla^2 \mathsf{W}_t \qquad \text{with } t=1, \ldots, T. \tag{9}$$

Equations (8) and (9) allow for the computation of momentum or force sequences from published financial statement data at a yearly or quarterly rate of change. Box *et al.* (1994, 12)



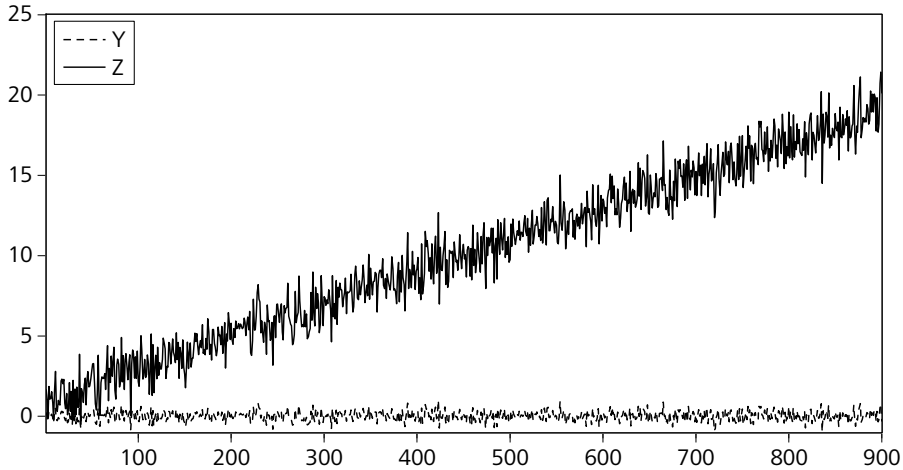
Time series 100 steps	1% level	ADF test	Prob*	1% level	PP test	Prob*
Y = stochastoc trend	-3.498	-12.596	0.000	-3.498	-12.482	0.000
Z = stochastoc trend	-3.499	-3.382	0.014	-3.498	-10.146	0.000

Figure 7 100 observations of two example time series:each with stochastic trend.



Time series 150 steps	1,10% level	ADF test	Prob*	1% level	PP test	Prob*
Y = stochastoc trend	-3.475	-12.995	0.000	-3.475	-14.593	0.000
Z = deterministic trend	-2.578	-2.007	0.283	-3.475	-9.060	0.000

Figure 8 150 observations of two example time series: only y has a stochastic trend.



Time series 900 steps	1,10% level	ADF test	Prob*	1,10% level	PP test	Prob*
Y = stochastoc trend	-3.437	-32.313	0.000	-3.437	-32.329	0.000
Z = deterministic trend	-2.568	-0.159	0.941	-2.568	-2.296	0.174

Figure 9 850 observations of two example time series: only y has a stochastic trend.

mention that in time series analysis, equations are often used in which the differential operator $D=\Delta/\Delta t$ for continuous data is replaced by the difference operator ∇ for discrete data. The financial accounting sequences for momentum (first difference) and force (second difference) are computed using the balance sheet or the income statement of firms listed on the two stock exchanges analysed (i.e. the component companies of the AEX and the DOW, FIGURE 5). The income statement in Ijiri's framework is considered to be a momentum measurement (FIGURE 2, page 2). The force sequence of operating income is calculated to balance force of total wealth in the econometric equations. The econometric models aggregate the values of simulated times series with a forecast function to the current value of net wealth (FIGURE 6).

2.3.2 *Trend behavior*

Wealth accounts, like many other economic and business time series, typically tend to accumulate and therefore usually exhibit trend behavior (Franses 1998A, 9). The essential idea of trend is that it represents smooth, relatively slowly changing, features of a time series (Kendall & Ord 1990, 27). For example, total wealth of 3M Company exhibits almost unchanging continuous growth (FIGURE 13, page 60). In econometrics, a distinction is made between time series that have a deterministic or a stochastic trend (Box e.a. 1994, 97, Koop 2005, 148). A deterministic trend is constant for the life of the whole series, irrespective of time, whereas a stochastic trend can shift signs, and be either positive or negative. In FIGURE 7, 8 & 9 example deterministic and a stochastic time series are presented of different length (100, 150 & 850 observations). Note that the times series with the deterministic trends does fluctuate but exhibits a steady growth whereas the stochastic time series fluctuates around zero.

A model migth exhibit a *deterministic trend* but still be *trend stationary* when it includes a *function of time* (δt). In contrast, time series that have a unit root are not stationary and contain a so-called *stochastic trend*, like operating income force of 3M (FIGURE 11, page 60). The trending behavior of a model of such time series arises from the sum of its past errors (Koop 2005, 148). These past errors (or shocks) are 'remembered,' accrued in accounting terminology, and are viewed by statisticians as random or 'stochastic.' Cooke & Tippett (2000, 266) recognize in their accounting theory that instantaneous changes in a firm's bookkeeping summary measures evolve in accordance with a vector system of stochastic differentials. This is a key property of nonstationary series and it implies that wealth and, most likely also momentum accounts (income), exhibit stochastic trend behavior. Such trend must be removed because, if not, it likely leads to spurious regression results (Phillips 1986, Koop 2005, 160). Indeed, in all of the cases studied here, the wealth accounts are not stationary and have a unit root. One solution for short term dynamic modeling is to difference the time series and model them as momentum or force equations. All accounting variables of this study were tested for the presence of a unit root with the Augmented Dickey-Fuller test (ADF) and the Phillips-Perron test (PP), see TABLE 5 and TABLE 6 for 3M as an example.[2]

[2] Koop (2005, 155) cautions that the ADF test results are not reliable when the time series exhibits structural breaks or a permanent level shift (Franses 2005, 139). Franses (2005, 151) recommends the so-called 5% rule of thumb to safely conclude that there is no unit root below -5.08 and there is one with a test statistic above -3.75. See also for this subject: Seiler (2004, 279-287).

	Augmented Dickey-Fuller test statistic	5% level	1% level	ADF	Prob.*
Y	Net Wealth (1)	-3.478305	-4.100935	1.493740	1.0000
X	Total Wealth (1)	-3.478305	-4.100935	-0.608726	0.9752
∇ X	Total Wealth Momentum (2)	-2.905519	-3.531592	-7.198408	0.0000
Z	Operating Income (momentum) (1)	-3.482763	-4.110440	-1.297001	0.8797
∇2 Y	Net Wealth Force (2)	-2.906210	-3.533204	-8.359680	0.0000
∇2 X	Total Wealth Force (2)	-2.906210	-3.533204	-9.548475	0.0000
∇ Z	Operating Income Force (2)	-2.907660	-3.536587	-3.675151	0.0068

*MacKinnon (1996) one-sided p-values. Incl. (1) constant & linear trend, (2) constant.

Table 5 3M. Augmented Dickey-Fuller unit root test statistics (1988Q1-2004Q4).

	Phillips-Perron test statistic	5% level	1% level	PP	Prob.*
Y	Net Wealth (1)	-3.478305	-4.100935	1.049438	0.9999
X	Total Wealth (1)	-3.478305	-4.100935	-0.417682	0.9850
∇ X	Total Wealth Momentum (2)	-2.905519	-3.531592	-7.307833	0.0000
Z	Operating Income (momentum) (1)	-3.478305	-4.100935	-3.050132	0.1269
∇2 Y	Net Wealth Force (2)	-2.905519	-3.531592	-14.505080	0.0000
∇2 X	Total Wealth Force (2)	-2.905519	-3.531592	-16.767890	0.0000
∇ Z	Operating Income Force (2)	-2.905519	-3.531592	-14.889090	0.0000

*MacKinnon (1996) one-sided p-values. Incl. (1) constant & linear trend, (2) constant.

Table 6 3M. Phillips-Perron unit root test statistics (1988Q1-2004Q4).

2.3.3 ARIMA *modeling*

The basic approach of the time series regression analysis used in this study is to model the dependent momentum or force variable as a function of independent TEMA variables (Startz 2007, 316). Box and Jenkins proposed that many time series could be explained in this manner by a relatively simple model (Box *et al.* 1994, Masters 1995, 182). In its most basic form, it consists of one or both of two elementary models. One possible component is called the *autoregressive* model (AR, in short) in which a variable sequence is predicted by means of a linear combination of one, two or more of its previous values ($\phi_n V_{t-n}$), plus a constant (α) and a disturbance term (u_t):

(10) AR, $$V_t = \alpha + \phi_1 V_{t-1} + \phi_2 V_{t-2} + \ldots + \phi_n V_{t-n} + u_t \qquad \text{with } t=1, \ldots, T.$$

The other possible component is called the *moving average* model (MA, in short) in which the current value of a variable sequence is equal to the weighted sum of a finite number of disturbance terms ($\theta_n u_{t-n}$), plus a constant (α) and the current disturbance (u_t):

(11) MA, $$V_t = \alpha + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \ldots + \theta_n u_{t-n} + u_t \qquad \text{with } t=1, \ldots, T.$$

The number of AR terms (not counting the constant) is traditionally called p, and the number of MA terms q (Box *et al.* 1994, 94, Masters 1995, 187 and Tabachnick & Fidell 2006, 18-8). One can speak of an ARMA(p,q) model where the terms are assumed to be contiguous, starting with a lag of one and extending then to lags numbered by p and q, respectively. It is possible to leave out intervening lags, using a single term at a more distant lag. In that case, Box *et al.* (1994) recommend the use of seasonal autoregressive or moving average terms for monthly or quarterly data with systematic seasonal movements; something typical for accounting variable time series. Then, p and q, respectively, refer to the number of AR and MA variables used. Indeed, in various cases of this study, including a seasonal autoregressive (SAR, in short), seasonal moving average (SMA, in short) terms, or both, was beneficial. To summarize, through ARIMA modeling the research hypothesis will be tested against the trend in time of TEMA variables. They will be decomposed according to FIGURE 5 and modeled according to FIGURE 6.

2.3.4 Differencing

With ARMA modelling it is assumed that the time series is weakly stationary and, hence, does not exhibit a stochastic or deterministic trend behavior (like in FIGURE 7). When they do, differenced series must be used instead and to this purpose ARIMA (autoregressive, integrated, moving average) models are defined by including a third term called d. If $d=0$, the original time series sequence is stationary. When the series is differenced once, which is noted down by $d=1$, the stochastic trend usually is removed (e.g. FIGURE 42, Franses 2005, 73). Sometimes double differencing is required, which is noted down by $d=2$. Franses (2005, 74) recommends double differencing to remove double stochastic trends that might occur when the growth rate has a time varying mean, something not uncommon in accounting time series. Double differencing can also act as a filter to remove seasonality that, from the econometric point of view, is some form of data contamination (Franses 1998A, 97, Kendall & Ord 1990, 15, 37). Given such a differenced model, we have to 'integrate' the differences to recover the levels (FIGURE 6, Startz 2007, 317). The original time series is then said to be 'integrated of order d' or to be an *I(d)* time series. Note that TEMA with its interlocking framework of derivative, integral and difference relationships between its variables, is in agreement with this econometric modelling procedure (FIGURE 1, page 2).

2.3.5 Balancing

An ARIMA model is self explanatory in the sense that it is developed using past data of the variable that is modeled. That suffices when force variables of companies are modeled in this study, which Ijiri recommends (1989, 10.5). In my studies, however, an extended model is also required that includes two force variables as well as the previous value of net wealth (to integrate momentum and wealth measures as in FIGURE 6). This implies that three accounting variables will be used in the complete dynamic TEMA model:

1. Net wealth is the dependent variable.
2. Total wealth is an independent variable.
   It is a proxy for balance sheet dynamics.
3. Operating income is an independent variable.
   It is a proxy for income statement dynamics.

Net wealth is expected to vary in value in response to changes in total wealth and operating income. In other words, one or two independent TEMA variables are presumed to potentially affect a dependent one. The independent variables will be tested together as well as separately for their explanatory and predictive power. In the following sections the development of the required equations is discussed. A final note is about the need to balance the complete model with these equations. The requirement is that the order of integration of the time series has to be equal. Following what was stated above, the optimal model, in my case, would be balanced when the time series in the equation are like:

$$I(0) = I(0) + I(0) \quad , \tag{12}$$

where the left side of the equation is the dependent, or explained, TEMA variable and the right side has the two independent, or explanatory, variables. This example equation is 'balanced' because all TEMA variables are *I(0)* time series with data that need no (further) differencing to meet the requirement of non stationarity.

2.3.6 Cointegration

Above, it was noted that both the dependent variable net wealth and the independent variables total wealth and operating income are likely to have a unit root (TABLE 1 & 2). Using them in a regression model might deliver misleading results due to spurious regression (Koop 2007, 164). However, when such time sequences exhibit cointegration it allows us to solve the problem of a possible spurious regression (Franses 2005, 213). Engle & Granger (1987) pointed out that a linear combination of two or more non-stationary series may be stationary. If such a stationary linear combination exists, the non-stationary time series are said to be cointegrated. The notion of cointegration is that the unit roots of two or more time series sequences 'cancel each other out,' and, therefore, that it is allowed to include them in a regression model (Koop 2007, 165).[3] The alternative model then is balanced as:

$$I(1) = I(1) + I(1) \quad , \tag{13}$$

because all variables are *I(1)* time series that cointegrate. In this case the data does not require differencing because the non stationarity requirement holds through cointegration. In the economics literature, cointegration also provides the intuition of equilibrium as a concept. When the dependent variable and the independent variables cointegrate, some form of equilibrium relationship exists between them and their trends cancel each other out (Koop 2007, 166). Also, the disturbance term should be rather small although disturbances and unexpected changes will occur. From an accounting theory perspective, we can expect cointegration between financial accounting variables. The trend of either income or total wealth should reflect in the trend of net wealth. Profits (not distributed) accrue into net wealth on the balance sheet. Increases and decreases of total wealth also reflect in a similar manner in net wealth.[4]

2.3.7 Independent variables

At this point it is worthwhile to consider the selection of total wealth force and operating income force as the independent variables. Why do I expect that with these two variables a meaningful relationship will be revealed, and why should I use both in one model? The answer to this question is that total wealth force is used here as a proxy for operational management decisions — as reflected in the financial accounts — because I expect that it foreshadows to a certain degree net wealth force. For example, increased business tends to be reflected in changes of total of assets (total wealth) as well as in asset composition. When such business is profitable, I also expect net wealth increases to follow and that such a pattern can be observed repeatedly. Similarly, fluctuations in operating income force should be followed by a similar behavior of net wealth force because profits accrue in that account on the liability side of the balance sheet. Conversely, it can be argued that changes in total wealth, or net wealth, foreshadow fluctuations in operating income. For example, an increase in total wealth could be the result of an increase of fixed assets which could be followed by an increase of operating income due to the investments made, e.g. in production capacity. In this study such a relation is not investigated in every possible detail because the focus of Ijiri's theory is on net wealth as the

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[3] Franses (2005, 235) mentions that seasonal adjustment of time series can lead to less cointegration and even to spurious cointegration. Therefore, in this study I did not undertake seasonal adjustment of any sort other then that I follow the recommendation that differencing removes seasonality to some extent (Franses 2005, 99).

[4] Naturally, net wealth can be regressed on total wealth. Yet, in Ijiri's framework the trend of net wealth is of special importance as a performance measure (Blommaert 1994, 215).

accounting variable to be used as a measurement of business performance. Hence, it is here the variable of interest to model as the independent variable.[5]

2.3.8 Force equations

I expect a functional relationship between TEMA variables because Y, net wealth, depends on X, either total wealth or operating income (or both, as we will see later). For my object of study, the regression equation should explain net wealth, or owners' equity of a firm:

(14) NW, $$Y_t = \alpha + Y_{t-1} + \beta_1 \nabla X_t + \beta_2 Z_t + u_t \qquad \text{with } t=1, \ldots, T,$$

where Y represents net wealth, ∇X total wealth momentum and Z operating income. This model does not balance, because the time series order of integration is *I(1) = I(0) + I(1)*. Behind EQUATION (14) lies the assumption that no feedback is present between the lagged value of the dependent variable Y and the independent variables X and Z. Thus, at any point in time Y, *net wealth*, is explained by the total sum of a constant term α, its previous value Y_{t-1}, the two independent variables ∇X and Z, and this regressions' disturbance term u. At the right hand side of EQUATION (5), the lagged variable Y has no coefficient (it is in fact 1) and thus, when Y_{t-1} is subtracted from both sides, following Koop (2005, 147), I obtain:

(15) NWM, $$\nabla Y_t = \alpha + \beta_3 \nabla X_t + \beta_4 Z_t + v_t \qquad \text{with } t=1, \ldots, T.$$

This equation shows that the right hand side of EQUATION (14) in fact models the first difference of Y or net wealth momentum. In other words, I test if net wealth momentum is explained by total wealth momentum, operating income, or both.[6] Note that EQUATION (15) not only allows for a more concise description but also removes the risk of spurious results because from the right side the dependent variable Y is removed. But, this model also does not balance, because the time series order of integration is now *I(0) = I(0) + I(1)*.

As TABLE 5 and TABLE 6 report for the example of 3M, the total and net wealth time series have unit roots and using them in an ordinary least squares model like EQUATION (14) increases the risk of spurious results (Koop 2005, 164). Instead, using EQUATION (15) with the first difference of net wealth decreases the likelihood that spurious regression occurs in the model. But, EQUATION (15) is not yet fully developed for my purpose. Firstly, it includes operating income (Z) which is a momentum measurement in Ijiri's TEMA framework (FIGURE 2, page 2) but it is not differenced as such and usually does exhibit trend behavior (for 3M compare FIGURE 14 with FIGURE 11, unit root test statistics are in TABLE 5 and TABLE 6). Secondly, and more importantly, both independent variables, being momentum measurements, get their sequences in Ijiri's TEMA framework by adding force up to their previous value (FIGURE 6). Therefore, I reformulate EQUATION (15) as a force regression:

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5 Some preliminary analysis showed that the relation between balance sheet accounts and fluctuations in operating income is very specific for particular accounts although this varies between firms. Hence, further research of this subject is encouraged.

6 To test individual independent variables one of the two ϕ coefficients is set at 0. Note that regression models that include lagged values of the dependent variable require the Breusch-Godfrey Lagrange Multiplier (BG LM, in short) test statistic of the equation residuals instead of the DW statistic (Startz 2007, 308). Autoregression can be the result of misspecification of the model and ungenuine autocorrelation due to the behavioral characteristics of the residuals. Essentially, this rests on the fact that, economic variables are usually autocorrelated and if such a relevant variable effect is included in the stochastic terms (u, v, w) the stochastic term will to that extent become autocorrelated (Studenmund 2001, 313-318).

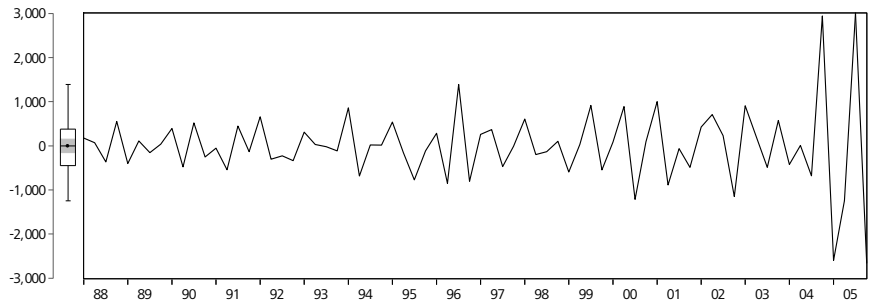

Figure 10 3M. Net wealth force (1988Q1-2005Q4).

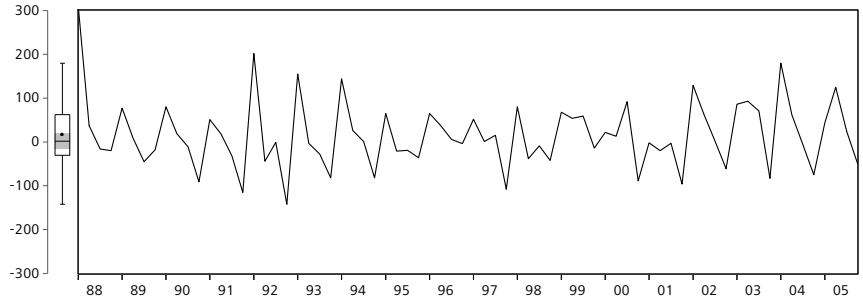

Figure 11 3M. Operating income force (1988Q1-2005Q4).

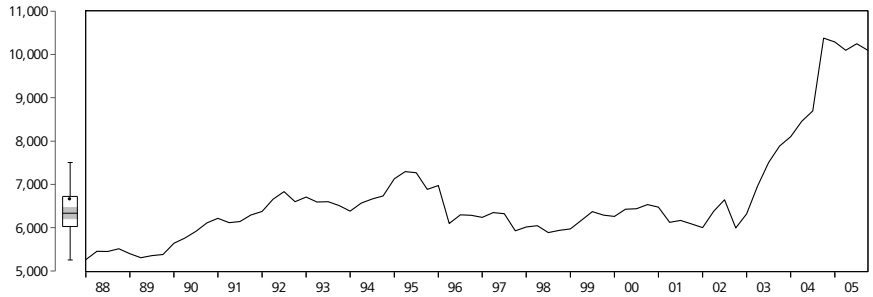

Figure 12 3M. Net wealth or equity (1988Q1-2005Q4).

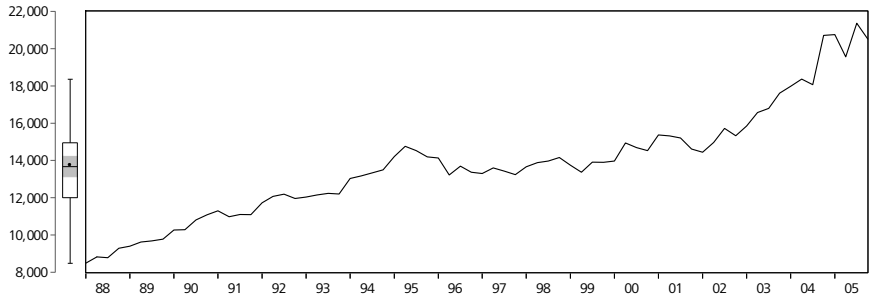

Figure 13 3M. Total wealth (1988Q1-2005Q4).

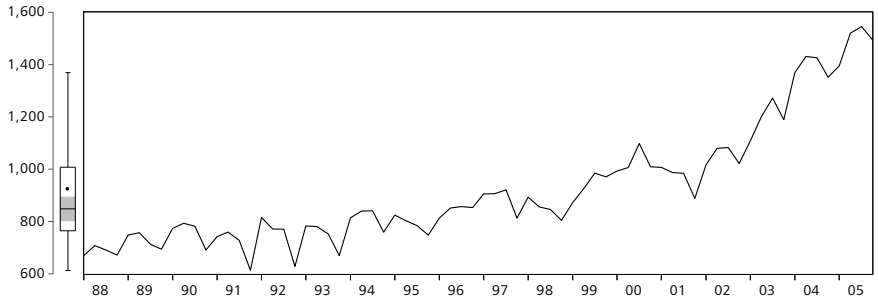

Figure 14 3M. Operating income (1988Q1-2005Q4).

(16) NWF, $$\nabla^2 Y_t = \alpha + \beta_5 \nabla^2 X_t + \beta_6 \nabla Z_t + w_t \qquad \text{with } t=1, \ldots, T.$$

Finally, this model balances, because the time series order of integration is *I(0) = I(0) + I(0)*. EQUATION (16) is a model to test the linear relationship, the association, between financial variables from Ijri's TEMA framework. Net wealth force is explained by total wealth force and operating income force. Net wealth momentum can be calculated by adding net wealth force to its previous value (FIGURE 6). Likewise, we get net wealth by adding net wealth momentum to the previous value of net wealth. Thus the force dynamics drive Ijiri's interlocking framework of TEMA accounts in the econometric models.

2.3.9 Regression analysis, the explanatory power of momentum accounting

In this section I present an example of the association between the financial accounting variables net wealth, total wealth and operating income within the TEMA framework of Yuji Ijiri for momentum accounting (FIGURE 2, page 2). From Standard & Poor's Compustat database, time series sequences of 3M Company were collected. 3M is a diversified technology company that does business, among other areas, in consumer and office, display, electronics and telecommunications, health care, industrial, safety, security and protection services and transportation. Compiled quarterly balance sheets and income statements are used for the period from the first quarter 1978 to the fourth quarter 2005. In this study I did not undertake seasonal adjustment of any sort other than that I follow the recommendation of Franses (2005, 99) that differencing removes seasonality to some extent.

Of each company's accounting variable time series, the period from the first quarter 2005 to the fourth quarter 2005 will be used as a hold-out sample to evaluate the explanatory power of the independent variables in the ordinary least squares regression model (Franses 2005, 95). To determine the start date of a model base period, EQUATION (16) is calculated successively from the first quarter 1978 onwards. By comparing the regression test statistics of the various models it is determined that a base period is viable for the example of 3M from the second quarter 1994 to the fourth quarter 2004, which are 43 observations.[7] TABLE 7 reports the various test statistics of the regression models. In this case, we cannot be very confident when only operating income force is used in the regression, i.e. when $\beta_5 = 0$ in EQUATION (16), because I cannot reject the null that the coefficient is zero because the P-value is 0.2966. This problematic result is also reflected by the extremely low value of its coefficient of determination — Adjusted $R^2 = 0.00$ — which tells us that the model fails completely to account for the variability of net wealth force.[8] Also, the Breusch-Godfrey Lagrange Multiplier (BG LM, in short) test for the presence of serial correlation is larger — 8.52 — than the threshold test statistic of 3.841 for one time lag at the 5% P-value.[9] Therefore, I can not engage in the regression analysis with only operating income force as the explanatory variable of 3M's net wealth force because it fails to explain net wealth force within the boundaries set by the appropriate test statistics. When both the independent variables are used the P-value of the coefficient of

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7 Time series with 20 observations or less cannot be expected to render reliable results.

8 R^2 is a statistic that will give some information about the goodness of fit of a model. Adjusted R^2 is a modification that adjusts for the number of explanatory terms in a model.

9 Note that BG LM also tests for the presence of AutoRegressive Conditional Heteroskedasticity, or ARCH in short, in the residuals of the regression. The *Eviews* software (see footnote 11) can correct standard errors to account for heteroskedasticity of equation residuals by using its least squares equation estimation option panel to generate Newley West consistent standard errors (Startz 2007, 325).

	Coefficient	Std. Error	t-Statistic	Prob.	Adj. R^2	BG LM*	Prob. χ^2
Total Wealth Force	0.44	0.06	7.8057	0.0000	0.60	2.612	0.106
Operating Income Force	1.29	0.66	1.9546	0.0575			
Intercept	23.72	43.98	0.5394	0.5925	0.56	3.297	0.069
Total Wealth Force	0.43	0.06	7.4200	0.0000			
Intercept	28.13	67.61	0.4161	0.6795	0.00	8.520	0.004
Operating Income Force	1.12	1.06	1.0572	0.2966			

* Breusch-Godfrey Serial Correlation LM Test for 1 lag (3.841).

Table 7 3M. Regression test statistics of independent variables for net wealth force (base period: 1994Q2-2004Q4).

Net wealth force models	AIC	RMSE	F-test	P-value
Total Wealth Force Operating Income Force	14.13	269.85	39.03	0.000
Total Wealth Force	14.21	281.15	55.06	0.000

Table 8 3M. Akaike Information Criterion (AIC) and Root Mean Square Error (RMSE) values of the two viable OLS regression models for net wealth force & F-test results (base period: 1994Q2-2004Q4).

operating income force is just above 5% (0.0575). This result is on the threshold of statistical validity. Nevertheless, I do engage with both the independent variables in the regression analysis of Equation (16) for 3M because of—when compared to the regression result with only total wealth force—the increased Adjusted R^2 of, respectively, 0.6 vs. 0.56, and the better BG LM test statistic of, respectively, 2.612 vs. 3.297 (the rejection threshold value is 3.841). According to Franses (2005, 65), there is no strict rule to select one model or the other, but he recommends to use the Akaike Information Criterion, AIC in short. Another selection criterion he advocates is the Root Mean Squared Error, or RMSE in short.[10] The lower the AIC or RMSE value, the more acceptable the model is. Reading Table 8, the results for the two viable 3M models show that, according to the AIC and RMSE values, the preferred model includes both total wealth force and operating income force. However, these results only assess the merit of the models to estimate the base period (ex post). We must evaluate their predictive performance separately.

2.3.10 3M, force equations

Equation 16 is the model with which the hold-out sample forecasts will be simulated. This requires equations for the independent variables total wealth force ($\nabla^2 X$) and operating income force (∇Z) as they drive the dynamics of the predictive model of net wealth force (Figure 6). In this section, ARIMA models of the independent variables of 3M are presented. The goal of ARIMA analysis is a parsimonious representation of the process under investigation (Box *et al.* 1994, 16, Enders 2005, 76). The idea behind this is that it is sufficient to populate an equation with coefficients to make a fairly accurate simulation of the true data-generating process. Only an adequate amount of AR and MA terms are sought. For this study a partly automated procedure is utilized for the computation of alternative ARIMA specifications. Through this I strive to reduce modeler bias. The Akaike Information Criterion (AIC) serves as a guide during the *identification* of the best alternative specification of the force variables (Franses 2005, 42, 59, 65). Alternative ARIMA models are listed in Table 9 with their AIC and Adjusted R^2 statistics. The

[10] For the RMSE equation I refer the interested reader to Franses (2005, 65). See also Startz 2007, 223 and Box *et al.* 1994, 178-180.

Operating Income Force	AIC	Adj. R^2	Total Wealth Force	AIC	Adj. R^2
ARIMA(1,1,1)	10.42	0.561	ARIMA(1,2,2)	15.55	0.475
ARIMA(1,1,1)*(1,1,0)4	10.88	0.363	ARIMA(0,2,1)	15.59	0.426
ARIMA(1,1,0)	10.78	0.354	ARIMA(1,2,1)	15.62	0.423

Table 9 3M. Akaike Information Criterion (AIC) and adjusted R^2 values of alternative specifications of force equations (base period: 1994Q2-2004Q4).

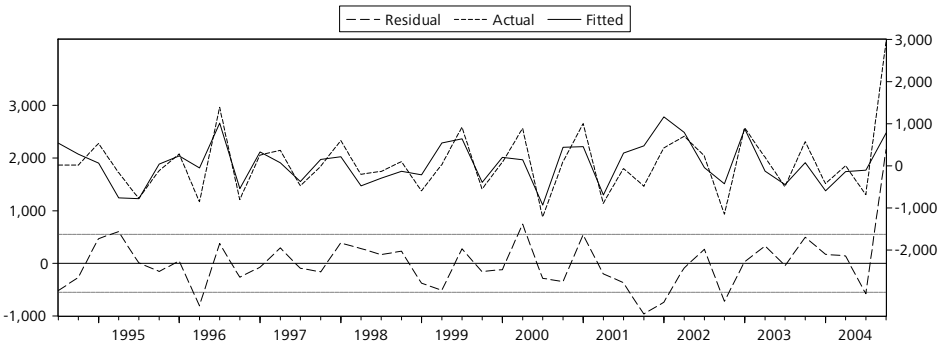


Figure 15 3M. ARIMA(1,2,2) result for total wealth force (1994Q2-2004Q4).

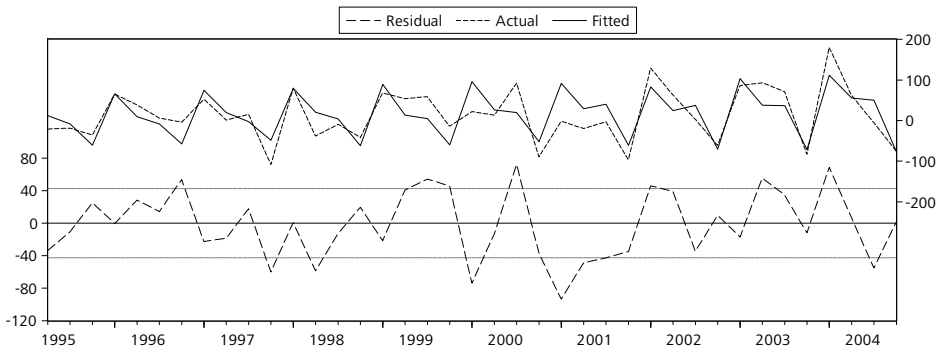


Figure 16 3M. ARIMA(1,1,1) result for operating income force (1994Q2-2004Q4).

selected 3M ARIMA models are:

(17) TWF, $$\nabla^2 X_t = \alpha + \phi_1 \nabla^2 X_{t-1} + \theta_1 u_{t-1} + \theta_2 u_{t-2} + u_t \qquad \text{with } t=1, \ldots, T,$$

(18) OIF, $$\nabla Z_t = \alpha + \phi_1 \nabla Z_{t-4} + \theta_1 v_{t-4} + v_t \qquad \text{with } t=1, \ldots, T.$$

FIGURE 15 is a combined line graph that shows the result of the base period simulation of the ARIMA model of total wealth force of 3M (1994Q2-2004Q4). The top area of the graph has two lines. The continuous line is the fitted simulation data while the dotted line is the ex post data, i.e. the actual data (TABLE 26, page 115). The success of the model can be determined by inspection of the lower area of the graph that has only one dashed line which is the simulation residual and with a horizontal upper and lower boundary line. The upper and lower boundary lines indicate the acceptable limit of one standard error of the simulation. As long as the dashed line of the simulation residual lies in between the boundary lines the fit of the model is good. Note that this is indeed the case for the ARIMA model of operating income force, as FIGURE 16 shows, as well as for total wealth force with the exception of the last month. That last deviation suggests that a shock has occurred that cannot be explained by the ARIMA model of the total wealth force time series of 3M.

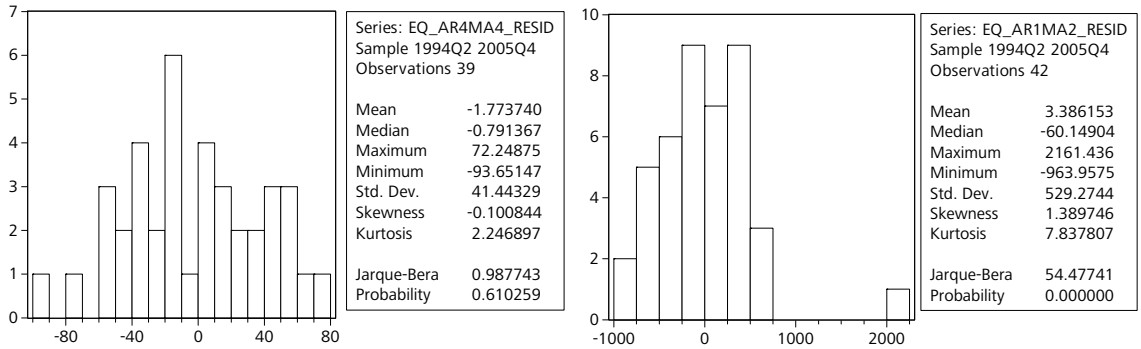


Figure 17 3M. Distribution of equation residuals. Left: operating income force. Right: total wealth force.

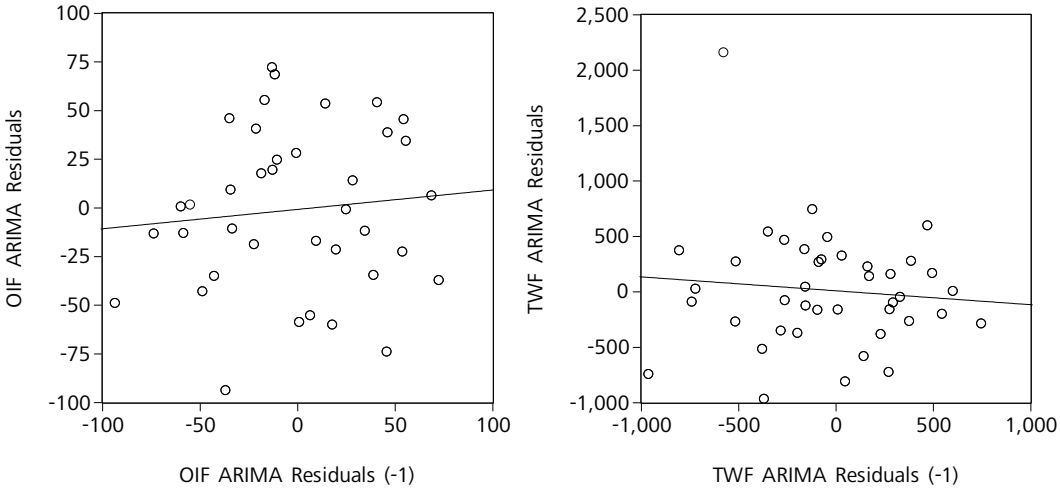
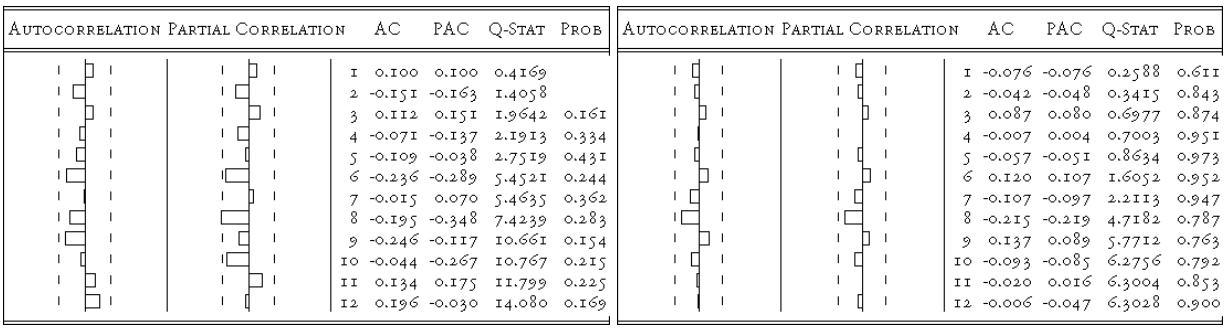


Figure 18 3M. Equation residuals vs. one time lag. Left: operating income force. Right: total wealth force.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.100	0.100	0.4169	
		2	-0.151	-0.163	1.4058	
		3	0.112	0.151	1.9642	0.161
		4	-0.071	-0.137	2.1913	0.334
		5	-0.109	-0.038	2.7519	0.431
		6	-0.236	-0.289	5.4521	0.244
		7	-0.015	0.070	5.4635	0.362
		8	-0.195	-0.348	7.4239	0.283
		9	-0.246	-0.117	10.661	0.154
		10	-0.044	-0.267	10.767	0.215
		11	0.134	0.175	11.799	0.225
		12	0.196	-0.030	14.080	0.169

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.076	-0.076	0.2588	0.611
		2	-0.042	-0.048	0.3415	0.843
		3	0.087	0.080	0.6977	0.874
		4	-0.007	0.004	0.7003	0.951
		5	-0.057	-0.051	0.8634	0.973
		6	0.120	0.107	1.6052	0.952
		7	-0.107	-0.097	2.2113	0.947
		8	-0.215	-0.219	4.7182	0.787
		9	0.137	0.089	5.7712	0.763
		10	-0.093	-0.085	6.2756	0.792
		11	-0.020	0.016	6.3004	0.853
		12	-0.006	-0.047	6.3028	0.900

Figure 19 3M. Correlogram of residuals. Left: operating income force. Right: total wealth force.

2.3.11 Diagnostic testing of equation residuals

Diagnostic tests are discussed as an example of the methodology followed with all other individual companies studied. Diagnostic testing of equation residuals (u) should include their distribution which has to be approximately normal. Franses (2005, 57-58) asserts that this is of importance for parameter estimation. To this purpose I use the Jarque-Bera test. If the residuals are normally distributed their histogram should be somewhat bell-shaped and the Jarque-Bera statistic should not be significant (Figure 17, left panel).[11] A high Jarque-Bera statistic indicates a skewed distribution as well as the possible presence of one or more outliers. In the

[11] All econometric models, and their tests, were made with the software *Eviews*, standard edition, version 5.1 and 6.0, Quantitative Micro Software, LLC.

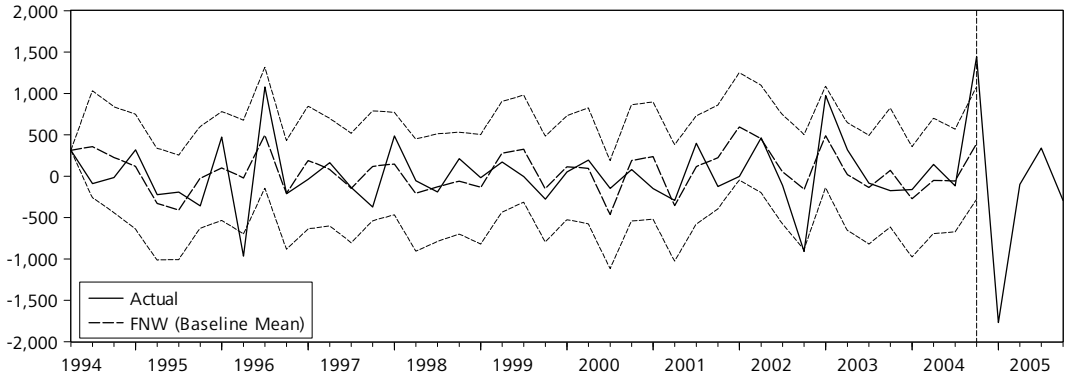


Figure 20 3M. Base period static forecast of net wealth force by total wealth force (1994Q2-2004Q4).

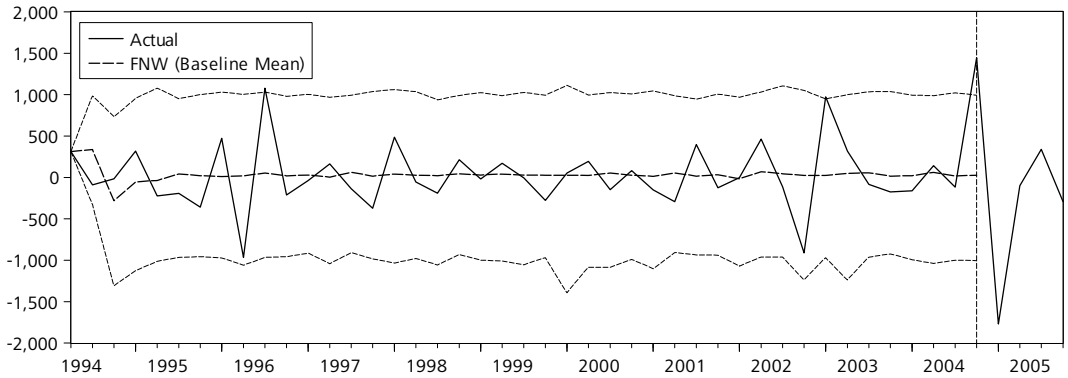


Figure 21 3M. Base period dynamic forecast of net wealth force by total wealth force (1994Q2-2004Q4).

example of 3M with total wealth force this is indeed the case (FIGURE 17, right panel). Nevertheless, as this is due to a single outlier and the rest of data appears normally distributed, this need not be of any concern.

Equation residuals also require inspection for the presence of autocorrelation (Franses 2005, 42, 52-53). For this study two visual methods are used (Startz 2007, 306). First, a scatter plot is created of *lagged residuals against residuals* (FIGURE 18). In the example of 3M, the time points are scattered throughout the two plots and do not cluster linearly. Therefore, I conclude that the lagged residual is a very poor predictor of the current residual for the 3M force equations and thus that serial correlation appears to be absent.

The *correlogram of residuals* is a second visual method to look directly at the pattern of correlations between residuals and their own past values (FIGURE 19). If serial or autocorrelation is absent, then at each lag it should be approximately zero. This is indicated graphically in the correlogram with the vertical solid line and for each time lag, a bar left or right signals negative or positive autocorrelation. The dashed lines in the correlogram are the approximate two standard error bounds. If the autocorrelation is within these bounds, it is not significantly different from zero at the 5% significance level. Serial correlation violates the standard assumption of regression theory that shocks are not correlated with previous shocks. When present, I am forced to discard the model and test the next alternative. Franses (2005, 57-58) notes that the function behind the test for *autocorrelation* (AC, in short) is more appropriate for a moving average model (MA), and that of the *partial autocorrelation* (PAC, in short) is more suitable for an autoregressive model (AR). Partial correlation measures the correlation of values that are periods apart after removing the correlation from the intervening lags. Therefore, with ARIMA models, diagnostic testing of the equations residuals residuals (u) should include both. The

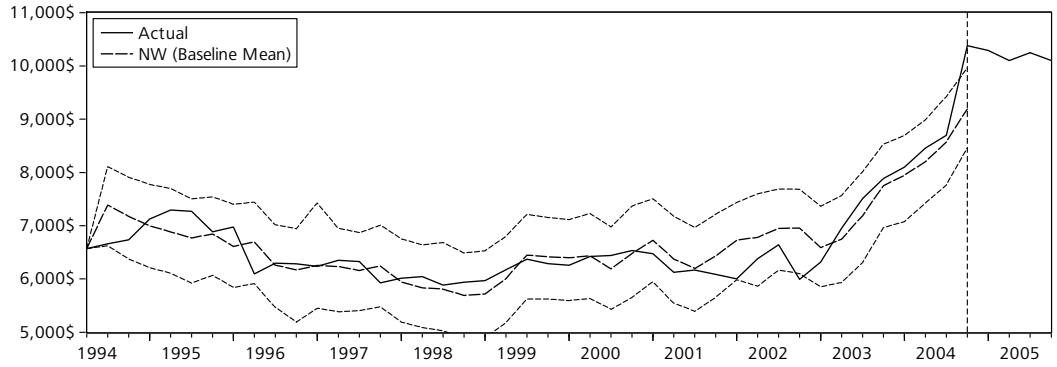


Figure 22 3M. Base period static forecast of net wealth by total wealth force (1994Q2-2004Q4).

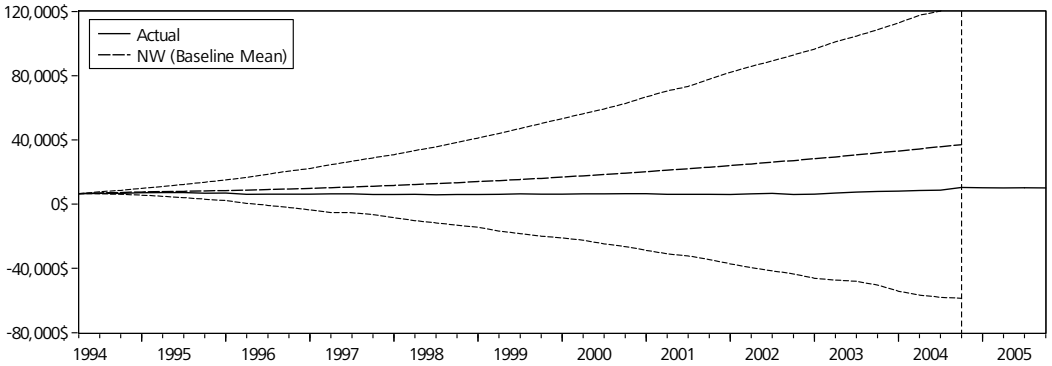


Figure 23 3M. Base period dynamic forecast of net wealth by total wealth force (1994Q2-2004Q4).

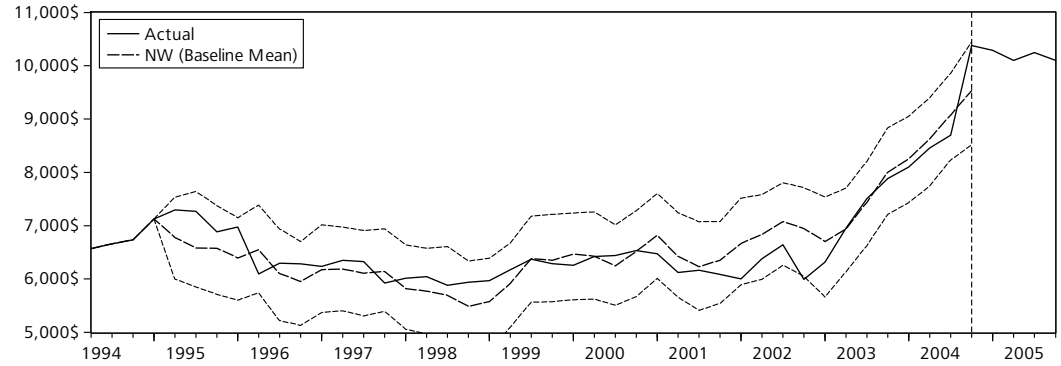


Figure 24 3M. Base period static forecast of net wealth by total wealth force & operating income force.

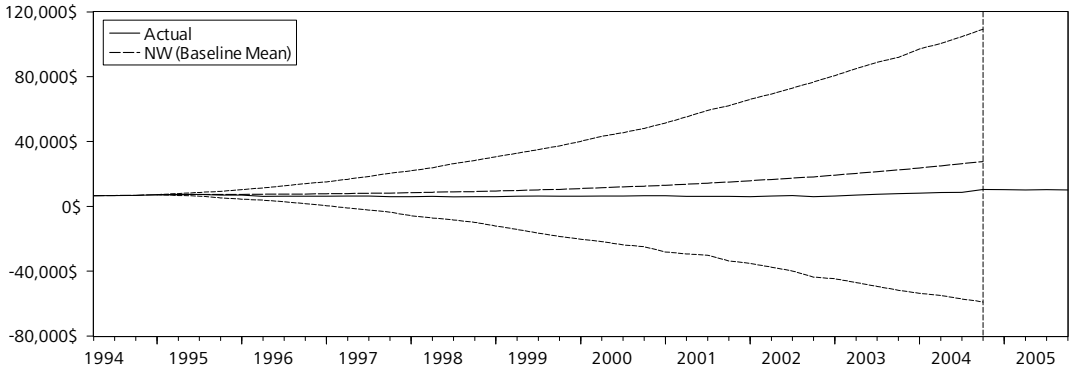


Figure 25 3M. Base period dynamic forecast of net wealth by total wealth force & operating income force.

autocorrelation and partial autocorrelation of each lag are respectively graphed beside each other for the 3M force equations in FIGURE 19. Their values are reported in the first two columns labeled AC and PAC. The Q-statistics are a test statistic for the null hypothesis that there is no autocorrelation up to the order k and their P-values in the last two columns of FIGURE 19 (QMS 2007A, 326). From this, I conclude that the ARIMA models of 3M operating income force and total wealth force meet the requirement of no autocorrelation in the residuals.

2.3.12 *Dynamic* TEMA *model—ex post simulation of 3M*

Force equations are used to find evidence with *ex post simulation* of the explanatory power of the momentum accounting theory of Yuji Ijiri. Dynamic econometric models calculate net wealth force, the dependent variable, from the independent variables total wealth force and operating income force by incorporating EQUATION (17) and (18) into EQUATION (16). In other words, the variables of the ordinary least regression are identical to those of the dynamic econometric model. Except, from the dynamic econometric model the independent variables are not static data that are regressed on the dependent variable but dynamic ARMA equations. This provides us with a *dynamic* TEMA *model* to forecast net wealth of, in this example, 3M. This model is consistent with the dimensions of the TEMA framework because forces integrate into momentum and momentum integrates into wealth (FIGURE 6, page 53). Because this TEMA model is based on force equations of differenced data, it integrates the data each observation or quarter to recover the levels (momentum and wealth). Hence, the ARMA equations of total wealth force and operating income force compute together as an AR-Integrated-MA, or ARIMA in short, in the econometric TEMA model of net wealth.

2.3.13 *Hold-out sample, static & dynamic forecasting*

The ARIMA force equations drive the TEMA model ex post as well as ex ante. Therefore, simulation can be employed with both static and dynamic forecasting. In FIGURE 20 and FIGURE 21 the result of the ex post simulation of total wealth force is presented. Both are hold-out sample forecasts because the equations were derived using data of the same period that is now forecasted. The difference between the two methods is considerable and of importance for this study. A *static forecast* uses the actual values of the independent variables of the last period in making the forecast based on the equations modeled (Startz 2007, 218). In other words, the model is reset at each simulation step and forecasts the next step value of the dependent variable incorporating the last known actual value of the independent variables. In analogy with financial reporting, the next quarters' value of a financial variable is forecasted on the basis of using data of the last quarter. This implies that the model can only compute one step ahead. The result for net wealth is in FIGURE 20 driven by total wealth force only and FIGURE 22 by total wealth force together with operating income force. Note that during the last two years the last model is more accurate than the first model. However, static forecasting assumes hold-out sample simulation and merely serves an academic interest into the stability of business momentum. Static forecasting is only applicable for one period ahead analysis. This might be sufficient for analytical purposes but it would be most welcome if it were possible to forecast more quarters into the future. To this purpose a *dynamic forecast* uses the forecast value of lagged dependent variables in place of the actual value of the dependent variables. Or, as Startz 2007 (218) phrases it: '...dynamic forecasting pretends that you don't have any information about the dependent variable during the period covered by the sample forecast.' This assumes that the process that drives the model exhibits some stable properties or else such forecasts tend

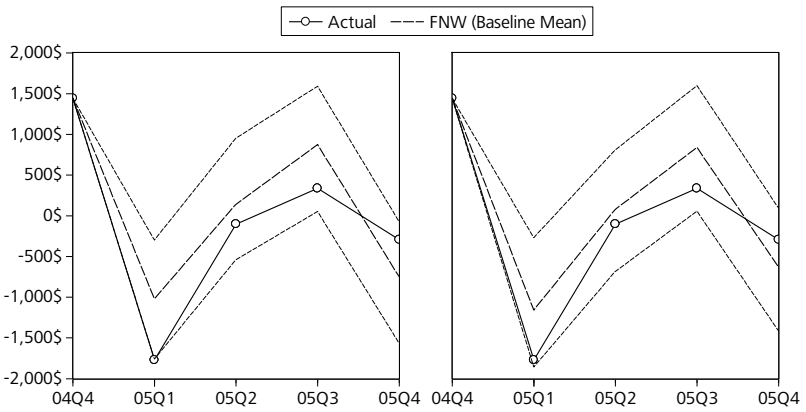


Figure 26 3M. Hold-out sample static forecast of net wealth force (2005Q1-Q4).
Left: total wealth force. Right: total wealth force & operating income force.

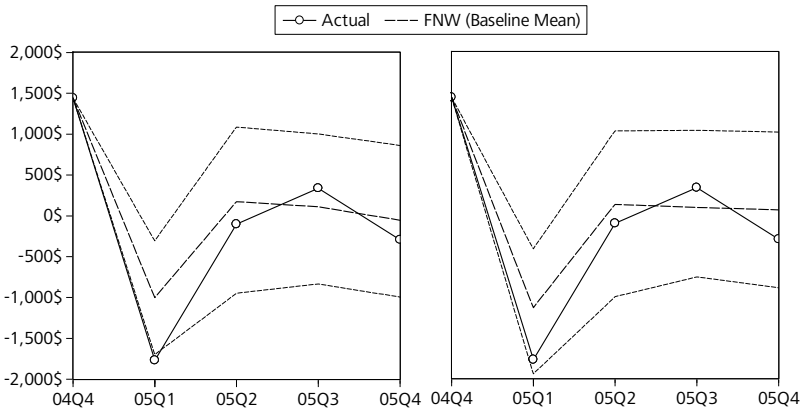


Figure 27 3M. Hold-out sample dynamic forecast of net wealth force (2005Q1-Q4).
Left: total wealth force. Right: total wealth force & operating income force.

A: static forecast	RMSPE	Mean Band	B: dynamic forecast	RMSPE	Mean Band
Total Wealth Force Operating Income Force	$ 280,410	$ 1,496	Total Wealth Force Operating Income Force	$ 193,673	$ 1,781
Total Wealth Force	$ 193,506	$ 1,533	Total Wealth Force	$ 161,715	$ 1,816

Table 10 3M. Root Mean Square Prediction Error (RMSPE) & simulation mean bandwith for net wealth.
Hold-out sample forecast: 2005Q1-2005Q4.

to be off target real quick, i.e. I expect a certain stability of momentum! The result for net wealth is in Figure 23 driven by total wealth force only and Figure 25 by total wealth force together with operating income force. Note that both models 'cover' the trend of net wealth (line with dots) but that in each model the standard errors bandwith grows very large, although this is much less so with the model driven by total wealth force. In economics, dynamic forecasts generally test better multi-period forecasts (Startz 2007, 316). Nevertheless, it does not seem prudent to use ARIMA models to dynamically forecast accounting variables too far into the future. This is also illustrated by comparison of the base period static forecast of 3M net wealth force with the dynamic forecast by total wealth force (respectively Figure 20 & Figure 21). The RMSPE value of the static forecast in this case is better than that of the dynamic forecast (respectively 126,252 & 190,782). This is explained by the fact that ARMA models quickly loose viability when they cannot correct their errors (Masters 1995, 191, Startz 2007, 218). The further out the forecast is made, the less the errors contribute to the accuracy of the

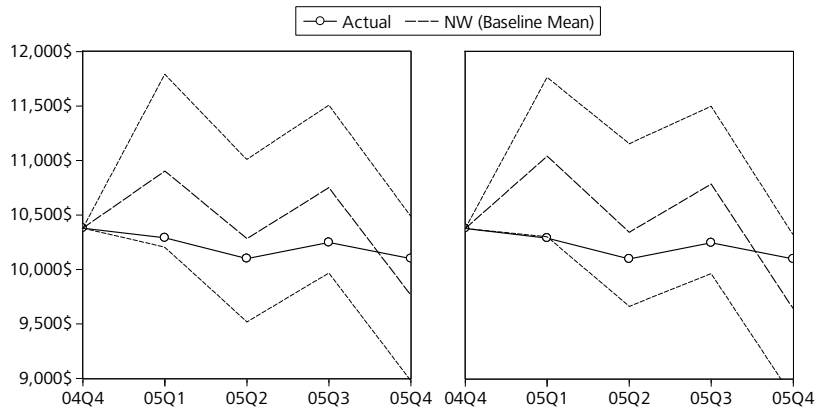


Figure 28 3M. Hold-out sample static forecast of net wealth (2005Q1-Q4).
Left: total wealth force. Right: total wealth force & operating income force.

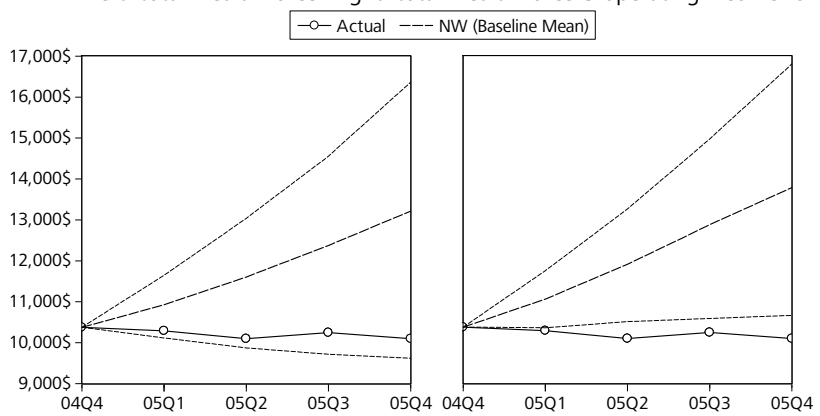


Figure 29 3M. Hold-out sample dynamic forecast of net wealth (2005Q1-Q4).
Left: total wealth force. Right: total wealth force & operating income force.

forecast.[12] Nonetheless, four to eight quarters ahead forecasts with acceptable accuracy might be perfectly acceptable for the users of financial statements or analysts.

2.3.14 *Dynamic* TEMA *model—ex ante simulation of 3M*

The dynamic TEMA model is also used to find evidence of the predictive power of the TEMA framework. We have the actual data available for the next four quarters to be able to assess the accuracy of the models' prediction. But, these, so called, hold-out data were not used to derive the force equations that drive the model. The result of the static forecast of net wealth force is presented in FIGURE 26 while FIGURE 27 gives the result of the dynamic forecast. In these figures, the left graph shows the forecast of net wealth force driven by total wealth force alone, whereas the right graph is driven jointly by total wealth force and operating income force. These graphs suggests that total wealth force alone gives the best forecast because the simulation Baseline Mean is more close to the actual data. Indeed, this is confirmed by the Root Mean Square Prediction Error (RMSPE) values presented in TABLE 10 (compare $193,506 with $280,410, and $161,715 with $193,673). In this example of 3M, the dynamic forecast renders a better result than the static forecast. But note that the band of upper and lower limits of two standard deviations is larger for the dynamic forecast than for the static forecast (indicated with the dotted lines above and below the dashed line of the simulation Baseline Mean). The

[12] For example, in an AR(1) model, when the autoregressive coefficient is estimated as 0.9 and the last residual is u_t, then including the error in the forecast adds $0.9u_t$, $0.81u_t$, $0729u_t$, ..., in the first three forecasting periods. Thus, the effect gradually declines to zero. (Note based on Startz 2007, 315).

mean band width of the static and the dynamic forecast is, respectively, for the model driven jointly by total wealth force and operating income force: $1,496 and $1,781. For the TEMA model only driven by total wealth force it is: $1,604 and $2,058. This implies that the probability distribition of 1,000 simulations of future values of the dynamic forecast is about 20% larger than that of the static forecast. The dynamic forecast is in this case more accurate but less certain (Box *et al.* 1994, 144).

In my evaluation of the predictive power of the 3M momenum accounting model I only forecast net wealth force up to four quarters. Should we try to extend the forecast period then the static forecast is likely to have a better chance of succes than a dynamic forecast because the ARIMA model will steadily decrease in variation converging to a constant (Masters 1995, 191). This has serious implications for the prediction of net wealth with a dynamic solution. The result of the static forecast of net wealth is presented in FIGURE 28 while FIGURE 29 gives the result of the dynamic forecast. Because during the simulation of the static solution the actual value of net wealth is used to 're-start' the model, the quarterly forecast is much more accurate. On the other hand, during the simulation of the dynamic solution the predicted value of net wealth is used and thus the forecast is less accurate. Actually, when the model is driven only by total wealth force we see that the actual value of net wealth lies within the acceptable simulation mean bandwith (FIGURE 29, left). But when the model is driven jointly by total wealth force and operating income force not a single quarter of net wealth is correctly forecasted (FIGURE 29, right).

2.3.15 Discussion

In this section the econometric methodology that is used in this study was explained. I presented a detailed analysis of 3M Company, one of the 30 component companies of the DOW. The following conclusions can be made on the basis of the results:

- Operating income force is associated with net wealth force.
  Thus, in the example of 3M Company, H 4_a holds.
- Total wealth force is associated with net wealth force.
  Thus, in the example of 3M Company, H 5_a holds.
- The TEMA time series modelled are stationary or trend-stationary.
  Thus, in the example of 3M Company, H 6_a holds.
- Operating income force and total wealth force can predict net wealth.
  Thus, in the example of 3M Company, H 7_a holds.
- A general relationship between variables from the TEMA framework is present by temporal association. Thus, in the example of 3M Company, H 3_a holds.
- Thus, in the example of 3M Company, some empirical evidence is provided for H 1_a.

Of course, this one example alone is not sufficient to draw a general conclusion about the validity of the generality assumption of the TEMA framework. But, the studies presented in the following chapters, in particular Chapters 7 and 8 will provide similar results for 17 companies of the AEX and the other 29 component companies of the DOW and this contributes to a more general conclusion for the selected cases. The use of forecasts of financial statements variables is justified by the practice in financial markets to evaluate a firm's performance on a quarterly basis. The quarterly result of the dynamic forecast of net wealth force above the static forecast in the example of 3M is encouraging as it increases the acceptable window from only a single quarter forecast, which renders identical results with both forecast methods, to at least four quarters. Assuming that we subscribe to the notion that the TEMA framework is a good repre-

sentation in this case of the structural relation of forces that associate with 3M's net wealth force, the actual result below or above the forecast, should trigger analysts' attention as well as that of management. However, the integration of force dynamics to momentum and wealth tends to be insufficient for the dynamic solution in this example and warrents further study.

2.4 Visual analytics

Visual analytics involves various scientific disciplines, such as knowledge management or statistical analysis, and includes the study of methodologies, technologies and tools (Wong & Thomas 2004). Various applications of visual analytics are in use. Farebrother (2002) uses graphical methods to visualize statistical models and concepts . Borgelt & Kruse (2002) use for data analysis and data mining graphical models and methods . Tufte (1983, 1990, 1997) wrote extensively on how complex information could be presented graphically (see also Cleveland 1993). In accounting, Brill (1964) used a rudimentary stock-flow diagram as a visual aid to explain the transfer between balance sheet accounts. Dull & Tegarden (1999) proposed a three dimensional graphic solution to present TEMA dynamics that includes color coding. Luft & Shields (2003A-B) applied graphical analysis to develop guidelines for theory-consistent empirical research in management accounting. The most relevant objective of visual analytics for this thesis is the exposure of unexpected relationships between variables of the TEMA framework.

2.4.1 Data reduction

Researchers of financial statements are faced with a staggering number of variables to select for regression analysis or econometric modeling. For example, it is unpractical to regress all the independent accounting variables of the 30 DOW component companies on the DOW index. Gilbert & Meijer (2005, 2006), Maddala (1998, 171, 226) and Masters (1995, 16) recommend in such case to reduce the number of variables by computing new variables, called *factors* or *principal components* dependent on the statistical method used, as linear combinations of the source variables (Thielemans *et al.* 1988, Wouters *et al.* 2003). Factors may operate in regression models as independent variables that summarize a particular informational aspect of the original source variables (Seiler 2004, 165-195). Arya *et al.* (2000) recognize the potential of linear algebra to describe dynamic systems and suspect that it may be beneficial in the study of accounting. I hope to show that they are correct.

The literature, e.g. Hair *et al.* (1992) and Reyment & Jöreskog (1993), offers a vast number of solutions of which *Principal Components Analysis* (PCA in short) is possibly best known in economics as well as in finance and accounting (e.g. Heij *et al.* 2006). Briefly, the goal is to find a single factor, a linear combination of the original variables, which accounts for the majority of the variation across the data. The importance of a factor is determined usually by its contribution to the variance. The rationale is that more variation contained implies greater relevance of that factor. Whether or not that is true will depend greatly on the application at hand and must be tested by other means. An important byproduct of PCA is that in mathematical terms the factors are *orthogonal*, i.e. the variation expressed by each factor is mutually independent or uncorrelated. Jolliffe (2002, 1) characterizes the central idea of PCA as the reduction of '…the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation.' The first factor found should capture the major part of the information of the source variables. Next, the second factor tries to capture most of the information left by the first factor. After that, the third factor is expected to capture what is

not explained by the first two factors, et cetera, until most information is contained in the new factors and the sum of variance explained approaches 100% (ideally). Not all data sets can be captured by only a few factors. Generally stated, the more uncorrelated the original variables are, the less likely such data reduction algorithms will succeed.

2.4.2 Spectral Map Analysis

In this study *Spectral Map Analysis*, SMA in short, or Spectral Mapping is applied. SMA is a method similar to PCA but especially suitable for the (graphical) analysis of contrast from log ratios (Greenacre & Lewi 2007). SMA is well described by Lewi (1976, 1982, 1989 and 1995) and Wouters *et al.* (2003). The method is of general use and has been applied in pharmaceutical research, competitive positioning and financial analysis (Lewi 2005). SMA involves double-centering of the data table before factorial analysis is applied; instead of only column-centering, which is typically done with PCA (Sánchez *et al.* 1994, Wouters *et al.* 2003). Double-centering can be thought of as a simultaneous correction for differences in size between columns or objects (e.g. balance sheet accounts) and for differences in importance between rows or measurements (e.g. time steps: end of year or end of quarter, or time periods: year or quarter). Lewi (1982, 41-51) asserts that it is natural to apply double-centering to two-way tabulations, such as financial accounting data.

SMA decomposes a data table into a smaller set of hypothetical variables by which a data space is constructed (Lewi 1982, 15). The SMA procedure involves a 'double decomposition' of the original data table into two groups of data space dimensions, one for the column items and, after table transposition, one for the row items. The decomposed dimensions of the data table are called factors and each represents the best 'linear fit' of the original data. Column items are represented in the row factor space by loadings and the row items are represented in the row factor space by scores that should thought of as dimensional coordinates. The procedure is further discussed in Chapter 6 where an example is provided (section 6.3, page 141). With the set of factors of each space a plot can be created to support the visual analysis of the decomposed data table. Thus, each space has its own plot of items with each table column and row represented, respectively, by a square and a circle but, alternatively, other symbols can be employed (e.g. FIGURE 65 and FIGURE 66 on page 142). This makes it possible to render a so-called *biplot* (Gower & Hand 1995), which is called a spectramap when derived with SMA. The spectramap biplot integrates the two decompositions of column items and row items into a single unified visualization or *data space* (e.g. FIGURE 67 on page 143). The relative position of columns and rows conveys their degree of association as well as the contrast amongst each other and relative to the table mean. Those closely located tend to be positively associated while those opposite of each other associate negatively. Items that are at an angle of about 90° are not associated. Those closely located to the center of the data space, usually called the *barycenter* of the plot, exhibit a profile similar to the table mean. This applies to static data as well as to time series when mean behavior should be thought of as the time average of a variable relative to that of the whole table. Spectramap may also supports the analysis of differences or ratios between items by means of calibrating object axes (e.g. FIGURE 49, page 121). Depending on the suitability of the decomposition into more than two factors, visual analysis can be extended to a truly six-dimensional data space (e.g. COLOR FIGURE 9, page 312). In short, spectramap decomposes multivariate data and offers a visual technique for exploratory data analysis and hypothesis generation as well as the creation of summary variables that can be used for regression equations or econometric models.

2.5 Color coding

Human perception thrives on contrast. Perception is the process of acquiring, interpreting, selecting, and organizing sensory information. Users of accounting data, financial statements data in particular, are confronted with mountains of numbers. The issue discussed in this section is how to facilitate 'number perception' by means of 'color perception.' To this purpose, a new methodology for color coding of accounting data is introduced to support the analysis of informational measures and decomposed balance sheet data in this study.[13]

2.5.1 Number perception

The oldest quantitative law in psychology is the so-called Weber-Fechner law, which quantifies the relationship between the intensity of physical stimuli and their perceptual effects. Ernst Heinrich Weber (1795–1878) found in one of his experiments that the weight increase felt by a blindfolded man, who was holding a weight, is not linear. Instead, Weber found that the response is proportional to a relative increase of the weight. For example, if the weight is 1 kg, an increase of a few grams will not be noticed. Rather, only when the mass is increased by a certain factor, an increase in weight is perceived. If the mass is doubled, the threshold to perceive the change in weight is also doubled. The relationship between the stimulus and its perception is logarithmic. This logarithmic relationship means that if a stimulus varies as a geometric progression (i.e. multiplied by a fixed factor), the corresponding perception is altered in an arithmetic progression (i.e. in additive constant amounts).[14]

Number neurons have been found that allow for a dissection of the neuronal implementation of number representation (Dehaene 2003). Analyzing both behavioral and neuronal representations of numerosity in the prefrontal cortex of rhesus monkeys, Nieder & Miller (2003) suggest that certain cognitive and perceptual-sensory representations share the same fundamental mechanisms and neural coding schemes. The results of Nieder & Merten (2007) confirm that both the behavioral and the neural test data obeyed the Weber-Fechner law and are closely related. From a series of human experiments, Roitman *et al.* (2007) provided further support for the hypothesis that adult humans share a nonverbal mechanism with animals for representing number as continuous quantities.

The implication of aforementioned research is that data patterns are better noticeable when they are scaled geometrically instead of linearly.[15] Bearing this in mind, the research of Nigrini (2000) about the phenomena of patterns in fraudulent data is even more relevant.[16] The concern for this study is that a rational approach to the analysis of larger sets of TEMA data has to be based on one form of geometrical scaling or another for the simple reason that linear differences tend to remain unnoticed.

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[13] For this section, material from http://www.wikipedia.org/ and Melse (2004B) were used.

[14] For example, if a stimulus is tripled in strength (i.e, 3x1), the corresponding perception may be two times as strong as its original value (i.e., 1+1). If the stimulus is tripled in strength again (i.e., 3x3x1), the corresponding perception will be three times as strong as its original value (i.e., 1+1+1). Hence, for multiplications in stimulus strength, the strength of perception only adds.

[15] Although it is a very relevant subject the scaling of data is not explored further. For more on this subject I refer to: Borgelt & Kruse 2002, Cleveland 1993 and Tukey 1977.

[16] The implication for auditing is that Nigrini (2000) found that fraudulent managers are not aware of the geometrical patterns in data that are formed by the occurrence of digits in numbers. Hence, it is possible to determine the likelihood of fraud by means of automated tests of the digits of accounting measurements to support auditors.

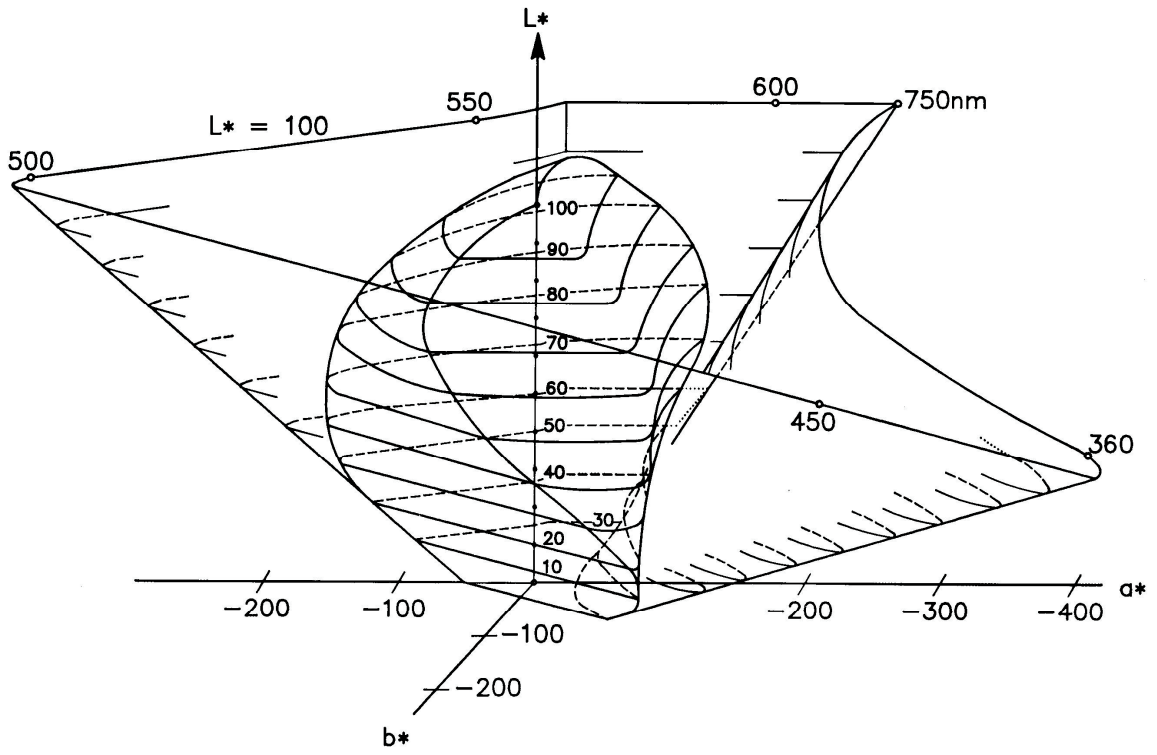

Figure 30 CIELAB uniform color space (based on Figure 2.87, Judd & Wyszecki 1975, 332, source: LOI).

2.5.2 *Color perception*

To be able to describe every color a three-dimensional system suffices. Ewald Hering proposed that three pairs of opposing color sensations produce all colors the human eye can perceive (Nassau 1998, 56-59). These are: red–green, yellow–blue and black–white, which are not colors of paint or of light emitting source but *primary color perceptions* (Color Figure 1, page 307). This method strives to describe human color perception and to provide a metric to compute equal distances between colors (Judd & Wyszecki 1975, 85-86).

2.5.3 Cielab *color space*

A standard setting regulatory body for color metrics, the commission internationale de l'Eclairage (cie in short), defines standards for such color difference equations and uniform color spaces (Billmeyer & Saltzman 1981). One of these is the so-called cielab uniform color space that is used to describe object or reflective color (as opposed to transparent color which has its own system called cieluv). The L dimension stands for the measure of perceived lightness, or the opponent colors: white–black, the A dimension stands for the opponent colors: red–green and the B dimension stands for the opponent colors: yellow–blue (Judd & Wyszecki 1975, 332).[17] Each object color, under certain lighting and viewing conditions, can be described using these three color dimensions. The technicalities of color measurement and subsequent computation is of little interest to this study except for the fact that cielab offers the required mathematics to color code data. These include graphs or Spectramap biplots of decomposed accounting variables and time points with one, two or three additional (color) dimensions. Instead of describing color perception by three coordinates, the cielab system is used by me in this study to *create color from data*.

[17] Note that these are 'true' dimensions, albeit dimensions of the psychophysical perception of color.

2.5.4 Color coding of data

Because the uniform color space is three-dimensional we can superimpose two systems of coordinates. The first system is that of the spatial or geometric three-dimensional Cartesian system of coordinates which is used to project the column and row items of a data table, e.g. balance sheet items and time points, after spectramap decomposition as a biplot, respectively by their loadings and scores on the first three factors (e.g. Color Figure 9, page 312). The second system of coordinates used is the cielab color space (Color Figure 1–6, page 307-309). The result could be a four, five or six-dimensional visualization of the decomposed data table. Color Figure 10, for example, shows the loadings of column items and the scores of row items on the fourth and fifth factor spatially on the x and y-axis as well as color coded by the opponent color dimensions red—green and yellow—blue. Note that in Color Figure 10, the metric of the Cartesian three-dimensional spatial system is aligned, parallel, with the metric of the cielab color space. However, Color Figure 11, page 313, offers the five-dimensional visualization with the color coded fourth and fifth factor mapped onto the spatial representation of the first three factors on the x, y and z-axis. The outline thickness of the symbols, squares and circles, is an indication of the position along the z-axis, which is orthogonal to the plane of projection (x, y). The thicker an outline is the higher above the plane of projection the object is positioned. Consequently, the thinner an outline is, the lower it is positioned below the plane of projection. This example of data color coding is further discussed in Chapter 6 (section 6.5, page 148). Color coding of (accounting) data by means of the cielab color space is a new visual analysis methodology developed during this study.

2.5.5 Impairment

Although color coding can potentially contribute to the visual analytics of accounting data, one should be aware that a constraint to its use is the fact that color blindness affects a significant number of people, although exact proportions vary among groups (Tufte 1983, 183).[18] The term 'color blindness' is somewhat misleading. People who cannot see all colors can still see things as clearly as people who do not suffer from color perception impairment. The term implies that a person cannot see some colors of a particular range, or sees them differently from other people who do not suffer from such impairment. Very few people are blind to all colors and even in such an extreme case it should not rule out the pursued of an artistic career (Sacks & Wasserman 1987).

It is possible to use all three color dimensions in the proposed method of color encoding in such manner that color differences can still be observed with equal precision by any observer, even those who suffer from color blindness like protanopia (red-green impairment) or tritanopia (blue-yellow impairment). When all three color dimensions code the same data then the resultant scale of colors is equally perceived by all observers, an example of this coding scheme is Color Figure 7 which is discussed in Chapter 4, page 111, where informational accounting measures are color coded.

[18] Color blindness (or dyschromatopsia) affects a significant number of people, although exact proportions vary among groups. Overall, 7 to 10% of men suffer from some degree of red-green color blindness. The gene coding for the blue receptor lies on the human chromosome seven, which is shared equally by men and women. Therefore, blue-yellow color blindness is equally distributed among males and females but with very low occurance (less than 0.5%).
For this footnote and paragraph reference material was used from http://www.Wikipedia.org/.

2.6 Conclusion

In this chapter the methodology was introduced by which I seek to provide evidence that is consistent with the generality assumption of the TEMA framework. My effort to explore and research the formal basis of TEMA requires a methodology to objectively examine the trend of TEMA variables and their association. To this purpose, as suggested by Ijiri (1989, 10.5), a standard method is applied by me for TEMA time series analysis: ARIMA modeling (Box *et al.* 1994, Franses 1998A, Harris & Sollis 2003, Seiler 2003, Silhan 1989). This allows me to examine the TEMA framework on a highly aggregated level, as suggested by Fraser (1993, 157). Following this line of investigation, I also circumvent the subjectivity criticism against TEMA raised by Fraser (Id. 156), Vaassen (2003, 33) and Wagensveld (1995). The various econometric tests that are applied by me in this study should reduce the risk of spurious regressions and ascertain model design with as little bias as possible (Startz 2007, 325). Furthermore, the explanatory and predictive power of alternative models will be determined and compared by me using econometric test measures as recommended by Franses (2005, 65).

In this thesis, two methods are applied to support visual analytics of accounting data: color coding and spectral map analysis. *Color coding* is used to provide a visual translation of the scale of data under inspection and is expected to expose the subtleties hidden in the data by means of a new research method based on the CIELAB color space of equidistant colors. Chapter 4 provides examples of the color coding of informational signals of TEMA variables. Color coding can also provide a separate and additional layer of visual information by coloring graphic symbols. Examples are discussed in Chapter 6 and in Chapter 10.

The objective of *spectral map analysis*, in short spectramap, is to reduce the number of variables of large sets of data—in this study time series of TEMA variables. Spectramap supports the exploratory analyses of the (expected) relationship between variables of the three dimensions of the TEMA framework. This is discussed further in Chapter 5 that extends my research of the decomposition of accounting variables, reported in Chapter 4, within the TEMA framework dimensions wealth, momentum & force. Color coding and spectramap are used together to increase the information content of decomposed balance sheet data in Chapter 6. Spectramap is also applied to reduce the number of independent variables in the econometric TEMA models through the decomposition of panels of TEMA variables into a smaller set of factors, as recommended by Masters (1995), Schilderinck (1977) and Jolliffe (2002, 167). This method is used in Chapter 9 to explain and predict the proportional change of 3M Company's wealth accounts. Finally, in Chapter 10 such econometric models are derived within the TEMA framework where decomposed TEMA variables turn out to be leading indicators of the Dow Jones index.

Part I

Data Analysis

3

Accounting in Three Dimensions
A Case for Momentum

The Journal of Risk Finance, Vol. 5, No. 3, 2004, pp. 49-53.

Balance Sheet, Vol. 12, No. 1, 2004, pp. 31-36.

The Journal of Risk Finance, Vol. 9, No. 4, 2008, pp. 334-350.

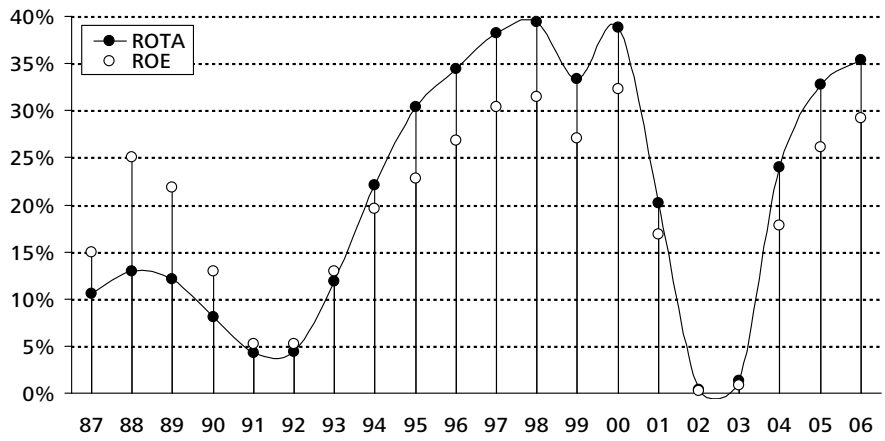

Figure 31 Robert Half. Return on total assets & return on equity ($\pi : \tau$).

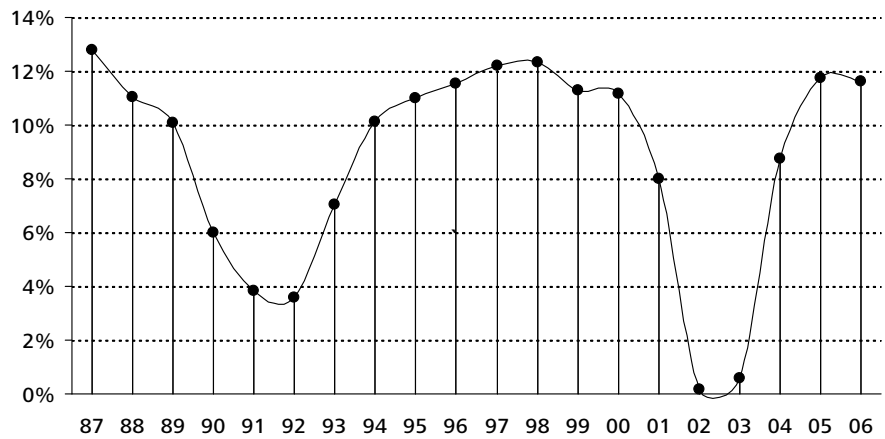

Figure 32 Robert Half. Sales margin ($\pi : \pi$).

	point	*point*	*period*	*period*	*period*	*ratio*	*ratio*	*ratio*
Year	Wealth	Net Wealth	Sales	PBIT	PAT	ROTA	ROE	Sales margin
1987	155.69	48.13	105.69	13.54	7.25	10.51%	14.91%	12.81%
1988	194.87	61.70	182.05	20.11	12.03	12.91%	24.99%	11.04%
1989	184.41	68.68	234.50	23.62	13.47	12.12%	21.83%	10.07%
1990	188.37	77.29	248.56	14.93	8.87	8.10%	12.91%	6.01%
1991	178.95	84.42	209.46	8.02	4.06	4.26%	5.25%	3.83%
1992	181.76	90.97	220.18	7.91	4.38	4.42%	5.19%	3.59%
1993	204.60	133.60	306.17	21.56	11.72	11.86%	12.89%	7.04%
1994	227.76	177.00	446.33	45.21	26.12	22.10%	19.55%	10.13%
1995	301.14	227.93	628.53	69.09	40.30	30.33%	22.77%	10.99%
1996	416.01	308.45	898.64	103.65	61.10	34.42%	26.81%	11.53%
1997	561.37	418.80	1302.88	158.83	93.70	38.18%	30.38%	12.19%
1998	703.72	522.47	1793.04	221.18	131.58	39.40%	31.42%	12.34%
1999	777.19	576.10	2081.32	234.70	141.44	33.35%	27.07%	11.28%
2000	971.03	718.54	2699.32	301.63	186.10	38.81%	32.30%	11.17%
2001	994.16	805.70	2452.85	196.28	121.11	20.21%	16.85%	8.00%
2002	935.67	744.97	1904.95	3.50	2.17	0.35%	0.27%	0.18%
2003	979.90	788.66	1974.99	11.72	6.39	1.25%	0.86%	0.59%
2004	1198.66	911.87	2675.70	234.67	140.60	23.95%	17.83%	8.77%
2005	1318.69	970.87	3338.44	392.17	237.87	32.72%	26.09%	11.75%
2006	1459.02	1042.67	4013.55	466.20	283.18	35.35%	29.17%	11.62%

Table 11 Robert Half. Time series (data in millions USD, source: Compustat/Thomson). Raw data scaling factor: millions U.S. Dollar.

3 Abstract

In this chapter, I present an example concerning certain performance measures of Robert Half International Inc. This may contribute to a better understanding of the use of the TEMA *framework for ratio analysis. I demonstrate that ratios like return on total assets, return on equity and the sales margin may have a similar trend but are not necessarily measures consistent within the* TEMA *framework of Yuji Ijiri. Therefore, I propose a new approach to ratio analysis by using accounting variables of the same informational dimension. Next, I recommend to use the 'part over total' method of ratio calculation for the advantage of disaggregated and segmental analysis. Finally, I introduce and evaluate the common size format momentum ratio. This example, so I hope, should encourage practitioners and academics to explore the usability of the* TEMA *framework as an alternative means of company performance analysis.*

3.1 Introduction

An intriguing question to answer is: what meaningful new information does the TEMA framework of Yuji Ijiri have to offer? Here I look at an example of ratio analysis.[1] Ratio analysis should provide an insight into the financial health of a firm by looking into its liquidity, solvability, profitability, activity, and capital & market structure.[2] In this chapter I limit myself to profitability.

Organization of this chapter

First, outside the TEMA framework, return on total assets and return on equity are compared with sales margin in section 3.2. The implication of financial ratio analysis on disaggregated data is also discussed and I present an alternative method. Second, in section 3.3, I elaborate within the TEMA framework on the calculation of force and momentum ratios. In section 3.4, I compare sales margin with net wealth momentum. I analyze with Foliomap, a visual analytics method, disaggregated balance sheet momentum in the light of profitability analysis. Section 3.5 completes this chapter with a discussion.

3.2 Financial ratio analysis

The data that is used is from Robert Half International Inc., a U.S. based firm whose principal activity is to provide specialized staffing services (Table 11).[3] Robert Half International pioneered specialized staffing services in 1948 and today is recognized as an industry leader. There is no reason to use this company's financial statement data other than for the purpose of illustrating outside and within the TEMA framework of Yuji Ijiri. It might be something of a surprise that a service company is used for this case study given the relative unimportance of assets in this type of industry. However, the movement of total assets, or wealth, over time is my proxy for financial dynamics of the firm (structure) whereas operating income is my proxy for business dynamics reflected by variation of income statement data (operations). In the following chapters of this thesis, the association of total wealth and operating income is investigated with the movement (growth trend) with net wealth for the compo-

[1] This chapter was published in Melse (2004a). A follow up study, with the time series extended to 2006, was published in Melse (2008). This chapter incorporates both publications.

[2] For an introduction to ratio analysis I refer to Walsh (1996) and Westwick (1981).

[3] Data source: Compustat provided by Thomson ONE Banker Analytics.

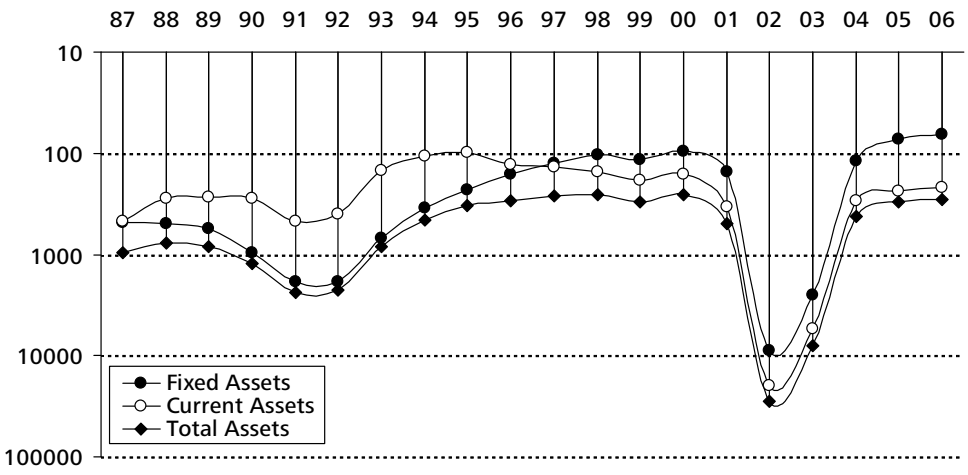

Figure 33 Robert Half. Return on assets by inverse calculation ($\tau : \pi$).

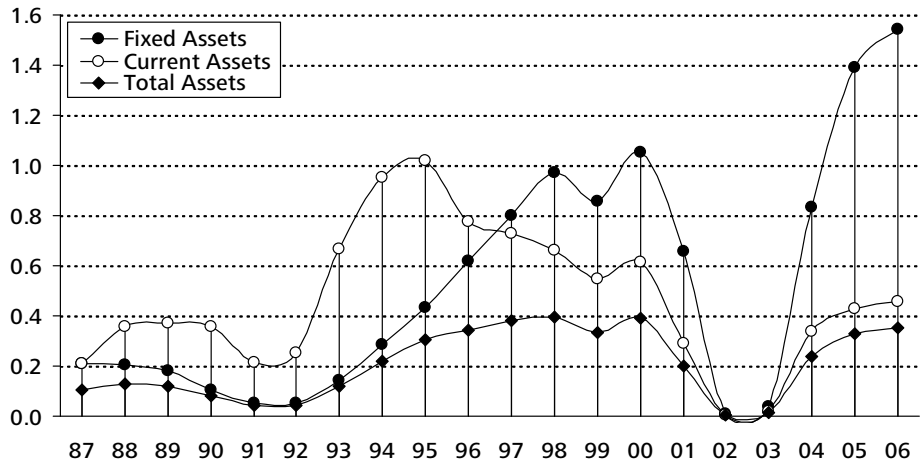

Figure 34 Robert Half. Return on assets ($\pi : \tau$)

	A: PBIT / Assets				B: Assets / PBIT			
Year	*Fixed*	*Current*	*Total*	*check*	*Fixed*	*Current*	*Total*	*check*
1987	0.21	0.21	0.11	-0.3153	4.76	4.75	9.51	0.0000
1988	0.20	0.36	0.13	-0.4294	4.93	2.81	7.74	0.0000
1989	0.18	0.37	0.12	-0.4307	5.57	2.69	8.25	0.0000
1990	0.10	0.36	0.08	-0.3795	9.54	2.81	12.35	0.0000
1991	0.05	0.21	0.04	-0.2228	18.77	4.71	23.48	0.0000
1992	0.05	0.25	0.04	-0.2610	18.66	3.97	22.63	0.0000
1993	0.14	0.67	0.12	-0.6924	6.93	1.50	8.43	0.0000
1994	0.29	0.95	0.22	-1.0192	3.48	1.05	4.53	0.0000
1995	0.43	1.02	0.30	-1.1488	2.32	0.98	3.30	0.0000
1996	0.62	0.78	0.34	-1.0501	1.62	1.29	2.91	0.0000
1997	0.80	0.73	0.38	-1.1487	1.25	1.37	2.62	0.0000
1998	0.97	0.66	0.39	-1.2410	1.03	1.51	2.54	0.0000
1999	0.86	0.55	0.33	-1.0705	1.16	1.83	3.00	0.0000
2000	1.05	0.61	0.39	-1.2790	0.95	1.63	2.58	0.0000
2001	0.66	0.29	0.20	-0.7457	1.53	3.42	4.95	0.0000
2002	0.01	0.01	0.00	-0.0129	88.12	196.17	284.29	0.0000
2003	0.04	0.02	0.01	-0.0457	24.97	54.90	79.87	0.0000
2004	0.83	0.34	0.24	-0.9307	1.20	2.98	4.18	0.0000
2005	1.39	0.43	0.33	-1.4898	0.72	2.34	3.06	0.0000
2006	1.54	0.46	0.35	-1.6498	0.65	2.18	2.83	0.0000

Table 12 Robert Half. Panel A: return on assets. Panel B: inverse calculation.

Variables			association
ROTA	vs.	ROE	$r = .918^{**}$
ROTA	vs.	Sales margin	$r = .797^{**}$
ROE	vs.	Sales margin	$r = .916^{**}$

Table 13 Robert Half. Association between return ratios and sales margin.

nent companies of the AEX and the DOW, firms active in various industries; including service industries. I expect that performance measures consisten with Ijiri's TEMA framework are relevant independent of the type of industry in which a firm operates. If this example firm active in the service industry gives meaningful new information one could argue that the TEMA framework of Yuji Ijiri has applicability independent from industry type. This would prov0069de some support for my hypothesis H 1 that there is a general relationship between variables in the TEMA framework.[4]

3.2.1 ROTA, ROE & *sales margin*

Ratio analysis from 1987 up to 2006 provides a clear view of the trend in operating efficiency and profitability of Robert Half. Return on total assets (ROTA) and return on equity (ROE) are two ratios used for this purpose. FIGURE 31 graphs both the ROTA and ROE time series of TABLE 11. We derive the ratio ROTA from the division of the return of profit before income tax (PBIT) by total assets. Likewise, we get ROE by division of profit after tax (PAT) by shareholder equity. During the period from 1989 to 1992, each ratio shows a sharp decline reaching a low point in 1991 and 1992, but gradually increases again to reach high points in 1998 and — after a small drop in 1999 — in 2000. The next two years again show a dramatic decrease to arrive at almost reaching 0% in 2002 and 2003. The last three years show a just as dramatic increase to reach in 2006, about the same level as in the period 1997-2000. Comparing FIGURE 31 with FIGURE 32, which graphs the sales margin during these years, it is obvious that the sales margin displays a trend similar to both ratios, notably ROE. Indeed, as reported in TABLE 13, the Pearson correlation coefficient indicates a positive and rather strong association between these three accounting ratios.

However, the data are time series and as such, these statistics have little meaning. Instead, we should look at their trending behavior and other time series properties, and test if they are stationary (which they are not).[5] But, even if we can transform these time series to meet econometric requirements, heuristically, it makes little sense to model them. The only point of interest here is the observation that ROTA, ROE, and sales margin are exchangeable ratios. In this example, they tell us the same 'business story,' we see similar 'ups and downs.'

3.2.2 ROTA *disaggregated*

Walsh (1996, 72) sees ROTA as the most important benchmark against which the performance of business operations can be measured. But, like any other ratio, as a single figure it is not much more than a target to aim for. It is of more interest to explain why such a ratio moves up or down when it does. However, using the ratios discussed above has a disadvantage. Westwick (1981, 6) points at the need to investigate the cause of the 'ups and downs' of a ratio and

[4] This argument applies also to firms active in financial industries, like banks. Usually such firms are excluded in financial statements analysis studies for their atypical properties. In this thesis firms active in financial industries are not excluded from the analysis, see the studies in Chapter 7, 8 and 10.

[5] For the particulars involved, the reader is referred to 2.3 Time series analysis, page 52.

for this purpose wants to be able to disaggregate from the 'total' to the 'parts.' For example, we can calculate the return not only on total assets but also on the disaggregated current and fixed assets. A digression on the calculation of ROTA as operating performance ratio to support my explanation. We get the following ratios by:

- *sales margin* = PBIT / sales;
- *turn over* = sales / total assets.

ROTA can be calculated by the product of sales margin times turn over. Because sales is the denominator of *sales margin* as well as the numerator of *turn over*, it is cancelled out in the alternatively ROTA calculation of: PBIT / total assets.

Now, following the above method of calculation, TABLE 12 gives the return on fixed assets, and on current assets for Robert Half in the first two columns of panel A. FIGURE 34 graphs ROTA and the time series of its two disaggregated ratios. Observe how the ratio *return on fixed assets* reaches a much higher value in 2006 compared to the period 1995-2000, or ROTA at that point (1.54). This is somewhat peculiar when we compare this to the return on total assets (0.35). Although these disaggregated ratios are correct, can we trust them? (No!) In the fourth column of panel A of TABLE 12, with the title *check*, the disaggregated return ratios are subtracted from the return on total assets. Clearly, in each year, there is a difference between the sum of the 'parts,' the disaggregated return ratios, and their 'total,' i.e. ROTA. In other words, disaggregated return ratios calculated as 'sales over assets' do not add up. As an alternative, Westwick (1981, 7) recommends to inverse the fraction terms as 'assets over sales.' TABLE 12, panel B, reports these time series and clearly, for each year, the inversed disaggregated ratios now do add up to their 'total.' However, solving one problem introduces another, the ratios themselves are now a bit more difficult to understand intuitively. They also tend to become very large when PBIT is very small, like in 2002 and 2003, respectively 284.29 and 79.87. Therefore, for my analysis, the disaggregated return ratios are first multiplied by 100 and then scaled by their natural logarithm to create FIGURE 33 with the y-axis inversed (because when the line 'drops' this is 'less good,' like in FIGURE 34). The disaggregated analysis of return on assets by inverse calculation reveals in a more balanced manner the shift in weight over time from fixed to current assets. FIGURE 33 reveals, from 1997 onwards to 2006, the increasing contribution of the return on current assets to ROTA. Due to a poor PBIT, this is particularly difficult to grasp for the years 2002 and 2003 using the regular return ratios in FIGURE 34. Hence, I propose inverse calculation of disaggregated ratios.

3.3 Force & momentum ratios

3.3.1 Point or period measurement

Of some concern is that accounting ratios are not necessarily timeless. To get ROTA or ROE, we divide period measurements, respectively PBIT and PAT, by point measurements, respectively total assets and shareholders' equity (net wealth).[6] Or, seen from a temporal perspective, we divide data related to period (π) measurements by data from point (τ) measurements ($\pi : \tau$).[7]

[6] It is a matter of taste to choose the point of measurement. One can opt for the period's closing balance sheet or the opening balance sheet (that is done in this study). A third alternative is to average the opening and closing balance sheet to get, in a manner of speaking, a point in the middle of the period. However, none of this methods mitigates the problem of temporal inconsistency of the ratio.

[7] Data is treated here as a plural noun. The word data is the plural of Latin datum. It also used as a plural in English, but it is perhaps more commonly treated as a mass noun and used in the singular, at least

In Ijiri's framework, this implies that the accounting ratio is calculated as a momentum measurement (income) divided by a wealth measurement, PBIT divided by total assets in the example of ROTA.

Ratios become unitless when they relate quantities of the same dimension. Within the TEMA framework this is clearly not the case for ROTA or ROE. Although the accounting data are in some way related to the same medium of exchange in use—i.e. *monetary values*—it is their time property I am uncomfortable with. ROTA and ROE are ratios that express 'return by point,' a *state at date*, which is something different than a *rate of change* or 'return by period.' A ratio like the sales margin is unitless and timeless because it relates two period measurements through the division of PBIT by sales ($\pi:\pi$). In economic accounting terminology, only when we divide stock accounts by stock accounts, or flow accounts by flow accounts, will we get unitless ratios.

3.3.2 Unitless & timeless ratios

To obtain unitless and timeless ratios, in the TEMA framework (FIGURE 1, page 2), we have to divide accounting variables of the same temporal 'dimension' *wealth*, *momentum* or *force*. In other words, unitless ratios are calculated *intra-dimensionally*, i.e. between accounting variables with the same temporal dimension. In this approach, an accounting ratio is a quantity that denotes the proportional amount or magnitude of one period accounting variable relative to another period accounting variable ($\pi:\pi$), or of one point relative to another point ($\tau:\tau$). Following this temporal decision rule, we can calculate ratios between items, like the current *ratio*, current assets by current liabilities (two wealth accounts), but not divide a balance sheet account by sales (i.e. divide a wealth measurement by a momentum measurement). For example, the well known *working capital to sales ratio* that tries to capture a dynamic perspective of short-term liquidity conflicts with this temporal decision rule (Walsh 1996, 118).[8] This is not to say that such ratios should not be used. The observation here is that such ratios are calculated *extra-dimensionally*, and therefore are not timeless, which possibly leads to less clear interpretations. This is a motivation to investigate what *intra-dimensional* ratios might have to offer over *extra-dimensional* ratios.

3.3.3 Common size momentum ratio

In Ijiri's framework, *momentum* accounts are *rates of change per period* that measure the change of a wealth account.[9] Once we divide one such momentum account by another we get a true ratio that can be expressed as a pure number or as a percentage. For momentum, such a ratio expresses the *proportion* of change per period relative to another change per period. Melse (2004A, 52) presented the momentum ratio of net wealth composition, i.e. relative to total wealth momentum. In the same manner, a momentum ratio of disaggregated balance sheet accounts can be calculated. When the momentum of balance sheet accounts is divided by total wealth momentum we get common size ratios, or percentages, i.e. a change fraction of the

in day-to-day usage. For example, 'This is all the data from the experiment.' This usage is inconsistent with the rules of Latin grammar, which would suggest, 'These are all the data from the experiment' instead. Each measurement or result is a single datum (see also: http://en.wikipedia.org).

8 A shortcoming of the current ratio is that point measurements are static data. It is possible to 'window dress' the accounts so that the ratio 'looks good' on that day. Period measurements possibly make this more difficult to do.

9 See section 1.3.2 Dimensions of accounting measurement, page 8, for an in depth discussion.

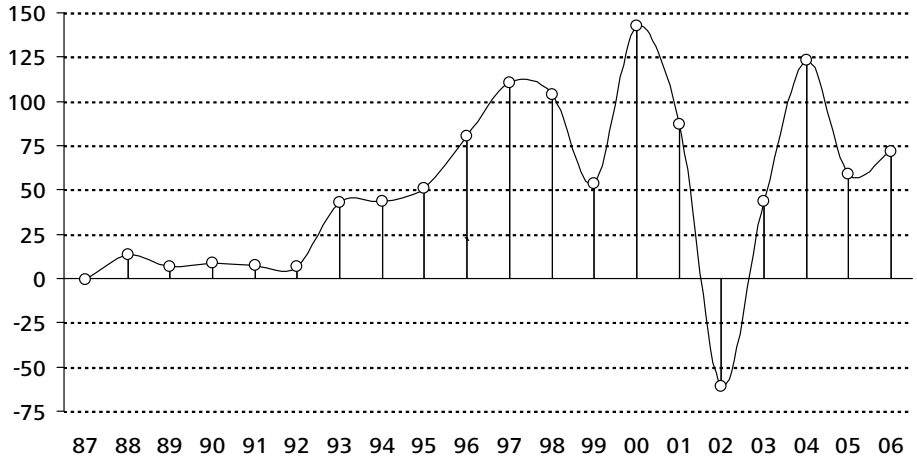

Figure 35 Robert Half. Net wealth momentum, raw data ($\pi : \pi$).

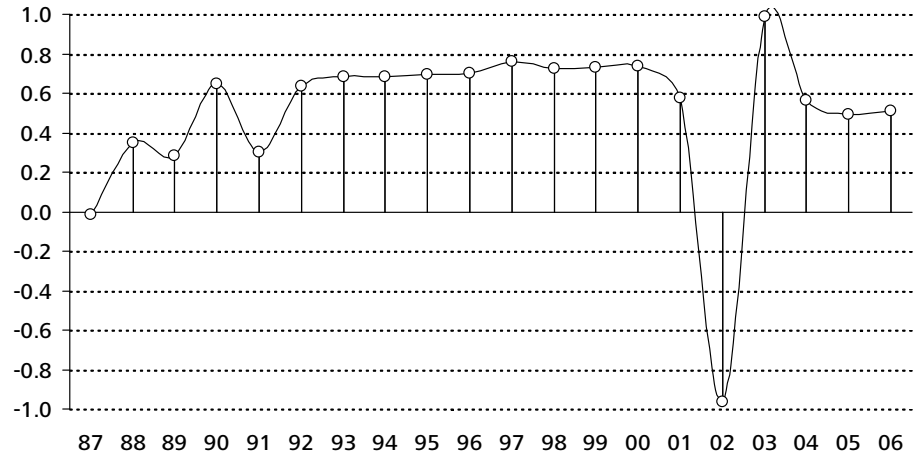

Figure 36 Robert Half. Net wealth momentum, common size ratio ($\pi : \pi$).

whole change. However, this requires that the sign of raw data negative momentum is first inversed to be included in the denominator before the fraction is calculated.[10] Assuming two disaggregated parts, EQUATION (19) gives the required logic:

(19) FOR A / B | A / (IF(A< 0 THEN −A ELSE A) + IF(B< 0 THEN −B ELSE B))

This renders unitless and timeless momentum ratios that can be compared with any other such ratio. TABLE 15 gives the common size momentum ratios for total liabilities and net wealth and TABLE 14 for current and fixed assets. Likewise, for *force* accounts, such ratios convey the *proportion* of the *rate of change per period squared* relative to the whole change of momentum per period squared. Thus, we can compare momentum or force ratios between periods of a single firm or between companies for panel analysis of markets or sectors. A whole new set of ratios is thus available in the TEMA framework to investigate business dynamics and possible relationships between the accounting variables from which they are derived.

[10] Consequently, the denominator of this division can be larger than the aggregate of the disaggregated momentum or force accounts.

3.4 Profitability

We limit ourselves here to the comparison of the sales margin and net wealth momentum of Robert Half. One way to look at sales margin is too see it as a momentum ratio because the accounting data involved are income related period measurements (π). When PBIT is divided by sales then the numerator and the denominator have the time dimension *momentum* in Ijiri's framework. Both are realized during the period in between the two moments when financial statements are drawn up, mostly a year. Consequently, it is more fitting to compare PBIT with net wealth momentum because both are period measurements (π). Additionally, sales margin can be compared with the net wealth momentum ratio, each being a period ratio ($\pi:\pi$). Before I discuss this in more detail, I first turn my attention to PBIT and net wealth momentum as individual momentum variables.

3.4.1 The common size format net wealth momentum ratio

First, net wealth momentum is calculated from net wealth by EQUATION (8), page 53 (TABLE 11, FIGURE 35). Second, likewise, total wealth momentum is calculated from total wealth (TABLE 11). Third, by EQUATION (19), page 86, the common size format ratio of net wealth momentum is calculated (TABLE 15, FIGURE 36). The common size format ratio of net wealth momentum is a fraction or percentage of total wealth momentum. It is calculated for each period by the *change of net wealth* (total shareholders' equity) relative to the *change of total wealth* of which it is a part. When we compare the graph of net wealth momentum raw data in FIGURE 35 with its common size format ratio in FIGURE 36, it is worthy to note that the net wealth momentum movement raw data and its common size ratio is similar in 2002 and 2003. However, before 2002 and after 2003, the trend of raw data and the common size format ratio is very different. Notably, the common size format ratio is characterized by a steady rate of change during the periods 1992-2001 and 2004-2006. On average the ratio is, respectively, 0.63 and 0.52. This implies that although net wealth momentum itself might fluctuate (FIGURE 35), relative to the fluctuation of total wealth it can still be stable (FIGURE 36). It is this *steady rate of change*, this *momentum*, that Ijiri considers to be of great importance in the appraisal of corporate performance. As far as the creation of net wealth is concerned, Robert Half is shown to be a reliable performer from 1992 onwards. Only during 2002 and 2003 stability is lost. Indeed, in those years the staffing industry experienced a major downturn in the United States of America and in Europe (Fleming 2002), as a result of the so-called 'dotcom crash,' from which it quickly recovered (Krampf 2004).[11]

The common size format ratio of net wealth momentum can also be seen as a coefficient. The Robert Half time series provides some evidence that there is a relation between the growth rate of total wealth and net wealth, and that it holds firm at the same level over several years (FIGURE 36). In this we should not only see an accounting logic—we can expect that net income is accrued into net wealth—but we should also read this as an economic phenomenon. That the amount of new net wealth gained and added to the balance sheet is about the same for a certain number of years might not be too big a surprise. But, that this firm, after experiencing large shocks during 2002 and 2003 in its business model, drives back (so quickly) to a stable level of momentum is striking. However, the difference between the new and the previous level of momentum, on average 0.11 lower, might be somewhat of a disappointment.

[11] Dated by Investopedia® in between March 11, 2000 and October 9, 2002 (www.investopedia.com).

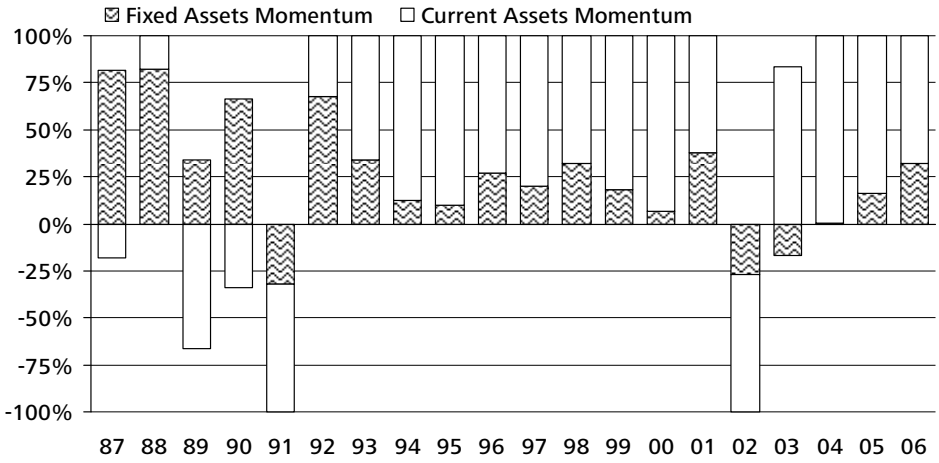

Figure 37 Robert Half. Current & fixed assets momentum, common size percentages.

	A: Raw data			B: Common size		
Year	period Wealth Momentum	period Net Wealth Momentum	period Liabilities Momentum	ratio Net Wealth Momentum	ratio Liabilities Momentum	sum check
1987	26.89	-0.50	27.38	-0.02	0.98	1.0000
1988	39.18	13.57	25.61	0.35	0.65	1.0000
1989	-10.46	6.97	-17.43	0.29	-0.71	1.0000
1990	3.95	8.62	-4.66	0.65	-0.35	1.0000
1991	-9.42	7.13	-16.55	0.30	-0.70	1.0000
1992	2.81	6.55	-3.74	0.64	-0.36	1.0000
1993	22.84	42.63	-19.79	0.68	-0.32	1.0000
1994	23.16	43.39	-20.23	0.68	-0.32	1.0000
1995	73.38	50.94	22.44	0.69	0.31	1.0000
1996	114.87	80.52	34.36	0.70	0.30	1.0000
1997	145.36	110.36	35.00	0.76	0.24	1.0000
1998	142.35	103.67	38.68	0.73	0.27	1.0000
1999	73.47	53.63	19.84	0.73	0.27	1.0000
2000	193.84	142.44	51.41	0.73	0.27	1.0000
2001	23.13	87.16	-64.02	0.58	-0.42	1.0000
2002	-58.49	-60.73	2.24	-0.96	0.04	1.0000
2003	44.23	43.69	0.54	0.99	0.01	1.0000
2004	218.75	123.21	95.55	0.56	0.44	1.0000
2005	120.03	59.00	61.03	0.49	0.51	1.0000
2006	140.34	71.80	68.54	0.51	0.49	1.0000

Table 14 Robert Half. Current & fixed assets momentum (millions U.S. Dollar), common size momentum ratios.

That the business model of Robert Half changed after 2003, compared to the period 1993-2001, can also be seen from the stacked bar graph, in FIGURE 38, of the net wealth and total liabilities momentum common size percentages. In FIGURE 38 each whole stacked bar represents the momentum of total wealth (of course that is always 100%). The lower half of each bar graphs total liabilities momentum, except for 2002, while the upper half is net wealth momentum. When the momentum is negative, i.e. when the balance sheet account decreases, the bar is drawn below the 0% line which indicates 'no change.' Thus, from FIGURE 38 it is clear that during the period 1989-1994 Robert Half successively reduced its debt whereas net wealth showed considerable growth. From 1995 to 2000, Robert Half kept increasing total assets, financing this with about 25% of debt. In 2001 the pattern shifts considerably with a substantial decrease of debt. Therefore, it is not without good reason reason that, during the market downturn, Fleming's (2002) comment was: 'Robert Half does have a firm financial

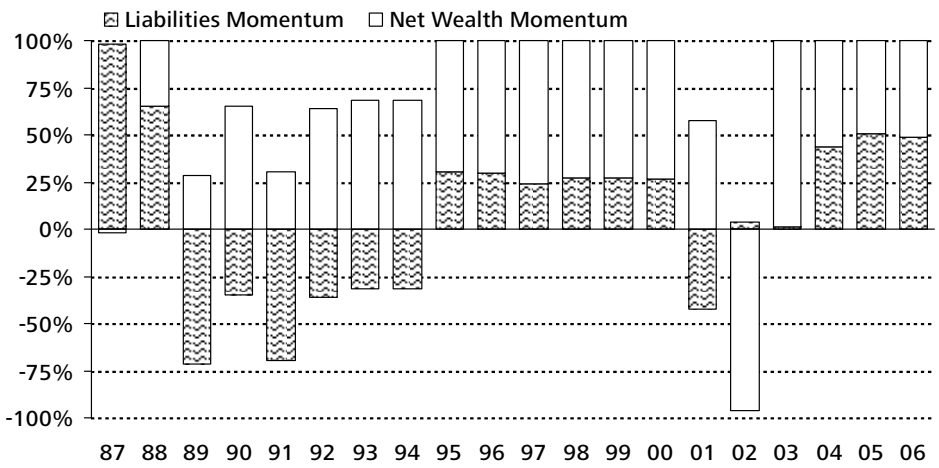

Figure 38 Robert Half. Net wealth & total liabilities momentum, common size percentages.

	A: Raw data			B: Common size		
Year	period Wealth Momentum	period Current Assets Momentum	period Fixed Assets Momentum	ratio Current Assets Momentum	ratio Fixed Assets Momentum	sum check
1987	26.89	-7.81	34.70	-0.18	0.82	1.0000
1988	39.18	6.94	32.24	0.18	0.82	1.0000
1989	-10.46	-21.44	10.98	-0.66	0.34	1.0000
1990	3.95	-4.18	8.13	-0.34	0.66	1.0000
1991	-9.42	-6.40	-3.02	-0.68	-0.32	-1.0000
1992	2.81	0.91	1.90	0.32	0.68	1.0000
1993	22.84	15.13	7.71	0.66	0.34	1.0000
1994	23.16	20.24	2.93	0.87	0.13	1.0000
1995	73.38	65.95	7.43	0.90	0.10	1.0000
1996	114.87	84.10	30.77	0.73	0.27	1.0000
1997	145.36	116.26	29.10	0.80	0.20	1.0000
1998	142.35	96.40	45.95	0.68	0.32	1.0000
1999	73.47	60.13	13.34	0.82	0.18	1.0000
2000	193.84	181.07	12.77	0.93	0.07	1.0000
2001	23.13	14.40	8.74	0.62	0.38	1.0000
2002	-58.49	-42.83	-15.66	-0.73	-0.27	-1.0000
2003	44.23	55.45	-11.21	0.83	-0.17	1.0000
2004	218.75	217.70	1.06	1.00	0.00	1.0000
2005	120.03	100.59	19.44	0.84	0.16	1.0000
2006	140.34	95.45	44.89	0.68	0.32	1.0000

Table 15 Robert Half. Net wealth & liabilities momentum (millions U.S. Dollar), common size momentum ratios.

foundation, with $303 million in cash, no debt and [a] healthy cash flow.' At the time, 'Robert Half announced that it would buy back as many as ten million of its own shares' (Id.), which we see reflected partly in the negative net wealth momentum of 2002 as well as in the negative current assets momentum (Table 14).[12] But, the recovery from this downturn is just as remarkable. In 2003 net wealth momentum is about the same as total wealth momentum, respectively $43.69 and $44.23 million (Table 15). These changes on the balance sheet of Robert Half illustrate the use of net wealth (equity) as a buffer of potential funds at the disposal of management to face bad times.

[12] Common Shares Outstanding were reduced from 174.929 in 2001 to 170.909 in 2002.

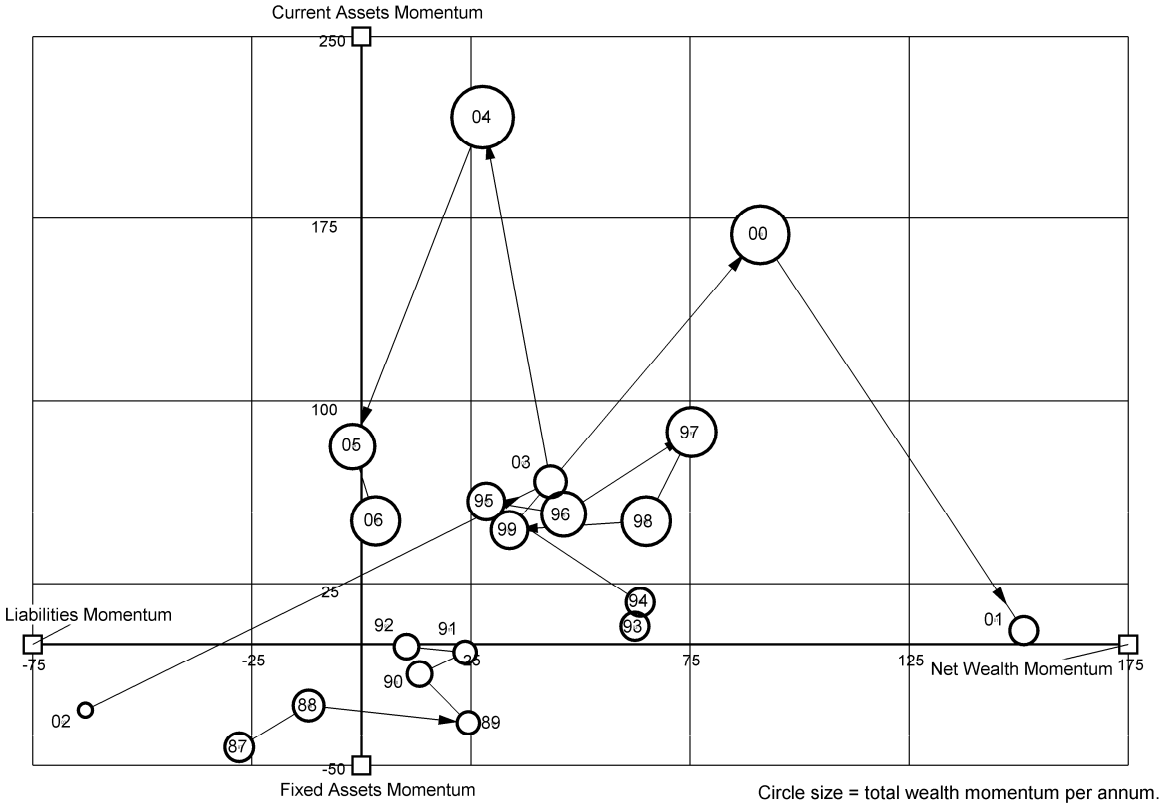

Figure 39 Robert Half. Balance sheet momentum, data differences (1987-2006).
Data scaling factor: millions U.S. Dollar.

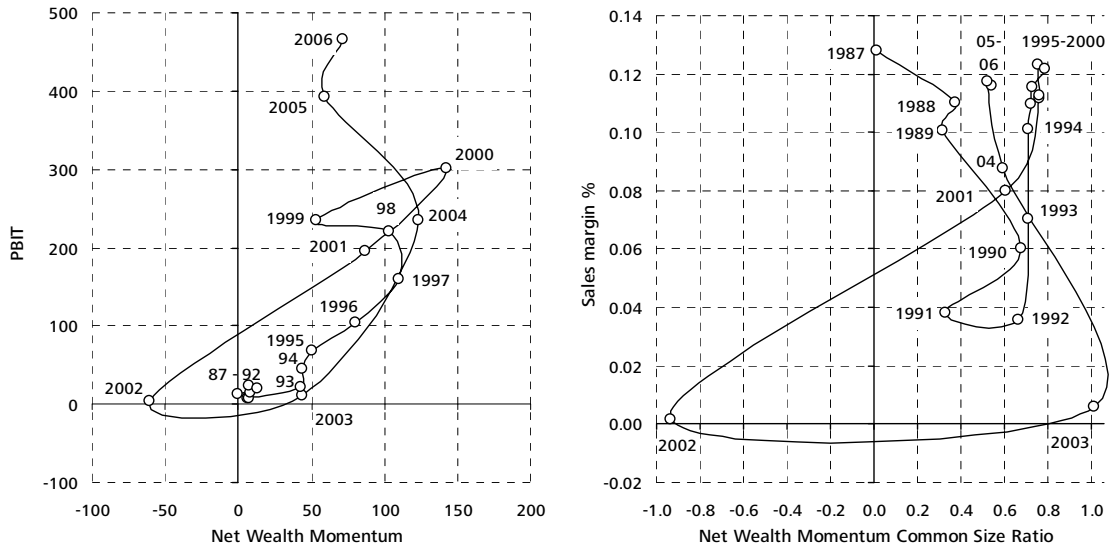

Figure 40 Robert Half. PBIT vs. net wealth momentum. Left: raw data. Right: ratios.
Data scaling factor: millions $.

period	wealth momentum disaggregated		sales margin	association
1987-1992	fixed assets momentum	vs.	downward trend	$r = .919^{**}$
1993-2001	liabilities momentum	vs.	leveling trend	$r = .836^{**}$
2002-2006	fixed assets momentum liabilities momentum	vs. vs.	upward trend	$r = .864^{**}$ $r = .870^{*}$

** = 1% level of significance, * = 5% level of significance.

Table 16 Robert Half. Period's feature and association of disaggregated wealth momentum & sales margin.

3.4.2 Balance sheet dynamics by foliomap

The horizontal and vertical axis of a Foliomap can be used to plot table row items, *subjects* or *measurements*, on a plane by *raw score* of a table column item, an *object* or *variable*. Likewise, a Foliomap can also display the *difference* between two variables by subtraction, or map the *quotient* by division of two variables. The two variables involved in either one of these arithmetic operations are drawn at the extremes of an axis of the Foliomap. The table row items are drawn on the Foliomap using a symbol, usually a circle, that can be set constant in size or scaled by a variable or, alternatively, the row total sum value. In Figure 39, each circle on the Foliomap represents a year: they are the table row items from panel A of Table 15 and Table 14. The size of each circle is scaled by total wealth momentum of that year. Each year's circle is mapped using the disaggregated momentum accounting variables (second and third column of panel A of Table 15 and Table 14). The horizontal axis maps the difference between net wealth and total liabilities momentum. The vertical axis maps the difference between current assets and fixed assets momentum. In Figure 39, three periods of successive years are connected; some segments have an arrow to indicate the time trajectory. Note how 2002 is different from the position of 2001 or 2003. Clearly, 2002 is a year that not only gives us a sales margin drop (Figure 32) but also a large difference in the disaggregated wealth momentum (Figure 39). Also 2001 and 2004 are markedly different years, 2001 has more net wealth momentum while 2004 has larger current assets momentum. The year 2000 has both these features.

The sales margin time series exhibits its own particular trends during the three periods: downward, leveling and upward (Figure 32). The disaggregated wealth momentum Foliomap of Robert Half has the same three distinctively different periods (Figure 39). Comparing the Foliomap with the sales margin time series one can ponder upon a possible association between momentum and sales margin. Table 16 reports the positive and rather high association between sales margin and, respectively, fixed assets momentum and total liabilities momentum and both.

3.4.3 Performance dynamics by scatter plot

In this section I focus on the analysis of the performance measures PBIT and net wealth momentum. Figure 40 contains two scatter plots. The data is displayed as a collection of points, each having one coordinate on the horizontal axis and one on the vertical axis with the time point serially connected. The left scatter plot represents the association (not causation) between net wealth momentum and PBIT (Table 11). The right scatter plot represents the association between the sales margin (Table 11) and the net wealth momentum common size ratio (Table 15). This comparison of accounting variables as well as the accounting quotients is time period consistent within the TEMA framework because PBIT and net wealth momentum are *income* measurements. The respective denominator sales and total wealth momentum are *income* measurements too and thus the ratios are dimensionless.

The two scatter plots of Figure 40 are of particular interest given the analysis of disaggregated wealth momentum in the previous section. We should compare them taking note of the three time periods observed. The raw data scatter plot displays the years of the first period (1987-1992) on top of each other because both PBIT and net wealth momentum are rather small and their proportion hardly changes. The next period (1993-2001) is characterized by a steady increase of both PBIT and net wealth momentum. In 2002 PBIT drops to almost nothing

($3.5 million) and net wealth momentum becomes negative ($-60.73 million). The next two years show a recovery to the level of previous years. However, these two years are markedly different as PBIT reaches its highest level but net wealth momentum falls back to about $65 million. Instead, we should expect as much as $100 million.

The scatter plot of the sales margin percentage and net wealth momentum common size ratio of FIGURE 40 confirms the conclusions based on the raw data and more. First, the period 1987-1992 now is more distinct by its gradual decrease of the sales margin and steady increase of net wealth momentum. Note that in 1992 net wealth momentum more than doubles to 64% while the sales margin decreases a little from 3.83% to 3.59%. In other words, only looking at the trend of the sales margin might not disclose the improving net wealth trend. Also, in this scatter plot, the period 2003-2006 shows stability like before close to a sales margin of 12%. But, net wealth momentum seriously runs out of steam in 2005 and 2006 and seems to settle for a new level at about 50% of total wealth momentum, considerably lower than the 69% average of the previous ten year period.

3.5 Discussion

The TEMA framework of Yuji Ijiri is a temporally determined source of information about company wealth and its change in magnitude and composition. A great advantage of the TEMA framework is that it allows for the temporal as well as the categorical analysis of accounting measurements. I analyzed return on total assets both as an aggregated and disaggregated performance measurement. I proposed to use an inverse method of ratio calculation for disaggregated ratio analysis. This will allow the comparison of disaggregated accounting variables relative to their aggregated totals in the TEMA framework. Preferably, we should not compare time period data with time step data.

With my example of Robert Half, I demonstrated that with the TEMA framework new information can be disclosed that is relevant for performance analysis. By comparing net wealth momentum with sales margin, I verified that it is beneficial to compare accounting ratios that are dimensionless. It is possibly more meaningful to limit the use of ratios to only intra-dimensional relations within the TEMA framework for the benefit of temporal correctness and improved interpretability of the data. Consequently, we should use the TEMA framework to search for more informative ratios. In this case, I was able to tell apart years that have a comparable net wealth momentum common size ratio but different sales margin. This, I think, adds new insight to how we should appreciate the structural aspects of the profitability of the firm. It sheds more light at a desirable stability of the firm's business model (De Groot *et al.* 2004). Vice versa, observing years that have a comparable ROTA but a different common size format ratio of net wealth momentum might deepen the analysis of balance sheet dynamics, something of interest to shareholders and analysts alike.

I conclude with the contention that implementing TEMA might be beneficial for strategic accounting purposes as well as for the ex post analysis of financial statements (Bell *et al.* 1997, Brouthers & Roozen 1999, Haskins & Sack 2006, Roslender & Hart 2003). Possibly, this will prompt a renewed interest in the practical use of the TEMA framework as a means to improve performance measurement and analysis.

4

Decomposition Analysis within the TEMA Framework

Panel A

	data 1969	data 1970	fractions 1969	fractions 1970	growth index	decomposition measure
Cash	$ 52,062	$ 79,497	0.041	0.060	1.468	0.02307
Receivables	$ 244,775	$ 179,087	0.193	0.135	0.703	-0.04765
Inventories	$ 500,417	$ 693,920	0.394	0.525	1.333	0.15081
Prepaid expenses	$ 129,643	$ 19,407	0.102	0.015	0.144	-0.02845
Investment in affiliates	$ 4,277	$ 4,184	0.003	0.003	0.940	-0.00019
Property, plant, equipment	$ 337,849	$ 343,446	0.266	0.260	0.977	-0.00598
Deferred charges	$ 2,421	$ 3,088	0.002	0.002	1.226	0.00048
Total	$ 1,271,444	$ 1,322,629	1.000	1.000		0.09208
					disaggregation measure δ	0.06851
					ρ^2	0.93149
					R^2	0.90434

Panel B

	data 1969	data 1970	fractions 1969	fractions 1970	growth index	decomposition measure
Cash	$ 10	$ 79,497	0.077	0.060	0.781	-0.01483
Receivables	$ 20	$ 179,087	0.154	0.135	0.880	-0.01729
Inventories	$ 30	$ 693,920	0.231	0.525	2.273	0.43091
Prepaid expenses	$ 10	$ 19,407	0.077	0.015	0.191	-0.02431
Investment in affiliates	$ 20	$ 4,184	0.154	0.003	0.021	-0.01229
Property, plant, equipment	$ 30	$ 343,446	0.231	0.260	1.125	0.03064
Deferred charges	$ 10	$ 3,088	0.077	0.002	0.030	-0.00816
Total	$ 130	$ 1,322,629	1.000	1.000		0.38467
					disaggregation measure δ	0.30735
					ρ^2	0.69265
					R^2	0.67012

Panel C

	data 1969	data 1970	fractions 1969	fractions 1970	growth index	decomposition measure
Cash	$ 79,497	$ 79,497	0.060	0.060	1.000	0.00000
Receivables	$ 179,087	$ 179,087	0.135	0.135	1.000	0.00000
Inventories	$ 693,920	$ 693,920	0.525	0.525	1.000	0.00000
Prepaid expenses	$ 19,407	$ 19,407	0.015	0.015	1.000	0.00000
Investment in affiliates	$ 4,184	$ 4,184	0.003	0.003	1.000	0.00000
Property, plant, equipment	$ 343,446	$ 343,446	0.260	0.260	1.000	0.00000
Deferred charges	$ 3,088	$ 3,088	0.002	0.002	1.000	0.00000
Total	$ 1,322,629	$ 1,322,629	1.000	1.000		0.00000
					disaggregation measure δ	0.00000
					ρ^2	1.00000
					R^2	1.00000

Table 17 Asset decomposition measures (based on Lev 1974).

4 Abstract

In this study I evaluate the use of decomposition analysis in the TEMA *framework. In business and economics, decomposition analysis is applied for the study of structural change, particularly changes over time in the relative proportions of accounts. I demonstrate that decomposition analysis with the decomposition measure of Baruch Lev is only possible for the wealth dimension of the* TEMA *framework. Alternatively, the disaggregation measure of Yuji Ijiri gives similar results for wealth. Moreover, it also allows for the analysis of the momentum and force measures, which is not possible with the decomposition measure. In the example of 3M Company, for wealth, neither the decomposition measure nor the disaggregation measure signal any substantial structural change. For momentum and force, the disaggregation measure does signal structural change but at about every point in time. All informational signals are also color coded to enable a more advanced visual analysis. My conclusion is that It could be possible that the informational signals of wealth suffer from 'under-signaling' whereas momentum and force are possibly 'over-signaling,' and therefore either one might be misleading. As such, these informational signals direct attention to the econometric properties of the accounting variable's time series. But, as discretionary tool for the analyst of financial statements the informational measures discussed seem to offer little guidance to decide if the (lack of) structural change warrants inspection of financial variables at a disaggregated level or not. Hence, I discourage the application of either the decomposition measure or the disaggregation measure for this purpose.*

4.1 Introduction

Having available a summary signal to guide the user of financial statements to particular line items might be beneficial. Of course, such a signal must be unambiguous and neither occurs too seldom nor too frequently for it otherwise will simply be neglected. Ideally, *informational measures* of financial statements should unequivocally attract attention at the right moment for the right reason. This is the objective of *decomposition analysis:* to study the changes over time in the allocation of a firm's inputs and outputs as reflected in its financial statements (Lev 1974, 57). In this chapter *decomposition measures* developed by Baruch Lev are compared with the *disaggregation measure* of Yuji Ijiri (1995) within the framework of force and momentum accounting. I have restricted myselve to using the example data of 3M Company as well as extensions of examples published by Lev and Ijiri.

Organization of this chapter

In section 4.2 the decomposition measures of Baruch Lev are defined, some of the criticisms it received discussed as well as some applications presented in the literature. Section 4.3 presents a fairly new disaggregation measure of Yuji Ijiri that does away with the non-negative constraint of Lev's decomposition measure. An example of Lev is compared with the result of Ijiri's approach. Furthermore, the disaggregation measure is applied to wealth momentum and force measures. In Section 4.4 Lev's and Ijiri's informational measures are applied on quarterly balance sheet time series of 3M Company within the TEMA framework. A new color coding method is applied to these informational measures to facilitate their visual analysis. Section 4.5, finally, completes this chapter with a discussion and gives references to further research presented in this thesis.

4.2 Measures of decomposition

In this section entropy is introduced as a concept of information theory that provides the foundation for the decomposition measure of Baruch Lev. The objective of decomposition analysis is explained. The use of entropy as a quantitative measure of uncertainty in economics and accounting is illustrated with an example. Lev's equations for the measures of assets, liabilities & balance sheet decomposition are presented. The critique Lev's method received is summarized as well as some of its applications.

4.2.1 Rationale

In decomposition analysis, financial statements are seen as numerical decompositions of certain total sums, i.e. as 'parts' of a 'whole' like total assets or total sales.[1] Theil (1967, 1969), Bostwick (1968), Caspari (1968) and Lev (1968, 1969, 1970, 1971, 1973, and 1974) are among the earliest authors to apply informational measures in economics and accounting. Theil probably developed the first application of decomposition analysis to financial statements. He argued that decomposition could be used as a '...summarizing descriptive device for changes in the composition of balance sheets' (Theil 1967, 1969, and 1972).

The economic rationale behind decomposition analysis is the suggestion that firms strive to maintain equilibrium relationships in their internal systems as well as in their relationships with the environment in which they operate (Lev 1974, 49). This idea is closely related with the concept of *homeostasis,* which is a major characteristic of living organisms and maintained by complex biological mechanisms that operate via the autonomic nervous system to offset disrupting changes. In accounting, economics, operations research, systems science and systems thinking, homeostasis is used in analogy by many authors to describe the action of negative feedback processes in maintaining the business system at a constant equilibrium state (Beer 1994 & 1997, Bell *et al.* 1997, Bertalanffy 1995, Bianchi *et al.* 1998, Checkland 1993, Forrester 1961, Geus, de 1997, Heij *et al.* 1997, Jackson 1993, Kosko 1992, Larsen & Lomi 1999, Legasto *et al.* 1980, Leeuw, de 1997, Lilienfeld 1978, Mattessich 1978, Richardson 1991, Roberts 1978, Ruth & Hannon 1997, Sage & Armstrong 2000, Smith & van Ackere 1999, Sterman 2000, Veld 1996 and Vennix 1996).

Lev posits that for any given level of activity optimal relationships exist between labor and capital inputs, inventory and sales, cash and short-term securities, debt and equity capital and so forth. However, as he puts it, the *actual* [sic.] relationships among inputs and outputs are presented in a firm's financial statements and these might, of course, deviate from the optimal ones. More importantly, the equilibrium state of optimal relationships of a firm might, and are likely, to change over time.[2] These changes can be the result of planned actions by management or unplanned changes resulting from unexpected events. Lev considers that both causes are of interest to the analyst trying to assess the firm's future performance. Thus, it is worthwhile to search for informational measures to facilitate analysis.

The study of changes in the relative shares of balance sheet and income statement items is well accepted in traditional financial analysis. The traditional method to analyze structural changes within financial statements is to transform them first to the *common size format* to

[1] Usually, shareholders' equity is added to long term liabilities to match fixed assets (Lev, 1974). However, the focus of the TEMA framework is on the growth (rate) of net wealth.

[2] This is illustrated by the change of the relative shares of assets of 3M discussed in Chapter 6.

remove the size difference that occur between points in time by dividing the individual items by some common base figure (Foster 1986, 58, Penman 2003A). Most data providers deliver both the data of financial statements and their common size fractions.[3] Lev is doubtful about the efficiency of such an analysis because all items of the financial statement, including their ratios, have to be considered for the various periods under study. He looks for a summary measure as a device to identify whether or not a significant change in the financial statement structure has occurred and where most of that change is located. In other words, Lev proposes to use an *informational measure* to focus our attention on possible disturbances of the equilibrium state of a firm. He wants a filter between the bulks of data and only spends time on those items that warrant in depth research. To this purpose, Lev employs the entropy concept of information and communication theory.

4.2.2 Entropy

Entropy in information and communication theory is regarded as a quantitative measure of uncertainty associated with the value of discrete random variable **X**.[4] Suppose 1000 bits (0s and 1s) have to be transmitted from one place to another. If these bits are known ahead of transmission, in the information theoretic sense, the conclusion then is that no information has been transmitted. Nothing is gained in the process; entropy is at its lowest possible level. This means that a certain value will be send and received with absolute probability. In contrast, suppose that each and every bit is equally and independently likely to be 0 or 1, then 1000 bits of information are transmitted. Everything is gained in the process; the entropy is present at some higher level, if not the highest. It is important to note that entropy as such is part of information theory based on probability theory and statistics with the *bit* as the most fundamental unit of information. This allows for entropy to be applied as a measure of the amount of uncertainty associated with the value of accounting variables. But, many have criticized this approach for the fact that accounting data are not the result of probabilistic processes.

4.2.3 Information

Simply stated, in information and communication theory, *information* is a message received and understood. Imagine that two persons are in communication and that they have agreed on an alphabet to use.[5] Before data are send, there is a certain measure of uncertainty (**H**BEFORE) at the recipient about what is about to be send. After the first datum is received, uncertainty decreases (to **H**AFTER). **H**AFTER is never zero because of noise in the communication system. The decrease in uncertainty is the information (**I**) that is gained during the communication process and is formulated as:

$$\mathbf{I} = \mathbf{H}_{\text{BEFORE}} - \mathbf{H}_{\text{AFTER}} \tag{20}$$

where **I** is the information measure and **H** is the uncertainty. Since **H**BEFORE and **H**AFTER are state functions, this makes **I** a function of state. From the perspective of accounting this is of interest because we reflect on two states when we compare two successive financial statements of a firm. For instance, the BEFORE we should see as the balance sheet at t_{-1} and the AFTER is as the balance sheet at t.

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3 Like Bureau van Dijk (Amadeus, Zephyr), Compustat, Edgar, IQ Info (Annual Reports Database), Thomson ISI (Datastream), Reuters (3000 EXTRA), etc.

4 Based on Pendlebury (1980) and http://en.wikipedia.org.

5 The example is based on the one of Schneider (2007).

4.2.4 Decomposition measures

A *decomposition measure*, as proposed by Lev, is like an index for the degree to which the decomposition of a balance sheet at t differs from the previous one. Lev (1974) defines the *assets decomposition* measure as:

$$\mathsf{I}_{\mathsf{A}} = \Sigma_{i=1}^{n} q_i(\text{LOG}\,(q_i \,/\, p_i)) \tag{21}$$

where q is the current measurement at t and p is the previous measurement at t-1. Note that EQUATION (21) allows for any distance in time between q and p. The relative shares of items are denoted by p_i with $i = 1, \ldots, n$, in the order of appearance on the financial statement.

Thus, in the example published by Lev (1974, 48) of Lockheed's assets for the end of years 1969 and 1970, data are first transformed to the common size format of fractions, i.e. the p_i (TABLE 17, panel A). The corresponding fractions of the later financial statement are denoted by q_i. Cash, for example, renders the fractions $q_1 = 0.06$ and $p_1 = 0.041$. The growth index $q_1 \,/\, p_1$ is for cash: 1.468, and the natural log of that datum is 0.38382, which is multiplied next by 0.06 (q_1) to finally get the item's equation element value of the asset decomposition measure of 0.02307, i.e. the change between statements of cash relative to total assets. This calculation of the equation element value is repeated for each item and summed to the total *assets decomposition* measure of, in this example, 0.09208, which is relatively low. In the last column of each panel of TABLE 17, each item's equation element value is reported separately as well as the decomposition measure with a border drawn around it (the measures reported below it are discussed in the next section).

The decomposition measure is a measure for the degree of change in the firm's assets decomposition constrained by the two selected financial statements. In TABLE 17, panel C, reports what the measure is when no change occurs whatsoever between the two periods: 0. But, the moment a change is observed the decomposition measure will take any value between 0 and its maximum of 1. For example, panel B reports a rather dramatic change, both in composition and in magnitude. The assets decomposition measure now is 0.38467, much higher than Lev's original example of Lockheed's assets in panel A, but still considerable lower than the possible maximum. This is explained by the fact that the decomposition measure considers changes in the allocation of a firm's assets, liabilities, costs, etc., and not the changes in absolute values. For example, inventories in panel B, more than double their proportion and thus have a rather large decomposition measure. But, the focus should really be on comparing decomposition measures between periods or companies. In the examples presented in TABLE 17, panel B warrants more attention than panel A for it has the larger decomposition measure. Panel C can simply be neglected.

The liabilities *decomposition* measure is defined in the same manner as the assets decomposition measure:

$$\mathsf{I}_{\mathsf{L}} = \Sigma_{j=1}^{n} q_j(\text{LOG}\,(q_j \,/\, p_j)) \tag{22}$$

where the only difference is the subscript j identifying the accounting variables of the liability side of the balance sheet. The two decomposition measures are integrated in a total *balance sheet decomposition* measure with:

$$\mathsf{I}_{\mathsf{BS}} = \Sigma_{i=1}^{n} \Sigma_{j=1}^{n} q_{ij}(\text{LOG}\,(q_{ij} \,/\, p_{ij})) \tag{23}$$

where each of assets' and liabilities' categories is assumed to be divided by twice the balance sheet totals to yield sets of non-negative fractions that sum to 1.

4.2.5 Critique of entropy based informational measures

Bernhardt & Copeland (1970) have the opinion that any 'loss' of information by comparing the composition of financial statements should be measured against some decision model to get an unambiguous informational measure. Moreover, they criticize Lev for admitting multiple admissible pairs within categories of accounts such as current and fixed assets and thus rely on exogenous criteria to choose the base and the items required for the calculation. Indeed, anyone can decide on these for whatever purpose. Abdel-Khalik (1974) rebutted Bernhardt & Copeland's criticism partially arguing that the decision model underlying '...general purpose external [financial] reporting...' is by definition unknown since it is intended '...*to whom it may concern*...' [sic.]. He looks for a solution of the decision model ambiguity problem by comparing admissible ways of aggregation of primary data under allowable accounting conventions. Users should then choose between competing acceptable aggregation alternatives on the basis of some quantitative measure, unsurprisingly, he proposes to use Lev's entropy based decomposition measures. A recent example that does just that was published by Krisement (1997). She showed that the harmonization effects of the 4th and 7th EC directives in individual European Community countries may be quantified by means of entropy and compared with accounting practice in countries not belonging to European Community. Babich (1975) is also highly skeptical about the practicalities involved with the computation of decomposition measures. Problems of data quality, interpretability, the necessity for integration and the inability to indicate the direction of any change between financial statements, are such that Babich does not think that Lev's decomposition analysis will ever become a fruitful method. Nevertheless, several authors have since reported some successful applications of the method.

4.2.6 Applications of entropy based informational measures

Decomposition analysis was applied for various applications in accounting. Balkaoui (1976) found by comparing a set of 25 acquired Canadian companies to a control group of 25 equivalent companies, using Lev's three informational measures (asset, liabilities and balance sheet decomposition) that the stability of firms taken over was significantly lower, i.e. their information measures were larger. Grossman's (1975) analysis of liquidity management of four companies in the automobile industry measures showed a difference in the management of the assets and liabilities by the respective firms. In his opinion, '...the entropy measures are more efficient ... they measure deviations from proportional development rather than solvency attributes, and they do not suffer from the "rules of thumb" as do financial ratios.' Ball *et al.* (1976) found that variations in firms' annual income are associated with balance sheet compositions. Lev & Theil (1978) applied the entropy approach to the choice of asset depreciation under the conditions of imperfect information concerning their pattern of use.

Moyer (1977) examined the explanatory power of the Altman bankruptcy model and compared it with a model using Lev's balance sheet decomposition measure to predict bankruptcy. In his study he found that the decomposition model generated significantly fewer Type I errors (classifying failing firms as non-failing) for two and three years before bankruptcy than the Altman model did (11% and 11% for Lev, against 20% and 30% for Altman). On the other hand, the Altman model made considerably fewer Type II errors (classifying non-failing firms as failing) than did Lev's decomposition model. Zavgren (1985) did the same for U.S.

firms and found the models were significant even five years prior to failure, and this increased up to the year immediately prior to failure. Keasey & McGuinness (1990) is a recent example of an entropy-based bankruptcy model of U.K. firms. Booth (1983) confirms Lev's (1971) and Walker's *et al.* (1979) findings that decomposition measures have different attributes for failed and non-failed companies. Specifically, he showed that certain decomposition measures based on balance sheet information are larger and less stable for failed companies than for non-failed companies. However, Booth & Hutchinson (1989) were unable to successfully discriminate between failed and growth firms. The only exception they found is the stability of the assets decomposition measure, being less stable for growth than failed firms. They concluded: '...whilst decomposition measures may be a useful scanning device in distinguishing between a group experiencing changes in financial structure ... they appear to be less useful in distinguishing between groups experiencing different types of change in financial structure, such as failing and growing firms.'

Walker *et al.* (1979) found in a sample of retail department and discount stores significant correlations between decomposition measures and changes in ratios or changes in linear combinations of ratios, which '...suggest that decomposition analysis would be a useful adjunct to, or replacement for, other techniques of monitoring financial statements.' More recently, Elliott & Jacobson (1994) applied the entropy measure for their analysis of the cost and benefits of business information disclosure. Holdren *et al.* (1994) applied Lev's balance sheet decomposition analysis in their study of 103 commercial bank holding companies, involved in acquisitions over the period 1974-1986, and found significant changes in asset and liability structure.

To mitigate the problem of aggregation that results from the consolidation process, i.e. that the users of group accounts are not going to be satisfied with by crude consolidated data alone, Pendlebury (1980) suggests to use Lev's informational measures as a 'data expansion index.' Blommaert (1995A, 1996) considered Lev's entropy approach in the similar context of consolidated financial statements. He appreciates the usefulness of decomposition analysis as a means to find a balance '...between the loss of information content on the one hand and "information overload" on the other.' However, Blommaert underwrites the concerns voiced by Bernhardt & Copeland (1970) and others that a limitation of the entropy concept is that it is not based on the relevance of the message to the receiver: '...consequently, there is no guarantee that the information value will be measured adequately.' He concludes that the entropy concept can play only a limited role in the consolidation process.

Courtis (2000) suggested the use of a single summary statistic of risk that '...should embrace a wide range of expectational issues about uncertainty, and be credible, understandable, objective and usable' to facilitate the *informational search strategy* of investors and others. Although he acknowledges Lev's decomposition analysis, he thinks it has failed as such a measure primarily because as a risk measure based on accounting data, i.e. measuring significant changes in asset and liability structure, it is prone to different definitions.

4.3 A measure of disaggregation

The model developed by Lev for decomposition analysis of financial statements is general and can be applied to any set of items that in a sensible way can be related to a base figure. However, as mentioned by Babich (1975), Lev's models are seriously limited by the fact that the decomposition equations cannot deal with negative values. In this section, Ijiri's alternative to Lev's decomposition measure is presented and discussed in the light of the TEMA framework.

4.3.1 Dealing with the direction of change

Possibly the most stringent criticism of Lev's decomposition analysis at the theoretical level, the inability to indicate the direction of change that the use of negative data necessitates, is addressed by the disaggregation measure of Ijiri (1995). Theil (1969) recommends to aggregate negative items with positive ones such that the sum is positive and use that instead. Of course, this alleviates the mathematical problem but disregards the informational content of the negative items in the procedure. Pendlebury (1980) proposed to separate negative line items from positive ones in a separate group and invert their sign. Thus, Lev's decomposition formulae could still be used on negative data. Nonetheless, such approach would double the number of decomposition measures! Just the opposite of Lev's objective is to have available a single informational measure of disaggregated data in an efficient manner for business performance appraisal.

4.3.2 The disaggregation measure

Ijiri (1995) introduced a new informational measure that does away with the non-negative constraint of Lev's decomposition measure. The so called *disaggregation measure* of Ijiri, denoted formally by δ, indicates the *fraction of variance* that can be eliminated by using the disaggregated data instead of their aggregated sum value. The disaggregation measure δ is one minus the 'aggregation measure' that is denoted by ρ^2 and computed as:

$$\delta = 1 - \rho^2 \tag{24}$$

where ρ^2 is computed as:

$$\rho^2 = \Sigma_{i=1}^{n} (p_i q_i)^2 / (\Sigma_{i=1}^{n} p_i^2)(\Sigma_{i=1}^{n} q_i^2) \tag{25}$$

where, similar to EQUATIONS (21), (22) and (23), p_i represents items of the current measurement and q_i represents items of the previous measurement, with $i = 1, \ldots, n$, in the order of appearance on the financial statement.

Using each panel's last column of TABLE 17, page 94, with Lev's example of Lockheed, we compare Lev's decomposition measure (a border drawn around it) with Ijiri's disaggregation measure δ reported below it, respectively: 0.09208 vs. 0.06851, 0.38467 vs. 0.30735 and 0 vs. 0). These measures are similar but not the same, except for the case of no change (panel C). Ijiri's disaggregation measure has the same objective as Lev's decomposition measure but it is based on a very different assumption, namely that of variance explained. Ijiri posits that ρ^2 is similar to the coefficient of determination R^2 in statistics, which indicates the proportion of variability in a data set that is accounted for by a statistical model, e.g. a linear regression.[6] For example, in TABLE 17, the data of 1969 are regressed on 1970 and their respective R^2 is reported on the bottom line of each panel in the last column. Above it Ijiri's aggregation measure

[6] For the details, the reader is referred to Ijiri 1995, 1971 and 1968.

ρ^2 is reported as well as the disaggregation measure δ. Clearly, in panel A and B, ρ^2 is similar to R^2, actually it is about 1.03 larger. The difference between Lev's and Ijiri's measure is far greater in panel A and B respectively 1.34 and 1.25. Pending further analysis a cautious conclusion should be that Ijiri's disaggregation measure is to be preferred for it is closely tied to the analysis of statistical dispersion or variability and thus might offer extension to other analytical methods like multivariate analysis, which is discussed in Chapter 5 and 6.

Like Lev's decomposition measure, Ijiri's disaggregation measure ranges between the minimum value of 0 and the maximum value of 1 (TABLE 18). TABLE 18 has four panels that are examples of values of the disaggregation measure. Panel A explains that $\delta = 0.5$ when 50% of accounts of equal value change by the maximum possible amount, i.e. in this case from 0 to 1 or vice versa. In panel B, $\delta = 1$ because each account of equal value changes by its whole amount or vice versa. The accounts in panel C, finally, do not change at all and thus $\delta = 0$ always. How should we read these values of δ in TABLE 18? Well, suppose we only receive a report with only the total value of the last column of each panel in combination with its value of δ. Then we now know that we need not bother looking at the disaggregated data of panel C; there is no variance left that can be eliminated by looking at the individual accounts that make up its total and their previous value. Likewise, disaggregating the total of panel B is more interesting than that of panel A for the fact that it has twice as much variance to explain. In other words, it will be twice as much more interesting to study the change in composition of the items of panel B than that of panel A. Of course, by comparing the totals of p and q in panel A and B, respectively 3 & 6 and 3 & 3, we would in this very simple example arrive at the same conclusion. But, in practice differences in totals might not be explained by differences in proportions, in which case we would also get $\delta = 0$; as panel D of TABLE 18 shows. It is almost impossible to 'guestimate' what changes contribute to the disaggregation measure. The objective is to signal that changes in composition have occurred and to be able to rank such changes as well to be able to select aggregated items for disaggregation are the benefits envisaged by Ijiri.

4.3.3 Disaggregation measures of income & wealth

There are two important differences between Ijiri's disaggregation measure and Lev's decomposition measures. Firstly and most importantly, the disaggregation measure makes it possible to compute the disaggregation measure with negative data due to the squaring of items.[7] Secondly, it is not necessary to transform financial statement's data to the common size format. The disaggregation measure will give the same result when computed on raw data or on fractions. TABLE 19 reproduces the disaggregation measures of operating income of AT&T from 1991 to 1994 as published by Ijiri (1995), but also for 1995. In each panel operating income data is broken down along three categories, namely, by revenue/expense, by industry and by geography. In panel A the raw data are presented together with the disaggregation measure of two successive years. Panel B shows the fractions based on operating income, together with the disaggregation measure, as originally calculated by Ijiri. Although the fractions total to 100%, the resulting fractions of the calculation taking operating income as the denominator are rather high. An alternative calculation, should fractions be required, is presented in panel D where the

[7] The use of the logarithm in Lev's measures makes it impossible to use negative data except for adjusting them, which is not a popular thing to do with accounting data.

Panel A

	q-3	*q-2*	*q-1*	*q*	*p*
Account 1	$ 1	$ 1	$ 1	$ 1	$ -
Account 2	$ -	$ 1	$ -	$ 1	$ 1
Account 3	$ 1	$ 1	$ 1	$ 1	$ -
Account 4	$ -	$ 1	$ -	$ 1	$ 1
Account 5	$ 1	$ 1	$ 1	$ 1	$ -
Account 6	$ -	$ 1	$ -	$ 1	$ 1
Total	$ 3	$ 6	$ 3	$ 6	$ 3
disaggregation measure δ		0.50000	0.50000	0.50000	0.50000

Panel B

	q-3	*q-2*	*q-1*	*q*	*p*
Account 1	$ 1	$ -	$ 1	$ -	$ 1
Account 2	$ -	$ 1	$ -	$ 1	$ -
Account 3	$ 1	$ -	$ 1	$ -	$ 1
Account 4	$ -	$ 1	$ -	$ 1	$ -
Account 5	$ 1	$ -	$ 1	$ -	$ 1
Account 6	$ -	$ 1	$ -	$ 1	$ -
Total	$ 3	$ 3	$ 3	$ 3	$ 3
disaggregation measure δ		1.00000	1.00000	1.00000	1.00000

Panel C

	q-3	*q-2*	*q-1*	*q*	*p*
Account 1	$ 1	$ 1	$ 1	$ 1	$ 1
Account 2	$ 1	$ 1	$ 1	$ 1	$ 1
Account 3	$ 1	$ 1	$ 1	$ 1	$ 1
Account 4	$ 1	$ 1	$ 1	$ 1	$ 1
Account 5	$ 1	$ 1	$ 1	$ 1	$ 1
Account 6	$ 1	$ 1	$ 1	$ 1	$ 1
Total	$ 6	$ 6	$ 6	$ 6	$ 6
disaggregation measure δ		0.00000	0.00000	0.00000	0.00000

Panel D

	q-3	*q-2*	*q-1*	*q*	*p*
Account 1	$ 0.5	$ 1.0	$ 0.5	$ 1.0	$ 0.5
Account 2	$ 0.5	$ 1.0	$ 0.5	$ 1.0	$ 0.5
Account 3	$ 0.5	$ 1.0	$ 0.5	$ 1.0	$ 0.5
Account 4	$ 0.5	$ 1.0	$ 0.5	$ 1.0	$ 0.5
Account 5	$ 0.5	$ 1.0	$ 0.5	$ 1.0	$ 0.5
Account 6	$ 0.5	$ 1.0	$ 0.5	$ 1.0	$ 0.5
Total	$ 3	$ 6	$ 3	$ 6	$ 3
disaggregation measure δ		0.00000	0.00000	0.00000	0.00000

Table 18 Example disaggregation measures.

base taken is the sum of the parts. This requires sign inversion of the negative value(s) before the fractions are calculated as formulated in EQUATION (19), page 86. Again, the disaggregation measure calculated on this data is identical to the result computed from the raw data in panel A or Ijiri's fractions in panel B. Panel C shows the last alternative only applicable to the revenue/expense category where total revenue is taken as the base value for the calculation of the fractions. Again, the disaggregation measure is identical to the result computed by the other data of this category. TABLE 13 reproduces in panel A the disaggregation measures of total assets of AT&T from 1991 to 1994 as published by Ijiri (1995) and again also for 1995, but now only the raw data. Moreover, in panel B wealth momentum is included and in panel C wealth force together with their disaggregation measures for successive periods.

	Panel A - Raw data					Panel B - Fractions based on Operating Income				
	1991	1992	1993	1994	1995	1991	1992	1993	1994	1995
I. Revenue/Expense										
Revenues	$ 63,089	$ 64,904	$ 67,156	$ 75,094	$ 79,609	7144.8%	1089.4%	1082.5%	998.9%	8514.3%
Expenses	$-62,206	$-58,946	$-60,952	$-67,576	$-78,674	-7044.8%	-989.4%	-982.5%	-898.9%	-8414.3%
Operating Income	$ 883	$ 5,958	$ 6,204	$ 7,518	$ 935	100.00%	100.00%	100.00%	100.00%	100.00%
Disaggregation measure δ		0.0017	0.0000	0.0000	0.0022		0.0017	0.0000	0.0000	0.0022
II. Industry										
Communications Service	$ 917	$ 5,765	$ 5,865	$ 7,124	$ 449	103.9%	96.8%	94.5%	94.8%	48.0%
Financial services	$ -34	$ 193	$ 339	$ 394	$ 486	-3.9%	3.2%	5.5%	5.2%	52.0%
Operating Income	$ 883	$ 5,958	$ 6,204	$ 7,518	$ 935	100.00%	100.00%	100.00%	100.00%	100.00%
Disaggregation measure δ		0.0050	0.0006	0.0000	0.4843		0.0050	0.0006	0.0000	0.4843
III. Geographical										
United States	$ 487	$ 6,006	$ 6,451	$ 7,668	$ 2,722	55.2%	100.8%	104.0%	102.0%	291.1%
Other geographic areas	$ 396	$ -48	$ -247	$ -150	$ -1,787	44.8%	-0.8%	-4.0%	-2.0%	-191.1%
Operating Income	$ 883	$ 5,958	$ 6,204	$ 7,518	$ 935	100.00%	100.00%	100.00%	100.00%	100.00%
Disaggregation measure δ		0.4059	0.0009	0.0004	0.2834		0.4059	0.0009	0.0004	0.2834

	Panel C - Fractions based on Revenues					Panel D - Fractions based on Total				
	1991	1992	1993	1994	1995	1991	1992	1993	1994	1995
I. Revenue/Expense										
Revenues	100.00%	100.00%	100.00%	100.00%	100.00%	50.35%	52.41%	52.42%	52.63%	50.30%
Expenses	98.60%	90.82%	90.76%	89.99%	98.83%	-49.65%	-47.59%	-47.58%	-47.37%	-49.70%
Operating Income	1.40%	9.18%	9.24%	10.01%	1.17%	100.00%	100.00%	100.00%	100.00%	100.00%
Disaggregation measure δ		0.0017	0.0000	0.0000	0.0022		0.0017	0.0000	0.0000	0.0022
II. Industry										
Communications Services						96.42%	96.76%	94.54%	94.76%	48.02%
Financial services						-3.58%	3.24%	5.46%	5.24%	51.98%
Operating Income						100.00%	100.00%	100.00%	100.00%	100.00%
Disaggregation measure δ							0.0050	0.0006	0.0000	0.4843
III. Geographical										
United States						55.15%	99.21%	96.31%	98.08%	60.37%
Other geographic areas						44.85%	-0.79%	-3.69%	-1.92%	-39.63%
Operating Income						100.00%	100.00%	100.00%	100.00%	100.00%
Disaggregation measure δ							0.4059	0.0009	0.0004	0.2834

Table 19 AT&T. Disaggregation measures of operating income (based on Ijiri 1995).

Observe that the categories by industry and by geography are identical to those used for operating income (disaggregated) in Table 19. Instead of the revenue/expense category of operating income, total assets are disaggregated, obviously, into current assets and noncurrent assets.

Concerning the disaggregation measures of operating income and total assets (wealth), I first concentrate on δ of wealth in panel A of Table 20. Practically all disaggregation measures are negligibly low. Only δ of the industry category for 1992 over 1991 (0.0084) signals that the proportions of segments changed to a larger degree than in any other category or successive period. Nevertheless, on a scale between 0 and 1, 0.0084 is not a value to get very excited about.

	Panel A - Wealth				
	1991	1992	1993	1994	1995
I. Liquidity					
Current Assets	$ 24,613	$ 26,514	$ 29,738	$ 37,611	$ 39,509
Noncurrent Assets	$ 28,742	$ 30,674	$ 31,028	$ 41,651	$ 49,375
Total Assets	$ 53,355	$ 57,188	$ 60,766	$ 79,262	$ 88,884
Disaggregation measure δ		0.0000	0.0026	0.0009	0.0036
II. Industry					
Communications Services	$ 43,546	$ 43,185	$ 43,733	$ 57,800	$ 67,516
Financial services	$ 9,809	$ 14,003	$ 17,033	$ 21,462	$ 21,368
Total Assets	$ 53,355	$ 57,188	$ 60,766	$ 79,262	$ 88,884
Disaggregation measure δ		0.0084	0.0033	0.0003	0.0024
III. Geographical					
United States	$ 48,424	$ 51,815	$ 53,865	$ 69,901	$ 76,799
Other geographic areas	$ 4,931	$ 5,373	$ 6,901	$ 9,361	$ 12,085
Total Assets	$ 53,355	$ 57,188	$ 60,766	$ 79,262	$ 88,884
Disaggregation measure δ		0.0000	0.0006	0.0000	0.0005

	Panel B - Wealth Momentum				Panel C - Wealth Force		
	1992	1993	1994	1995	1993	1994	1995
I. Liquidity							
Current Assets	$ 1,901	$ 3,224	$ 7,873	$ 1,898	$ 1,323	$ 4,649	$ -5,975
Noncurrent Assets	$ 1,932	$ 354	$ 10,623	$ 7,724	$ -1,578	$ 10,269	$ -2,899
Total Assets	$ 3,833	$ 3,578	$ 18,496	$ 9,622	$ -255	$ 14,918	$ -8,874
Disaggregation measure δ		0.3994	0.5382	0.1494		0.8124	0.4091
II. Industry							
Communications Services	$ -361	$ 548	$ 14,067	$ 9,716	$ 909	$ 13,519	$ -4,351
Financial services	$ 4,194	$ 3,030	$ 4,429	$ -94	$ -1,164	$ 1,399	$ -4,523
Total Assets	$ 3,833	$ 3,578	$ 18,496	$ 9,622	$ -255	$ 14,918	$ -8,874
Disaggregation measure δ		0.0685	0.7835	0.0958		0.7179	0.4167
III. Geographical							
United States	$ 3,391	$ 2,050	$ 16,036	$ 6,898	$ -1,341	$ 13,986	$ -9,138
Other geographic areas	$ 442	$ 1,528	$ 2,460	$ 2,724	$ 1,086	$ 932	$ 264
Total Assets	$ 3,833	$ 3,578	$ 18,496	$ 9,622	$ -255	$ 14,918	$ -8,874
Disaggregation measure δ		0.2391	0.2201	0.0493		0.4619	0.0091

Table 20 AT&T. Disaggregation measures of categories' wealth, momentum and force (based on Ijiri 1995).

Operating income presents a similar picture. All categories and periods have a δ of 0 or negligibly low, except for the geographical category in 1992 that has rather high δ of 0.4059. Inspection of its disaggregated segments Other geographic areas and U.S. income shows a dramatic change of proportions between the two over the period 1991-1992. Naturally, anyone inspecting the raw data would not very likely fail to miss the increase of U.S. income in either the raw data or the fractions, nor the decrease of income from other geographic areas in between these two years. But, the argument is that by using δ in this case, we can be sure not to spend much time on any of the other segments or periods.

4.3.4 Disaggregation measures of momentum & force

Ijiri himself did not apply the disaggregation measure on momentum or force measures. Nonetheless, because negative data can be included in the calculation of the change of proportions between items in between periods it makes good sense to apply Ijiri's disaggregation measure within the TEMA framework (FIGURE 1, page 2). To this purpose, disaggregation measures of categories' momentum and force are presented, respectively, in panel B and C of TABLE 20. The momentum and force measures were calculated with EQUATION (8) and (9), page 53. Clearly, the disaggregation measures δ of the momentum and force measures provide a more dynamic picture than those of the different wealth segments in panel A. Not only are there larger differences between the δ of consecutive periods of a segment, e.g. industry (0.0685, 0.7835, 0.0958), but also between the segments of a particular period, e.g. 1993 (0.3994, 0.0685, 0.2391). How should we interpret these disaggregation measures of consecutive periods or segments of the momentum and force measures? As explained before, the δ measures above all are a measure of change based on variance. This implies that δ reports how the proportional change between items of one segment's period compares to another. In that sense, for industry, it is more relevant to study the disaggregated items of the 1994 momentum than of 1995 or 1993. Likewise, in 1993 it is more relevant to study the disaggregated items of the liquidity segment although an investigation of the geographical segments momentum is not superficies given the fact that its δ is not much lower.

We should give some attention to the fact that disaggregation measures of momentum and force of this example data are so very different from those of the wealth measures. Why is it that the last are mostly so very close to zero whilst the others are signaling the occurrence of a structural change all the time? Well, the economic explanation, following Lev, would be that the state variables, the balance sheet items, reflect the homeostasis property of the firm. From that perspective, we should expect that momentum and force variables are more dynamic, certainly of wealth accounts, because these reflect the corrective response to any disturbance of the homeostatic maintenance of internal relationships. But, still, observing the informational measures of wealth accounts is the primary objective of decomposition analysis of Lev and Ijiri and not their momentum or force measures. It is therefore somewhat troublesome that the informational measures of wealth accounts signal a lack of structural change whereas momentum and force are hardly stable. Moreover, considering income statement variables seems to further complicate matters.

Income, in Ijiri's accounting framework, is a momentum variable as it involves period related measures. Therefore, for a valid judgment of income related business dynamics, expressed by the disaggregation measure, we should compare operating income force with wealth force of the same segment and period (see TABLE 20, panel C). First, I consider the disaggregation measures of operating income force reported in TABLE 21. Values range in between 0.001 and 0.6393 in different categories and periods, which is similar to that of either wealth force disaggregation measures as well as the various momentum disaggregation measures. In other words, again a picture emerges of rather dynamic adjustments of internal relationships. Furthermore, attention should be given to the manifestation of periods of little structural change of force proportions after a clear dramatic shift, like in the revenue/expense category for 1994 (0.001) compared to 1993 (0.9525), in the industry category for 1995 (0.0033) compared to 1994 (0.6393), or in the geographical category for 1995 (0.0565) compared to 1994 (0.2299). But, periods with a rather substantial structural change also appear, year after year, like in the

industry category for 1994 compared to 1993 (0.6393), and for 1993 compared to 1992 (0.6363). When the disaggregation measures of operating income force are compared to those of wealth force, periods are observed where one does not change structurally but the other does, like in 1995 for industry (0.0033 versus 0.4167), or both do just about as much, like in 1994 (0.6393 versus 0.7179). Even with this small and not very complicated example, trying to find some logic in the corresponding or incongruent measurements, one can certainly understand Babich's (1975) criticism that interpretability poses too big a problem for decomposition analysis to become popular. However, maybe the above observations are due to the use of *annual* financial statements data, so I investigate next if using *quarterly* data will shed more and, hopefully, also a more clear light on this matter.

4.4 Decomposition measures of 3M

In this section I apply Lev's and Ijiri's informational measures on quarterly time series of 3M Company within the TEMA framework. First, decomposition measures of balance sheet items are compared to disaggregation measures as a quasi robustness test of the last, i.e. I want to know whether Ijiri's method is as effective as that of Lev. Next, disaggregation measures of wealth momentum and force of the same balance sheet items are analyzed. Beside the quantitative result also a new color coding method is applied to these decomposition measures to facilitate visual analytics.

4.4.1 Measurement of wealth decomposition

Quarterly time series of 3M Company from the fourth quarter of 1993 to the fourth quarter of 2003 are analyzed on two disaggregated levels, B and C, where level A is the total balance sheet value, or total wealth in Ijiri's TEMA framework (TABLE 24). TABLE 22 has at level B the balance sheet data as well as common size percentages. In TABLE 23 the decomposition measu-

	Operating Income Force			
	1992	1993	1994	1995
I. Revenue/Expense				
Revenues	$ 4,515	$ 7,938	$ 2,252	$ 1,815
Expenses	$-11,098	$ -6,624	$ -2,006	$ 3,260
Operating Income	$ -6,583	$ 1,314	$ 246	$ 5,075
Disaggregation measure δ		0.9525	0.0010	0.2207
Wealth disaggregation measure δ			0.8124	0.4091
II. Industry				
Communications Services	$ -1,070	$ -1,064	$ -644	$ -1,075
Financial services	$ -6,675	$ 1,259	$ 100	$ 4,848
Operating Income	$ 92	$ 55	$ 146	$ 227
Disaggregation measure δ		0.6363	0.6393	0.0033
Wealth disaggregation measure δ			0.7179	0.4167
III. Geographical				
United States	$ 3,792	$ 8,732	$ 7,095	$ 7,081
Other geographic areas	$ -1,070	$ -1,064	$ -644	$ -1,075
Operating Income	$ -4,946	$ 1,217	$ 445	$ 5,519
Disaggregation measure δ		0.1114	0.2299	0.0565
Wealth disaggregation measure δ			0.4619	0.0091

Table 21 AT&T. Disaggregation measures operating income force (1993-1995).

	Panel A	Panel B - Uses of wealth				Panel C - Sources of wealth					
	Total Assets	Current Assets		Non Current Assets		Current Liabilities		Non Current Liabilities		Net Wealth (Shareholders' Equity)	
93Q4	$12,197	$6,363	26.08%	$5,834	23.92%	$3,282	13.45%	$2,403	9.85%	$6,512	26.70%
94Q1	$13,024	$6,763	25.96%	$6,261	24.04%	$3,661	14.05%	$2,979	11.44%	$6,384	24.51%
94Q2	$13,164	$6,802	25.84%	$6,362	24.16%	$3,412	12.96%	$3,184	12.09%	$6,568	24.95%
94Q3	$13,323	$6,863	25.76%	$6,460	24.24%	$3,566	13.38%	$3,097	11.62%	$6,660	24.99%
94Q4	$13,496	$6,928	25.67%	$6,568	24.33%	$3,605	13.36%	$3,157	11.70%	$6,734	24.95%
95Q1	$14,203	$7,436	26.18%	$6,767	23.82%	$3,609	12.71%	$3,468	12.21%	$7,126	25.09%
95Q2	$14,751	$7,783	26.38%	$6,968	23.62%	$3,907	13.24%	$3,550	12.03%	$7,294	24.72%
95Q3	$14,525	$7,613	26.21%	$6,912	23.79%	$3,826	13.17%	$3,431	11.81%	$7,268	25.02%
95Q4	$14,183	$6,395	22.54%	$7,788	27.46%	$3,724	13.13%	$3,575	12.60%	$6,884	24.27%
96Q1	$14,123	$6,452	22.84%	$7,671	27.16%	$3,864	13.68%	$3,286	11.63%	$6,973	24.69%
96Q2	$13,211	$6,642	25.14%	$6,569	24.86%	$3,980	15.06%	$3,136	11.87%	$6,095	23.07%
96Q3	$13,689	$7,044	25.73%	$6,645	24.27%	$4,351	15.89%	$3,043	11.11%	$6,295	22.99%
96Q4	$13,364	$6,486	24.27%	$6,878	25.73%	$3,789	14.18%	$3,291	12.31%	$6,284	23.51%
97Q1	$13,296	$6,437	24.21%	$6,859	25.79%	$3,685	13.86%	$3,375	12.69%	$6,236	23.45%
97Q2	$13,594	$6,718	24.71%	$6,876	25.29%	$3,535	13.00%	$3,710	13.65%	$6,349	23.35%
97Q3	$13,421	$6,623	24.67%	$6,798	25.33%	$3,483	12.98%	$3,614	13.46%	$6,324	23.56%
97Q4	$13,238	$6,168	23.30%	$7,070	26.70%	$3,983	15.04%	$3,329	12.57%	$5,926	22.38%
98Q1	$13,657	$6,372	23.33%	$7,285	26.67%	$4,212	15.42%	$3,432	12.56%	$6,013	22.01%
98Q2	$13,878	$6,366	22.94%	$7,512	27.06%	$4,383	15.79%	$3,451	12.43%	$6,044	21.78%
98Q3	$13,965	$6,490	23.24%	$7,475	26.76%	$4,500	16.11%	$3,581	12.82%	$5,884	21.07%
98Q4	$14,153	$6,318	22.32%	$7,835	27.68%	$4,386	15.49%	$3,831	13.53%	$5,936	20.97%
99Q1	$13,746	$6,056	22.03%	$7,690	27.97%	$3,982	14.48%	$3,795	13.80%	$5,969	21.71%
99Q2	$13,367	$6,238	23.33%	$7,129	26.67%	$3,680	13.77%	$3,514	13.14%	$6,173	23.09%
99Q3	$13,905	$6,583	23.67%	$7,322	26.33%	$3,865	13.90%	$3,670	13.20%	$6,370	22.91%
99Q4	$13,896	$6,066	21.83%	$7,830	28.17%	$3,819	13.74%	$3,788	13.63%	$6,289	22.63%
00Q1	$13,969	$6,107	21.86%	$7,862	28.14%	$3,942	14.11%	$3,768	13.49%	$6,259	22.40%
00Q2	$14,933	$6,754	22.61%	$8,179	27.39%	$4,974	16.65%	$3,536	11.84%	$6,423	21.51%
00Q3	$14,682	$6,651	22.65%	$8,031	27.35%	$4,830	16.45%	$3,415	11.63%	$6,437	21.92%
00Q4	$14,522	$6,379	21.96%	$8,143	28.04%	$4,754	16.37%	$3,237	11.15%	$6,531	22.49%
01Q1	$15,364	$6,825	22.21%	$8,539	27.79%	$5,434	17.68%	$3,457	11.25%	$6,473	21.07%
01Q2	$15,317	$6,791	22.17%	$8,526	27.83%	$5,520	18.02%	$3,676	12.00%	$6,121	19.98%
01Q3	$15,205	$6,556	21.56%	$8,649	28.44%	$5,006	16.46%	$4,033	13.26%	$6,166	20.28%
01Q4	$14,606	$6,296	21.55%	$8,310	28.45%	$4,509	15.44%	$4,011	13.73%	$6,086	20.83%
02Q1	$14,431	$6,273	21.73%	$8,158	28.27%	$4,012	13.90%	$4,417	15.30%	$6,002	20.80%
02Q2	$14,961	$6,623	22.13%	$8,338	27.87%	$4,186	13.99%	$4,395	14.69%	$6,380	21.32%
02Q3	$15,719	$6,556	20.85%	$9,163	29.15%	$4,511	14.35%	$4,565	14.52%	$6,643	21.13%
02Q4	$15,329	$6,059	19.76%	$9,270	30.24%	$4,457	14.54%	$4,879	15.91%	$5,993	19.55%
03Q1	$15,845	$6,464	20.40%	$9,381	29.60%	$4,692	14.81%	$4,837	15.26%	$6,316	19.93%
03Q2	$16,566	$7,037	21.24%	$9,529	28.76%	$4,827	14.57%	$4,784	14.44%	$6,955	20.99%
03Q3	$16,797	$7,342	21.86%	$9,455	28.14%	$4,968	14.79%	$4,321	12.86%	$7,508	22.35%
03Q4	$17,593	$7,713	21.92%	$9,880	28.08%	$5,082	14.44%	$4,645	13.20%	$7,866	22.36%

Table 22 3M. Balance sheet level B. Data in U.S. dollar & common size format (1993Q4-2003Q4).

rement of Lev, based on the entropy concept, is reported in panel A. The disaggregation measurement of Ijiri, based on the variance concept is reported in panel B. Comparing these results, as indicators of the usefulness of using disaggregated data to analyze the change of wealth composition between two periods, it is safe to conclude that nothing substantial occurred for ten years at 3M. At level C, the only possible exceptions are the fourth quarter of 1995 (0.097, 0.032) and 1997 (0.046, 0.015). But, what is somewhat disquieting is the fact that neither Lev's nor Ijiri's measure at level B signal a substantial change in these years (respectively 0.006, 0.013, and 0.003, 0.005). The average level C signal during the time series of 41 quarters is for Lev's decomposition measurement 11.68 times larger and for Ijiri's disaggregation measurement 2.6 times larger. On the basis of only this example, the impression now is that the change of balance sheet composition is best measured by using the lowest possible level of disaggregation. Another issue is whether or not the lack of any higher value of

	Panel A - Wealth		Panel B- Wealth		Panel C - Momentum		Panel D - Force	
	(B) Lev decomposition measure	(C) Lev decomposition measure	(B) Ijiri disaggregation measure	(C) Ijiri disaggregation measure	(B) Ijiri disaggregation measure	(C) Ijiri disaggregation measure	(B) Ijiri disaggregation measure	(C) Ijiri disaggregation measure
93Q4	0.0004	0.0032	0.0004	0.0009	0.9621	0.9964	0.8923	0.7451
94Q1	0.0023	0.0201	0.0033	0.0078	0.9406	0.9881	0.8013	0.9901
94Q2	0.0007	0.0090	0.0008	0.0023	0.9722	0.9562	0.1245	0.2562
94Q3	0.0002	0.0007	0.0002	0.0003	0.9084	0.9997	0.8535	0.6606
94Q4	0.0000	0.0012	0.0000	0.0005	0.6512	0.9494	0.1532	0.7826
95Q1	0.0004	0.0080	0.0006	0.0019	0.2785	0.9396	0.8900	0.9207
95Q2	0.0002	0.0052	0.0002	0.0009	0.3885	0.8868	0.4446	0.3559
95Q3	0.0001	0.0002	0.0001	0.0001	0.2256	0.5521	0.9690	0.9770
95Q4	0.0057	0.0973	0.0128	0.0323	0.8050	0.8900	0.9111	0.9565
96Q1	0.0006	0.0036	0.0007	0.0013	0.7792	0.9003	0.0252	0.0258
96Q2	0.0034	0.0484	0.0069	0.0225	0.9442	0.9954	0.9349	0.9063
96Q3	0.0006	0.0031	0.0009	0.0012	0.9782	0.9855	0.0876	0.0659
96Q4	0.0025	0.0088	0.0041	0.0040	0.2621	0.7373	0.9590	0.9199
97Q1	0.0001	0.0032	0.0001	0.0010	0.3810	0.9933	0.0914	0.3254
97Q2	0.0007	0.0057	0.0010	0.0018	0.8872	0.9957	0.9271	0.9605
97Q3	0.0000	0.0114	0.0000	0.0039	0.5140	0.9956	0.0620	0.9330
97Q4	0.0029	0.0462	0.0048	0.0145	0.9479	0.4584	0.6868	0.7551
98Q1	0.0001	0.0033	0.0001	0.0015	0.9979	0.9397	0.3340	0.1234
98Q2	0.0001	0.0023	0.0002	0.0012	0.3582	0.9993	0.3531	0.3009
98Q3	0.0002	0.0037	0.0004	0.0019	0.9883	0.7829	0.9157	0.3854
98Q4	0.0007	0.0036	0.0012	0.0021	0.9673	0.8654	0.4958	0.8135
99Q1	0.0005	0.0040	0.0008	0.0017	0.9835	0.9388	0.8628	0.8575
99Q2	0.0015	0.0152	0.0029	0.0048	0.7917	0.7407	0.7869	0.9787
99Q3	0.0001	0.0026	0.0001	0.0009	0.9223	0.9735	0.8130	0.6145
99Q4	0.0015	0.0246	0.0033	0.0090	0.9463	0.7649	0.9991	0.9820
00Q1	0.0001	0.0040	0.0001	0.0009	0.9894	0.7234	0.1957	0.1087
00Q2	0.0036	0.0182	0.0052	0.0069	0.1626	0.9984	0.8043	0.7776
00Q3	0.0001	0.0026	0.0001	0.0011	0.5260	0.7195	0.0208	0.0596
00Q4	0.0004	0.0088	0.0007	0.0034	0.7737	0.7138	0.9648	0.6516
01Q1	0.0010	0.0107	0.0018	0.0041	0.7402	0.9890	0.9936	0.8132
01Q2	0.0006	0.0055	0.0009	0.0029	0.9274	0.9901	0.3365	0.8988
01Q3	0.0015	0.0070	0.0023	0.0034	0.9928	0.8849	0.8423	0.9767
01Q4	0.0005	0.0114	0.0007	0.0040	0.6574	0.9609	0.8702	0.6956
02Q1	0.0017	0.0079	0.0023	0.0035	0.5268	0.9718	0.3704	0.2445
02Q2	0.0003	0.0034	0.0005	0.0017	0.8182	0.9990	0.9960	0.8933
02Q3	0.0007	0.0185	0.0016	0.0112	0.7367	0.9865	0.9992	0.9996
02Q4	0.0018	0.0095	0.0032	0.0063	0.9997	0.8702	0.9614	0.6083
03Q1	0.0004	0.0042	0.0007	0.0021	0.3156	0.5939	0.3805	0.4505
03Q2	0.0008	0.0097	0.0015	0.0038	0.0922	0.6430	0.3146	0.9237
03Q3	0.0015	0.0066	0.0024	0.0040	0.3683	0.5240	0.8586	0.8323
03Q4	0.0001	0.0069	0.0001	0.0030	0.9411	0.8047	0.3017	0.4760

Table 23 3M. Disaggregation measures of balance sheet wealth, momentum and force (1993Q4-2003Q4).

wealth decomposition measures of either Lev or Ijiri in the 3M time series is correct or if they are 'under-signaling' and therefore possibly misleading? In the following chapter I will discuss an alternative method of decomposition with spectramap of level B. The structural decomposition of level C is discussed in Chapter 6. Both will show that indeed there is more to the decomposition analysis of this data than meets the eye with the informational measures of Lev and Ijiri.

Panel C of TABLE 23 reports the disaggregation measurement of balance sheet momentum and panel D of balance sheet force. Clearly, the picture is again very different compared to that of wealth (recall the findings of the AT&T example in Section 0). The average signal value is on level B and C, respectively, for momentum 0.699 and 0.609, and for force 0.848 and 0.643. The disaggregation measurement of level B is on average 1.21 times larger and on level C 1.06 times larger. This is an indication that both momentum and force exhibit similarly strong dyna-

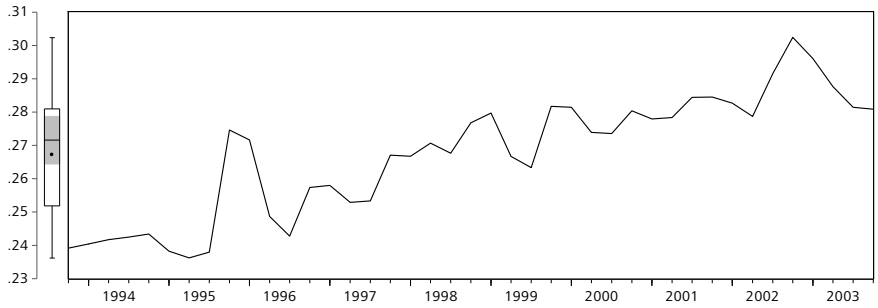

Figure 41 3M. Noncurrent assets, fractions, upward trend (1993Q4-2003Q4).

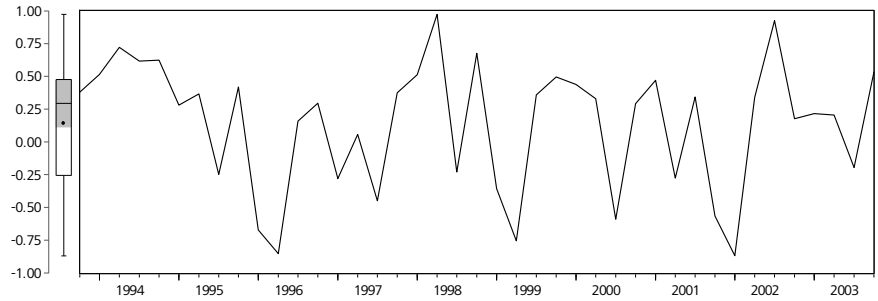

Figure 42 3M. Noncurrent assets momentum, fractions (1993Q4-2003Q4).

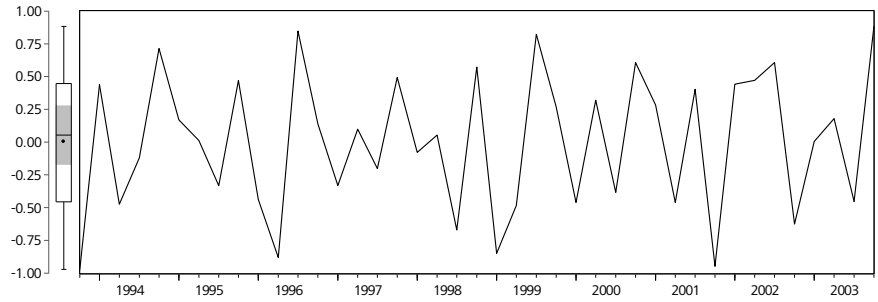

Figure 43 3M. Noncurrent assets force, fractions (1993Q4-2003Q4).

Level A	Level B	Level C
	decomposition measurement	*decomposition measurement*
Total wealth	Uses of wealth	Uses of wealth
	current assets	cash, receivables, other current assets, inventories
	noncurrent assets	other noncurrent assets, deposits & other assets, net property & equipment
	Sources of wealth	Sources of wealth
	current liabilities	notes payable, accounts payable, other current liabilities
	noncurrent liabilities	long term debt, other long term liabilities
	shareholders' equity (net wealth)	common stock & surplus, equity net

Table 24 Levels of balance sheet decomposition.

mics throughout the time series and that the change of composition of either wealth momentum or wealth force is at each level of decomposition about the same. For example, compare respectively noncurrent assets and net wealth for momentum in FIGURE 42

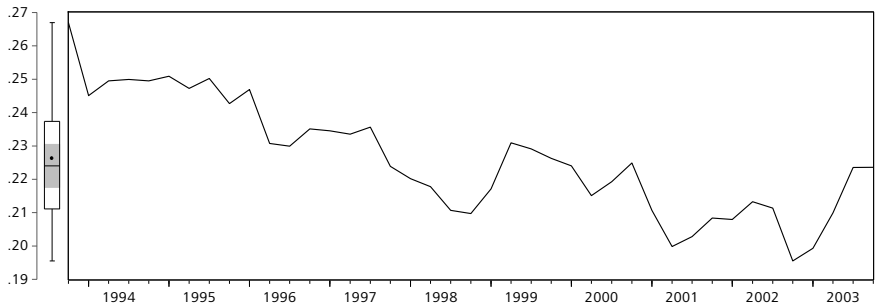

Figure 44 3M. Net wealth (equity), fractions, downward trend (1993Q4-2003Q4).

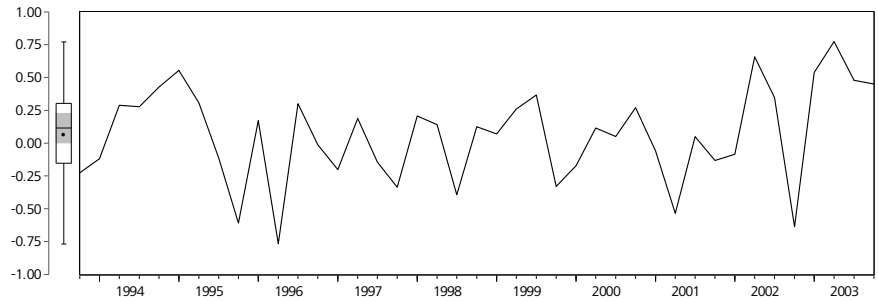

Figure 45 3M. Net wealth momentum, fractions (1993Q4-2003Q4).

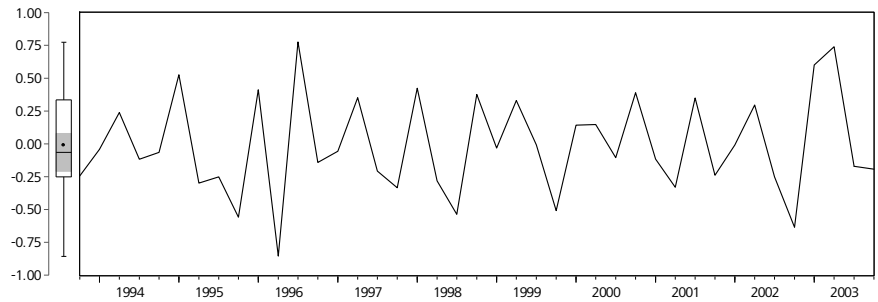

Figure 46 3M. Net wealth force, fractions (1993Q4-2003Q4).

with FIGURE 45 and for force FIGURE 43 with FIGURE 46. In other words, disaggregation analysis of total wealth momentum at either level B or level C renders signals of a rather high magnitude that remain stable over time (TABLE 25, panel A). The force measures strengthen this observation. This implies that the disaggregation measure of total wealth momentum or force typically seem to give the opposite signal of total wealth itself. As a result, we have to face the question if total wealth momentum or force disaggregation measures are 'over-signaling' because, as theory prescribes, observing them like this would compel the analyst each and every quarter to disaggregate the data.

4.4.2 Color coding of informational measures

Color coding allows for a qualitative assessment of quantitative data. COLOR FIGURE 7, page 310, presents row wise the informational measures of balance sheet wealth, momentum and force (TABLE 23). Each measurement is color coded by the three color dimensions of the CIE-LAB color space. The lower a measure is the grayer or achromatic it will be. Conversely, the higher a measure is the more colorful or chromatic it will be, in this coding a bright yellowish orange. Since all color dimensions are used, color differences can be observed with equal precision by any observer. In this case, viewing the color codes, one can quickly perceive that:

- For *wealth*, both the decomposition measures of Lev and the disaggregation measures of Ijiri signal the complete absence of structural change during each successive period at either level B or level C.
- For *wealth momentum*, the disaggregation measures of Ijiri signal the continuous structural change during each successive period at both level B and level C.
- For *wealth force*, the disaggregation measures of Ijiri also signal the continuous structural change during each successive period at both level B and level C.
- With *wealth momentum*, in some cases the disaggregation measures at level B signal structural change to a lesser degree than at level C (e.g. 2003Q2, 2002Q2, 1996Q4).
- With *wealth force*, in those cases that the disaggregation measures at level B signal structural change to a lesser degree this is done likewise on level C (e.g. 2000Q3, 2000Q1, 1996Q3, 1996Q1).

Visual analysis does show the difference between the decomposition and disaggregation measures of wealth, and the disaggregation measures of its momentum or force. Color coding, again, shows that the 'under-signaling' of wealth measures is in stark contrast with the 'over-signaling' of the disaggregation measures of wealth momentum or force. This seems to reflect the nonstationary trend of wealth time series, like those of noncurrent assets (upward trend, FIGURE 41) or net wealth (downward trend, FIGURE 44), as well as the stationary trend of the momentum and force time series, like those of noncurrent assets or net wealth (respectively FIGURE 42 and FIGURE 43, or FIGURE 45 and FIGURE 46). The balance sheet accounts of 3M are unwaveringly accumulating upwards, or downwards, whereas their momentum and force values continuously change in sign, i.e. they change direction and keep altering back and forth around some mean value. These properties of the 3M financial statements' time series data are of some importance for econometric modeling that will be discussed in later chapters.

4.4.3 Color coding of momentum & force measures

Color coding also allows for a qualitative assessment of the wealth momentum and force data. COLOR FIGURE 8, page 311, presents row wise the time series of balance sheet momentum (TABLE 25, panel B). Because momentum and force have a positive (increase) or negative sign (decrease), color coding is done with a coding scheme of opposite colors, i.e. perceptually opposite. Each opposite fully saturated color either codes the minimum or the maximum value of the scale used. Because the data of the common size format is used, the minimum value possible of the *data set* is −1 (−100%) and the maximum value possible is 1 (100%). Each side of the balance sheet has its own coding scheme:

- Assets, uses of funds
  positive/increase = green vs. negative/decrease = violet
- Liabilities & shareholders' equity (net wealth), sources of funds
  positive/increase = cyan blue vs. negative/decrease = brown

where the minimum value of the *coding scale* is set to −1 and the maximum value is set to 1. In COLOR FIGURE 8, the coding scheme of assets and liabilities is included with a separate series at the top and bottom, like a legend. The color coding space itself is enhanced to get optimal color reproduction. In COLOR FIGURE 8, those are correctly coded colors, for balance sheet momentum and force, respectively, 95.5% and 96.5%.

The closer a momentum or force measure is to zero the more gray, or achromatic, the color will be. In that case little or no change of proportions between two points in time occurs for that account relative to the other accounts at its side of the balance sheet. For example,

current assets momentum is –0.075 in 2002Q3 and is thus color coded gray or, likewise, current liabilities momentum is 0.005 in 1995Q1. But, once negative or positive momentum occurs, then a measure is more colored, more chromatic. This is best observed in COLOR FIGURE 8, left, during the last five quarters of the time series of current assets and shareholder's equity, net wealth. Both decrease considerably in relative proportion in the fourth quarter of 2002, respectively –0.823 and –0.639, and hence are color coded strongly by a strong violet and brown tone. The following four quarters both balance sheet items grow strongly, on average respectively 0.713 and 0.560, and hence are also color coded strongly chromatic with various tones of green and cyan blue. What is of interest is that apparently, relatively speaking, during the whole year 2003 each quarters' momentum is positive and stable for current assets and shareholder's equity whereas the other (disaggregated) accounts have a similar trend but less strongly (current liabilities) or experience a sign conversion (third quarter: noncurrent assets and fourth quarter: noncurrent liabilities). Of course, the same conclusion can be drawn from the fractions reported in TABLE 25, panel B. But the human eye is more apt to notice such a stable trend period and trend changes viewing such color coded series of measures instead of reading the data, either raw or transformed to the common size format. TABLE 26 reports the balance sheet force time series that are color coded in COLOR FIGURE 8, right. The coding scheme is the same as applied for momentum. Comparing the force and momentum measures, the overall impression is that the force color codes differ in trend. Of course, this is due to the fact that when momentum is stable, upwards or downwards, force fractions will be very small and thus their color code is grayish (e.g. shareholder's equity in the third and fourth quarter of 2003).

The visual representation as coded colors of the momentum and force fractions make vividly clear that these time series alternates between extremes, positive or negative. In other words, the momentum and force time series, in this case, exhibit strong fluctuating dynamics which are typical for stationary variables. As already mentioned in the previous section, this is of some importance because it allows for the econometric modeling of such variables.

4.5 Discussion

In this chapter entropy as a the concept of information theory was introduced on which basis Baruch Lev formulated his decomposition measure to study the changes over time in the allocation of a firm's inputs and outputs as reflected in its financial statements (Lev 1974). Within the framework of momentum and force accounting the decomposition measures of Lev can only be applied to study the structural change of wealth accounts, i.e. the balance sheet. Lev's decomposition measures cannot be used for momentum or force measures because its equation cannot process negative data. As an alternative, I applied the disaggregation measure of Ijiri that indicates the fraction of variance that can be eliminated by using the disaggregated data instead of their aggregated sum value.

A minor disadvantage of Ijiri's equation, namely, that rather large fractions of disaggregated items are the result of his computation, was averted by the introduction in this thesis of an alternative equation. Instead of taking the result datum as the base for fraction calculation, like operating income, the disaggregated items sum value is used, after inversion of any negative datum in that set. By inverting the negative fractions, they always add up with the positive fractions to 100%. The advantage of this solution is that any set of positive and negative disaggregated financial variables can be transformed to the common size format without loosing

	Panel A - Wealth Momentum, data in usdlr						Panel B - Wealth Momentum, data in fractions				
	Total Wealth	Current Assets	Non Current Assets	Current Liabilities	Non Current Liabilities	Net Wealth	Current Assets	Non Current Assets	Current Liabilities	Non Current Liabilities	Net Wealth
93Q4	-32	-82	50	-122	178	-88	-0.621	0.379	-0.314	0.459	-0.227
94Q1	827	400	427	379	576	-128	0.484	0.516	0.350	0.532	-0.118
94Q2	140	39	101	-249	205	184	0.279	0.721	-0.390	0.321	0.288
94Q3	159	61	98	154	-87	92	0.384	0.616	0.462	-0.261	0.276
94Q4	173	65	108	39	60	74	0.376	0.624	0.225	0.347	0.428
95Q1	707	508	199	4	311	392	0.719	0.281	0.006	0.440	0.554
95Q2	548	347	201	298	82	168	0.633	0.367	0.544	0.150	0.307
95Q3	-226	-170	-56	-81	-119	-26	-0.752	-0.248	-0.358	-0.527	-0.115
95Q4	-342	-1,218	876	-102	144	-384	-0.582	0.418	-0.162	0.229	-0.610
96Q1	-60	57	-117	140	-289	89	0.328	-0.672	0.270	-0.558	0.172
96Q2	-912	190	-1,102	116	-150	-878	0.147	-0.853	0.101	-0.131	-0.767
96Q3	478	402	76	371	-93	200	0.841	0.159	0.559	-0.140	0.301
96Q4	-325	-558	233	-562	248	-11	-0.705	0.295	-0.685	0.302	-0.013
97Q1	-68	-49	-19	-104	84	-48	-0.721	-0.279	-0.441	0.356	-0.203
97Q2	298	281	17	-150	335	113	0.943	0.057	-0.251	0.560	0.189
97Q3	-173	-95	-78	-52	-96	-25	-0.549	-0.451	-0.301	-0.555	-0.145
97Q4	-183	-455	272	500	-285	-398	-0.626	0.374	0.423	-0.241	-0.336
98Q1	419	204	215	229	103	87	0.487	0.513	0.547	0.246	0.208
98Q2	221	-6	227	171	19	31	-0.026	0.974	0.774	0.086	0.140
98Q3	87	124	-37	117	130	-160	0.770	-0.230	0.287	0.319	-0.393
98Q4	188	-172	360	-114	250	52	-0.323	0.677	-0.274	0.601	0.125
99Q1	-407	-262	-145	-404	-36	33	-0.644	-0.356	-0.854	-0.076	0.070
99Q2	-379	182	-561	-302	-281	204	0.245	-0.755	-0.384	-0.357	0.259
99Q3	538	345	193	185	156	197	0.641	0.359	0.344	0.290	0.366
99Q4	-9	-517	508	-46	118	-81	-0.504	0.496	-0.188	0.482	-0.331
00Q1	73	41	32	123	-20	-30	0.562	0.438	0.711	-0.116	-0.173
00Q2	964	647	317	1,032	-232	164	0.671	0.329	0.723	-0.162	0.115
00Q3	-251	-103	-148	-144	-121	14	-0.410	-0.590	-0.516	-0.434	0.050
00Q4	-160	-272	112	-76	-178	94	-0.708	0.292	-0.218	-0.511	0.270
01Q1	842	446	396	680	220	-58	0.530	0.470	0.710	0.230	-0.061
01Q2	-47	-34	-13	86	219	-352	-0.723	-0.277	0.131	0.333	-0.536
01Q3	-112	-235	123	-514	357	45	-0.656	0.344	-0.561	0.390	0.049
01Q4	-599	-260	-339	-497	-22	-80	-0.434	-0.566	-0.830	-0.037	-0.134
02Q1	-175	-23	-152	-497	406	-84	-0.131	-0.869	-0.504	0.411	-0.085
02Q2	530	350	180	174	-22	378	0.660	0.340	0.303	-0.038	0.659
02Q3	758	-67	825	325	170	263	-0.075	0.925	0.429	0.224	0.347
02Q4	-390	-497	107	-54	314	-650	-0.823	0.177	-0.053	0.308	-0.639
03Q1	516	405	111	235	-42	323	0.785	0.215	0.392	-0.070	0.538
03Q2	721	573	148	135	-53	639	0.795	0.205	0.163	-0.064	0.773
03Q3	231	305	-74	141	-463	553	0.805	-0.195	0.122	-0.400	0.478
03Q4	796	371	425	114	324	358	0.466	0.534	0.143	0.407	0.450

Table 25 3M. Measures of balance sheet momentum (level B, 1993Q4-2003Q4).

their sign. I demonstrated, using Ijiri's published example, that the calculation based on such common size fractions result in the same informational measures.

The decomposition measures and the disaggregation measures were calculated for 3M financial statements from the fourth quarter of 1993 to the fourth quarter on two disaggregated levels, B and C, where level A is total wealth in Ijiri's TEMA framework. Both the decomposition measures and the disaggregation measures render about the same result. This confirms the usability for the wealth dimension of the disaggregation measure of Ijiri as an alternative for the decomposition measure of Lev. Moreover, Ijiri's disaggregation measure can be applied to momentum and force measures because its equation can process negative data.

	Panel A - Wealth Force, data in usdlr						Panel B - Wealth Force, data in fractions				
	Total Wealth	Current Assets	Non Current Assets	Current Liabilities	Non Current Liabilities	Net Wealth	Current Assets	Non Current Assets	Current Liabilities	Non Current Liabilities	Net Wealth
93Q4	-116	-145	-4,784	-161	143	-98	-0.029	-0.971	-0.400	0.356	-0.244
94Q1	859	482	377	501	398	-40	0.561	0.439	0.534	0.424	-0.043
94Q2	-687	-361	-326	-628	-371	312	-0.525	-0.475	-0.479	-0.283	0.238
94Q3	19	22	-3	403	-292	-92	0.880	-0.120	0.512	-0.371	-0.117
94Q4	14	4	10	-115	147	-18	0.286	0.714	-0.411	0.525	-0.064
95Q1	534	443	91	-35	251	318	0.830	0.170	-0.058	0.416	0.526
95Q2	-159	-161	2	294	-229	-224	-0.988	0.012	0.394	-0.307	-0.300
95Q3	-774	-517	-257	-379	-201	-194	-0.668	-0.332	-0.490	-0.260	-0.251
95Q4	-116	-1,048	932	-21	263	-358	-0.529	0.471	-0.033	0.410	-0.558
96Q1	282	1,275	-993	242	-433	473	0.562	-0.438	0.211	-0.377	0.412
96Q2	-852	133	-985	-24	139	-967	0.119	-0.881	-0.021	0.123	-0.856
96Q3	1,390	212	1,178	255	57	1,078	0.153	0.847	0.183	0.041	0.776
96Q4	-803	-960	157	-933	341	-211	-0.859	0.141	-0.628	0.230	-0.142
97Q1	257	509	-252	458	-164	-37	0.669	-0.331	0.695	-0.249	-0.056
97Q2	366	330	36	-46	251	161	0.902	0.098	-0.100	0.548	0.352
97Q3	-471	-376	-95	98	-431	-138	-0.798	-0.202	0.147	-0.646	-0.207
97Q4	-10	-360	350	552	-189	-373	-0.507	0.493	0.496	-0.170	-0.335
98Q1	602	659	-57	-271	388	485	0.920	-0.080	-0.237	0.339	0.424
98Q2	-198	-210	12	-58	-84	-56	-0.946	0.054	-0.293	-0.424	-0.283
98Q3	-134	130	-264	-54	111	-191	0.330	-0.670	-0.152	0.312	-0.537
98Q4	101	-296	397	-231	120	212	-0.427	0.573	-0.410	0.213	0.377
99Q1	-595	-90	-505	-290	-286	-19	-0.151	-0.849	-0.487	-0.481	-0.032
99Q2	28	444	-416	102	-245	171	0.516	-0.484	0.197	-0.473	0.330
99Q3	917	163	754	487	437	-7	0.178	0.822	0.523	0.469	-0.008
99Q4	-547	-862	315	-231	-38	-278	-0.732	0.268	-0.422	-0.069	-0.508
00Q1	82	558	-476	169	-138	51	0.540	-0.460	0.472	-0.385	0.142
00Q2	891	606	285	909	-212	194	0.680	0.320	0.691	-0.161	0.148
00Q3	-1,215	-750	-465	-1,176	111	-150	-0.617	-0.383	-0.818	0.077	-0.104
00Q4	91	-169	260	68	-57	80	-0.394	0.606	0.332	-0.278	0.390
01Q1	1,002	718	284	756	398	-152	0.717	0.283	0.579	0.305	-0.116
01Q2	-889	-480	-409	-594	-1	-294	-0.540	-0.460	-0.668	-0.001	-0.331
01Q3	-65	-201	136	-600	138	397	-0.596	0.404	-0.529	0.122	0.350
01Q4	-487	-25	-462	17	-379	-125	-0.051	-0.949	0.033	-0.727	-0.240
02Q1	424	237	187	0	428	-4	0.559	0.441	0.000	0.991	-0.009
02Q2	705	373	332	671	-428	462	0.529	0.471	0.430	-0.274	0.296
02Q3	228	-417	645	151	192	-115	-0.393	0.607	0.330	0.419	-0.251
02Q4	-1,148	-430	-718	-379	144	-913	-0.375	-0.625	-0.264	0.100	-0.636
03Q1	906	902	4	289	-356	973	0.996	0.004	0.179	-0.220	0.601
03Q2	205	168	37	-100	-11	316	0.820	0.180	-0.234	-0.026	0.740
03Q3	-490	-268	-222	6	-410	-86	-0.547	-0.453	0.012	-0.817	-0.171
03Q4	565	66	499	-27	787	-195	0.117	0.883	-0.027	0.780	-0.193

Table 26 3M. Measures of balance sheet force (level B, 1993Q4-2003Q4).

Color coding provides a visual translation of informational disaggregation measures for a qualitative assessment of the quantitative data. In an equivocal manner, the disaggregation measures of 3M's balance sheet momentum and force time series signal continuous structural change of the proportion between the accounts. In contrast, the disaggregation measures of 3M's wealth time series signal the complete absence of structural change. This result raises the question whether or not the informational measures of wealth are 'under-signaling' and if those of momentum and force are 'over-signaling.' Therefore, suspicion is raised that either one is misleading and possibly both. This topic will be discussed further in Chapter 5 for level B and in Chapter 6 for level C. The implications of these findings for time series econometric modeling will be discussed further in Chapters 7 and 8.

I conclude that decomposition analysis, at least in the example studied, has little to offer as a summary measure of firm dynamics in the TEMA framework. Therefore, in agreement with Babich (1975) and Blommaert (1995A, 1996), I suggest that informational measures should be used with great caution as a decision indicator whether or not to disaggregate financial statements data for further analysis within the TEMA framework.

5

Spectral Map Decomposition of Wealth, Momentum & Force

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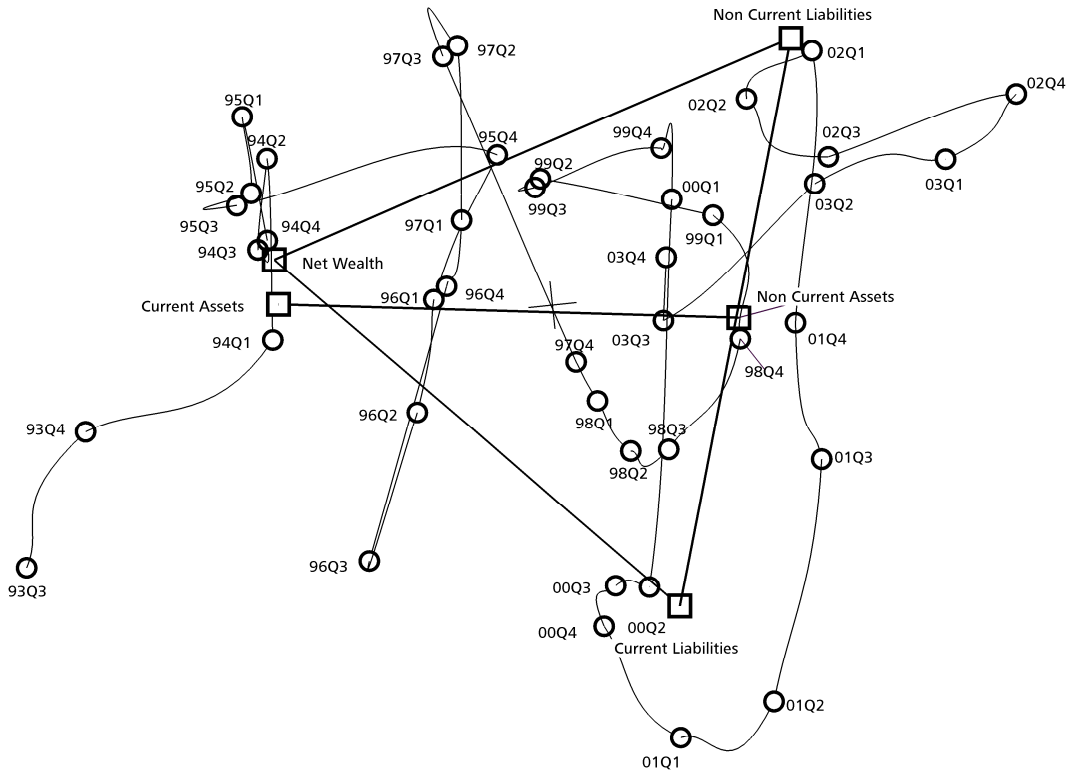

Figure 47 3M. Spectramap decomposition of wealth accounts (level B, 1993Q4-2003Q4).

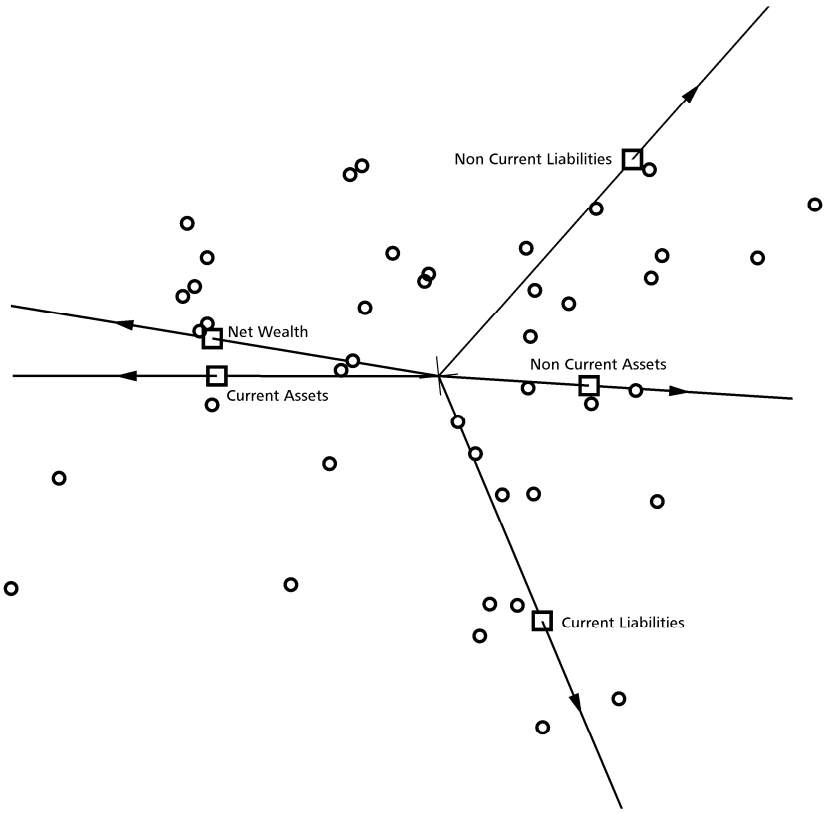

Figure 48 3M. Association between wealth accounts (level B, 1993Q4-2003Q4).

5 Abstract

A new approach is proposed by me for decomposition analysis of financial statements by using multivariate data analysis. Spectral Map Analysis is used in this study to decompose the balance sheet for all three dimensions of the TEMA *framework — wealth, momentum and force — into a smaller set of components, or factors. The components are a static structure that can be visualized in three dimensions. A single Spectramap biplot visualizes both the structure of the accounting variables and each time point they are measured. Supported by correlation analysis, it is shown that wealth, momentum and force decomposition is a visual illustration of the association between the accounting variables. The wealth Spectramap exhibits distinct series of quarters where the composition between the balance sheet accounts is similar along one direction, or component, but different on another. Also, it is clear that during the whole time series the structural relationship changes gradually, but more spectacular changes occur as well. Hence, the suspicion that the informational signals of wealth are 'under-signaling' is founded. In contrast, I draw the conclusion that the informational measures of momentum and force are not 'over-signaling' because the momentum and force spectramap show that the time points have hardly a sequential structural relationship. In other words, their relative position changes all the time. However, also other structural properties of the momentum and force measures are visualized by Spectramap biplots. Firstly, association is detected between the disaggregated accounting variables by visual analysis in all three dimensions of the* TEMA *framework. This is confirmed by statistical correlation analysis. Secondly, the structural position of the accounting variables in the momentum and force decomposition is very similar. Moreover, their position in the wealth decomposition is nearly identical. This implies that their association is duplicated in all three dimensions of the* TEMA *framework. A possible benefit of this observation is that both force and momentum variables can be used as explanatory variables in econometric models. Another insight is that some congruence appears to exist between total wealth momentum and the ordering of quarters in the decomposed structure of accounting variables. This can be understood as an indication that structural properties of the financial statements data at a lower level are indeed aggregated to a higher level. Depending on particular needs, the benefit of these findings is that an econometric model can be developed in adherence with the* TEMA *framework with either momentum or force variables at various levels of detail.*

5.1 Introduction

In the previous chapter, informational measures of my example 3M Company failed to signal unambiguously the occurrence of any structural change, or not, between balance sheet accounting variables. In this chapter, Spectral Map decomposition is applied to the same time series as were analyzed with the informational measures of Lev and Ijiri. The advantage of Spectral Map Analysis, SMA in short, of common size format financial data is that also force and momentum measures can be decomposed. Also, Spectral Map decomposition enables the visualization of both the accounting variables and the time points they were measured in a three dimensional figure, a so called biplot.[1] Various spectramap biplots are discussed of force, momentum and wealth. It is shown that spectramap decomposition renders not only a much better impression of the structural change of wealth accounts over time but that it also contradicts the informa-

[1] Actually, spectramap decomposes into two sets of components, one for table columns and one for table rows. Through alignment of their metrics it is possible to plot them both into a three dimensional Cartesian space that charts the scores of rows and the loadings of columns, hence the name *biplot*.

tional measures' conclusion that no such change occurred. On the other hand, spectral Map decomposition of the force and momentum measures does confirm the informational measures' conclusion of continuous change. Especially the last finding has implications for the econometric modeling effort that is undertaken in later chapters of this thesis.

Organization of this chapter

In section 5.2, spectral Map Analysis is introduced of 3M Company balance sheet data at level B of the time series 1993Q4–2003Q4. In Section 5.2.1 the decomposition of the wealth measures is analyzed and compared with that of the informational measures. The decomposition of momentum & force measures is discussed in section 5.2.4. In section 5.2.5 additional analysis is presented of bivariate and trivariate mapping of wealth momentum. My final analysis is presented in section 5.2.6 and concerns the dynamics of total wealth momentum from the view of the five decomposed accounts. In section 5.3 the findings of this chapter are discussed.

5.2 Spectral Map Analysis

Color coding, as applied in the case of 3M and discussed in the previous chapter, cannot inform us if the decomposition or disaggregation measures of wealth are truly 'under-signaling' or if the disaggregation measures of wealth momentum and force are 'over-signaling.' It is possible that either one is possibly misleading or maybe both. To find an answer to this question the data of the financial statements data of 3M is decomposed at level B with an alternative method for visual analysis: spectral Map Analysis. Spectral Map Analysis is a multivariate data analysis and visualization method (Lewi 1982, 1995). Level C decomposition is discussed in the following Chapter 6.

Spectral Map Analysis, SMA in short, of this data into a smaller set of uncorrelated factors provides us with the means to visualize the structural relation between wealth accounts at level B as well as the points of the time series (1993Q4–2003Q4). The variance explained by SMA of wealth, wealth momentum and wealth force is reported in Table 27. Clearly the first two SMA factors capture most of the variance of the data tables although the contribution of the third SMA factor is larger for wealth momentum and wealth force. This result is not unexpected given the fact that the momentum and force data exhibit random properties, i.e. these time series do not have trend behavior: they have a unit root.

5.2.1 Wealth decomposition

The common size format fractions of the balance sheet wealth accounts of 3M are used for SMA (Table 22, page 108). In Figure 47, the wealth accounts, symbolized by squares, are mapped together with the quarters that are symbolized by small circles. The circles are connected sequentially to indicate the progress of time and the subsequent changes of proportions between accounts. We can make an assessment of the changes in proportion between the five disaggregated accounts by dropping a line from a time point perpendicular to the axis between accounts. For example, in Figure 49 projection lines are drawn from selected quarters to the axis between current assets and noncurrent assets to show the difference between their proportions. Clearly, when a time point is positioned more rightwards the difference increases whereas in the opposite direction the difference decreases and becomes negative when noncurrent assets have a larger proportion than current assets. It is interesting to observe that certain quarters hardly change their position, e.g. the first and second quarter of 2001, which is in agreement with the 'no change' signal computed by the informational measures discussed in

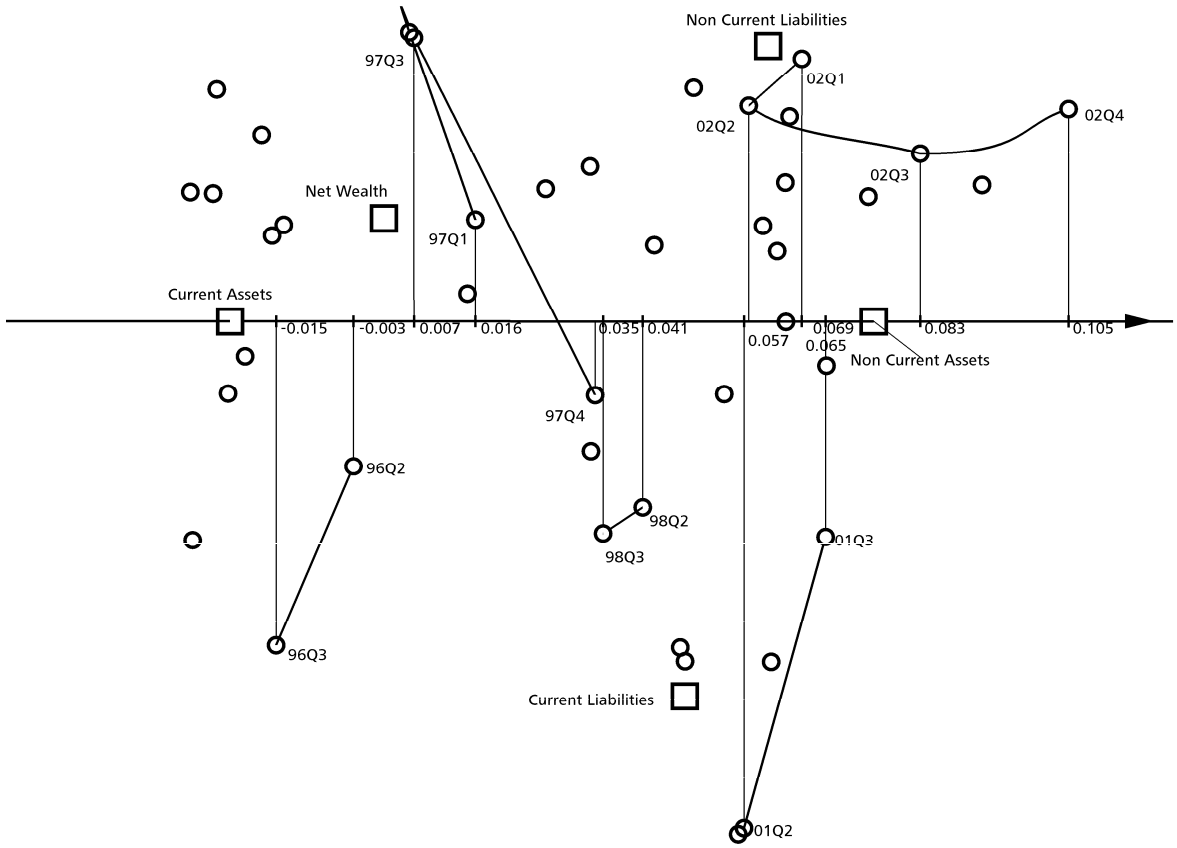

Figure 49 3M. Projection lines to differences between current assets and noncurrent assets.

the previous chapter (Lev 0.0006 and Ijiri 0.0009 in Table 23, page 109). But, comparing most other quarters rather large changes can be observed, like with the second and third quarter 2001 when current assets is 1,2% larger (the proportion between noncurrent liabilities and current liabilities also changes but this not scaled with axes in Figure 47). The informational measures now are for Lev 0.0015 and for Ijiri 0.0023 (in Table 23).

The advantage of the spectramap biplot in Figure 47 is that rather subtle changes are visualized relative to the change between all accounts during the whole time series. Proportional change between wealth accounts is not only more dramatic, than suggested by the informational measures discussed in the previous chapter, it persits during the whole time series. By using spectramap biplot visualization, I conclude that the decomposition and disaggregation measures 'undersignal' the structural change of 3M's balance sheet composition.

The time sequence progresses in Figure 47 from the fourth quarter of 1993 at the left side of the plot to the fourth quarter of 2002 at the right side. The final quarters of this time series are also positioned at right side but somewhat closer to the barycenter of the spectramap, which is indicated with a cross. All quarters from the period 1993Q4–1995Q3 group together at the left side of the plot. Next, the biplot shows distinct series of quarters where the composition of the balance sheet accounts is similar horizontally but differ vertically. For example, the next distinct period is 1995Q4–1997Q3 where the proportion between noncurrent assets and current assets hardly changes whereas the change of proportion between noncurrent liabilities and current liabilities can be characterized as rather dramatic. Then for three years from the fourth quarter of 1997 to the fourth quarter of 2000 the balance shifts back and forth between

	Panel A		Panel B		Panel C	
	wealth		wealth momentum		wealth force	
	eigenvalue	cumulative	eigenvalue	cumulative	eigenvalue	cumulative
Factor 1	0.663		0.498		0.478	
Factor 2	0.289	0.952	0.249	0.747	0.250	0.728
Factor 3	0.048	1.000	0.176	0.923	0.188	0.916
Factor 4	0.000	1.000	0.077	1.000	0.084	1.000

Table 27 3M. Variance explained by Spectramap decomposition (level B 1993Q4-2003Q4).

	Current Assets	Non Current Assets	Current Liabilities	Non Current Liabilities	Shareholders' Equity
Current Assets		-1.000	-0.446	-0.668	0.847
Non Current Assets	-1.000		0.446	0.668	-0.847
Current Liabilities	-0.446	0.446		-0.141	-0.670
Non Current Liabilities	-0.668	0.668	-0.141		-0.641
Shareholders' Equity	0.847	-0.847	-0.670	-0.641	

Each correlation is significant at the 0.01 level.

Table 28 3M. Association between wealth accounts (level B, 1993Q4-2003Q4).

	Current Assets	Non Current Assets	Current Liabilities	Non Current Liabilities	Shareholders' Equity	Total Wealth Scaled
Current Assets		-0.186	0.517**	-0.062	0.540**	0.688**
Non Current Assets	-0.186		0.314*	0.387**	0.259	0.585**
Current Liabilities	0.517**	0.314**		-0.237	0.092	0.659**
Non Current Liabilities	-0.062	0.387**	-0.237		-0.145	0.235
Shareholders' Equity	0.540**	0.259	0.092	-0.145		0.637**

** Correlation is significant at the 0.01 level. * Correlation is significant at the 0.05 level.

Table 29 3M. Association between wealth momentum variables (level B, 1993Q4-2003Q4).

	Current Assets	Non Current Assets	Current Liabilities	Non Current Liabilities	Shareholders' Equity	Total Wealth Scaled
Current Assets		0.0508	0.4556**	0.2414	0.4865**	0.658**
Non Current Assets	0.0508		0.2730	0.4815**	0.3214*	0.610**
Current Liabilities	0.4556**	0.2730		-0.1352	0.1131	0.643**
Non Current Liabilities	0.2414	0.4815**	-0.1352		-0.0339	0.309*
Net Wealth	0.4865**	0.3214*	0.1131	-0.0339		0.581**

** Correlation is significant at the 0.01 level. * Correlation is significant at the 0.05 level.

Table 30 3M. Association between wealth force variables (level B, 1993Q4-2003Q4).

the assets' variables but at the same time the proportion between the liabilities' variables shifts up and down. Clearly, during these three years, the contrast between current and noncurrent assets (horizontally) is considerably less than between current and noncurrent liabilities (vertically). Starting with the first quarter of 2001, the shift of proportions between both liabilities and assets are markedly different. Not only does the proportion of noncurrent liabilities increase, the same is occurring with noncurrent assets. It is only during the last two quarters of 2003 that the balance shifts backwards somewhat due to the increased proportion of net wealth and current assets.

5.2.2 Association

In addition to the analysis of the time points, FIGURE 48 offers also analysis of the association between accounting variables by looking at the angle between the axes drawn from the barycenter of the spectramap through the accounts. The angle is a visual indication of the association between the accounting variables, which is reported in TABLE 28. It is not surprising to learn that current assets and noncurrent assets are perfectly and negatively associated because they are the only two disaggregated accounts of the assets' side of the balance sheet. Any increase or decrease of the one account must reflect the same decrease or increase in the other account. A similar mirror-like association we can expect between the three disaggregated accounts of the liabilities' side of the balance sheet. But, this is much less so between noncurrent liabilities and current liabilities (–0.141) and much more between them and shareholder's equity, respectively –0.641 and –0.670. Looking at FIGURE 48 it is not difficult to see that shareholder's equity (net wealth) is strongly associated with current assets (0.847) and hence inversely with noncurrent assets (–0.847). Possibly this is the most relevant observation we can make from the spectramap biplot of the wealth accounts, that the trend of net wealth is very similar to that of current assets and inversely dissimilar with that of noncurrent assets.

5.2.3 Calibration

FIGURE 49 is identical to FIGURE 47 and FIGURE 48 except that now an axis is drawn through noncurrent assets and current assets. This enables the projection of a line from a quarter to this axis and to read the difference between current assets and noncurrent assets at that time. For example, for the fourth quarter of 2002 (on the spectramap at the right top side) the difference between noncurrent assets and current assets is 0.105 (or 10.5%). For the third quarter of 1997 (on the spectramap at the left top side) the difference is only 0.007 (or 0.7%). One year before, noncurrent assets were larger, for the third quarter of 1996 the difference is –0.015 (or –1.5%). In FIGURE 47 the complete time series of quarters is connected with a line to visualize the trajectory and make clear the gradual but permanent shift of proportions between balance sheet accounts. In FIGURE 49 only a limited number of quarters have been connected sequentially to visualize the fact that sometimes the change of proportions is rather dramatic compared to others where little change occurs. For example, during 2002 the shift of proportions is almost exclusively limited to current and noncurrent assets. In contrast, the other periods connected in FIGURE 49 simultaneously see their proportions also change, and much more, between current and noncurrent liabilities. Spectramap provides through visual analysis the possibility to analyze this structural change even if it is rather subtle and small.

5.2.4 Decomposition of momentum & force measures

The common size format fractions of balance sheet momentum and force of 3M are used for spectramap decomposition and visualization (TABLE 25 & TABLE 26, page 114). FIGURE 50 and FIGURE 52 show, respectively, the biplots of the spectramap decomposition of the momentum and the force of 3M balance sheet accounts. FIGURE 51 and FIGURE 53 are the same biplots but with the axes drawn through the accounts from the barycenter of the spectramap to visualize the association between the accounting variables by angle between them. TABLE 29 and TABLE 30 report, respectively, the Pearson correlations of these variables and their significance. As noted before, we should treat these statistics at this point only as a confirmation of their association and most certainly not as any measure of causation.

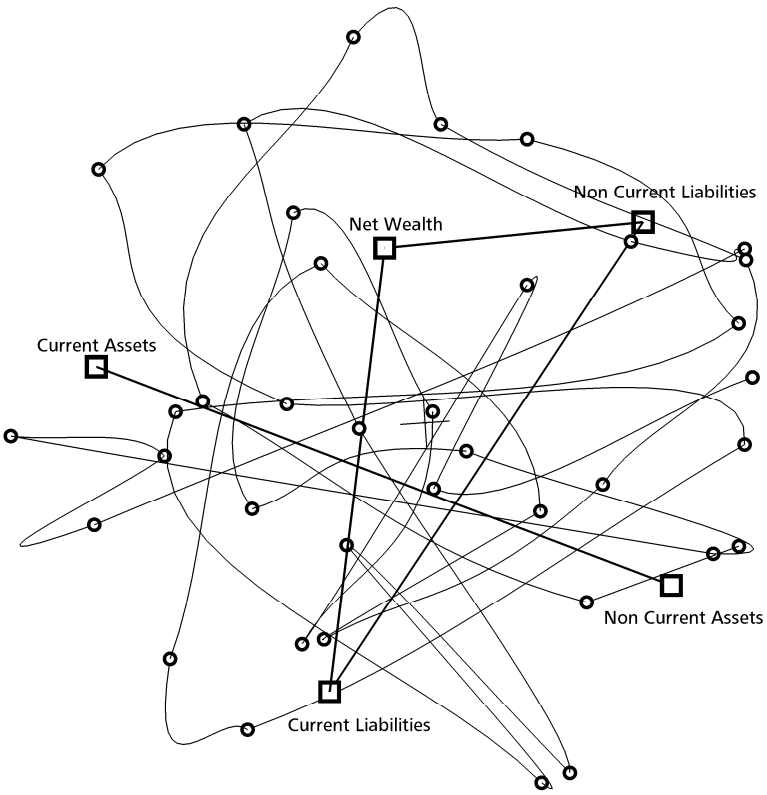

Figure 50 3M. Spectramap decomposition of wealth momentum accounts (level B, 1993Q4-2003Q4).

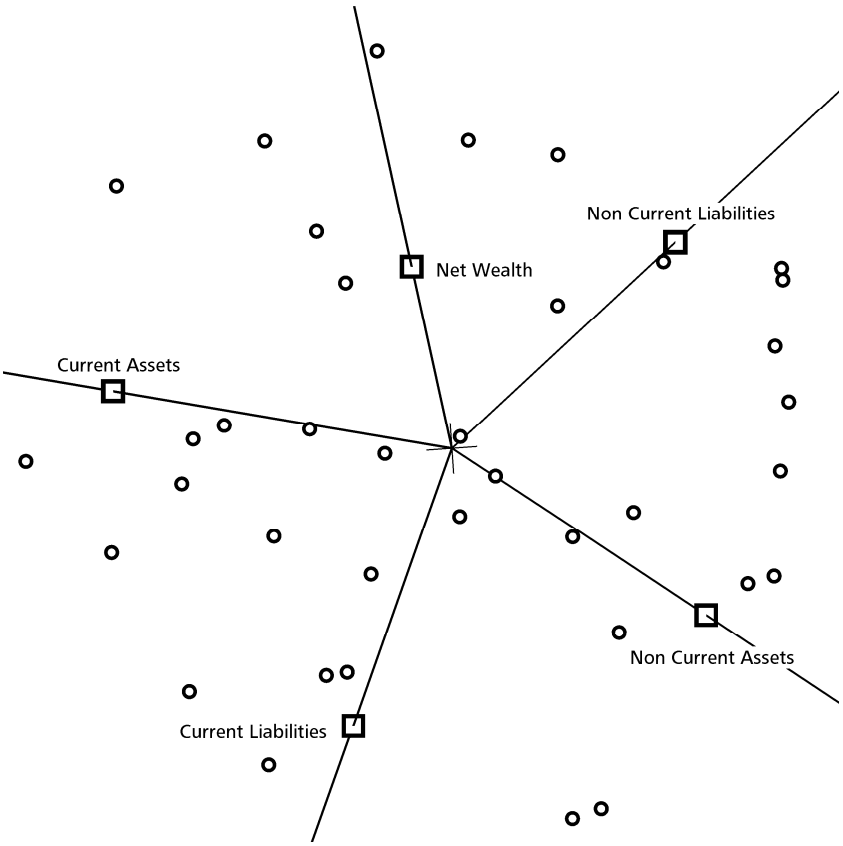

Figure 51 3M. Association between wealth momentum accounts (level B, 1993Q4-2003Q4).

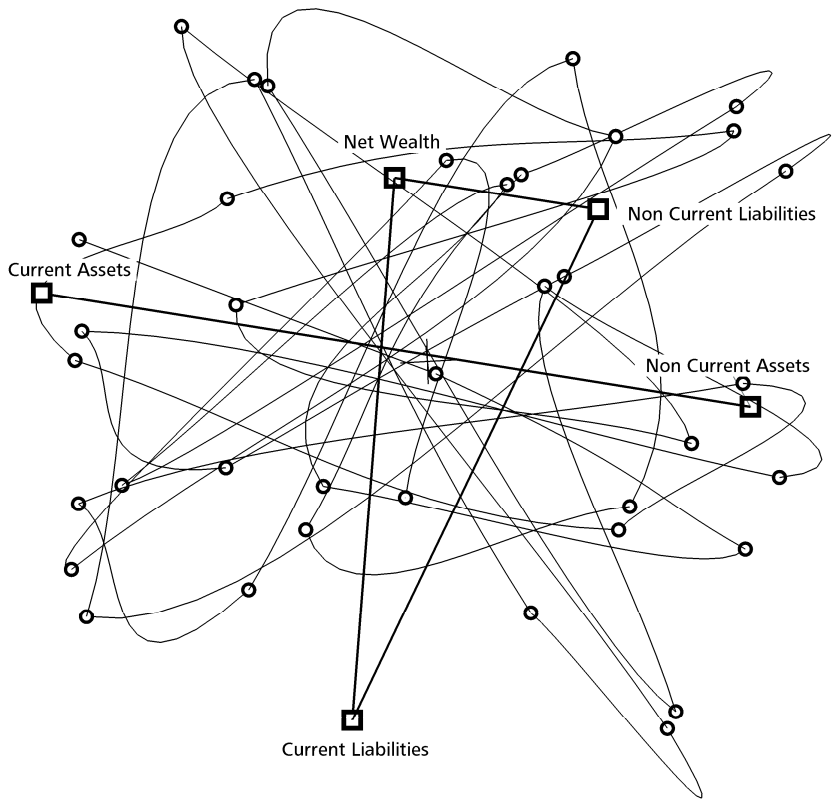

Figure 52 3M. Spectramap decomposition of wealth force accounts (level B, 1993Q4-2003Q4).

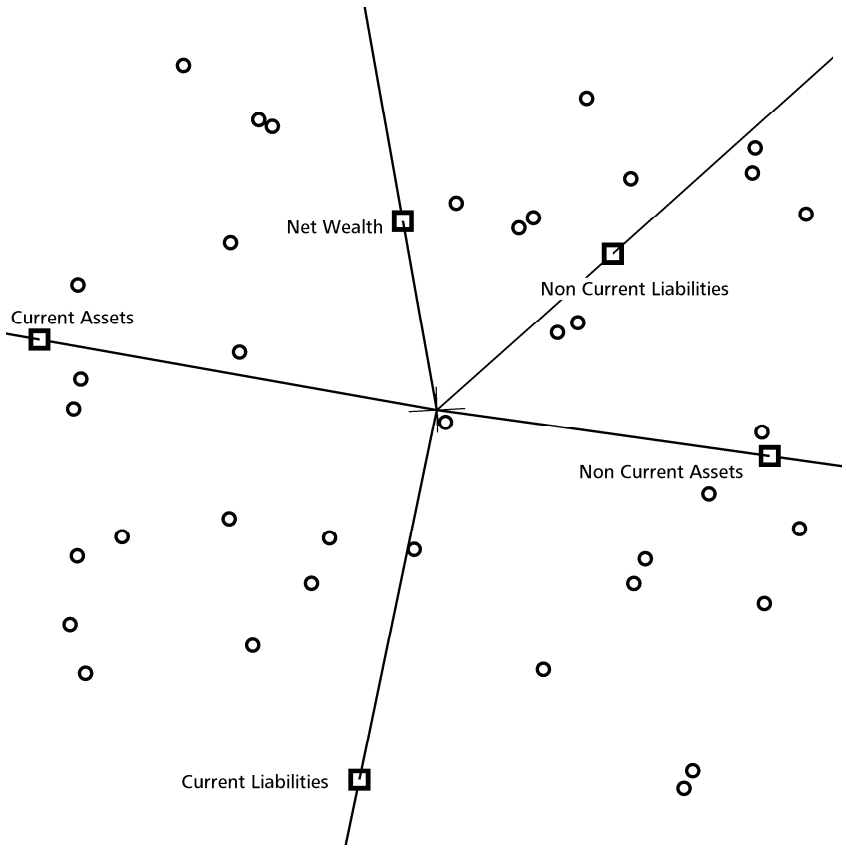

Figure 53 3M. Association between wealth force accounts (level B, 1993Q4-2003Q4).

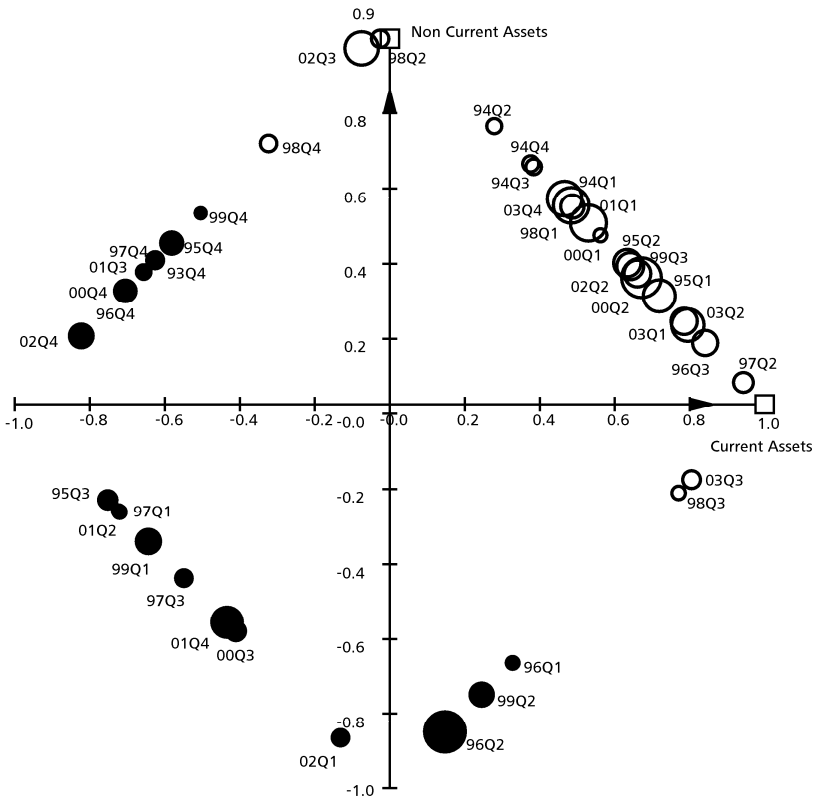

Figure 54 3M. Foliomap between current and noncurrent assets momentum (1993Q4-2003Q4).

A clear difference between the spectramap of balance sheet momentum and force and that of wealth is the time trajectory of quarters. While the time sequence of momentum and force jumps from one side of the plot to another side in a somewhat haphazard manner appears that of wealth to be more directional as well as gradual. Obviously, this is because the momentum and force measures are the differences of the wealth data. In the previous chapter it was noted that the wealth data are trend series (e.g. FIGURE 41, page 110). The momentum and force measures are stationary time series (e.g. FIGURE 45 & FIGURE 46, page 111). On first glance, spectramap decomposition gives the impression that the quarters are scattered more or less randomly throughout the plot of the first three factor scores (FIGURE 50 and FIGURE 52). However, that this might not be the case is indicated by the position of the accounting variables in these spectramaps. Both for momentum and force we can see in FIGURE 51 and FIGURE 53 that the position of the accounts and the angles between their axes is very similar to that of the wealth spectramap (FIGURE 48). The Pearson correlations of the momentum measures that are significant at the 1% level are the same for the force measures with the exception of noncurrent assets and current liabilities. Spectramap decomposition highlights that some association is present between the accounting variables and this is confirmed statistically, although we should be cautious to base any conclusion on this.

The spectramap of wealth, momentum and force also emphasizes that the dynamics in all three dimensions of Ijiri's framework occur between assets and liabilities. Net wealth has its own particular trend behavior that matches closely that of current assets in all three dimensions (wealth, momentum & force). This result is possibly driven by the fact that the balance sheet was decomposed to only five accounts. But, in the next chapter, the same is found with the decomposition to a larger number of accounts.

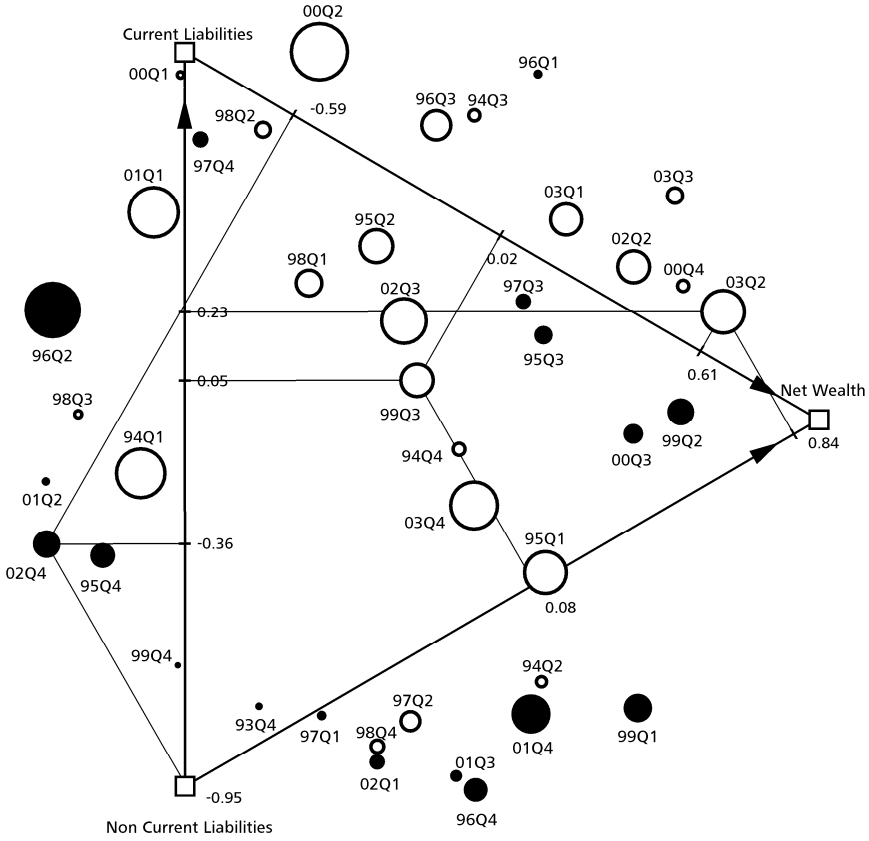

Figure 55 3M. Triangular plot of momentum differences (1993Q4-2003Q4, R^2 = 100%)

5.2.5 *Bivariate & trivariate mapping of wealth momentum*

The analysis of the common size format fractions of balance sheet momentum and force of 3M is continued in this section with bivariate and trivariate mapping. FIGURE 54 is a bivariate map and is very similar to the scatter graph that uses Cartesian coordinates to display values for two variables. This bivariate graph, or FOliomap, uses the same graphical symbols as the spectramap: circles for table row items and squares for table column items.[2] In this case quarters and accounting variables. Furthermore, there are two modifications of the symbols that represent the quarters on the FOliomap, as well as on the spectramap that will be discussed further down:

1. The area of the circles indicate if total wealth momentum is positive or negative, respectively by the achromatic color white or black.
2. The size of the circles is scaled by the value of total wealth momentum, i.e. the larger the circle the larger the increase or decrease.

[2] The term *folio* refers to the bookbinding practice of folding a piece of paper in half to make two leaves in a codex. The two axes of the FOliomap 'fold' the plane twice: either left & right or top & bottom. Also, like any Cartesian x,y diagram, the intersection of the two axes creates four regions, called quadrants; each with its own possible interpretation. That also refers to the BCG matrix product portfolio method, originally created by Bruce Henderson for the Boston Consulting Group in 1970 to help corporations with analyzing their business units or product lines. Based on the product life cycle theory it is used to determine what priorities should be given in the product portfolio. A diagram is developed with on the x-axis relative market share (cash generation) and on the y-axis the market growth rate (cash usage). Products are mapped in the BCG matrix with circles that are scaled in size by the value of its sales; hence, the similarity in purpose, design and use of its symbol with the FOliomap.

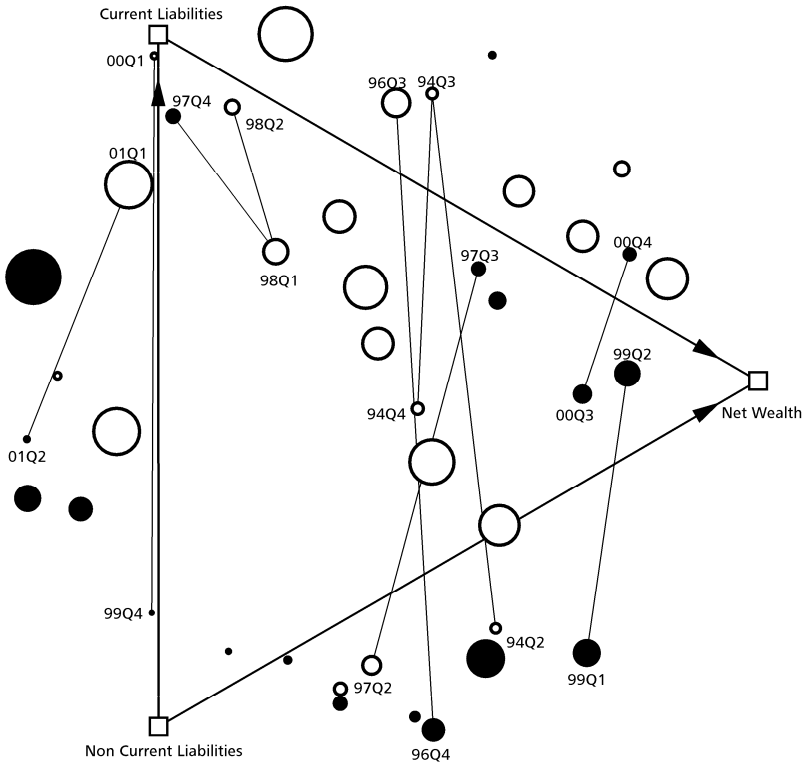

Figure 56 3M. Triangular plot, proportional changes between current & noncurrent liabilities momentum.

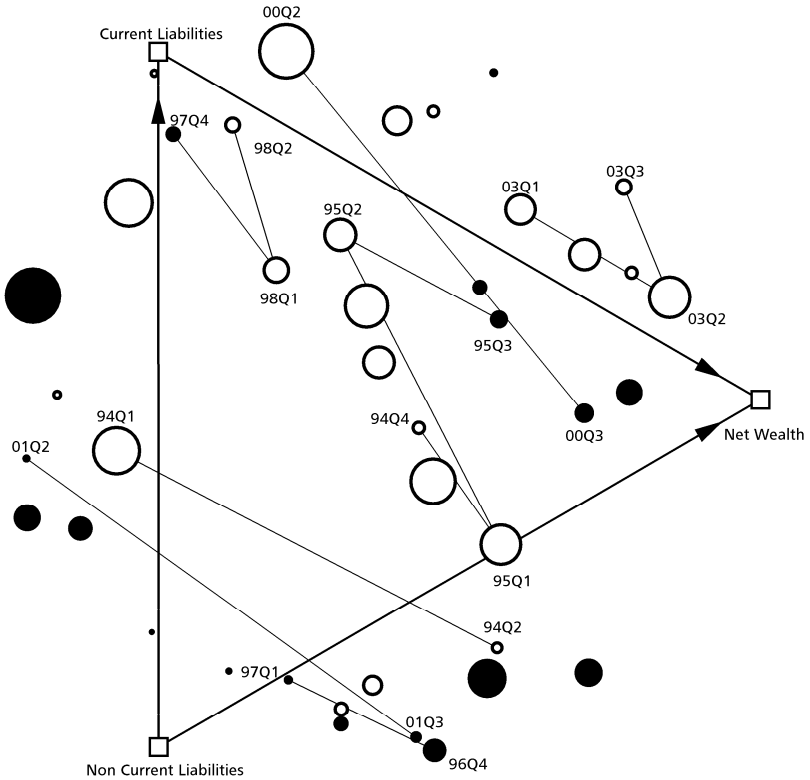

Figure 57 3M. Triangular plot, proportional changes between current liabilities & net wealth momentum.

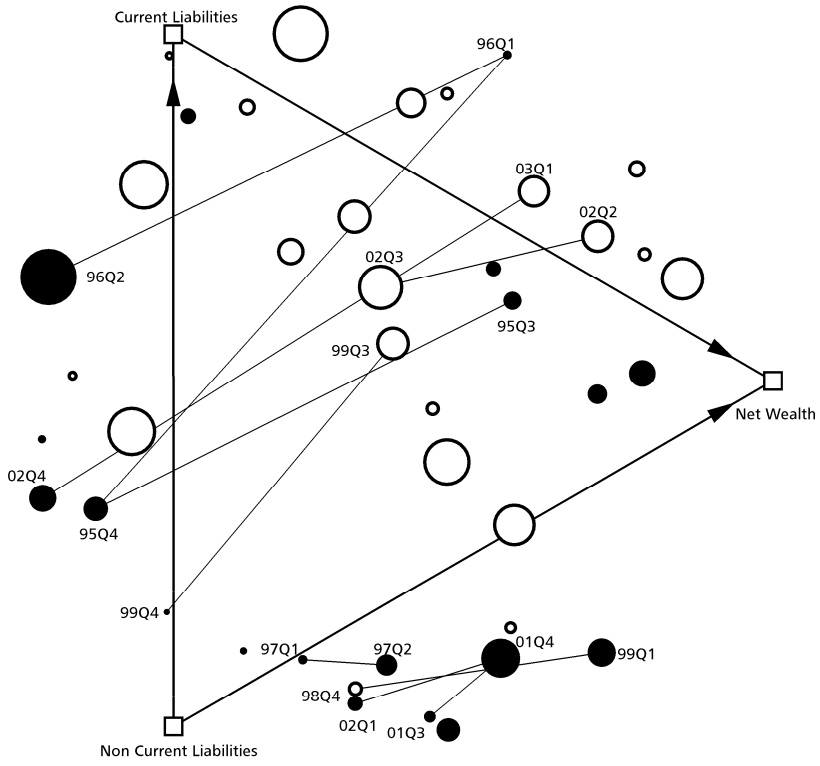

Figure 58 3M. Triangular plot, proportional changes between noncurrent liabilities & net wealth momentum.

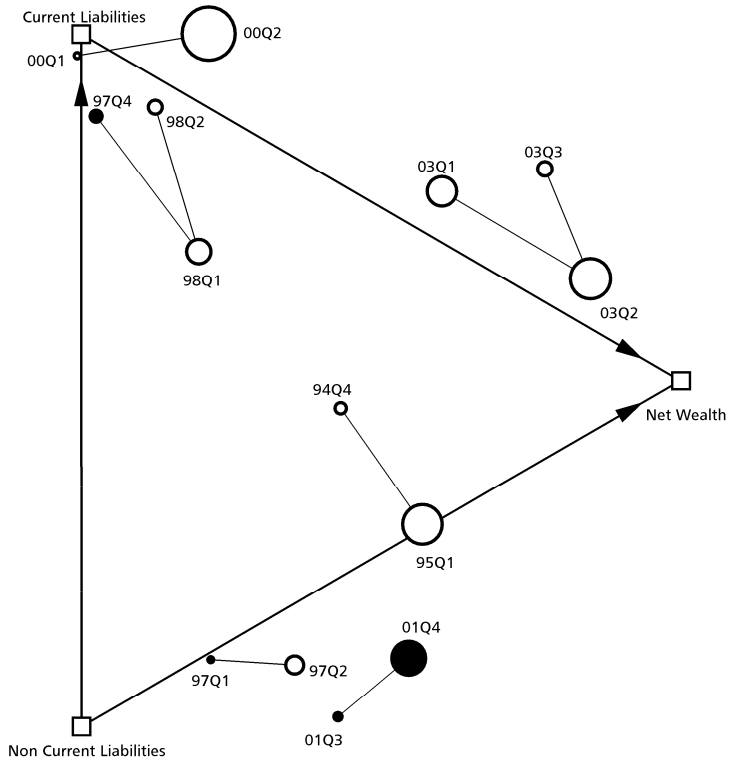

Figure 59 3M. Triangular plot, with relative small proportional changes between accounting variables.

The x-axis of FIGURE 54 displays the values of current assets momentum and the y-axis that of noncurrent assets momentum. The axes intersect each other at their zero value, i.e. their point of origin where no change occurs. Observe that the right top quadrant of the foliomap only has quarters that show an increase of both assets' momentum. Opposite that, the left bottom quadrant only has quarters where each momentum decreases. The left top and right bottom quadrant have quarters whereby either current assets or noncurrent assets momentum decreases while the other increases. Note that the same quarter of different years can return on a similar position. For example, the third quarter of 1998 and 2003 (right bottom quadrant) has an increase of current assets momentum and a decrease of noncurrent assets momentum. The fourth quarter of nine years has a decrease of current assets (left folio) against two years that have an increase (right top quadrant). Seven of nine have a rather large decrease of current assets against an increase of noncurrent assets and are years with negative total assets momentum (left top quadrant). Furthermore, of the seventeen quarters that have an increase of both asset accounts there are six of the first quarter and six of the second quarter (right top quadrant). The change of proportion between the momentum assets accounts clearly exhibits some form of seasonality. In FIGURE 55 we can analyze in a similar fashion the profile of quarters but now from the perspective of liabilities and net wealth, the sources of funds. This plot is also a spectramap but now with only three column items, the accounting variables. The projection of this plot is such that all symbols are on the plane of projection.[3] There are three object axes drawn:

1. Between current liabilities and noncurrent liabilities (vertical from top to bottom).
2. Between net wealth and noncurrent liabilities (right to left bottom).
3. Between net wealth and current liabilities (right to left top).

The arrow on each object axis indicates the direction in which the differences are calculated between the accounting variables. As an example, from three selected quarters projection lines are drawn to each axis so these differences can be read. For instance, the difference between net wealth momentum and noncurrent liabilities momentum is in the third quarter of 2003: 84% (0.84 = 0.773 – (–0.064); see TABLE 22, page 108). The difference between net wealth momentum and current liabilities momentum is 61% (0.61) and the difference between current liabilities momentum and noncurrent liabilities momentum is 23% (0.23).

Worth mentioning is the position of the quarters that have a decrease of total wealth (total assets): they are mostly found at the left bottom part of the spectramap. For decreasing quarters the mean difference between net wealth and noncurrent liabilities is –0.16 (–16%) whereas the mean difference between current liabilities and noncurrent liabilities is –0.28 (–28%). Therefore, this spectramap shows that when total wealth decreases, non current liabilities increases proportionally. In contrast, when total wealth increases, net wealth and current liabilities increase proportionally. In other words, quarters with positive total wealth momentum, or negative, occupy different areas on the spectramap because they tend to have their own characteristic proportions between accounting variables.

As quarters that have a particular momentum in common occupy the same area, i.e. have comparable proportions, the next question we can ask is if the change in position on the biplot between such quarters also exhibit the same structural properties. The following three biplots indeed show that some successive quarters change their proportions in a similar direction.

[3] In other words: it is a perfect two-dimensional projection of a three-dimensional object space.

FIGURE 56 has quarters connected that have a specific proportional change between current and noncurrent liabilities momentum. FIGURE 57 has quarters connected with a specific proportional change between current liabilities and net wealth momentum. FIGURE 58 has quarters connected that exhibit a particular proportional change between noncurrent liabilities and net wealth momentum. However, note that in all of these three figures also the proportions relative to the other account change but to a smaller degree. Finally, FIGURE 59 shows the seven quarters of the time series that have relative small proportional changes between current and noncurrent liabilities momentum, and net wealth momentum. Compared to the other figures such changes are less frequent. The impression I get from the above is that balance sheet momentum is rather volatile. Apparently, the disaggregation measures of 3M's wealth momentum, discussed in the previous chapter, are not 'under-signaling' and therefore, analyzing the change of proportion between variables is warranted.

5.2.6 Total wealth momentum

Our final analysis concerns the dynamics of total wealth momentum from the view of the five decomposed accounts. FIGURE 60 is the same spectramap as FIGURE 47 except that it has been rotated so that most of the quarters that have a negative momentum are on the left side of the plot and most of the quarters that have a positive momentum are on the right side. The quarters are without labels because what interests us here is merely their position relative to the accounting variables. I now see 'noncurrent' accounting variables at the left side and 'current' accounting variables at the right side of the spectramap. As indicated by the barycenter's cross hair, one factor is horizontally aligned, it is the first factor, which explains about 49.8% of the variance (TABLE 27, panel B). Of the 19 quarters with negative total wealth momentum, 13 have a negative score on the first factor (68.4%) and 6 have a positive score. The intuition is that in the multivariate accounting data, aggregated dynamics is reproduced at a lower level of decomposition. Some structural property of total wealth momentum shines through its disaggregated accounting variables. Spectramap decomposition analysis concentrates this back into a single factor polarity of 'liquidity' with 'noncurrent-ness' at one extremity and 'current-ness' at the other extremity. It is such insight that spectramap contributes to financial statement analysis. FIGURE 60 also gives rise to the question if momentum and force measures of the accounting variables are associated with that of total wealth. TABLE 29 and TABLE 30 report, respectively, the correlation between total wealth momentum and total wealth force and its disaggregated accounting variables. Apart from noncurrent liabilities, they all correlate at the 1% level of significance. Only noncurrent liabilities are correlated with total wealth by force at the 5% level of significance. This result is in itself not surprising because wealth is disaggregated to level B which only has five accounts. Therefore, I expect a strong association between these variables with total wealth momentum or force. However, what is of interest is that this association is expressed near identical at each dimension. This confirms the other analysis that the association between selected accounting variables holds for all three dimensions of the TEMA framework. Thus, confidence increases in their possible use for time series regression models to find evidence in support of the TEMA framework. A final word on the correlation statistics of net wealth, my dependent accounting variable of interest. Note that its association is strongest with that of total wealth momentum and total wealth force. Hence, for my modeling purposes, total wealth momentum or, alternatively, total wealth force can be tested as an explanatory or independent variable of the trend of net wealth momentum or net wealth force. In the TEMA framework, total wealth momentum models use *I(1)* time series whereas total

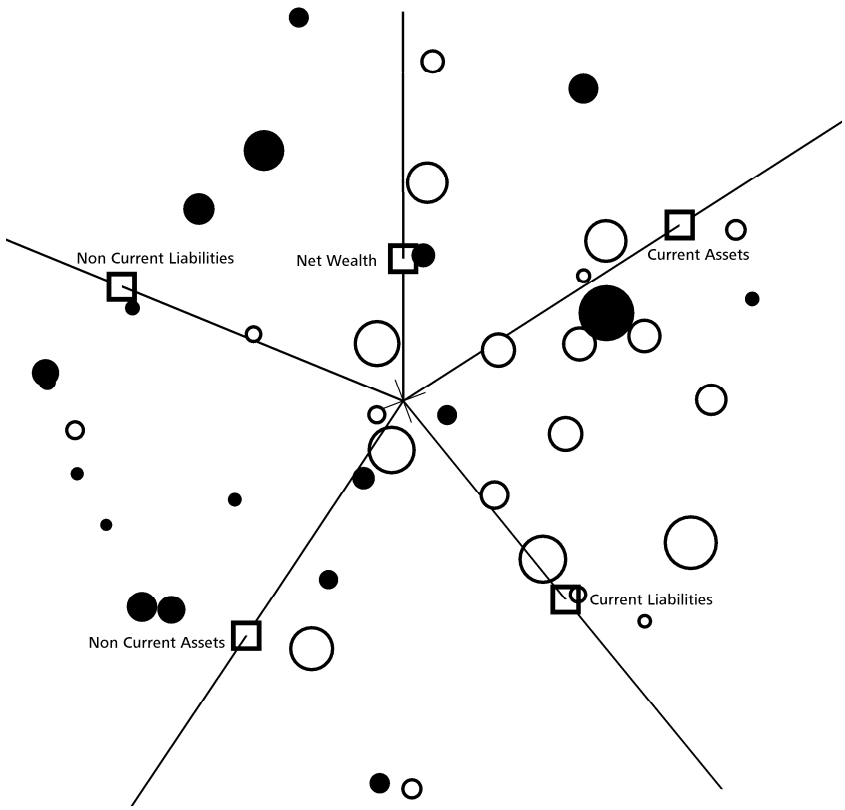

Figure 60 3M. Spectramap biploy, position of quarters with total wealth increase (white circles) or decrease (black circles) level B decomposition (1993Q4-2003Q4, R^2 = 80.16%).

wealth force models use *I(2)* time series. Which solution is selected depends on the result of the required econometric tests of the stationarity of the (in this study) differenced time series, but each can be used (following FIGURE 5 and FIGURE 6, page 53).

5.3 Discussion

Spectramap decomposition and visualization offers a new view on balance sheet data in the TEMA framework. The analysis of my example, 3M company, reveals the structure very well of the accounting variables and their measurements in time. The first question I answered is whether the informational measures of wealth are 'under-signaling' and, indeed, this is clearly the case. For neither momentum nor force any indication was found for 'over-signaling' of the informational disaggregation measures of wealth momentum and force. Still, such continuous strong signaling, I expect, will not be helpful for my analysis.

It was also shown that spectramap decomposition is a visual illustration of the association between the accounting variables. Visual analysis of the wealth, momentum and force data made clear that the association holds, in this example, between all three dimensions of the TEMA framework. Next, the example suggests that some structural relation is present between momentum and force of total wealth and the disaggregated accounting variables of these dimensions. It seems that the association between the dynamics of the aggregate and the disaggregated accounts holds for momentum and force of balance sheet composition. This finding is particularly relevant concerning the development of econometric models. My confidence increases in their possible use for time series regression models to find evidence in support of the TEMA framework.

For time series models specific properties are required for both the independent variables and the dependent variable. Two approaches to this effort are possible. Depending on the result of testing for these properties, for example for the presence of a unit root, it might very well be possible to use variables from either one of the three dimensions of the TEMA framework in such models. An alternative approach would be to use the SMA factors derived from the original accounting variables of any dimension of the TEMA framework. Schilderinck (1977, 59) recommends this as a method of economic research and Seiler (2004, 165) recommends it to perform financial studies. Because the SMA factors are orthogonal, and therefore not associated with each other, statistical problems, such as multicollinearity, can be substantially reduced if not eliminated altogether. This study continues with examples of each approach.

6

Color Coding of Accounting Information

Balance Sheet, Vol. 12, No. 4, 2004, pp. 17-32.

Der Credit Manager, No. 1, 2005, pp. 16-22.

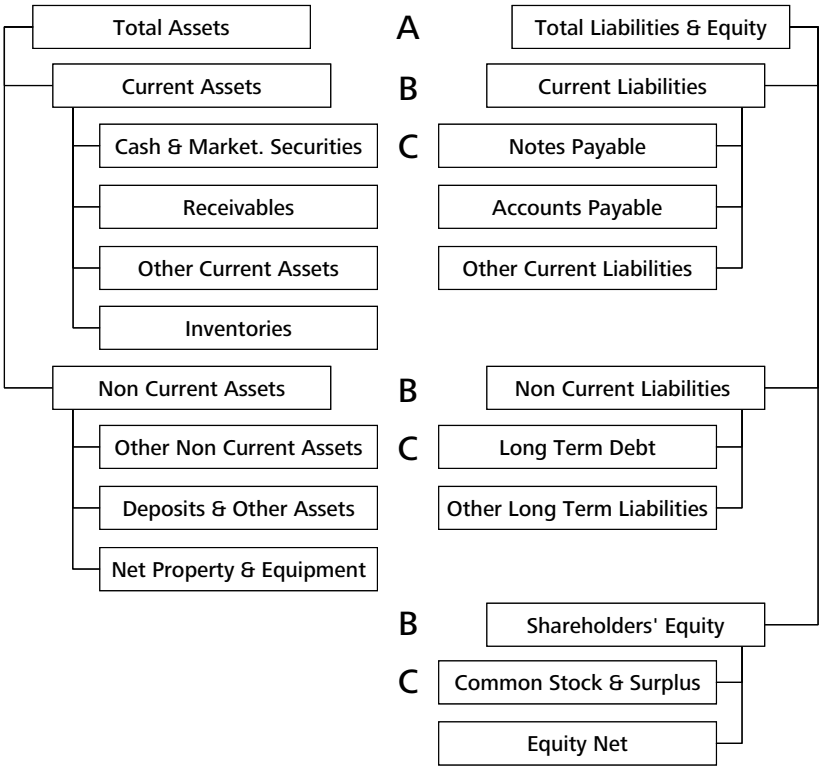

Figure 61 Balance sheet accounts with 3 levels of aggregation: A, B and C (SEC format).

Assets	03Q4	03Q3	...	93Q4	93Q3	03Q4	03Q3	...	93Q4	93Q3
Cash	$ 1,836	$ 1,279	...	$ 656	$ 665	10.44%	7.61%	...	5.38%	5.44%
Receivables	$ 2,714	$ 2,791	...	$ 2,610	$ 2,687	15.43%	16.62%	...	21.40%	21.97%
Other Current Assets	$ 1,347	$ 1,390	...	$ 696	$ 723	7.66%	8.28%	...	5.71%	5.91%
Inventories	$ 1,816	$ 1,882	...	$ 2,401	$ 2,370	10.32%	11.20%	...	19.69%	19.38%
Current Assets	$ 7,713	$ 7,342	...	$ 6,363	$ 6,445	43.84%	43.71%	...	52.17%	52.70%
Other Non-Current Assets	$ 218	$ 214	...	$ 455	$ 465	1.24%	1.27%	...	3.73%	3.80%
Deposits & Other Assets	$ 4,053	$ 3,774	...	$ 549	$ 473	23.04%	22.47%	...	4.50%	3.87%
Net Property & Equipment	$ 5,609	$ 5,467	...	$ 4,830	$ 4,846	31.88%	32.55%	...	39.60%	39.63%
Non Current Assets	$ 9,880	$ 9,455	...	$ 5,834	$ 5,784	56.16%	56.29%	...	47.83%	47.30%
Total Assets	$17,593	$16,797	...	$12,197	$12,229	100.00%	100.00%	...	100.00%	100.00%
Liabilities & Net Wealth	**03Q4**	**03Q3**	**...**	**93Q4**	**93Q3**	**03Q4**	**03Q3**	**...**	**93Q4**	**93Q3**
Notes Payable	$ 1,202	$ 1,255	...	$ 697	$ 796	6.83%	7.47%	...	5.71%	6.51%
Accounts Payable	$ 1,087	$ 969	...	$ 878	$ 762	6.18%	5.77%	...	7.20%	6.23%
Other Current Liabilities	$ 2,793	$ 2,744	...	$ 1,707	$ 1,846	15.88%	16.34%	...	14.00%	15.10%
Current Liabilities	$ 5,082	$ 4,968	...	$ 3,282	$ 3,404	28.89%	29.58%	...	26.91%	27.84%
Long Term Debt	$ 1,735	$ 1,738	...	$ 796	$ 682	9.86%	10.35%	...	6.53%	5.58%
Other Long Term Liabilities	$ 2,910	$ 2,583	...	$ 1,607	$ 1,543	16.54%	15.38%	...	13.18%	12.62%
Non Current Liabilities	$ 4,645	$ 4,321	...	$ 2,403	$ 2,225	26.40%	25.72%	...	19.70%	18.19%
Common Stock & Surplus	$ 296	$ 296	...	$ 296	$ 296	1.68%	1.76%	...	2.43%	2.42%
Equity Net	$ 7,570	$ 7,212	...	$ 6,216	$ 6,304	43.03%	42.94%	...	50.96%	51.55%
Shareholders' Equity (Net Wealth)	$ 7,866	$ 7,508	...	$ 6,512	$ 6,600	44.71%	44.70%	...	53.39%	53.97%
Total Liabilities & Net Wealth	$17,593	$16,797	...	$12,197	$12,229	100.00%	100.00%	...	100.00%	100.00%

Table 31 3M. Balance sheet by quarter (Source: SEC, raw data in millions $ and common size format in %).

6 Abstract

The growing need for more relevant detail in financial statements proper to be produced annually, quarterly or monthly, and possibly continuously, translates into an urgent need for more advanced methods and tools for trend analysis. In this chapter I study the dynamic of balance sheet items at different levels of aggregation. With Spectramap multivariate analysis and visualization a decomposed structure is produced by all balance sheet items and their time points. This approach to balance sheet analysis provides a new method to determine the relevance and materiality of accounting information. Instead of computing balance sheet ratios separately, I use Spectramap biplots to explore the change of proportions of the balance sheet of my example: 3M Company. I study ten-years of quarterly balance sheet data and discuss some trends by comparing scatter plots with spectramap analysis together with color coding to expose the 'structure' hidden in the balance sheet data. I substantiate that I can explain the larger part of variance present in the time series in a more meaningful manner. I also seek to find evidence for the generality assumption that underlies the structure of the balance sheet.

6.1 Introduction

Financial statement analysis is not an easy task when faced with the ever-growing volume of data. The growing need for more detail in financial statements proper not only produced annually, quarterly or monthly, and possibly continuously, translates into an urgent need for more advanced methods and tools for balance sheet trend analysis (Penman 2003B, Lev 1999, Lymer *et al.* 1999). The objective of such analysis is to reduce the amount of data and the complexity that comes with it. Naturally, different purposes require different methods and tools.[1] Ratio analysis, for example, provides an insight into the financial health of a firm by looking into its liquidity, solvability, profitability, activity, and capital & market structure.[2]

This chapter takes a broader view at the trend of balance sheet items as a whole.[3] I will expose the structure produced by all balance sheet items that normally remains hidden in the data. Also, I will observe at the highest level of aggregation the trend of balance sheet items and compare it with the next level of detail. This innovative approach to balance sheet analysis provides a new method to determine the relevance and materiality of accounting information. Instead of computing accounting ratios, I apply spectramap multivariate analysis and visualization to explore the 'data space' of the balance sheet. My notion is that if the trend of several balance sheet items moves identically in time they will occupy a similar location. By looking only at data tables or trend line graphics of individual items, it is very difficult to grasp inherent trends because of the volume and complexity of the data. As an alternative, I introduce and use spectramap biplots to expose latent components hidden in the data. Exploratory data analysis, like spectramap, is a method common in natural science and industrial practice (Lewi 1982, Reyment & Jöreskog 1993). I apply it with color coding to look at the structure and trend of balance sheet data of 3M Company, filed at the U.S. securities and Exchange Commission (SEC), with up to five dimensions of trend information.

[1] The classic textbook on the subject is from Foster (1986).

[2] For an extensive introduction to ratio analysis I refer to Walsh (1996).

[3] This chapter was published in Melse (2004B).

Organization of this chapter

In Section 6.2, the generality assumption is defined together with the relevance of balance sheet information. My data sample is also described. Section 6.3 discusses the spectramap decomposition of the 3M balance sheet time series at the second level of disaggregation. In Section 6.4 color coding is applied to the higher factors of the decomposition to signal more subtle associations between quarters and the accounting variables. Section 6.5 integrates the decomposition into a five dimensional analysis of the Cartesian three dimensional data space together with two dimensions of the CIELAB color space of equidistant colors. Section 6.6 concludes this chapter with a discussion.

6.2 Wealth and the balance sheet

On the balance sheet, which is one of the financial statements, reside various items classified as assets, liabilities and shareholders' equity, or net wealth. Together, they comprise the composition of wealth—its *use* and *source*—and are the first accounting dimension. It is important to observe that from a temporal perspective, data presented on the balance sheet are a measurement at a given point in time. It reflects the financial status quo of an enterprise, which we could also understand as the then current summation of accounts that shape the value cycle (Vaassen 2002, 38).[4] At the liability side, shareholders invested capital and, possibly, at later points, dividend was distributed back, reducing residual interest or net wealth. Meanwhile, management uses capital to acquire semi-permanent assets to enable the production of goods or the delivery of services to customers. At the assets side, their value is accounted for, together with other probable future economic benefits obtained or controlled by the enterprise as a result of past transactions or events. All the time, accounts like debtors and creditors (or their American counter parts: receivables and accounts payable) increase or decrease following the dynamics of business. Similar trends we may observe with cash, the only 'hard' monetary measure of asset value at current 'price,' and inventories. From a management accounting perspective, I expect that a certain rate of growth in income or total assets is reflected in the magnitude and composition of assets and liabilities as a whole, and other performance measures (Walsh 1996). For example, when market share increases, I expect a higher turnover rate as well as a steady increase in magnitude of debtors and cash. Another illustration: improvements in credit management might accordingly reflect in a decrease of debtors and increase in cash. An ex post analysis of balance sheet data should reveal such proportional changes in composition and their temporal trend are what interests us in this chapter.

6.2.1 The generality assumption

The concept of the generality level, or *generality assumption*, refers to the logical organization of individual accounting transactions by their property or 'nature' such that when measurements are accrued no conceptual conflict occurs (Lim 1966, 646). At the uppermost aggregation level, we can distinguish between total assets and total liabilities & equity (level A in FIGURE 61). One level downwards, we can break these up into their current and noncurrent parts (level B). Next, we find items that branch out from level B further down to level C. The

[4] Although it is a relevant and important subject, I do not discuss issues related to the valuation of assets or liabilities. It is not important what the purpose of the balance sheet is (fiscal, economic or liquidation) nor the method of valuation (e.g. historical cost or current worth at market value). The generality assumption discussed further down should hold in every design, for each purpose and all cases.

assumption is that when we observe a trend with an item at a higher level, it is likely that we can observe a similar trend at the next lower level in one or more items that are aggregated into it. Moving in either direction, aggregating or disaggregating balance sheet items is expected to preserve such a trend. If that is not the case, then we should question the materiality or nature of the items involved, or both. I strive to demonstrate that the generality assumption holds for 3M Company quarterly balance sheets from 1993 to 2003 (Table 31).

6.2.2 *Relevance of balance sheet information*

Relevance of a balance sheet item is defined differently from textbook to national standard, but a good definition is provided by Epstein & Mirza (1997, 54, 61): 'An item is relevant if the information about it has the capacity to make a difference in investors,' creditors,' or other users' decisions. The relevance of information is affected by its nature and materiality … Information is material if its omission or misstatement or nondisclosure could influence the economic decisions of users taken on the basis of the financial statements.' Most certainly! Nonetheless, the problem that looms over the concept of relevance and materiality is that it is incredibly difficult to objectively determine whether omission, misstatement or nondisclosure indeed would influence '…the economic decisions of users…' or not.[5] I put aside completely the issue of users' perspectives and considerations of economic decision-making. Primarily, I am interested only in the trend of the data and the change of their composition. I seek to contribute a new method to study trends in balance sheet data as a whole and expose its latent static structure of components through exploratory data analysis with Spectramap.

6.2.3 *Data sample*

To my purpose, I use compiled quarterly balance sheet filings of 3M Company for the U.S. Securities and Exchange Commission (SEC), for the period from the first quarter 1993 to the fourth quarter 2003 (unaudited), and are publicly available data. 3M is a 16 billion U.S. Dollar diversified technology company that does business, among other areas, in consumer and office, display, electronics and telecommunications, health care, industrial, safety, security and protection services and transportation. I corrected a few errors and complemented missing data in the SEC filings. Some of the line items of the SEC filings were aggregated for the purpose of this analysis. I aggregated accrued expense and income taxes into other current liabilities, and common stock net and capital surplus into common stock & surplus. Next, I transformed the raw accounting numbers to *common size format* to achieve control for the effect of firm size (i.e. the difference in magnitude over time, Foster 1986, 58). I divide balance sheet line items by their total so I get a percentage instead of the monetary value (Table 31).

[5] Nobel laureates are among the researchers of this problematic subject (Tversky & Kahneman, 1986).

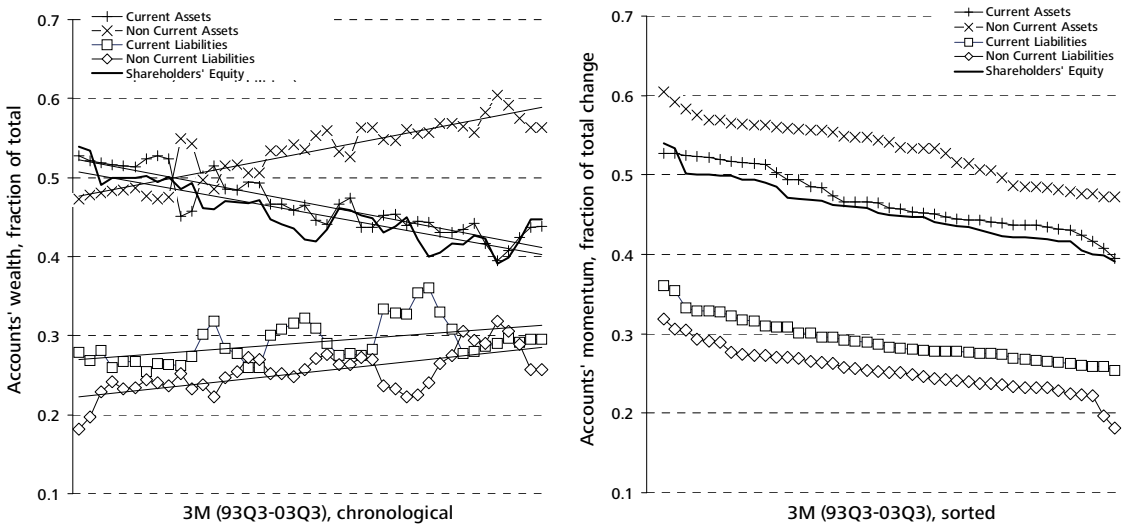

Figure 62 3M. Aggregated assets & liabilities (left: longitudinal order & right, rank order).

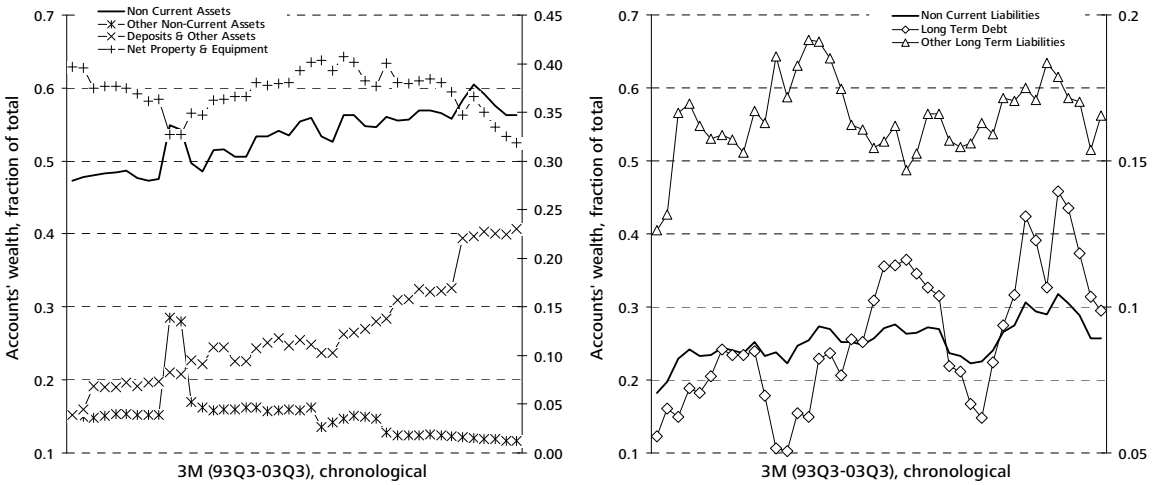

Figure 63 3M. Noncurrent assets (left) & noncurrent liabilities (right).
The left y-axis scales each account and the right y-axis scales its disaggregated items.

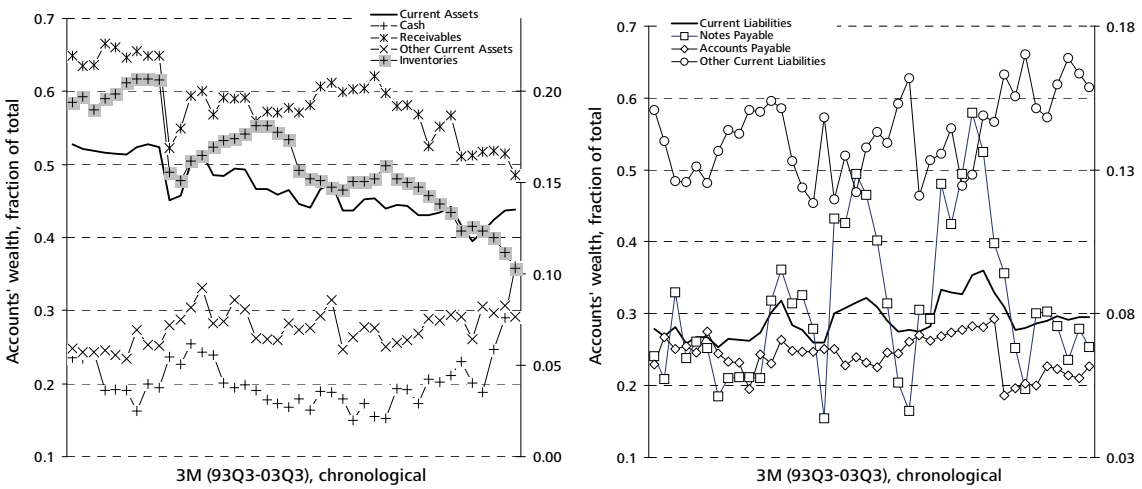

Figure 64 3M. Current assets (left) & current liabilities (right).
The left y-axis scales each account and the right y-axis scales its disaggregated items.

6.2.4 Data analysis

From this data, I expect a signal that will strike us as a meaningful indicator of:

1. the presence of one or more trends, and, in that case I expect to note,
2. the relevance of individual balance sheet items for such trends, and,
3. the data space structure that visualizes the association between balance sheet items.

A more traditional visualization of balance sheet data can already indicate if one or more trends are present. FIGURE 62, left, is a scatter plot of 3M balance sheet items at level B that are connected in chronological order (horizontal axis). Their position varies vertically depending on the then current fraction of total wealth of the item. Each item has a very clear trend upwards or downwards that indicates a structural pattern during the ten-year period. For each item a linear regression line is drawn. It is remarkable that regression lines of shareholders' equity and current assets are running parallel. Similarly, current and noncurrent liabilities are increasing in about the same direction although their fractions vary in opposite direction at most of the time points of measurement. In other words, during most of the period increases in current liabilities are matched against decreases in noncurrent liabilities, whereas their sum is increasing gradually. Hence, shareholders' equity is decreasing proportionally. One can think of many causes to explain this somewhat dramatic and structural change in fractions at this aggregation level. For example, the relatively large increase in noncurrent assets from about 47% in 1993, third quarter, to about 16% in 2003, fourth quarter (FIGURE 62, left), is explained by the increase from about 4% to 23% in deposits & other assets (FIGURE 63, left). Such change is dramatic enough to draw the attention of any reader of the financial statement. What has happened is that 3M, during the second half of this ten-year period, activated intangible assets, like patents. This trend marched opposite in time with a decrease in inventories ('good') and cash ('not so good'). That the generality assumption holds, I conclude from visual inspection of the scatter plots of FIGURE 63 and FIGURE 64. In each plot, a solid line draws the trend of the aggregated items (i.e. from level C to level B, FIGURE 61). Aggregation averages out the dispersion of items but maintains the general direction of the particular set of balance sheet items. These trends are not that difficult to observe when I study scatter plots. Nevertheless, when the variance is large, for example with most of the liabilities (FIGURE 63 & FIGURE 64, right), it becomes more difficult to read such trends unambiguously. Moreover, it is not possible to decide if trends of individual items of a category are associated upon first inspection. With scatter plots it is even more difficult to unveil if a trend covariates between items.

6.3 Spectral Map Analysis

Spectral Map Analysis, spectramap in short, is a statistical application of the algebra of the so-called Eigen values and Eigen vectors to the factor analysis of multivariate data, and used here in an informal manner (Lewi 1982, Reyment & Jöreskog 1993). 'A factor problem,...' as Thurstone points out (1947, 55), '...starts with the hope or conviction that a certain domain is not so chaotic as it looks.' I assume that financial statement users working in banking, financial services, insurance, multinational corporations, consultancies, accountancy firms, government and regulatory bodies subscribe to the notion that the balance sheet is not chaotic.

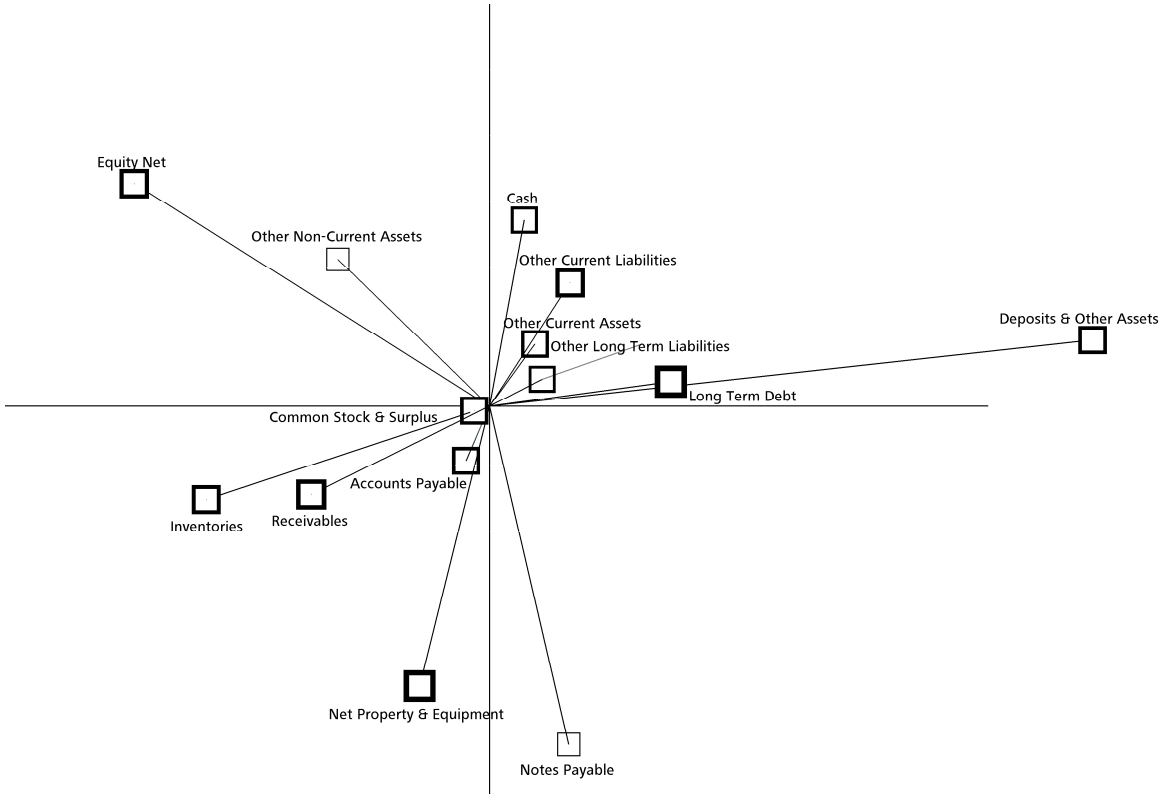

Figure 65 3M. Spectramap row space decomposition of balance sheet accounts (level C, 1993Q3-2003Q4). Table column loadings are visualized as squares, in this case with a constant size.

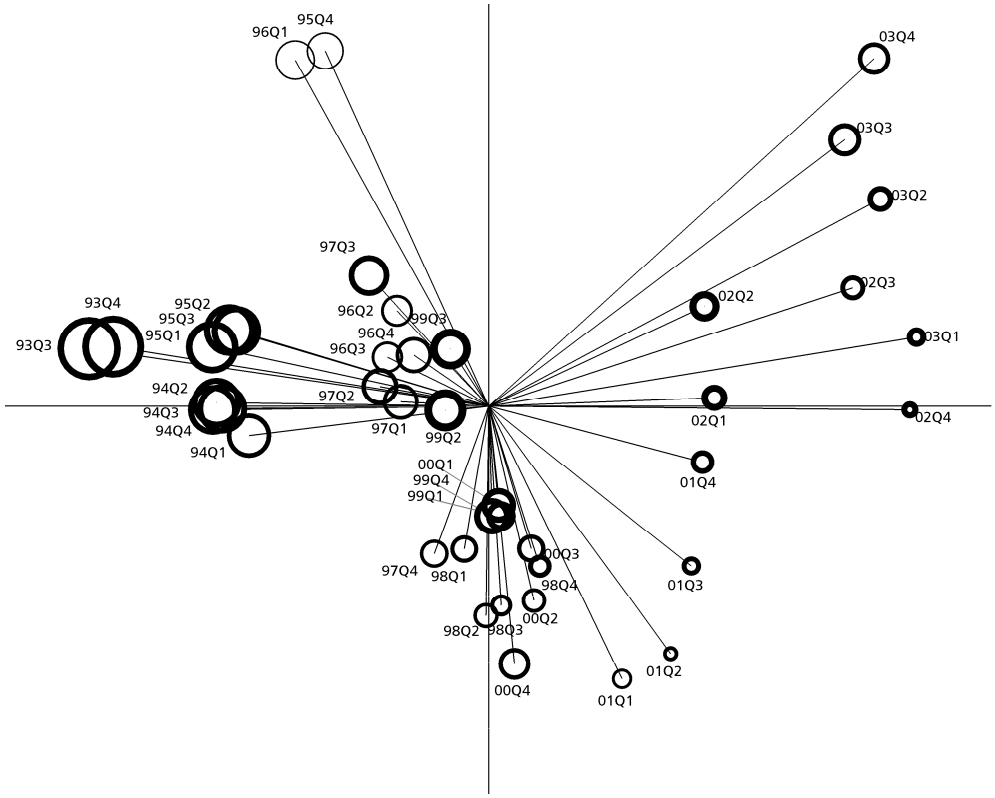

Figure 66 3M. Spectramap column space decomposition of balance sheet quarters (level C, 1993Q3-2003Q4). Table row scores are visualized as circles, in this case with their size scaled by net wealth.

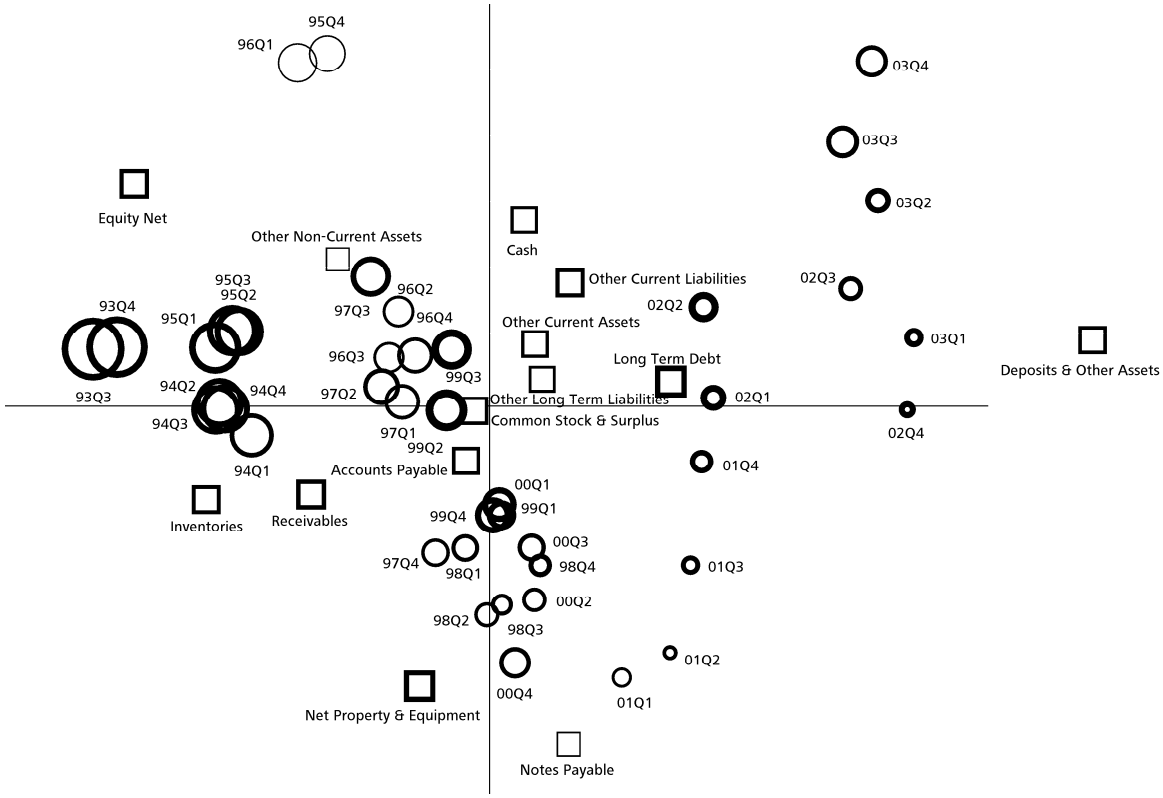

Figure 67 3M. Spectramap double space decomposition of wealth accounts (level C, 1993Q3-2003Q4). Biplot visualization of accounts & time points, scores and loadings on factor 1, 2 & 3 (outlines).

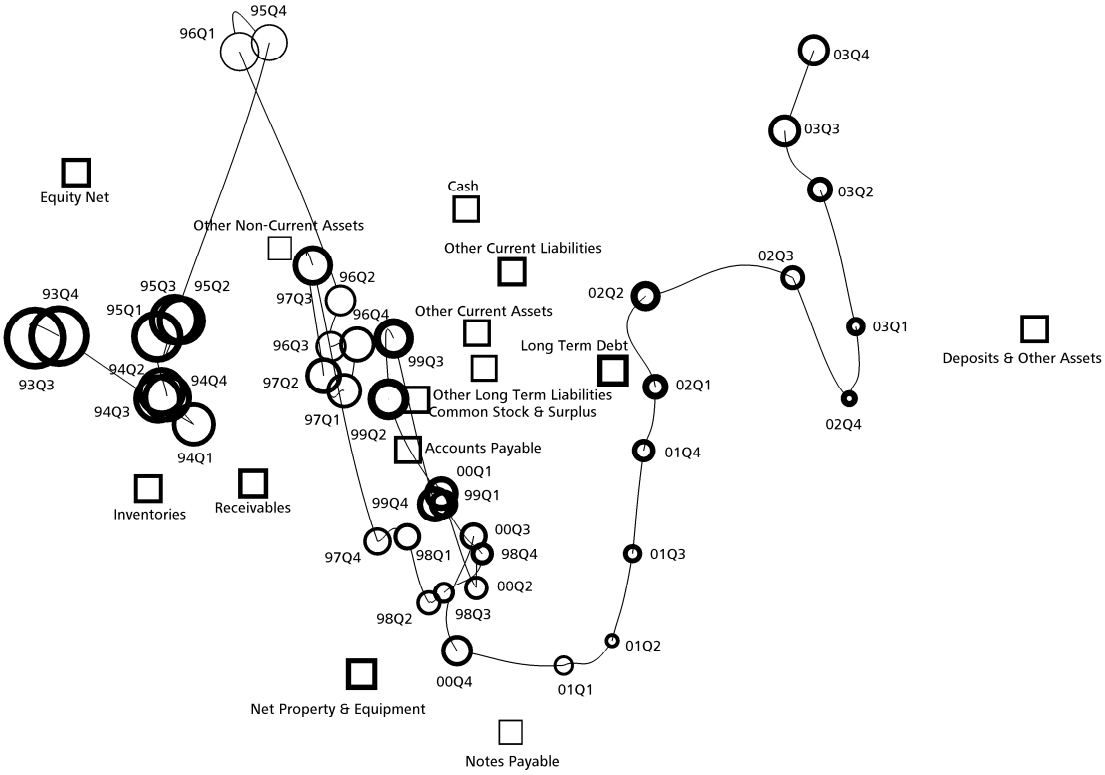

Figure 68 3M. Spectramap biplot with time points connected sequentially.

This notion is foundational to the generality assumption and, dare I say, to accounting as a discipline. The principal aim of spectramap analysis is the decomposition of a set of variables, in this case balance sheet items, in terms of smaller set of 'factors' or 'components.' The possible number of individual scatter plots (like FIGURE 63 and FIGURE 64) are condensed into a single biplot: the spectramap (FIGURE 67). In fact, the spectramap biplot is created by two factor solutions (hence the term *biplot*). The first is the row space decomposition of the 3M balance sheet accounts and discloses the variance of the table's columns (FIGURE 65). The second is the column space decomposition of 3M balance sheet quarters and discloses the variance of the table's rows, the time point measurements (FIGURE 66). Variance is an appropriate measure of dispersion for continuous variables and that are balance sheet data as well as their fractions.[6] Spectramap is a factor based multivariate decomposition method of variance and unique in combining these two 'data spaces,' or 'perspectives,' in the sense that column items and row items of a data table are treated in the same manner, statistically and conceptually. In both cases, we plot items against three orthogonal Cartesian axes, two of which we quickly recognize in FIGURE 65, FIGURE 66 and FIGURE 67. The third axis, the z-axis, is not displayed in these plots, as it is now perfectly perpendicular to the plane of projection. An impression of three dimensional structures of these plots is provided with COLOR FIGURE 9. The outline of an object symbol, respectively, squares and circles for table columns and rows, is an indication of the location of the item along the third factor, the z-axis. When the outline of an object symbol is thicker than it is positioned above the plane of projection (e.g. net property & equipment), and when the outline is thinner than it is positioned below the plane of projection (e.g. notes payable). This tells us that net property & equipment and notes payable have to some extent a similar overall trend during the ten-year period, but that they differ in contrast at particular points in time, which is explained by their third factor contrast signaled by the difference in outline thickness.

The spectramap axes are factors or latent variables that represent the best 'linear fit' of the balance sheet accounts and time points. They express the contrast that is present in the data in decreasing degree (TABLE 32). In FIGURE 65 and FIGURE 66, a line is drawn from the centre of the 'data space' to the symbol that represents, respectively, squares and circles for accounts and time points. Quick comparison of the angle of these lines with the horizontal and vertical axis of the plot can tell how much each balance sheet item correlates with the dominant contrast expressed by the components. In addition, the distance of each object from the centre is meaningful information. It is a measure of how much the trend of a variable differs from the trend of the data set as a whole. For example, common stock & surplus and accounts payable march in time very similar to the balance sheet as a whole, they are located very close to the centre. The same is valid for other current assets and other long term liabilities. However, the first two items have a thicker outline whereas the second group of items has a somewhat thinner outline. This signals that these accounts have a lot in common as well as a little difference. They share a similar profile for the first two components but differ for the third component. How important is this? To evaluate that we can check the variance explained by each factor in TABLE 32. Clearly, the first two factors are most relevant because together they explain 77% of variance of the original data table. This means that just by looking at FIGURE 67 we can understand

[6] This is not to say that balance sheet items cannot be classified; they can and are classified as assets and liabilities & equity. However, for data to be eligible for multivariate decomposition, measurement on a continuous scale is preferred.

77% of the information that is present in the quarterly balance sheets! Information defined here as the variance of objects from the mean value of rows or columns. The differences in outline thickness of the objects in FIGURE 67 accounts for another 8.8% of the information. That is large enough to be of interest and I will discuss further down the impact of that for my trend analysis together with the impact of the fourth and the fifth factor (together another 9%).

With spectramap, because here I use common size format balance sheets, I am able to measure the non-size related residual variation in the variables concerned across balance sheet line items on a time series basis (Sudarsanam & Taffler, 1995). This is of great advantage when we explore the 'nature' or trend of balance sheet items, as I expect that to be expressed in the spectramap biplots. It is interesting to observe that the balance sheet items vary greatly in position in FIGURE 67. This is a strong indication of balance sheet dynamics. It points at the fact that the relative proportion between balance sheet items is vastly different at the beginning of the ten-year period compared to the fractions at the end. We already learned this from the scatter plots at higher and lower levels of aggregation (FIGURE 63 and FIGURE 64). Spectramap not only confirms this, it also shows us which balance sheet items turn out to be the most responsible for this trend: equity net and inventories (left position: larger fraction at the start) and deposits & other assets (right position: larger fraction at the end). Yet again, this confirms that the generality assumption holds because the spectramap analysis is consistent with the scatter plot analysis.

Spectramap can reveal an aspect of time series that is not possible with scatter plot analysis: whether or not the time series has structural properties. In a scatter plot, like those of FIGURE 63 and FIGURE 64, the time series are fixed. Time progresses discretely along an axis, which has the advantage of readability, we can quickly pinpoint a variable measured against a date selected. But, this leaves unanswered the question if time itself can explain a change in the structure of the balance sheet. FIGURE 66 gives us the impression of an 'explosion' of time points. This is not intentional, this structure arises from the variance of the data in the quarterly balance sheets. FIGURE 66 explains to us that during the ten-year period, the 3M balance sheets changed dramatically in composition. FIGURE 68 shows just how spectacular this change really is. The direction of time's arrow runs from the left (1993) to the right (2003). This trend is neither linear nor random, which we can observe by looking at the curved line that connects each time point. Moreover, the time path wriggles at successive phases vertically, most noticeably from the first quarter 2001 to the fourth quarter in 2003. This indicates the impact of the second factor on the items. It explains the vertical trend following shifts in fractions of accounts like equity net, cash (upwards in FIGURE 68), and net property & equipment (downwards in FIGURE 68). With equity net we can make out how subtle such trends in time are. As we can observe from the decrease in size of the circles that represent each time point, as well as from their horizontal displacement from left to right, equity net proportionally decreases. Nevertheless, at the end of the time series, the time points move upwards. That signals the relatively small proportional increase of equity net during that time compared to previous points. In other words, although equity net in 2003 is still a smaller fraction of wealth compared to 1993, it is larger compared to 2001. To be able to detect such subtleties in a balance sheet is, in my opinion, like finding needles in a haystack.

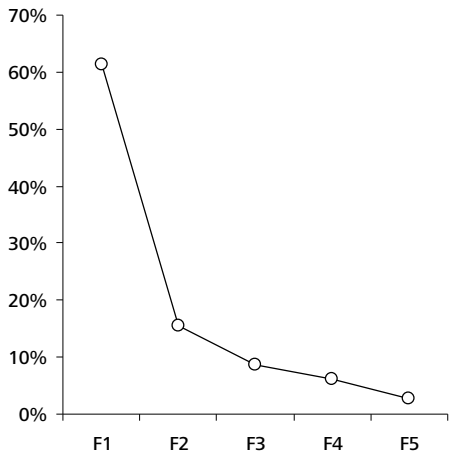

Figure 69 3M. Variance scree plot of factors.

	Panel A		Panel B	
	wealth		color coding	
	eigenvalue	cumulative	eigenvalue	cumulative
Factor 1	0.614			
Factor 2	0.156	0.770		
Factor 3	0.088	0.858		
Factor 4	0.062	0.920	0.062	
Factor 5	0.028	0.948	0.028	0.090

Table 32 3M. Variance explained by factor.

Spectramap balance sheet decomposition at level C (1993Q3-2003Q4).

6.4 Color coding of balance sheet items

By means of color coding the balance sheets items with one, two or three color dimensions, we are able to increase the information expressed by spectramap. Not only the horizontal axis, the vertical axis and the depth axis (outline) can visualize and explain the trends in the data—also, the color of balance sheet items can disclose trends as well. Strange as it may sound, whether or not balance sheet items are material in Color Figure 10 depends on their measure of color. From Table 32, we can read that the fourth and fifth factor explains 9% of the variance.

6.4.1 Higher factor's contribution

Statisticians recommend that, with multivariate decomposition analysis, we should ignore lower percentages of variance expressed by higher dimension factors or principle components.[7] The argument to do this is that it is likely that such variance is due to random noise and cannot provide information relevant to the analyst. To determine where the 'cut off point' is they employ a so called scree plot. The *scree plot* is a simple line segment plot that shows the fraction of total variance in the data as explained or represented by each factor. The rule of thumb is to plot all the Eigen values in their decreasing order along the x-axis (Figure 69).[8] The plot usually looks like the side of a mountain, and 'scree' refers to the debris fallen from a mountain and lying at its base. The *scree test* proposes to stop using sma factors for analysis at the point where the mountain side ends and the debris (likely random noise) starts to be collected, i.e. where the line segment takes a turn. In my case, as Figure 69 shows, that after the second factor it supposedly is no longer useful to employ the other factors.

Well, I am interested to learn if that is indeed the case with the balance sheets of 3M. Figure 70 is a spectramap that combines the geography of the fourth factor (horizontal arrow) and the fifth factor (vertical arrow), with that of two color dimensions: red—green color coding (vertical) and yellow—blue color coding (horizontal) in Color Figure 10, page 312. Naturally, this spectramap positions the balance sheet items and time points very differently

7 This section extends the original publication (Melse 2004b).

8 The term *eigen* can be translated as 'own,' 'peculiar to,' 'characteristic' or 'individual,' which emphasizes that eigenvalues define the unique nature of a specific transformation (this note is based on the Wikipedia lemma *Eigenvalue* from http://en.wikipedia.org).

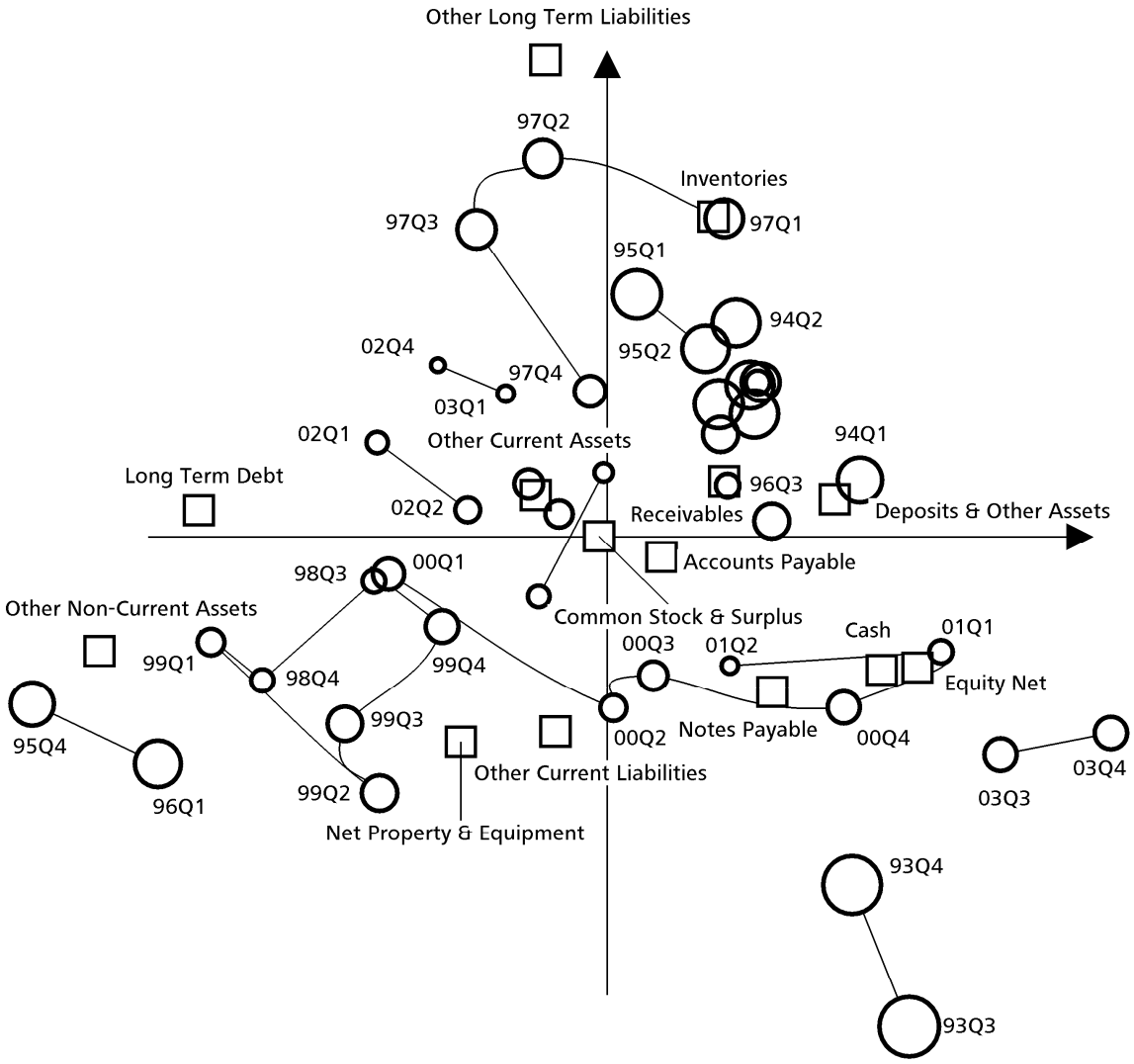

Figure 70 3M. Spectramap biplot of wealth accounts loadings and time points scores on factor 4 & 5 (level C, 1993Q3-2003Q4).

compared to Figure 68. Indeed, their position looks less organized when we study the time points. We cannot observe in Figure 70 the clear chronological order of Figure 68. In Figure 70, shorter periods of successive quarters do show a trend, which is indicated with lines that connect two or more quarters. Such trends do stop abruptly. This is also 'information' in the sense that we now can observe a series of trends that are more subtle, because less dominant in contrast. However, this contrast is still relevant to the analyst although it accounts only for 9% of the variance. We can diagnose in Figure 70 which balance sheet items are relevant by looking at their color as well as their position. Gray items, Color Figure 10, page 312, do not have variance expressed at all by factor four and five. Therefore, these achromatic objects are positioned at the centre of this spectramap. When items are positioned further away from the centre then they also will be colored: they are chromatic. Their hue, being yellow, green, blue, purple, red or orange indicates their uniqueness. For example, long term debt and other non-current assets are blue balance sheet items. But, they are of different natures: a liability item and an asset item respectively. Therefore, under the generality assumption, we should not claim a logical relation. However, we now can recognize that they do covariate with the fourth factor

(coded blue), and, for that reason, we must recognize their temporal relation: 'noncurrent-ness.' At the opposite end of the fourth factor (coded yellow[9]), we find current assets: cash, deposits and other assets, and a current liability: notes payable. Equity net is also located there, which seems to conflict with the inference that the fourth factor is about the opposition of 'noncurrent-ness' and 'current-ness.' Probably, we should read that cash and equity net covariate. That makes good sense as well. Short term cash increases or decreases will match parallel changes in the magnitude of equity net.[10]

6.5 Five dimensional analysis

Our final step in balance sheet analysis is the visualization of five principal components of variance explained. This is accomplished by the combination of Figure 68, the first three factors and color coding with the next two factors of Figure 70 & Color Figure 10 into Color Figure 11. This discloses the color of the balance sheet items and time points in the now familiar chronological structure. Color Figure 11 is structurally identical to Figure 68 but color coded. This adds a new layer of information together with the existing biplot. In terms of variance, color coding ads 9% to 85.8% already visualized to the total of 94.8% (Table 32). Color Figure 12 has the same quarters connected as in Color Figure 10. The fact that the sequence of these accounts is not at all haphazard, or random, indicates that there is specific and meaningful information present in the higher spectramap factors. Even though the scree plot suggests disregarding the third, fourth and fifth factor of the decomposition, in the present analysis that does not seem to be a sensible thing to do.

Close inspection of the location of color coded quarters and accounting variables leads to more understanding of the subtle associations between them. To highlight these, two more color figures are used that are identical to Color Figure 11 but which are rotated. Color Figure 13 and 11 are structurally identical to Color Figure 11 but each is rotated. They differ in projection because the data space was rotated to display in Color Figure 13 the triangular position of assets' contrast determined by deposits & other assets, other noncurrent assets and net property & equipment. Similarly, in Color Figure 14, equity net, notes payable and long term debt determine the triangular position of liabilities' contrast. Figure 68, Color Figure 13 and 11 are not different data spaces, but different views on the same three-dimensional structure of a single data space I established by the first three factors. In Figure 68 and Color Figure 11, the z-axis of the projection is perpendicular to the plane of projection. This is different in Color Figure 13 and 11, and indicated in the barycenter of the plot with three small red, green and blue lines for x, y and z. The outline thickness of the symbols again indicates the position of the object relative to the plane of projection, above or below that. However, the outline thickness is no longer only coupled with the distance along the data

[9] Yellow is a perceptual color that has a very high lightness level. At lower lightness levels yellow perceptually becomes greenish. This is a visual phenomena. When all other color stimuli are excluded to reach the retina – the thin layer of neural cells that lines the back of the eyeball that contains photoreceptor cells (rods and cones) that respond to light – yellow light at lower lightness levels is still seen as yellow but darker. I acknowledge Dr J. Walraven for allowing me to experience this perceptual phenomena at the Instituut voor Technische Menskunde TNO, Soesterberg.

[10] Recall that I came to the same conclusion in the previous chapter when the decomposition of total assets to first level of disaggregation was studied (level B). Apparently, the association between net wealth and cash is maintened at this lower level of disaggregation (level C), albeit in the more specific fourth component.

space z-axis that is identical to the relative position below or above the plot's plane of projection in FIGURE 68 and COLOR FIGURE 11 and 9. Instead, in COLOR FIGURE 13 and 11 the outline thickness is only coupled with the relative position below or above the plot's plane of projection.

One cannot fail to notice the striking patterns of color that we can observe in the spectramap of both the assets plane and the liabilities plane. In total, I explicate with the spectramap biplot 94.8% of the variance and that seems to make considerable difference. Can we infer more information from COLOR FIGURE 13 and 11 than from FIGURE 68? Indeed, I think that is the case. For example, the liabilities plane visualizes vertically located groups of successive periods with their unique color: reddish from third quarter 1994 up to third quarter 1997, bluish from third quarter 1998 up to fourth quarter 1999. This matches with particular accounts, respectively: inventories and other long term liabilities, and with other noncurrent assets and long term debt. This signals the dominance of these balance sheet items on a more subtle level during a certain time-period. Another interesting feature that strikes the eye is that single time points are colored univocally. For example, fourth quarter 2003 is a bright yellow, which we cannot match with a balance sheet item on the spectramap. How should we read this yellow color? Recall how the color system of opposite sensations works. Against yellow we find blue. We can interpret opposite colors straightforwardly in spectramap as opposite factor loadings (see COLOR FIGURE 10). The fact that we see no 'yellow balance sheet item' on the spectramap does not prohibit analysis of the time point measurement. What it means is that this quarterly balance sheet discloses dynamics opposite that of the blue colored items: other noncurrent assets and net property & equipment. I see this confirmed through the assets plane in COLOR FIGURE 13. Fourth quarter 2003 is located far away from these two items. In addition, I notice that the third dominant asset — deposits & other assets — is ochre colored, i.e. a more dark yellow. There is also logic in this univocal color code. Clearly, the chronological trend shifts in favor of that item: away from blue colored assets.

Finally, observe that the assets plane and the liabilities plane are structurally more or less orthogonal related. This means that apparently opposing dynamics 'have been at work' during the ten-year period. It makes a lot of sense, thinking back to the scatter plot of FIGURE 62, left. At 3M, noncurrent liabilities are growing proportionally, current assets are decreasing at the same time, this I see confirmed at a disaggregated level in spectramap in five dimensions. What better evidence in support of the generality assumption can I ask for?

6.6 Conclusion

What I strived to contribute in this chepter is an objective method to determine if and how much variance, present in balance sheets, is traceable to one or more trends in time. If these can be associated to balance sheet items and if it is possible to derive one simple structure that encapsulates all these trends and that points at relationships between them, then, possibly, I am able to form an opinion of corporate financial development as a whole. This should increase the usability of balance sheet data and underpin the explanatory power of this financial statement.

In this study I recognized a structure of balance sheet items as an essential constituent or characteristic of a company's development over time. It is of considerable importance to be able to detect that such trends arise from the data rather then to assume them and impose it on

the analysis. Considering the TEMA framework, such trends arise from forces I seek to disclose. When clusters of balance sheet items are grouped together I am more safe to assume that they covariate over time. On the other hand, the fact that balance sheet items are positioned at greater distances from each other in such structure, or data space, this force me to recognize that a considerable contrast may also exist within the data. Depending on their position at opposite ends of the path of time points, I can detect a relative decrease or increase of their importance or weight on the whole balance sheet. When balance sheet items are placed perpendicular to the time path I concluded that a continuous but stable contrast is apparent. For 3M company the conclusion is that both these contrasts apply.

My analysis benefited greatly from the ability to color code the three-dimensional data space structure of the balance sheet with an additional two dimensions of the CIELAB color space. Most revealing is the fact those successive periods in the series of quarterly balance sheets code noticeably with the same color whereas other points in time spring out univocally. What is also of interest is that the color codes of time points match individual balance sheet items, either in harmony or in opposition. My conclusion is that this signals contrast in addition to the trend of the balance sheet as a whole. I read this as a signal that could trigger the auditor or analyst of financial statements to focus her enquiry to particular balance sheet items in relation to one or more points in time. This method offers a novel approach to investigate the development of a company over time as well as a new means to quickly focus the attention to a change of trend in general or a balance sheet item in particular. Moreover, I expect that spectramap analysis together with color coding will provide further insight into the structure of accounts in ther accounting dimensions of the TEMA framework (Melse 2004A). I envisage that this is of interest to any financial statement user and recognize its potential benefits for auditing (Bell *et al.* 1997), as well as for strategic accounting and control (Brouthers & Roozen 1999, Roslender & Hart 2003). Ideally, further research and practice could enable any company to disclose the color of its balance sheet.

Part II

Time Series Analyses

7

The Explanatory & Predictive Power of TEMA — the AEX

An Empirical Study of the Amsterdam Stock Exchange Component Companies.

Kwartaalschrift Economie, December 2005, Vol. 2, No. 4., pp. 361-389.

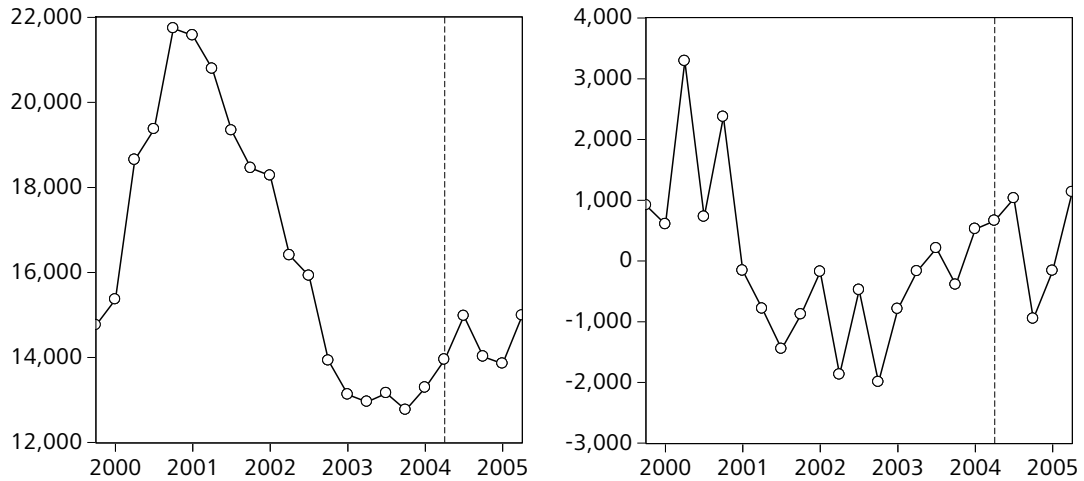

Figure 71 Philips. Left: net wealth, right: net wealth momentum (1999Q4-2005Q2).

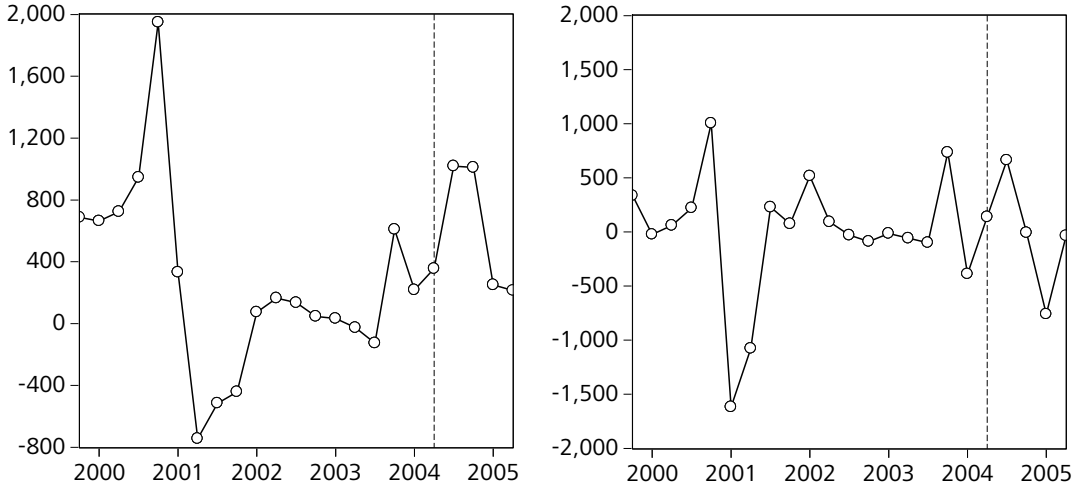

Figure 72 Philips. Left: operating income, right: operating income force (1999Q4-2005Q2).

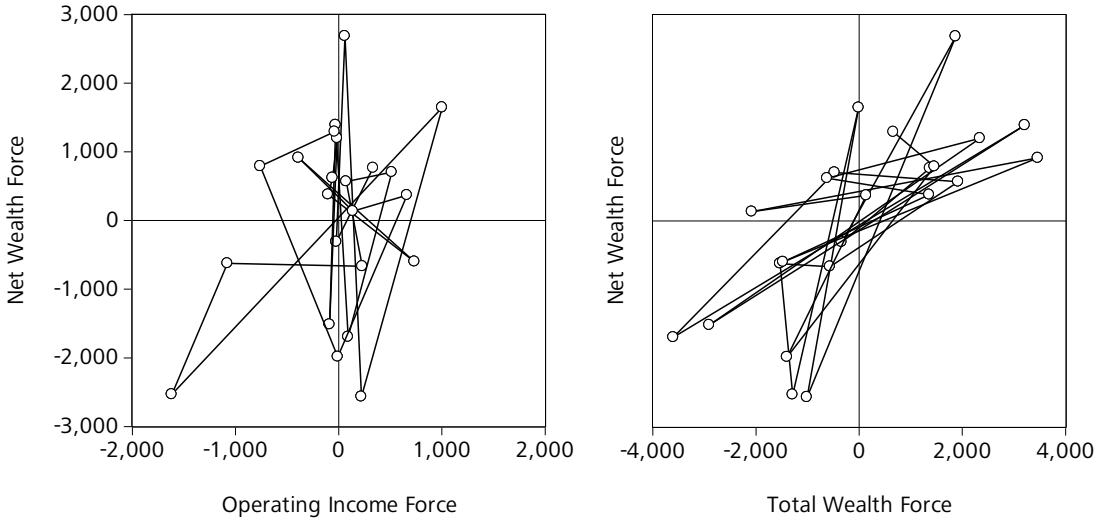

Figure 73 Philips. Net wealth force versus operating income force (left) & total wealth force (right).

7 Abstract

This chapter is the first study of the second part of this thesis, which are studies of the econometric TEMA *models, and presents a detailed discussion of Royal Philips Electronics N.V. It explains ex post and forecasts ex ante as well as the trend of net wealth, or equity. The conclusion is that in this case each of the three* TEMA *models has sufficient explanatory power. The ex ante static simulation has a success rate of about 83% for both net wealth force and the aggregated measure of net wealth. The implication is that the generality assumption of the* TEMA *framework is confirmed. My analysis of the quarterly financial statement data of Philips leads to the question if we can expect similar results with all other firms listed on the* AEX.

The analysis is presented of the directional change of force and momentum of the 24 companies that are listed on the AEX. *Directional change analysis is a methodology to study the association between the change dynamics of momentum and force variables. The directional change of operating income and net wealth momentum is shown to be consistent and does not seem to vary much relative to the number of years available per firm or to the selected set of firms to be modeled. However, the force measures are a little less consistent which is somewhat disturbing because it appears rather difficult to 'guestimate' how net wealth force will tend to behave given the trend of operating income force or total wealth force.*

For 17 of the AEX *companies also the explanatory and predictive power is analyzed in this study. Explanatory power is shown to be significant for operating income (71%), total wealth (94%) as well as for the combination in a joint* TEMA *model (82%). Their predictive power, however, with a time horizon of three years is much lower for the modeled time series, respectively 64%, 79% and 52%. This might be due to fact that annual time series were used for lack of the availability of quarterly data. The result of my investigation of 17* AEX *firms is encouraging and gives ample support for the main research thesis* H 1_a *that there is a general relationship between accounting variables in the dimensions of the* TEMA *framework of Ijiri. This study confirms also the research hypotheses* H 4_a, H 5_a *and* H 7_a. *Operating income and total wealth are associated with net wealth and can forecast its trend. The* TEMA *framework is decisive in the selection of accounting variables that have the same temporal dimension. Hence, I argue that* ARIMA *based* TEMA *models, as suggested by Ijiri, are a viable alternative for more detailed triple-entry bookkeeping and financial reporting.*

7.1 Introduction

As example I present in this chapter Royal Philips Electronics N.V.[1] Although the option is not available in this study to generalize the result of this example on a statistical basis to a population I will try to replicate it with other firms (Vaus 2002, 148). To this purpose I use data of 17 of the 24 firms that that are listed on the AEX, the Amsterdam stock exchange. I presuppose that when I find more confirmatory examples my confidence may grow in the underlying (accounting) theory. The research question I want to answer in this chapter is: have the financial variables of the TEMA framework any explanatory and predictive power?

[1] This chapter is the English translation of the original Dutch publication (Melse 2005). It was updated and cross-referenced to other chapters of this thesis. The introductory sections and some other sections were modified and moved to the Dutch summary, Chapter 12. The econometric analysis of the quarterly time series of Philips was repeated with time series extended to the second quarter of 2005.

	quarter	Philips Net Wealth NW	Net Wealth Momentum ∇NW	Net Wealth Force ∇²NW	Philips Total Wh TW	Total Wh Momentum TWM	Total Wh Force ∇²TWF	Operating Income OI	Oper. Inc. Force OIF
	1999Q2	13,702	-	-	27,464	-	-	-	-
	1999Q3	13,846	144	-	27,795	331	-	352	-
EP 1	1999Q4	14,757	911	767	29,496	1,701	1,370	687	335
EP 2	2000Q1	15,358	601	-310	30,861	1,365	-336	663	-24
EP 3	2000Q2	18,645	3,287	2,686	34,099	3,238	1,873	724	61
EP 4	2000Q3	19,367	722	-2,565	36,325	2,226	-1,012	945	221
EP 5	2000Q4	21,736	2,369	1,647	38,541	2,216	-10	1,949	1,004
EP 6	2001Q1	21,574	-162	-2,531	39,469	928	-1,288	332	-1,617
EP 7	2001Q2	20,788	-786	-624	38,866	-603	-1,531	-745	-1,077
EP 8	2001Q3	19,336	-1,452	-666	37,700	-1,166	-563	-516	229
EP 9	2001Q4	18,453	-883	569	38,454	754	1,920	-442	74
EP 10	2002Q1	18,274	-179	704	38,734	280	-474	73	515
EP 11	2002Q2	16,399	-1,875	-1,696	35,412	-3,322	-3,602	165	92
EP 12	2002Q3	15,917	-482	1,393	35,303	-109	3,213	135	-30
EP 13	2002Q4	13,919	-1,998	-1,516	32,289	-3,014	-2,905	47	-88
EP 14	2003Q1	13,124	-795	1,203	31,621	-668	2,346	32	-15
EP 15	2003Q2	12,950	-174	621	30,333	-1,288	-620	-26	-58
EP 16	2003Q3	13,156	206	380	30,404	71	1,359	-126	-100
EP 17	2003Q4	12,763	-393	-599	29,000	-1,404	-1,475	608	734
EP 18	2004Q1	13,286	523	916	31,061	2,061	3,465	218	-390
EP 19	2004Q2	13,944	658	135	31,042	-19	-2,080	356	138
EA 1	2004Q3	14,972	1,028	370	31,160	118	137	1,019	663
EA 2	2004Q4	14,016	-956	-1,984	29,879	-1,281	-1,399	1,010	-9
EA 3	2005Q1	13,851	-165	791	30,057	178	1,459	250	-760
EA 4	2005Q2	14,980	1,129	1,294	30,899	842	664	213	-37

EP = ex post, base period time series. EA = ex ante, hold-out sample. Financial data x 1.000.000. Source: Reuters.

Table 33 Philips. Momentum and force measures. The data from 1999Q4-2004Q2 were used for the regression models the ex post simulation. 2004Q3-2005Q2 is the hold-out sample period for the ex ante simulation.

Royal Philips N.V.	test	ADF	t-value	p-value	test	PP	t-value	p-value
Net wealth (1)	-4.5326	1%	-4.0291	0.0260	-3.2774	10%	-2.2340	0.4461
Net wealth momentum (1)	-3.2774	10%	-2.7471	0.2309	-3.0300	5%	-2.6880	0.0943
Net wealth force (2)	-3.8315	1%	-7.9351	0.0000	-3.8315	1%	-7.5100	0.0000
Total wealth (1)	-3.6736	5%	-3.3459	0.0890	-3.2774	10%	-2.3073	0.4107
Total wealth momentum (1)	-3.6736	5%	-3.4585	0.0733	-3.6736	5%	-3.5304	0.0646
Total wealth force (2)	-3.8315	1%	-8.0898	0.0000	-3.8315	1%	-8.0898	0.0000
Operating income (2)	-2.6552	10%	-2.2585	0.1941	-2.6552	10%	-2.3519	0.1673
Operating income force (2)	-3.8315	1%	-4.2528	0.0042	-3.8315	1%	-4.6444	0.0018

ADF = Augmented Dickey-Fuller. PP = Phillips-Perron. TEST = test critical value.

Incl. (1) constant & linear trend, (2) constant. Base period sample: 1999Q4-2004Q2.

Table 34 Philips. Unit root test statistics.

Therefore, my focus is on the hypotheses H 4_a, H 5_a and H 7_a of this thesis (see section 1.8, page 29). Empirical data is used: quarterly financial statements data of Royal Philips Electronics N.V. and the annual financial statements data of 17 out of the 24 AEX listed firms. My analysis shows — which are discussed in section 7.2 and 7.3 — that it is possible to explain ex post the trend of net wealth of Philips as well as for 17 of the AEX listed firms and in more than halve of those cases the trend can be forecasted ahead one to three years.[2]

[2] Chapter 1 discusses this more extensively as well as the larger research objective and motivation.

7.2 Royal Philips Electronics N.V.

I employ quarterly balance sheet and income statement data to explain and predict with TEMA models the trend of net wealth of Royal Philips Electronics N.V. Econometric models using quarterly data are only possible for a limited number of the AEX listed firms. Only 6 out of 24 firms have time series of sufficient length, namely 20 quarters or more.[3] One of these is Philips and my choice for this firm is notional and serves only as an example of the application and corroboration of the TEMA framework (FIGURE 1).

7.2.1 Econometric tests

The basic approach of the time series regression analysis is to model the dependent variable as a function of independent variables that are possibly lagged (Startz 2007, 316). It is assumed that such time series are (weakly) stationary and do not exhibit stochastic or deterministic trend behavior (Koop 2000, 132). FIGURE 71, left, of the net wealth time series by quarter of Philips is a good example of a time series with stochastic trend behavior. When such data is used in a regression model we have the risk that spurious regression occurs between the dependent and the independent variables (Id. 133-134, 148). To exclude this risk, two so called *unit root* tests are performed on the variables of this study: the Augmented Dickey-Fuller test (ADF) and the Phillips-Perron test (PP). Both have as their null hypothesis that the time series has a unit root and does not exhibit the desired property of stationary or mean reverting behavior. Should a time series have a *unit root* then it has a tendency to rise or decline continuously. Indeed, this is the case with net wealth time series of Philips as it keeps growing in the period 1999-2000 but, thereafter, it keeps decreasing during in the period 2001-2003 (FIGURE 71, left). The alternative is to use the first difference of the time series which is a momentum measurement, in the terminology of the TEMA framework of Ijiri.[4] However, this in itself is not a guarantee that stationarity will then be present in the time series. For example, note that the ADF and PP. test for net wealth momentum fail to reject the null of the presence of a unit root, respectively at the 10% and 5% confidence level (TABLE 34). Therefore, differencing the time series a second time is required, which is a force measurement in the terminology of the TEMA framework. Both the ADF and PP. test now reject the null at the 1% confidence level (TABLE 34).[5]

Momentum and force measurements are calculated by the difference of two quarters of data, by EQUATION (8) for momentum and EQUATION (9) for force (page 53). In this manner, the Philips' time series are 23 measurements long (1999Q4-2005Q2, TABLE 33). FIGURE 71, right, is the net wealth momentum of Philips and the stationary character of the times series can be observed in the steady decrease from the first quarter of 2000 to the third quarter of 2002. Noteworthy is that the speed of growth of net wealth increases from that point onwards for a year to the third quarter of 2003. Likewise, when we observe operating income in FIGURE 72, left, a momentum measurement (FIGURE 1, page 2), it also does not show signs of a stationary pattern. After a steep increase during 2000, we observe first a declining trend in this the time series followed by a recovery after the third quarter of 2003

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3 I.e. at the time when the original publication was written. To be able to develop reliable econometric models time series with a minimum of 20 measurements are required.

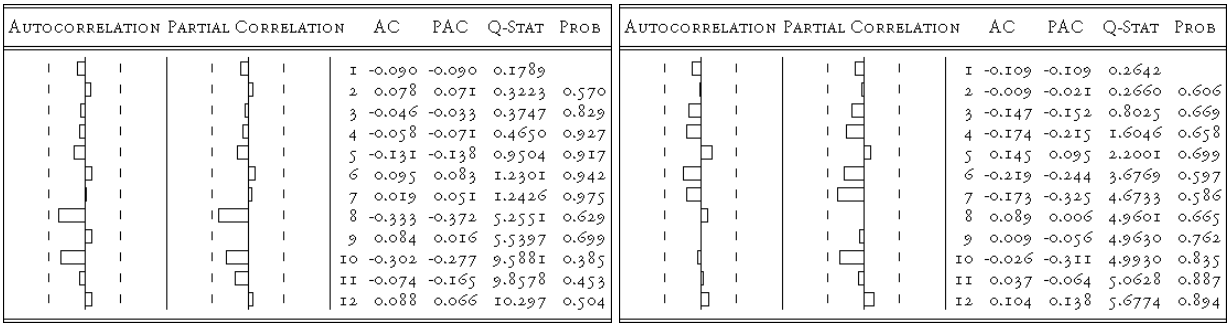
4 The required calculations are explained in section 2.3.1, page 52.

5 All econometric models, and their tests, were made with the software *Eviews*, standard edition, version 5.1, Quantitative Micro Software, LLC.

	A: Model statistics			B: 95% Confidence Interval*		
	Joint Model	Total Wealth Force	Operating Income Force	Joint Model	Total Wealth Force	Operating Income Force
Intercept	20.67	15.20	52.00	[-102, 144]	[-143, 174]	[-205, 309]
Standard Error	71.05	91.77	148.52	246	317	514
Total Wealth Force	0.53	0.59		[0.31, 0.74]	[0.34, 0.85]	
Standard Error	0.13	0.15		0.43	0.51	
P-value	0.0008	0.0010				
Operating Income Force	0.42		0.84	[0.09, 0.75]		[0.35, 1.33]
Standard Error	0.19		0.28	0.66		0.98
P-value	0.0425		0.0095			
AR(1)	-0.74	-0.77	-0.61	[-0.99, -0.49]	[-1.07, -0.46]	[-0.83, -0.38]
Standard Error	0.14	0.17	0.13	0.50	0.60	0.46
P-value	0.0001	0.0004	0.0003			
Standard Error model	696.73	737.23	1,080.42			
Adjusted R2	0.75	0.72	0.41			
Aikake Inf. Criterion	16.12	16.19	16.95			
F-statistic	19.41	24.70	7.22			
P-value (two tailed test)	0.0000	0.0000	0.0058			
Durbin-Watson AC	2.33	2.19	2.08			
Breusch-Godfrey LM	1.44	0.43	0.45			
P-value $\chi 2$	0.2309	0.5134	0.5017			
White Heteroskedasticit	1.00	1.34	0.35			
P-value $\chi 2$	0.6055	0.2465	0.5516			

* Lower and upper 95% between brackets and interval.

Table 35 Philips. Regression test statistics for net wealth force (base period: 1999Q4-2004Q2).



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.090	-0.090	0.1789	
		2	0.078	0.071	0.3223	0.570
		3	-0.046	-0.033	0.3747	0.829
		4	-0.058	-0.071	0.4650	0.927
		5	-0.131	-0.138	0.9504	0.917
		6	0.095	0.083	1.2301	0.942
		7	0.019	0.051	1.2426	0.975
		8	-0.333	-0.372	5.2551	0.629
		9	0.084	0.016	5.5397	0.699
		10	-0.302	-0.277	9.5881	0.385
		11	-0.074	-0.165	9.8578	0.453
		12	0.088	0.066	10.297	0.504

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.109	-0.109	0.2642	
		2	-0.009	-0.021	0.2660	0.606
		3	-0.147	-0.152	0.8025	0.669
		4	-0.174	-0.215	1.6046	0.658
		5	0.145	0.095	2.2001	0.699
		6	-0.219	-0.244	3.6769	0.597
		7	-0.173	-0.325	4.6733	0.586
		8	0.089	0.006	4.9601	0.665
		9	0.009	-0.056	4.9630	0.762
		10	-0.026	-0.311	4.9930	0.835
		11	0.037	-0.064	5.0628	0.887
		12	0.104	0.138	5.6774	0.894

Figure 74 Philips. Correlogram of NWF model residuals. Left: operating income force. Right: total wealth force.

A: static forecast	RMSPE	Mean Band
Total Wealth Force Operating Income Force	2,201,462	4,059
Total Wealth Force	1,817,691	4,240
Operating Income Force	1,933,133	4,666

B: dynamic forecast	RMSPE	Mean Band
Total Wealth Force Operating Income Force	1,848,266	4,817
Total Wealth Force	1,966,941	4,900
Operating Income Force	1,535,045	5,143

Table 36 Philips. Root Mean Square Prediction Error (RMSPE) values of net wealth force model simulations. Panel A: hold-out period static forecast. Panel B: hold-out period dynamic forecast.

to new average. During the seven quarters of the period 1999Q3-1999Q3 the mean is 807 (547) and during the period 2003Q4-2005Q2 the mean is 525 (362). Note that the standard deviation is smaller for the second period at the end of the time series indicating that it exhibits less dispersion. However, the coefficient of variation is about the same for both periods: 0.678

and 0.688, respectively.[6] The implication is that the structural dynamic of operating income exhibits some similarity during these two periods. Such property could be of importance for the econometric modeling of income and, I expect, that should also be exposed as explanatory and predictive power of TEMA variables for Philips.

7.2.2 *Regression models*

In this section I present for Philips the association between the financial accounting variables net wealth, operating income and total wealth within the TEMA framework (FIGURE 2, page 2). To illustrate the choice for the selection of operating income force and total wealth force as the independent variables observe FIGURE 73. In the two figures, the x-axis plots the trend of, respectively left and right, operating income force and total wealth force against net wealth force which is plotted by the y-axis. The quarters have a tendency to plot around a trend line, respectively vertical and diagonal, for operating income force and total wealth force. However, econometric analysis should provide evidence that is consistent with this visual impression and corresponds to some degree with explanatory regression models.

The dynamics of operating income force, total wealth force or both drive the model. When we aggregate *force* into *momentum* and that into *wealth* we recover the net wealth time series (FIGURE 6, page 53). Of the accounting variable time series, the base period used is from the fourth quarter 1999 to the second quarter 2004 to test ex post the explanatory power (TABLE 33). The period from the third quarter 2004 to the second quarter 2005 will be used as a hold-out sample to evaluate ex ante the predictive power of the independent variables in the ordinary least squares regression models. To be consistent in the TEMA framework I use operating income force and total wealth force to explain net wealth force in a balanced regression model (EQUATION 15), page 59). Additionaly, the autoregressive (AR) variable is added to correct for the presence of first order autocorrelation which was diagnosed. Thus, the regression model used to explain the dependent variable net wealth force ($\nabla^2 \mathsf{Y}$) has the general form:

(26) PHILIPS NWF, $\nabla^2 \mathsf{Y}_t = \alpha + \beta_1 \nabla^2 \mathsf{X}_t + \beta_2 \nabla \mathsf{Z}_t + \phi_1 \mathsf{V}_{t-1} + \mathsf{u}_t$ with t=1, …, T,

and now includes three independent variables: total wealth force ($\nabla^2 \mathsf{X}$), operating income force ($\nabla \mathsf{Z}$) and the AR variable to correct for first order autoregression ($\phi_1 \mathsf{u}_{t-1}$). The models were run with the Newey-West correction for heteroskedasticity and autocorrelation consistent standard errors. This modeling methodology leads to a more compact simulation mean band while the equal regression coefficients' remain the same as without correction.

7.2.3 *Test statistics*

I briefly discuss the statistic results from the three regression models of net wealth force time series that are reported in TABLE 35. The incremental effect of operating income force, total wealth force as well as the joint model is strongly significant because the P-value of the F-statistics is less than 1% for all three models. Thus, I am confident that the coefficients differ from zero (Startz 2007, 66). The overall fit of the operating income model differs considerably from the total wealth force model. Respectively, the Adjusted R^2 values of explained variance are 41% and 72% (0.41, 0.72). The joint model has the best overall fit, namely: 75% (0.75). This finding is confirmed by the result of the Akaike Information Criterion which has the lowest

[6] The coefficient of variation of a sample is a dimensionless number that can be used to compare the amount of variance between populations, in this example time period measurements, with different means and is the ratio of the standard deviation to the mean.

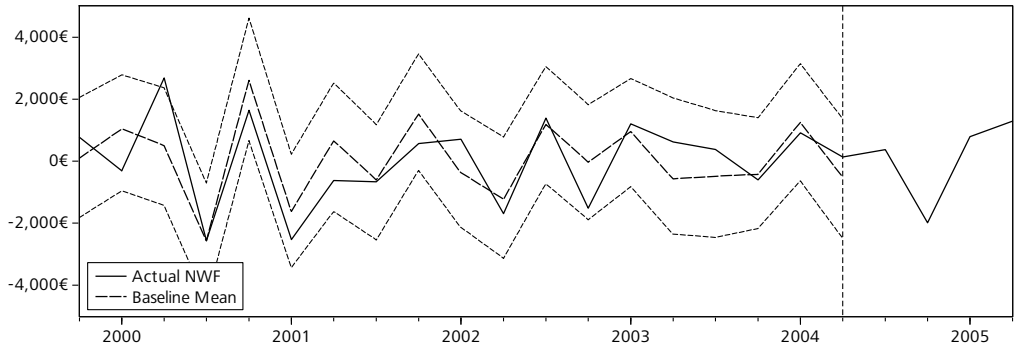


Figure 75 Philips. Base period static forecast of net wealth force by total wealth force & operating income force.

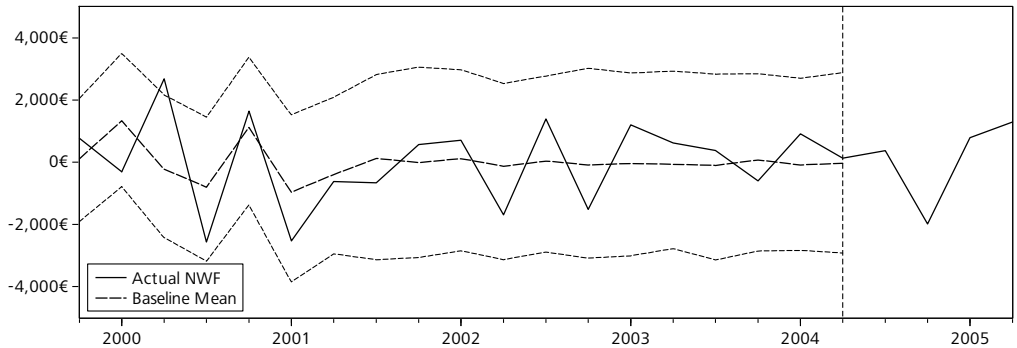


Figure 76 Philips. Base period dynamic forecast of net wealth force by total wealth force & operating income force.

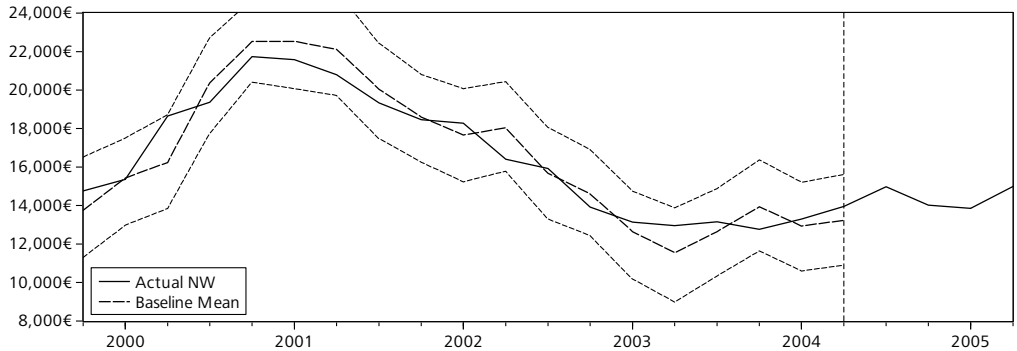


Figure 77 Philips. Base period static forecast of net wealth by operating income force.

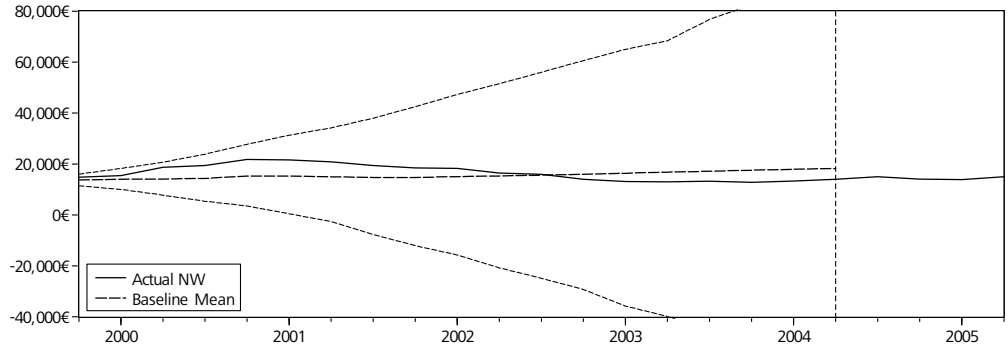


Figure 78 Philips. Base period dynamic forecast of net wealth by operating income force.

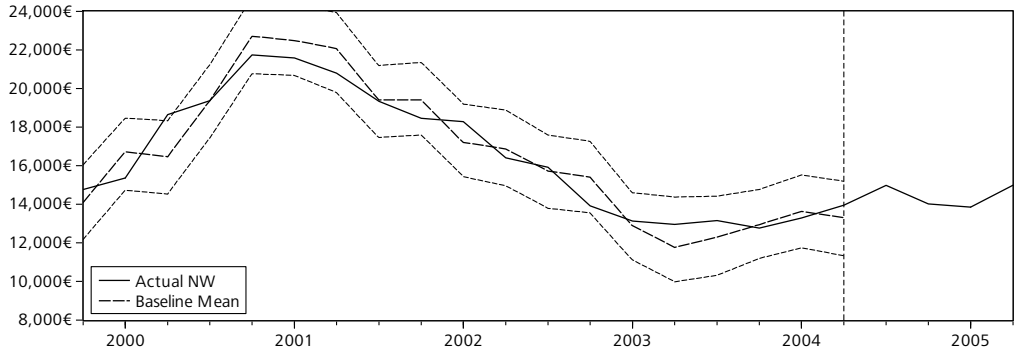


Figure 79 Philips. Base period static forecast of net wealth by total wealth force & operating income force.

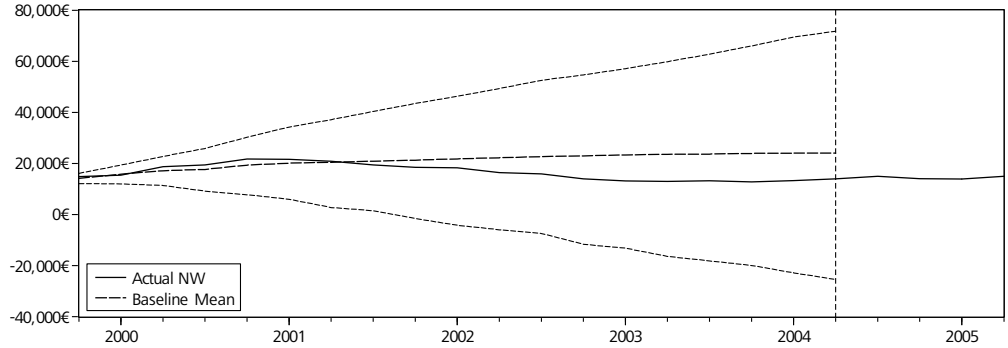


Figure 80 Philips. Base period dynamic forecast of net wealth by total wealth force & operating income force.

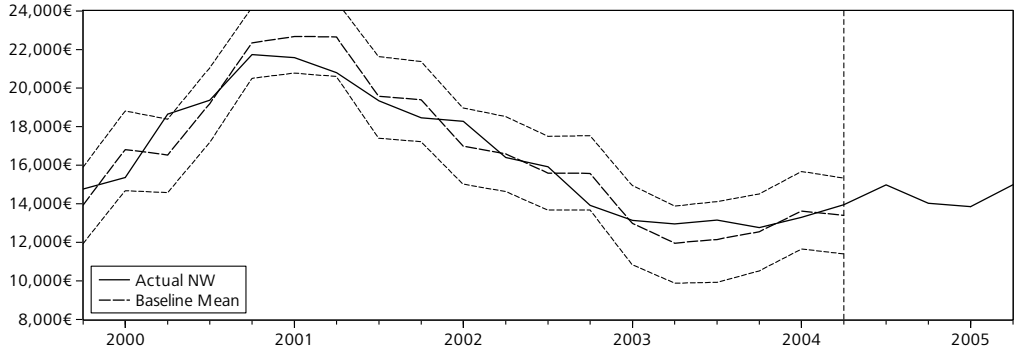


Figure 81 Philips. Base period static forecast of net wealth by total wealth force.

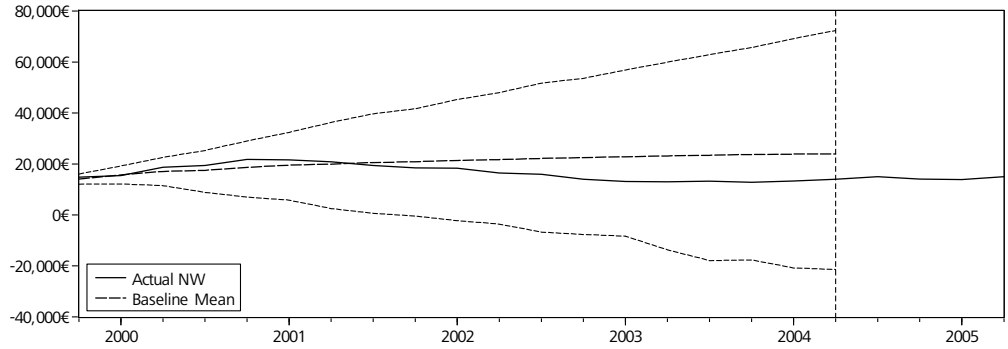


Figure 82 Philips. Base period dynamic forecast of net wealth by total wealth force.

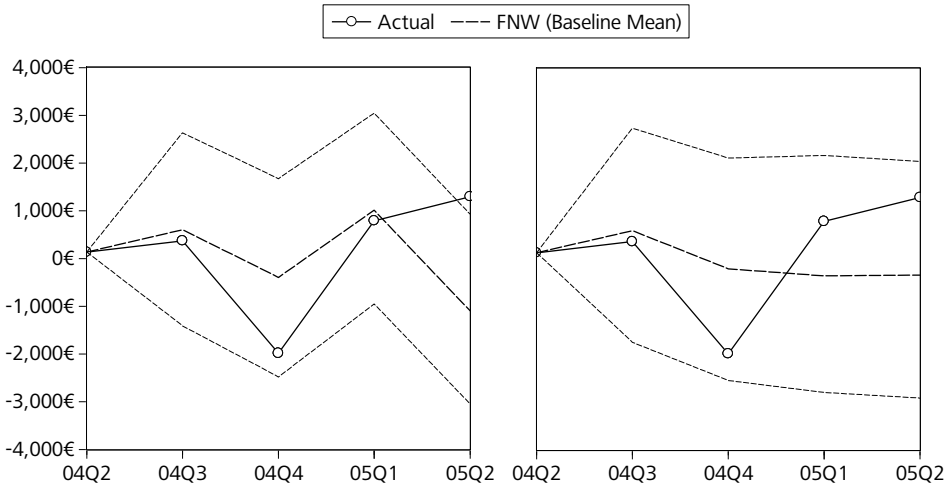


Figure 83 Philips. Hold-out sample forecast of net wealth force by total wealth force & operating income force. Left: static forecast & right: dynamic forecast (2004Q2-2005Q2).

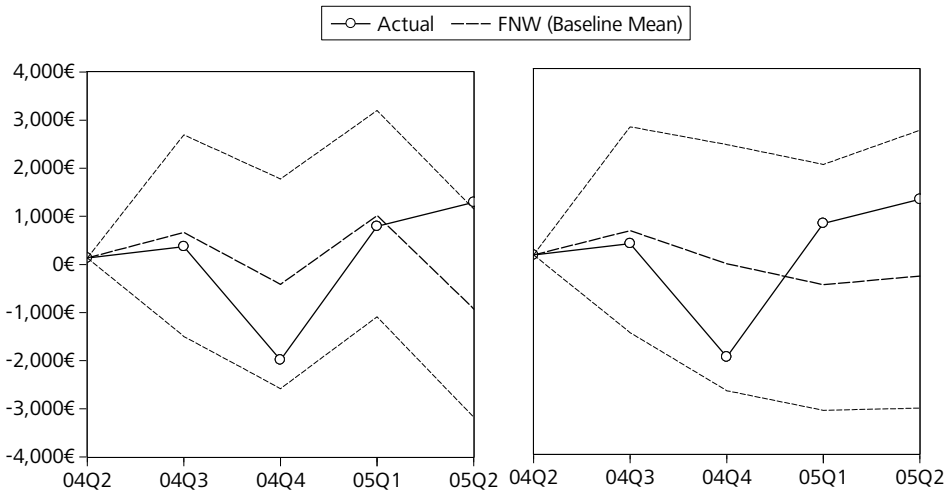


Figure 84 Philips. Hold-out sample forecast of net wealth force by total wealth force. Left: static forecast & right: dynamic forecast (2004Q2-2005Q2).

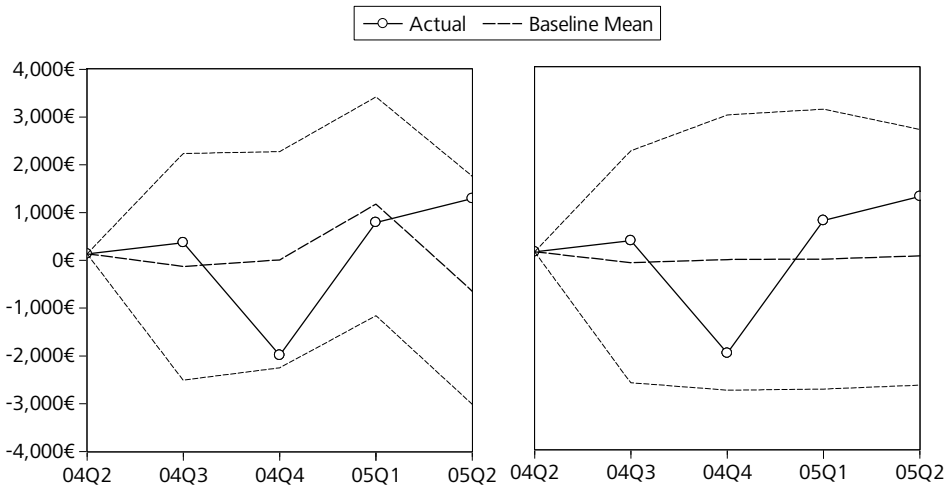


Figure 85 Philips. Hold-out sample forecast of net wealth force by operating income force. Left: static forecast & right: dynamic forecast (2004Q2-2005Q2).

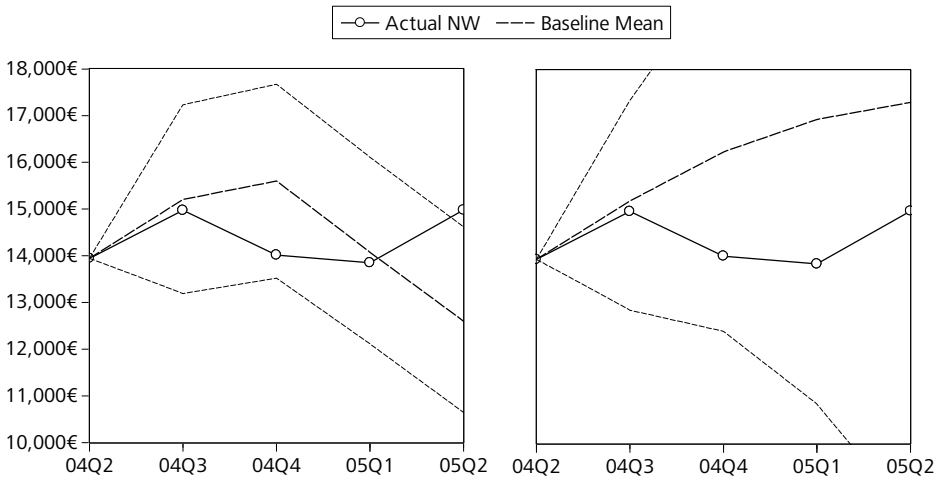


Figure 86 Philips. Hold-out sample forecast of net wealth by total wealth force & operating income force. Left: static forecast & right: dynamic forecast (2004Q2-2005Q2).

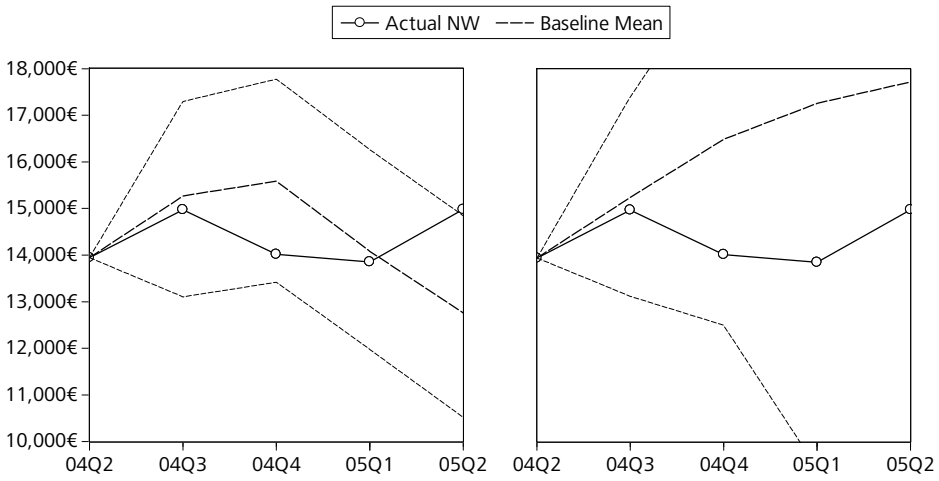


Figure 87 Philips. Hold-out sample forecast of net wealth by total wealth force. Left: static forecast & right: dynamic forecast (2004Q2-2005Q2).

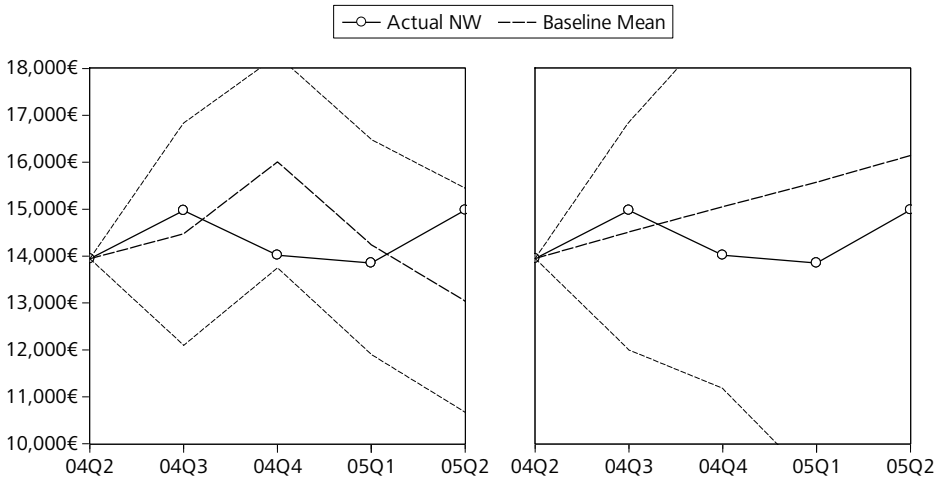
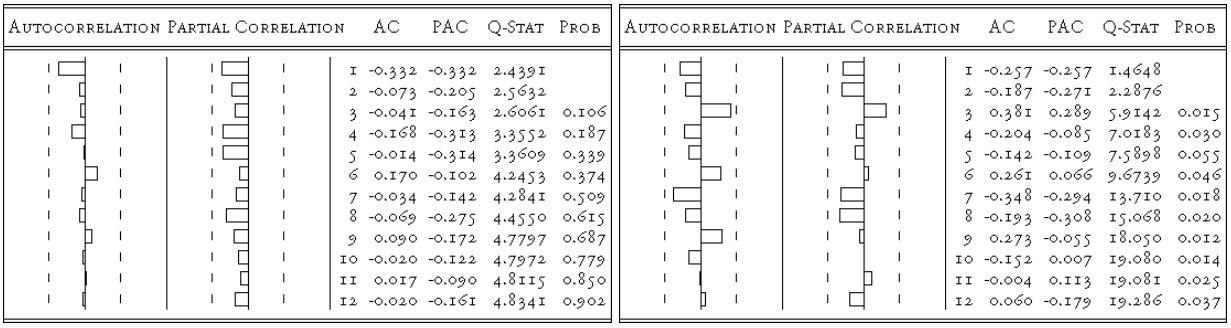


Figure 88 Philips. Hold-out sample forecast of net wealth by operating income force. Left: static forecast & right: dynamic forecast (2004Q2-2005Q2).

	Total Wealth Force	Operating Income Force
Intercept	139.32	18.41
Standard Error	129.1796	63.9121
AR(1), AR(1)	-0.80	-0.19
Standard Error	0.1453	0.2289
P-value	0.0000	0.4132
MA(7), MA(10)	-0.96	-0.98
Standard Error	0.0514	0.0353
P-value	0.0000	0.0000
Standard Error model	983.27	199.51
Adjusted R2	0.76	0.88
F-statistic	29.61	67.52
P-value (two tailed test)	0.0000	0.0000
Durbin-Watson AC	2.39	2.62
Breusch-Godfrey LM	1.60	4.59
P-value $\chi 2$	0.2066	0.0321

Table 37 Philips. Regression test statistics for ARIMA models base period estimation: 1999Q4-2004Q2.



	AC	PAC	Q-Stat	Prob
1	-0.332	-0.332	2.4391	
2	-0.073	-0.205	2.5632	
3	-0.041	-0.163	2.6061	0.106
4	-0.168	-0.313	3.3552	0.187
5	-0.014	-0.314	3.3609	0.339
6	0.170	-0.102	4.2453	0.374
7	-0.034	-0.142	4.2841	0.509
8	-0.069	-0.275	4.4550	0.615
9	0.090	-0.172	4.7797	0.687
10	-0.020	-0.122	4.7972	0.779
11	0.017	-0.090	4.8115	0.850
12	-0.020	-0.161	4.8341	0.902

	AC	PAC	Q-Stat	Prob
1	-0.257	-0.257	1.4648	
2	-0.187	-0.271	2.2876	
3	0.381	0.289	5.9142	0.015
4	-0.204	-0.085	7.0183	0.030
5	-0.142	-0.109	7.5898	0.055
6	0.261	0.066	9.6739	0.046
7	-0.348	-0.294	13.710	0.018
8	-0.193	-0.308	15.068	0.020
9	0.273	-0.055	18.050	0.012
10	-0.152	0.007	19.080	0.014
11	-0.004	0.113	19.081	0.025
12	0.060	-0.179	19.286	0.037

Figure 89 Philips. Correlogram of ARIMA model residuals. Left: total wealth force. Right: operating income force.

value for the joint model and the highest value for the regression model with operating income force.[7] The same ordered result is found for the standard Error of each coefficient, except for the AR term. Also note that there is a 95% probability that the true value of the β of each TEMA variable lies in the 95% confidence interval. Note that the joint model has the smaller confidence intervals, except—again—for the AR term. Therefore, the most compact simulation mean band I expect is for the joint regression model (which indeed the ex ante forecast mean band statistics show in TABLE 36).

Of some importance is the diagnostic testing of the regression equation residuals.[8] Two tests were used for the presence of auto- or serial correlation: the Durbin-Watson *d* test and the Breusch-Godfrey Lagrange Multiplier (BG LM) test. Because the models do not include a lagged value of the dependent variable the Durbin-Watson test for positive serial correlation is relevant. None of three models has residuals that suffer from autocorrelation because each test statistic is above the critical one-sided upper threshold value of 1.78 (Studenmund 2006, 329). This finding is confirmed with a BG LM first order test. Not one of the models has a statistic that is larger than the critical χ^2 value for one time lag, which implies that I can reject with

7 The Aikake Information Criterion is explained in section 2.3.9, page 61.

8 This is discussed more extensively in section 0, page 63.

confidence the null for the presence of serial correlation.[9] FIGURE 74 shows a correlogram up to 12 lags of the residuals for operating income force (left) and total wealth force (right). This visual method allows us to look at the pattern of correlations between residuals and their own past values. If autocorrelation is absent, then at each lag it should be nearly zero. This is indicated graphically in the correlogram with the vertical solid line. A bar left or right signals negative or positive autocorrelation. The dashed lines in the correlogram are the two standard error bounds. If the autocorrelation is within these bounds, it is not significantly different from zero at the 5% significance level. Finally, the models are tested for the presence of heteroskedasticity in the residuals with the white test (Studenmund 2006, 329, White 1980). The null hypothesis of homoskedasticity cannot be rejected in any model since the result is far below the critical χ^2 value (Studenmund 2006, 622).[10] In conclusion, all three regression models of net wealth force are viable.

7.2.4 ARIMA *models*

EQUATION (26) is the model with which the ex post base period and ex ante forecast of the hold-out sample period will be simulated. This requires equations for the independent variables total wealth force ($\nabla^2 \mathsf{X}$) and operating income force ($\nabla \mathsf{Z}$) as they drive the dynamics of the predictive model of net wealth force (FIGURE 6, page 53). In this section, the ARIMA models of the independent variables of Philips are presented. The goal of ARIMA analysis is in this study a parsimonious representation of force dynamics (Box *et al.* 1994, 16, Enders 2005, 76). For this study a partly automated procedure is utilized for the computation of alternative ARIMA specifications to reduce modeler bias. The Akaike Information Criterion (AIC) serves as a guide during the *identification* of the finest alternative specification of the force variables (Franses 2005, 42, 59, AND 65). The selected ARIMA models for Philips are:

(27) PHILIPS TWF, $$\nabla^2 \mathsf{X}_t = \alpha + \phi_1 \nabla^2 \mathsf{X}_{t-1} + \theta_1 \mathsf{u}_{t-7} + \mathsf{u}_t \qquad \text{with } t=1, \ldots, T,$$

(28) PHILIPS OIF, $$\nabla \mathsf{Z}_t = \alpha + \phi_1 \nabla \mathsf{Z}_{t-1} + \theta_1 \mathsf{v}_{t-10} + \mathsf{v}_t \qquad \text{with } t=1, \ldots, T.$$

The statistic results of the two ARIMA models are reported in TABLE 37. The marginal effect for both is strongly significant because the P-value of the F-statistic is less than 1%. I can be confident that the coefficients of the complete model differ from zero. The Adjusted R^2 values of the explained variance of each model are acceptable, respectively for total wealth force and operating income force: 76% and 88% (0.76, 0.88). The Durbin-Watson *d* test indicates that autocorrelation is not present in the residuals as each test statistic is above the critical one-sided upper threshold value of 1.78 (2.39, 2.62). However, for operating income force the result is mixed as the BG LM first order test result of 4.59 (vs. 5.02) leads to the rejection of the null of no serial correlation at the 2.5% level. FIGURE 89 shows a correlogram up to 12 lags of the residuals for total wealth force (left) and operating income force (right). In each model the autocorrelation is within the acceptable two standard error 5% bounds indicated by the dashed lines in the correlogram. In conclusion, the two ARIMA force models are sufficient to drive the dynamics of the net wealth force accounting model.

9 For each model this is 6.63, 5.02, 3.84 or 2.71, respectively, at 1%, 2.5%, 5% or 10% P-value.

10 For the joint model this is 23.2 and for the other two models this is 13.28, at a 1% P-value.

7.2.5 Simulation ex post

The analysis proceeds with the ex post simulation of the three models using the same data for the base period forecast as is was used during their development. FIGURE 75 and FIGURE 76 show, respectively, the ex post static and dynamic base period forecast of net wealth force by total wealth force & operating income force. FIGURE 77, FIGURE 81 and FIGURE 79 display the static base period forecast of net wealth by, respectively, operating income force, total wealth force and the joint model.

The dynamic the static base period forecast of net wealth is likewise shown in FIGURE 78, FIGURE 82 and FIGURE 80. Because the dynamic forecast uses the forecast value of lagged dependent variables in place of the actual value of the dependent variables in the long run the standard error 5% bounds of the dynamic simulation tend to increase beyond a tolerable level. Hence, to assess the explanatory power of the base period forecast, the static simulation is preferred. All three models are able to forecast the base period correctly with the exception of first quarter of 2001.

This result shows that the three econometric TEMA models of Philips have sufficient explanatory power ex post for the trend of net wealth for the base period 1999Q4-2004Q2. I conclude, therefore, that for Philips total wealth force and operating income force are associated with net wealth force. Hence, the research hypothesis H 4_a and H 5_a are (again) confirmed and my confidence increases in the temporal basis of the generality assumption of the TEMA framework (H 1_a). The implication is that proxy accounting variables of the TEMA framework, at least for ex post time series, provide meaningful new information about the trend of net wealth. Total wealth force and operating income force can in a meaningful manner be regressed on net wealth force for annual data of Philips.

7.2.6 Simulation ex ante

Is it possible to articulate a forecast for four quarters with these econometric TEMA models with sufficiently valid results? To answer this question, ex ante simulations are done for the hold-out sample of the four quarters 2004Q3-2005Q2. The result of the static and the dynamic simulation of the joint model, the total wealth model and the operating income model can be inspected with, respectively, FIGURE 83, FIGURE 84 and FIGURE 85. The ex ante static simulation has a success rate of 83.33% for net wealth force excluding the border line case of total wealth force in the second quarter of 2005. The ex ante dynamic simulation has a 100% success rate, but the mean band with is, of course, much wider. Compare in TABLE 36 the mean band value of the narrowest static forecast with that of the dynamic forecast, respectively: 4,059 and 4,817.

FIGURE 86, FIGURE 87 and FIGURE 88 show the result of the hold-out sample forecast for the aggregated value of net wealth (employing the TEMA framework as indicated in FIGURE 6, page 53). Observe that the success rate of 83.33% for net wealth is the same as for net wealth force but that models differ. The joint model fails to forecast net wealth correctly in the second quarter of 2005 whereas it is correct with the model that has only operating income force as the independent variable. The implication is that the generality assumption of the TEMA framework is again confirmed but now with the result of the forecasts.

My final conclusion of the analysis of the econometric TEMA models for Philips net wealth is that each of the three models has sufficient and significant explanatory power. These findings provide additional support for the main hypothesis of this thesis that the generality assumption

holds of the TEMA framework (H 1_a). Dynamic TEMA models of net wealth force of Philips confirm the temporal association of variables within the TEMA framework (H 3_a). The forward looking disclosure of accounting information from the ARIMA models of operating income force and total wealth force can forecast net wealth force is considerably accurate (H 7_a).

7.3 The AEX

My analysis of the quarterly financial statement data of Philips leads to the question if we can expect similar results with all other firms listed on the AEX. The length of the time series of annual financial statement data was sufficient to develop reliable econometric models for 17 out of the 24 AEX listed firms.[11] This offers the opportunity to further investigate the explanatory and predictive power of the TEMA framework of momentum accounting and evaluate it from the perspective of the AEX as an index of Dutch firms. My methodology with the modeling and analysis of the annual data is identical to the Philips example previously discussed. The statistical results of each firm are not presented here in detail.[12] All the regular test criteria are met, or not, as reported in TABLE 39, in which case I refrain from further analysis. In this section I limit myself to the discussion of the result of the analysis of the AEX as a whole.

7.3.1 Directional change

In this section, I consider for all 24 AEX listed firms the directional change of their operating income, total wealth versus net wealth. With directional change analysis we study if and in which direction an independent and dependent variable move (De Mortanges & Van Riel 2003). First, we determine if momentum or force is positive or negative.[13] Using that binary data it is determined if parallel directional change occurs (either ++ or −−) or if it is contra (either +− or −+). Thus, directional change is a binary variable with which we count the occurrence of identical momentum or force between an independent and dependent variable. I presume a certain degree of association between the change dynamics of momentum or force between variables of the TEMA framework according to the generality assumption (H 1_a). Return on total assets is used as the momentum measure of operating income. When momentum or force measures of total wealth or operating income are positive (increasing) I expect that net wealth momentum or force is positive too.

With directional change analysis we count the instances of parallel and contra directional changes of each of the 24 AEX component companies of the modeled time series for 23/19 years (1982/86-2004) and for the excluded time series 14/4 years (1990/2000-2004). TABLE 38 shows that on average only 74.8% of the AEX listed firms exhibit *parallel* directional change. Of course, the average directional change *contra* is: 25.2%. When weighted by the number of years measured of each firm that mean figure is somewhat less: 74.3%. Of the 17 AEX listed firms that have suitably time series to be included for econometric modeling the mean parallel directional change is 74.4%. These results hardly differ from each other. The conclusion is therefore that the directional change of operating income and net wealth momentum is consistent and does not seem to vary much relative to the number of years available per firm or to

[11] I.e. at the time of the writing of the original publication. Not of all firms (complete) quarterly financial statement data are available and therefore my analysis proceeds with annual data.

[12] These are available upon request.

[13] See EQUATION (29), page 177.

			Operating Profit vs. Net Wealth				Total Wealth vs. Net Wealth			
			Momentum		Force		Momentum		Force	
	from	to	parallel	contra	parallel	contra	parallel	contra	parallel	contra
ABN AMRO	1985	2004	85.0%	15.0%	50.0%	50.0%	90.0%	10.0%	55.0%	45.0%
Aegon	1983	2004	78.3%	21.7%	65.2%	34.8%	82.6%	17.4%	71.4%	28.6%
Ahold	1982	2004	83.3%	16.7%	50.0%	50.0%	91.7%	8.3%	60.9%	39.1%
AKZO Nobel	1982	2004	87.5%	12.5%	58.3%	41.7%	66.7%	33.3%	47.8%	52.2%
Buhrmann	1982	2004	62.5%	37.5%	50.0%	50.0%	79.2%	20.8%	65.2%	34.8%
DSM	1982	2004	70.8%	29.2%	60.9%	39.1%	62.5%	37.5%	73.9%	26.1%
Reed Elsevier	1982	2004	58.3%	41.7%	50.0%	50.0%	87.5%	12.5%	95.7%	4.3%
Getronics	1986	2004	85.0%	15.0%	50.0%	50.0%	70.0%	30.0%	73.7%	26.3%
Hagemeyer	1982	2004	66.7%	33.3%	62.5%	37.5%	75.0%	25.0%	82.6%	17.4%
Heineken	1982	2004	83.3%	16.7%	45.8%	54.2%	75.0%	25.0%	65.2%	34.8%
Royal Numico	1985	2004	85.7%	14.3%	66.7%	33.3%	85.7%	14.3%	55.0%	45.0%
Royal Philips	1982	2004	75.0%	25.0%	70.8%	29.2%	79.2%	20.8%	69.6%	30.4%
Royal Dutch Shell	1982	2004	66.7%	33.3%	50.0%	50.0%	83.3%	16.7%	69.6%	30.4%
SBM Offshore	1985	2004	81.0%	19.0%	66.7%	33.3%	85.7%	14.3%	55.0%	45.0%
Unilever	1985	2004	61.9%	38.1%	42.9%	57.1%	76.2%	23.8%	80.0%	20.0%
VNU	1982	2004	62.5%	37.5%	70.8%	29.2%	83.3%	16.7%	69.6%	30.4%
Wolters Kluwer	1982	2004	70.8%	29.2%	58.3%	41.7%	79.2%	20.8%	68.2%	31.8%
ASML	1993	2004	61.5%	38.5%	38.5%	61.5%	61.5%	38.5%	75.0%	25.0%
Fortis	1997	2004	77.8%	22.2%	50.0%	50.0%	77.8%	22.2%	75.0%	25.0%
ING	1990	2004	78.6%	21.4%	61.5%	38.5%	75.0%	25.0%	66.7%	33.3%
KPN	1992	2004	78.6%	21.4%	57.1%	42.9%	78.6%	21.4%	53.8%	46.2%
TNT	1998	2004	87.5%	12.5%	50.0%	50.0%	62.5%	37.5%	28.6%	71.4%
Vedior	1999	2004	85.7%	14.3%	42.9%	57.1%	71.4%	28.6%	83.3%	16.7%
Versatel	2000	2004	60.0%	40.0%	40.0%	60.0%	60.0%	40.0%	80.0%	20.0%
AEX mean (17 firms modeled):			74.4%	25.6%	57.0%	43.0%	79.6%	20.4%	68.1%	31.9%
AEX mean (24 firms):			74.8%	25.2%	54.5%	45.5%	76.6%	23.4%	67.5%	32.5%
AEX mean average (24 firms):			74.3%	25.7%	56.2%	43.8%	78.3%	21.7%	67.8%	32.2%

Table 38 AEX. Directional analysis of momentum and force measures.
Parallel directional change = ++ or −−. Opposite directional change contra = +− or −+.

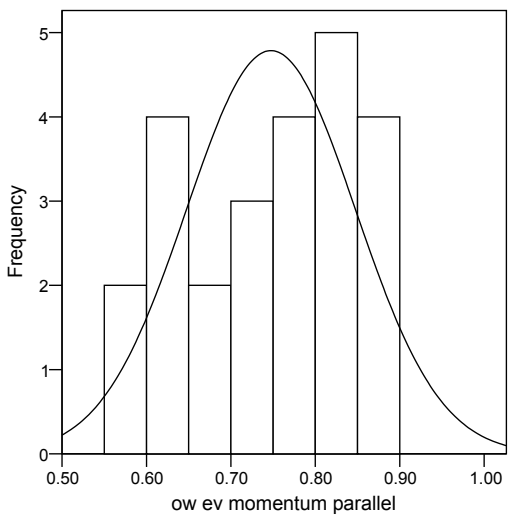


Figure 90 AEX. Histogram of parallel directional change of operating income versus net wealth momentum.

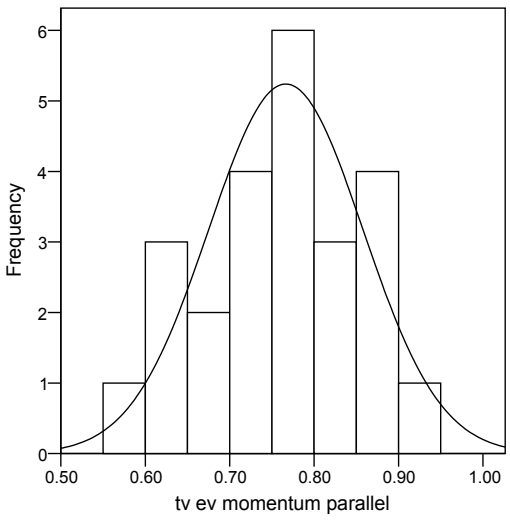


Figure 91 AEX. Histogram of parallel directional change of total wealth momentum versus net wealth momentum.

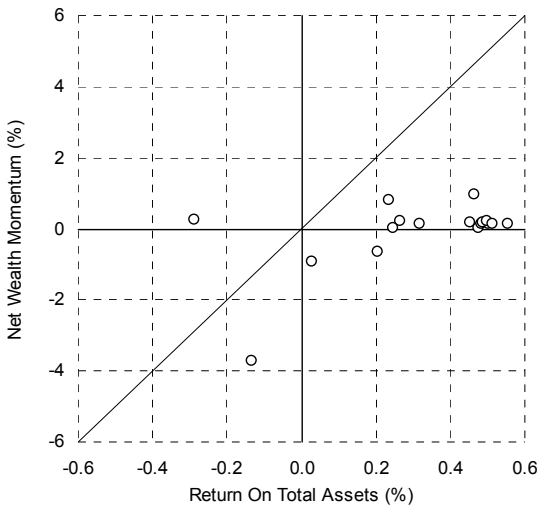


Figure 92 Royal Numico. ROTA versus net wealth momentum (1985-2004).

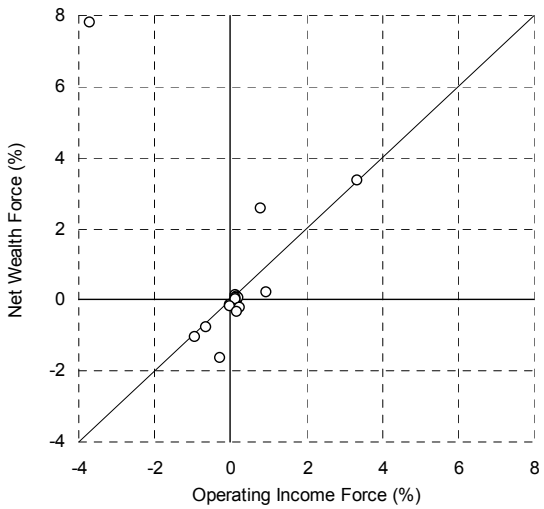


Figure 93 Royal Numico. Operating income force versus net wealth force (1985-2004).

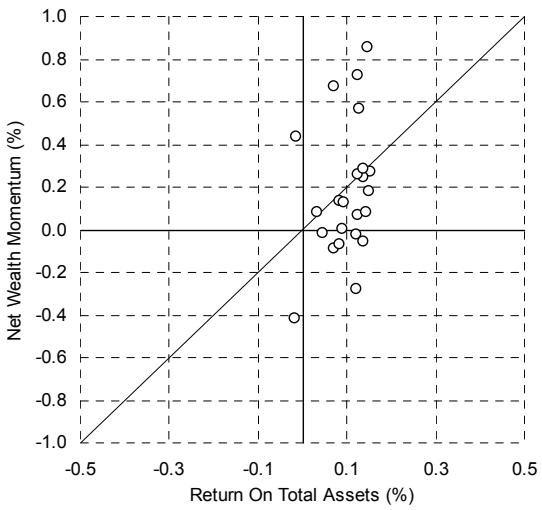


Figure 94 Hagemeyer. ROTA versus net wealth momentum (1982-2004).

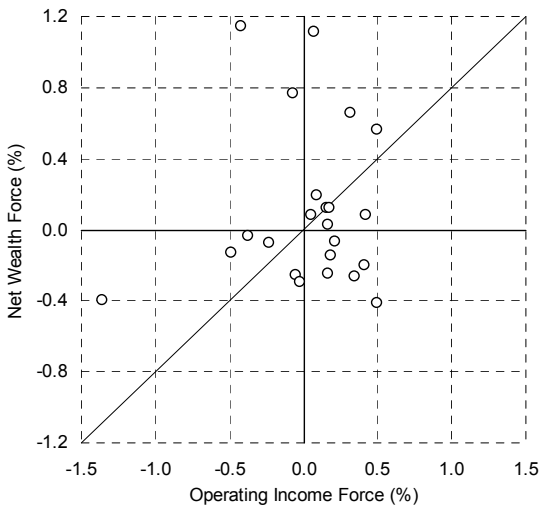


Figure 95 Hagemeyer. Operating income force versus net wealth force (1982-2004).

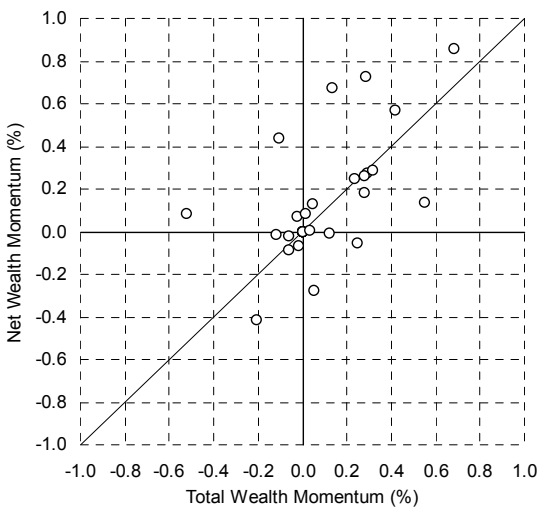


Figure 96 Hagemeyer. Total wealth momentum versus net wealth momentum (1982-2004).

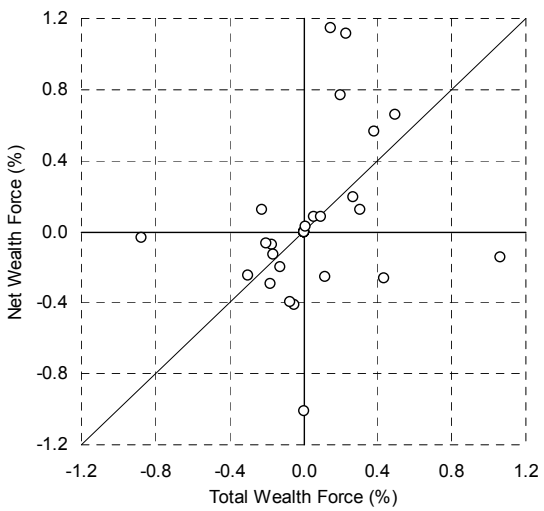


Figure 97 Hagemeyer. Total wealth force versus net wealth force (1982-2004).

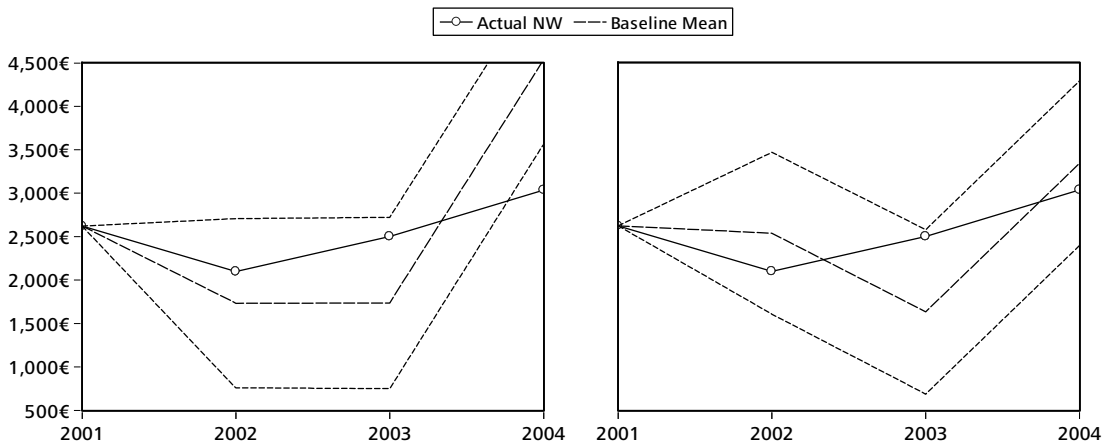


Figure 98 Akzo Nobel. Hold-out static forecast of net wealth by total wealth force (left) and total wealth force & operating income force (right).

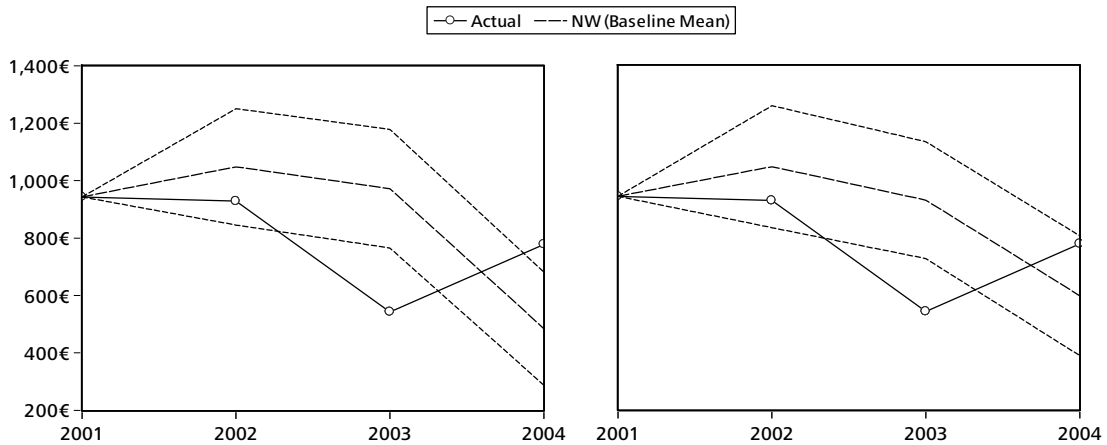


Figure 99 Hagemeyer. Hold-out static forecast of net wealth by operating income force (left) and by total wealth force & operating income force.

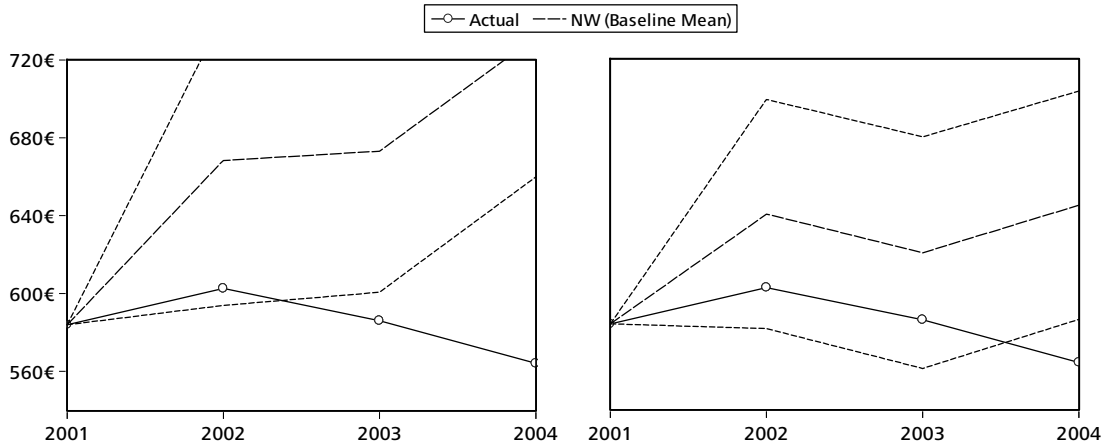


Figure 100 SBM Offshore. Hold-out static forecast of net wealth by operating income force (left) and by total wealth force (right).

the selected set of firms to be modeled. The force measures are a little less consistent. For all AEX listed firms directional change of force parallel-contra is on average 69.7%-30.3% and with the 17 firms to be modeled the mean is 71.4%-28.6%. Visual inspection of the pattern of measurements of ROTA or total wealth momentum versus net wealth momentum reveals also the consistency of their association. Compare FIGURE 92 of Royal Numico with FIGURE 94 of Hagemeyer. We can observe that the net wealth momentum of Hagemeyer varies between -0.4

		Annual Statements			Annual Statements		
		Ex Post Explanation			Ex Ante Prediction		
	from	OI	TWM	OI+TWM	OI	TWM	OI+TWM
ABN AMRO	1985	1	*1*	0	67%	67%	N.A.
Aegon	1983	*1*	*1*	1	100%	100%	33%
Ahold	1982	*1*	*1*	*1*	33%	33%	67%
AKZO Nobel	1982	0	1	1	N.A.	100%	67%
Buhrmann	1982	*1*	1	*1*	67%	67%	67%
DSM	1982	*1*	*1*	**1**	100%	100%	100%
Reed Elsevier	1982	*1*	1	**1**	67%	100%	33%
Getronics	1986	0	1	**1**	N.A.	67%	0%
Hagemeyer	1982	1	*1*	**1**	33%	100%	67%
Heineken	1982	*1*	1	0	33%	67%	N.A.
Royal Numico	1985	1	*1*	1	33%	33%	0%
Royal Philips	1982	0	*1*	**1**	N.A.	67%	33%
Royal Dutch Shell	1982	0	1	*1*	N.A.	100%	100%
SBM Offshore	1985	1	1	**1**	33%	67%	67%
Unilever	1985	0	0	0	N.A.	N.A.	N.A.
VNU	1982	*1*	*1*	**1**	100%	100%	33%
Wolters Kluwer	1982	*1*	*1*	*1*	100%	100%	67%
AEX mean success rate:		71%	94%	82%	64%	79%	52%

Correct models: 1 = raw data, *1* = log data, **1** = PCA of OI and TW covariance, ***1*** = PCA of log data.

Table 39 AEX. Econometric TEMA models that explain (ex post) and forecast (ex ante) net wealth.

and 0.8 whereas ROTA hardly varies. With Royal Numico, in contrast, the directional change fluctuates the other way around: here net wealth momentum varies slightly at very different ROTA percentages. At Royal Numico ROTA increases or decreases are barely reflected in a change of its net wealth momentum. When we compare FIGURE 93 with FIGURE 95 we observe with Hagemeyer that the directional change of operating income force and net wealth force has a greater variance whereas at Royal Numico the association is nearly linear with the exception of 2003 which is due to a large loss as well as an increase of owner's equity.

The directional change of momentum and force of Hagemeyer is plotted against net wealth in FIGURE 96 and FIGURE 97. The cloud of measurements in these two graphs lies more or less parallel to the diagonal that runs through the point of origin of the x, y plane. This seems to indicate certain stability in the pattern of force and momentum measures. In TABLE 38 of each AEX listed firm the percentage is included of the directional change parallel or contra of momentum and force measures. FIGURE 90 and FIGURE 91 are a frequency histogram of these percentages for the AEX as a whole, respectively, of operating income and total wealth momentum. Little statistical reasoning is possible on this data due to the small number of firms that is not a representative sample for the Dutch economy. Nevertheless, the fact that both frequency histograms are nearly normally distributed does raise the question if the directional momentum changes at AEX listed firms do have a cohesive pattern. Moreover, even the force dynamics of operating income and total wealth suggest this, albeit a different pattern. Note first that the percentages of operating income force and total wealth force versus net wealth force are rather different on average as well as by firm. The counts of parallel force change are higher for total wealth force then for operating income force. The implication is that positive net wealth change is more likely associated with balance sheet dynamics than with the profitability of the firm. This becomes also clearer when we inspect the operating income force percentages more closely. Only with 11 of the 24 listed firms does net wealth force move parallel with operating

income force. For five firms it moves contra and for eight firms it is an even split. That makes it much more difficult to 'guestimate' how net wealth force will tend to behave given the trend of operating income force or total wealth force.

7.3.2 Simulation ex post & ex ante

TEMA models were developed for 17 firms listed on the AEX. For each firm ARIMA models explain net wealth with operating income, total wealth or both. In TABLE 39 a '1' or '0' indicate if the ex post regression met the statistical criteria, or not. In those cases where the model does not have explanatory power it is naturally also not possible to perform ex ante simulations and test for predictive power. Hence, in those cases the next columns report 'not applicable' (N.A.). The mean ex post success rates calculated of the 17 AEX firms tested are, respectively, 71%, 94% and 82% for operating income, total wealth and the joint model. TABLE 39 also provides the success rates of the ex ante forecast of the hold-out sample of three years by firm and model. Weighted by the number of valid models (12, 16 and 15) these are, respectively 64%, 79% and 52%. My conclusion is that the three TEMA models have predictive power and forecast net wealth with ex ante simulation reasonably successfully, especially the total wealth model.

7.4 Conclusion

In this chapter three regression models of Philips were presented with accounting variables from the TEMA framework of momentum accounting. Ex post base period simulation was accurate with each model ex ante static simulation of the hold-out period has a success rate of about 83% for net wealth force. These models have adequate explanatory and predictive power. This study was repeated with 17 firms listed on the AEX. With these, significant explanatory power was found for operating income (71%), total wealth (94%) as well as for the combination in a joint TEMA model (82%). Their predictive power, however, with a time horizon of three years is much lower for the modeled time series, respectively 64%, 79% and 52%. This might be due to fact that annual time series were used for lack of the availability of quarterly data. The result of my investigation of 17 AEX firms is encouraging and gives ample support for the main research thesis H 1_a that there is a general relationship between accounting variables in the dimensions of the TEMA framework of Ijiri. This study confirms also the research hypotheses H 4_a, H 5_a and H 7_a of this thesis (section 1.8, page 29). Operating income and total wealth dynamics are associated with net wealth and can forecast its trend. The TEMA framework of Ijiri is decisive in the selection of accounting variables that have the same temporal dimension. The econometric TEMA models are also balanced on the basis of their statistical properties. This study of 17 AEX firms shows that the TEMA models have explanatory and predictive power ex post as well as ex ante. Hence, I argue that ARIMA based TEMA models, as suggested by Ijiri (1989, 10.5), are a viable alternative for more detailed triple-entry bookkeeping and financial reporting. TEMA models can provide meaningful (new) accounting information about the firm. Moreover, such models enable the study of business dynamics and the disclosure of forward looking information.

8

The Explanatory & Predictive Power of TEMA — the Dow

An Empirical Study of the Dow Jones Industrial Average Component Companies.

	Company Name	RIC (US)	Weight	Sector
1	3M Co.	MMM.N	5.646%	Forest Products & Paper
2	AlCoa Inc.	AA.N	2.161%	Metals - Non Ferrous
3	Altria Group Inc.	MO.N	5.616%	Food & Household Products
4	American Express Co.	AXP.N	3.857%	Financial Services
5	American International Group Inc.	AIG.N	5.006%	Insurance
6	AT&T	T.N	1.854%	Telecommunications
7	Boeing Co.	BA.N	4.989%	Aerospace & Military Technology
8	Caterpillar Inc.	CAT.N	4.561%	Machinery & Engineering
9	Citigroup Inc.	C.N	3.428%	Banking
10	Coca-Cola Co.	KO.N	3.008%	Beverages & Tobacco
11	E I du Pont de Nemours and Co.	DD.N	2.965%	Chemicals
12	Exxon Mobil Corp.	XOM.N	4.542%	Energy Sources
13	General Electric Co.	GE.N	2.504%	Electrical & Electronics
14	General Motors Corp.	GM.N	1.504%	Automobiles
15	Hewlett-Packard Co.	HPQ.N	2.381%	Data Processing & Reproduction
16	Home Depot Inc.	HD.N	3.014%	Merchandising
17	Honeywell International Inc.	HON.N	2.689%	Industrial Components
18	IBM Corp.	IBM.N	6.105%	Data Processing & Reproduction
19	Intel Corp.	INTC.O	1.632%	Electronic Components & Instruments
20	Johnson & Johnson	JNJ.N	4.562%	Health & Personal Care
21	JPMorgan Chase & Co.	JPM.N	2.855%	Financial Services
22	McDonald's Corp.	MCD.N	2.691%	Leisure & Tourism
23	Merck & Co Inc.	MRK.N	2.495%	Health & Personal Care
24	Microsoft Corp.	MSFT.O	1.984%	Business & Public Services
25	Pfizer Inc.	PFE.N	1.854%	Health & Personal Care
26	Procter & Gamble Co.	PG.N	4.340%	Food & Household Products
27	United Technologies Corp.	UTX.N	4.128%	Aerospace & Military Technology
28	Verizon Communications Inc.	VZ.N	2.322%	Telecommunications
29	Wal-Mart Stores Inc.	WMT.N	3.377%	Merchandising
30	Walt Disney Co.	DIS.N	1.930%	Broadcasting & Publishing
	Dow Jones Industrial Average Index	DJI	100.000%	

Table 40 Dow. Component companies and their weight as of April 8, 2004 (Dow Jones).

	1% level	5% level
Operating Income Force	7.31	4.08
Total Wealth Force	7.31	4.08
Operating Income Force & Total Wealth Force	5.18	3.23

Table 41 *F*-test critical values.

8 Abstract

This chapter presents the econometric models using TEMA *variables of the 30 component companies of the Dow Jones Industrial Average. I argue that the* TEMA *framework is instrumental for the selection of the independent variables that explain and predict the trend of net wealth of these firms. I use financial statement data to derive force variables of all the Dow component companies. Except for one firm, Coca-Cola, it is possible to regress total wealth force and operating income force on net wealth force with explanatory* TEMA *models. Next,* ARIMA *equations are developed for total wealth force and operating income force for each* DOW *component company. Ex ante forecast are made for within sample static and dynamic simulation of 4 and 8 quarters. Static and dynamic 4 quarter simulation, respectively, forecasts net wealth force correctly by total wealth force 83.6% and 86.2% on average, whereas the joint models are correct by 82.5% and 87.5%. Operating income force forecast 85% correctly with both static and dynamic simulation. The aggregate value of net wealth, is on average correct with static simulation by 83.6% for the total wealth, and by 83.3% for the operating income and the joint models. I conclude that force variables clearly are reliable leading indicators of the trend of net wealth for the selected examples. This result is also noteworthy given the findings of Gomaa et al. (2008) who found that when a decision aid is 80% reliable it tends to be used in about 60% of the cases with only a single performance pressure and that this percentage increases to about 80% with up to four pressures to perform. This study suggests that the ability to analyse financial statements dynamically can be improved with ex post explanatory and ex ante predictive* TEMA *models.*

8.1 Introduction

In this chapter, I extend the TEMA framework of Ijiri that was introduced in Chapter 1 and I try to find evidence in support of the generality assumption. The focus is on submitting evidence that the foundational assumption of momentum accounting is valid, namely: that the TEMA framework *provides new and valuable information*. I do not elaborate here on the methodology used to calculate the various TEMA variables or the construction of the econometric TEMA models as this is described in Chapter 2. This study aims to ascertain that associations are present between accounting variables in the three informational dimensions of the TEMA framework. The possible presence of these associations is tested ex post with econometric regression models that explain past trends and ex ante with TEMA models that should forecast the future net wealth trend of the DOW companies. The study thus should offer support for the TEMA theory of Ijiri. I have:

1. extended Ijiri's system of causal linkages between the accounting dimensions, to explain the growth of net wealth with force accounts that describe the change rate of balance sheet accounts used to report on wealth composition (FIGURE 5, page 53);
2. used archival data of the 30 component companies, which are included in the DOW Jones Industrial Average index, for analysis with three econometric TEMA models each;
3. tested all TEMA variables that I use in the econometric models, for their statistical time series properties so that their explanatory and predictive power can be tested without the risk of spurious regression results (see Section 2.3, page 52).

I utilize the TEMA framework for econometric time series analysis as recommended by Ijiri (1989, 10.5). My approach compares to that of Silhan (1989) who applied ARIMA analysis to forecast corporate earnings using quarterly sales and margins as explanatory variables.

Organization of this chapter

This chapter proceeds in several sections. The next section sets out the hypotheses, data set, research design and the main research question are also presented in section 8.2. The result of my study is presented in section 8.3 and 8.4. In section 8.3, a directional change analysis is presented of the independent and the dependent variables of all the DOW component companies. Both a visual analysis and statistical analysis of association is discussed. Section 8.4, contains a brief introduction of the regression models used and the result of the ex post and ex ante simulation. Necessary data and statistical details are presented in tables and figures. The last section contains conclusions.

8.2 Research question & hypotheses

This chapter addresses the research question: is it possible to find further evidence in support of the main thesis of the theory of momentum accounting with empirical data? Central in my effort is the association I expect between the trend in time of the accounting variables that are involved in the measurement of the speed, and its change, of both the growth of wealth and its composition (FIGURE 2, page 2 & FIGURE 5, page 53).

8.2.1 Association

Only the association is researched between operating income and that of total wealth momentum with net wealth momentum. Operating income serves as a proxy for business dynamics reflected by variation of income statement data. In addition, dynamics of the structural composition of the balance sheet as a whole is expected to be associated with the growth trend of net wealth. Moreover, their combined association with the momentum of net wealth is tested for explanatory power and, when present, predictive power. Thus, the structural or long running association should be exposed between the growth of net wealth and that of total wealth and business success reflected in operating income time series.

8.2.2 Research hypotheses

Several hypotheses of this study, discussed in Chapter 1, section 1.8, page 29, will be tested. It is expected on theoretical grounds that force and momentum accounting variables exhibit variation that meet the econometric requirement for modeling of stationarity or trend-stationarity.[1] This is because force and momentum accounting variables can be calculated by the first and second difference of wealth accounts (EQUATIONS (8) and (9), page 53). If so, evidence in support of hypothesis H 6_a is found. Then it follows that it should be possible to develop econometric models without the risk of spurious regression. Also, when association is present between operating income or total wealth and net wealth, these accounting variables can be employed as independent variables in the econometric models. When such models are well specified, i.e. without serial correlation in the models' residuals or heteroskedasticity, and when the independent variables of a company's model explains and predicts the dependent variable (net wealth) then evidence is found in support of hypotheses H 3_a, H 4_a, H 5_a and H 7_a. Should evidence be found in support of these hypotheses then the main hypothesis of this study is also supported in this case, namely, that there is a general relationship between variables in the TEMA framework of Yuji Ijiri (H 1_a).

[1] This is discussed in Chapter 2, section 2.3, page 52.

8.2.3 Quarterly financial statements' data

The data sets used are compiled quarterly financial statements of the Dow Jones Industrial Average component companies filed with the U.S. securities and exchange commission (SEC, not audited). The Dow Jones Industrial Average, DOW in short, was created in 1896 by Charles Dow, one of the founders of *The Wall Street Journal*, and is a price-weighted market index calculated from 30 component companies.[2] Component changes are rare, only 49 occured since 1896 and the last one was made on April 8, 2004.

8.2.4 Research design

The trend of net wealth growth of each of the 30 component companies of the DOW was analysed, modeled and simulated for this study. FIGURE 4, page 48, explains the procedure employed to test my hypothesis. I start with testing the correlation of directional change to determine the degree of association between independent variables and the dependent variable. This should bring support, or not, for the hypotheses H 1_a and H 3_a. Next, I calculate force variables between quarters either from the raw data or their log normal values. I perform unit root tests to determine the presence of auto correlation. This leads to support of hypothesis H 6_a. Once the base periods accounting variables are viable for my modeling purposes, the ex post explanatory power is tested. This is done in two steps. Firstly, regression models are made with only operating income force and total wealth force as the independent variable or both as the independent variables. The regression residual is tested for the presence of auto correlation. This should support, or not, hypotheses H 4_a and H 5_a. Secondly, force equations are developed and likewise tested. This is in agreement with hypothesis H 6_a. Lastly, the models are employed for the prediction of the last 4 quarters of the net wealth time series of the DOW companies. When the results are valid this provides support for hypothesis H 7_a and my main hypothesis H 1_a. An analysis of 3M is presented in Chapter 2, section 2.3, page 52, as an depth example of the used research methodology. There also the intricacies of time series analysis and the used test statistics are introduced.

8.3 Directional change analysis

With directional change analysis we study if and in which direction an independent and dependent variable move (De Mortanges & Van Riel 2003). First, we determine if momentum or force is positive or negative. EQUATION (29) gives the required logic:

(29) FOR x | IF(x< 0 THEN 0 ELSE 1)

Using that binary data it is determined if directional change occurs parallel (either ++ or −−) or if directional change is contra (either +− or −+). Thus, directional change is a binary variable with which I count the occurrence of identical momentum or force between an independent and dependent variable. I expect a certain degree of association between the change dynamics of momentum and force of total wealth and that of net wealth. When total wealth momentum or force is positive (increasing) it is likely that net wealth momentum or force is positive too. Return on total assets is used here as the momentum measurement of operating income.[3] When

[2] Browse http://www.djindexes.com/ for more information and documentation.

[3] Recall that in the TEMA framework income related variables are momentum variables when I set the rate of change equal to the period in between balance sheets; in our case one quarter. For directional analysis it makes no difference if we use ROTA or raw or transformed data of operating income. But, for scaling

				Operating Income vs. Net Wealth				Total Wealth vs. Net Wealth			
				Momentum		Force		Momentum		Force	
	RIC	from	to	parallel	contra	parallel	contra	parallel	contra	parallel	contra
1	MMM	1990Q2	2005Q2	62.3%	37.7%	51.7%	48.3%	73.8%	26.2%	80.3%	19.7%
2	AA	1990Q2	2005Q2	67.2%	32.8%	47.5%	52.5%	63.9%	36.1%	63.9%	36.1%
3	MO	1990Q2	2005Q2	70.5%	29.5%	65.6%	34.4%	67.2%	32.8%	55.7%	44.3%
4	AXP	1991Q1	2005Q2	77.6%	22.4%	56.9%	43.1%	56.9%	43.1%	55.2%	44.8%
5	AIG	1989Q4	2005Q2	93.5%	6.5%	49.2%	50.8%	91.9%	8.1%	69.8%	30.2%
6	T	1989Q4	2005Q2	79.4%	20.6%	60.3%	39.7%	74.6%	25.4%	82.5%	17.5%
7	BA	1990Q2	2005Q2	72.1%	27.9%	47.5%	52.5%	77.0%	23.0%	72.1%	27.9%
8	CAT	1989Q4	2005Q2	73.0%	27.0%	41.3%	58.7%	68.3%	31.7%	46.0%	54.0%
9	C	1990Q3	2005Q2	90.0%	10.0%	46.7%	53.3%	80.0%	20.0%	68.3%	31.7%
10	KO	1990Q1	2005Q2	75.8%	24.2%	71.0%	29.0%	71.0%	29.0%	75.8%	24.2%
11	DD	1989Q3	2005Q2	76.6%	23.4%	71.9%	28.1%	67.2%	32.8%	59.4%	40.6%
12	XOM	1991Q3	2005Q2	76.8%	23.2%	75.0%	25.0%	71.4%	28.6%	78.6%	21.4%
13	GE	1990Q1	2005Q2	83.9%	16.1%	77.4%	22.6%	83.9%	16.1%	64.5%	35.5%
14	GM	1990Q2	2005Q2	68.9%	31.1%	67.2%	32.8%	57.4%	42.6%	57.4%	42.6%
15	HPQ	1990Q1	2005Q2	77.4%	22.6%	61.3%	38.7%	80.6%	19.4%	59.7%	40.3%
16	HD	1989Q3	2005Q2	95.3%	4.7%	82.8%	17.2%	93.8%	6.3%	39.1%	60.9%
17	HON	1990Q1	2005Q2	83.9%	16.1%	48.4%	51.6%	71.0%	29.0%	50.0%	50.0%
18	IBM	1990Q2	2005Q2	68.9%	31.1%	67.2%	32.8%	70.5%	29.5%	75.4%	24.6%
19	INTC	1990Q2	2005Q2	85.2%	14.8%	77.0%	23.0%	83.6%	16.4%	63.9%	36.1%
20	JNJ	1990Q2	2005Q2	90.2%	9.8%	67.2%	32.8%	86.9%	13.1%	62.3%	37.7%
21	JPM	1990Q2	2005Q2	83.6%	16.4%	59.0%	41.0%	62.3%	37.7%	60.7%	39.3%
22	MCD	1990Q2	2005Q2	77.0%	23.0%	62.3%	37.7%	73.8%	26.2%	65.6%	34.4%
23	MRK	1990Q2	2005Q2	75.4%	24.6%	54.1%	45.9%	83.6%	16.4%	60.7%	39.3%
24	MSFT	1989Q4	2005Q2	92.1%	7.9%	65.1%	34.9%	96.8%	3.2%	73.0%	27.0%
25	PFE	1990Q3	2005Q2	75.0%	25.0%	68.3%	31.7%	73.3%	26.7%	56.7%	43.3%
26	PG	1989Q4	2005Q2	76.2%	23.8%	76.2%	23.8%	71.4%	28.6%	63.5%	36.5%
27	UTX	1990Q2	2005Q2	80.3%	19.7%	58.3%	41.7%	70.5%	29.5%	73.3%	26.7%
28	VZ	1990Q4	2005Q2	78.0%	22.0%	66.1%	33.9%	64.4%	35.6%	55.9%	44.1%
29	WMT	1989Q4	2005Q2	93.7%	6.3%	79.4%	20.6%	73.0%	27.0%	41.3%	58.7%
30	DIS	1990Q3	2005Q2	86.7%	13.3%	75.0%	25.0%	60.0%	40.0%	51.7%	48.3%
	Dow Jones companies' average directional change percentages:			79.5%	20.5%	63.2%	36.8%	74.0%	26.0%	62.7%	37.3%

RIC = Reuters Instrument Code.

Table 42 Dow. Directional change percentages of component companies for operating income or total wealth versus net wealth, momentum and force accounting variable time series.

operating income is positive, i.e. when the firm is profitable, that net wealth momentum or force is positive as well. The next step in directional change analysis is that I count the parallel and contra directional changes of each of the 30 Dow component companies of the time series for about 62 quarters (1990Q1-2005Q2).

8.3.1 Momentum & force

When we consult Table 42, that lists the parallel and contra directional change percentages of each Dow component company, we can observe that the average parallel directional change is 79.5% for operating income versus net wealth momentum. Nonetheless, there are several companies that do have a higher score and that appears to confirm my assumption in these cases that when operating income is positive or negative also net wealth momentum is positive or negative: Home Depot (95.3%), American Wal-Mart Stores (93.7%), International Group (93.5%), Microsoft (92.1%) and Johnson & Johnson (90.2%). Notet that 3M has the lowest average parallel directional change for operating income versus net wealth momentum: 62.3%.

purposes of the xy-plots with momentum it is better to use ROTA as the preferred ratio.

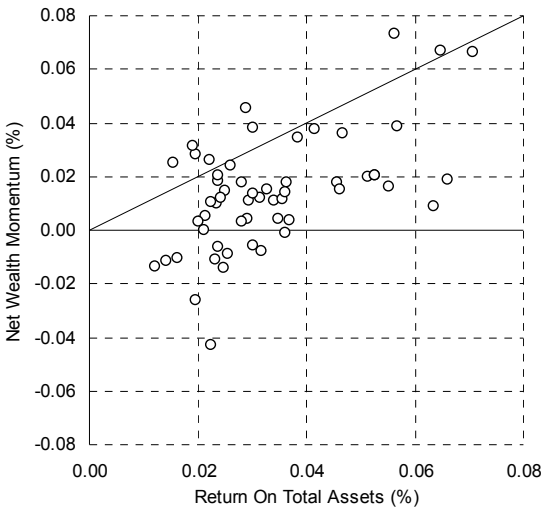


Figure 101 Exxon Mobil Corp. ROTA vs. net wealth momentum (1991Q3-2005Q2).

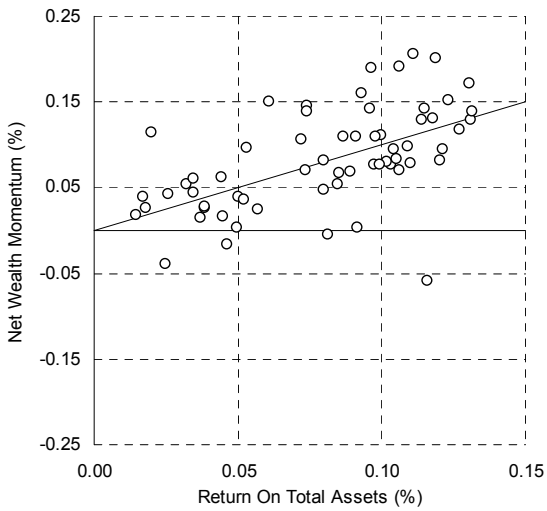


Figure 102 Microsoft Corp. ROTA vs. net wealth momentum (1989Q4-2005Q2).

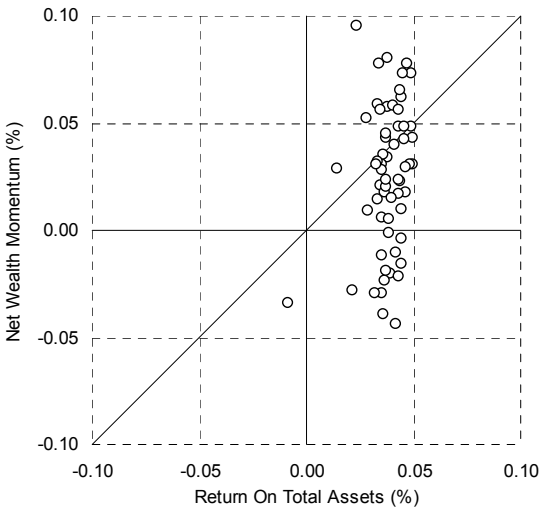


Figure 103 McDonald's Corp. ROTA vs. net wealth momentum (1990Q2-2005Q2).

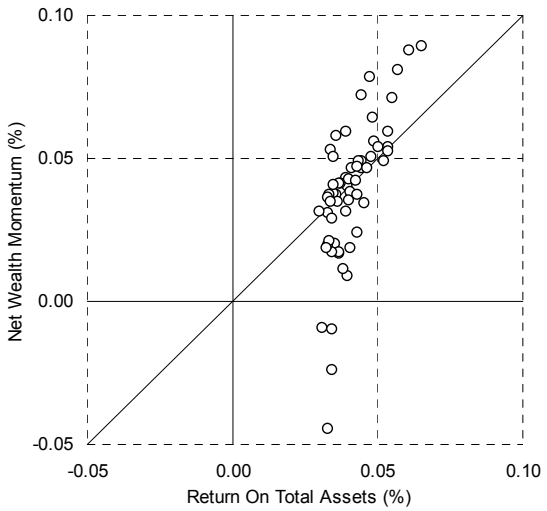


Figure 104 Wal-Mart Stores Inc. ROTA vs. net wealth momentum (1989Q4-2005Q2).

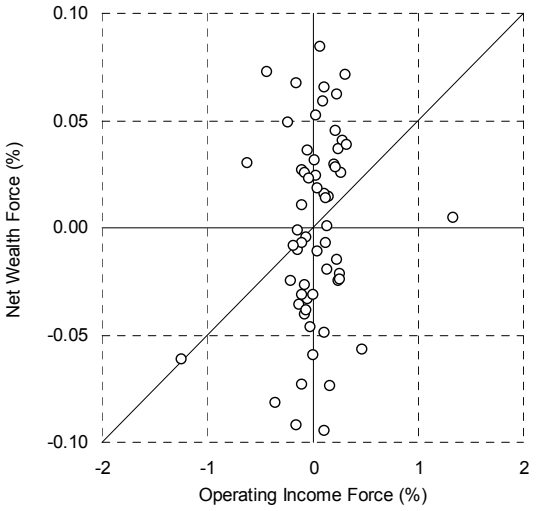


Figure 105 McDonald's Corp. Operating income force vs. net wealth force.

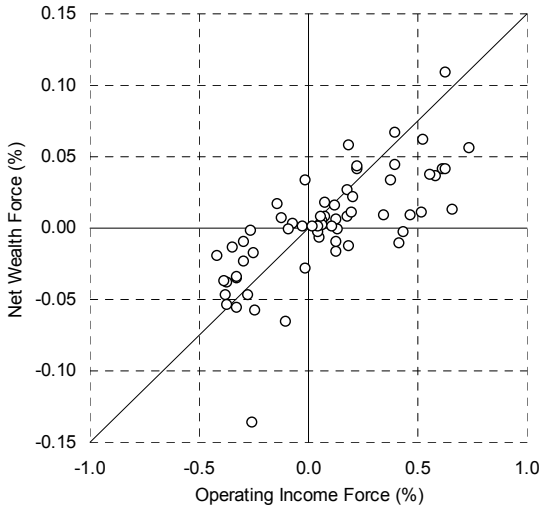


Figure 106 Wal-Mart Stores Inc. Operating income force vs. net wealth force.

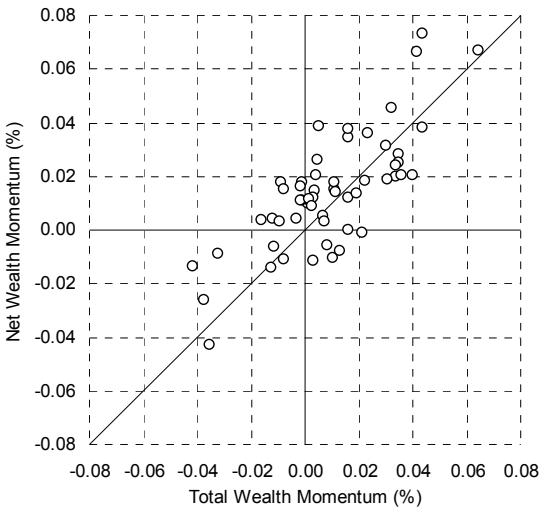


Figure 107 Exxon Mobil Corp. Total wealth momentum vs. net wealth momentum.

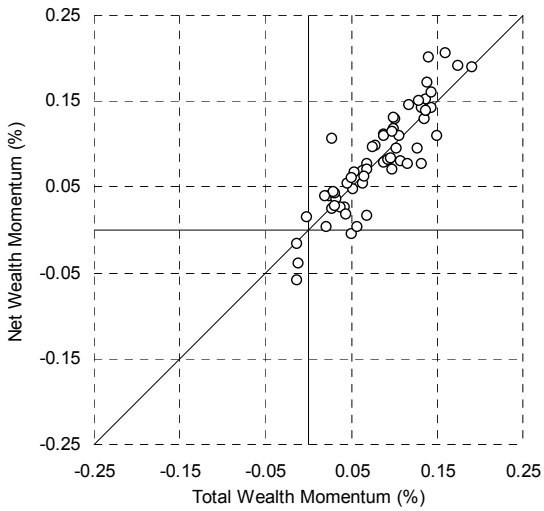


Figure 108 Microsoft Corp. Total wealth momentum vs. net wealth momentum.

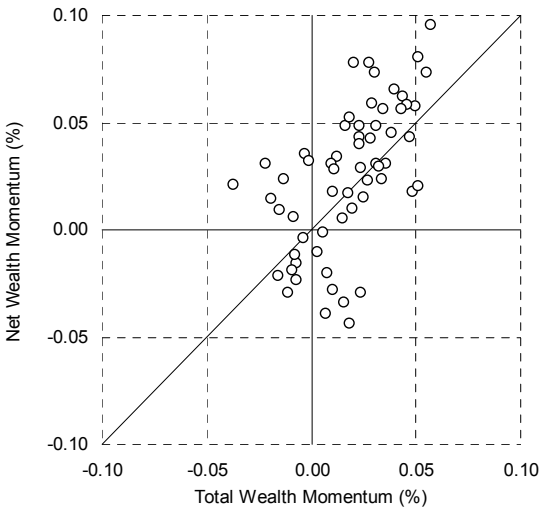


Figure 109 McDonald's Corp. Total wealth momentum vs. net wealth momentum.

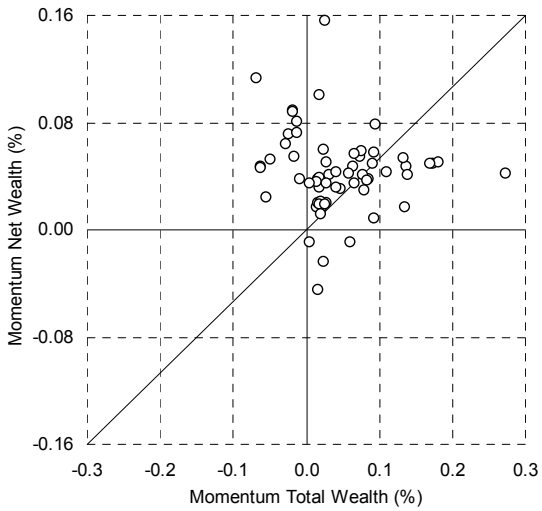


Figure 110 Wal-Mart Stores Inc. Total wealth momentum vs. net wealth momentum.

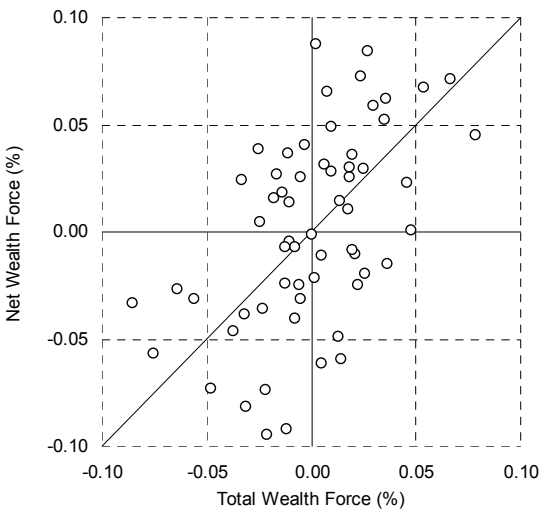


Figure 111 McDonald's Corp. Total wealth force vs. net wealth force (1990Q2-2005Q2).

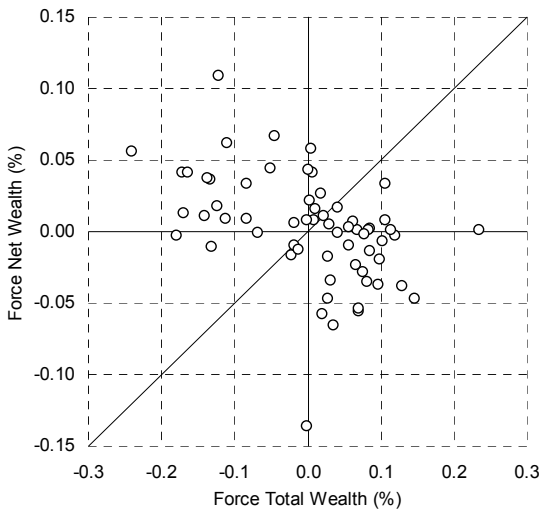


Figure 112 Wal-Mart Stores Inc. Total wealth force vs. net wealth force (1989Q4-2005Q2).

For total wealth momentum versus net wealth momentum the average parallel directional change is 74.0% with the highest score for Microsoft (96.8%) and the lowest score for American Express (56.9%). The force parallel or contra directional change scores are a little less distinct for either operating income versus net wealth or total wealth versus net wealth. Respectively, the average of parallel force is 63.2% for operating income and 62.7% for total wealth. The highest scores are here for Home Depot (82.8%) and for SBC (82.5%).

8.3.2 Visual analysis

A few examples of scatter plots might illustrate this further. FIGURE 101 up to 99 are scatter plots of operating income versus momentum net wealth. FIGURE 105 and 101 are the force variables of the same momentum variables as in FIGURE 103 and 99. Clearly, all six scatter plots exhibit more or less clustered patterns and the relationship appears to be linear; particularly with McDonald's and Wal-mart Stores (FIGURE 105 & FIGURE 106). There are periods where operating income and net wealth momentum are identical, namely: all those points that are on the directional diagonal that runs through the point of origin of the x and y-axis. For Exxon Mobil, most periods the momentum net wealth fraction is smaller than the operating income fraction (all those points that are below the directional diagonal in FIGURE 101). Noteworthy are those periods where operating income is positive but momentum net wealth is negative (all those points that are below the 0 of the y-axis for net wealth momentum). Microsoft exhibits a samilar pattern but the scale ratio between net wealth momentum and operating income is not 1, as with Exxon Mobil, but 1.67 (0.25/0.15, FIGURE 102), i.e. the growth rate of net wealth is in this case relatively higher than that of operating income. McDonald's and Wal-Mart Stores exhibit a similar tight linear relationship between operating income and momentum net wealth (FIGURE 103 & FIGURE 104). Both companies appear to have about the same return on total assets (±4%) and both vary greatly in their net wealth momentum. When we compare the scatter plots with the directional change percentages, the apparent lack of a tight directional change is confirmed by McDonald's low score: 77% (TABLE 42). On the other hand, Wal-Mart has a very high score 93.7% and this remarkable difference can be traced (visually) in the force dynamics of these companies (FIGURE 105 & FIGURE 106). McDonald's exhibits a similar pattern in force as in momentum and has a lower force score: 62.3%. In contrast, Wal-Mart exhibits a more tight directional change in force dynamics which is reflected in a higher score than the average: 79.4% (vs. 63.2%). From this example, I infer that the period clusters of directional change have to be evaluated together with their scores to determine whether the association appears to be tight or not in between the dimension of force and momentum in the TEMA framework.

For the same companies scatter plots are provided in FIGURE 107 up to FIGURE 110 of momentum or force of total wealth versus net wealth. It is all too apparent that these plots exhibit comparable clusters of quarters as well as linear relationships as with operating income versus net wealth (FIGURE 101 up to FIGURE 104). But, there are also differences. In the case of Exxon Mobil and Microsoft the directional change fractions of total wealth and net wealth are analogous, which is elucidated by the more tight periods' position to the directional diagonal (FIGURE 107 & FIGURE 108). In contrast, with McDonald's and Wal-Mart the opposite appears to be the case (FIGURE 109 & FIGURE 110). Here I do not see the linear relationship as was the case between operating income and net wealth momentum (FIGURE 103 & FIGURE 104). Noteworthy with Wal-Mart is that the linear relationship

	RIC	from	to	Nonparametric Correlations[1]				Correlations[2]			
				TWM-NWM	OI-NWM	TWF-NWF	OIF-NWF	TWM-NWM	OI-NWM	TWF-NWF	OIF-NWF
1	MMM	1990Q2	2005Q2	0.497**	0.345**	0.536**	0.197*	0.690**	0.441**	0.742**	0.202
		N = 61		0.000	0.000	0.000	0.015	0.000	0.000	0.000	0.059
2	AA	1990Q2	2005Q2	0.312**	0.249	0.249**	0.061	0.820**	0.322	0.727**	0.036
		N = 61		0.001	0.006	0.004	0.251	0.000	0.006	0.000	0.392
3	MO	1990Q2	2005Q2	0.193*	-0.041	0.192*	0.422**	0.110	0.129	0.121	0.347**
		N = 61		0.022	0.342	0.021	0.000	0.199	0.160	0.177	0.003
4	AXP	1991Q1	2005Q2	0.086	-0.012	0.067	0.088	0.034	0.122	0.022	0.063
		N = 58		0.188	0.460	0.239	0.173	0.401	0.181	0.435	0.319
5	AIG	1989Q4	2005Q2	0.377**	-0.106	0.405**	-0.087	0.863**	-0.194	0.859**	-0.162
		N = 63		0.000	0.168	0.000	0.167	0.000	0.064	0.000	0.103
6	T	1989Q4	2005Q2	0.544**	0.259**	0.612**	-0.025	0.893**	0.096	0.894**	-0.263*
		N = 63		0.000	0.004	0.000	0.390	0.000	0.228	0.000	0.019
7	BA	1990Q2	2005Q2	0.329**	0.169*	0.297**	-0.067	0.116	0.144	0.062	-0.195
		N = 61		0.000	0.046	0.001	0.227	0.187	0.134	0.316	0.066
8	CAT	1989Q4	2005Q2	0.217*	0.441**	0.000	-0.056	-0.257*	0.357**	0.386**	0.055
		N = 63		0.011	0.000	0.500	0.264	0.002	0.002	0.001	0.344
9	C	1990Q3	2005Q2	0.416**	0.149	0.495**	-0.064	0.648**	0.055	0.696**	0.059
		N = 60		0.000	0.089	0.000	0.242	0.000	0.339	0.000	0.326
10	KO	1990Q1	2005Q2	0.371**	0.304**	0.299**	0.354**	0.425**	0.409**	0.326**	0.323**
		N = 62		0.000	0.001	0.000	0.000	0.000	0.000	0.005	0.005
11	DD	1989Q3	2005Q2	0.228**	0.437**	0.222**	0.187*	0.295**	0.256*	0.290*	0.064
		N = 64		0.006	0.000	0.006	0.016	0.009	0.021	0.010	0.309
12	XOM	1991Q3	2005Q2	0.561**	0.410**	0.582**	0.278**	0.750**	0.569**	0.732**	0.442**
		N = 56		0.000	0.000	0.000	0.002	0.000	0.000	0.000	0.000
13	GE	1990Q1	2005Q2	0.119	0.215*	0.232**	0.389**	0.190	0.252*	0.212*	0.440**
		N = 62		0.102	0.025	0.006	0.000	0.069	0.024	0.049	0.000
14	GM	1990Q2	2005Q2	0.127	0.389**	0.001	0.186*	0.099	0.253*	-0.140	0.027
		N = 61		0.088	0.001	0.497	0.018	0.224	0.025	0.140	0.417
15	HPQ	1990Q1	2005Q2	0.307**	0.414**	0.215*	0.131	0.968**	-0.631**	0.947**	-0.535**
		N = 62		0.001	0.000	0.010	0.073	0.000	0.000	0.000	0.000
16	HD	1989Q3	2005Q2	0.102	0.269**	0.018	0.340**	0.494**	0.044	0.696**	0.221*
		N = 64		0.139	0.004	0.423	0.000	0.000	0.365	0.000	0.040
17	HON	1990Q1	2005Q2	0.177*	0.373**	-0.015	-0.039	-0.036	0.626**	0.765**	-0.034
		N = 62		0.031	0.000	0.436	0.332	0.392	0.000	0.000	0.398
18	IBM	1990Q2	2005Q2	0.377**	0.427**	0.439**	0.235**	0.416**	0.768**	0.350**	-0.184
		N = 61		0.000	0.000	0.000	0.004	0.000	0.000	0.003	0.078
19	INTC	1990Q2	2005Q2	0.098	0.211*	0.211**	0.383**	0.181	0.255*	0.208	0.432**
		N = 61		0.152	0.023	0.009	0.000	0.081	0.024	0.054	0.000
20	JNJ	1990Q2	2005Q2	0.352**	0.314**	0.191*	0.369**	0.299**	0.311**	0.148	0.072
		N = 61		0.000	0.001	0.023	0.000	0.010	0.007	0.128	0.290
21	JPM	1990Q2	2005Q2	0.165*	0.239**	0.156*	0.180*	0.762**	0.024	0.646**	-0.097
		N = 61		0.042	0.008	0.045	0.024	0.000	0.427	0.000	0.229
22	MCD	1990Q2	2005Q2	0.483**	0.147	0.402**	0.094	0.592**	0.190	0.541**	-0.153
		N = 61		0.000	0.078	0.000	0.149	0.000	0.071	0.000	0.119
23	MRK	1990Q2	2005Q2	0.230**	0.276**	0.276**	0.139	0.900**	0.158	0.874**	0.191
		N = 61		0.008	0.002	0.002	0.063	0.000	0.113	0.000	0.070
24	MSFT	1989Q4	2005Q2	0.757**	0.456**	0.628**	0.106	0.947**	0.471**	0.941**	-0.108
		N = 63		0.000	0.000	0.000	0.118	0.000	0.000	0.000	0.200
25	PFE	1990Q3	2005Q2	0.403**	0.272**	0.364**	0.272**	0.981**	-0.434**	0.963**	-0.056
		N = 60		0.000	0.002	0.000	0.001	0.000	0.000	0.000	0.336
26	PG	1989Q4	2005Q2	0.389**	0.228**	0.380**	0.375**	0.380**	0.691**	0.274*	-0.121
		N = 63		0.000	0.010	0.000	0.000	0.005	0.000	0.015	0.173
27	UTX	1990Q2	2005Q2	0.340**	0.361**	0.314**	0.111	0.668**	0.501**	0.542**	0.156
		N = 61		0.000	0.000	0.000	0.109	0.000	0.000	0.000	0.115
28	VZ	1990Q4	2005Q2	0.340**	0.312**	0.440**	0.159*	0.894**	0.326**	0.884**	-0.015
		N = 59		0.000	0.001	0.000	0.041	0.000	0.006	0.000	0.336
29	WMT	1989Q4	2005Q2	-0.014	0.594**	-0.380**	0.594**	-0.088	0.736**	-0.464**	0.724**
		N = 63		0.442	0.000	0.000	0.000	0.246	0.000	0.000	0.000
30	DIS	1990Q3	2005Q2	0.284**	0.443**	0.306**	0.297**	0.976**	-0.122	0.954**	-0.416**
		N = 60		0.001	0.000	0.001	0.001	0.000	0.176	0.000	0.000
			Significantly correlated:	80.0%	80.0%	83.3%	56.7%	73.3%	60.0%	80.0%	33.3%

1 = Kendall's τ-b.

2 = Pearson correlation. ** = Significant at the 1% level, * = Significant at the 5% level (1-tailed). RIC = Reuters Instrument Code.

Table 43 Dow. Directional change correlation test statistics of the component companies.

between total wealth force and net wealth force appears to be inverse to that of operating income force and net wealth force (compare FIGURE 112 with FIGURE 106). McDonald's directional change of force now plots along the directional diagonal but with a wide spread (compare FIGURE 111 with FIGURE 105). On the basis of only these example scatter plots it suffices to conclude that associations are likely to be present but that they differ greatly among companies and between dimensions of the TEMA framework.

8.3.3 Association statistics

At this point, I posit that a certain association seems to be present in the accounting variables between the independent variables operating income and total wealth and the dependent variable net wealth. Therefore, the same data was tested for the presence of any significant correlation with one-tailed probabilities test of significance as the direction of associa-tion is known to validate or falsify hypothesis H 4_a and H 5_a.[4] The association between force or momentum variables is one directional for either total wealth or operating income to net wealth. Both Pearson's correlation and Kendall's τ-b coefficients are provided in TABLE 43. These results have to be read with some caution. Not all variables meet the requirement of normally distributed data to make the Pearson's correlation coefficient a reliable test statistic. Therefore, Kendall's τ-b coefficient is here a more reliable test statistic. Something that indeed seems to be reflected in the average score percentages of the nonparametric correlations: 80% for both MTW and OI compared to the parametric correlations 73.3% and 60% (TABLE 43). Nevertheless, in many cases the results of either statistic appears to be in agreement (e.g. Microsoft, United Technologies and Wal-Mart). Of special interest is the fact that, except for American Express, all DOW component companies appear to have one or more significantly correlated momentum or force variables of total wealth or operating income versus net wealth and the greater part is significant at the 1% level (86%). Therefore, this data seems to provide ample support for my hypothesis H 4_a and H 5_a.

8.3.4 Discussion

Notwithstanding the encouraging result of the directional change visual and statistical analysis, it is of little value as support for my main hypothesis (H 1_a): that there is a general relationship between accounting variables in the dimensions of the TEMA framework. So far, I have only increased my confidence that, during the periods studied, the net wealth growth rate of the DOW component companies is associated to some degree with the growth rate of operating income or total wealth. However, this relationship is studied with directional change analysis only by quarter. In other words, now only the association is investigated between variables at the same point or period in time. Therefore, like decomposition analysis investigated in Chapter 4 and 5, directional change analysis is basically a static method. It cannot determine whether the association between variables extends over longer periods of time or not. Economic intuition suggests that this is likely to occur because forces that contribute to the increase of total wealth momentum, and thus to total wealth, might have some effect on net wealth beyond the horizon of the same or next quarter. Thus, instead of only investigating the association between accounting variables from a *static perspective* I have to approach the data next from a *dynamic perspective*. Time series regression, modeling and simulation provides the means to perform such studies.

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4 Analyses were done with the software: *SPSS for Windows*, release 13.0.1, build December 12, 2004, SPSS Inc.

		Regression		Ex Post Explanation		
	Dow Component Company - RIC	Start	Obs.	TWF	OIF	TWF+OIF
1	3M Co. - MMM	1995Q2	43	1	1	1
2	Alcoa Inc. - AA	1998Q4	25	1	1	1
3	Altria Group Inc. - MO	1994Q1	44	1	1	1
4	American Express Co. - AXP	1993Q1	36	1	1	1
5	*American International Group Inc. - AIG*	1981Q4	93	*1*	*1*	*1*
6	AT&T - T	1995Q3	38	1	1	1
7	Boeing Co. - BA	1998Q1	28	1	1	1
8	Caterpillar Inc. - CAT	1993Q3	46	*1*	*1*	*1*
9	Citigroup Inc. - C	1998Q1	28	1	1	1
10	Coca-Cola Co. - KO	1992Q1	52	0	1	1
11	E I du Pont de Nemours and Co. - DD	1997Q2	35	1	1	1
12	Exxon Mobil Corp. - XOM	1994Q2	43	1	1	1
13	General Electric Co. - GE	1991Q4	53	1	1	1
14	General Motors Corp. - GM	1990Q3	58	1	1	1
15	Hewlett-Packard Co. - HPQ	1996Q3	34	1	1	1
16	*Home Depot Inc. - HD*	1995Q2	39	*1*	*1*	*1*
17	Honeywell International Inc. - HON	1992Q4	49	1	1	1
18	IBM Corp. - IBM	1995Q4	37	1	1	1
19	Intel Corp. - INTC	1994Q2	43	1	1	1
20	Johnson & Johnson - JNJ	1992Q4	49	1	1	1
21	JPMorgan Chase & Co. - JPM	1993Q3	46	1	1	1
22	McDonald's Corp. - MCD	1998Q1	28	1	1	1
23	Merck & Co. Inc. - MRK	1983Q2	87	1	1	1
24	*Microsoft Corp. - MSFT*	1996Q3	34	*1*	*1*	*1*
25	Pfizer Inc. - PFE	1992Q4	49	1	1	1
26	Procter & Gamble Co. - PG	1994Q1	44	1	1	1
27	United Technologies Corp. - UTX	1992Q1	52	*1*	*1*	*1*
28	Verizon Communications Inc. - VZ	1992Q1	52	1	1	1
29	*Wal-Mart Stores Inc. - WMT*	1996Q3	34	*1*	*1*	*1*
30	Walt Disney Co. - DIS	1997Q1	32	1	1	1
	Average of correct regression models (%):			96.7%	100%	100%

OIF = operating Income Force. TWF = Total Wealth Force. RIC = Reuters Instrument Code.
1 = model with raw (accounting) data, *1* = model with log normal (transformed) data.

Table 44 Dow. Regression model success scores for ex post explanation.

8.4 Time series analysis of Dow component companies

In this section the time series analysis of Dow component companies is presented. The econometric methodology used is discussed with some detail in Chapter 2, section 2.3, page 52, using 3M as an example (however with a shorter time series).[5]

8.4.1 Regression models

In Table 44 the success scores for ex post explanation is reported of the three TEMA models for each Dow component company. Each model explains the trend of net wealth (equity). The first by total wealth force (TWF), the second by operating income force (OIF), and the third is the joint model (TWF & OIF). Successful ex post explanation is indicated with a '1' whereas a '0' indicates a failure to explain within the bounds of econometric assumptions (Studenmund 2006, 161). In this study, the only model that fails to meet those test criteria is that of Coca Cola Co. (KO), which uses total wealth force, and, consequently, it is excluded from predictive simulation and further analysis. Table 45 provides the test statistics of the viable regression models: Adjusted R^2, the F-test and the BG LM test and their P-values.

[5] Analyses were done with the software: *Eviews*, standard edition, version 5.1, build July 20, 2005, Quantitative Micro Software, LLC.

	Dow Component Company - RIC	Total Wealth Force			Operating Income Force			TWF + OIF		
		Adj. R^2	F-test P-value	BGLM P-value	Adj. R^2	F-test P-value	BGLM P-value	Adj. R^2	F-test P-value	BGLM P-value
1	3M Co. - MMM	0.83	47.48 0.000	0.00 1.000	0.57	13.42 0.000	1.25 0.263	0.86	47.84 0.000	0.00 1.000
2	Alcoa Inc. - AA	0.92	137.31 0.000	0.03 0.864	0.62	8.71 0.000	0.08 0.777	0.94	64.15 0.000	1.46 0.228
3	Altria Group Inc. - MO	0.51	10.02 0.000	0.90 0.343	0.47	11.86 0.000	1.13 0.289	0.64	16.14 0.000	1.31 0.253
4	American Express Co. - AXP	0.69	27.68 0.000	0.32 0.574	0.69	27.35 0.000	0.00 1.000	0.71	24.21 0.000	0.00 1.000
5	American International Group Inc. - AIG	0.63	53.82 0.000	0.02 0.895	0.43	24.01 0.000	0.49 0.486	0.64	41.40 0.000	0.00 0.979
6	AT&T - T	0.83	61.45 0.000	0.96 0.327	0.54	11.76 0.000	0.63 0.427	0.92	12.60 0.000	0.00 0.979
7	Boeing Co. - BA	0.63	12.65 0.000	0.96 0.328	0.48	9.33 0.000	0.00 1.000	0.61	9.52 0.000	0.61 0.436
8	Caterpillar Inc. - CAT	0.43	9.34 0.000	0.01 0.905	0.46	10.68 0.000	0.06 0.800	0.47	9.07 0.000	0.11 0.736
9	Citigroup Inc. - C	0.77	45.78 0.000	0.62 0.429	0.86	34.13 0.000	2.70 0.100	0.82	40.73 0.000	1.26 0.262
10	Coca-Cola Co. - KO	N.A.			0.66	25.35 0.000	0.71 0.399	0.67	22.12 0.000	1.56 0.212
11	E I du Pont de Nemours and Co. - DD	0.51	11.57 0.000	0.62 0.433	0.41	11.48 0.000	0.55 0.460	0.62	13.36 0.000	0.00 1.000
12	Exxon Mobil Corp. - XOM	0.94	345.95 0.000	0.13 0.716	0.49	14.24 0.000	0.00 0.951	0.95	202.49 0.000	2.48 0.115
13	General Electric Co. - GE	0.46	23.32 0.000	0.82 0.366	0.66	21.09 0.000	0.93 0.336	0.66	17.66 0.000	2.38 0.123
14	General Motors Corp. - GM	0.74	32.77 0.000	0.18 0.672	0.41	12.44 0.000	2.65 0.104	0.75	34.82 0.000	0.00 1.000
15	Hewlett-Packard Co. - HPQ	0.94	180.57 0.000	3.03 0.082	0.35	5.50 0.002	0.15 0.703	0.95	148.75 0.000	2.71 0.100
16	Home Depot Inc. - HD	0.63	36.93 0.000	1.99 0.158	0.34	16.07 0.000	0.64 0.425	0.66	34.42 0.000	0.19 0.663
17	Honeywell International Inc. - HON	0.56	16.01 0.000	0.89 0.344	0.68	21.85 0.000	3.15 0.076	0.82	32.14 0.000	0.00 1.000
18	IBM Corp. - IBM	0.48	11.94 0.000	0.15 0.702	0.47	11.65 0.000	0.00 0.989	0.48	9.34 0.000	0.01 0.927
19	Intel Corp. - INTC	0.81	59.21 0.000	0.18 0.671	0.16	3.72 0.019	0.77 0.381	0.88	0.00 0.000	0.00 0.000
20	Johnson & Johnson - JNJ	0.26	4.41 0.003	0.79 0.376	0.25	4.27 0.003	0.40 0.528	0.28	3.69 0.003	0.05 0.831
21	JPMorgan Chase & Co. - JPM	0.84	79.51 0.000	0.74 0.390	0.62	15.80 0.000	2.34 0.126	0.87	49.28 0.000	1.26 0.261
22	McDonald's Corp. - MCD	0.63	16.43 0.000	1.48 0.224	0.61	9.58 0.000	0.91 0.341	0.66	9.78 0.000	1.01 0.316
23	Merck & Co. Inc. - MRK	0.79	82.66 0.000	1.08 0.299	0.48	12.34 0.000	1.75 0.186	0.80	44.80 0.000	1.56 0.211
24	Microsoft Corp. - MSFT	0.93	147.88 0.000	2.53 0.112	0.79	26.00 0.000	3.51 0.061	0.96	137.11 0.000	1.03 0.311
25	Pfizer Inc. - PFE	0.99	1389.9 0.000	1.85 0.174	0.57	13.96 0.000	0.11 0.744	1.00	2750.9 0.000	3.57 0.059
26	Procter & Gamble Co. - PG	0.31	10.65 0.000	2.37 0.124	0.40	15.59 0.000	1.45 0.228	0.42	11.40 0.000	1.75 0.185
27	United Technologies Corp. - UTX	0.64	23.47 0.000	0.21 0.647	0.54	11.08 0.000	0.00 1.000	0.80	29.43 0.000	0.56 0.456
28	Verizon Communications Inc. - VZ	0.93	234.34 0.000	0.30 0.587	0.60	16.37 0.000	0.19 0.663	0.95	177.14 0.000	0.73 0.392
29	Wal-Mart Stores Inc. - WMT	0.55	41.18 0.000	0.73 0.393	0.72	64.61 0.000	0.00 0.973	0.74	48.01 0.000	0.00 1.000
30	Walt Disney Co. - DIS	0.42	8.39 0.000	1.01 0.316	0.46	13.95 0.000	0.77 0.380	0.65	9.40 0.000	0.06 0.801

Adj. R^2 = Adjusted R^2. Test statistics apply to the base period (up to 2005Q4).
BGLM = Breusch-Godfrey Lagrange Multiplier test for serial correlation at 1 lag (Obs.*R^2).
OIF = operating Income Force. TWF = Total Wealth Force. RIC = Reuters Instrument Code.

Table 45 Dow component companies. Test statistics of the regression models (ex post).

			Wealth measures		Momentum measures			Force measures		
	RIC	Start	TW	NW	TWM	NWM	OI	NWF	TWF	OIF
1	MMM	1995Q2	0.9956	1.0000	0.0001	0.0085	0.9915	0.0000	0.0000	0.1466
2	AA	1998Q4	0.5981	0.5648	0.0005	0.0002	0.2829	0.0000	0.0000	0.0006
3	MO	1994Q1	0.5926	0.9985	0.0000	0.0000	0.1932	0.0000	0.0000	0.0010
4	AXP	1993Q1	0.8927	0.6302	0.0000	0.0000	0.0375	0.0000	0.0000	0.0000
5	*AIG*	1981Q4	*0.7484*	*0.6465*	0.0000	0.0000	*0.8644*	0.0001	0.0000	0.0000
6	T	1995Q3	0.5145	0.2788	0.0018	0.0013	0.2407	0.0000	0.0000	0.0000
7	BA	1998Q1	0.4526	0.8882	0.0018	0.0004	0.1036	0.0000	0.0000	0.0000
8	*CAT*	1993Q3	*0.4967*	*0.0005*	0.0000	0.0162	*0.0365*	0.0000	0.0000	0.0094
9	C	1998Q1	0.0940	0.2113	0.0000	0.0000	0.0070	0.0001	0.0000	0.0000
10	KO	1992Q1	0.5677	0.6635	0.1425	0.0000	0.4336	0.0000	0.0000	0.0001
11	DD	1997Q2	0.6943	0.5992	0.0000	0.0000	0.0418	0.0000	0.0000	0.0000
12	XOM	1994Q2	0.6061	0.8377	0.0000	0.0000	0.9878	0.0000	0.0000	0.0010
13	GE	1991Q4	0.9971	1.0000	0.0363	1.0000	0.7011	0.0029	0.0000	0.0000
14	GM	1990Q3	0.9994	0.2778	0.0001	0.0000	0.0015	0.0000	0.0000	0.0000
15	HPQ	1996Q3	0.6651	0.6902	0.0000	0.0000	0.2166	0.0000	0.0000	0.0001
16	*HD*	1995Q2	0.6639	0.3915	0.4630	0.0003	0.9997	0.0000	0.0001	0.2099
17	HON	1992Q4	0.4627	0.1306	0.0000	0.0000	0.3731	0.0000	0.0000	0.0259
18	IBM	1995Q4	0.7692	0.9277	0.2496	0.0000	0.0030	0.0000	0.0000	0.0000
19	INTC	1994Q2	0.8144	0.8421	0.0029	0.0111	0.3208	0.0000	0.0000	0.0000
20	JNJ	1992Q4	0.9579	0.3020	0.0000	0.0019	0.9998	0.0000	0.0000	0.0024
21	JPM	1993Q3	0.7119	0.9330	0.0000	0.0000	0.9038	0.0000	0.0000	0.0000
22	MCD	1998Q1	0.5842	0.9971	0.0002	0.7235	0.7977	0.0000	0.0000	0.1672
23	MRK	1983Q2	0.5718	0.2383	0.0000	0.0000	0.7412	0.0000	0.0000	0.0000
24	*MSFT*	1996Q3	*0.7826*	*0.7794*	0.0561	0.2312	*0.5631*	0.0001	0.0001	0.0001
25	PFE	1992Q4	0.8832	1.0000	0.0000	0.0000	0.9983	0.0000	0.0000	0.0000
26	PG	1994Q1	1.0000	0.8196	0.0000	0.0000	0.9546	0.0000	0.0000	0.0012
27	*UTX*	1992Q1	*0.8598*	*0.3305*	0.0000	0.0000	*0.3007*	0.0000	0.0000	0.0000
28	VZ	1992Q1	0.6284	0.5353	0.0000	0.0000	0.8028	0.0000	0.0000	0.0000
29	*WMT*	1996Q3	0.9262	0.9403	0.5258	0.7308	0.0302	0.0094	0.1664	0.0210
30	DIS	1997Q1	0.0174	0.7703	0.0000	0.0001	0.6027	0.0000	0.0000	0.0000

NW = net wealth (equity), NWM = net wealth momentum, NWF = net wealth force. *Italic* = log normal transformed data
TW = Total Wealth (assets), TWM = total wealth momentum, TWF = total wealth force.
OI = operating income, OIF = operating Income Force. RIC = Reuters Instrument Cod ADF test including constant

Table 46 Dow component companies. P-value of the Augmented Dickey-Fuller unit root test (up to 2005Q4).

8.4.2 Test statistics

All Dow companies accounting variables time series were tested for the presence of autocorreltation with unit root tests on the variables, including a constant: the Augmented Dickey-Fuller test (ADF) and the Phillips-Perron test (PP).[6] The unit root tests are applied to the sample base periods, i.e. the ex ante quarters used to develop the regression models. The last four quarters of the time series are left out as an hold-out sample because the explanatory regression models are developed from the base period data (ex post). Of each model is indicated in Table 48 between brackets the P-value of the *t*-test statistic of the coefficient of the independent variable(s) of each model. The F-test of overall statistical significance of each Dow model is reported in Table 45. The null hypothesis of the F-test of overall statistical significance is that the slope coefficients of the independent variables in an equation equal zero simultaneously (Studenmund 2006, 154).[7] The test critical value of the F-test depends on the degrees of freedom of the underlying F-ratio and is determined by the number of independent variables and the number of time points for which the model is calculated (Studenmund 2006, 155). Thus, the appropriate critical F-value varies between models and time

[6] Only the unit root tests result of the accounting variables of 3M were presented earlier in Chapter 2 as an procedural example (Table 5 and Table 6, page 56).

[7] If there is only one independent variable, then a F-test and a T-test will have the same result.

			Wealth measures		Momentum measures			Force measures		
	RIC	Start	TW	NW	TWM	NWM	OI	NWF	TWF	OIF
1	MMM	1995Q2	1.0000	1.0000	0.0001	0.0042	0.9700	0.0000	0.0000	0.0000
2	AA	1998Q4	0.5396	0.5531	0.0005	0.0002	0.2612	0.0001	0.0000	0.0006
3	MO	1994Q1	0.9977	0.9984	0.0000	0.0000	0.0632	0.0001	0.0001	0.0000
4	AXP	1993Q1	0.2419	0.7490	0.0000	0.0000	0.0519	0.0001	0.0001	0.0000
5	*AIG*	1981Q4	*0.9315*	*0.5877*	0.0000	0.0000	*0.2199*	0.0001	0.0001	0.0000
6	T	1995Q3	0.9633	0.2547	0.0035	0.0013	0.1977	0.0000	0.0000	0.0000
7	BA	1998Q1	0.9352	0.8561	0.0020	0.0004	0.0998	0.0001	0.0001	0.0000
8	*CAT*	1993Q3	*0.9797*	*0.0008*	0.0000	0.0000	*0.0306*	0.0001	0.0001	0.0000
9	C	1998Q1	0.9386	0.2139	0.0000	0.0000	0.0070	0.0001	0.0001	0.0000
10	KO	1992Q1	1.0000	0.8033	0.0000	0.0000	0.0147	0.0001	0.0001	0.0000
11	DD	1997Q2	0.9614	0.7016	0.0000	0.0000	0.0487	0.0001	0.0001	0.0000
12	XOM	1994Q2	0.9744	0.8258	0.0000	0.0000	0.9759	0.0001	0.0001	0.0014
13	GE	1991Q4	1.0000	1.0000	0.0000	0.0324	0.7906	0.0001	0.0001	0.0000
14	GM	1990Q3	1.0000	0.2212	0.0001	0.0000	0.0016	0.0000	0.0001	0.0000
15	HPQ	1996Q3	0.8993	0.6650	0.0000	0.0000	0.1965	0.0001	0.0001	0.0000
16	*HD*	1995Q2	0.9971	0.3949	0.0000	0.0003	0.7128	0.0000	0.0001	0.0000
17	HON	1992Q4	0.9606	0.1306	0.0000	0.0000	0.4963	0.0001	0.0001	0.0000
18	IBM	1995Q4	0.9937	0.9720	0.0000	0.0000	0.0000	0.0001	0.0001	0.0001
19	INTC	1994Q2	0.5886	0.9151	0.0030	0.0100	0.3949	0.0000	0.0000	0.0000
20	JNJ	1992Q4	1.0000	0.7136	0.0000	0.0039	0.5714	0.0001	0.0001	0.0000
21	JPM	1993Q3	0.9936	0.9330	0.0000	0.0000	0.9715	0.0000	0.0000	0.0000
22	MCD	1998Q1	0.9985	0.9998	0.0001	0.0022	0.3859	0.0000	0.0000	0.0000
23	MRK	1983Q2	0.9701	0.2184	0.0000	0.0000	0.5998	0.0001	0.0001	0.0001
24	*MSFT*	1996Q3	*0.5619*	*0.7757*	0.0001	0.0000	*0.5542*	0.0001	0.0001	0.0001
25	PFE	1992Q4	0.9846	0.8496	0.0000	0.0000	0.9877	0.0001	0.0001	0.0000
26	PG	1994Q1	1.0000	0.7346	0.0000	0.0000	0.0990	0.0000	0.0000	0.0000
27	*UTX*	1992Q1	*0.9999*	*0.4116*	0.0000	0.0000	*0.0203*	0.0001	0.0001	0.0000
28	VZ	1992Q1	0.8935	0.5353	0.0000	0.0000	0.7773	0.0001	0.0001	0.0000
29	*WMT*	1996Q3	0.0001	0.9783	0.0001	0.0000	0.3340	0.0001	0.0001	0.0001
30	DIS	1997Q1	0.8932	0.7054	0.0001	0.0001	0.2556	0.0000	0.0001	0.0000

NW = net wealth (equity), NWM = net wealth momentum, NWF = net wealth force. *Italic* = log normal transformed data
TW = Total Wealth (assets), TWM = total wealth momentum, TWF = total wealth force.
OI = operating income, OIF = operating Income Force. RIC = Reuters Instrument Cod PP test including constant

Table 47 Dow component companies. P-value of the Phillips-Perron unit root test (up to 2005Q4).

series. Given the length of the base period time series, the critical F-value for the models is 4.08 at the 5% level of significance and 3.23 at the 5% level for the models with only one explanatory variable (TABLE 41). The decision rule for the F-test tells us to reject the null hypothesis if the reported F-test statistic is *above* the critical F-value. The probability value of the F-test statistic provides an alternative approach to assess overall statistical significance. When the probability value of the F-test statistic is *below* a chosen critical value (0.05 or 0.01) the null hypothesis of zero coefficients should be rejected. As TABLE 45 shows this is the case with all models of the DOW component companies. For example, compare the statistics of the 3M models (MMM).[8] The F-test of the operating income model, the total wealth model and the joint model rejects the null hypothesis, respectively, even at the 1% level of significance with 47.84, 13.42 and 47.84 versus 7.31, 7.31 and 5.18. This is also confirmed by the P-value: 0.000 of each test. Apparently the association over time between the dependent variable net wealth force and the independent variables total wealth and operating income force is rather strong, which is also the case with the joint model. Hence, evidence in support of my hypothesis H 3_a is found in the 3M models, namely, that there is a general relationship between the accounting variables by temporal association. Moreover, all TEMA models have a similar result.

[8] Recall that the 3M operating income model of the shorter time series discussed in Chapter 2 failed to meet this test criterium.

		Coefficient [Confidence Interval] Bandwith			
	RIC	TWF	OIF	TWF	OIF
1	MMM	0.44 [0.38, 0.51] 0.13	1.68 [0.78, 2.58] 1.8	0.47 [0.43, 0.50] 0.07	0.84 [0.53, 1.16] 0.63
2	AA	0.37 [0.35, 0.38] 0.04	2.02 [0.07, 3.98] 3.9	0.3 [0.26, 0.34] 0.09	0.96 [0.48, 1.44] 0.97
3	MO	0.11 [0.11, 0.12] 0.01	1.51 [0.61, 2.42] 1.81	0.04 [0.005, 0.08] 0.08	-0.96 [-1.27, -0.65] 0.63
4	AXP	-0.01 [-0.02, -0.01] 0.01	2.22 [1.41, 3.02] 1.61	-0.01 [-0.02, -0.004] 0.01	1.97 [1.24, 2.70] 1.46
5	AIG	0.38 [0.29, 0.46] 0.16	0.002 [0.0001, 0.004] 0.004	0.37 [0.29, 0.45] 0.16	0.002 [0.0001, 0.003] 0.003
6	T	0.27 [0.19, 0.36] 0.17	0.5 [0.13, 0.88] 0.76	0.26 [0.21, 0.3] 0.09	0.55 [0.38, 0.71] 0.33
7	BA	-0.61 [-1.15, -0.08] 1.07	-0.61 [-1.15, -0.08] 1.07	-0.21 [-0.42, -0.01] 0.41	-0.98 [-1.51, -0.45] 1.06
8	CAT	0.5 [0.21, 0.79] 0.58	0.12 [0.04, 0.2] 0.15	0.36 [0.08, 0.64] 0.56	0.11 [0.03, 0.18] 0.16
9	C	0.06 [0.05, 0.07] 0.02	0.86 [0.48, 1.25] 0.77	0.06 [0.05, 0.07] 0.02	0.74 [0.03, 1.45] 1.41
10	KO	N.A.	0.98 [0.5, 1.45] 0.95	0.12 [0.06, 0.17] 0.12	0.83 [0.28, 1.38] 1.1
11	DD	-0.03 [-0.04, -0.02] 0.02	1.33 [0.69, 1.96] 1.27	-0.02 [-0.03, -0.02] 0.01	1.14 [0.56, 1.72] 1.16
12	XOM	0.39 [0.37, 0.4] 0.03	0.42 [0.11, 0.72] 0.61	0.38 [0.37, 0.4] 0.03	0.3 [0.09, 0.52] 0.43
13	GE	0.05 [0.02, 0.1] 0.06	-0.54 [-0.61, -0.46] 0.16	0.03 [0.02, 0.04] 0.02	0.6 [0.39, 0.82] 0.43
14	GM	-0.24 [-0.30, -0.17] 0.13	0.69 [0.24, 1.15] 0.91	-0.29 [-0.35, -0.23] 0.12	0.35 [0.12, 0.58] 0.46
15	HPQ	0.56 [0.54, 0.59] 0.06	-8.52 [-12.06, -4.98] 7.07	0.57 [0.54, 0.6] 0.06	-1.1 [-2.03, -0.18] 1.84
16	HD	0.25 [0.01, 0.5] 0.49	0.06 [0.002, 0.12] 0.12	0.3 [0.05, 0.55] 0.5	0.14 [0.07, 0.21] 0.14
17	HON	0.26 [0.11, 0.4] 0.3	0.71 [0.12, 1.31] 1.19	0.21 [0.11, 0.3] 0.19	0.46 [0.09, 0.82] 0.74
18	IBM	0.08 [0.02, 0.15] 0.13	0.40 [0.18, 0.63] 0.46	0.06 [0.0001, 0.11] 0.11	0.23 [0.02, 0.44] 0.43
19	INTC	0.52 [0.44, 0.6] 0.15	0.5 [0.44, 0.6] 0.15	0.55 [0.47, 0.64] 0.17	0.18 [0.05, 0.3] 0.25
20	JNJ	0.34 [0.03, 0.65] 0.62	0.37 [0.03, 0.72] 0.69	0.27 [0.05, 0.49] 0.44	0.39 [0.01, 0.76] 0.75
21	JPM	0.1 [0.04, 0.16] 0.12	5.82 [0.91, 10.72] 9.81	2.23 [2.17, 2.29] 0.12	2.23 [1.31, 3.15] 1.84
22	MCD	0.43 [0.27, 0.58] 0.31	1.19 [0.31, 2.06] 1.74	0.44 [0.30, 0.58] 0.28	0.83 [0.09, 1.58] 1.49
23	MRK	0.5 [0.36, 0.63] 0.28	0.21 [0.004, 0.42] 0.42	0.5 [0.35, 0.64] 0.29	-0.3 [-0.58, -0.01] 0.57
24	MSFT	1.05 [0.92, 1.18] 0.26	0.02 [0.01, 0.04] 0.02	1.08 [0.99, 1.17] 0.19	-0.01* [-0.02, -0.003] 0.02
25	PFE	0.65 [0.64, 0.66] 0.02	-8.83 [-14.08, -3.58] 10.5	0.65 [0.65, 0.66] 0.02	-0.08 [-0.15, -0.01] 0.14
26	PG	0.14 [0.10, 0.18] 0.08	0.95 [0.56, 1.35] 0.8	0.07 [0.005, 0.13] 0.13	0.76 [0.28, 1.24] 0.96
27	UTX	1.86 [1.27, 2.45] 1.19	0.01 [0.001, 0.03] 0.03	1.81 [1.49, 2.12] 0.64	-0.03 [-0.06, -0.0001] 0.06
28	VZ	0.19 [0.19, 0.2] 0.01	0.51 [0.09, 0.94] 0.85	0.19 [0.18, 0.2] 0.02	-0.22 [-0.41, -0.02] 0.39
29	WMT	-0.19 [-0.25, -0.13] 0.12	0.08 [0.06, 0.1] 0.03	-0.05 [-0.1, -0.01] 0.09	0.07 [0.05, 0.09] 0.04
30	DIS	0.09 [0.01, 0.17] 0.16	0.75 [0.24, 1.26] 1.01	0.08 [0.01, 0.14] 0.13	0.46 [0.14, 0.79] 0.65

OIF = operating Income Force. TWF = Total Wealth Force. RIC = Reuters Instrument Code.
RIC = Reuters Instrument Code. * = confidence interval at 10%, all other models at 5%.

Table 48 Dow component companies. Regression models coefficients and their confidence interval.

The aformentioned modeling approach, test procedures, ex post and ex ante simulations were repeated for all Dow companies to extend my findings with the example company 3M. The probability test results of the F-test are in most cases excellent. The only model for which the F-test has a P-value with less than zero digits is the operating income force of Intel Corp.: 0.019, which is still below the critical 5% level.

Possibly the most important test of reliability of econometric time series regression models is that for the presence of serial correlation in the residual errors of the equations. Serial correlation causes bias in dynamic models (Studenmund 2006, 431). Table 45 provides the required test statistics for all Dow component companies. The null hypothesis of the Breusch-Godfrey Lagrange Multiplier (BG LM) test is that there is no serial correlation in the residuals up to the specified order (in my study 1 lag). The test critical value is 3.841 in this study as we test for first-order serial correlation. A value *below* it signals that serial correlation is not present in the residuals and we should accept the null. The probability value of the OBS*R^2 statistic of the BG LM test represents the chance that we are incorrect when we reject the null hypothesis of no serial correlation up to lag order 1 at the 95% confidence level (Type I error). Thus, for all test results where the probability value of the OBS*R^2 statistic is *above* 0.05 I am confident to reject the null hypothesis of first-order serial correlation. As Table 45 shows this is the case with all TEMA models used of the Dow component companies.

All TEMA variables of this study were tested for the presence of a unit root with the Aug-

mented Dickey-Fuller test (ADF) and the Phillips-Perron test (PP), see TABLE 46 and TABLE 47 for P-value as a summary test statistic. The constraint that must be met is that the modeled time series are not trending and thus do not contain a unit root. In that case the TEMA variables are stationary or trend-stationary and my conditional research hypothesis H 6_a is met. The risk of spurious regression is also reduced because the econometric models are balanced as each variable does not require (further) differencing. Note that TABLE 46 and TABLE 47 illustrate how the TEMA framework is instrumental in the selection of the independent variables which are necesseraly in most cases force variables. There are a few examples where operating income and total wealth momentum (both momentum measurements) could be used because they are stationary or trend-stationary, like, Citygroup (C), du Pont de Nemours (DD) and General Motors (GM). Three firms have a contradictory ADF and PP. test result for their operating income time series: 3M (MMM), Home Depot (HD) and McDonald's (MCD). This sheds some doubt on the stationarity of these variables.

Possibly the definitive test for model viability is to calculate the coefficient interval of the regression coefficients of the independent variables of each regression model. The confidence interval is used to indicate the reliability of the coefficient estimate. This is reported in TABLE 48. It includes of each component company TEMA model the coefficients of the independent variables, their confidence interval and its bandwith. What I seek to confirm is that with 95% confidence I can be certain that zero is excluded from the interval. Observe that some TEMA variables have a negative coefficient. Also in that case zero should be excluded from the interval. TABLE 48 shows that this indeed is the case for all TEMA models of all DOW component companies. Given this result, I can proceed with the ex ante forecasts.

8.4.3 Ex ante forecasts

For each DOW component company, ARIMA equations were developed for total wealth force and operating income force. Within sample ex ante forecasts were made for four and eigth quarters with static and dynamic simulation. The TEMA models successfully forecasted net wealth force and net wealth for four quarters with static simulation, respectively, by total wealth force, operating income force and jointly, by 83.6%–83.6%, 85%–83.3% and 82.5%–83.3% (TABLE 49). Likewise, dynamic simulation, forecasted successfully, by 86.2%–78.4%, 85%–82.5% and 87.5%–84.2%. Moreover, the TEMA models success witht the hold-out sample of the next eight quarters with static simulation is, respectively, by 78.9%–81.5%, 80%–80.4% and 77.9%–79.2% (TABLE 50). Dynamic simulation, forecasts successfully for eight quarters, respectively, by 84.5%–81.5%, 84.2%–82.5% and 87.1%–81.3%. However, we should keep in mind that the dynamic simulation results are always much less tightly spread around the Baseline Mean than those of the static simulation.

I present the TEMA models' ex ante forecasts of three DOW companies: Intel (FIGURE 113), Altria Group Inc. (FIGURE 114) and Honeywell International Inc. (FIGURE 115). These are illustrative cases of a downward, upward and stationary net wealth trend (except for the last quarter in the example of Honeywell). I reason that the methodology developed to test the TEMA framework holds in all these cases. Of interest is to observe that both operating income force and total wealth force have predictive power separately and jointly. Comparing the forecasts of the TEMA models can offer new insight in the dynamics of a company, even at the aggregated level of financial statements (Arya *et al.* 2000, 2004). The Intel fore-

		Forecast success of Net Wealth Force, 4 quarters (2005).						Forecast success of Net Wealth, 4 quarters (2005).					
		Panel A - Ex Ante Static			Panel B - Ex Ante Dynamic			Panel C - Ex Ante Static			Panel D - Ex Ante Dynamic		
	RIC	TWF	OIF	TWF+OIF	TWF	OIF	TWF+OIF	TWF	OIF	TWF+OIF	TWF	OIF	TWF+OIF
1	MMM	75%	75%	100%	75%	75%	100%	75%	50%	100%	100%	0%	100%
2	AA	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
3	MO	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
4	AXP	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%
5	*AIG*	*75%*	*75%*	*75%*	*100%*	*100%*	*100%*	*75%*	*75%*	*75%*	*75%*	*75%*	*75%*
6	T	75%	75%	75%	75%	75%	75%	75%	75%	75%	100%	75%	100%
7	BA	75%	100%	50%	75%	75%	75%	75%	100%	50%	50%	100%	100%
8	*CAT*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*
9	C	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
10	KO	N.A.	75%	75%	N.A.	75%	75%	N.A.	75%	100%	N.A.	100%	100%
11	DD	50%	50%	25%	50%	50%	50%	50%	50%	25%	50%	50%	25%
12	XOM	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
13	GE	50%	50%	25%	50%	25%	25%	50%	50%	25%	25%	50%	25%
14	GM	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
15	HPQ	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
16	*HD*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*
17	HON	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
18	IBM	100%	75%	75%	100%	75%	100%	100%	75%	75%	100%	100%	100%
19	INTC	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
20	JNJ	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
21	JPM	75%	50%	100%	50%	50%	100%	75%	50%	100%	25%	50%	50%
22	MCD	100%	75%	75%	100%	75%	75%	100%	75%	75%	25%	25%	25%
23	MRK	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
24	*MSFT*	*25%*	*50%*	*25%*	*50%*	*50%*	*50%*	*25%*	*50%*	*25%*	*25%*	*25%*	*25%*
25	PFE	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
26	PG	25%	75%	75%	50%	75%	50%	25%	75%	75%	25%	75%	50%
27	*UTX*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*
28	VZ	100%	100%	100%	100%	100%	100%	100%	75%	100%	100%	100%	100%
29	*WMT*	*75%*	*100%*	*75%*	*75%*	*100%*	*100%*	*75%*	*100%*	*75%*	*25%*	*100%*	*100%*
30	DIS	75%	75%	75%	100%	100%	100%	75%	75%	75%	100%	100%	100%
	Average:	83.6%	85.0%	82.5%	86.2%	85.0%	87.5%	83.6%	83.3%	83.3%	78.4%	82.5%	84.2%

OIF = operating Income Force. TWF = Total Wealth Force. *Italic* = model with log normal wealth data. RIC = Reuters Instrument Code.

Table 49 Dow component companies. Hold-out static & dynamic forecast result for four quarters (2005).

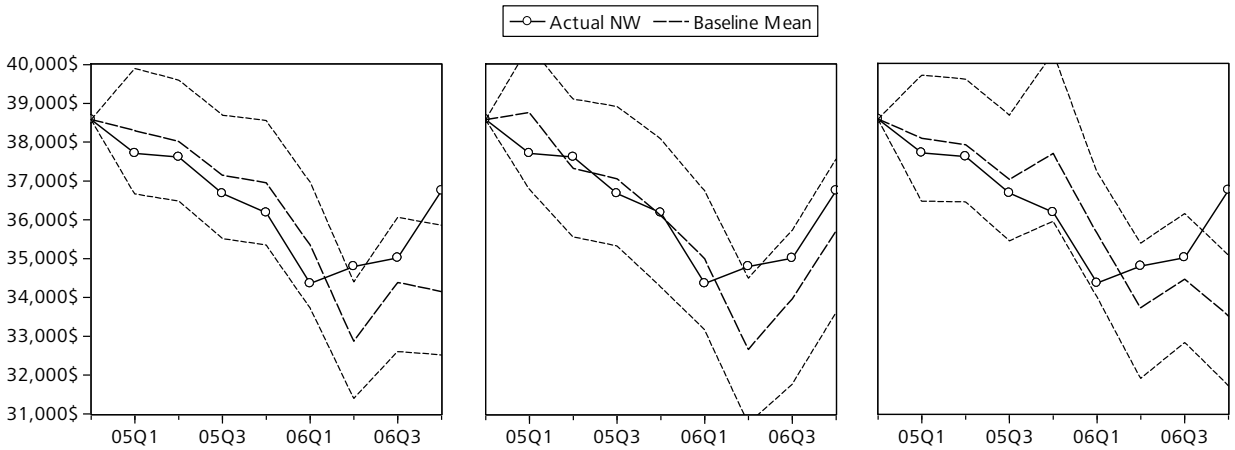


Figure 113 Intel Corp. Hold-out static forecast of net wealth by total wealth force (left), operating income force (middle) and both forces (right).

cast provides some insight in the issue which TEMA variable is the better leading indicator (compare FIGURE 113 middle, with left & right)? Clearly, the operating income force model provides a more tight forecast around actual net wealth and even forecast successfully the last two quarters. Like with 3M (FIGURE 26, page 68), the joint model of Altria Group Inc. predicts net wealth correctly more tightly around the Baseline Mean than with only total wealth force of operating income force (compare FIGURE 114 right, with left & middle).

		Forecast success of Net Wealth Force, 8 quarters (2005-6).						Forecast success of Net Wealth, 8 quarters (2005-6).					
		Panel A - Ex Ante Static			Panel B - Ex Ante Dynamic			Panel C - Ex Ante Static			Panel D - Ex Ante Dynamic		
	RIC	TWF	OIF	TWF+OIF	TWF	OIF	TWF+OIF	TWF	OIF	TWF+OIF	TWF	OIF	TWF+OIF
1	MMM	88%	100%	88%	75%	100%	88%	88%	100%	88%	100%	100%	63%
2	AA	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
3	MO	50%	88%	88%	88%	100%	88%	75%	88%	88%	100%	100%	100%
4	AXP	50%	63%	63%	75%	75%	75%	50%	75%	75%	25%	25%	25%
5	*AIG*	*75%*	*88%*	*75%*	*88%*	*100%*	*88%*	*75%*	*75%*	*75%*	*100%*	*100%*	*100%*
6	T	63%	75%	63%	63%	63%	63%	63%	75%	63%	88%	38%	88%
7	BA	75%	88%	75%	75%	75%	88%	75%	88%	88%	50%	88%	75%
8	*CAT*	*88%*	*88%*	*88%*	*88%*	*88%*	*88%*	*88%*	*88%*	*88%*	*88%*	*100%*	*100%*
9	C	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
10	KO	N.A.	75%	75%	N.A.	75%	75%	N.A.	88%	88%	N.A.	100%	100%
11	DD	50%	63%	25%	75%	75%	75%	50%	63%	25%	25%	25%	13%
12	XOM	88%	88%	88%	100%	100%	100%	100%	88%	88%	100%	100%	100%
13	GE	75%	25%	63%	88%	25%	88%	75%	25%	63%	13%	25%	13%
14	GM	88%	88%	88%	88%	88%	88%	88%	88%	88%	100%	100%	100%
15	HPQ	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
16	*HD*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*
17	HON	88%	88%	88%	88%	88%	88%	88%	88%	88%	100%	100%	100%
18	IBM	88%	75%	75%	75%	63%	75%	88%	75%	75%	100%	100%	100%
19	INTC	75%	88%	100%	75%	88%	88%	75%	88%	88%	100%	100%	100%
20	JNJ	75%	75%	63%	75%	75%	75%	75%	75%	75%	100%	100%	100%
21	JPM	75%	25%	63%	75%	50%	100%	88%	25%	50%	75%	50%	100%
22	MCD	100%	75%	75%	100%	88%	88%	100%	75%	75%	75%	13%	13%
23	MRK	88%	88%	88%	100%	100%	100%	88%	88%	88%	100%	100%	100%
24	*MSFT*	*50%*	*63%*	*50%*	*75%*	*75%*	*75%*	*63%*	*63%*	*63%*	*13%*	*63%*	*13%*
25	PFE	100%	100%	88%	100%	100%	100%	100%	100%	88%	100%	100%	100%
26	PG	25%	50%	50%	50%	75%	75%	38%	38%	50%	50%	50%	50%
27	*UTX*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*
28	VZ	88%	100%	88%	88%	100%	100%	88%	100%	88%	100%	100%	100%
29	*WMT*	*88%*	*100%*	*88%*	*88%*	*100%*	*100%*	*88%*	*100%*	*88%*	*63%*	*100%*	*100%*
30	DIS	63%	50%	50%	63%	63%	50%	63%	63%	50%	100%	100%	88%
	Average:	78.9%	80.0%	77.9%	84.5%	84.2%	87.1%	81.5%	80.4%	79.2%	81.5%	82.5%	81.3%

OIF = operating Income Force. TWF = Total Wealth Force. *Italic* = model with log normal wealth data. RIC = Reuters Instrument Code.

Table 50 Dow component companies. Hold-out static & dynamic forecast result for eight quarters (2005-2006).

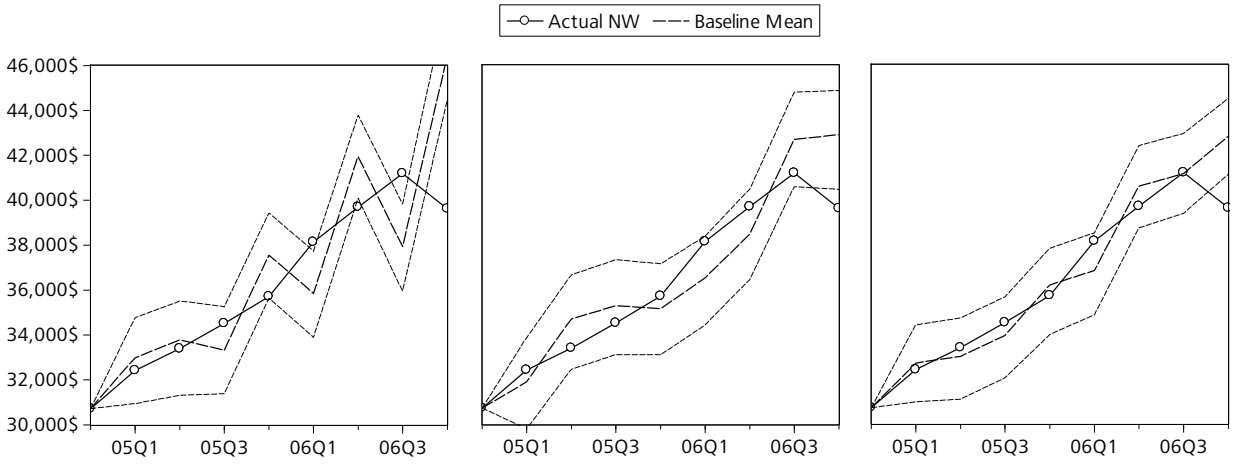


Figure 114 Altria Group Inc. Hold-out static forecast of net wealth by total wealth force (left), operating income force (middle) and both forces (right).

Trend breaks are another relevant informational signal we could get from TEMA models. For the Altria Group Inc., the forecast of the fourth quarter of 2006 is clearly above actual net wealth. Possibly, this might not be a model failure but an example of a business performance below (model) expectation! Such insight is what Ijiri is looking for with momentum accounting so that the variance from the expected trend is disclosed.

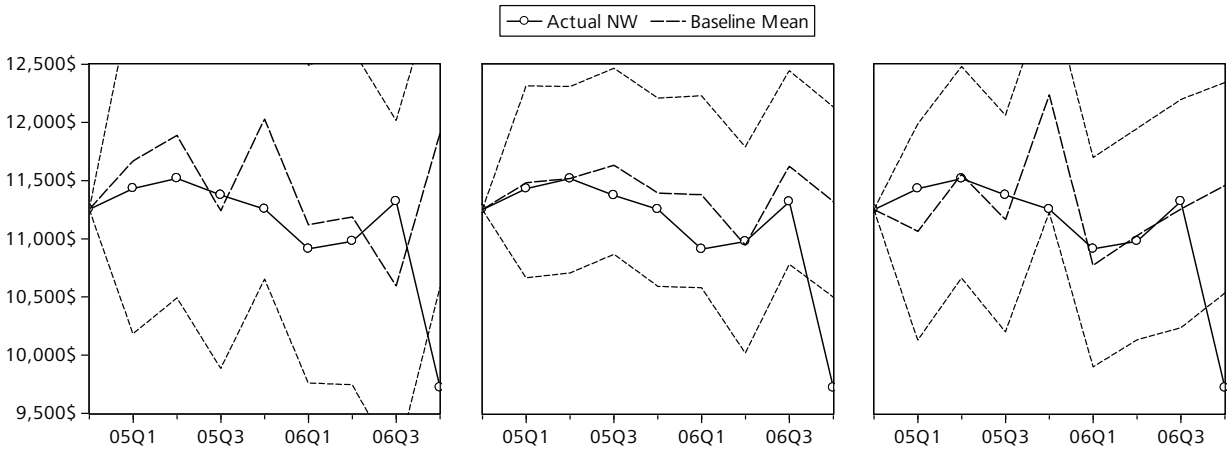


Figure 115 Honeywell International Inc. Hold-out static forecast of net wealth by total wealth force (left), operating income force (middle) and both forces (right).

8.5 Discussion

In this chapter, I presented econometric TEMA models of the 30 DOW component companies that use total wealth force and operating income force as the independent variables to predict the increase or decrease of net wealth force, the dependent variable. Total wealth force only explains for 29 of the 30 companies net wealth force ex post (96.7%). The operating income force models and the joint models explain for all firms the trend of net wealth. The forecast by the TEMA models of the four quarters hold-out sample with static simulation of net wealth force, and net wealth, is on average correct, respectively, by 83.6% and 83.4%. Likewise, dynamic simulation forecasted successfully by 86.2% and 81.7%. The results of the eight quarters hold-out sample are, respectively for static and dynamic simulation, 78.9% and 80.3%; 85.2% and 81.7%. From these results, I conclude that force accounting variables are leading indicators of the trend of net wealth. This analysis of DOW companies' net wealth trend with econometric TEMA models confirms my hypothesis H 3_a: there is a general relationship between variables by temporal association, as well as my hypothesis H 7_a: operating income and total wealth can predict net wealth. The explanatory and predictive power of these models is further support for my main research hypothesis, H 1_a, that there is a general relationship between accounting variables in the dimensions of the TEMA framework of Yuji Ijiri. Improving the ability to analyse trends can benefit all users of financial statements. TEMA offers the framework with potential to study the trends in the composition of wealth together with trends of other period related financial data as well as with non-financial data. The analysis and comparison of companies on such basis is only a first and small step towards a broader use of TEMA for business planning, management control and auditing. I recommend to broaden the analysis of financial statements and extend them with momentum and force measures. In this case, evidence in support of the TEMA theory of Yuji Ijiri was found by me with econometric models for ex post explanation and ex ante prediction of the trend of net wealth. Further research should show if the association between TEMA variables I have observed can be found in other cases.

9

Proportional Change of the Balance Sheet of 3M

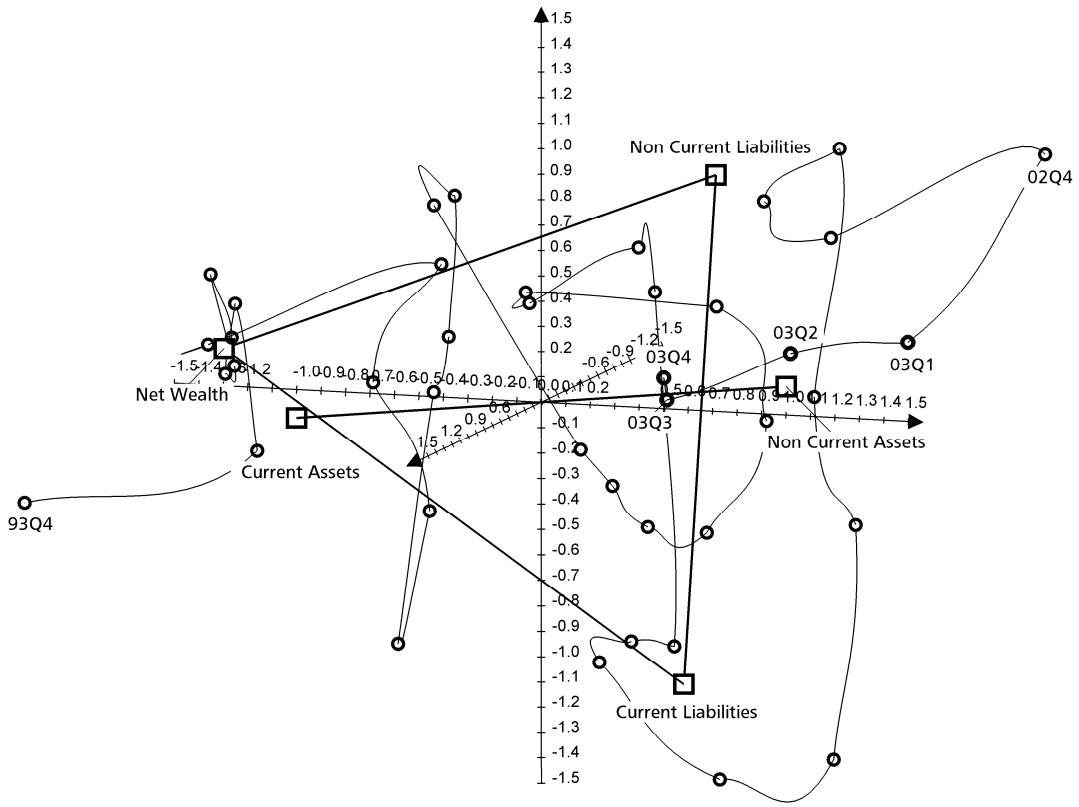


Figure 116 3M. Spectramap biplot of the decomposed wealth factors with hold-out sample (2003Q1-Q4).

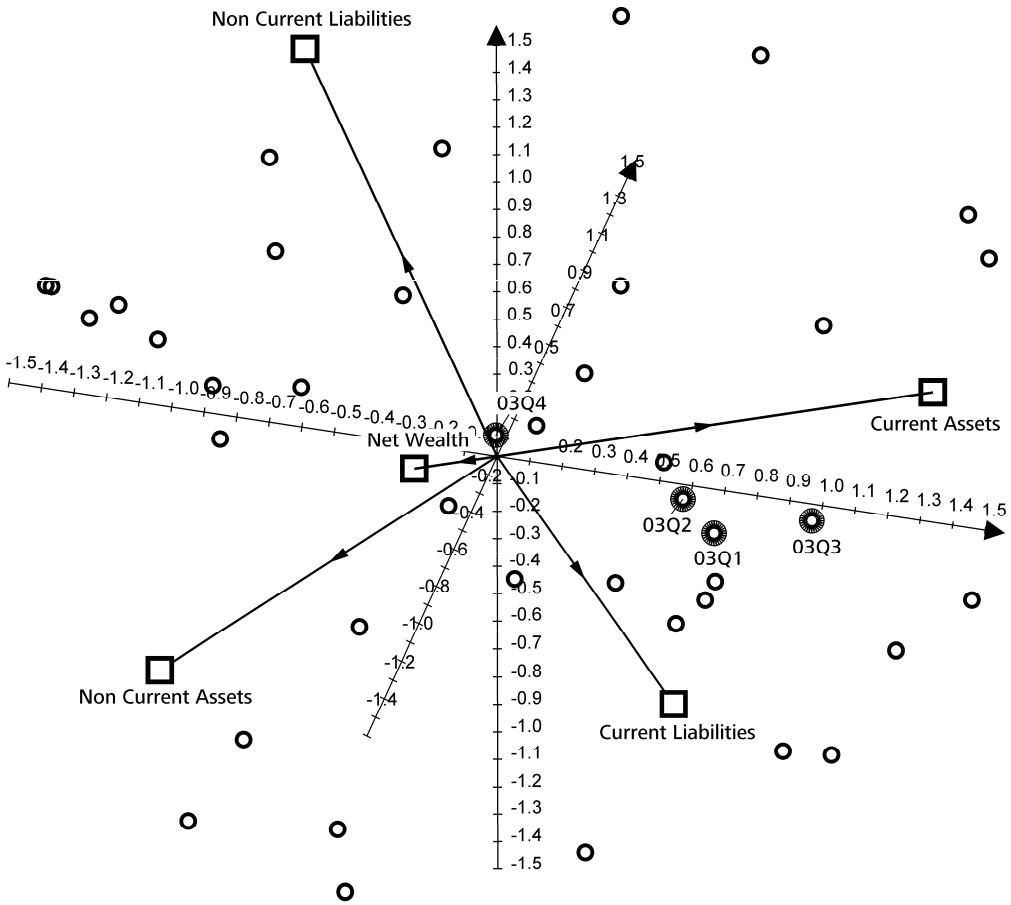


Figure 117 3M. Spectramap biplot of the decomposed wealth momentum factors with hold-out sample (2003Q1-Q4).

9 Abstract

Earlier in this study, the 3M balance sheet was decomposed into a smaller set of components with Spectramap decomposition for wealth and momentum. The biplots of these components visualize the static structure of accounting variables and time points in three dimensions. In this chapter the static analysis of the structural relationship of the balance sheet is extended with a dynamic analysis of the temporal properties of wealth and momentum measures. Firstly, regression models are developed for each decomposed wealth factor. Secondly, for the momentum factors that will drive the dynamic models ARIMA *models are developed. Thirdly, a static and dynamic simulation of a hold-out sample of four quarters is evaluated against the actual factor scores of the time series.*

The result of the momentum driven simulation of balance sheet dynamics in this study of an individual firm has an overall success rate of 92%. Moreover, the position of the last simulated quarter in three dimensional Spectramap biplot is near identical with that of the actual data of that last quarter. This implies that the temporal relation of balance sheet variables is decomposed rather well by the Spectramap factors and that it captures the near term trend. This can be interpreted as an indication that structural as well as dynamic properties of the financial transactions data are indeed aggregated in the balance sheet. This mitigates the criticism of Fraser against the TEMA *framework that it is not possible to express a 'contemporary commercial reality' with the financial accounting system.*

In this chapter, I am able to find evidence in support of the research hypothesis $H\ 8_a$ *that with decomposed balance sheet variables of company it is possible to model and simulate balance sheet dynamics of an individual firm with significant accuracy both ex ante and ex post. Therefore, in this case also the research hypothesis* $H\ 1_a$ *holds that there is a compository as well as a temporal association between variables of the* TEMA *framework.*

A possible benefit of this study is that factors of force and momentum variables can be used as explanatory variables in econometric models of the balance sheet of firms. Another insight is that congruence appears to exist between the structure and dynamics of TEMA *factors and the ordering of time measurements in the Spectramap decomposition of the balance sheet. This can be explained by the typical properties of Spectramap decomposition. Spectramap factors each capture a certain amount of variance, characteristic for the data under investigation, and are not correlated (orthogonal). This makes Spectramap factors good candidates for independent variables in regression models and is more likely to provide significant explanatory and predictive power.*

Depending on particular needs, the benefit of these findings is that an econometric model of the balance sheet can be developed in adherence with the TEMA *framework with either momentum or force variables. I see this as further confirmation that examples can be found where the generality assumption holds for the* TEMA *framework.*

9.1 Introduction

Spectramap decomposition renders a visual impression of the structural change of wealth accounts over time by means of factors (FIGURE 116). These factors are used here as the dependent and the independent variables to develop econometric TEMA models (Masters 1995, 16, Seiler 2003, 165). The economic intuition behind this effort is that the basis

	Panel A - Wealth			Panel B - Wealth Difference			Panel C - Wealth Momentum			
	$\mu 1$	$\mu 2$	$\mu 3$	$\nabla\mu 1$	$\nabla\mu 2$	$\nabla\mu 3$	$\lambda 1$	$\lambda 2$	$\lambda 3$	$\lambda 4$
93Q4	-1.776	-0.329	1.015				-1.254	0.096	0.342	-0.075
94Q1	-1.229	-0.283	-0.204	0.547	0.046	-1.220	0.052	-0.236	0.810	-0.612
94Q2	-1.290	0.309	-0.117	-0.061	0.592	0.087	-0.473	0.494	-0.482	-1.351
94Q3	-1.274	0.056	0.054	0.016	-0.253	0.171	0.472	-0.843	-0.756	-0.412
94Q4	-1.234	0.091	0.062	0.040	0.035	0.008	-0.061	0.033	-0.331	-0.389
95Q1	-1.437	0.397	-0.256	-0.203	0.305	-0.318	0.438	0.844	-0.212	-0.522
95Q2	-1.419	0.116	-0.464	0.018	-0.281	-0.208	0.688	-0.287	-0.068	-0.116
95Q3	-1.429	0.127	-0.203	-0.010	0.011	0.261	-0.218	-0.139	-0.770	0.594
95Q4	-0.041	0.712	1.111	1.389	0.585	1.314	-1.028	-0.569	0.662	-0.376
96Q1	-0.235	0.272	1.367	-0.194	-0.440	0.256	1.574	0.050	-0.431	0.889
96Q2	-0.619	-0.533	-0.493	-0.384	-0.805	-1.860	1.138	-0.022	1.399	0.475
96Q3	-0.796	-1.084	-0.636	-0.177	-0.552	-0.144	1.290	-0.311	-0.242	-0.188
96Q4	-0.435	0.020	0.015	0.361	1.105	0.652	-1.310	0.580	-0.284	-0.233
97Q1	-0.401	0.229	-0.070	0.033	0.209	-0.085	-0.812	0.657	0.425	0.722
97Q2	-0.547	0.700	-0.587	-0.146	0.471	-0.517	0.669	1.218	0.536	-1.119
97Q3	-0.584	0.683	-0.440	-0.036	-0.017	0.147	0.208	-0.018	-0.578	0.651
97Q4	0.150	-0.184	-0.032	0.734	-0.867	0.408	-0.475	-1.398	-0.063	0.589
98Q1	0.226	-0.347	-0.197	0.075	-0.163	-0.166	0.343	-0.451	0.075	-0.172
98Q2	0.412	-0.481	-0.070	0.187	-0.133	0.127	-0.384	-1.434	-0.317	0.053
98Q3	0.477	-0.580	-0.603	0.065	-0.100	-0.534	1.081	0.144	1.373	-0.384
98Q4	0.802	-0.087	-0.359	0.325	0.493	0.244	-1.246	0.298	-0.026	-0.430
99Q1	0.725	0.419	0.026	-0.077	0.506	0.386	-0.521	1.056	-0.593	0.250
99Q2	-0.029	0.450	0.106	-0.754	0.032	0.079	1.153	1.058	-0.553	0.364
99Q3	-0.098	0.365	-0.150	-0.069	-0.086	-0.256	0.527	0.109	-0.054	-0.284
99Q4	0.578	0.723	0.546	0.676	0.358	0.696	-1.189	-0.157	0.547	-0.282
00Q1	0.620	0.539	0.471	0.042	-0.184	-0.075	0.796	-1.134	0.304	-0.396
00Q2	0.583	-0.912	0.120	-0.037	-1.450	-0.351	1.046	-0.847	-0.073	-0.145
00Q3	0.475	-0.867	0.323	-0.108	0.045	0.203	0.304	0.629	-0.682	0.578
00Q4	0.572	-0.840	1.012	0.097	0.027	0.689	-0.551	-0.411	-1.497	0.355
01Q1	0.821	-1.402	0.278	0.250	-0.562	-0.734	0.495	-0.799	0.537	-0.182
01Q2	1.087	-1.404	-0.327	0.266	-0.001	-0.604	-0.582	-0.258	1.095	1.201
01Q3	1.218	-0.453	-0.204	0.130	0.950	0.123	-1.308	0.538	-0.227	-0.108
01Q4	1.088	0.062	-0.083	-0.129	0.515	0.121	-0.147	1.150	-0.078	0.138
02Q1	1.033	0.967	-0.563	-0.055	0.905	-0.481	0.241	1.534	0.768	0.796
02Q2	0.779	0.772	-0.397	-0.254	-0.194	0.166	0.783	0.121	-0.873	-0.206
02Q3	1.249	0.741	0.197	0.470	-0.032	0.595	-0.628	-0.754	-0.571	-0.061
02Q4	1.977	1.038	-0.247	0.728	0.297	-0.445	-1.111	-0.541	0.887	0.388
03Q1	1.479	0.302	-0.059	-0.499	-0.736	0.189	0.735	0.025	-0.256	-0.055
03Q2	1.016	0.242	-0.007	-0.463	-0.060	0.051	0.686	0.258	-0.429	-0.086
03Q3	0.560	0.058	0.142	-0.456	-0.183	0.149	1.060	0.190	-0.347	-0.061
03Q4	0.539	0.140	0.116	-0.021	0.081	-0.026	0.024	0.153	-0.105	-0.131

Table 51 3M. Spectramap factor scores (base period 1993Q1-2002Q4, hold-out sample 2003Q1-Q4 positioned).

of financial accounting is a system model (Blommaert & Blommaert 1990-1, 48, Churchman 1971, Correa 1976 & 1977, Kefford 1995, Mattessich 1978, Thomsen 1998). The accounts that are reported on the balance sheet and income statement are part of a coupled 'whole,' an all encompassing or holistic system. I expect that (decomposed) wealth momentum measures (change) associate with the trend of wealth (magnitude). I try to find evidence that the dynamics of the balance sheet can be explained with dynamic momentum models in adherence to econometric requirements and the TEMA framework of Ijiri (FIGURE 2, page 2).

Ijiri (1986) assumes implicit and explicit linkages in the accounts. In the previous Chapter 5, page 119, spectramap decomposition was already applied to the same time series of the variables of the 3M balance sheet (FIGURE 47, page 118). It was demonstrated that the association between accounting variables is duplicated in all three dimensions of the TEMA framework. Therefore, it should be possible to develop econometric models within the TEMA framework that explain ex post and predict ex ante the dynamics of the balance sheet. My objective is to see if these features indeed have structural and temporal properties that confirm the general relationship between wealth and momentum in the TEMA framework.

Organization of this chapter

The methodology, research question, research hypotheses and data set used are presented in section 9.2 including the time series properties test results. The empirical result of the study is presented in section 9.3. Smaller sections describe the regression models used, the ARIMA models of factors of the balance sheet momentum, the ex post and ex ante simulations and their analyses. Necessary data and statistical details are presented in tables and figures. The last section discusses the result in comparison with existing literature and the conclusion.

9.2 Methodology

9.2.1 Research question

This study addresses the following research question: can I find evidence in the empirical data used in support of the main thesis of momentum accounting theory that a financial accounting statement, in particular the balance sheet, may contain forward-looking information? Principal in this effort is the association that is expected between the dimensions of the TEMA framework: wealth, momentum and force (FIGURE 2, page 2).

9.2.2 Research hypotheses

Several hypotheses of this study, discussed in Chapter 1, section 1.8, page 29, will be tested. Because momentum data are calculated by the first difference of the balance sheet item time series it is expected that they meet the econometric requirement of stationarity or trend-stationarity (EQUATION (8), page 53). The same should apply to the SMA factor time series of the momentum data. If so, hypothesis H 6_a is supported by the evidence for these wealth momentum factors in this case. The factors of the decomposed balance sheet (wealth accounts) are also tested whether they meet the econometric requirement of stationarity or trend-stationarity. If not, their differenced data will be used as dependent variables. Then it follows that it should be possible to develop econometric models without the risk of spurious regression. When the models are well specified, i.e. without serial correlation or heteroskedasticity in the regression residuals, and when the decomposed independent variables of balance sheet momentum explain and predict the dependent variables (the three balance sheet factor scores) evidence in support of hypothesis H 8_a is found for these cases (section 1.8.4, page 34). We should then conclude that, in the example of the balance sheet of 3M, ARIMA models of momentum factors from Ijiri's TEMA framework are drivers of the growth trend of their wealth factors. This would provide further support for the main hypothesis of this study, namely, that evidence for the general relationship between (decomposed) variables in the TEMA framework can be found also at higher aggregation levels (H 1_a).

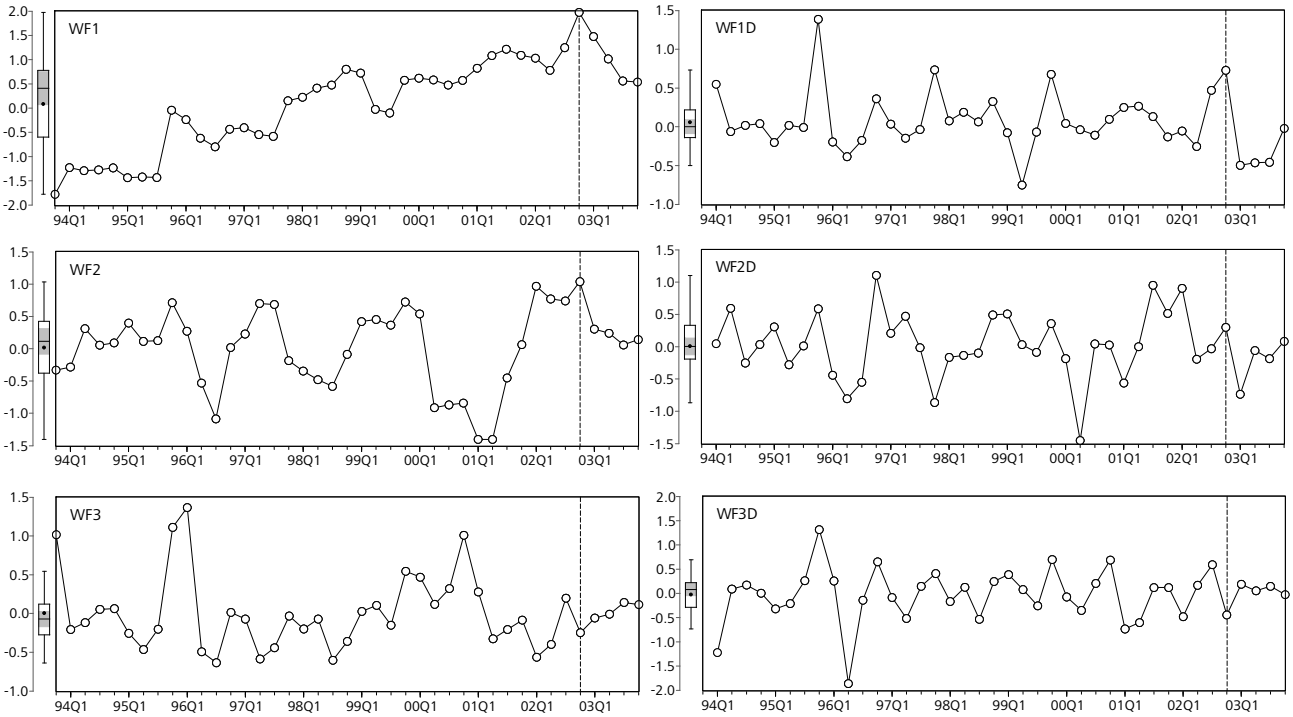


Figure 118 3M. Wealth factor scores & wealth factor difference scores.

	Panel A		Panel B	
	wealth		wealth momentum	
	eigenvalue	cumulative	eigenvalue	cumulative
Factor 1	0.776		0.469	
Factor 2	0.168	0.944	0.270	0.739
Factor 3	0.056	1.000	0.178	0.917
Factor 4			0.083	1.000

Table 52 3M. Variance explained by Spectramap decomposition with hold-out sample (2003Q1-Q4).

Level B Decomposition	TEST	ADF	t-value	p-value	TEST	PP	t-value	p-value
Wealth μ1	-3.6394	1%	-0.6501	0.8459	-3.6268	1%	-0.3357	0.9095
Wealth μ2	-3.6329	1%	-3.0894	0.0366	-3.6268	1%	-2.3103	0.1743
Wealth μ3	-3.6394	1%	-2.6039	0.1020	-3.6268	1%	-4.5806	0.0008
Wealth ∇μ1*	-3.6394	1%	-5.6599	0.0000	-3.6329	1%	-8.6924	0.0000
Wealth ∇μ2*	-3.6329	1%	-4.9933	0.0003	-3.6329	1%	-4.9354	0.0003
Wealth ∇μ3*	-3.6394	1%	-8.4481	0.0000	-3.6329	1%	-12.5857	0.0000
Wealth Momentum λ1**	-3.6329	1%	-5.8541	0.0000	-3.6268	1%	-7.5181	0.0000
Wealth Momentum λ2**	-3.6268	1%	-4.0226	0.0036	-3.6268	1%	-3.9264	0.0046
Wealth Momentum λ3**	-3.6329	1%	-5.9471	0.0000	-3.6268	1%	-11.4881	0.0000
Wealth Momentum λ4**	-3.6268	1%	-5.7476	0.0000	-3.6268	1%	-5.8088	0.0000

ADF = Augmented Dickey-Fuller. PP = Phillips-Perron. TEST = test critical value. Incl. constant.

Base period sample: 1993Q4-2002Q4. * = Explained variable. ** = Explanatory variable.

Table 53 3M. Unit root test statistics of the Spectramap factor variables (1993Q4-2002Q4).

9.2.3 3M balance sheet data

Quarterly time series of 3M Company from the fourth quarter of 1993 to the fourth quarter of 2003 are analyzed on the disaggregated level B which includes current and non current assets, current and non current liabilities as well as net wealth (Table 22, page 108). The last year of the time series is used as the hold-out sample of actual values (2003Q1 – Q4).

9.2.4 Spectral Map Analysis

The raw data of the balance sheet variables and their momentum data are decomposed into a lower number of factors with Spectral Map Analysis. The factor scores of wealth and momentum are respectively in panel A and panel C of Table 51. Using their factor scores, the quarters are visualized in a biplot with the x, y and z-axes in Figure 116 for wealth and in Figure 117 for momentum. In these figures the positioned time series of the hold-out sample are visualized with circles that have a hatched outline (2003Q1 – Q4).

With the solution space of spectramap factors of the 3M balance sheet it is possible to fit or position measurements that did not contribute to the multivariate decomposition. Thus, the four quarters of the hold-out sample are not included in the spectramap decomposition and their scores result from positioning afterwards (Table 51).[1] Therefore, the hold-out sample does not contribute any information to the decomposition of the balance sheet to the factor variables. This allows us to use the factors as independent variables in the regression models and (try to) forecast the hold-out sample. Furthermore, the scores of the econometric simulation forecast can be compared with the scores of the positioned quarters to evaluate its success (Figure 129). The variance explained by Spectramap decomposition of wealth and wealth momentum is reported in Table 52. Compared with the result of the full balance sheet decomposition in Table 27, page 122, the differences are minor. Clearly the first wealth factor captures a little more of the variance (11%) whereas the first momentum factor captures a little less of the variance (-3%). This has little bearing on the regression analysis itself.

9.2.5 Time series properties

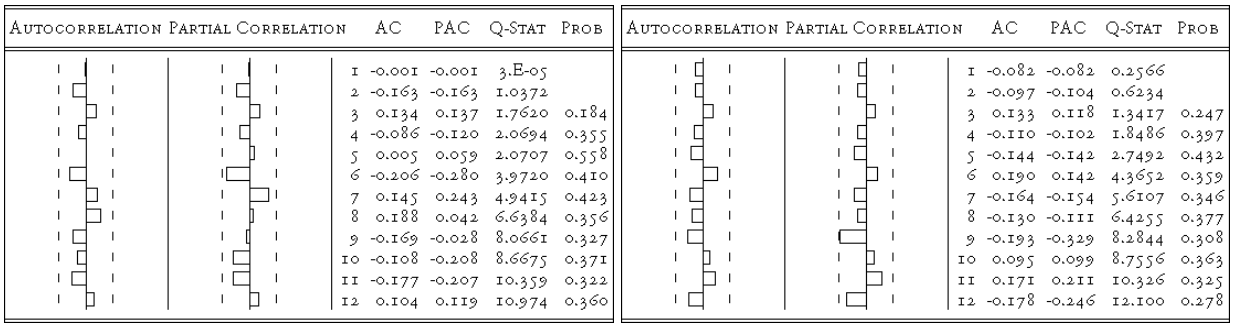
Before regression models can be built with the wealth factors as the dependent variables and the momentum factors as the independent variables their time series properties require inspection. In Table 53 the unit root tests are reported of the wealth and momentum factor variables for the base period of 37 time points from 1993Q4 to 2002Q4. The ADF and the PP. test of the wealth factors ($\mu_{1...3}$) show that these scores are not stationary over time because the test P-values are above the 5% threshold level. Note that the test result of the second and third wealth factor is ambiguous. Therefore, I opt for using the differenced wealth factor scores because the test statistics show that it is not likely that they contain a unit root ($\nabla\mu_{1...3}$, scores in panel B of Table 51).

[1] Naturally, there is a limit to how good such a fit will be. The measurements to be positioned should not deviate too much from the decomposed data. Figure 47, page 118, and Figure 116 provide a visual analysis of the hold-out sample fit that is rather good in the decomposition of the base period sample. We can appreciate this as an indication that the structure of the 3M balance sheet is rather stable and that our chances of developing successful econometric momentum models are good.

	Panel A - Model statistics			Panel B - 95% Confidence Interval*		
	WEALTH $\nabla\mu 1$	WEALTH $\nabla\mu 2$	WEALTH $\nabla\mu 3$	WEALTH $\nabla\mu 1$	WEALTH $\nabla\mu 2$	WEALTH $\nabla\mu 3$
Intercept	0.10	0.03	0.02	[0.08, 0.12]	[0.01, 0.04]	[-0.01, 0.04]
Standard Error	0.01	0.01	0.01	0.03	0.02	0.05
Momentum $\lambda 1$	-0.24	-0.39	-0.28	[-0.28, -0.20]	[-0.47, -0.32]	[-0.33, -0.22]
Standard Error	0.02	0.04	0.03	0.08	0.15	0.11
P-value	0.0000	0.0000	0.0000			
Momentum $\lambda 2$	-0.21	0.45		[-0.27, -0.15]	[0.36, 0.54]	
Standard Error	0.04	0.05		0.13	0.17	
P-value	0.0000	0.0000				
Momentum $\lambda 3$	0.25		-0.40	[0.19, 0.31]		[-0.50, -0.29]
Standard Error	0.04		0.06	0.12		0.22
P-value	0.0000		0.0000			
Momentum $\lambda 4$	-0.11			[-0.18, -0.04]		
Standard Error	0.04			0.14		
P-value	0.0116					
AR(1)	0.46	0.50		[0.24, 0.68]	[0.25, 0.75]	
Standard Error	0.13	0.15		0.45	0.50	
P-value	0.0017	0.0022				
MA(1)	-0.94	-0.97	-0.93	[-0.98, -0.90]	[-1.02, -0.93]	[-0.98, -0.89]
Standard Error	0.02	0.03	0.03	0.08	0.09	0.09
P-value	0.0000	0.0000	0.0000			
Standard Error model	0.16	0.23	0.33			
Adjusted R^2	0.82	0.81	0.67			
F-statistic	26.65	37.29	24.80			
P-value (two tailed test)	0.0000	0.0000	0.0000			
Durbin-Watson AC	1.97	2.12	1.61			
Breusch-Godfrey LM	0.00	0.44	1.25			
P-value χ^2	1.0000	0.5056	0.2635			
White Heteroskedasticity	0.51	3.65	1.00			
P-value $\chi 2$	0.9722	0.1614	0.6055			

* Lower and upper 95% between brackets and under that the interval.

Table 54 3M. Regression test statistics for the 3 wealth difference factors (base period: 1993Q4-2003Q4).



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.001	-0.001	3.E-05	
		2	-0.163	-0.163	1.0372	
		3	0.134	0.137	1.7620	0.184
		4	-0.086	-0.120	2.0694	0.355
		5	0.005	0.059	2.0707	0.558
		6	-0.206	-0.280	3.9720	0.410
		7	0.145	0.243	4.9415	0.423
		8	0.188	0.042	6.6384	0.356
		9	-0.169	-0.028	8.0661	0.327
		10	-0.108	-0.208	8.6675	0.371
		11	-0.177	-0.207	10.359	0.322
		12	0.104	0.119	10.974	0.360

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.082	-0.082	0.2566	
		2	-0.097	-0.104	0.6234	
		3	0.133	0.118	1.3417	0.247
		4	-0.110	-0.102	1.8486	0.397
		5	-0.144	-0.142	2.7492	0.432
		6	0.190	0.142	4.3652	0.359
		7	-0.164	-0.154	5.6107	0.346
		8	-0.130	-0.111	6.4255	0.377
		9	-0.193	-0.329	8.2844	0.308
		10	0.095	0.099	8.7556	0.363
		11	0.171	0.211	10.326	0.325
		12	-0.178	-0.246	12.100	0.278

Figure 119 3M. Correlogram of balance sheet model residuals. Left: wealth factor 1. Right: wealth factor 2.

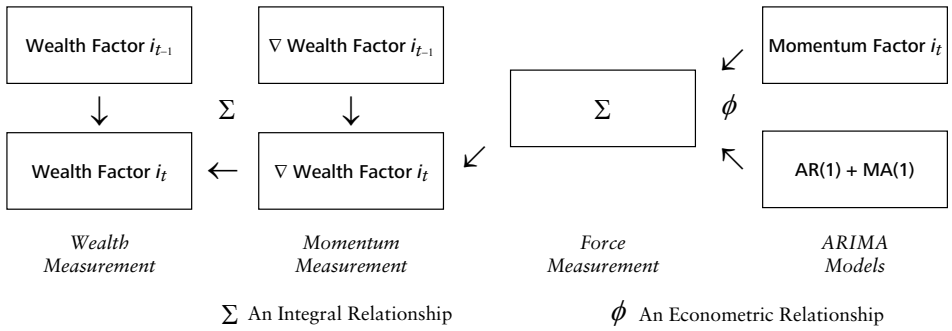


Figure 120 3M. Aggregation of momentum factor scores from ARIMA models in the TEMA framework.

9.3 Empirical results

In this section I present for 3M the association between the decomposed financial accounting variables of the balance sheet: three wealth factors and four wealth momentum factors (panel B and C of TABLE 51). It is assumed that the dynamics or compositional change between balance sheet variables are associated in a meaningfull manner within the TEMA framework (FIGURE 2, page 2). By means of ARIMA modeling of momentum factor dynamics, the wealth factor scores will be calculated through the aggregation of the previous time step score and the simulated factor score difference.

9.3.1 *Momentum based regression analysis*

The dynamics of momentum factors drive the econometric model of the balance sheet or wealth factors. Of the decomposed balance sheet variable time series, the base period is used to test ex post the explanatory power. The period from the first quarter 2004 to the fourth quarter 2004 will be used as a hold-out sample to evaluate ex ante the predictive power of the independent variables in ordinary least squares regression models.

To be consistent in the TEMA framework, I use the wealth momentum factors to explain the wealth factors in a balanced regression model (like EQUATION 15, page 59). Due to the fact that the wealth factors do not meet the requirement of stationarity or have an ambiguous test result (TABLE 53), their differenced time series are used (panel B of TABLE 51, FIGURE 118). An additional autoregressive (AR) or moving average (MA) variable is added to correct for the presence of first order autocorrelation but only if the overal model fit improves which is measured by comparing the Adjusted R^2 and F-statistic. In this manner, the regression models used to explain the three dependent variable wealth factors are:

(30) 3M WF1, $$\nabla\mu_{1t} = \alpha + \beta_1\lambda_{1t} \ldots \beta_4\lambda_{4t} + \phi_1 V_{t-1} + \theta_1 u_{t-1} + u_t \quad \text{with } t=1, \ldots, T,$$

(31) 3M WF2, $$\nabla\mu_{2t} = \alpha + \beta_1\lambda_{1t} + \beta_2\lambda_{2t} + \phi_1 V_{t-1} + \theta_1 u_{t-1} + u_t \quad \text{with } t=1, \ldots, T,$$

(32) 3M WF3, $$\nabla\mu_{3t} = \alpha + \beta_1\lambda_{1t} + \beta_2\lambda_{3t} + \theta_1 u_{t-1} + u_t \quad \text{with } t=1, \ldots, T.$$

The regression models were run with the Newey-West correction for heteroskedasticity and autocorrelation consistent standard errors. This modeling methodology leads to a more compact simulation mean band while the equal regression coefficients' remain the same as without correction. When we aggregate the simulated momentum scores into the wealth scores we recover the wealth factor scores (FIGURE 120).

9.3.2 *Test statistics*

We discuss in this section the test statistic results of the three wealth regression models (30), (31) and (32) that are reported in TABLE 54. The marginal effect of the wealth momentum factors in these models is strongly significant because the P-value of their F-statistics is less than 1%. Thus, I can be confident that the coefficients differ from zero (Startz 2007, 66). However, the overall fit of the wealth models differs considerably. The Adjusted R^2 values of explained variance of the three wealth factors are, respectively, 82%, 81% and 67% (0.82, 0.81 and 0.67). I find the same ordered result for the standard Error of each model (0.16, 0.23 and 0.33). Therefore, I can expect the most compact simulation mean band for the first decomposed wealth factor model (which the ex ante forecasts indeed reveal: TABLE 56). The required condition that heteroskedasticity should not occur in the residuals is met within acceptable

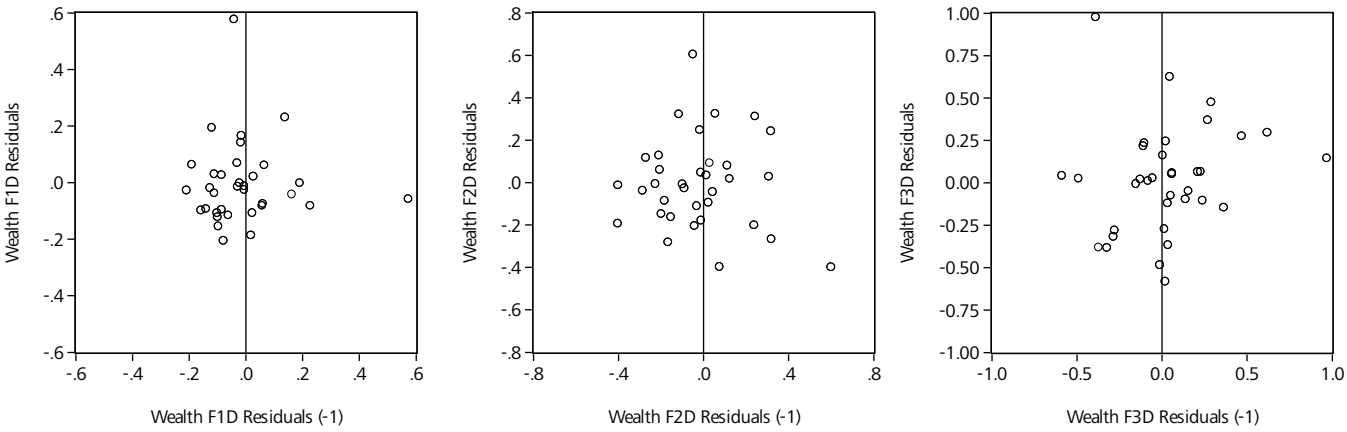


Figure 121 3M. Equation residuals vs. one time lag of the three wealth difference factors.

limits given the fact that all three regression equations have χ^2 P-values far above 5% for their white tests (Table 54). The null hypothesis of homoskedasticity cannot be rejected in any model since the result is far below their critical χ^2 value (Studenmund 2006, 622).[2] Two tests were used for the presence of auto- or serial correlation: the Durbin Watson d test and the Breusch-Godfrey Lagrange Multiplier test. We can use the DW d test for positive serial correlation because the models do not include a lagged value of the dependent variable. The models of the first two wealth factors have residuals that are not likely to suffer from autocorrelation because each test statistic is above the critical one-sided upper threshold value (Figure 121, Studenmund 2006, 329).[3] But, DW d test result of the third wealth factor of 1.61 is just below the upper threshold value: 1.65 and thus lies in the inconclusive region. Yet, not one of the models has a BG LM test statistic that is larger than the critical χ^2 value for one time lag (3.84), which implies that I can reject with considerable confidence the null for the presence of serial correlation. This is also confirmed by visual inspection for the presence of autocorrelation using scatter plots of lagged residuals against residuals (Figure 121). The time points are scattered throughout the three plots and do not cluster linearly. A second visual inspection method for the presence of autocorrelation is provided by a correlogram up to 12 lags of the residuals for, in this case, the regression model of the first and second wealth factor difference (respectively left & right in Figure 119). This visual method allows us to look at the pattern of correlations between residuals and their own past values. If autocorrelation is absent, then at each lag it should be nearly zero. This is indicated graphically in the correlogram with the vertical solid line. A horizontal bar pointing left or right signals negative or positive autocorrelation. The dashed lines in the correlogram are the two standard error bounds. If the autocorrelation is within these bounds, it is not significantly different from zero at the 5% significance level. In conclusion, these two regression models are viable (as well as the third not included here).

[2] For the three models the critical χ^2 value for the White test is, respectively: 37.6, 29.1, 21.7 at the 1% P-value.

[3] For the DW d test the $d_L - d_U$ values are, respectively for models $\nabla\mu_{1\ldots3}$: 1.10–1.88, 1.22–1.73 and 1.30–1.65 at the 5% P-value.

	Panel A - Model statistics				Panel B - 95% Confidence Interval*			
	λ_1	λ_2	λ_3	λ_4	λ_1	λ_2	λ_3	λ_4
Intercept	-0.18	0.02	-0.16	0.10	[-0.52, 0.16]	[-0.01, 0.05]	[-0.48, 0.16]	[-0.06, 0.25]
Standard Error	0.20	0.02	0.19	0.09	0.67	0.06	0.65	0.31
AR(8), AR(3), AR(6), AR(8)	0.36	-0.44	0.57	-0.31	[0.09, 0.63]	[-0.66, -0.23]	[0.28, 0.86]	[-0.57, -0.04]
Standard Error	0.16	0.13	0.17	0.16	0.54	0.43	0.58	0.53
P-value	0.0351	0.0016	0.0024	0.0647				
MA(9), MA(4), MA(8), MA(9)	-0.89	-0.97	-0.89	0.89	[-0.95, -0.83]	[-1.03, -0.91]	[-0.95, -0.84]	[0.83, 0.96]
Standard Error	0.04	0.04	0.03	0.04	0.12	0.13	0.11	0.14
P-value	0.0000	0.0000	0.0000	0.0000				
Standard Error model	0.57	0.50	0.47	0.34				
Adjusted R2	0.60	0.57	0.53	0.55				
F-statistic	22.14	22.91	17.69	17.90				
P-value (two tailed test)	0.0000	0.0000	0.0000	0.0000				
Durbin-Watson AC	2.18	1.54	2.15	2.10				
Breusch-Godfrey LM	0.00	0.17	0.34	0.00				
P-value $\chi 2$	1.0000	0.6778	0.5573	1.0000				

* Lower and upper 95% between brackets and under that the interval.

Table 55 3M. Regression test statistics for ARIMA models base period estimation: 1993Q4-2003Q4.

9.3.3 Modeling momentum

EQUATION (30), (31) and (32) are the regression models with which the ex post base period will be simulated as well as the ex ante forecast of the hold-out sample period. This requires equations for each one of the independent momentum factor variables ($\lambda_{1...4}$) as they drive the dynamics of the predictive model of each wealth factor difference (FIGURE 120). In this section, these ARIMA models are discussed. The goal of ARIMA analysis is a parsimonious representation of momentum dynamics (Box *et al.* 1994, 16, Enders 2005, 76). Ijiri (1989, 10.5) suggested that 'ARIMA models ... may be considered in momentum measurement' as an alternative for the measurement of forces and their aggregation into momentum variables. The selected ARIMA models for the factors of 3M balance sheet momentum are:

(33) MOMENTUM F1, $\lambda_{1t} = \alpha + \phi_1 V_{t-8} + \theta_1 u_{t-9} + u_t$ with t=1, ..., T,

(34) MOMENTUM F2, $\lambda_{2t} = \alpha + \phi_2 V_{t-3} + \theta_2 u_{t-4} + u_t$ with t=1, ..., T,

(35) MOMENTUM F3, $\lambda_{3t} = \alpha + \phi_3 V_{t-6} + \theta_3 u_{t-8} + u_t$ with t=1, ..., T,

(36) MOMENTUM F4, $\lambda_{4t} = \alpha + \phi_4 V_{t-8} + \theta_4 u_{t-9} + u_t$ with t=1, ..., T.

The test statistics of these four ARIMA models are reported in TABLE 55. The marginal effect of each model is strongly significant because the P-value of the F-statistic is less than 1%. I am confident that the joint coefficients of these ARIMA models differs from zero. Also note that the coefficient interval of the ARIMA coefficients does not include zero either. The Adjusted R^2 value of the explained variance of each ARIMA model is acceptable, respectively: 60%, 57%, 53% and 55% (0.60, 0.57, 0.53 and 0.55). With the exception of the second momentum factor, the Durbin-Watson d test indicates that autocorrelation is not present in the residuals as the test statistic is above the critical one-sided upper threshold value.[4] However, the BG LM first order test results does not lead to the rejection of the null of no serial correlation at the 5% level (vs. 3.84). However, following Franses (2005, 42, 52-53), visual inspection

[4] For the DW d test the $d_L - d_U$ values are, respectively for models $\lambda_{1...4}$: 1.27–1.56, 1.28–1.57, 1.30–1.57 and 1.27–1.56 at the 5% P-value.

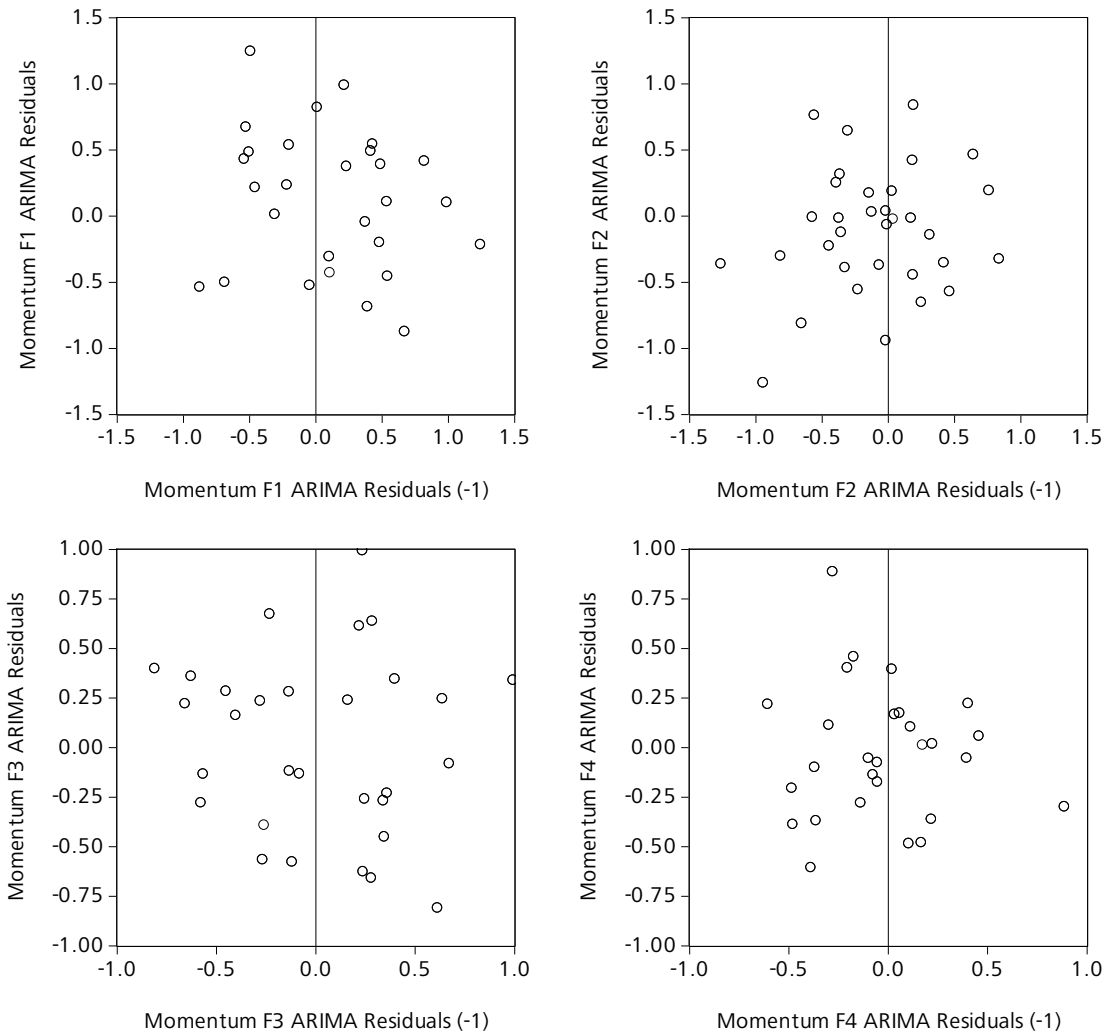


Figure 122 3M. Equation residuals vs. one time lag of the 4 momentum factor ARIMA models.

of the scatter plot of lagged residuals against residuals of each ARIMA equation confirms that it is not likely that autocorrelation is present (FIGURE 122). In conclusion, each of the four ARIMA equations of a decomposed balance sheet momentum factor is sufficient to drive the dynamics of the wealth factor difference models.

9.3.4 Balance sheet simulation ex post

The next step in my analysis is the ex post simulation using the same data of the base period for the forecast as was used during their development of the three regression models. FIGURE 123 and FIGURE 125 show, respectively, the ex post static base period forecast of the first two wealth factor difference scores. FIGURE 124 and FIGURE 126 are the static base period forecast of the first two wealth factor scores following aggregation according to TEMA framework (FIGURE 120). Most scores are predicted with reasonable accuracy, in particular during the last six quarters. This result shows that the three econometric TEMA models of the decomposed balance sheet of 3M have sufficient explanatory power ex post for the wealth factor differences for the base period 1993Q4-2002Q4. I conclude, therefore, that for this example the research hypothesis H 8_a is confirmed, namely that with decomposed variables of company it is possible that balance sheet dynamics can be modeled. Therefore, my confidence increases further in the temporal basis of the generality assumption of the TEMA framework (H 1_a).

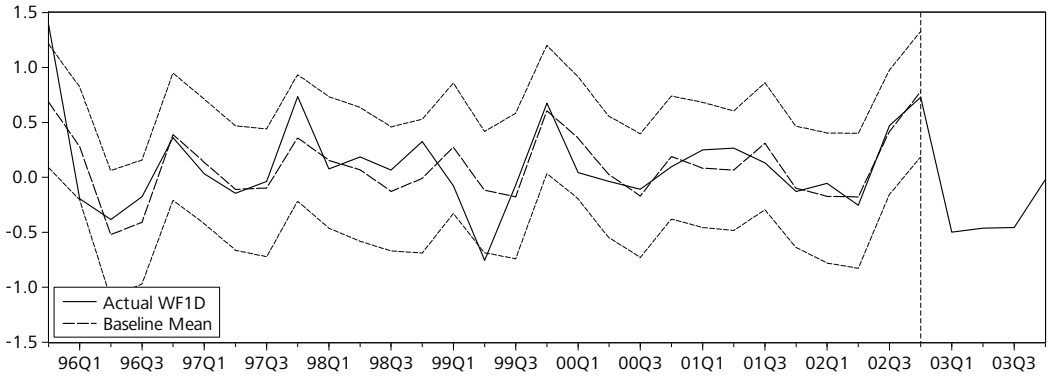


Figure 123 3M. Base period static forecast of the first wealth factor difference.

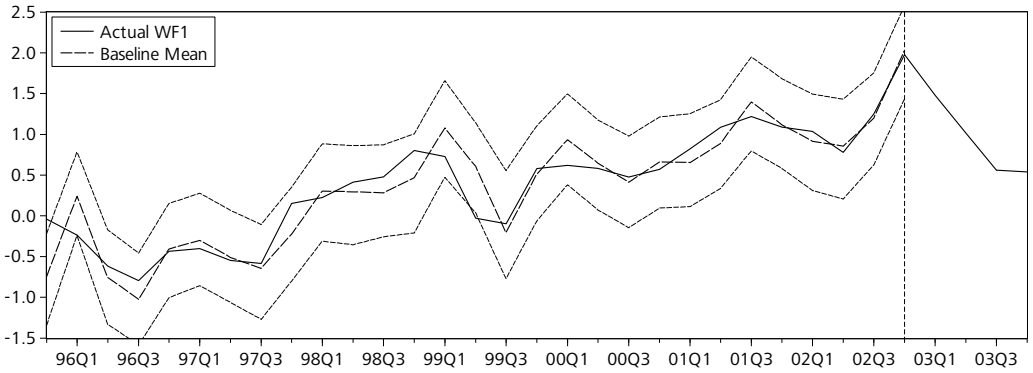


Figure 124 3M. Base period static forecast of the first wealth factor.

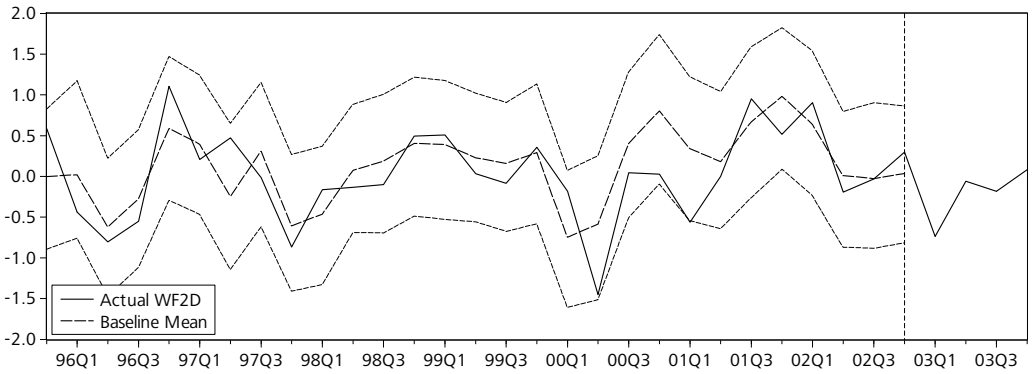


Figure 125 3M. Base period static forecast of the second wealth factor difference.

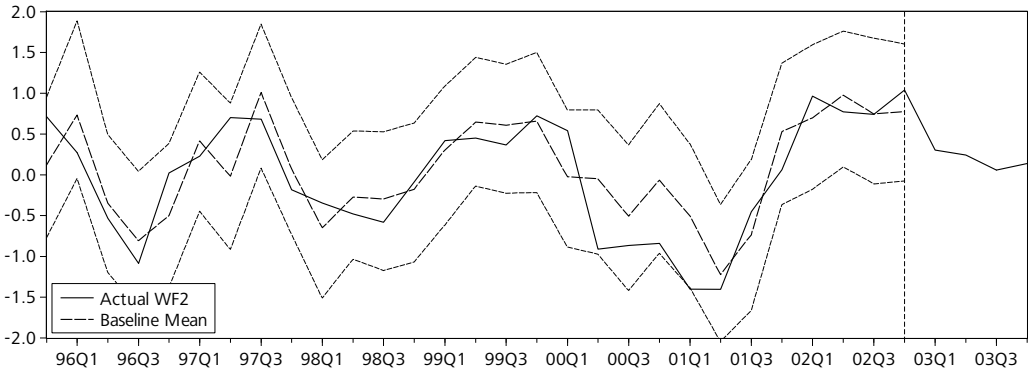


Figure 126 3M. Base period static forecast of the second wealth factor.

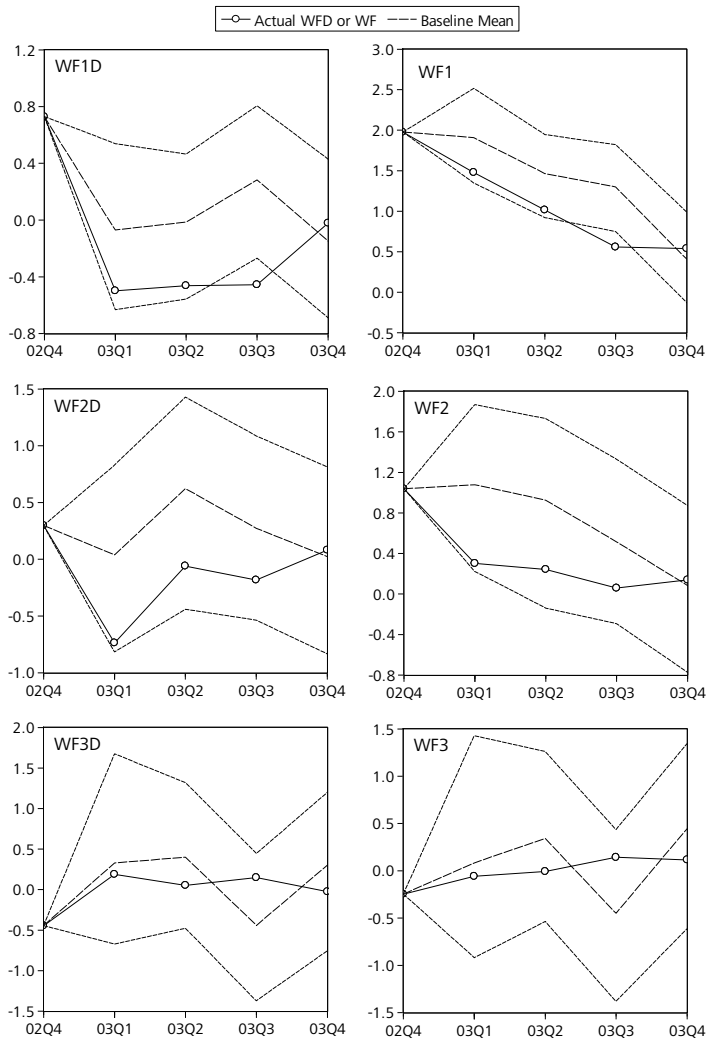


Figure 127 3M. Hold-out sample static forecast of the three balance sheet factor (2003Q1-Q4). Left: differenced wealth factor scores. Right: aggregated wealth factor scores.

Panel A - Static Forecast	RMSPE	Mean Band
∇ Wealth Factor 1	0.237	1.097
∇ Wealth Factor 2	0.319	1.697
∇ Wealth Factor 3	0.150	1.979

Panel B - Dynamic Forecast	RMSPE	Mean Band
∇ Wealth Factor 1	0.229	1.172
∇ Wealth Factor 2	0.237	1.780
∇ Wealth Factor 3	0.134	1.867

Table 56 3M. Root Mean Square Prediction Error (RMSPE) values of the differenced wealth factor simulations. Panel A: hold-out period static forecast. Panel B: hold-out period dynamic forecast.

9.3.5 *Balance sheet simulation ex ante*

Would it be possible to forecast for four quarters with these econometric TEMA models of the decomposed balance sheet of 3M with sufficiently valid results? To answer this question, ex ante simulations are done for the hold-out sample of the four quarters 2003Q1-2003Q4. The result of the static and the dynamic simulation of each model can be inspected with, respectively, FIGURE 127 and FIGURE 128. The ex ante static simulation has a success rate of

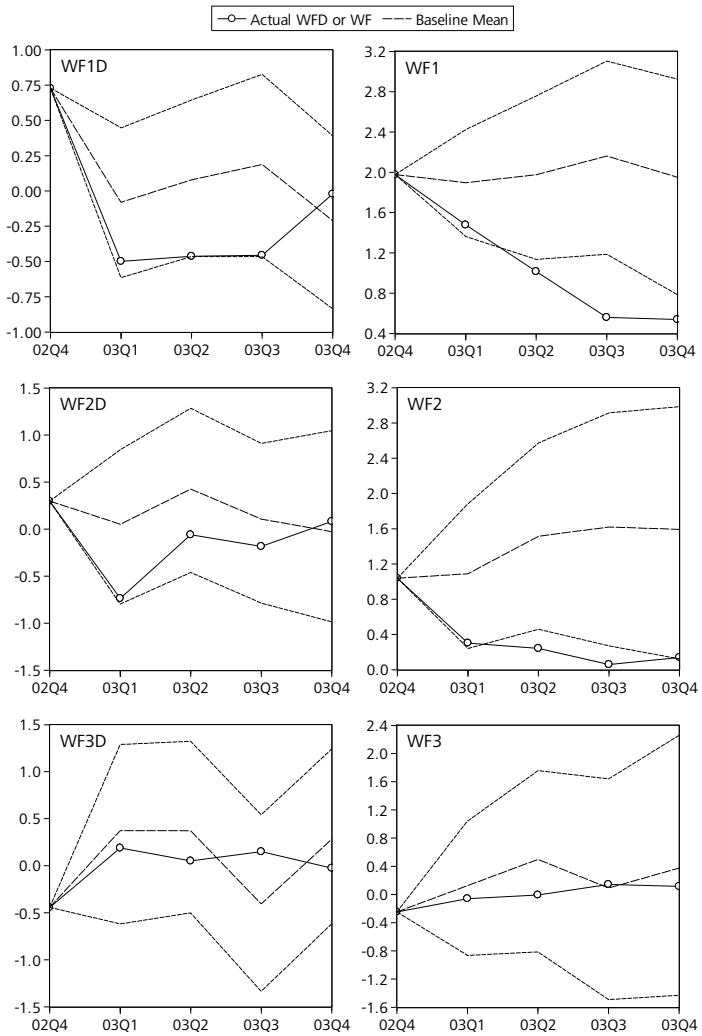


Figure 128 3M. Hold-out sample dynamic forecast of the three balance sheet factor (2003Q1-Q4). Left: differenced wealth factor scores. Right: aggregated wealth factor scores.

91.67% for both the wealth factor difference scores and the aggregated wealth factor scores. The ex ante dynamic simulation has a 100% success rate with the wealth factor difference scores but only 58.33% with the aggregated wealth factor scores. This is because the mean band of dynamic simulation is, of course, much wider, plus the error accumulates during the simulation. Compare in Table 56 for the first factor the mean band value of the narrowest static forecast with that of the dynamic forecast, respectively: 1.097 and 1.172. Figure 129 and Figure 130 show, respectively, the result of the hold-out sample forecast for the three wealth factor scores and for the first three wealth momentum factor scores.[5] The forecasted values are visualized in these figures with circles that have a more bold outline together with the positioned time series of the hold-out sample (with a hatched circle outline). Observe that in Figure 130 the temporal trajectory of forecasted quarters is more or less aligned with that of the positioned quarters. In particular the last quarter is accurately forecasted (2003Q4F). This can, of course, also be readily observed with the individual time series of each of the wealth factor scores (Figure 127).

[5] The fourth wealth momentum factor scores are forecasted as well and used in the regression models but are not displayed in this three-dimensional biplot (it would require color coding).

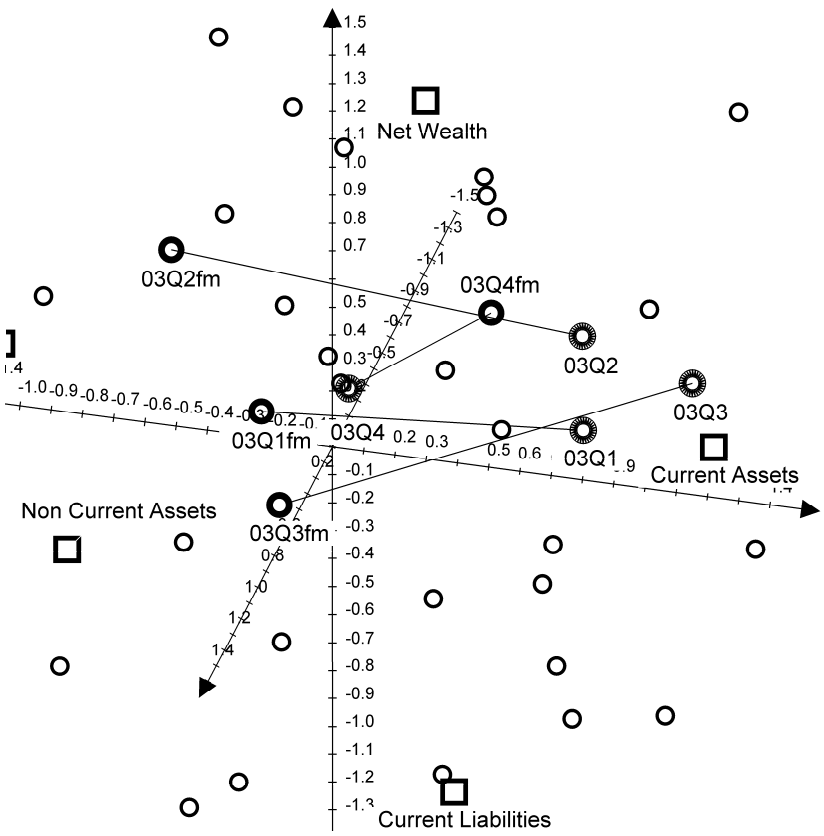


Figure 129 3M. Spectramap biplot of the wealth momentum factor scores (static simulation, detail, 2003Q1fm-Q4fm).

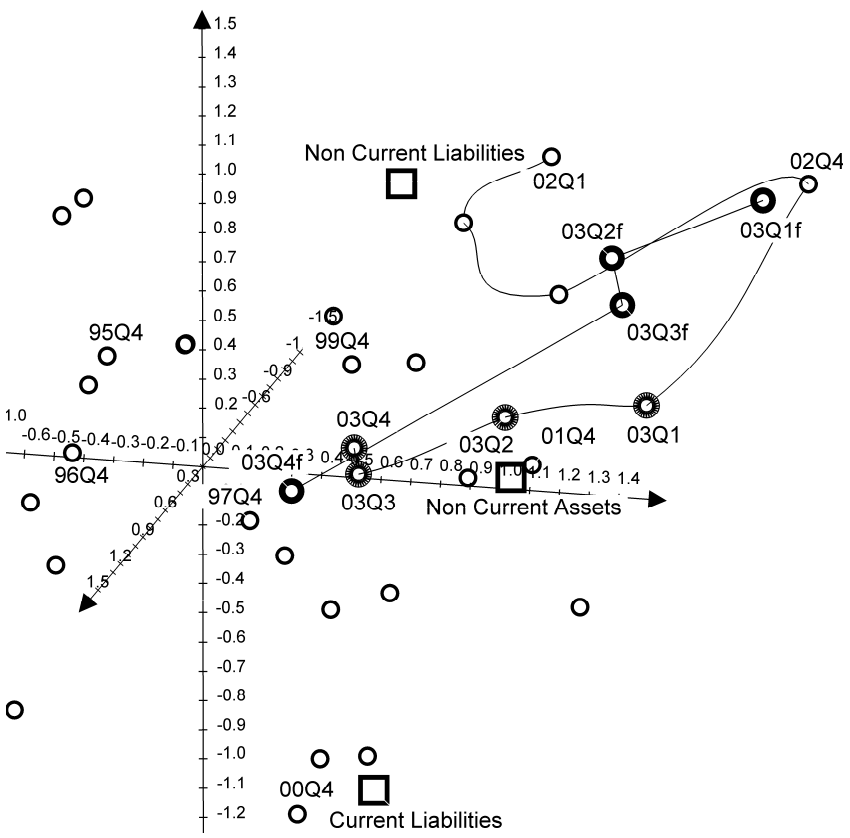


Figure 130 3M. Spectramap biplot of the wealth factor scores (static simulation, detail, 2003Q1f-4f).

My conclusion is that for the decomposed balance sheet of 3M each of the econometric TEMA models has sufficient predictive power for the three wealth factor scores. These findings provide additional support for the main hypothesis of this thesis that the generality assumption holds for the TEMA framework (H 1_a). Dynamic TEMA models of the wealth factors of 3M confirm the temporal association of variables within the TEMA framework (H 3_a). Forward looking disclosure of accounting information from the ARIMA models can forecast wealth considerably accurate (H 8_a).

9.4 Discussion

Recently, Medeiros (2005) developed an econometric model — in this case a simultaneous equations structural model — designed to represent a firm's financial statements empirically connecting macro and microeconomic (market) variables with accounting variables. He was able to explain a firm's balance sheet by means of the impact of macro and microeconomic variables, together with the interaction between the accounting variables. His findings are confirmed in this study albeit from the microeconomic perspective of the TEMA framework. Earlier, Stowe *et al.* (1980) underlined the canonical association between variables of the balance sheet.

My own conclusion from this study is that it in this case evidence was found that it is possible to explain and predict the trend of a firm's balance sheet using SMA factor variables of wealth and momentum. In my opinion, the economic intuition behind this is that business model dynamics are reflected in the longitudinal pattern of linear combinations of balance sheet variables. Another conclusion I draw is about the fact that quarterly balance sheet time series can be decomposed and modeled as regression equations that have explanatory as well as predictive power. This provides in my opinion, in this case, some empirical evidence for the momentum accounting theory of Ijiri. I recommend spectramap decomposition of balance sheet data for further empirical analysis to proceed with TEMA modeling when there are too many variables available. Research topics concerning financial statements might include predicting bankruptcy, ratings, defaults or risk measures. Furthermore, such factor variables, which are linear combinations of balance sheet proportions, might be employed instead of the usual financial ratios.

10

Momentum Accounts as Leading Indicators of the Dow

Explaining and Predicting with the Dynamics of Operating Income and Total Wealth Momentum of the Dow Component Companies.

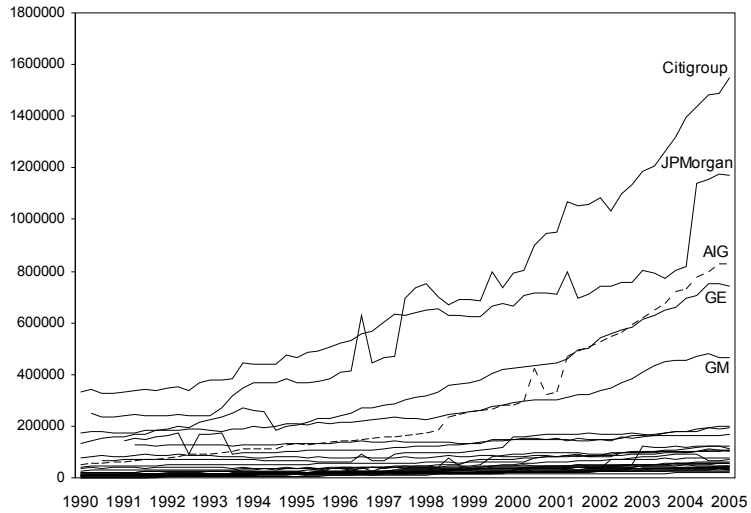


Figure 131 Dow companies. Total wealth, data source: Reuters, Dow Jones (1990Q2-2005Q2).

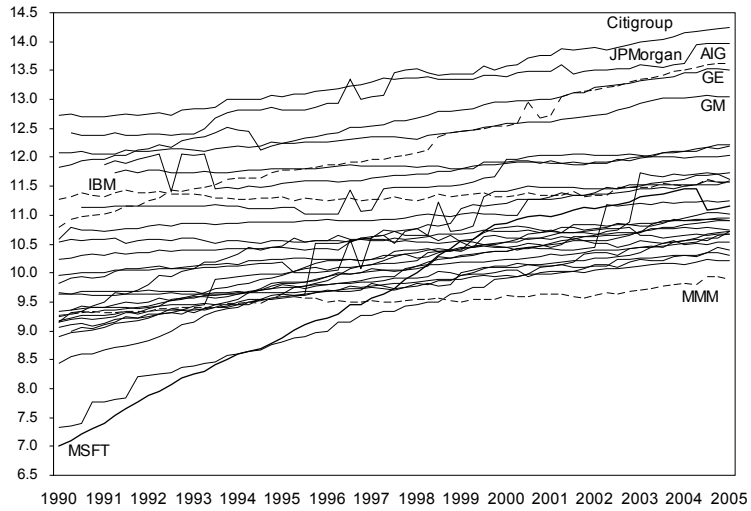


Figure 132 Dow companies. Total wealth lognormal transformed data (1990Q2-2005Q2).

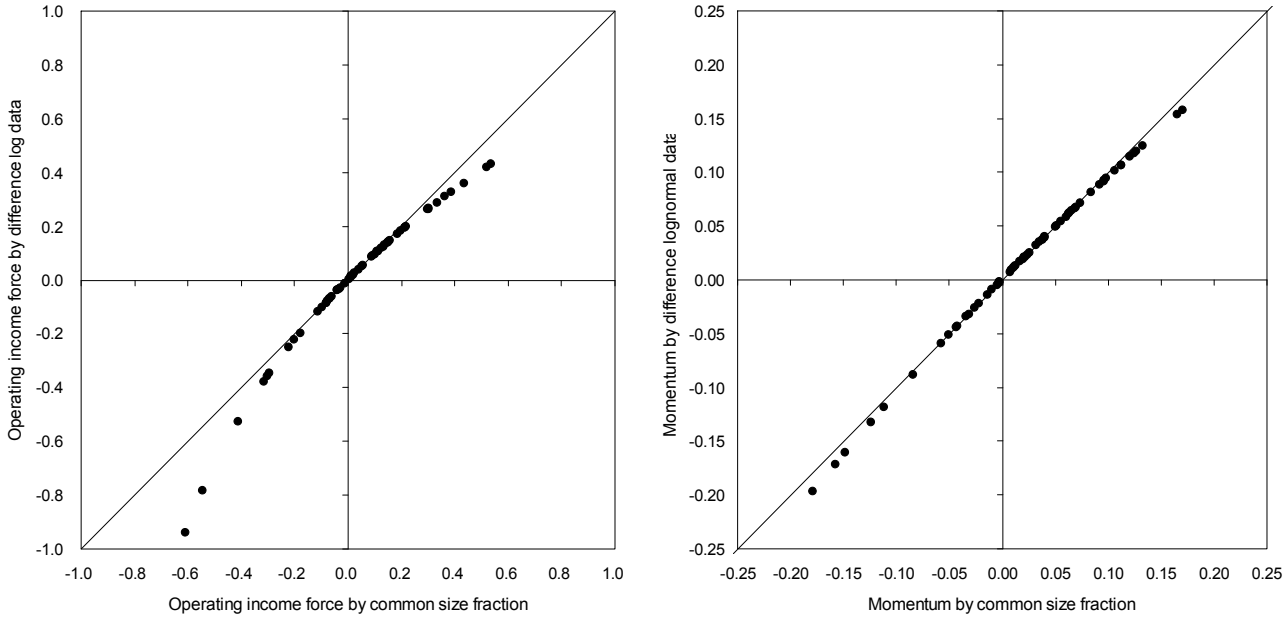


Figure 133 Scatter plot of common size format ratios vs. lognormal differences (1990Q2-2005Q2).
Left: Microsoft operating income force measures. Right: Dow Jones index momentum measures.

10 Abstract

The overall purpose of this chapter is to investigate the relevance of momentum accounting theory for market index explanation and prediction. The TEMA *framework of Yuji Ijiri aims to innovate financial accounting so that management or the auditor are better facilitated to disclose trends that have future bearings. Econometric time series modeling, simulation and analysis is employed within the* TEMA *framework. The objective is to let the 'data demonstrate itself' whether or not evidence can be found that* TEMA *variables have explanatory and predictive power. Indeed, the results of this study are evidence that this is so. It is possible to explain the growth trend of the Dow ex post with two leading indicators: operating income and total wealth momentum. Moreover, the models predict the Dow Jones index ex ante correctly for each quarter simulated but with varying degrees of precision. This result is further evidence in support of the main thesis of this study that there is a general relationship between variables in the* TEMA *framework. The relevance of* TEMA *not only pertains to financial accounting measures but also to the indexed market value of firms.*

10.1 Introduction

This study aims to test the association between the trend of the DOW Jones Industrial Average index and the dynamics of accounting variables from the TEMA framework.[1] Financial accounting data is used from the 30 component companies of DOW. Instead of using data of each company as an independent variable, the panel of data is decomposed to factors using Spectral Map Analysis, or spectramap in short. With these factors, econometric regression models are developed to test the explanatory power of momentum models. Next ARIMA models are created of the factors' time series to drive the momentum models with which the DOW is forecasted using a hold-out data sample of four quarters.

I search for evidence of a possible link between the collective dynamics of TEMA variable time series of the DOW component companies and the index of their market value without a clear understanding of how this link is supposed to work. My assumption is that somehow the trend of total wealth or operating income, or both, is translated into market value. In investigate this link not by indivual firm or stock but by the collective trend of the DOW component companies and their value, measured by the DOW index, When such link is found, the result will offer some support for the TEMA theory of Yuji Ijiri because that proposes the measurement of the momentum of financial accounting variables as an alternative for other more widely used measurements of firm value, like EVA or ROTA (Melse 2008). This study contributes to the accounting and economic literature by providing some empirical evidence concerning the explanatory and predictive power of the TEMA framework. It applies the TEMA theory of Yuji Ijiri to explain and predict a market index of listed companies, i.e. the DOW. The focus is on submitting evidence in support of the assumption that momentum accounting provides new and valuable information to determine firm value at the aggregated level of the DOW.

This study could be of some importance for researchers of accounting and finance who are interested in extending the current financial accounting system with (more) means to disclose forward-looking information and to forecast financial accounting variables. Sloan (1999) points at the continuing debate among academics and practitioners whether or not the accrual

[1] The TEMA framework is discussed in Chapter 1, section 1.2, page 4.

components (of earnings) are reliable variables to forecast fundamentals and determine company value. He is concerned that '...our understanding of the properties of cash flows and accruals and the extent to which these properties are reflected in stock prices is not enhanced much beyond previous research.' This study presents a possible alternative approach to understand more of the determinants of the forecasting properties—assuming these exist—of financial accounting data from the TEMA theory of Yuji Ijiri.

Organization of this chapter

This chapter proceeds in several sections. The next section sets out briefly the methodology that is followed. The main research question, hypotheses and data set used are presented in section 2. The empirical result of the study is presented in section 3. The measurement method of force and momentum is summarized and the method of Spectral Map Analysis briefly introduced. Smaller sections, included in section 3, contain a brief introduction of the regression models used, the simulations and their analyses. Necessary data and statistical details are presented in tables and figures. The last section discusses the result in comparison with existing literature and the conclusion.

10.2 Methodology

10.2.1 Research question

This study addresses the question: can I find evidence in the empirical data that supports a main assumption of the momentum accounting theory of Yuji Ijiri, namely, financial accounting statements contain forward-looking information? Central in this effort is the association that I expect between the movement of the DOW as an index of the market value of its component companies and that of the accounting variables operating income and total wealth of the component companies.

10.2.2 Research hypotheses

Several hypotheses of this study, discussed in Chapter 1, section 1.8, page 29, will be tested. Because force and momentum data are calculated by the first or second difference of the time series of financial accounting variables, I expect that they meet the econometric requirement of stationarity or trend-stationarity (EQUATIONS (8) and (9), page 53). If so, evidence in support of hypothesis H 6_a is found. The same should apply to the SMA factor time series of this data. Then it follows that it should be possible to develop econometric models without the risk of spurious regression. If such models are well specified, i.e. without serial correlation in the models' residuals or heteroskedasticity, and when decomposed independent variables of the component companies model the dependent variable (the DOW index) then evidence in support of hypothesis H 9_a is found. Then financial accounting variables from the TEMA framework of component companies are leading indicators of the growth trend of their market index: the DOW. Should evidence in support for all hypotheses be found then this also provides support for the main hypothesis of this study: that there is a general relationship between variables in the TEMA framework (H 1_a).

10.2.3 Regression models

The objective of the TEMA theory of Yuji Ijiri is to add a dynamic perspective to the accounting system for the purpose of analysis and decision making concerning performance measurement and corporate control. The accounting dimensions of the TEMA framework are temporally determined sources of information (Melse 2004c, Figure 2). Through the accounts it should be possible at any point in time to explain how (1D) wealth was acquired (liabilities & equity) and used (assets), whether or not new wealth was created (2D) and what expenses and income were involved. To this system of accounts, Ijiri (1986) adds the ability to account for the capacity to create new wealth in the future (3D) with force and momentum variables (FIGURE 1). These variables are used in this study to explain and predict the growth of the DOW Jones Industrial Average index with econometric TEMA models. To be able to develop the required econometric regression models:

1. empirical data is used of the 30 component companies of the DOW Jones Industrial Average index for an econometric analysis of accounting models;
2. each panel of financial accounting variables of the DOW component companies is decomposed with spectramap decomposition into six factors of accounting variables;
3. the factors of accounting variables are tested for their statistical time series properties;
4. the factors of accounting variables are used in three regression models to investigate their explanatory power (ex post);
5. ARIMA models are developed of the factors of accounting variables to investigate their predictive power with dynamic TEMA models of the DOW (ex ante).

10.2.4 The data

Quarterly data from the fourth quarter of 1990 to the second quarter of 2005 are used of the 30 component companies of the Dow Jones Industrial Average, DOW in short.[2] Investors refer to the DOW as *the market* because it is a carefully diversified index representing a price-weighted average of its component companies (TABLE 40, page 174). The DOW usually accounts for about 25%–30% of the total market value of all U.S. stocks. The index represents the leading companies in the industries driving the U.S. stock market. With 110 years of performance behind it, the DOW is considered by many to be the ultimate stock market indicator.

10.2.5 Financial accounting information

Published financial statements are usually the only as well as the most extensive source of financial information available to outside observers (see: Lev 1999, McEnroe & Martens 2004). Nissim & Penman (2001) argue that in the area of equity analysis, where accounting ratios of individual companies are judged against benchmarks from comparable companies, research in finance has not been successful. This study carries recent financial accounting research of Ijiri's momentum theory to the field of finance and market value. The growth trend of the DOW component companies' financial accounting variables are assessed for their explanatory and predictive power of their indexed market value. The (possible) association is researched between the trend of operating income, net wealth and total wealth with the trend of the DOW. The growth dynamics of financial statements' accounting variables is measured with momentum and force data (Ijiri 1986, 1987, 1989). Three independent financial accounting variables are used in the econometric models: operating income, net wealth and total wealth. Operating

[2] See also Chapter 8, section 8.2.3, page 177.

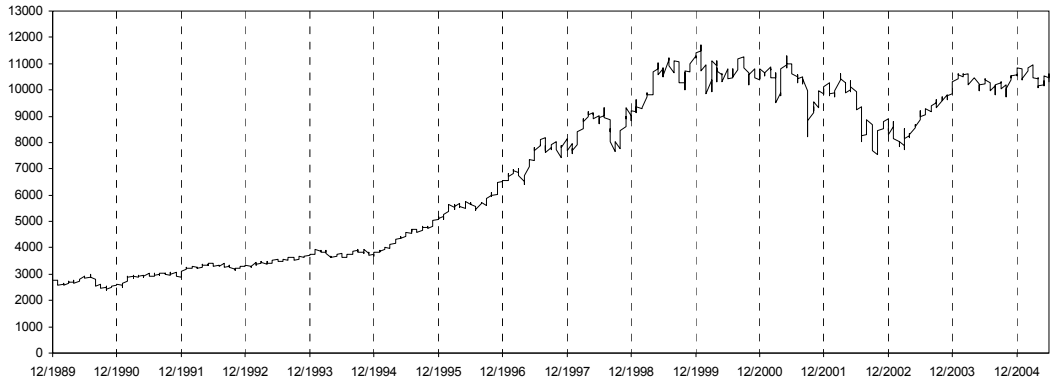


Figure 134 Dow. Close end of week (1990Q4-2005Q2), source: Reuters, Dow Jones.

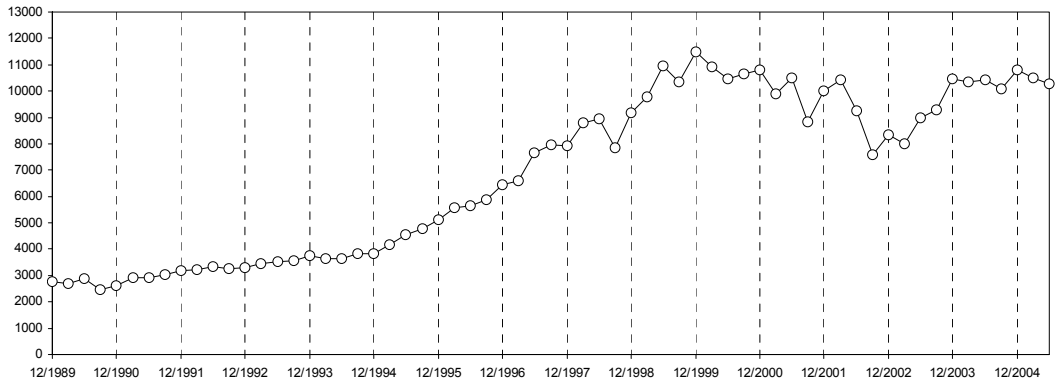


Figure 135 Dow. Close end of quarter (1990Q4-2005Q2), source: Reuters, Dow Jones.

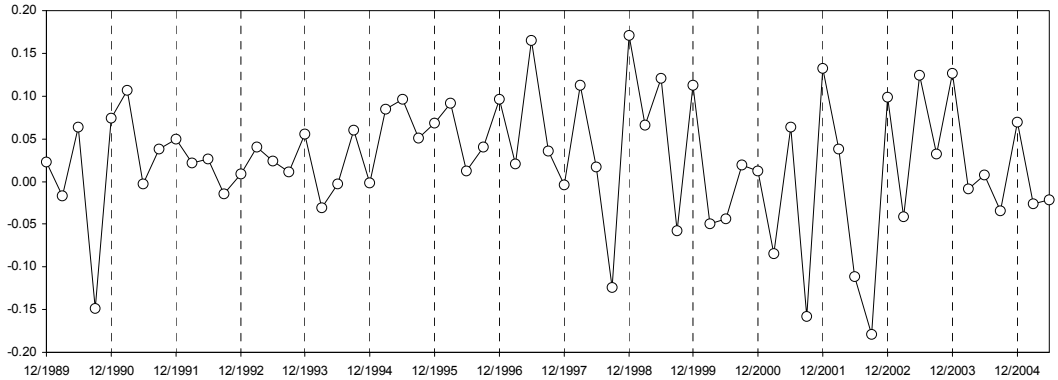


Figure 136 Dow. Momentum by quarter (first difference, 1990Q4-2005Q2).

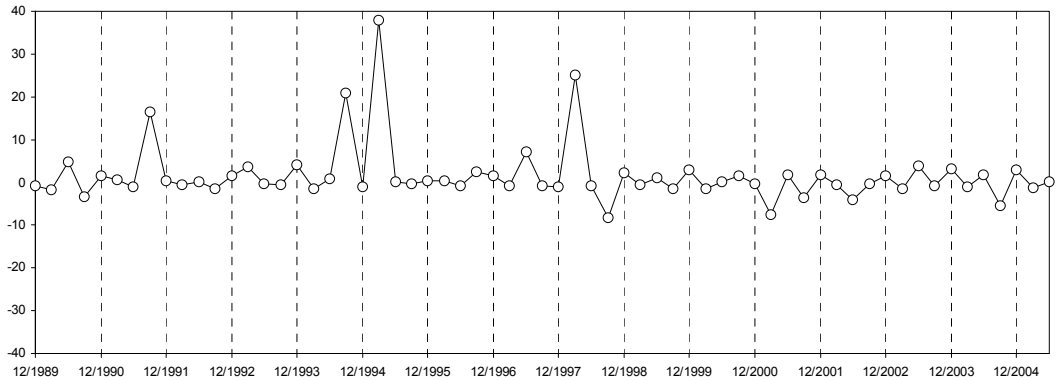


Figure 137 Dow. Force by quarter (second difference, 1990Q4-2005Q2).

income or its force serves as a proxy for business dynamics reflected by variation of income statement data. Net wealth momentum or force serves as a proxy for the dynamics of the structural composition of the balance sheet as well as dynamics pertaining to financing. Lastly, total wealth momentum or force measures the dynamics of total book value. In addition, the joint association of independent variables is tested for possible explanatory power and, when present, their predictive power. Therefore, I expect to expose the dynamic association between operating income and balance sheet time series as leading indicators of the Dow.

Fama & French (2000) are concerned by the use of annual accounting measurements in time-series models. To enhance the power of such models, formal tests require 20 years of data or more, but, according to Fama & French, this leads to survivor bias. Instead, in this study 57 quarters of data are used of the 30 component companies of the Dow. Thus, the power of the models is improved. Survivor bias is not in question in my study because the dependent variable of the econometric models is the Dow. The set of selected companies is pre-determined, limited and closed. It serves as a 'statistic' of the total market value of all U.S. stocks. On the one hand, we could perceive that as a biased selection of firms, but, on the other hand, by its objective of market representation, the long term survival of the Dow component companies is a required characteristic of this index.

10.2.6 Measurement of force & momentum

To mitigate the scaling problem, the original time series (x) of the component companies is lognormal transformed by Equation (37):

$$a_t = \log_e x_t \quad . \tag{37}$$

Superposition of the raw data of the Dow companies total wealth time series in Figure 131 and the lognormal data in Figure 132 provides a good impression of the scale improvement. However, such series might suffer from the presence of a unit root. In that case such data trend and make them unreliable for econometric modeling. The common approach in econometrics, recommended for example by Koop (2000, 124), to acquire a non-stationary time series from a stationary time series is to compute their difference by Equation (38):

$$\nabla a_t = a_t - a_{t-1} \qquad \text{with } t=1, \ldots, T. \tag{38}$$

The advantage is that the differences thus computed are almost identical to the growth rate percentages of the original lognormal values. Equation (39) calculates the growth rate:

$$\Delta x_t = x_t / x_{t-1} \quad , \tag{39}$$

while Equation (40) expresses the approximation of its result and that of Equation (38):

$$\Delta x_t \approx \nabla a_t \qquad \text{with } t=1, \ldots, T. \tag{40}$$

An alternative approach that turns out to be of practical use in this study is to take the momentum and force values directly by differencing the raw data (i.e. using Equation (8) and (9), page 53, see Table 57 for the Dow and the example of Microsoft). The next step is to transform that data to fractions with the previous time step of its wealth or income data as the base (Table 58).[3] In the case of first difference data this is the growth rate.

[3] The possible advantage of this procedure is discussed in Chapter 3, section 3.3, page 84.

	quarter	Dow Jones Index Dow	Dow** Momentum ∇Dow	Dow Force ∇²Dow	Total Wealth TW	Total W.** Momentum TWM	Total W. Force TWF	Operating Income** OI	Oper. Inc. Force OIF
	1989Q4	*2,753*	*60*	*-192*	$ 922	$ 113	$ 24	$ 106	$ 38
	1990Q1	*2,707*	*-46*	*-106*	$ 1,015	$ 94	$ -19	$ 105	$ -1
EP 1	1990Q2	*2,881*	*173*	*219*	$ 1,105	$ 90	$ -3	$ 101	$ -3
EP 2	1990Q3	*2,452*	*-428*	*-602*	$ 1,204	$ 98	$ 8	$ 122	$ 20
EP 3	1990Q4	*2,634*	*181*	*609*	$ 1,366	$ 163	$ 64	$ 158	$ 36
EP 4	1991Q1	*2,914*	*280*	*99*	$ 1,502	$ 136	$ -26	$ 174	$ 16
EP 5	1991Q2	*2,907*	*-7*	*-287*	$ 1,644	$ 142	$ 5	$ 181	$ 7
EP 6	1991Q3	*3,017*	*110*	*117*	$ 1,870	$ 226	$ 84	$ 203	$ 22
EP 7	1991Q4	*3,168*	*151*	*41*	$ 2,128	$ 258	$ 32	$ 246	$ 43
EP 8	1992Q1	*3,235*	*68*	*-83*	$ 2,341	$ 213	$ -46	$ 251	$ 5
EP 9	1992Q2	*3,319*	*83*	*15*	$ 2,640	$ 299	$ 86	$ 284	$ 33
EP 10	1992Q3	*3,272*	*-47*	*-130*	$ 2,849	$ 209	$ -90	$ 288	$ 4
EP 11	1992Q4	*3,301*	*29*	*76*	$ 3,226	$ 377	$ 168	$ 328	$ 40
EP 12	1993Q1	*3,435*	*134*	*105*	$ 3,560	$ 334	$ -43	$ 336	$ 8
EP 13	1993Q2	*3,516*	*81*	*-53*	$ 3,805	$ 245	$ -89	$ 367	$ 31
EP 14	1993Q3	*3,555*	*39*	*-42*	$ 4,048	$ 243	$ -2	$ 339	$ -28
EP 15	1993Q4	*3,754*	*199*	*160*	$ 4,486	$ 438	$ 195	$ 413	$ 74
EP 16	1994Q1	*3,636*	*-118*	*-317*	$ 4,926	$ 440	$ 2	$ 476	$ 63
EP 17	1994Q2	*3,625*	*-11*	*107*	$ 5,363	$ 437	$ -3	$ 482	$ 6
EP 18	1994Q3	*3,843*	*218*	*229*	$ 5,637	$ 274	$ -163	$ 435	$ -47
EP 19	1994Q4	*3,834*	*-9*	*-227*	$ 5,961	$ 324	$ 50	$ 515	$ 80
EP 20	1995Q0	*4,158*	*323*	*332*	$ 6,592	$ 631	$ 307	$ 544	$ 29
EP 21	1995Q0	*4,556*	*398*	*75*	$ 7,210	$ 618	$ -13	$ 528	$ -16
EP 22	1995Q0	*4,789*	*233*	*-165*	$ 8,160	$ 950	$ 332	$ 704	$ 176
EP 23	1995Q4	*5,117*	*328*	*95*	$ 9,106	$ 946	$ -4	$ 809	$ 105
EP 24	1996Q1	*5,587*	*470*	*142*	$ 9,590	$ 484	$ -462	$ 778	$ -31
EP 25	1996Q2	*5,655*	*67*	*-403*	$ 10,093	$ 503	$ 19	$ 768	$ -10
EP 26	1996Q3	*5,882*	*228*	*160*	$ 10,740	$ 647	$ 144	$ 853	$ 85
EP 27	1996Q4	*6,448*	*566*	*339*	$ 12,786	$ 2,046	$ 1,399	$ 1,035	$ 182
EP 28	1997Q1	*6,583*	*135*	*-431*	$ 12,613	$ -173	$ -2,219	$ 1,484	$ 449
EP 29	1997Q2	*7,673*	*1,089*	*954*	$ 14,387	$ 1,774	$ 1,947	$ 1,499	$ 15
EP 30	1997Q3	*7,945*	*272*	*-817*	$ 15,366	$ 979	$ -795	$ 1,060	$ -439
EP 31	1997Q4	*7,908*	*-37*	*-309*	$ 16,840	$ 1,474	$ 495	$ 1,613	$ 553
EP 32	1998Q1	*8,800*	*892*	*929*	$ 19,545	$ 2,705	$ 1,231	$ 1,867	$ 254
EP 33	1998Q2	*8,952*	*152*	*-739*	$ 22,357	$ 2,812	$ 107	$ 1,874	$ 7
EP 34	1998Q3	*7,843*	*-1,109*	*-1,262*	$ 25,569	$ 3,212	$ 400	$ 2,082	$ 208
EP 35	1998Q4	*9,181*	*1,339*	*2,448*	$ 30,049	$ 4,480	$ 1,268	$ 2,714	$ 632
EP 36	1999Q1	*9,786*	*605*	*-734*	$ 33,561	$ 3,512	$ -968	$ 2,229	$ -485
EP 37	1999Q2	*10,971*	*1,185*	*580*	$ 38,625	$ 5,064	$ 1,552	$ 2,903	$ 674
EP 38	1999Q3	*10,337*	*-634*	*-1,818*	$ 39,672	$ 1,047	$ -4,017	$ 2,789	$ -114
EP 39	1999Q4	*11,497*	*1,160*	*1,794*	$ 45,093	$ 5,421	$ 4,374	$ 2,931	$ 142
EP 40	2000Q1	*10,922*	*-575*	*-1,735*	$ 50,895	$ 5,802	$ 381	$ 2,735	$ -196
EP 41	2000Q2	*10,448*	*-474*	*101*	$ 52,150	$ 1,255	$ -4,547	$ 2,551	$ -184
EP 42	2000Q3	*10,651*	*203*	*677*	$ 56,089	$ 3,939	$ 2,684	$ 2,777	$ 226
EP 43	2000Q4	*10,787*	*136*	*-67*	$ 57,691	$ 1,602	$ -2,337	$ 3,194	$ 417
EP 44	2001Q1	*9,879*	*-908*	*-1,044*	$ 59,605	$ 1,914	$ 312	$ 2,998	$ -196
EP 45	2001Q2	*10,502*	*624*	*1,532*	$ 58,830	$ -775	$ -2,689	$ 2,751	$ -247
EP 46	2001Q3	*8,848*	*-1,655*	*-2,278*	$ 61,367	$ 2,537	$ 3,312	$ 1,073	$ -1,678
EP 47	2001Q4	*10,022*	*1,174*	*2,829*	$ 65,387	$ 4,020	$ 1,483	$ 2,714	$ 1,641
EP 48	2002Q1	*10,404*	*382*	*-792*	$ 68,379	$ 2,992	$ -1,028	$ 2,112	$ -602
EP 49	2002Q2	*9,243*	*-1,161*	*-1,543*	$ 67,646	$ -733	$ -3,725	$ 1,688	$ -424
EP 50	2002Q3	*7,592*	*-1,651*	*-491*	$ 70,235	$ 2,589	$ 3,322	$ 2,594	$ 906
EP 51	2002Q4	*8,342*	*750*	*2,401*	$ 72,359	$ 2,124	$ -465	$ 1,812	$ -782
EP 52	2003Q1	*7,992*	*-349*	*-1,099*	$ 74,482	$ 2,123	$ -1	$ 2,510	$ 698
EP 53	2003Q2	*8,985*	*993*	*1,343*	$ 81,732	$ 7,250	$ 5,127	$ 1,479	$ -1,031
EP 54	2003Q3	*9,275*	*290*	*-704*	$ 84,281	$ 2,549	$ -4,701	$ 3,130	$ 1,651
EP 55	2003Q4	*10,454*	*1,179*	*889*	$ 85,937	$ 1,656	$ -893	$ 1,432	$ -1,698
EP 56	2004Q1	*10,358*	*-96*	*-1,275*	$ 89,767	$ 3,830	$ 2,174	$ 1,273	$ -159
EP 57	2004Q2	*10,435*	*78*	*174*	$ 94,368	$ 4,601	$ 771	$ 3,117	$ 1,844
EA 1	2004Q3	*10,080*	*-355*	*-433*	$ 94,268	$ -100	$ -4,701	$ 3,471	$ 354
EA 2	2004Q4	*10,783*	*703*	*1,058*	$ 64,941	$ -29,327	$ -29,227	$ 4,733	$ 1,262
EA 3	2005Q1	*10,504*	*-279*	*-982*	$ 66,275	$ 1,334	$ 30,661	$ 3,236	$ -1,497
EA 4	2005Q2	*10,275*	*-229*	*50*	$ 70,815	$ 4,540	$ 3,206	$ 2,969	$ -267

* = Independent variable. ** = Dependent variable. Italic data = Dow Jones Index data.

EP = ex post, base period time series. EA = ex ante, hold-out sample. Financial data x 1.000.000.

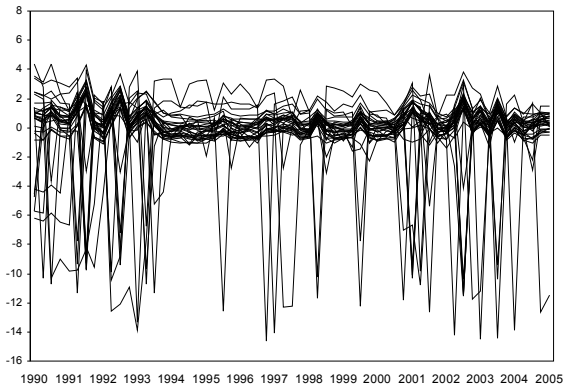
Table 57 Dow index and financial data of Microsoft (source: Reuters Thomson).

	quarter	Dow Jones Index Dow	Dow** Momentum ∇Dow	Dow Force ∇²Dow	Total Wealth TW	Total W.* Momentum TWM	Total W. Force TWF	Operating Income* OI	Oper. Inc. Force OIF
	1989Q4	7.92	0.02	-0.76	6.83	0.14	0.03	4.66	0.55
	1990Q1	7.90	-0.02	-1.76	6.92	0.10	-0.02	4.65	-0.01
EP 1	1990Q2	7.97	0.06	4.77	7.01	0.09	0.00	4.62	-0.03
EP 2	1990Q3	7.80	-0.15	-3.47	7.09	0.09	0.01	4.80	0.20
EP 3	1990Q4	7.88	0.07	1.42	7.22	0.14	0.05	5.06	0.30
EP 4	1991Q1	7.98	0.11	0.55	7.31	0.10	-0.02	5.16	0.10
EP 5	1991Q2	7.97	0.00	-1.03	7.41	0.09	0.00	5.20	0.04
EP 6	1991Q3	8.01	0.04	16.47	7.53	0.14	0.05	5.31	0.12
EP 7	1991Q4	8.06	0.05	0.37	7.66	0.14	0.02	5.51	0.21
EP 8	1992Q1	8.08	0.02	-0.55	7.76	0.10	-0.02	5.53	0.02
EP 9	1992Q2	8.11	0.03	0.23	7.88	0.13	0.04	5.65	0.13
EP 10	1992Q3	8.09	-0.01	-1.56	7.95	0.08	-0.03	5.66	0.01
EP 11	1992Q4	8.10	0.01	1.63	8.08	0.13	0.06	5.79	0.14
EP 12	1993Q1	8.14	0.04	3.55	8.18	0.10	-0.01	5.82	0.02
EP 13	1993Q2	8.17	0.02	-0.40	8.24	0.07	-0.03	5.91	0.09
EP 14	1993Q3	8.18	0.01	-0.52	8.31	0.06	0.00	5.83	-0.08
EP 15	1993Q4	8.23	0.06	4.10	8.41	0.11	0.05	6.02	0.22
EP 16	1994Q1	8.20	-0.03	-1.59	8.50	0.10	0.00	6.17	0.15
EP 17	1994Q2	8.20	0.00	0.91	8.59	0.09	0.00	6.18	0.01
EP 18	1994Q3	8.25	0.06	20.84	8.64	0.05	-0.03	6.08	-0.10
EP 19	1994Q4	8.25	0.00	-1.04	8.69	0.06	0.01	6.24	0.18
EP 20	1995Q0	8.33	0.08	37.94	8.79	0.11	0.05	6.30	0.06
EP 21	1995Q0	8.42	0.10	0.23	8.88	0.09	0.00	6.27	-0.03
EP 22	1995Q0	8.47	0.05	-0.42	9.01	0.13	0.05	6.56	0.33
EP 23	1995Q4	8.54	0.07	0.41	9.12	0.12	0.00	6.70	0.15
EP 24	1996Q1	8.63	0.09	0.43	9.17	0.05	-0.05	6.66	-0.04
EP 25	1996Q2	8.64	0.01	-0.86	9.22	0.05	0.00	6.64	-0.01
EP 26	1996Q3	8.68	0.04	2.37	9.28	0.06	0.01	6.75	0.11
EP 27	1996Q4	8.77	0.10	1.49	9.46	0.19	0.13	6.94	0.21
EP 28	1997Q1	8.79	0.02	-0.76	9.44	-0.01	-0.17	7.30	0.43
EP 29	1997Q2	8.95	0.17	7.06	9.57	0.14	0.15	7.31	0.01
EP 30	1997Q3	8.98	0.04	-0.75	9.64	0.07	-0.06	6.97	-0.29
EP 31	1997Q4	8.98	0.00	-1.14	9.73	0.10	0.03	7.39	0.52
EP 32	1998Q1	9.08	0.11	25.09	9.88	0.16	0.07	7.53	0.16
EP 33	1998Q2	9.10	0.02	-0.83	10.01	0.14	0.01	7.54	0.00
EP 34	1998Q3	8.97	-0.12	-8.29	10.15	0.14	0.02	7.64	0.11
EP 35	1998Q4	9.12	0.17	2.21	10.31	0.18	0.05	7.91	0.30
EP 36	1999Q1	9.19	0.07	-0.55	10.42	0.12	-0.03	7.71	-0.18
EP 37	1999Q2	9.30	0.12	0.96	10.56	0.15	0.05	7.97	0.30
EP 38	1999Q3	9.24	-0.06	-1.54	10.59	0.03	-0.10	7.93	-0.04
EP 39	1999Q4	9.35	0.11	2.83	10.72	0.14	0.11	7.98	0.05
EP 40	2000Q1	9.30	-0.05	-1.50	10.84	0.13	0.01	7.91	-0.07
EP 41	2000Q2	9.25	-0.04	0.18	10.86	0.02	-0.09	7.84	-0.07
EP 42	2000Q3	9.27	0.02	1.43	10.93	0.08	0.05	7.93	0.09
EP 43	2000Q4	9.29	0.01	-0.33	10.96	0.03	-0.04	8.07	0.15
EP 44	2001Q1	9.20	-0.08	-7.68	11.00	0.03	0.01	8.01	-0.06
EP 45	2001Q2	9.26	0.06	1.69	10.98	-0.01	-0.05	7.92	-0.08
EP 46	2001Q3	9.09	-0.16	-3.65	11.02	0.04	0.06	6.98	-0.61
EP 47	2001Q4	9.21	0.13	1.71	11.09	0.07	0.02	7.91	1.53
EP 48	2002Q1	9.25	0.04	-0.67	11.13	0.05	-0.02	7.66	-0.22
EP 49	2002Q2	9.13	-0.11	-4.03	11.12	-0.01	-0.05	7.43	-0.20
EP 50	2002Q3	8.93	-0.18	-0.42	11.16	0.04	0.05	7.86	0.54
EP 51	2002Q4	9.03	0.10	1.45	11.19	0.03	-0.01	7.50	-0.30
EP 52	2003Q1	8.99	-0.04	-1.47	11.22	0.03	0.00	7.83	0.39
EP 53	2003Q2	9.10	0.12	3.84	11.31	0.10	0.07	7.30	-0.41
EP 54	2003Q3	9.14	0.03	-0.71	11.34	0.03	-0.06	8.05	1.12
EP 55	2003Q4	9.25	0.13	3.07	11.36	0.02	-0.01	7.27	-0.54
EP 56	2004Q1	9.25	-0.01	-1.08	11.40	0.04	0.03	7.15	-0.11
EP 57	2004Q2	9.25	0.01	1.81	11.45	0.05	0.01	8.04	1.45
EA 1	2004Q3	9.22	-0.03	-5.57	11.45	0.00	-0.05	8.15	0.11
EA 2	2004Q4	9.29	0.07	2.98	11.08	-0.31	-0.31	8.46	0.36
EA 3	2005Q1	9.26	-0.03	-1.40	11.10	0.02	0.47	8.08	-0.32
EA 4	2005Q2	9.24	-0.02	0.18	11.17	0.07	0.05	8.00	-0.08

* = Independent variable. ** = Dependent variable. Dow Jones Index & wealth data is log normal transformed.

EP = ex post, base period time series. EA = ex ante, hold-out sample. Momentum & force data in common size fractions.

Table 58 Dow index and financial data of Microsoft, wealth (LogN), momentum & force measures (fractions).



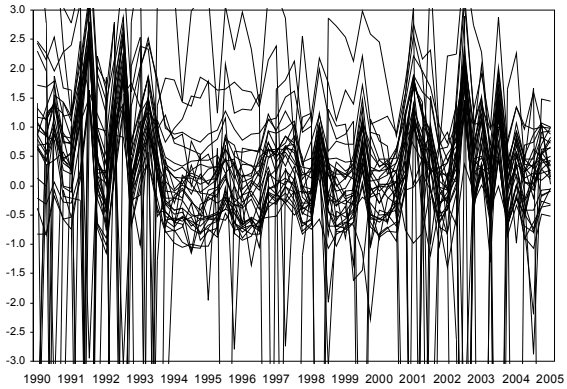
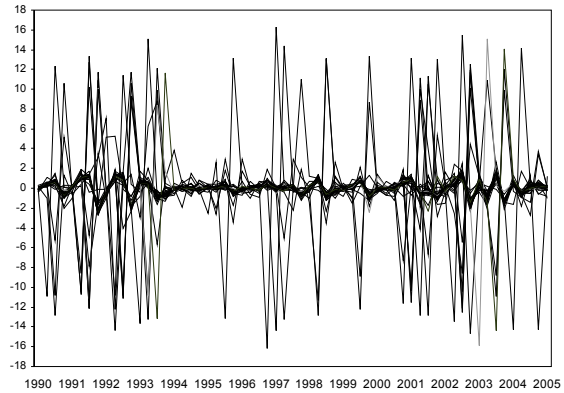


Figure 138 Operating income of Dow companies. Double centered base period lognormal data.

Axis bounded between -3.0 & 3.0.



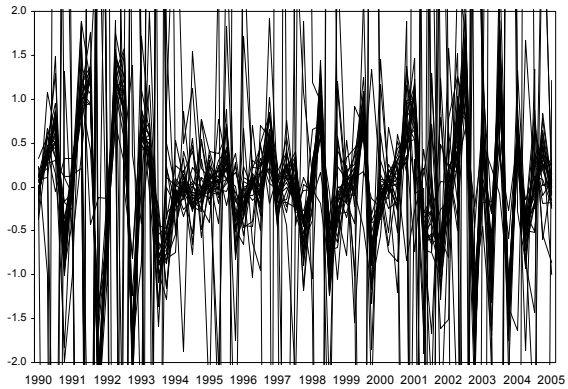
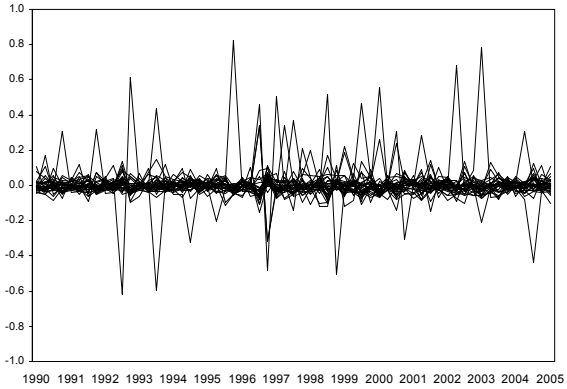


Figure 139 Operating income force of Dow companies. Double centered base period fractions.

Axis bounded between -2.0 & 2.0.



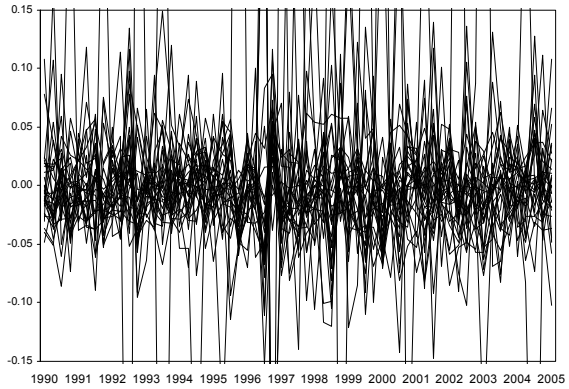
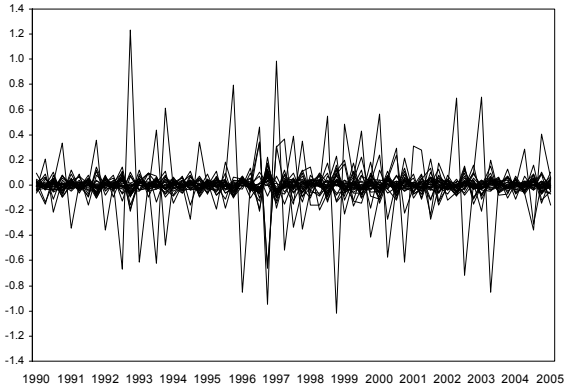


Figure 140 Total wealth momentum of Dow companies. Double centered base period fractions.

Axis bounded between -0.15 & 0.15.



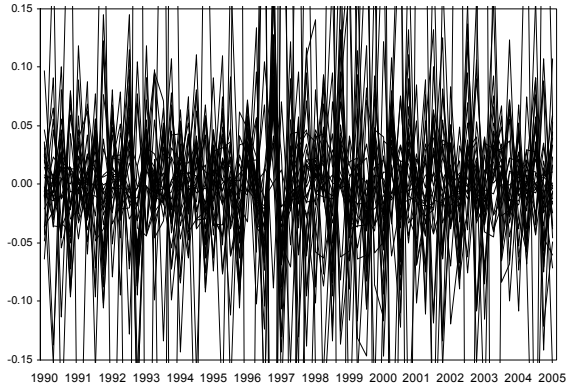


Figure 141 Total wealth force of Dow companies. Double centered base period fractions.

Axis bounded between -0.15 & 0.15.

Figure 133 has two scatter plots of common size format ratio vis-à-vis the lognormal difference from the second quarter of 1990 to the second quarter of 2005. The plot left is of the operating income force measures of Microsoft and the plot right is of the momentum measures of the Dow. The rates of change are plotted in each graph by common size format ratio on the x-axis and by the difference of natural log values on the y-axis. When each method renders the same result a quarter's dot is drawn on the diagonal that runs through the point of origin of the axes. However, as the growth rate calculated by the common size format ratio increases or decreases, the growth rate calculated by the difference of natural log values tends to undervalue when positive and to overvalue when negative. Hence, the difference of natural log values is less precise at the larger increasing or decreasing growth rates. Therefore, in the models of this study, momentum and force data are processed as raw data or calculated directly by their common size format ratio and not by subtraction of natural log values of the original wealth or income time series.

Table 57 presents the variables for Microsoft that is used in the same manner as the other 29 Dow component companies. E.g. total wealth at the end of the second quarter 2005 is $70,815,000,000 and at the end of the first quarter 2005 it is $66,275,000,000. Thus, total wealth momentum is by Equation (8), page 53, in the second quarter 2005 $4,540,000,000, i.e. it is *positive*. As reported in Table 58, that is 0.07 by $4,540,000,000/$66,275,000,000 (rounded). Interestingly, at that particular quarter Microsoft has *negative* operating income force (–$267,000,000 or -0.08) but *positive* net wealth momentum and force (respectively, $742,000,000 and $601,000,000, or 0.02 and 0.01). Of interest for this study is whether or not such measures of force and momentum of Microsoft, or the other 29 component companies, associate with the growth of the Dow itself (Figure 134 & 109). When modeled as a market aggregate, I investigate if such association holds over time and if the growth of market value of these companies, indexed by the Dow, can be explained and predicted from financial variables of the TEMA framework.

10.2.7 Data reduction

It is not practical, if not impossible, to regress the accounting variables of all the 30 Dow component companies on the Dow index in a single equation. In such a case Masters (1995, 16), Maddala & Kim (1998, 171, 226) and Seiler (2004, 165-195) recommend to reduce the number of variables by computing new variables, called *factors*, as linear combinations of the old variables. In regression models factors can serve as independent variables that summarize a particular informational aspect of the original source variables. Arya *et al.* (2000) recognize the potential of linear algebra to describe dynamic systems and suspect that it maybe is beneficial in the study of accounting. The literature, e.g. Reyment & Jöreskog (1993), offers a vast number of solutions of which Principal Components Analysis (PCA) is possibly best known (see Jolliffe 2002). Briefly, the goal is to find a single factor, a linear combination of the original variables that accounts for the majority of the variation across the data. The importance of a factor is determined usually, but, as this study will show not necessarily, by its contribution to the variance of contrasts, and is called factor variance. The rationale is that when more variation is captured by a factor it presumably implies greater relevance of that factor. Whether or not that is true will depend greatly on the application at hand and must be tested with other means (e.g. its use as a predictive variable). An important byproduct of PCA is that in mathematical terms the factors are *orthogonal*, i.e. the variation expressed by each factor is mutually independent or uncorrelated. The first factor found should capture the major part of the infor-

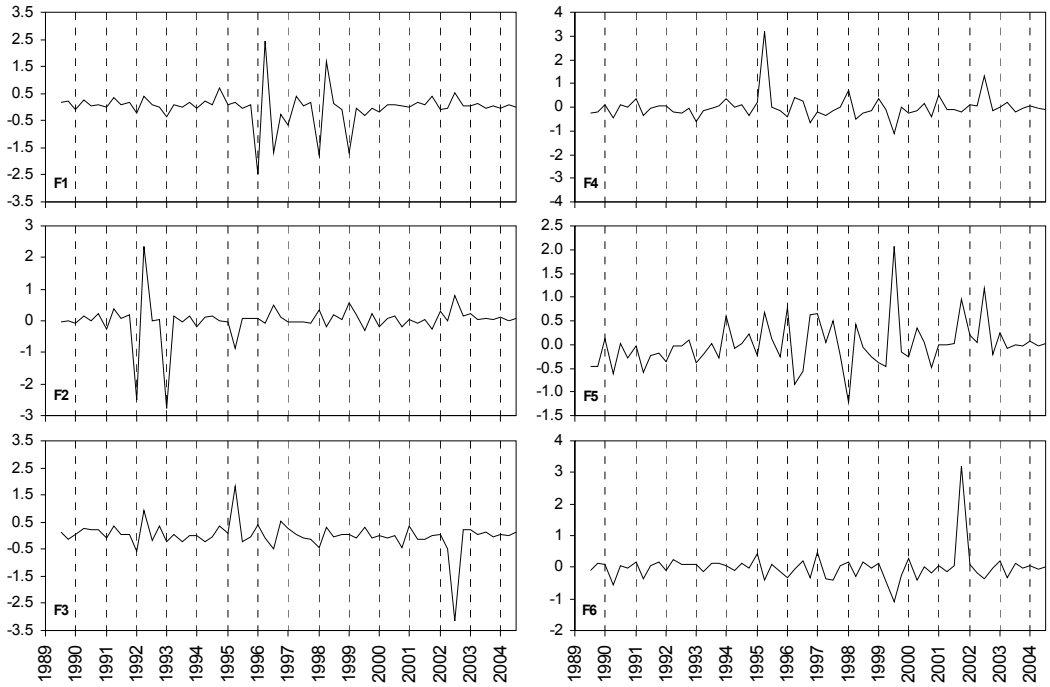


Figure 142 Dow companies. Spectramap factor decomposition of total wealth momentum.

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
TWM Eigenvalues	22.10%	15.97%	9.13%	9.07%	6.68%	6.37%
TWM Cumulative Eigenvalues	22.10%	38.08%	47.20%	56.28%	62.95%	69.32%
TWF Eigenvalues	27.79%	18.10%	8.13%	7.67%	6.28%	5.47%
TWF Cumulative Eigenvalues	27.79%	45.89%	54.02%	61.70%	67.97%	73.44%
OI Eigenvalues	22.58%	13.80%	11.86%	10.75%	6.79%	6.55%
OI Cumulative Eigenvalues	22.58%	36.38%	48.24%	58.99%	65.78%	72.33%
OIF Eigenvalues	22.60%	14.28%	12.11%	9.13%	7.85%	6.57%
OIF Cumulative Eigenvalues	22.60%	36.88%	48.99%	58.12%	65.97%	72.54%

Table 59 Dow companies. Variance explained by Spectramap factor Eigenvalue of the sample period.

	×	ADF	t-value	p-value	×	PP	t-value	p-value
Dow Jones Index lognormal data	-3.1748	10% 2	-1.2549	0.8887	-3.1748	10% 2	-1.1339	0.9137
Dow Jones Index momentum* fractions	-3.5527	1% 1	-9.0528	0.0000	-3.5527	1% 1	-9.0105	0.0000
Dow Jones Index force fractions	-3.5527	1% 1	-8.3785	0.0000	-3.5527	1% 1	-45.8846	0.0000
F1, total wealth momentum** scores	-3.5527	1% 2	-4.9738	0.0001	-3.5527	1% 2	-4.9806	0.0001
F2, total wealth momentum** scores	-3.5527	1% 2	-5.3460	0.0000	-3.5527	1% 2	-5.4054	0.0000
F3, total wealth momentum** scores	-3.5527	1% 2	-5.7208	0.0000	-3.5527	1% 2	-5.7208	0.0000
F4, total wealth momentum** scores	-3.5527	1% 2	-6.1417	0.0000	-3.5527	1% 2	-6.2407	0.0000
F5, total wealth momentum** scores	-3.5527	1% 2	-6.8506	0.0000	-3.5527	1% 2	-6.8980	0.0000
F6, total wealth momentum** scores	-3.5527	1% 2	-6.2328	0.0000	-3.5527	1% 2	-6.2000	0.0000
F1, operating income (momentum)** scores	-3.5527	1% 2	-12.3741	0.0000	-3.5527	1% 2	-12.6213	0.0000
F2, operating income (momentum)** scores	-3.5575	1% 2	-7.0669	0.0000	-3.5527	1% 2	-12.2831	0.0000
F3, operating income (momentum)** scores	-3.5527	1% 2	-7.5541	0.0000	-3.5527	1% 2	-7.5541	0.0000
F4, operating income (momentum)** scores	-3.5527	1% 2	-7.3041	0.0000	-3.5527	1% 2	-7.3076	0.0000
F5, operating income (momentum)** scores	-3.5527	1% 2	-8.3549	0.0000	-3.5527	1% 2	-8.3743	0.0000
F6, operating income (momentum)** scores	-3.5527	1% 2	-7.2986	0.0000	-3.5527	1% 2	-7.2990	0.0000

* = Explained variable. ** = Explanatory variable. Unit root test with: 1 = No exogenous variable(s), 2 = Constant.
× = test critical value for the % used in the unit root tests. ADF = Augmented Dickey-Fuller. PP = Phillips-Perron.
Unit root test performed on time series data from the base period (1990Q2-2004Q2, 57 observations).

Table 60 Dow. Unit root tests of the base period time series and the Spectramap factor variables.

mation of the source variables. Next, the second factor tries to capture most of the information left by the first factor. After that, the third factor is expected to capture what is not explained by the first two factors, et cetera, until most information is contained in the new factors or variables and the sum of variance explained approaches 100% (ideally). Not all data sets can be captured by only a limited number of factors. In general, the more uncorrelated the original variables are, the more the likelyhood decreases of data reduction to a limited number of factors.

10.2.8 Spectral Map Analysis

In this study a factorial method s applied for data decomposition. Spectral Map Analysis, SMA in short, is a method similar to Principal Component Analysis, PCA in short, but especially suitable for the (graphical) analysis of contrast from log ratios. SMA is well described by Lewi (1976, 1982), Wouters *et al.* (2003) and Greenacre & Lewi (2007). The method is of general use and has been applied in pharmaceutical research, competitive positioning and financial analysis (Lewi 1989, 2005). Before factorial decomposition is applied, SMA involves double-centering of the data instead of only column-centering as is done with PCA.[4] After the computation of force and momentum fractions, double-centering was applied to each set of accounting variables of the 30 Dow component companies. Double-centering involves the subtraction of row and column means. Double-centering can be thought of as a simultaneous correction for differences in size between objects (i.e. the accounts) and for differences in importance between measures (i.e. the time steps, Wouters *et al.* 2003 or Greenacre & Lewi 2007). Lewi asserts (1982, 41-51) that it is natural to apply double-centering to two-way tabulations, such as financial accounting data, as we deal with proportions rather than with differences.

After double centering, the mean value is zero (rounded) at each time period. The momentum and force time series of the 30 Dow component companies are shown from Figure 138 to Figure 141 with full scales (left) and with bounded scales of the y-axis (right). Figure 138 is operating income which is a momentum measure in the TEMA framework. Figure 139 is operating income force. Figure 140 is total wealth momentum and Figure 141 is total wealth force.[5] Comparing the figures that have a full scale with those that have their y-axis scale bounded gives an impression of the stationarity of these transformed time series; in particular for total wealth momentum and force. Not unexpectedly, with the exception of operating income, the impression is that of a mean reverting process around zero. The operating income time series consists of lognormal data that tends to vary around zero but these series are somewhat distorted because of the occurrence of negative values due to a negative result (for Microsoft see Table 57).[6] Formal econometric tests can substantiate this suggestion of mean reverting behavior of these time series. Only the econometric test results are presented here of each

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4 I do not elaborate on the matrix algebra of factor analysis and other mathematical procedures that are used for multivariate data analysis as this is abundantly available in the literature, e.g. Greenacre & Lewi (2007), Reyment & Jöreskog (1993) or Everitt & Dunn (2001).

5 The figures of the net wealth momentum and of net wealth force have very similar characteristics as those of total wealth and are not included here for the sake of brevity.

6 Lognormal transformation of negative values is, of course, not possible. Hence, I employ an artificial solution to include negative accounting data. The negative data are inverted to positive values before lognormal transformation is computed. Next, the result values are again inverted and included in the analysis. The equation of this solution is $-\log_e(-x)$.This is only practical with data that is bound to be larger than 1 or smaller than −1 as the lognormal of positive values smaller than 1 are negative. Accounting time series like those used in this study seldomly have positive values smaller than 1.

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Vector
XOM	0.102	-0.018	-0.032	-0.016	-0.012	-0.001	0.110
MCD	0.084	-0.175	-0.073	-0.041	-0.043	0.045	0.220
UTX	0.198	-0.037	-0.066	-0.119	-0.095	-0.020	0.262
HON	0.061	-0.116	-0.098	0.085	-0.185	-0.056	0.268
BA	0.189	-0.037	0.120	-0.122	0.029	-0.099	0.278
IBM	-0.143	0.070	-0.067	0.043	-0.084	0.217	0.293
JPM	0.192	0.108	-0.082	-0.093	-0.109	-0.122	0.301
MMM	0.226	-0.075	-0.148	-0.120	0.004	-0.003	0.304
PG	0.179	0.004	0.092	-0.066	-0.189	0.140	0.317
MO	0.242	-0.025	-0.071	-0.064	-0.181	0.077	0.327
GM	0.131	-0.175	-0.251	-0.000	-0.042	0.065	0.342
MSFT	-0.140	-0.133	-0.056	-0.090	-0.282	-0.117	0.377
KO	0.115	-0.168	-0.289	0.126	-0.061	-0.119	0.398
CAT	0.235	-0.254	-0.036	-0.033	-0.003	-0.200	0.403
JNJ	0.103	-0.009	-0.186	0.280	-0.235	-0.021	0.424
INTC	0.065	-0.141	0.236	-0.126	-0.333	-0.052	0.458
GE	0.054	0.162	0.079	-0.238	-0.352	0.021	0.466
DD	0.439	0.097	-0.058	0.038	-0.207	-0.338	0.604
WMT	0.583	0.221	0.174	-0.442	-0.331	0.096	0.856
AIG	-0.027	-0.394	-0.335	-0.056	-0.802	0.213	0.979
MRK	0.090	-0.933	0.351	-0.532	-0.548	0.115	1.265
HD	0.721	0.071	0.254	-0.347	-0.727	-0.695	1.312
C	-1.014	-0.233	0.207	-0.497	0.818	-0.195	1.443
AA	0.135	-0.322	0.124	-0.576	1.246	-0.715	1.591
VZ	-0.978	-0.124	0.433	-0.838	1.256	-0.554	1.935
HPQ	0.341	-0.417	0.150	-0.159	0.756	2.381	2.565
PFE	0.518	0.491	-2.306	0.982	0.781	-0.196	2.728
DIS	0.118	-0.890	1.367	2.383	0.402	-0.279	2.932
AXP	0.357	3.011	0.909	0.194	0.194	0.185	3.182
SBC	-3.177	0.444	-0.342	0.445	-0.662	0.227	3.331

Table 61 Dow companies. Loadings for the 6 total wealth momentum Spectramap factors ranked by vector length.

panel of accounting variables reduced with spectramap to six factors (Table 60).[7] As an example, Table 61 provides the factor scores of each company for total wealth momentum. Note that the sample period time series that was processed has four quarters less than the actual time series (1989Q4-2004Q2). These are not included in the decomposition because the resulting factors are used to develop the econometric models that not only will explain the sample period time series but are also expected to predict the next four quarters. By not including the last four quarters in the spectramap decomposition I exclude their variance and thus the forecast will be based only on variance that originates from the base period. When the forecasts are successful I will be able to more firmly claim that the original TEMA variables have predictive power and that they are leading indicators of the Dow.

Figure 142 shows the time series of the six spectramap factors that decompose total wealth momentum of the 30 Dow companies (Figure 140). Table 61 reports the scores of each Dow component company of the six factors of total wealth momentum sorted by their sum vector rank. The sum vector provides a six-dimensional measure of contrast of each company with the mean value of the whole data panel and is computed by $\sqrt{(\Sigma\lambda_i^2)}$. The sum vector measure is an important indicator that will be discussed further below. Table 59 reports the variance described by each of the six factors of total wealth momentum and the other five decomposed accounting variables of the Dow component companies. Noticeably, the first factor of each variable explains most of the variance from 22.1% for total wealth momentum

7 The ADF and PP. test for the presence of a unit root was performed for all these data (Chapter 8).

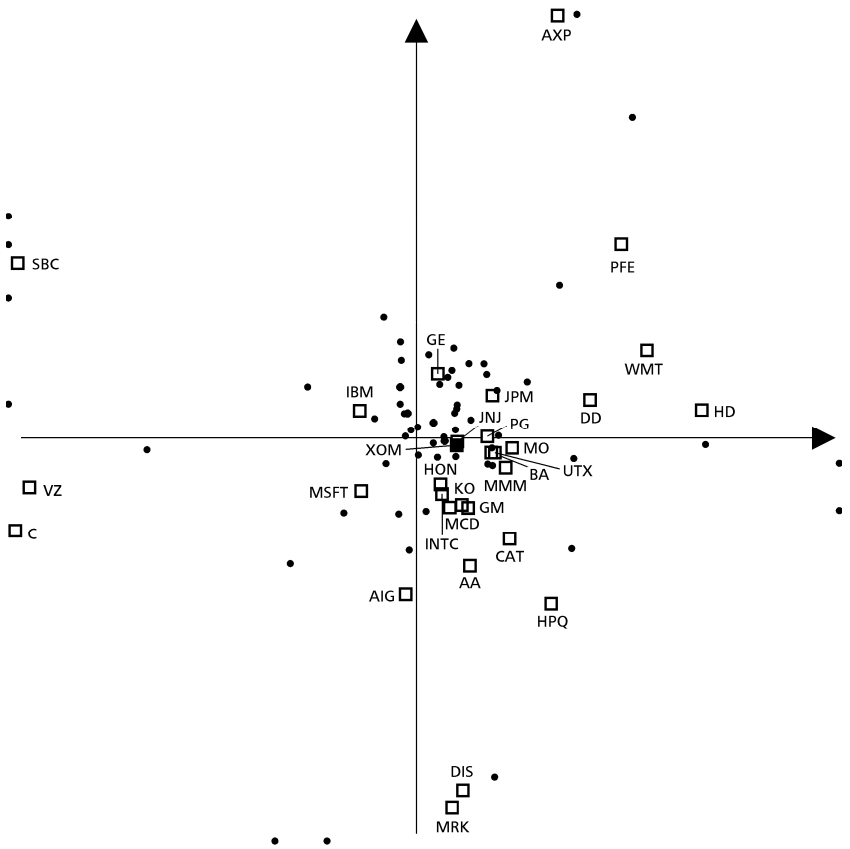


Figure 143 Dow. Biplot of companies for Spectramap factors 1 & 2 of total wealth momentum.

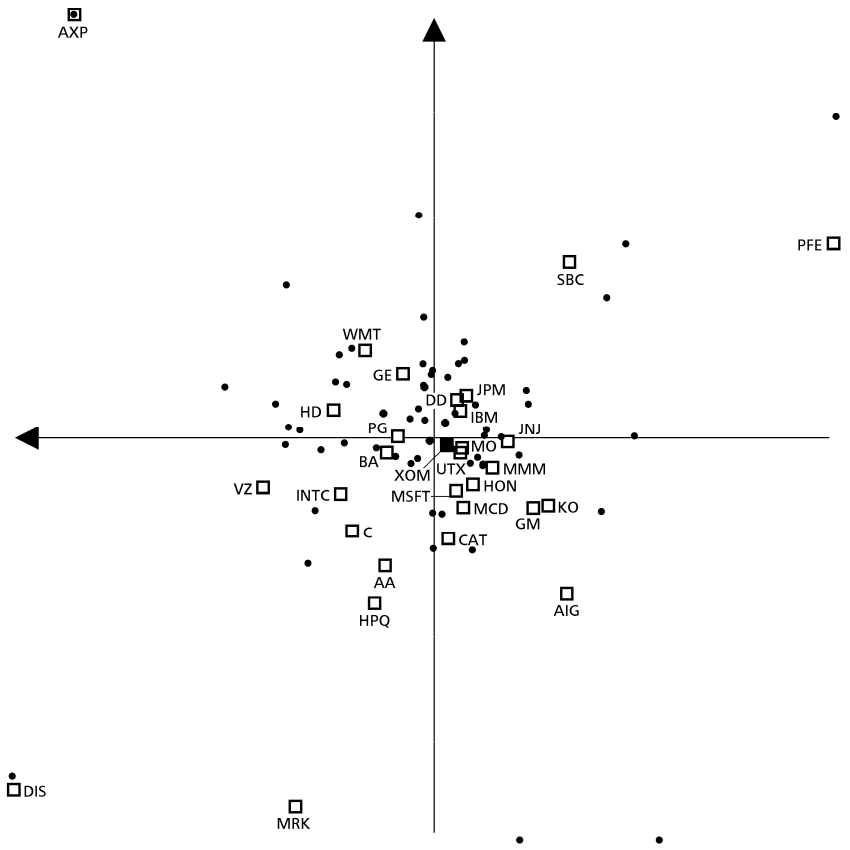


Figure 144 Dow. Biplot of companies for Spectramap factors 3 & 2 of total wealth momentum.

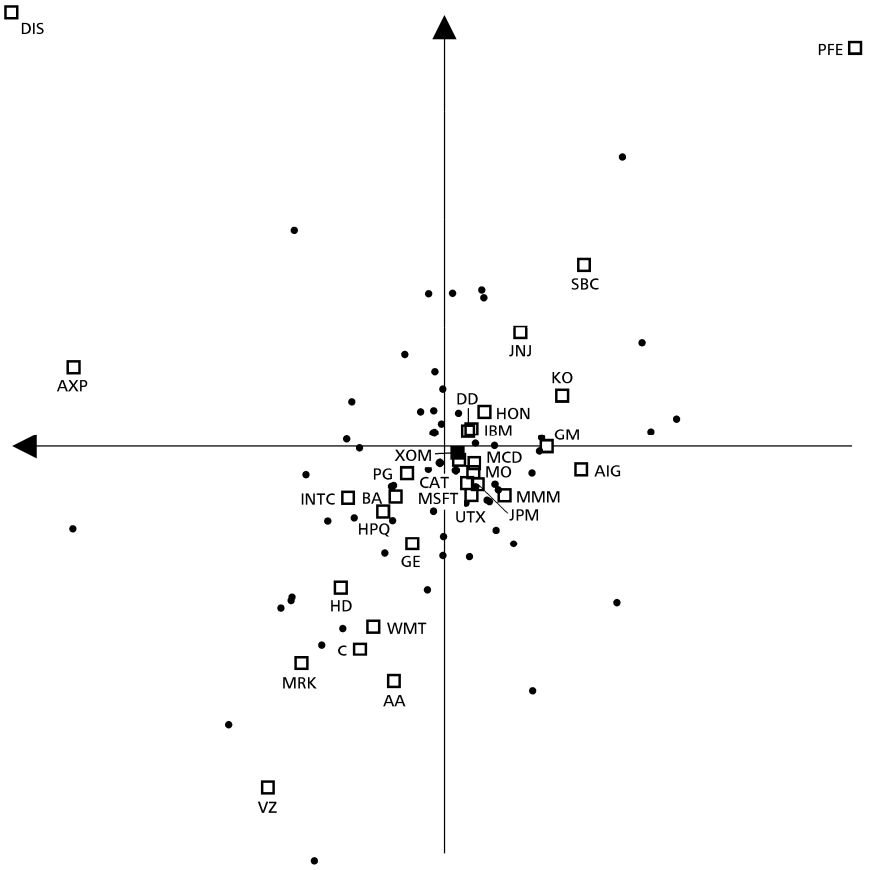


Figure 145 Dow. Biplot of companies for Spectramap factors 3 & 4 of total wealth momentum.

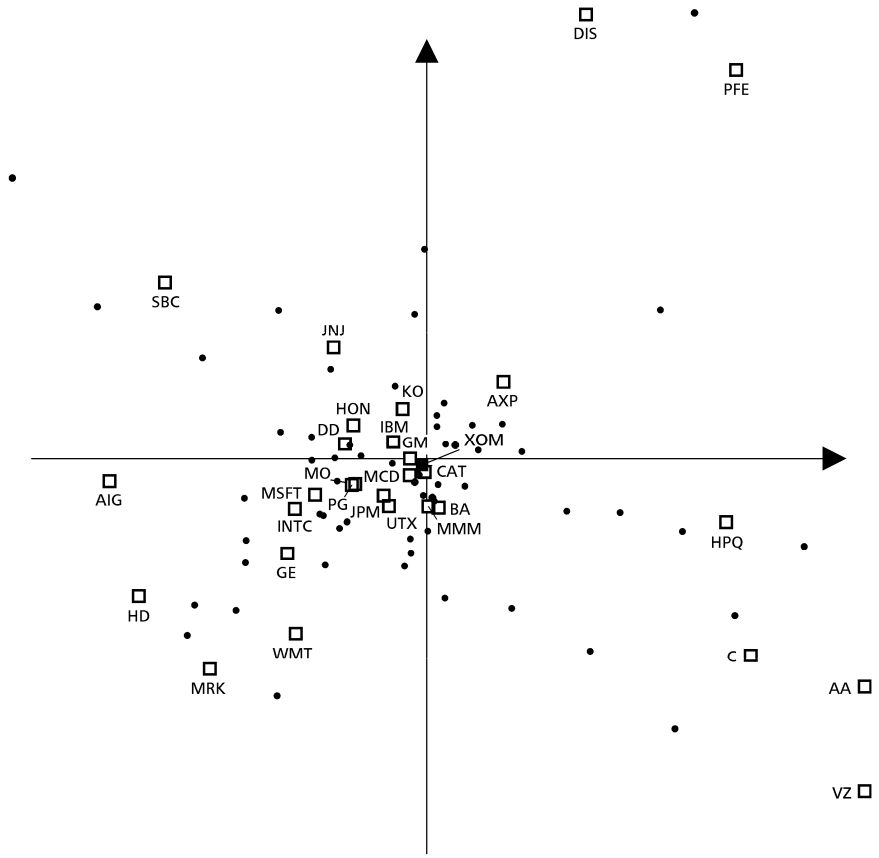


Figure 146 Dow. Biplot of companies for Spectramap factors 4 & 5 of total wealth momentum.

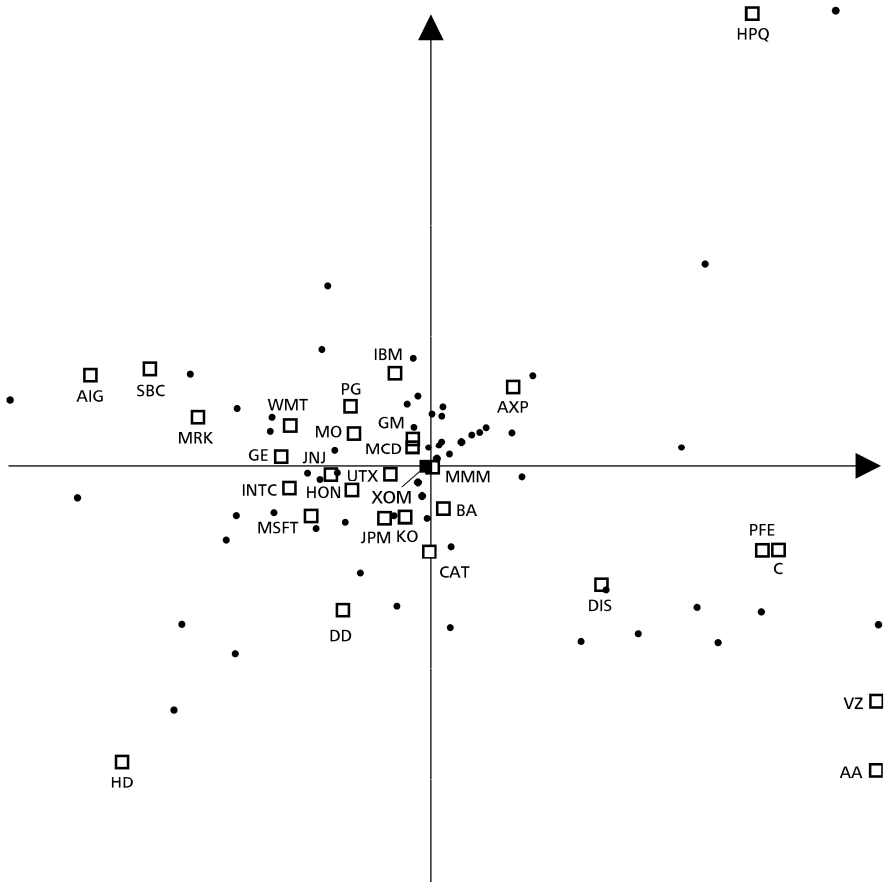


Figure 147 Dow. Biplot of companies for Spectramap factors 5 & 6 of total wealth momentum.

to 22.58% for operating income. With six factors, the major part of variance is explained from 69.32% for total wealth momentum to 72.33% for operating income.

10.2.9 Structural analysis

Sma offers another view on the decomposed momentum time series of the Dow companies. Figure 143 is a so-called Spectramap biplot (bi for both the table column items, or variables, and the table row items, or measures) of the sma factors 1 and 2 of total wealth momentum. Figure 144 up to Figure 147 show the same but, respectively with factors 2 and 3, 3 and 4, 4 and 5, and finally, 5 and 6. These spectramap biplots chart both the Dow component companies and each measurement of the time series. The time periods, quarters, are visualized with black dots. The Dow component companies are visualized by small white squares. These spectramap biplots are two-dimensional visualizations or maps of the sma loadings of the time periods and the sma scores of the companies (Table 61) on the two factors that are displayed as the horizontal and the vertical axes with an arrow to the right or left, and the top, respectively. Of special interest for the structural analysis is the position of the companies on these spectramap biplots. The closer a company is located at the cross point of the two axes, the closer its trend moves like the mean of the time series of the whole panel (i.e. the 30 Dow companies). The further away a company is located from the center of the spectramap biplot the more specific its dynamic is. For example, Exxon Mobil (xom) is near the mean position in all spectramap biplots. In contrast, Alcoa (aa), Citigroup (c), Hewlett-Packard (hpq), Home Depot (hd), Merck (mrk), Pfizer (pfe), Verizon Communications (vz) and Walt Disney (dis) are all located at a greater distance from the center in most Spectramap biplots.

The intuition is that these companies each have their own (very) specific dynamic within the panel of 30 Dow companies. It is interesting to observe that adjacent companies compete in the same sector. For example, Home Depot (HD) and Wal-Mart Stores (WMT) are positioned nearby in five out of six Spectramap biplots. This implies that these two companies have a similar dynamic behavior expressed by the first five decomposed variables. In Figure 143, the Spectramap biplot of SMA factors 1 and 2, Merck (MRK) and Walt Disney (DIS) also have the same position but note that these two companies are both positioned opposite of American Express (AXP). This implies that Merck and Walt Disney have a negative association with American Express. Compare to these companies, Citigroup (C), Verizon Communications (VZ) and AT&T (T) are positioned at an angle of about 90°, which implies that neither one of these three companies is associated with Merck or Walt Disney, or with American Express. What the Spectramap biplots reveal is that the Dow component companies might associate positively, negatively or not at all, but that the Dow on the whole seems to be composed of companies that exhibit total wealth momentum dynamics that seem to balance out rather well.

10.2.10 Time series properties

Problems associated with inter-company comparisons do not rise in this study because the econometric models are developed from the SMA factors of the original accounting variables. However, statistical requirements particular to time series modeling must be met (Koop 2000). To exclude non stationarity in the time series, two, so-called, *unit root* tests of the factor variables are reported in Table 60: the Augmented Dickey-Fuller test (ADF) and the Phillips-Perron test (PP). Both have as their null-hypothesis that a time series is stationary. The unit root tests are applied to the sample base periods, i.e. the ex post quarterly periods used to develop the regression models further on this study. The last four quarters are left out the unit root test because I will develop regression models from only the sample period data (ex post) and try to predict the last quarters (ex ante). As Koop recommends (2000, 142), the null of the presence of a unit root is rejected if the P-value of the ADF or PP. test is less than 0.05 (5%). Clearly, this is the case with all the SMA factors. This good result enables the regression of these factors on Dow momentum without the risk that a model is developed with spurious regression. Note that the time series of the Dow itself fails to reject the null of a unit root with a P-value of 0.8887 and 0.9137 for, respectively, the ADF and the PP. test at the 10% level. This means that to include the Dow as the explained variable in the econometric models I have to use the Dow momentum measure (first difference). The unit root test statistics indicate that the Dow momentum time series are stationary. Thus, hypothesis H 6_a is validated for this study's data: all time series are stationary. This implies that balanced econometric models can be developed with Dow momentum as the dependent variable and as the independent variables the Spectramap factors of decomposed total wealth momentum and operating income.

10.3 Empirical Results

In terms of the accounting system of Ijiri the first and second derivative of the accounting time series, decomposed as SMA factors, are measurements of momentum and force. The analogy between the econometric method and Ijiri's system of momentum accounting is of great importance to this study. The objective is to find evidence in support of my main thesis that econometric TEMA models have explanatory and predictive power. It is elegant to tie the temporal accounting dimensions of the TEMA framework to the mathematical building blocks of econometric regression models.

Neither mathematically nor theoretically is it of much interest to try to model the growth of the Dow with its own momentum for that would be self-explanatory. Figure 134, page 216, shows the Dow close data at the end of the week, and Figure 135 at the end of the quarter close data. The growth pattern of both measurements in time is similar and by using the Dow's quarterly data I will not lose that much information.[8] Figure 136 is the first difference of the quarterly time series, or momentum, and Figure 137 shows the second difference of the data, or force (Table 57, Table 58, pages 218 and 219).

Without special consideration, Dow index data cannot be included in a regression model because, as the ADF and the PP. test showed, that data is not stationary (Table 60). Observe the trend of this time series (Figure 135). First increasing steadily for 10 years from the fourth quarter of 1989 until fourth quarter of 1999, then, the next year more or less stationary, to decline gradually until the third quarter of 2003, and to pick up a new growth trend until the end of the time series. Instead of developing a self explanatory *autoregression* model of the Dow with its own momentum or force I make use of the financial accounting information, i.e. book values and operating income of its component companies, as leading indicators.

10.3.1 Modeling the Dow

To explain the growth trend of the Dow three TEMA models will be developed. First a joint model is used that includes the SMA factors of total wealth momentum and operating income. Second, a model with only the total wealth momentum SMA factors and third those of operating income:

1. Model 1 is the joint regression of the independent variables operating income (OI), a momentum measurement, and total wealth momentum (TWM) on the dependent variable Dow momentum with twelve spectramap factors.
2. Model 2 is the regression of the independent variable total wealth momentum (TWM) on the dependent variable Dow momentum with six spectramap factors.
3. Model 3 is the regression of the independent variable operating income (OI), on the dependent variable Dow momentum with six spectramap factors.

Suppose that I model the Dow with the original financial accounting measurements of all the 30 component companies then this would require a rather large regression equation. In Equation (41), Dow momentum is the dependent variable $\nabla \mathbf{D}_t$ and the independent variables are the 30 total wealth momentum measures $\mathbf{X}_{1\ldots30}$ and the 30 operating income measures $\mathbf{Z}_{1\ldots30}$:

(41) DOW M,
$$\nabla \mathbf{D}_t = \alpha + \beta_1 \nabla \mathbf{X}_{1t?} + \ldots + \beta_{30} \nabla \mathbf{X}_{30t?} + \beta_{31} \mathbf{Z}_{1t?} + \ldots + \beta_{60} \mathbf{Z}_{30t?} + \mathbf{u}_t \qquad \text{with } t=1, \ldots, T.$$

Obviously, there is little chance that such a regression equation will render reliable results. Besides the problem of over specification with so many independent variables, this model will not be balanced because most if not all operating income time series will not be stationary and thus induce spurious results. The alternative would be to develop a force model by taking the second difference of the Dow and total wealth data and the first difference of the operating income data. But that would still leave us with 60 independent variables. As an alternative the SMA factors of the two sets of momentum measures are used. In Equation (42), Dow momentum is again the dependent variable $\nabla \mathbf{D}_t$ but the independent variables are now the six total wealth momentum SMA factors $\mu_{1\ldots6}$ and the six operating income SMA factors $\lambda_{1\ldots6}$:

[8] Because the financial accounting variables are quarterly data we require quarterly Dow data as well.

(42) DOW M, $$\nabla \mathbf{D}_t = \alpha + \beta_1 \mu_{1t?} + \ldots + \beta_6 \mu_{6t?} + \beta_7 \lambda_{1t?} + \ldots + \beta_{12} \lambda_{6t?} + \mathbf{u}_t \quad \text{with } t=1, \ldots, T.$$

Note that EQUATION (42) is the joint model of twelve decomposed SMA factors of total wealth momentum together with operating income. EQUATION (43) is the second model with only the six decomposed SMA factors of total wealth momentum and EQUATION (44) is the third model with only the six decomposed SMA factors of operating income:

(43) DOW M, $$\nabla \mathbf{D}_t = \alpha + \beta_1 \mu 1_{t?} + \ldots + \beta_6 \mu 6_{t?} + \mathbf{v}_t \quad \text{with } t=1, \ldots, T,$$

(44) DOW M, $$\nabla \mathbf{D}_t = \alpha + \beta_1 \lambda 1_{t?} + \ldots + \beta_6 \lambda 6_{t?} + \mathbf{w}_t \quad \text{with } t=1, \ldots, T.$$

I am confident that these three models are balanced because the DOW momentum time series are stationary as well as their decomposed SMA factor time series (TABLE 60). However, at this point I do not know the temporal association between the independent variables and the dependent variable and this is indicated with the '?' after each variable's time subscript. Preliminary testing revealed that alternative regression models fail to explain the DOW momentum measure with the independent factor variables when they all have the same temporal subscript. Removal of one or more of the independent variables did not improve the regression result. This implies that any dynamic of total wealth momentum or operating income does not have an immediate impact on the movement of the DOW Jones index. Therefore, an unbiased method is required to determine if the independent factor variables need to be delayed and, should that be the case, by how many lags.

10.3.2 Structural association

For each decomposed SMA factor a table was created that included DOW momentum, the factor time series data and seven additional columns with that same data but now from one to seven quarters delay. Next, each of the twelve tables was analyzed for its structural association by means of standardized Principal Components Analysis (SPCA). The SPCA decomposition procedure assumes that the data are column centered and thus standardized to have a zero mean column wise and unit variance (Jolliffe 1992, 72, 2002). The plot of loadings of all the independent variables (column items, in this case a SMA factor and its time lags) provides a visual analysis of the structural association between them and the dependent variable DOW momentum. This association will be positive when DOW momentum and a SMA factor, or its time lag, appear to trend positively or negative when they trend in opposite directions. For example, in the SPCA plot of FIGURE 148, left, DOW momentum and the first total wealth momentum SMA factor with seven lags are located near each other (the variables are indicated by a diamond symbol). The angle between the lines drawn from the plot center, where the x and y-axis crosses, to each item is an indication of the measure and direction of their association. When the angle is between 0° and 90° the association is positive and when the angle is between 90° and 180° the association is negative. The association is strongest when the angle is close(r) to 0° or 180° and absent when the angle gets close to 90°. Clearly, the association between DOW momentum and $\mu 1_{t-7}$ is strong and positive.

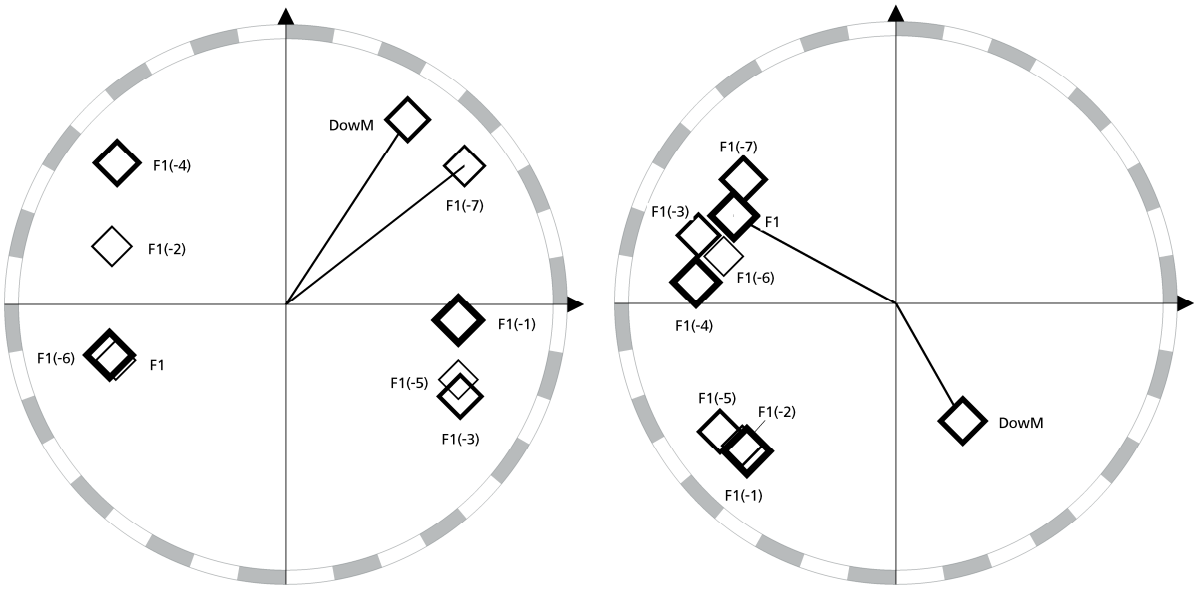


Figure 148 Plot of the association between Dow momentum and lagged values of SMA factors. Left: total wealth momentum factor 1. Right: operating income factor 1.

The association between Dow momentum and the first a SMA factor of operating income (λ_{1t}) is also strong but negative (Figure 148, right). Four other lagged variables also come into view as candidates to be included in the regression equation as an independent variable: λ_{1t-3}, λ_{1t-4}, λ_{1t-6} and λ_{1t-7}. How should we evaluate them in this plot, apart from testing them in regression models? The SPCA analysis results in more than two principal components that are used for the x and y-axis of the plots of Figure 148. Table 62 reports the loadings of the lagged SMA factors for each of the six principal components together with the variance explained by each Eigenvalue. The third component is used to plot the z-axis (not displayed) in the plots of Figure 148. The thickness of the outline of the diamond symbol indicates the position of the variables along it. When it is thick it is positioned above the x,y-plane of projection and it is below it when the outline is thin. The difference in outline is already an indication that these five independent variables are not identical in all aspects. Color Figure 15, page 316, includes the same plot but now all variables are also color coded by their association with the Dow momentum calculated with all six principal components. Note that the color scale scores from a bright orange over gray to a dark blue. When the association is strong and positive the color of the independent variable (i.e. the SMA factor) will be near identical with that of the Dow momentum (bright orange). When the association is strong and negative the color will be dark blue. When any association is absent the independent factor variable will be coded with a grayish color. Now we can observe that the operating income SMA factor without a time lag has the strongest negative association as it is coded by a saturated dark blue color and at the widest angle with Dow momentum. The alternative lagged SMA factor values are either not associated or to a smaller degree.

These differences in color are subtle but important as the econometric regression model statistics will show. The same procedure is followed for total wealth momentum factors. Color Figure 16 has the plots of the principal components of the lagged total wealth momentum SMA factors. Table 63 reports the loadings of the lagged SMA factor variables for each of the six principal components together with the variance explained by each Eigenvalue.

	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6
OI Factor 1 Eigenvalues	33.55%	14.49%	12.70%	11.29%	8.79%	6.42%
Cumulative Eigenvalues	33.55%	48.05%	60.74%	72.04%	80.83%	87.24%
∇D_t loadings	0.238	-0.420	0.175	-0.792	0.212	0.109
λ_{1t} loadings	-0.575	0.311	0.402	0.215	0.343	0.425
λ_{1t-1} loadings	-0.529	-0.528	0.466	0.093	0.063	0.117
λ_{1t-2} loadings	-0.546	-0.508	-0.415	0.106	0.315	-0.169
λ_{1t-3} loadings	-0.701	0.242	-0.162	-0.134	0.438	-0.286
λ_{1t-4} loadings	-0.710	0.076	0.403	0.034	-0.261	-0.366
λ_{1t-5} loadings	-0.625	-0.458	-0.112	0.023	-0.450	0.130
λ_{1t-6} loadings	-0.612	0.168	-0.593	-0.118	-0.121	0.331
λ_{1t-7} loadings	-0.542	0.439	0.092	-0.538	-0.219	-0.022

Table 62 Dow. Variance explained by standardized principal components analysis of momentum and 7 lagged steps of the first operating income (momentum) factor and their loadings.

	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6
TWM Factor 1 Eigenvalues	35.82%	13.73%	12.33%	10.38%	10.13%	7.19%
Cumulative Eigenvalues	35.82%	49.55%	61.88%	72.25%	82.38%	89.57%
∇D_t loadings	0.433	0.661	0.051	0.117	0.005	0.590
μ_{1t} loadings	-0.604	-0.200	-0.377	0.419	-0.335	0.235
μ_{1t-1} loadings	0.613	-0.057	0.555	-0.294	-0.311	0.007
μ_{1t-2} loadings	-0.618	0.208	-0.356	-0.440	0.375	0.063
μ_{1t-3} loadings	0.620	-0.328	0.051	0.530	0.331	0.049
μ_{1t-4} loadings	-0.599	0.505	0.200	0.178	-0.404	-0.183
μ_{1t-5} loadings	0.613	-0.269	-0.428	-0.368	-0.289	0.218
μ_{1t-6} loadings	-0.626	-0.182	0.503	-0.073	0.361	0.283
μ_{1t-7} loadings	0.635	0.495	-0.226	0.109	0.273	-0.276

Table 63 Dow. Variance explained by standardized principal components analysis of momentum and 7 lagged steps of the first total wealth momentum factor and their loadings.

10.3.3 Momentum based regression analysis

With the result of the structural analysis of the association between Dow momentum and the decomposed lagged sma factors of total wealth momentum and operating income the temporal subscripts can now be specified as:

$$(45)\ \text{DOW M},\qquad \nabla \mathbf{D}_t = \alpha + \beta_1\mu_{1t-7} + \beta_2\mu_{2t-7} + \beta_3\mu_{3t-5} + \beta_4\mu_{4t} + \beta_6\mu_{5t-6} + \beta_6\mu_{6t} +$$
$$\beta_7\lambda_{1t} + \beta_{12}\lambda_{2t-1} + \beta_{12}\lambda_{3t-5} + \beta_{12}\lambda_{4t-3} + \beta_{12}\lambda_{5t-4} + \beta_{12}\lambda_{6t-5} + \mathbf{u}_t \qquad \text{with } t=1, \ldots, T.$$

Table 64, panel a, reports the test statistics of the joint model, and of the regression of only the total wealth momentum as well as of the operating income factor variables. My confidence is rather high as all three models have f-test statistics at the 1% level of significance. Also the econometrics test criteria for the presence of autocorrelation in the regression residuals (bg lm) or the presence of heteroskedasticity (White) are met well within acceptable limits. However, the overall fit of the models varies considerably. The joint model has the best fit at 63% of explained variance (Adjusted R^2). The regression with only the decomposed sma factors of total wealth momentum has a fit of 39% while the operating income factor variables explain a little less with a fit of 36%. At this point, a final check of the appropriateness of the joint tema model can be made by means of another structural analysis of the base period sample time series (Table 65). Color Figure 20, page 321, is a spectramap biplot of the variables by their

A: Regression model statistics	BG LM	White	*F*-stat.	Adj. R^2
TWM & OI(M) joint model	2.442*	8.961*	8.064*	0.63
Total wealth momentum factor model	2.634*	22.300*	6.244*	0.39
Operating income factor model	3.978**	14.994*	5.551*	0.36

Level of significance at 1%=*, 2,5%=**. Base period sample from 1990Q2 to 2004Q2.

B: Joint TWM & OI (m) model	Coefficient	Std. error	95% Confidence interval	t-stat.	p-value
α	0.022	0.007	[0.01, 0.03] 0.02	3.086	0.004
μ1(-7)	0.033	0.010	[0.02, 0.05] 0.03	3.223	0.003
μ2(-7)	-0.028	0.011	[-0.05, -0.01] 0.04	-2.659	0.012
μ3(-5)	0.059	0.020	[0.03, 0.09] 0.07	3.010	0.005
μ4	0.027	0.012	[0.01, 0.05] 0.04	2.301	0.027
μ5(-6)	0.054	0.014	[0.03, 0.08] 0.05	3.697	0.001
μ6	-0.041	0.013	[-0.06, -0.02] 0.04	-3.234	0.003
λ1	-0.028	0.012	[-0.05, -0.01] 0.04	-2.301	0.027
λ2(-1)	-0.027	0.013	[-0.05, -0.01] 0.04	-2.173	0.036
λ3(-5)	0.041	0.013	[0.02, 0.06] 0.04	3.134	0.003
λ4(-3)	-0.031	0.013	[-0.05, -0.01] 0.04	-2.303	0.027
λ5(-4)	0.065	0.015	[0.04, 0.09] 0.05	4.325	0.000
λ6(-5)	0.038	0.015	[0.01, 0.06] 0.05	2.501	0.017
C: TWM model	coefficient	std. error	95% confidence interval	t-stat.	p-value
α	0.025	0.009	[0.01, 0.04] 0.03	2.880	0.006
μ1(-7)	0.035	0.012	[0.01, 0.06] 0.04	2.860	0.007
μ2(-7)	-0.026	0.013	[-0.05, 0.00] 0.04	-1.962	0.056
μ3(-5)	0.054	0.025	[0.01, 0.09] 0.08	2.174	0.035
μ4	0.033	0.015	[0.01, 0.06] 0.05	2.188	0.034
μ5(-6)	0.052	0.017	[0.02, 0.08] 0.06	3.032	0.004
μ6	-0.047	0.016	[-0.07, -0.02] 0.05	-2.873	0.006
D: OI (m) model	coefficient	std. error	95% confidence interval	t-stat.	p-value
α	0.024	0.009	[0.01, 0.04] 0.03	2.673	0.011
λ1	-0.048	0.015	[-0.07, -0.02] 0.05	-3.203	0.003
λ2(-7)	-0.031	0.016	[-0.06, 0.00] 0.05	-1.928	0.061
λ3(-6)	0.044	0.017	[0.02, 0.07] 0.06	2.599	0.013
λ4(-7)	0.040	0.015	[0.01, 0.07] 0.05	2.571	0.014
λ5(-4)	0.074	0.019	[0.04, 0.11] 0.06	3.954	0.000
λ6(-1)	-0.043	0.019	[-0.07, -0.01] 0.06	-2.331	0.025

Table 64 Dow. Regression statistics of the TEMA models.

loading on the first three SMA factors while the next three factors are used for color coding.[9] The color coded plot visualizes 74% of the variance of Table 65. This plot confirms that the independent variables each model a separate informational aspect of the original accounting data because the projection planes that can be thought to intersect the sets of three SMA factors are either near orthogonal with each other (MTWF1-2-3 vs. MOIF1-2-3), or congruent with the projection plane of the first SMA three factors of the other independent variable (MTWF1-2-3 vs. MOIF4-5-6, MTWF4-5-6 vs. MOIF1-2-3). This is indicated in each color figure with triangles between MTWF1-2-3, MTWF4-5-6, MOIF1-2-3 and MOIF4-5-6. Two other plots confirm this. Color Figure 17 and Color Figure 18 are identical to Color Figure 20 but rotated. Color Figure 17 visualizes the first three SMA factors of total wealth momentum together with the last three SMA factors of operating income. Color Figure 18, has the complementary perspective of the plane of projection that runs through the first three SMA factors of operating income which is congruent with the last three SMA factors of total wealth momentum.

9 This plot, as well as color figures 13 to 15, is actually a biplot but without the time points.

		Dow** momentum	Total Wealth Momentum* Spectramap decomposition factors						Operating Income (momentum)* Spectramap decomposition factors					
	quarter	∇Dow	$\mu 1(-7)$	$\mu 2(-7)$	$\mu 3(-5)$	$\mu 4$	$\mu 5(-6)$	$\mu 6$	$\lambda 1$	$\lambda 2(-1)$	$\lambda 3(-5)$	$\lambda 4(-3)$	$\lambda 5(-4)$	$\lambda 6(-5)$
EP 8	1992Q1	0.02	0.19	-0.03	0.06	-0.37	-0.46	-0.46	0.34	-0.99	0.78	0.81	-0.05	-0.04
EP 9	1992Q2	0.03	0.21	0.01	0.25	-0.06	0.11	0.11	-0.25	0.25	0.43	1.23	-0.01	0.08
EP 10	1992Q3	-0.01	-0.08	-0.06	0.23	0.03	-0.60	-0.60	1.47	-0.06	0.36	-0.46	-0.48	0.09
EP 11	1992Q4	0.01	0.28	0.14	0.21	0.07	0.03	0.03	2.18	-0.54	0.19	0.66	1.26	-1.37
EP 12	1993Q1	0.04	0.04	-0.01	-0.10	-0.20	-0.29	-0.29	0.24	-0.17	-0.03	0.27	0.04	0.67
EP 13	1993Q2	0.02	0.09	0.23	0.37	-0.24	-0.03	-0.03	0.28	-1.07	0.31	1.35	-0.14	0.37
EP 14	1993Q3	0.01	-0.02	-0.28	0.04	-0.07	-0.59	-0.59	1.61	-1.64	-0.03	-0.73	0.10	0.32
EP 15	1993Q4	0.06	0.36	0.39	0.03	-0.60	-0.23	-0.23	-0.31	-0.73	-0.41	0.33	0.30	-0.73
EP 16	1994Q1	-0.03	0.10	0.07	-0.57	-0.16	-0.19	-0.19	-0.36	-0.20	-0.92	0.27	0.12	-0.70
EP 17	1994Q2	0.00	0.17	0.19	0.91	-0.07	-0.37	-0.37	-0.42	-0.19	-0.93	-0.82	-0.77	-0.12
EP 18	1994Q3	0.06	-0.23	-2.52	-0.17	0.06	-0.04	-0.04	-0.26	-0.20	-1.48	-0.03	0.47	-0.34
EP 19	1994Q4	0.00	0.41	2.36	0.34	0.38	-0.04	-0.04	-0.42	-0.08	0.27	0.16	-0.01	0.32
EP 20	1995Q0	0.08	0.07	0.00	-0.22	-0.01	0.10	0.10	-0.45	-0.11	0.22	0.13	-0.06	1.14
EP 21	1995Q0	0.10	-0.01	0.02	0.03	0.08	-0.38	-0.38	-0.54	-0.13	-0.21	0.16	-0.20	0.24
EP 22	1995Q0	0.05	-0.36	-2.77	-0.21	-0.38	-0.20	-0.20	-0.17	-0.22	-0.12	0.09	-0.16	0.16
EP 23	1995Q4	0.07	0.11	0.13	0.01	0.23	0.03	0.03	-0.79	-0.23	0.00	0.13	-0.13	0.15
EP 24	1996Q1	0.09	0.00	-0.04	-0.02	3.18	-0.29	-0.29	-0.41	-0.55	-0.06	0.03	-0.19	0.18
EP 25	1996Q2	0.01	0.18	0.16	-0.23	0.02	0.59	0.59	-0.41	-0.04	-0.07	0.22	-0.12	0.14
EP 26	1996Q3	0.04	-0.04	-0.19	-0.03	-0.14	-0.09	-0.09	-0.36	-0.15	0.14	-0.29	-0.12	-0.05
EP 27	1996Q4	0.10	0.20	0.12	0.38	-0.40	0.03	0.03	-0.29	-0.11	-0.12	0.14	0.42	0.07
EP 28	1997Q1	0.02	0.08	0.15	0.10	0.38	0.21	0.21	0.37	-0.07	0.98	0.11	-0.05	-0.93
EP 29	1997Q2	0.17	0.73	-0.02	1.81	0.25	-0.24	-0.24	-0.58	-1.38	-0.13	0.12	-0.18	0.14
EP 30	1997Q3	0.04	0.10	-0.05	-0.24	-0.68	0.68	0.68	-0.55	-0.26	-0.08	0.10	-0.13	0.12
EP 31	1997Q4	0.00	0.20	-0.86	-0.05	-0.18	0.13	0.13	-0.53	-0.52	-0.05	0.35	-0.10	0.15
EP 32	1998Q1	0.11	-0.04	0.09	0.40	-0.35	-0.27	-0.27	-0.39	-0.42	0.01	0.30	0.12	0.18
EP 33	1998Q2	0.02	0.10	0.06	-0.09	-0.14	0.78	0.78	-0.27	-0.19	-1.15	-0.72	-0.40	-0.37
EP 34	1998Q3	-0.12	-2.50	0.09	-0.48	0.00	-0.83	-0.83	1.20	-0.08	-0.02	-0.34	0.35	0.37
EP 35	1998Q4	0.17	2.44	-0.06	0.53	0.71	-0.57	-0.57	-0.42	0.62	1.03	0.01	0.47	-0.81
EP 36	1999Q1	0.07	-1.68	0.49	0.29	-0.49	0.63	0.63	-0.35	-0.12	1.09	0.08	-0.04	-0.89
EP 37	1999Q2	0.12	-0.27	0.13	0.04	-0.27	0.65	0.65	-0.37	-0.14	0.05	-0.76	-0.17	0.01
EP 38	1999Q3	-0.06	-0.68	-0.03	-0.11	-0.14	0.05	0.05	-0.25	-0.10	0.03	0.10	-0.10	0.08
EP 39	1999Q4	0.11	0.40	-0.05	-0.12	0.38	0.49	0.49	0.35	-0.11	0.76	0.03	-0.16	0.40
EP 40	2000Q1	-0.05	0.05	-0.05	-0.44	-0.10	-0.23	-0.23	-0.35	0.49	0.03	0.02	-0.18	0.18
EP 41	2000Q2	-0.04	0.19	-0.07	0.30	-1.11	-1.23	-1.23	-0.34	-0.21	-0.07	-0.07	-0.23	0.13
EP 42	2000Q3	0.02	-1.78	0.35	-0.06	0.01	0.41	0.41	-0.26	-0.13	-0.04	-1.71	-0.16	0.15
EP 43	2000Q4	0.01	1.70	-0.18	0.06	-0.27	-0.06	-0.06	-0.14	-0.04	-0.01	-0.02	-0.53	0.16
EP 44	2001Q1	-0.08	0.13	0.19	0.04	-0.13	-0.26	-0.26	-0.28	0.02	-0.21	-0.02	-0.15	-0.20
EP 45	2001Q2	0.06	-0.11	0.05	-0.08	0.14	-0.37	-0.37	0.11	0.55	0.00	-0.01	-0.22	0.11
EP 46	2001Q3	-0.16	-1.70	0.56	0.32	-0.38	-0.46	-0.46	0.76	0.52	-0.07	-0.09	-0.15	0.14
EP 47	2001Q4	0.13	-0.04	0.20	-0.08	0.53	2.06	2.06	-0.65	1.35	-0.05	-0.23	-0.12	0.09
EP 48	2002Q1	0.04	-0.32	-0.32	0.00	-0.09	-0.17	-0.17	-0.17	0.64	-0.03	-1.85	-0.60	0.11
EP 49	2002Q2	-0.11	-0.04	0.24	-0.10	-0.11	-0.26	-0.26	-0.19	0.00	-0.43	-0.13	-1.51	-0.62
EP 50	2002Q3	-0.18	-0.18	-0.19	0.00	-0.22	0.35	0.35	-0.49	-0.15	-0.70	0.09	-0.21	-0.27
EP 51	2002Q4	0.10	0.10	0.08	-0.42	0.09	0.04	0.04	-0.81	0.21	-0.09	0.07	1.35	-0.92
EP 52	2003Q1	-0.04	0.09	0.17	0.37	0.04	-0.48	-0.48	-0.68	1.67	-0.69	-0.05	-0.13	0.48
EP 53	2003Q2	0.12	0.02	-0.18	-0.12	1.29	-0.01	-0.01	-0.44	-0.46	-0.08	-0.42	-0.18	0.14
EP 54	2003Q3	0.03	0.00	0.03	-0.13	-0.17	-0.01	-0.01	-0.14	-1.00	-0.27	-0.76	-0.41	0.09
EP 55	2003Q4	0.13	0.18	-0.07	0.00	0.02	0.02	0.02	1.12	0.01	-0.35	-0.37	1.59	0.15
EP 56	2004Q1	-0.01	0.10	0.02	0.03	0.18	0.95	0.95	-0.24	0.76	-1.76	-0.59	0.39	-0.64
EP 57	2004Q2	0.01	0.39	-0.28	-0.51	-0.18	0.19	0.19	-0.57	-0.06	0.79	-0.16	0.96	-0.95

EP = ex post, base period time series. ** Dependent variable. * Independent variables.

Table 65 Dow. Joint TEMA model time series.

Visual analysis of these figures indicates that:

- The first three SMA factors of operating income and total wealth momentum are almost orthogonal and thus each seems to capture distinct trend dynamics.
- The last three SMA factors of operating income and total wealth momentum are congruent with the projection plane of the first three SMA factors of the other independent variable.

The economic intuition of the last observation is that the one accounting variable, total wealth momentum or operating income, captures with its lower SMA factors similar trend dynamics as the higher SMA factors of the other, and vice versa. However, there are also distinct differences which is indicated by the position of certain SMA factors above the plane of projection in Color Figure 17 and Color Figure 18.[10] Color Figure 19 plots and color codes the lower SMA factors 4, 5 & 6. The distant position of each lower SMA factor of both independent variables, strongly and individually color coded, is further confirmation of the high informational value of each of the lower SMA factors of operating income and total wealth momentum. Note that Dow momentumis at the center in both plots (Color Figure 19 & Color Figure 20). This is in agreement with the expectation that the mean behavior is modeled of Dow momentum, the dependent variable, whereas the independent variables themselves do not associate.[11] The conclusion of this analysis is that each SMA factor of total wealth momentum and operating income has its own specific contribution to the overall fit of the regression model that explains the momentum of the Dow Jones index. Therefore, I proceed with the econometric modeling of the independent variables of the dynamic Dow momentum model.

10.3.4 Modeling momentum

Our analysis proceeds to the next step: the modeling of the independent variables to facilitate the ex post and the ex ante simulation of the Dow. ARIMA models are required for each of the SMA factors as they drive the dynamic momentum model of the Dow. Ijiri (1989, 10.5) suggested that '...ARIMA models ... may be considered in momentum measurement...' as an alternative for financial accounting measures as independent variables. This approach is in agreement with the TEMA framework of Ijiri (Figure 1, page 2). Income accounts are flow accounts under the convention of classical accounting theory. However, under the convention of Ijiri's momentum accounting theory, income accounts are seen as stock accounts. He asserts that income is a stock account because in his framework momentum persists and changes through positive or negative forces (Figure 2). Income thus accrues into net wealth at a certain rate (in my case by quarter). Therefore, it is acceptable to model operating income through past data and its period force to be defined with an autoregressive function (Equation (10)) and, if required, with the moving average of past errors (Equation (11)). Table 66 provides test statistics of the ARIMA model of each independent variable that was found following a search procedure among 120 alternative specifications. In Table 66 the overall significance of each ARIMA model is at the 1% level as reported by the F-test. With the one-sided Durbin-Watson *d* test, the presence is investigated of positive serial correlation in the regression residuals. Durbin-Watson test values

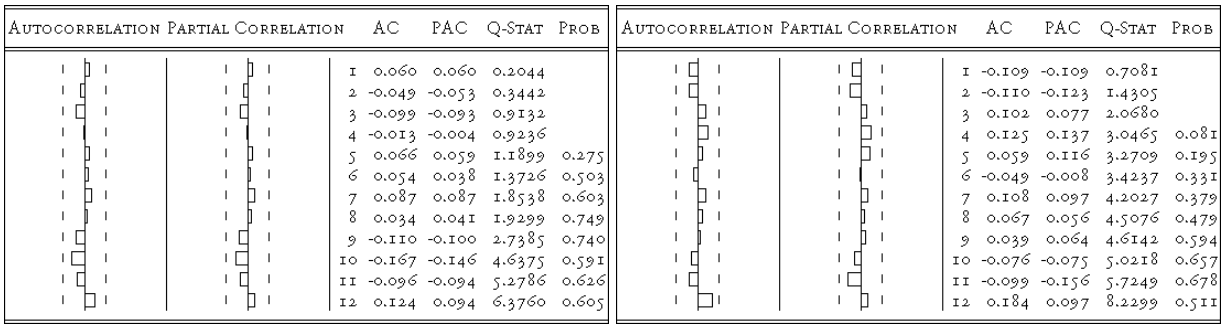
[10] Shown, respectively, by the thicker outline of MOIF6 and MTWF6.

[11] Should they associate then we run into the statistical problem of multicollinearity. Spectral Map Analysis, like Principal Component Analysis, should prevent this from occurring because the factors, or principal components, by definition are decomposed orthogonal to each other and therefore should not associate. However, as I employ lagged values of the decomposed Spectramap factors I can no longer by definition exclude multicollinearity.

Operating income (momentum)	Adj. R^2	*F*-stat.	DW-*d*	*d* U
$\lambda_{1t} = \alpha + \phi_1 V_{t-4} + \theta_1 u_{t-4} + \theta_2 u_{t-8} + u_t$	0.53	20.435*	1.927	1.675
$\lambda_{2t} = \alpha + \phi_1 V_{t-1} + \phi_2 V_{T-2} + \theta_1 u_{t-4} + \theta_2 u_{t-10} + u_t$	0.45	11.586*	1.827	1.720
$\lambda_{3t} = \alpha + \phi_1 V_{t-1} + \phi_2 V_{T-5} + \theta_1 u_{t-4} + \theta_2 u_{t-10} + u_t$	0.31	6.612*	1.853	1.720
$\lambda_{4t} = \alpha + \phi_1 V_{t-4} + \theta_1 u_{t-4} + u_t$	0.40	18.505*	2.247	1.635
$\lambda_{5t} = \alpha + \phi_1 V_{t-1} + \phi_2 V_{T-4} + \theta_1 u_{t-10} + u_t$	0.33	9.557*	1.891	1.675
$\lambda_{6t} = \alpha + \phi_1 V_{t-6} + \theta_1 u_{t-10} + u_t$	0.37	15.559*	1.851	1.635
Total wealth momentum				
$\mu_{1t} = \alpha + \phi_1 V_{t-1} + \theta_1 u_{t-1} + \theta_2 u_{t-7} + u_t$	0.37	10.575*	2.125	1.675
$\mu_{2t} = \alpha + \phi_1 V_{t-1} + \phi_2 V_{T-7} + \theta_1 u_{t-2} + \theta_2 u_{t-8} + u_t$	0.85	70.103*	1.843	1.720
$\mu_{3t} = \alpha + \phi_1 V_{t-2} + \theta_1 u_{t-2} + u_t$	0.24	9.714*	2.054	1.635
$\mu_{4t} = \alpha + \phi_1 V_{t-3} + \theta_1 u_{t-2} + \theta_2 u_{t-3} + u_t$	0.51	19.471*	2.138	1.675
$\mu_{5t} = \alpha + \phi_1 V_{t-2} + \phi_2 V_{T-6} + \theta_1 u_{t-2} + \theta_2 u_{t-8} + u_t$	0.27	5.385*	2.284	1.720
$\mu_{6t} = \alpha + \theta_1 u_{t-9} + u_t$	0.33	28.187*	2.153	1.595

* = Level of significance at 1%. DW = Durbin Watson test of residual autocorrelation.

Table 66 Dow. Test statistics of the ARIMA models of TEMA model factor variables.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.060	0.060	0.2044	
		2	-0.049	-0.053	0.3442	
		3	-0.099	-0.093	0.9132	
		4	-0.013	-0.004	0.9236	
		5	0.066	0.059	1.1899	0.275
		6	0.054	0.038	1.3726	0.503
		7	0.087	0.087	1.8538	0.603
		8	0.034	0.041	1.9299	0.749
		9	-0.110	-0.100	2.7385	0.740
		10	-0.167	-0.146	4.6375	0.591
		11	-0.096	-0.094	5.2786	0.626
		12	0.124	0.094	6.3760	0.605

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.109	-0.109	0.7081	
		2	-0.110	-0.123	1.4305	
		3	0.102	0.077	2.0680	
		4	0.125	0.137	3.0465	0.081
		5	0.059	0.116	3.2709	0.195
		6	-0.049	-0.008	3.4237	0.331
		7	0.108	0.097	4.2027	0.379
		8	0.067	0.056	4.5076	0.479
		9	0.039	0.064	4.6142	0.594
		10	-0.076	-0.075	5.0218	0.657
		11	-0.099	-0.156	5.7249	0.678
		12	0.184	0.097	8.2299	0.511

Figure 149 Dow. Correlogram of TEMA residuals. Left: operating income. Right: total wealth momentum.

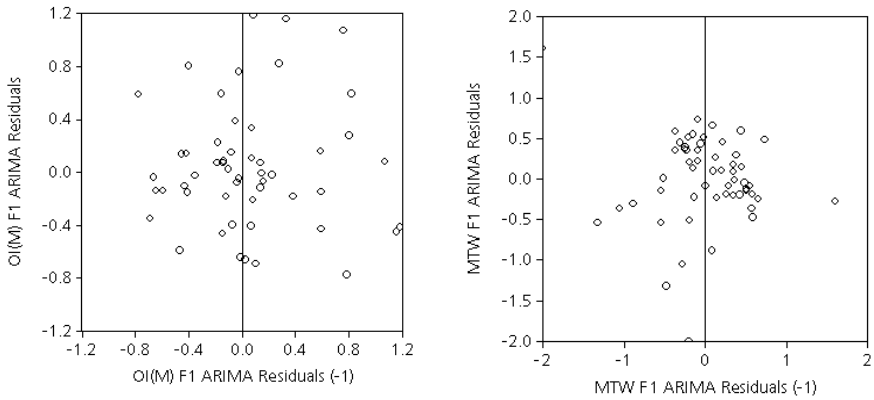


Figure 150 Dow. Equation residuals vs. one time lag. Left: operating income. Right: total wealth momentum.

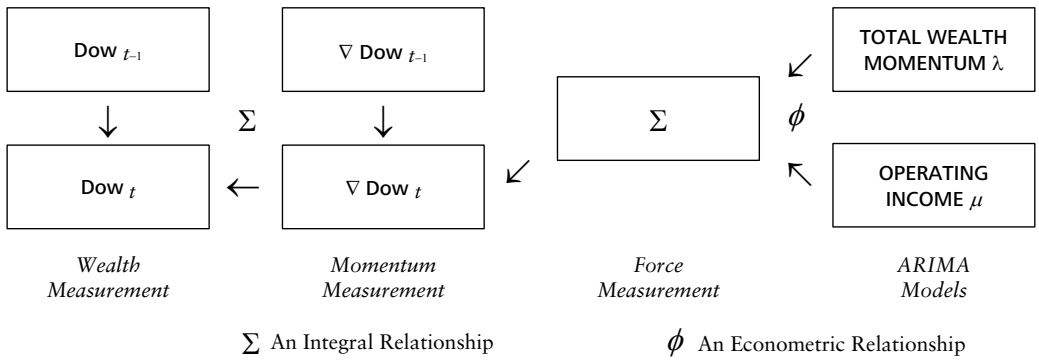


Figure 151 Dow. Aggregation of momentum data from ARIMA models in the TEMA framework.

above the critical value *d*U indicates that there is no evidence of positive residual serial correlation, which indeed is the case for all equations. Furthermore, equation residuals were inspected for the presence of autocorrelation with a scatter plot of lagged residuals against residuals (e.g. Figure 150) and a correlogram of residuals (e.g. Figure 149).[12] The ARIMA model's fit varies considerably between as much as 85% of explained variance (Adjusted R^2) for μ_2 and as little as 24% for μ_3. Whether or not the lower result of model fit of some ARIMA models of SMA factors poses a problem for the simulation of the Dow ex post or ante is discussed in the following two sub-sections.

10.3.5 Dow simulation ex post

Regression models explain the growth trend of Dow momentum through SMA factors of operating income and total wealth momentum (Table 64, panel A). Together with the ARIMA models of each momentum factor (Table 6) these regression models are used as dynamic momentum models. Each econometric model can be understood as a multivariate representation of the component companies of the Dow within the TEMA framework of Ijiri (Figure 151). I simulate ex post the Dow for the periods from the fourth quarter 1990 up to the second quarter of 2004 to test their reliability. Figure 152 to Figure 154 show the result of the static simulation ex post of the three models.[13] The four lines—the unbroken line for the actual data, the dashed line for the simulation mean and the two dotted lines for the acceptable standard deviation[14]—are drawn on top of each other from the start of the simulation for some quarters. This follows from the use of an autoregression function (AR) in the formulation of the ARIMA models of the independent variables which requires a so-called *back cast*. The ex post simulation then does start from the quarter where these lines diverge. I observe that the dashed line of the simulation mean follows the unbroken line of Dow momentum rather well with the exception of the second quarter of 2002. Apart from this minor model failure which we can attribute to some shock in the market, the conclusion has to be that the simulation bandwidth of these apparently reasonable reliable models fits well on the actual Dow data. Reading Table 67, the Root Mean Square Prediction Error (RMSPE) values of the three momentum models show that the preferred model of the static simulation is includes both total wealth momentum and operating income. The dynamic simulation RMSPE values indicate that the model with only total wealth momentum is to be preferred (but the mean bandwidth is much greater). Thus, with ex post simulation of the Dow Jones index evidence is found in support of hypothesis H 9_a. However, these results only assess the merit of the models to estimate the base period. Their predictive performance I evaluate separately in the next sub section.

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[12] The DW test is here appropriate instead of the BG LM test because the ARIMA model of each independent variable includes an intercept term, serial correlation is assumed to be first-order and the regression model does not include a lagged dependent variable (Studenmund 2006, 326). Positive serial correlation implies that if the error term u_t takes a rather high value in one time period, subsequent observations would tend to retain a portion of this value (Studenmund 2006, 315). In our case this implies that the equation fails to model momentum completely and independently from the regression errors. Such result would mean that it would be difficult to find evidence of the generality assumption of the TEMA framework with the decomposed panel data of Dow component companies.

[13] Which implies that the actual values of the independent variables of the last period are used in making the forecast. See also Chapter 2, section 2.3.13, page 67.

[14] The standard error of the regression is a summary measure based on the estimated variance of the residuals. *EViews* will plot the forecasts with plus and minus two standard error bands. These two standard error bands provide an approximate 95% forecast interval. The actual value of the dependent variable will have to fall *inside* these bounds 95% of the time with the forecasts of models to be well specified.

10.3.6 Dow simulation ex ante

Can we make an accurate forecast for four quarters of the Dow with these econometric TEMA models? Figure 155 to Figure 157 are the static and the dynamic forecast of the Dow from the third quarter of 2004 to the second quarter of 2005, respectively by the joint model of total wealth momentum and operating income, total wealth momentum, and operating income. Noteworthy is that with every model the dynamic forecast delivers a similar result to the static forecast. The forecasts of the total wealth momentum model are particularly successful with a 100% success rate although the first quarter lies on the higher boundary line in both simulations. Evaluated by RMSPE values, the dynamic simulation of total wealth momentum model and of the operating income model have a slightly better result. The error of the dynamic forecast is respectively 94% and 92% of that of the static forecast. The RMSPE value of the dynamic forecast of the joint model is much greater (147%) but as Figure 155 shows it succeeds forecasting the first two quarters rather well. However, the joint model dynamic forecast clearly overshoots the actual Dow trend in the next two quarters. Clearly, both the static and the dynamic forecast by total wealth momentum has the best fit at the end of both the static and the dynamic ex ante simulation. This encourages possible future research into the quality and duration of the predictive power of leading financial accounting indicators in dynamic simulation models. These findings with the ex ante simulation of the Dow are evidence in support of hypothesis H 9_a. This offers also support for my main thesis that evidence might be found with empirical archival data and that the TEMA generality assumption holds in this case.

10.3.7 Momentum models of individual Dow component companies

Exxon Mobil (XOM) is located near to the mean position in Figure 143 — Figure 147, respectively page 225 – 227, i.e. at the bary center of the spectramap where each factor score is close to 0 (Table 61). This suggests that Exxon Mobil's total wealth momentum 'moves' during the base period time series in the same manner as the average of all the 30 Dow component companies. The last column of Table 61 has the vector length of each company in the six-dimensional space of SMA factors of total wealth momentum. Table 61 is sorted by this vector ascending in length. Note that Exxon Mobil (XOM) has the shortest vector over the six factors: 0.11. This confirms that this firm of all the 30 component companies indeed is closest to the panel mean decomposition.

This brings up the question if it could be possible that Exxon Mobil can explain and predict the Dow individually? To investigate for the Dow the explanatory and predictive power of the 30 component companies the same econometric modeling procedure was followed. The same tests were applied as described in the previous sections. Only five of the 30 Dow component companies are found to exhibit explanatory power with the regression model with total wealth momentum as the independent TEMA variable: Hewlett-Packard (HPQ), 3M (MMM), Microsoft (MSFT), Wal-Mart Stores (WMT) and — as expected — Exxon Mobil (Table 69). However, Wal-Mart Stores model fails the White test for the presence heteroskedasticity (P-value of 0.029) and is therefore excluded from further analysis. Only for Microsoft and Exxon Mobil it is shown to be possible to develop a valid total wealth momentum model, which also excludes Hewlett-Packard and 3M. Although the static simulation of Microsoft is correctly forecasting the Dow trend ex post, the ex ante the forecast completely fails to predict the Dow trend (Figure 158, left). As the structural spectramap analysis already indicated (Figure 143 — Figure 147), total wealth momentum of Exxon

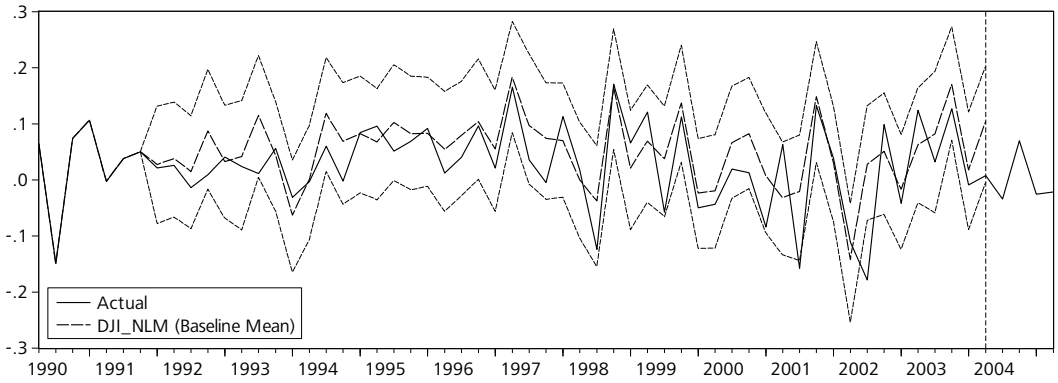

Figure 152 Spectramap factors of total wealth momentum and operating income explain Dow momentum (ex post).

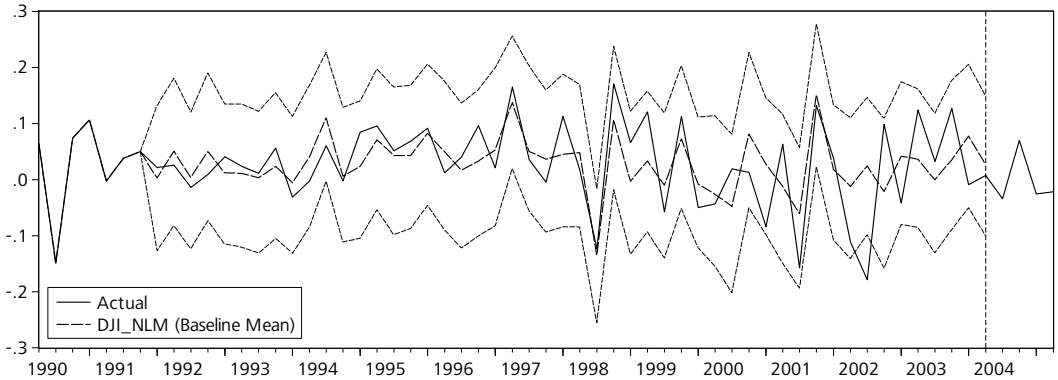

Figure 153 Spectramap factors of total wealth momentum explain the Dow (ex post).

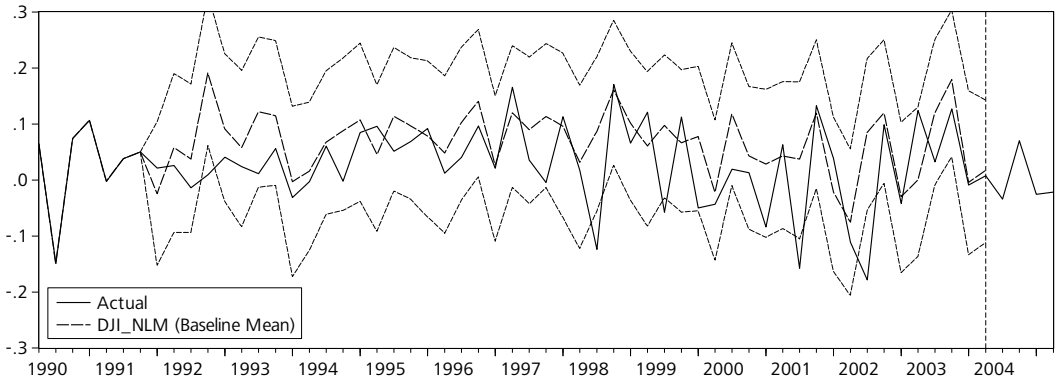

Figure 154 Spectramap factors of operating income (momentum) explains Dow momentum (ex post).

A: static forecast	RMSPE	Mean Band
Total Wealth Momentum Operating Income	0.0449	2.6097
Total Wealth Momentum	0.0471	3.1852
Operating Income	0.0891	3.3379

B: dynamic forecast	RMSPE	Mean Band
Total Wealth Momentum Operating Income	0.0729	4.5179
Total Wealth Momentum	0.0715	4.0317
Operating Income	0.0905	4.6025

Table 67 Root Mean Square Prediction Error (RMSPE) & simulation mean bandwidth for Dow momentum. Within sample forecast: 1990Q1-2004Q2 (ex post).

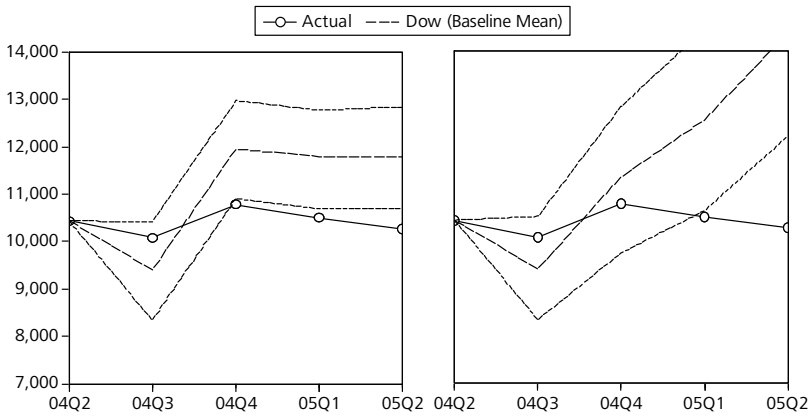

Figure 155 Dow Jones index. Hold-out sample forecast by total wealth momentum & operating income. Left: static forecast & right: dynamic forecast (2004Q2-2005Q2).

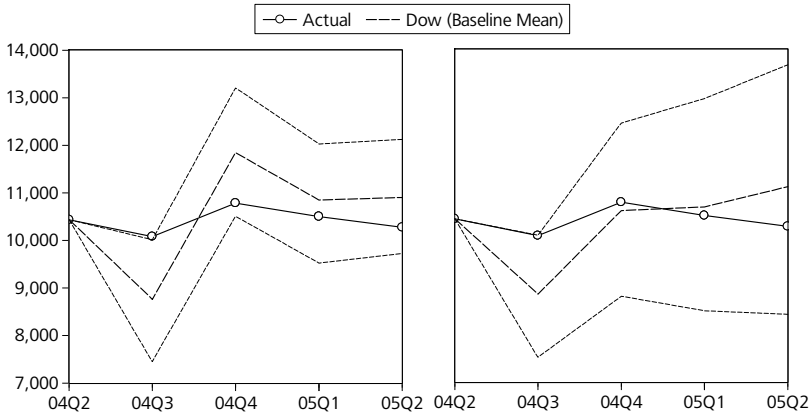

Figure 156 Dow Jones index. Hold-out sample forecast by total wealth momentum. Left: static forecast & right: dynamic forecast (2004Q2-2005Q2).

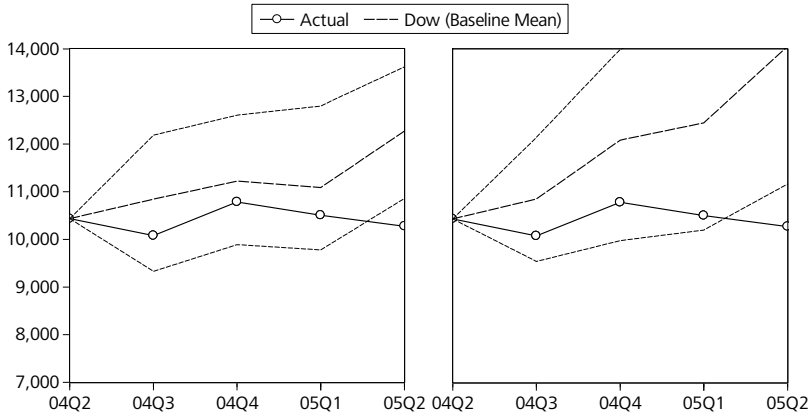

Figure 157 Dow Jones index. Hold-out sample forecast by operating income. Left: static forecast & right: dynamic forecast (2004Q2-2005Q2).

A: static forecast	RMSPE	Mean Band
Total Wealth Momentum Operating Income	0.0138	0.2056
Total Wealth Momentum	0.0081	0.2497
Operating Income	0.0123	0.2787

B: dynamic forecast	RMSPE	Mean Band
Total Wealth Momentum Operating Income	0.0203	0.2197
Total Wealth Momentum	0.0076	0.2531
Operating Income	0.0113	0.2704

Table 68 Dow Jones index. Root Mean Square Prediction Error & simulation mean bandwidth for momentum. Within sample forecast: 1990Q1-2004Q2 (ex post).

	var.	coeff.	s.e.	95% Conf. interval	t-value	p-value	BG LM	F-stat	white	F-stat	DW	*Adj.R^2
Model HPQ: DJI = DJI(-1)+α+β*HPQ MTW	α	0.023	0.010	[0.01, 0.04] 0.03	2.34	0.023	2.614	1.273	9.299	1.991	N.A.	0.978
	β	-0.267	0.100	[-0.43, -0.10] 0.34	-2.66	0.010	[0.271]	[0.288]	[0.098]	[0.096]		
Model MMM: DJI = DJI(-1)+α+β*MMM MTW	α	0.023	0.010	[0.01, 0.04] 0.03	2.33	0.024	1.327	0.631	4.585	0.892	N.A.	0.977
	β	-0.792	0.335	[-1.35, -0.23] 1.12	-2.36	0.022	[0.515]	[0.536]	[0.469]	[0.494]		
Model MSFT: DJI = DJI(-1)+α+β*MSFT MTW	α	0.023	0.010	[0.01, 0.04] 0.03	2.33	0.024	2.781	1.359	6.170	1.238	N.A.	0.978
	β	0.631	0.238	[0.23, 1.03] 0.80	2.65	0.011	[0.249]	[0.266]	[0.290]	[0.305]		
Model WMT: DJI = DJI(-1)+α+β*WMT MTW	α	0.023	0.010	[0.01, 0.04] 0.03	2.26	0.028	0.896	0.423	12.463	2.863	N.A.	0.977
	β	-0.315	0.154	[-0.57, -0.06] 0.51	-2.05	0.045	[0.639]	[0.657]	[0.029]	[0.024]		
Model XOM: DJI = DJI(-1)+α+β*XOM MTW	α	0.025	0.010	[0.01, 0.04] 0.03	2.40	0.020	1.438	0.682	5.870	1.171	N.A.	0.978
	β	-0.983	0.508	[-1.83, -0.13] 1.70	-1.94	0.059	[0.487]	[0.511]	[0.319]	[0.338]		
MSFT MTW = C1*MSFT FTW+ C2*AR(1)+C3*AR(6)+C4 *MA(2)+C5*SMA(9)	C1	0.495	0.015	[0.47, 0.52] 0.05	33.35	0.000	0.095 [0.954]	0.316 [0.731]	0.195 [0.907]	0.092 [0.912]	2.08	0.884
	C2	1.118	0.013	[1.10, 1.14] 0.04	89.38	0.000						
	C3	-0.156	0.027	[-0.20, -0.11] 0.09	-5.73	0.000						
	C4	-0.995	0.107	[-1.17, -0.82] 0.36	-9.27	0.000						
	C5	-0.891	0.039	[-0.96, -0.83] 0.13	-23.04	0.000						
MSFT FTW = C1*AR(2)+C2*MA(2)+ C3*SMA(9)	C1	-0.825	0.104	[-1.00, -0.65] 0.35	-7.93	0.000	4.606 [0.099]	2.313 [0.109]	N.A.	N.A.	2.00	0.592
	C2	-0.465	0.154	[-0.72, -0.21] 0.51	-3.03	0.004						
	C3	-0.897	0.030	[-0.95, -0.85] 0.10	-29.59	0.000						
XOM MTW = C1*XOM FTW+ C2*AR(1)+C3*AR(6)+ C4*MA(2)+C5*SMA(9)	C1	0.491	0.025	[0.45, 0.53] 0.08	19.60	0.000	0.189 [0.910]	0.099 [0.906]	0.554 [0.758]	0.263 [0.770]	1.94	0.545
	C2	0.530	0.143	[0.29, 0.77] 0.48	3.71	0.001						
	C3	0.858	0.127	[0.65, 1.07] 0.42	6.76	0.000						
	C4	-0.729	0.098	[-0.89, -0.57] 0.33	-7.44	0.000						
XOM FTW = C1*AR(1)+C2*AR(3)+ C3*MA(1)+C4*SMA(9)	C1	-0.324	0.084	[-0.46, -0.18] 0.28	-3.88	0.000	0.326 [0.850]	0.767 [0.470]	N.A.	N.A.	1.91	0.682
	C2	0.394	0.149	[0.14, 0.64] 0.50	2.64	0.013						
	C3	-0.821	0.102	[-0.99, -0.65] 0.34	-8.08	0.000						
	C4	-0.869	0.045	[-0.94, -0.79] 0.15	-19.23	0.000						

Serial correlation: DW = Durbin-Watson, BG LM = Breusch-Godfrey Lagrange Multiplier (obs*R^2, [$p\chi^2$]). N.A. = not applicable. *Adj. R^2 = Adjusted R^2. white = white heteroskedasticity test. Models & test statistics apply to sample period (1990Q4-2004Q2).

Table 69 Test statistics for model validity and presence of auto correlation and heteroskedasticity of the momentum total wealth regression models of five individual Dow component companies.

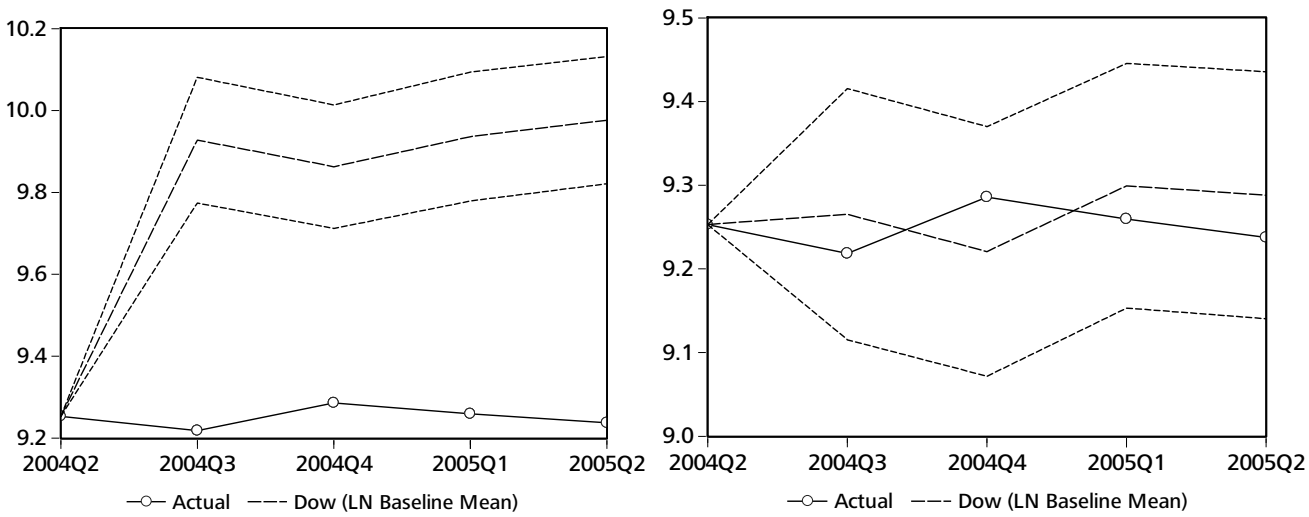

Figure 158 Hold-out sample static forecast of the Dow by total wealth momentum (2004Q3-2005Q2). Left: Microsoft. Right: Exxon Mobil.

Mobil indeed trends like the Dow, it is the only component company that here predicts the Dow correctly (Figure 158, right). Exxon Mobil is all four quarters within acceptable limits; the simulation Baseline Mean diverges not much from the actual trend of the Dow.

10.4 Discussion

The results of this study can only be compared with a limited literature since to date not many other empirical studies are available that investigate the explanatory or predictive power of accounting variables of component companies simultaneously on a market index like the Dow. Lendasse *et al.* (2001) applied data reduction by linear transformation of PCA in their artificial neural network model of the BEL20 market index[15] and compared it with the result of a non-linear method: Curvilinear Component Analysis. They used these methods for the preprocessing of 42 technical indicators of the BEL20 instead of processing the financial accounting data of the component companies as a leading indicator of the market index (as was done in this study). They report that PCA gave in their study a slightly better result above the non-linear approach. My findings certainly do not disagree with their result. This study is more of an economic accounting investigation into the structure of firm dynamics, as documented by accounting measurement in the TEMA framework of Yuji Ijiri. The fact that there is a rather strong association between decomposed TEMA variables of the Dow component companies and the Dow itself is, in my opinion, in this case evidence that a 'relation' exists between firm dynamics and their market value, albeit as a market index. But, I do not make any claim about how this 'relation' actually works! I decomposed and only modelled highly aggregated TEMA time series data. Having said that, the Spectramap biplot clearly does visualize individual Dow component companies in a meaningful manner. It is possible to anlyze their position in the biplot relative to the whole data structure. The fact that the TEMA model of Exxon Mobil (XOM) can forecast the trend of the Dow in the same manner as the decomposed TEMA variables is some support for my general hypothesis that the TEMA framework discloses new information. Note that none of the other 29 Dow component companies did individually forecast correctly. This study finds evidence in support of TEMA through the use of ARIMA models of financial accounting variables for the ex post and ex ante simulation of (indexed) market value. TEMA is a methodology with potential to study trends in the composition of wealth and its change, together with trends of other period related financial and non-financial data like the index of the market value of a panel of companies. In this study econometric models of the 30 Dow component companies were presented that use total wealth momentum and operating income to predict Dow momentum, the dependent variable. With spectramap, the panel data was decomposed into six factors that associate with Dow momentum at various time lags. Employing these factors as independent variables effectively explained the Dow momentum in their joint combination as well as separately. This success rate of the static of dynamic forecast of the TEMA models for the hold-out sample of the next four quarters varies between 50%–100%, and is on average correct, respectively, by 75%–83%. From this result, I conclude that the TEMA framework offers alternative variables for the specification of econometric models that possibly can explain and forecast market value. Further research should show if the association between the TEMA variables observed in this study also exists in other cases.

[15] The twenty most representative shares of the Belgian stock market.

11

Summary & Conclusion

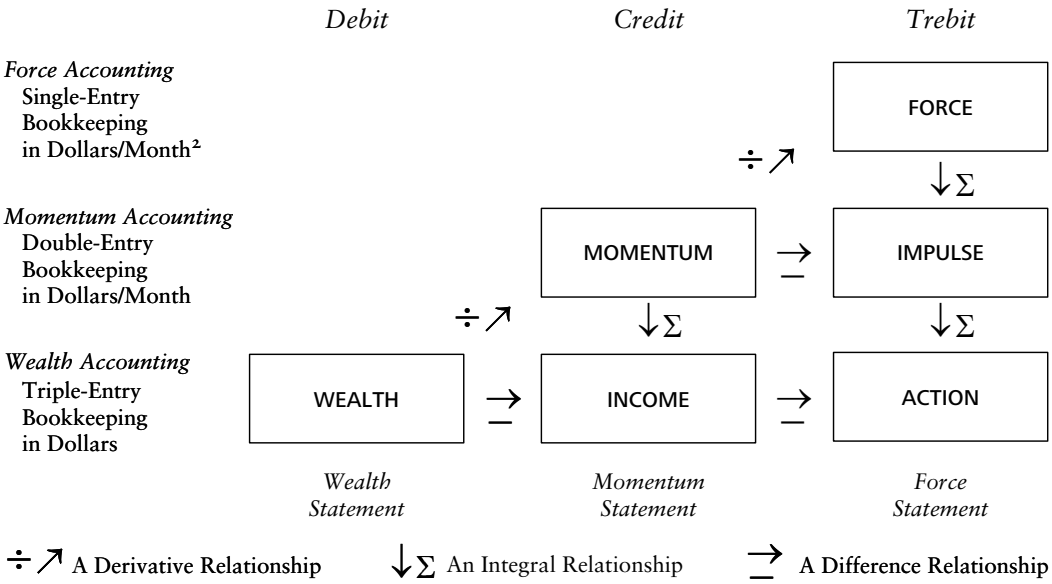

Figure 1 A framework for triple-entry and momentum accounting (after Ijiri, 1986).

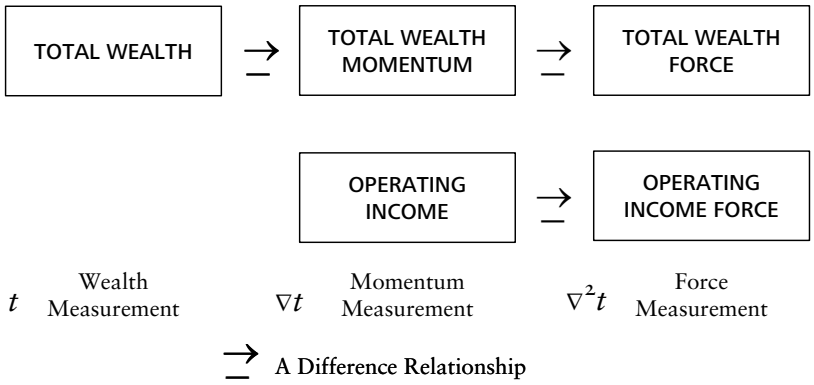

Figure 5 Determination of momentum & force variables from double-entry accounting time series.

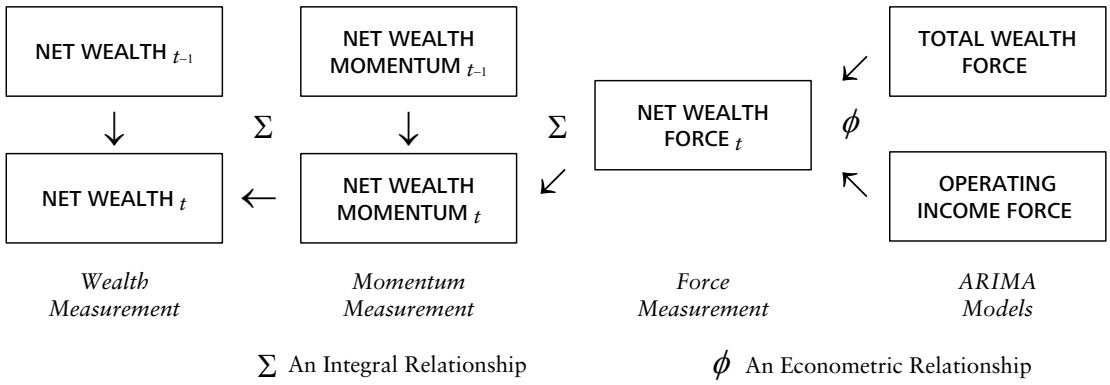

Figure 6 Aggregation of data from ARIMA models in the TEMA framework.

11 Summary

This research seeks to find evidence in support of the TEMA *framework, proposed by Yuji Ijiri (*1982, 1984, 1986, 1987, 1988 *and* 1989*); to validate its relevance, explanatory and predictive power. Fraser* (1993, 157) *challenged Ijiri's triple-entry bookkeeping & momentum accounting theory,* TEMA *in short, for lack of clear objectives, unclear benefits, likely practical difficulties, deficient internal logic, as well as unpromising prospects to sustain the argument that there is a general relationship between income, wealth and momentum. Furthermore, most damagingly, his criticism is that …'useful information is likely to result by accident, rather than by design.' Fraser has the opinion that it is not possible to find evidence in support of the general relationship between* TEMA *accounting variables because historical costing lies beneath the financial statements. Except for cash, debtors and creditors, in his words, '…accounts do not express a contemporary commercial reality.' His notion is that for this reason accounting variables of the* TEMA *framework do not hold explanatory or predictive power. As I see it, no association is expected between* TEMA *variables by Fraser and, consequently, Ijiri's triple-entry bookkeeping & momentum accounting theory appears to offer him little scientific nor practical value.*

To find support for TEMA*, I investigated financial statements of* AEX *and* DOW *component companies in an effort to acquire new knowledge about the relevance and empirical validity of the* TEMA *framework for selected examples. Eight studies were presented in two parts in this thesis. The first four studies addressed the informational relevance of accounting variables from the* TEMA *framework. To further advance the study of business momentum and to disclose forward-looking accounting information, Ijiri recommends* ARIMA *time series modeling as an alternative for a fully fledged implementation of triple-entry bookkeeping. The second part ventures along that line of investigation and includes four studies that test with econometric models the explanatory and predictive power of accounting variables of the* TEMA *framework.*

In the first study, annual financial statements data of Robert Half International Inc. was used to investigate the informational relevance of a new accounting ratio introduced in this thesis: the common size format momentum or force ratio. My conclusion is that information about the stability of a firm's earning capacity, or lack thereof, can be disclosed with such ratios and that TEMA *is therefore relevant for performance analysis.*

Next, in the second study, I evaluated two informational measures of financial statements as a summary signal of structural change in a firm's balance sheet. I demonstrated that Ijiri's disaggregation measure is superior to Lev's decomposition measures because negative data can be included in the calculation of the change of proportions between items in between periods. However, when applied to wealth, momentum and force time series, suspicion raised that the informational measures of wealth are 'under-signaling' and those of momentum and force are 'over-signaling.' This seems to make informational measures unreliable decision indicators to decide whether or not to disaggregate financial statements data for further analysis within the TEMA *framework. Moreover, the disaggregation measures of 3M's balance sheet momentum and force time series seem to signal continuous structural change of the proportion between accounts. In contrast, the disaggregation measures of 3M's wealth time series signal the complete absence of such structural change. This suggests that momentum and force variables are possibly stationary time series which would make them usable for econometric modeling purposes (as indeed is here the case).*

In the third study, a new approach was proposed by me for the decomposition of financial statements by using Spectramap multivariate data analysis as developed by Lewi (1989). Supported by correlation analysis, it was shown that wealth, momentum and force decompositions and Spectramap biplots offer a visual illustration of the association between TEMA *variables. The suspicion that the informational signals of wealth are 'under-signaling' was founded. But the informational measures of momentum and force appeared not to be 'over-signaling' because the momentum and force biplots showed that the time points do not have a sequential structural relationship. This, I suggest, is another indication that both force and momentum variables are likely candidates to be used as explanatory variables in econometric* TEMA *models.*

The fourth study investigated the dynamics of balance sheet items at different levels of aggregation of 3M, a DOW *component company. With Spectramap a decomposed data structure was produced with all balance sheet items and their time points. The larger part of variance present in the time series was visualized in a more meaningful manner with the application of a new color coding method developed for this study. Color coding of (accounting) data based on the* CIELAB *uniform color space increases the dimensions of biplot visualization to six and this was used in various ways in other studies. Most revealing was the fact that successive time points in the series of quarterly balance sheets code noticeably with the same color whereas other points in time spring out univocally. What was also of interest is that the color codes of certain time points match individual balance sheet items, either in color harmony or in color opposition. My conclusion is that these signals align or contrast with each other or the trend of the balance sheet as a whole. I read them as relevant informational signals that could trigger the auditor or analyst of financial statements to focus her enquiry to particular balance sheet items in relation to one or more points in time.*

I think that the above four studies show that the TEMA *framework is instrumental for the disclosure of new information and has the capacity to make a difference in the decisions of investors,' creditors,' or other users' of financial statements (Epstein & Mirza* 1997, 54, 61).

With the second part of this thesis, which includes four time series studies, I strived with econometric modeling to find evidence in support of the validity of the general relationship between the informational dimensions of the TEMA *framework: force, momentum and wealth. Momentum and force variables were used for ex post regression analysis as well as for dynamic ex post and ex ante simulation. Econometric* TEMA *models were used in two studies to explain and predict the trend of net wealth of the component companies of the* AEX *and the* DOW. *With Spectramap, in a third study, I decomposed the balance sheet of 3M and, in a fourth study, the panel data of* TEMA *variable time series of the Dow's* 30 *component companies.*

Furthermore, color coding of PCA *decomposed panels of a dependent variable and lagged values of an independent variable enabled the unbiased selection of the required time lag. Econometric modeling of such decomposed financial accounting data made it possible to forecast the trend of the* DOW *Jones index trend rather well: up to four quarters.*

I demonstrate with the studies of this thesis that the assumption holds that a general relationship exists between the informational accounting dimensions wealth, momentum and force. The TEMA *framework was instrumental in the selection of temporally viable variables that were used for time series regression analysis and econometric* TEMA *models. Driven by* ARIMA *force or momentum equations, the explanatory power of the models is shown to be rather high for base period simulations as well as the predictive power of within sample simulations. This*

result is put forward by me as support for the main hypothesis of this thesis, namely, that a general relationship exists between accounting variables in the dimensions of the TEMA *framework. Hence, my conclusion is that the criticism of Fraser (*1993, 157*)—namely, that triple-entry bookkeeping and momentum accounting offer little new information to existing formats of accounting disclosure—is refuted by my findings. The results of this research may be of interest to auditors, controllers, managers and investors, as it could be of practical use to provide more forward-looking information for decision-making, corporate governance, auditing and capital markets.*

11.1 Introduction

The key idea in Ijiri's work on accounting theory is the introduction of new measurement units: *momentum* or the rate of change, and its change by *forces*. In addition to the conventional—*static*—measurement of wealth, i.e. with a monetary unit like the U.S. dollar, Yen, Euro, Pound Sterling, etc. (Ijiri 1975), the new—*dynamic*—units are time related (e.g., U.S. dollars per unit of time). While the present measurement of income can be thought of as a realized, ex post, momentum measure, the key development in Ijiri's work is to see momentum as a rate, i.e. as the speed of the earning capacity of a firm and to account for the change in momentum with forces (measured per unit of time squared). To this purpose, Ijiri developed the so-called framework of Triple-Entry/Momentum Accounting, or TEMA in short, that is composed of these three informational dimensions (FIGURE 1). Firstly, *wealth accounts* measure the magnitude and composition of capital sources and uses. Secondly, *momentum accounts* measure the change of wealth, or new value realized. Thirdly, *force accounts* measure the change of the capacity to acquire new wealth, or value, and this includes various internal and external business or economic forces. Ijiri's objective is to account for existing and new momentum created by management during the reporting period in between the opening and closing balance sheet. The objective of momentum accounting is to improve management accounting practices and corporate disclosure for governance purposes (Ijiri's 1989, Chapter 7). In recent publications, however, Ijiri extended the usability of the TEMA framework to the fields of brand accounting (Farquhar *et al.* 1992A, B), brand management (Farquhar & Ijiri 1993) and e-commerce (Glover & Ijiri 2002). The application for auditing, equity valuation or economic analysis was rarely mentioned by Ijiri. This research examines whether momentum or force models provide forward-looking information of single or aggregate firm performance. If so, the TEMA framework might contain variables that are leading performance indicators.

Organization of this chapter

In Section 11.2, the results are summarized of the first part of this study into the relevance of the TEMA framework. Section 11.3 summarizes the second part of this study into the explanatory and predictive power of the econometric TEMA models. In Section 11.4, I discuss the limitations of this research. Section 11.5 concludes this chapter with a discussion of the implications and possible directions for future research.

11.2 The relevance of TEMA

In this section the main findings of the first part of the thesis are summarized. According to Epstein & Mirza (1997, 54, 61), accounting information is relevant if: '...it has the capacity to make a difference in investors,' creditors,' or other users' decisions.' In this thesis, a formal

approach was taken to ascertain the relevance of accounting information within the TEMA framework. Traditional performance indicators were compared with a new momentum measure in Chapter 3. Informational measures developed by Lev and Ijiri to ascertain (relevant) changes in the composition of financial statements were compared with momentum and force measures in Chapter 4. Finally, in Chapters 5 and 6, the generality assumption that underlies the structure of the balance sheet was investigated at different levels of aggregation of the balance sheet of my example: 3M. Decomposition analysis of multivariate data with spectramap was used to determine relevant hidden structures between wealth, momentum and force measures in Chapter 5. To determine the relevance of accounting information, in Chapter 6, the balance sheet of 3M was also visualized with color coding.

11.2.1 Performance measurement

In Chapter 3, I introduced a new financial accounting ratio that can be used to investigate the change in composition of TEMA variables: the *common size format momentum ratio* or *force ratio*. With a notional example of the company studied, Robert Half International Inc., it became clear that during a period of 19 years the sales margin as well as return on assets ratios exhibit fluctuations. The same is observed with the raw net wealth momentum measures. However, the common size format ratio of net wealth momentum of this firm is stable both before and after the so-called 'dotcom crash' over many years. Thus, I concluded that the common size format momentum ratio may add new insight to how we should appreciate the structural aspects of a firm's financial performance. Not including force or momentum measures in performance analysis could lead to the false impression that the profitability of a firm has improved (or deteriorated) whilst the net wealth growth rate has remained stable instead. Observing years that have a comparable ROTA but a different common size format ratio of net wealth momentum, or vice versa, might deepen the analysis of the financial statements. Structural business dynamics at the micro economic level, as well as on the macro economic level, ought to get the attention of management, shareholders and analysts alike (De Groot *et al.* 2004).

11.2.2 Informational measures

It was demonstrated in Chapter 4 that decomposition analysis with the measures of Baruch Lev is only possible for the wealth dimension of the TEMA framework. The disaggregation measure of Yuji Ijiri not only gives similar results for wealth, but, it also allows for the analysis of momentum and force measures. In the example of 3M Company, for wealth, neither Lev's decomposition measures nor Ijiri's disaggregation measure signal structural any substantial change. For momentum and force, however, the disaggregation measure of Ijiri does signal structural change but at about every point in time. It became clear in this study that the informational signals of wealth suffer from 'under-signaling' whereas momentum and force are possibly 'over-signaling,' and therefore either one might be misleading. As such, these informational signals direct attention to the econometric properties of the TEMA time series. But, as discretionary tool for the analyst of financial statements the informational measures investigated seem to offer little guidance to decide if the (lack of) structural change warrants further inspection of financial variables at a disaggregated level or not. Hence, like Babich (1975) and Blommaert (1995A, 1996), I discourage the application of either the decomposition measures of Lev or the disaggregation measure of Ijiri for this purpose.

11.2.3 Balance sheet decomposition

Changes in balance sheet composition were also analyzed in two studies of one of the Dow component companies: 3M. In the first study, reported in Chapter 5, the trend is investigated of balance sheet proportions between five accounting variables. It was demonstrated that the static relationship can be visualized by decomposition to three factors through spectramap analysis with a cumulative explained variance of 100% (Lewi 1982). This holds in each of the three dimensions of the TEMA framework: wealth, momentum and force. Spectramap decomposition provides an illustration of the association between the accounting variables. Visual analysis of wealth, momentum and force made clear that the association holds, in this example, between all three dimensions of the TEMA framework. At a more detailed level, reported in Chapter 6, 14 accounting variables were successfully reduced to five factors by spectramap decomposition with a cumulative explained variance of about 95%. Color coding of the financial accounts and time points using the scores of the last two factors revealed meaningful contrasts between asset and liability accounting variables.

The spectramap decomposition is a visual illustration of the association between the accounting variables. Visual analysis of the wealth, momentum and force data made clear in this case that the association holds between all three dimensions of the TEMA framework. This example suggests that some structural relation is present between momentum and force of total wealth and the disaggregated accounting variables of these dimensions. It appears, in my opinion, that the association between the dynamics of the aggregate and the disaggregated accounts holds for momentum and force of balance sheet composition. This finding is particularly relevant concerning the development of econometric TEMA models.

11.2.4 Directional change

The directional change in time of accounting variables was investigated in Chapter 5 and 6 for the component companies of the AEX and the Dow (Pahud de Mortanges & van Riel 2003, 524). Parallel directional change is on average for operating income versus net wealth momentum, respectively, about 74% for the AEX and about 80% for the Dow. For the force measures of these variables it is, respectively, about 71% for the AEX and 63% for the Dow. The average parallel directional change is for total wealth momentum versus net wealth momentum, respectively, is about 78% for the AEX and 74% for the Dow. For the force measures of these variables it is, respectively, about 61% for the AEX and 63% for the Dow. These results are indicative of the possible (temporal) association between the TEMA variables that indeed is confirmed by regression analysis and the econometric TEMA models of this study.

11.2.5 Color coding

Hering suggested that three pairs of opposing color sensations produce all colors humans can perceive (Judd & Wyszecki 1975, Nassau 1998). A standard setting regulatory body for color metrics, the Commission Internationale de l'Eclairage (CIE), defined the so-called CIELAB uniform color space for reflective light sources. Colors in CIELAB color space have metric distances. Human color perception follows the Weber-Fechner law, which implies a logarithmic relationship between the geometric progression of various stimuli and the corresponding perception altered as an arithmetic progression. Recent studies suggest that certain cognitive and perceptual-sensory representations in the human mind share the same fundamental mechanisms and neural coding schemes to perceive numbers or colors. The implication is that humans seem to perceive numbers as continuous quantities which makes it suitable to devise an integrated

analytical system that concerns numerosity, geometry and colorimetry. The color coded spectramap biplot is such a system that can visualize a decomposed multivariate data table with up to six dimensions, three for its geometry and three for its colorimetry.[1] In this thesis, I proposed in Chapter 2 a new method for color coding of data that employs the CIELAB color space dimensions (COLOR FIGURE 1–6, page 307-309). Color coding was applied by me in various studies to:

1. visualize the informational signal strength of decomposition and disaggregation measures by an achromatic to chromatic color scale (Chapter 4, page 111, COLOR FIGURE 7);
2. visualize the directional signal strength of momentum and force time series by two scales of opponent colors (Chapter 4, page 112, COLOR FIGURE 8);
3. increase the number of dimensions to graph with a spectramap biplot by CIELAB color space dimensions (Chapter 6, page 146, COLOR FIGURE 10–14);
4. determine the required time lag and direction of association between the independent and the dependent regression variable (Chapter 10, page 230, COLOR FIGURE 15–16);
5. visualize the structural contrast between a dependent and all its independent variables in time series regression (Chapter 10, page 232, COLOR FIGURE 17–20).

SMA factors with lower percentages of explained variance were used to color code spectramap biplots to investigate the presence of possible associations between accounting variables ranging over five or six dimensions. Meaningful associations indeed were found in Chapter 6 and 10. In Chapter 9, another objective was to unveil unsuspected structural relations between all accounting variables of a balance sheet or, in Chapter 10, between the time series of one TEMA variable of a panel of companies. The unbiased selection with color coding of the required time lag of independent variables in time series regression models in Chapter 10 was effective. In the example of these TEMA models; they explain and forecast the trend of the DOW up to four quarters with sufficient reliability.

11.3 Explanatory & predictive power

This research attempts to build an econometric specification of the accounting measurement model proposed by Yuji Ijiri in his work on the TEMA framework (Ijiri 1982, 1984, 1986, 1987, 1988, 1989). The TEMA framework was instrumental in my study to model the trend of net wealth of most AEX and DOW component companies (Corielli & Marcellino 2006). My TEMA models explain correctly about 96.7–100% and 93%, respectively, for the component companies of the DOW and the AEX. The TEMA models forecast with static simulation net wealth correctly on average, respectively for the DOW and the AEX component companies, about 83% for four quarters and 65% for three years. The DOW component companies eigth quarters forecast with static simulation is correct about 85% and with dynamic simulation 82%. The four quarters forecast with dynamic simulation has the same result: 82%.

The TEMA models with factor solutions of the time series variations of the DOW component companies' total wealth momentum or operating income forecast the DOW Jones index accurately for four quarters. Furthermore, by spectramap decomposition and biplot visualization one component company was identified that exhibits the same market variance as the DOW — Exxon Mobil — and, its TEMA model, gives the same correct forecast of the DOW index. None

[1] Data involves us with the numerosity of information (about world phenomena) and is subject of a more fundamental investigation into our world perception and its quantification (e.g. Lewi 1999).

of the other 29 DOW component companies did individually forecast correctly. From this result, I draw three conclusions:

1. Evidence in support of the TEMA framework was found by me with empirical research of AEX and DOW component companies. Thus, it is shown in the case of the selected example companies that the TEMA framework offers by 'design' useful information.
2. The use of models from the TEMA framework is not limited to performance measurement of an individual firm but may be extended to the domain of stock index tracking.
3. The econometric specification of dynamic accounting models with the TEMA framework might facilitate decision makers given its rather higher success rate.

Gomaa *et al.* (2008) investigated the effects of decision aid reliability and pressure to perform and found that with increasing levels of accuracy, decision makers tend to rely more on them. Noteworthy is their finding that when a decision aid is 80% reliable it tends to be used in about 60% of the cases with only a single performance pressure but that percentage increases to about 80% with four pressures to perform. Moreover, when a decision aid is 90% reliable decision makers were confident to use it in about 90% of the cases independent of the number of pressures. Static simulation forecasts of my econometric TEMA models are successful between 79%–84% for the net wealth trend of the DOW component companies and between 75%–83% for the DOW Jones index. Therefore, I suggest that models based the TEMA framework might facilitate decision makers.

Consequently, in addition to earlier research of Blommaert (1994), Blommaert & Blommaert (1990A, B), and Olders (1995), this study mitigates the most important objections of Fraser (1993, 155-157) against triple-entry bookkeeping and momentum accounting, as well as some of the concerns of Vaassen (2000, 33) and Wagensveld (1995).

11.3.1 Force & momentum measurements

For lack of time series data with a smaller time step difference than one year or one quarter the incremental time period in the momentum and force models was kept constant in this study at either one year or one quarter. To measure momentum or force by means of wealth (or income) accounts the unit time period was set at either a year or a quarter ($\Delta t = 1$ and thus: $\Delta t^2 = 1$). Because both the momentum and the force time period is set to 'one' quarter or year, the econometric TEMA models are based on differenced time series (∇t or ∇t^2, FIGURE 5). Instead of the administration and aggregation of force and momentum accounts by a triple-entry bookkeeping system, publicly available financial statements data of firms was used.

The transformation of momentum and force accounting measures required in some cases a series of statistical manipulations (Koop 2000). First, to meet statistical assumptions, for about 50% of the AEX component companies, Euro amounts were logged, so all resulting momentum and force measures were expressed in fractions (or percentage growth). Second, in each study, accounting variables or factors were excluded from regression analysis when either autocorrelation or heteroskedasticity was present in equation residuals. Third, in the market study of the DOW Jones index the panels of momentum and force measures were double centered by time series (1989Q4–2005Q2) and cross-sectional means (the 30 DOW firms). Fourth, for each quarter in the DOW study, the double centered variables were subjected to spectramap decomposition to reduce the 180 original TEMA variables to 36 orthogonal factors of contrast (six factors for each of the 30 momentum or force measures).

The usual approach to econometric time series modelling is to log transform the data to meet statistical assumptions and for the beneficial side effect that the difference of such series is about the same as their growth rate (Koop 2000, 124). However, in Chapter 10, I observed, by comparing growth rates calculated by the difference of log transformed TEMA variables and by the common size format ratio increases or decreases, that natural log based growth rates tends to undervalue when positive and to overvalue when negative (FIGURE 133). This implies that the differences of natural log transformed wealth variables are less precise at the larger increasing or decreasing values. Consequently, to prevent an upper or lower value bias in the TEMA models of this study, momentum and force data were processed either as raw data or calculated directly by their common size format ratio and not by subtraction of natural log values of their original wealth or momentum time series.

11.3.2 Econometric studies

Dynamic econometric TEMA models were developed such that force variables aggregate into momentum variables that in turn aggregate into the performance measurement variable (either net wealth or the DOW Jones index, FIGURE 6). The required econometric equations are found by means of a semi-automatic search of about 65-200 valid solutions of 700-750 possible equations that include AR, MA and ARIMA specifications in between one to eight preceding quarters of the base period. The econometric equations finally used were selected by the lowest rank order of the Akaike Information Criterion that also implies the highest Adjusted R^2 value. With four econometric studies evidence was found that forward looking accounting information can be disclosed by variables from the informational dimensions of the TEMA framework.

In two studies, reported in Chapter 7 and 8, the trend of net wealth of the AEX and the DOW component companies is explained and forecasted with total wealth force and operating income force as well as with these two TEMA variables combined. The explanatory power as well as the predictive power of the ARIMA models of operating income force and total wealth force is considerably accurate in these cases. This result supports the hypothesis H 7_a that operating income and total wealth can predict net wealth as proxies of business and financial dynamics.

In the third study, reported in Chapter 9, the dynamic relationship was established between decomposed wealth and momentum factors of the balance sheet of 3M. Econometric models explained and predicted the time series with a success rate of about 92% for both the wealth factor difference scores and the aggregated wealth factor scores. The result of the aggregated scores was close enough to the time path to be viable (FIGURE 130, page 208).

In a fourth study, reported in Chapter 10, the empirical setting (or sample) is the 30 component companies of the DOW and their aggregate performance measured by the DOW Jones index. The TEMA models explain and forecast with decomposed Spectramap factors of total wealth momentum and operating income as the independent variables. Standardized Principal Components Analysis and color coding was used to determine in an unbaised manner the required lags of the independent factor variables.

The results of these four studies provide in my opinion some empirical evidence in support of the research hypothesis that accounting variables of the three informational dimensions have explanatory and predictive power in the TEMA framework of Yuji Ijiri. Therefore, the generality assumption holds in the econometric models studied.

11.4 Limitations

11.4.1 Objectivity

In this study, I addressed the subjectivity criticism raised by Vaassen (2002, 33) against triple-entry bookkeeping and momentum accounting because I did not undertake any subjective translation of non-financial facts into financial facts. One could argue that the econometric modeling of force or momentum time series is a subjective act on behalf of the modeler. However, the methodology applied does limit the risk of subjectivity. First, the statistical properties of the time series were tested for the presence of a unit root. A rather large number of alternative equations were developed using procedures that reduce the risk of bias on behalf of the modeler. Next, their success in simulating the time series ex post was evaluated with objective econometric measures for the presence of auto correlation or heteroskedasticity in the residuals.

11.4.2 Spuriousness

It is possible that the econometric models developed to find evidence in support of the generality assumption of the TEMA framework exhibit spurious correlations. The risk cannot be excluded that two variables do not have any direct relation between them but to another variable (not measured). Still, by my strict adherence to the appropriate test procedures I am confident that the risk of spurious regression has been limited to an acceptable level. Moreover, I performed the same analysis with the component companies of the DOW index and the AEX and had very similar results. Therefore, it is with some confidence that I argue that the association is valid between total wealth force and operating income force as independent variables that explain and predict net wealth force as the dependent variable. With spectramap decomposition I developed a visual but static analysis of this association between variables in all three dimensions of the TEMA framework. These associations between the common size format transformed data are confirmed by correlation analysis done with SPSS. Hence, both the static and the dynamic models exhibited the same associations and these do have explanatory and predictive power. Spuriousness in this research is, therefore, hardly a limitation to be much concerned about.

11.4.3 Data or information

The companies analyzed and modeled were not selected to get a representative sample of the markets they operate in. Naturally, this is a limitation and a serious constraint for the extrapolation of my findings, let alone their generalization to a law. Two remarks in defense.

The primary objective of this thesis was to find evidence in support of the generality assumption of the TEMA framework. This should counter the criticism of Fraser that we can expect information only by accident for the simple reason that accounting data does not contain any forward-looking information nor that it represents a reality. Nevertheless, this study's evidence show the opposite in the selected examples. Beside the good result on the level of an individual company it also was possible to explain and predict the trend of a market index using TEMA variables. My methodology involved the decomposition of momentum and force data of the component companies into spectramap factors. Thereby, common information was preserved. With the spectramap factors it was possible to explain and predict the trend of the DOW index. Moreover, with the spectramap momentum data space structure I identified a single company, Exxon Mobile, which positions close to the market mean. That enabled me to

develop a new model using only that company's TEMA variables to explain the DOW trend. This provides some backing to my conclusion that momentum and force *data* do contain *information*. The information exposed is that somehow the DOW index is a translation of business dynamics of its component companies as administered by the financial accounting system. The findings of this study support Ijiri's assumption that with ARIMA models it could be possible to model force dynamics on a financial statement-basis (Ijiri, 1989, 9.1).

A more formal defense of my limitation to financial statements data of the component companies of two stock market indices is that such an index is a closed sample of its own. I view them as a 'population' of their own because the index 'sample' is complete, perfect when all component companies are included in the research. Moreover, the DOW itself can be viewed as a representative sample of the U.S. stock market. Having said that, it will be worthwhile to broaden this research to a larger population now that it has been shown that financial variables from the TEMA framework have explanatory as well as predictive power.

11.4.4 The right index

Some argue the DOW cannot function as an index of overall market performance even though it is the most cited and most widely recognized of all the stock market indices. However, historically, it has performed very much in concordance with the U.S. market. Moreover, the DOW index is criticized for being a price-weighted average. This gives higher-priced stocks relatively more influence over the average than their lower-priced counterparts (TABLE 40). For instance, a $1 increase in a lower-priced stock can be annulled by a $1 decrease in a higher-priced stock, even if the first stock had a larger percentage change. Some critics of the DOW recommend the float-adjusted market-value weighted S&P 500 or the DOW Jones Wilshire 5000, the latter of which includes all U.S. securities with readily available prices, as the better indicators of the U.S. market.

Another concern are the time series of the panel of DOW companies used by me to decompose the TEMA variables to Spectramap factors that were used for the econometric DOW models. The issue is that the time series go back before the date of the composition used: April 8, 2004. However, I have sought consistency in the TEMA data given my research objective: corroborating the TEMA framework. I wanted to know if operating income and/or total wealth momentum associate given the current set of firms and if the econometric TEMA models can forecast the DOW with some degree of confidence. Hence, my within sample forecast period determines the data panel on which the decomposition and ARIMA modelling is based. This requires using financial statements data from before April 8, 2004, because I am interested in the trend of TEMA variables of the current DOW component companies and not the past ones.

11.5 Implications & future research directions

Improving the ability to analyze trends in accounting data can benefit all users of financial statements. TEMA is a framework and a methodology with potential to disclose and study trends in the composition of the wealth together with other period related non-financial data. I discussed various recent developments relevant to this study, like Accounting Information Systems, the REA framework, virtual close, XBRL and the continuous audit, corporate governance, strategic accounting and auditing. Furthermore, I believe that Ijiri's theory is relevant from the perspective of value creation, measurement and management. My opinion is that the TEMA framework has a lot to offer to academics as well as to practitioners because it provides

the formal basis and the practical means to include more forward-looking measures in financial *and* non-financial business reporting for various decision making purposes.

To paraphrase Sutton (2000), 'the face of accounting' is indeed changing in an information technology dominated world. This research is a response to the growing need for more forward-looking information by management and external stakeholders. Momentum accounting is grounded in a well developed triple-entry accounting theory which is a logical extension of the currently used double-entry bookkeeping system. The TEMA framework appears to me to offer a sound methodological basis to develop and implement practical solutions and to aid the users of financial statements with a set of 'uncommunicateds' that can disclose the income capacity of the firm and much more (Haskins & Sack 2006).

11.5.1 Additional disclosure

The hereforeto held opinion about the nature of financial accounting variables is that they are lagged indicators of business or market performance (Kaplan & Norton 1996). This study showed that TEMA variables have properties such that they are leading indicators of the performance of a firm (net wealth) or market value (stock index). I showed that it is possible to explain the trend of net wealth *ex post* with two TEMA variables: total wealth force and operating income force, as proxies of financial and business dynamics. Moreover, TEMA models forecast net wealth *ex ante* correctly in many cases up to eight quarters. A question that remains unanswered is if TEMA models of more detailed financial or operational variables will replicate my findings.[2] Further research should show if the association between accounting variables that I have observed with the AEX and DOW companies will also be found in other cases, and with other time series; including non-financial variables.

Like Blommaert (1994A), I recommend to broaden the disclosure of financial statements and to extend them with force and momentum measurements including the change of balance sheet composition. For example, the *common size format momentum* or *force ratio*, developed in this thesis, is a relatively simple measure to include. It is easy to compute and not particularly difficult to understand for those who already are used to common size format financial statements.

11.5.2 Analysts' forecasts

Keil *et al.* (2004) showed that analysts' forecasts of earnings are not perfectly correlated with actual earnings. They concluded from their research of earnings estimates from more than 100 security analysts: '…one statistical consequence is that the most optimistic and most pessimistic forecasts are usually too optimistic and too pessimistic. The forecasts' accuracy can be improved by shrinking them towards the mean.' Keil *et al.* think that this may partly explain why contrarian investment strategies are more successful.

This study did not intend to test the predictive ability of the TEMA framework to forecast earnings or the market value of individual company's stock value. Instead, I sought to find evidence in support of the general relationship of variables in the TEMA framework. I used Spectramap factor decomposition of momentum variables of the component companies of the DOW. With the SMA factors it was possible to explain and predict the trend of the DOW Jones

[2] In preliminary work on TEMA segment models it is possible to explain and predict net wealth with only one out of four segments.

index. Furthermore, visual analysis of spectramap biplots of the loadings of the component companies in six dimensions made it very clear that only one of the 30 component companies is positioned near the barycenter and thus behaves like the Dow index mean: Exxon Mobil (XOM). Next, a TEMA model of only Exxon Mobil independent TEMA variables was able to forecast the trend of the Dow Jones index correctly up to four quarters (FIGURE 123, page 205).

An extension of the findings of this research is to study the possible association between wealth accounting variables of listed companies and the market performance of their stock as an alternative to models with only earnings' variables (Barniv & Myring 2006, Bird *et al.* 2001, Damant 2001). A second line of investigation would be to compare the forecast success rate of TEMA models with that of alternative valuation models or analysts' earnings forecasts (Jenkins 2003, Richardson & Tinaikar 2004). A third line of investigation could be to investigate if spectramap factor decomposition and visualization can be employed for investment portfolio management. Beside the identification of firms that exhibit mean-like behavior, locating companies that occupy contrasting positions in the decomposed data space might be useful to balance portfolios (Haensley 2003). Further research of the explanatory and predictive power of TEMA models of other market indices is therefore advisable but probably will have to be limited to sub-panels of industry segments.

11.5.3 Conclusion

With this research, I found evidence with the selected examples that the assumption holds that a general relationship exists between the informational accounting dimensions wealth, momentum & force of the TEMA framework of Yuji Ijiri (1986). Annual and quarterly financial statements data was used to investigate if force measures have explanatory and predictive power for net wealth of the AEX and Dow component companies to a significant degree. Spectramap decomposition of TEMA variables of a single firm as well as the complete panel of Dow component companies provided further evidence that with the TEMA framework new and relevant information can be disclosed. TEMA variables of the Dow component companies decomposed to spectramap factors also showed explanatory and predictive power for the Dow Jones index. Thus, with some confidence, based on evidence from the cases studied, I reject the criticism of Fraser (1993, 157) that: '...useful information is likely to result by accident, rather than by design.' On the contrary, each study presented in this thesis sheds new light on business dynamics that is reflected in ARIMA models of force or momentum. This finding is in agreement with a larger economic and accounting literature that takes the view that commercial organizations tend to grow to a level where they can sustain a profitable equilibrium. Momentum accounting theory of Yuji Ijiri strives to the full disclosure of this economic property of firms with forward-looking information.

Lee (1999, 415) stated that:

> *'... fundamental analysis may be viewed as the art of using existing information, such as historical financial statements, to make better forecasts. Much of this task involves studying historical financial statements and their relation to future events.'*

The objective of the TEMA framework is not to forecast or predict the growth of net wealth. On the contrary, it is supposed *to account* for the rate of growth of future net wealth, or any other accounting variable, based on existing contracts, past transactions and other facts that can be substantiated. Thus, forward-looking disclosure generated by a triple-entry book-

keeping system is not a forecast but a *statement*. However, Ijiri himself is the first to admit that the implementation of triple-entry bookkeeping based on the granularity of individual transactions and documents will be a laborious task that will require much further research to be able grow to its full potential. I have argued that before any future effort in that direction is undertaken, evidence should be found that the generality assumption behind the TEMA framework holds. During this research, it has become clear to me that the TEMA framework can be applied as a fundamental analysis tool of the general relationship between TEMA variables *ex post* and also *ex ante* to facilitate forecasting. Firstly, I showed that it is possible with econometric TEMA models to forecast the balance sheet trend of individual firms for the selected examples. Next, I showed the same for the trend of the indexed market value of multiple firms on the basis of Spectramap decompositions of TEMA variables of the DOW 30 component companies.

In my opinion, TEMA is a larger promise to business than just the extension of the current system of double-entry bookkeeping. It offers a consistent mathematical approach to model variables, financial as well as non-financial, from a temporal perspective to analyze business dynamics at any conceptual level, operational or strategic. Ijiri recommends ARIMA time series modeling as an alternative to consider the measurement of business momentum and force. This research ventured along that line of investigation. Evidence was found of the association between financial accounting variables of the TEMA framework in static multidimensional data structures with Spectramap but also in dynamic temporal relationships with Eviews econometric software. The results are in agreement with the appropriate test criteria for econometric time series analysis and, in my opinion, most encouraging.

The contribution of this research is the knowledge that business dynamics are captured with their financial accounting measurement using TEMA. Controllers, accountants, auditors, analysts and investors can search for trends, explain and forecast them with sufficient reliability to employ TEMA models as a decision aid (Gomaa *et al.* 2008). It is tempting to extend the scope of this research to other data sources like those present in Enterprise Resource Planning systems, Customer Relationship Management systems, Business Intelligence systems, etc. The research put forward in this thesis on the basis of the TEMA framework is thus a first and small step towards a broader use of momentum accounting for business planning, management control, strategic accounting, corporate governance, auditing, portfolio management and index tracking.

12

Summary in Dutch
Nederlandse samenvatting

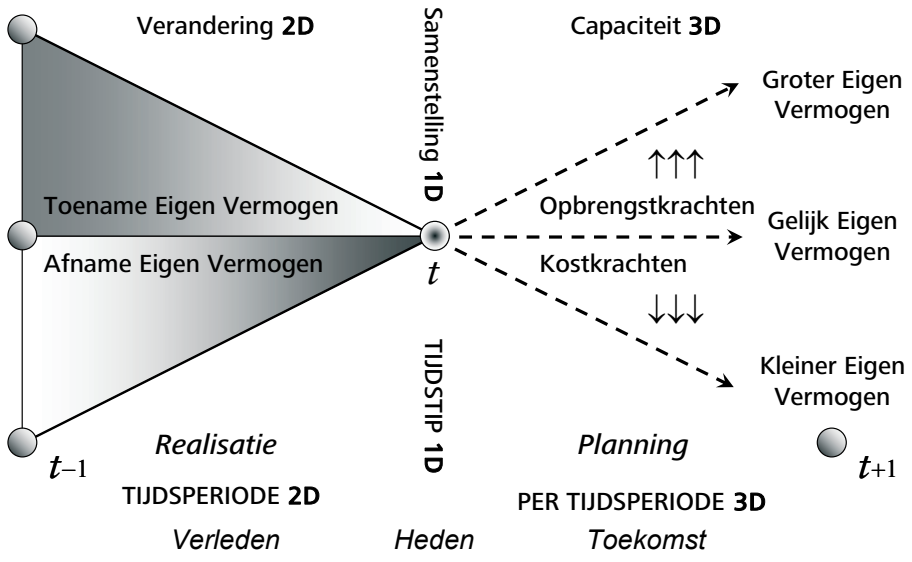

Figure 159 De drie accountingdimensies: een temporeel stelsel van informatiebronnen.

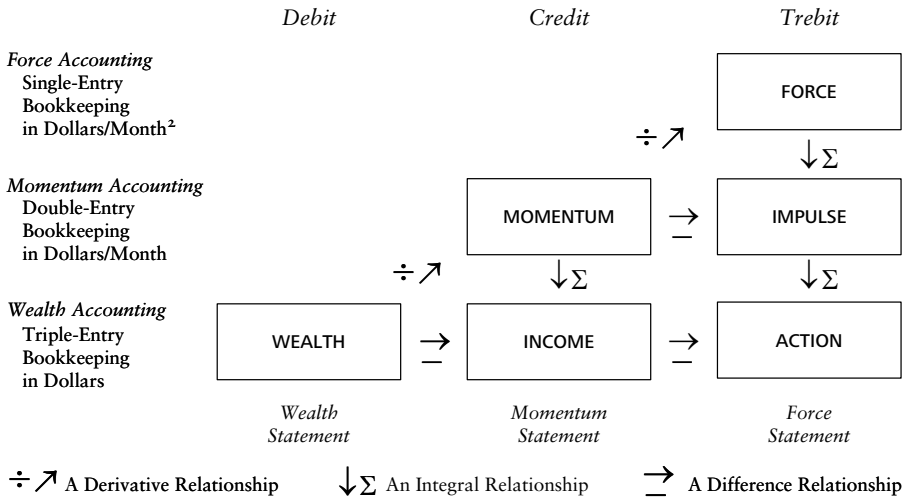

Figure 160 Het triple-entry raamwerk van het momentum accountingsysteem van Ijiri (1986, 749). Ter verklaring van de winstcapaciteit van het eigen vermogen (growth rate of wealth.)

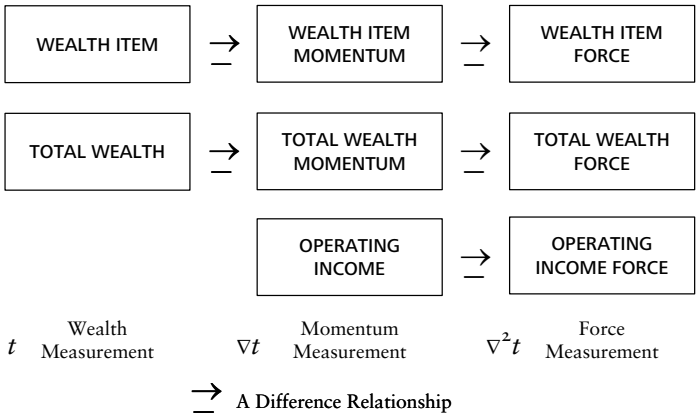

Figure 161 De verklaring van de wijziging van de samenstelling èn de omvang van het vermogen. (Change rate of wealth composition & growth rate of wealth accounts)

12 Samenvatting

Het doel van dit onderzoek is om het verklarend en het voorspelled vermogen te toetsen van driedimensionaal boekhouden en momentum accounting, zoals voorgesteld door Yuji Ijiri, alsmede om hiervan de relevantie aan te tonen. Fraser verwerpt Ijiri's momentum accounting theorie op grond van het ontbreken van een duidelijk gebruiksdoel, onduidelijke voordelen, mogelijke gebruiksproblemen, ontoereikende interne logica en een geringe slaagkans om de stelling te valideren dat een algemene relatie bestaat tussen inkomen, vermogen en momentum. Daarbovenop komt zijn kritiek dat '…nuttige informatie waarschijnlijk eerder het resultaat zal zijn van toeval dan door ontwerp [van het systeem].' Naar zijn mening is het niet mogelijk om empirisch de algemene relatie aan te tonen omdat de financiële administratie uitsluitend administreert op basis van historische kosten. Uitgezonderd de kas, debiteuren en crediteuren, beschrijven rekeningen niet, in zijn woorden, een 'hedendaagse commerciële realiteit.' Om op basis van het accounting systeem uitspraken te doen over de toekomst is in de ogen van Fraser dus zinloos. Met empirisch onderzoek poogt deze studie de geldigheid aan te tonen van het drie-dimensioneel raamwerk van de momentum accounting theory van Yuji Ijiri. Met Spectramap decompositie analyse wordt de structuur tussen variabelen zichtbaar gemaakt van jaarrekeningen van bedrijven die deel uitmaken van een beursindex: de aex en de Dow Jones. De algemene relatie tussen de accounting dimensies force, momentum en wealth wordt aangetoond met econometrische modellen. Momentum en force variabelen van het drie-dimensioneel raamwerk worden gebruikt voor ex post regressie-analyse alsook voor dynamische ex post en ex ante simulatie van TEMA *modellen. Modellen zijn ontwikkeld om de trend te verklaren van ondernemingen die deel uitmaken van de* AEX *of de* DOW*, de trend van de samenstelling van de balans van 3M alsook de trend van de* DOW *Jones index. Het voorspellend vermogen van deze modellen, gebaseerd op* ARIMA *force en momentum formules, is significant hoog. Dit bevestigt de algemene hypothese van deze studie dat een algemene relatie bestaat tussen accounting variabelen van de dimensies van het drie-dimensioneel raamwerk van het momentum accounting systeem. Het resultaat van deze studie is van belang voor auditors, controllers en managers, omdat het praktisch nut heeft bij het verstrekken van meer stelselmatige, toekomstgerichte informatie voor besluitvorming, controlling, corporate governance en auditing.*

12.1 Introductie

De niet af te remmen versnelling in de economie maakt dat de behoefte toeneemt aan toekomstgerichte informatie in de verslaggeving van ondernemingen. Recente ontwikkelingen in het kader van corporate governance zijn ook aanleiding voor hernieuwde aandacht voor de vraag of de betrouwbaarheid van de financiële rapportage is te vergroten en de effectiviteit daarvan is te verbeteren vanuit het administratieve systeem zelf en dus niet alleen vanuit de periferie van het systeem. Het inzicht dat de jaarrekening dient te geven in de samenstelling en de omvang van het vermogen blijft in alle omstandigheden prevaleren. IFRS biedt zicht op internationalisering van één en dezelfde standaard voor de financiële verslaggeving van beursgenoteerde ondernemingen met, naar ik verwacht, als voordeel dat gepubliceerde jaarrekeningen onderling beter vergelijkbaar worden.[1]

[1] IFRS breekt min of meer met de gewoonte van waardering naar historische kosten. Bij waardering naar marktwaarden is waardecreatie (naast waarderealisatie) van groot belang. Markten immers waarderen nieuw afgesloten contracten, nieuwe research doorbraken, olieprijs veranderingen e.d. nadrukkelijk. Dat deze feiten en effecten dan nog niet in het (klassieke) boekhouden zijn geoormerkt, is voor de waardering

Indeling van dit hoofdstuk

Paragraaf 12.2 introduceert de momentum accounting theorie van Yuji Ijiri. Het economisch en econometrisch perspectief wordt geschetst van Triple-Entry/Momentum Accounting, afgekort TEMA. In paragraaf 12.3 wordt het driedimensionaal TEMA raamwerk nader toegelicht, haar mogelijke rol als informatiebron voor besluitvorming door managers en investeerders en de wetenschappelijke kritiek hierop. Paragraaf 12.4 bevat de onderzoeksvraag en de doelstelling van deze studie naar het verklarend en voorspellend vermogen van momentum accounting voor het administreren van de winstkrachten van een onderneming. Het onderzoeksresultaat wordt besproken in twee aparte paragrafen. In paragraaf 12.5. komt het onderzoeksresultaat naar de relevantie van op TEMA gebaseerde informatie aan bod. Het onderzoeksresultaat naar het verklarend en het voorspellend vermogen van TEMA op basis van econometrische studies komt aan de orde in paragraaf 12.6. In paragraaf 12.7 wordt ingegaan op de vraag in hoeverre driedimensionaal boekhouden danwel momentum accounting deel kan uitmaken van de financiele administratie. Ook de implicaties worden besproken en de mogelijkheden voor vervolgonderzoek.

12.2 Momentum accounting theorie

12.2.1 Systeemdenken

Het model dat aan de basis ligt van de vermogens- en verantwoordingsadministratie is een *systeemmodel* (Blommaert & Blommaert 1990A, 48, Mattessich 1978). De vermogens- en resultaatrekeningen maken deel uit van een samenhangend geheel, een alomvattend of *holistisch stelsel*. Als inderdaad sprake is van een holistisch stelsel dan mogen we veronderstellen dat de structuur hiervan ook kan worden verklaard vanuit een samenhangende accountingtheorie. De informatie die het oplevert moet deze samenhang zichtbaar en toetsbaar maken. In de literatuur is hierover echter minder overeenstemming, zie voor een discussie hierover bijvoorbeeld Mattessich (1995). Of hiervan sprake is wil ik in dit onderzoek vaststellen voor wat betreft het driedimensionaal TEMA raamwerk.

12.2.2 Momentum accounting

Momentum accounting is gericht op de administratie van de snelheid waarmee het eigen vermogen groeit. Dit biedt een aanvullend financieel-economisch beeld over de huidige en toekomstige conditie van de onderneming zowel aan managers als investeerders. Naast het gebruikelijke overzicht van de bedrijfsresultaten met de verlies- en winstrekening en de balans kan de ontwikkeling in de capaciteit tot vermogensgroei worden toegelicht met ex post en ex ante tijdreeksen. De financiële rapportage van een onderneming pretendeert een volledig en accuraat beeld van de huidige toestand te geven. Desalniettemin, accounting informatie is uitsluitend 'historisch' omdat de jaarrekening altijd is gebaseerd op gepasseerde feiten (*ex post facto* ofwel op het verleden betrokken).[2] Vaak vindt men in de memorie van toelichting bij verschillende posten wel informatie over de toekomstverwachtingen van het management. Vanzelfsprekend geven in het verleden behaalde resultaten geen enkele garantie voor het rendement in de toekomst — dergelijke uitspraken zijn in wezen alleen indicatief. Desalniettemin wordt door de meeste gebruikers van jaarrekeningen veel belang gehecht aan zowel de historische cijfers als de

door markten of marktpartijen irrelevant.

[2] Selectief in de zin dat uitsluitend mutaties in de omvang en/of de samenstelling van het eigen vermogen worden bijgehouden.

memorie van toelichting, zie bijvoorbeeld Blij (2001, 421). Wel is sprake van een inhoudelijk verschil tussen aanvullende opmerkingen en het controleerbare cijfermateriaal dat de financiële administratie oplevert. De verwerking van gegevens door de administratie is onderworpen aan strikte regels. Het management moet derhalve rapporteren binnen welomgrensde kaders die wet- en regelgeving stellen, zie Schoonderbeek (2004) voor recente ontwikkelingen in Nederland. Het beoogde voordeel is dat de betrouwbaarheid (in principe) toeneemt naarmate de opzet en verwerking transparant zijn voor externe belanghebbenden.[3] Belangrijk voor het onderwerp van dit onderzoek is dat hiermee de vergelijkbaarheid van ondernemingen wordt vergroot. Dit voordeel komt ook tot uitdrukking op een meer fundamenteel niveau.

12.2.3 Meting van force & momentum

De analyse van jaarrekeningen moet met enige omzichtigheid ter hand worden genomen (zie hiervoor bijv. Foster 1986). Afgezien van inhoudelijke aspecten, bijvoorbeeld het verschil tussen ondernemingen die bedrijvig zijn in verschillende sectoren (het voorkomen van de vergelijking van 'appels' met 'peren'), zijn ook de nodige methodologische valkuilen aanwezig. De eerste opgave is om te zorgen voor een gestandaardiseerde opstelling van de jaarrekening. Tot op heden voorzien marktpartijen hierin.[4] Voor beursgenoteerde ondernemingen in de Verenigde Staten geldt de plicht om kwartaal- en jaarcijfers in een standaardformaat te deponeren bij de U.S. Securities and Exchange Commission (SEC). De gestandaardiseerde publicatie van jaarrekeningen op het Internet zal het opvragen van brongegevens en de onderlinge vergelijking binnenkort verder vergemakkelijken.[5] Daarnaast moet vooral het verstorend effect worden vermeden dat ontstaat door het vergelijken van ondernemingen met grote verschillen in balanstotaal en omzet. Daarom is het gebruikelijk het ruwe cijfermateriaal zowel om te rekenen — te transformeren — naar fracties of logaritmische waarden, als om financiële ratios te berekenen zodat een meer valide onderlinge vergelijking mogelijk wordt (zie hiervoor: Foster 1986, Fridson & Alvarez 2002, Lev 1974, Melse 2004A en Penman 2003). Ik beperk mij hier tot het illustreren van het achterliggende concept van momentum accounting door het verschil te berekenen van enkele accountingvariabelen per kwartaal of per jaar (zie TABLE 15, pagina 89, TABLE 25 & 27, pagina 114 en TABLE 33, pagina 156). Dit levert volgens formule (8), pagina 53, de *momentum*-meting op, bijvoorbeeld van het totaal vermogen of het eigen vermogen. Op elk moment staat ∇X_t voor het verschil van een accountingvariabele met het tijdstip van de meting daarvoor. In het accounting systeem van Ijiri (1986, 1988A) is dit gelijk aan de *snelheid* of *momentum* waarmee het eigen vermogen toeneemt. Met formule (9), pagina 53, wordt ook de *force*-meting van de operationele winst of het totaal vermogen bepaald en $\nabla^2 X_t$

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[3] Dat desondanks sprake kan zijn van aanzienlijke misrepresentatie van feiten is een onderwerp dat in ditonderzoek niet wordt besproken maar daarom niet minder relevant of problematisch. Wel ben ik van mening dat driedimensioneel boekhouden de transparantie vergroot en daardoor het risico op misrepresentatie van feiten zal doen afnemen (zie ook Blommaert 1994A, 230).

[4] Zoals, bijvoorbeeld: Dun & Bradstreet http://www.dunbradstreet.com/, Edgar http://www.edgar-online.com/, Reuters http://www.reuters.com/, en Thomson http://banker.analytics.thomsonib.com/.

[5] Het initiatief om jaarrekeningen op het Internet te publiceren volgens de XBRL standaard is hiervan een goed voorbeeld. Zie onder meer hiervoor: www.xbrl.org en www.xbrl-nederland.nl/. Het ministerie van Financiën en het ministerie van Justitie werken samen in het Nederlands Taxonomie Project (NTP) om de weg te effenen naar administratieve lastenverlichting in de financiële rapportageketens door de Nederlandse XBRL taxonomie te ondersteunen die (ook) door de overheid zal worden gebruikt (*Nota over de toestand van 's Rijks financiën, Tekstgedeelte van de Miljoenennota 2005*, aangeboden aan de Tweede Kamer der Staten Generaal, 21 september 2004, 164).

staat daarmee voor het verschil tussen twee verschillen ofwel de *snelheidsverandering* of *force* (FIGURE 160). Van belang in dit kader is te begrijpen dat de periode tussen de twee meetmomenten naar keuze instelbaar is. Ik stel met het balansmomentum de tijdsdimensie van de gekozen variabelen gelijk aan die van de resultatenrekening, namelijk het 'kwartaal' of het 'jaar' tussen twee balansmomenten (FIGURE 159). Momentum variabelen zijn derhalve de snelheidscoëfficiënten van de balans en de resultatenrekening. In deze studies betreft het de snelheid per kwartaal maar de berekening is evengoed toepasbaar per maand, week of dag. In mijn analyse van de aan de AEX genoteerde ondernemingen reken ik met een jaar (hoofdstuk 7). De modellen van de aan de DOW genoteerde ondernemingen rekenen per kwartaal (hoofdstuk 8) evenals bij de individuele studies van 3M (hoofdstuk 9) en de DOW Jones (hoofdstuk 10).

12.2.4 Economisch & econometrisch perspectief

Met de meting van force en momentum vinden we aansluiting met het klassieke economisch model van voorraadgrootheden per meetmoment en stroomgrootheden per tussenliggende periode (zie hiervoor bijv. Bouma 1990, 12-32). Snelheidsmeting voorziet ook in de groeiende behoefte aan een meer regelmatige financiële rapportage (Bell *et al.* 1997, Blij 2001). Ondernemingen die de zogeheten *fast close* invoeren kunnen over rapportages beschikken per maand, week of dag en kunnen voortdurend de force en het momentum meten van hun accounting variabelen (Barrett 2003). Vanuit een econometrisch perspectief bezien beschouw ik *momentum*, de winstsnelheid, als de eerste afgeleide van het eigen vermogen en *force*, de winstversnelling, als de tweede afgeleide (Blommaert 1994A, 158). Ofschoon Ijiri als primair oogmerk heeft om de winstcapaciteit van een onderneming te beschouwen als een snelheidsmeting op enig moment in de tijd kunnen we zijn methodologie probleemloos toepassen op elke variabele in het accounting- of bedrijfeconomisch model. In analogie met De Groot *et al.* (2004) brengen ik hiermee de 'motoriek' van de onderneming in beeld. Hierbij heeft het wel mijn voorkeur om de TEMA metingen uitsluitend aan elkaar te relateren wanneer zij dezelfde temporele positie hebben (zie hiervoor hoofdstuk 3). Immers, ik vergelijk dan variabelen met elkaar die een snelheid per tijdseenheid uitdrukken danwel de snelheidsverandering op een tijdstip. Mijn doel is om de stroomsnelheid van het eigen vermogen te verklaren vanuit de stroomsnelheid van het totaal vermogen, de operationele winst of beide tegelijk. Het perspectief is hierbij om vast te stellen in hoeverre deze accountingvariabelen hetzelfde 'marstempo' hebben, vooroplopen danwel achterlopen. Financiële variabelen worden in de *Balanced Scorecard* methode aangeduid als *outcome* of *lagging indicators* (Kaplan & Norton 1996, 32), dat wil zeggen als een resultaatmeting (Id. 24): 'Financial measures are inadequate for guiding and evaluating organizations' trajectories through competitive environments. They are lagging indicators that fail to capture much of the value that has been created or destroyed by managers' actions in the most recent accounting period.' De implicatie van dit standpunt is dat het niet mogelijk zal zijn om op basis van financiële variabelen econometrische modellen te ontwikkelen die de trend van het eigen vermogen kunnen verklaren, laat staan voorspellen. Op basis van mijn resultaten stel ik vast dat TEMA variabelen wel degelijk over verklarend vermogen beschikken als *leading indicator* van de stroomsnelheid van het eigen vermogen.

12.3 TEMA

TEMA voegt een dynamisch perspectief toe aan het accounting systeem voor analyse en besluitvorming inzake bedrijfsvoering en beoordeling. TEMA is gericht op de causale verbanden in het bedrijfsmodel. Met TEMA administreert de onderneming bedrijfseconomische feiten met een

effect in de toekomst die nu buiten het domein vallen van de boekhouding. Hieruit volgt dat de systematiek van het boekhouden wordt gebruikt om het financiële effect van niet-financiële transacties, dat wil zeggen bedrijfseconomische transacties, te administreren. Hierdoor vervaagt de grens tussen *financial accounting* en *management accounting* (controlling). Glover & Ijiri (2002) noemen *revenue accounting* als voorbeeld. Farquhar *et al.* (1992) en Farquhar & Ijiri (1993) beschrijven een marketing toepassing van momentum accounting. Het denken in termen van *momentum* — positieve autocorrelatie — is al jaren gebruikelijk bij financieel analisten (bijv. Asness 1997, Chan *et al.* 2004, Lui *et al.* 1999, Grundy & Martin 2001) en verzekeringsmaatschappijen (Lane & Beckwith 2003, 71). Pahud de Mortanges & Van Riel (2003, 524) relateren de *directional change* van merknamen gezien in de tijd aan de ontwikkeling van de waarde van een bedrijfsaandeel. Dat naast de financiële disciplines het begrip momentum ook wordt gebruikt in de sociologie (Koponen 2002), bedrijfsstrategie (Larreche 2008), personeel- en organisatieontwikkeling duidt op de brede toepasbaarheid van het achterliggende concept (Jansen 2004, Kelly & Amburgey 1991, 601, Landsberg 2001, 4, Nevin 2002 en Pollitt 2002).

12.3.1 Drie accounting dimensies

Yuji Ijiri heeft de mathematische grondslag van accounting onderzocht en stelt voor om het huidige systeem voor dubbel boekhouden uit te breiden met een derde dimensie (1967, 1975, 1982, 1984, 1986, 1987, 1988A, 1988B en 1989). Bij het verwoorden van zijn theorie maakt Ijiri gebruik van een metafoor op basis van de natuurkundige bewegingswetten zoals opgesteld door Sir Isaac Newton (Cohen 2002, 57-84). In de klassieke mechanica wordt de beweging van een object in een frictievrije omgeving omschreven als de integraal van het produkt van de massa van het object en de richting en intensiteit van de impuls die het per tijdseenheid ontvangt. In analogie met Newton's definitie van massa als *quantitas materiae* stelt Ijiri voor om het (netto) vermogen te beschouwen als een bedrijfseconomische 'massa' met een bepaalde snelheid, een bepaald momentum.[6] Hiermee poneert Ijiri dat de capaciteit tot het verwerven van nieuw vermogen een zekere continuïteit vertoont gegeven de aanwezigheid van een bepaalde massa met een bepaalde snelheid, De vraag hierbij is natuurlijk wel hoe we dit kunnen meten als bedrijfseconoom, controller, accountant of auditor. Ijiri wil het financieel-bedrijfseconomisch 'object' — de onderneming — meten èn administreren in de boekhouding aan de hand van drie dimensies:[7]

1. *Wealth*—vermogen, de eerste dimensie inzake de *samenstelling van het vermogen*, met accountingvariabelen te onderscheiden naar activa en passiva;
2. *Income*—inkomen, de tweede dimensie inzake de *verandering van de omvang van het vermogen*, met accountingvariabelen te onderscheiden naar kosten en opbrengsten;
3. *Force*—kracht, c.q. winstkracht, de derde dimensie inzake de *capaciteit tot het in de toekomst verwerven van nieuw vermogen*. Via negatieve en positieve impulsen zijn accountingvariabelen te onderscheiden die de dan geldende winstcapaciteit doen veranderen (per toekomstige tijdsperiode).

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[6] Dat deze aanname nog niet zo vreemd is mag blijken uit het gegeven dat in de macro-economie wordt gewerkt met een vergelijkbare metafoor: het *gravity model* (Baier & Bergstrand 2001, 3). In dit model, dat oorspronkelijk is opgesteld door Nobelprijswinnaar Jan Tinbergen (1962, 262-293), worden internationale handelsstromen geformuleerd als een functie van het nationaal inkomen, de populatie, geografische afstand en naburigheid, Het nationaal inkomen fungeert als 'massa' in dit model.

[7] Het antwoord op de vraag wat een relevant bedrijfseconomisch feit is ligt besloten in de definitie van de accountingdimensies maar wordt vanzelfsprekend in de praktijk gedicteerd door wet- en regelgeving.

In FIGURE 159 wordt de samenhang weergegeven tussen de drie accountingdimensies (zie ook Melse 2004A). Het doel dat Ijiri voor ogen staat is om de ontwikkeling van het (eigen) vermogen langs drie verschillende wegen gestalte te geven met het raamwerk van Triple-Entry/Momentum Accounting, afgekort TEMA. Hier is geen sprake van een Cartesiaans systeem waarbij we ons elke dimensie moeten voorstellen als een as van het geometrisch bepaalde x,y,z-stelsel. We meten en projecteren dus niet de ruimtelijke 'locatie' van een bedrijfseconomisch feit. In plaats daarvan, meten we met de drie accountingdimensies het zogeheten *temporele aspect* van transacties met accountingvariabelen–de grootboekrekeningen (Melse 2004C). Blommaert & Blommaert (1990A-B, 88), Blommaert (1994A-B) en ook Olders (1995) beschrijven in detail de methodiek van het zogeheten *driedimensioneel boekhouden* of *triple-entry accounting*.

12.3.2 Accounting dimensies als informatiebron

Gezien als modelvariabelen van het bedrijfseconomisch systeem — de onderneming — zijn de drie accountingdimensies aan de tijd verbonden *informatiebronnen* (FIGURE 159). Aan de hand van de boekhouding wordt op enig tijdspunt verklaard hoe (1D) het vermogen is verkregen (passiva) en gebruikt (activa), of sprake is van nieuw vermogen (2D), dat wil zeggen vermogensgroei, en welke kosten en opbrengsten daarmee zijn verbonden. Ijiri voegt hieraan toe de mogelijkheid om de capaciteit te administreren tot het realiseren van nieuw vermogen in de toekomst (3D). Hij wil traceerbaar maken in welke mate (tot op het heden) die capaciteit is vergroot dan wel afgenomen in vergelijking met enig tijdspunt in het verleden. Als de 'opbrengstkrachten' groter zijn dan de 'kostkrachten' dan ontstaat een positief saldo: het netto vermogen zal toenemen in de toekomst.[8] In de omgekeerde situatie neemt het netto vermogen vanzelfsprekend af. Als derde mogelijkheid blijft het netto vermogen gelijk, de positie van de onderneming is in dit geval stabiel. Bij deze laatste twee situaties stelt Ijiri wel de vraag of het management haar werk naar verwachting heeft gedaan (Ijiri 1988A, 163-165). Hij stelt dat het management in dat geval lager moet worden beloond. Immers, het netto vermogen neemt af of blijkt gelijk: het management heeft het momentum niet vergroot. Managers moeten naar zijn mening apart worden beloond voor het laten groeien van de winstcapaciteit en in mindere mate voor het instandhouden van de reeds aanwezige winstcapaciteit. Wat Ijiri betreft hoeft het management niet te worden beloond met een bonus voor het realiseren van in het verleden opgebouwde winstcapaciteit, dat volgt immers uit de aanwezige *steady state*, de huidige toestand.[9] Hier is dus sprake van een raakvlak tussen driedimensionaal boekhouden als beschrijvend instrument en als beslissingsondersteunend instrument voor management control en corporate governance. Uit de door mij besproken voorbeelden en de econometrische analyse van AEX en DOW ondernemingen blijkt dat de groeisnelheid van het eigen vermogen inderdaad voor een belangrijk deel significant is te verklaren met het eerder opgebouwde momentum van het totaal vermogen, de operationele winst of beide.

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8 Omwille van de verklaring van de principes van driedimensionaal boekhouden en momentum accounting laat ik aspecten inzake financiering en belasting achterwege. Vanzelfsprekend hebben deze invloed op de capaciteit tot het vergroten of verkleinen van het netto vermogen.

9 Anders gezegd: *waardecreatie* (= toename winstcapaciteit van het eigen vermogen, 3D) is zeker zo waardevol als *waarderealisatie* (toename van de omvang van het eigen vermogen, 2D) en is wellicht zelfs van groter belang omdat het een basis legt voor de toekomst. Momentum accounting is als zodanig een uitbreiding van het bestaande twee-dimensionele administratieve systeem dat uitsluitend waarderealisatie systematisch en stelselmatig vastlegt. Dit resulteert mogelijk in een meer representatieve voorstelling van zaken hetgeen het systeem bevordert van *corporate governance* bij de onderneming.

12.3.3 Administreren in drie dimensies

De omschrijving van de derde dimensie oogt misschien enigszins cryptisch. Een voorbeeld ter verduidelijking: een onderneming sluit een lease-overeenkomst waarbij men een maandelijkse betalingsverplichting aangaat voor een periode van twee jaar. In de beleving van Ijiri is dit bedrijfseconomisch feit aanleiding om te administreren dat de komende twee jaar elke maand het kostenniveau hoger is, de kostkrachten zijn zogezegd toegenomen. Deze procedure is vergelijkbaar met het afschrijven van een investering in een actief.[10] De redenering van Ijiri is dat een 'historische' verplichting tot het doen van uitgaven net zo concreet een bedrijfseconomisch feit is als een 'historische' uitgave. Deze redenering is evenzeer van toepassing op verwachte inkomsten, bijvoorbeeld naar aanleiding van het ondertekenen van een meerjarig onderhoudscontract waarbij de betaling in termijnen zal plaatsvinden. Centraal staat steeds het gegeven dat op enig moment in de tijd bij een onderneming objectief kan worden vastgesteld welke verplichtingen zijn aangegaan: te onderscheiden naar kosten en opbrengsten. Blommaert (1994A) geeft hiervan talrijke voorbeelden. Deze informatie is veelal voorhanden in de vorm van orderboeken, de contractadministratie en dergelijke.[11] Met het oog op meer inzicht in de toekomst wil Ijiri deze gegevens gebruiken om trends in de bedrijfsvoering van de onderneming betrouwbaar te administreren en vervolgens leesbaar maken (en dus ook toetsbaar!). Dit is relevant bij het nemen van operationele alsook bij meer strategische beslissingen. Brouthers & Roozen (1999, 312), bijvoorbeeld, rapporteren over hun onderzoek naar het gebruik van accounting informatiesystemen bij 12 managers van zes leidende Nederlandse ondernemingen dat grote behoefte bestaat aan meer toekomstgerichte informatie van hoge kwaliteit. In navolging van Tillema (2003, 217) stel ik vast dat TEMA een geavanceerd management instrument is.

12.3.4 Comptabele implementatie

Vaassen (2002, 33) is van mening dat driedimensionaal boekhouden minder geschikt is omdat het subjectief is in de vertaling van niet-financiële gegevens naar financiële gegevens. Net als in elk ander boekhoudsysteem wordt een 'momentum' feit geboekt in een van te voren bepaald rekeningenschema (dat bestaat uit accountingvariabelen). Zijn alternatief is om het rekeningenschema als structurerend idee geheel los te laten en te vervangen door principes van de gegevensmodellering. Volgens hem zijn het immers de informatiesystemen die de flexibiliteit bieden waar de dynamiek van het huidig tijdsgewricht om vraagt. Dit beeld wordt bevestigd door Koning (2004, 346) die observeert dat de 'typologie' van Starreveld niet langer toereikend is en pleit voor het introduceren van logistieke begrippen en bijhorende toepassingen in het interne betrouwbaarheidssysteem, dat wil zeggen op de betrouwbaarheid van de financiële rapportages (als vanouds) aangepast aan de eisen van deze tijd (zie hiervoor ook Hunton 2002). Desalniettemen, het management heeft als meest geïnformeerde partij de verplichting de bedrijfsgegevens zodanig voor te (laten) bewerken dat daarmee een niet-ambigu beeld bij de gebruiker wordt opgeroepen. Bij onbewerkte, of op 'maat' bewerkte, gegevens ontbreekt dit perspectief en dit resulteert, naar onze mening, in een quasi objectiviteit. Ik pleit voor controleerbare subjectiviteit, dat immers is de basis van alle professionele verslaglegging. Ook momentum accounting moet aan deze hoge eis voldoen (Blommaert 1994A, 10).

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[10] Het *permanence* principe is welbekend bij dubbelboekhouden en is in wezen nauw verwant met de gedachte achter *force* en *momentum accounting*.

[11] Veel van dit type administratieve feiten wordt thans als 'off balance' informatie bij jaarrekeningen gevoegd. Hiermee wordt expliciet aangegeven dat dergelijke feiten weliswaar hun koppeling met het reguliere administratieve systeem hebben maar dat zij dat systeem nog niet volledig hebben doorlopen.

12.3.5 Administratie, management accounting & control

We moeten driedimensionaal boekhouden niet beschouwen als een methode om de toekomst mee te voorspellen. Wel is het mogelijk om hiermee vast wat de financiële positie van een onderneming wordt in de toekomst gegeven de dan bekende feiten! Het is een methode om te administreren dat wat in het heden bekend is (oorzaak) en haar werking heeft in de toekomst (gevolg). Zie hiervoor ook Glover & Ijiri (2002). Dit maakt TEMA tot een alternatief voor de Balanced Scorecard van Kaplan & Norton(1996) in de zin dat de causale verbanden in het bedrijfsmodel op een gestructureerde wijze worden geadministreerd. Alhoewel Ijiri in zijn latere publicaties de Balanced Scorecard niet als methode noemt of zich daarmee vergelijkt stel ik vast dat TEMA een brug slaat tussen de financiële administratie enerzijds en management accounting en control anderzijds (zoals overigens wel wordt beoogd door Kaplan en Norton). Ik zie TEMA als een initiatief tot innovatie van de financiële administratie zodat de controller, accountant of auditor worden gefaciliteerd onder druk van de verdere convergentie van management control, internal control en corporate governance. Hieraan is behoefte volgens Vaassen (2003, 154) om als controller waardevol inzetbaar te blijven in een dynamische omgeving. Naar ik aanneem heeft TEMA een grotere trefzekerheid omdat de ervaring met een stelselmatige gegevensverwerking (en de controle daarop door auditors) groot is en wereldwijd als methode aanvaard, zoals is bevestigd met onderzoek van Blommaert (1994A, 221-231).

12.3.6 Kritiek

Fraser (1993, 156) vindt dit echter een veel te optimistisch beeld en meent dat Ijiri onderschat hoeveel praktische problemen moeten worden opgelost voordat er sprake kan zijn van een zinvolle comptabele implementatie. Wagensveld (1995, 13) ziet wel voordelen in momentum accounting maar meent dat het beter is om te wachten met comptabele implementatie totdat wetenschappelijk is vastgesteld of daarmee ook zinvolle nieuwe informatie kan worden aangeleverd. Hij vraagt aandacht voor het belangrijkste punt van kritiek die Fraser (1993, 157) geeft, namelijk '...nuttige informatie is waarschijnlijk eerder een toevalsresultaat in plaats van dat het volgt uit het ontwerp,...' dat wil zeggen het TEMA raamwerk. Zonder empirische onderbouwing van het structurele verband tussen de drie accountingdimensies lijkt comptabele implementatie dus discutabel volgens deze critici. Dit onderzoek beoogt daarom het benodigde verband vast te stellen en dit te beschrijven in de vorm van econometrisch modellen. Hiermee test ik ex post en simuleer ik ex ante, respectievelijk, het verklarend en voorspellend vermogen van het TEMA raamwerk. Als ondernemingen aan de hand van de wet- en regelgeving administreren dan zal dit leiden tot impliciete en expliciete verbanden in de boekhouding. Dit zijn misschien geen vanzelfsprekende verbanden en het is evenmin eenduidig of deze algemeen geldend zijn voor bepaalde marksegmenten. Ik geef Fraser (1993, 155) hierin volkomen gelijk: '...het zal moeilijk zijn om het argument te onderbouwen dat sprake is van een *algemene* relatie tussen inkomen, vermogen en momentum aangezien deze relatie afhankelijk is van het model dat wordt gehanteerd bij de meting van inkomen en vermogen (d.w.z. historische kostprijs, inkomen op basis van de marktwaarde, etc.) en van het distributieniveau in iedere rapportageperiode.' Vooralsnog blijft mijn uitgangspunt dat àls er sprake is van een *algemene relatie* dit aannemelijk moet worden gemaakt met jaarrekeningen ondanks alle inhoudelijke beperkingen die het gebruik hiervan met zich meebrengt. De reden hiervoor is eenvoudig: ik (en de rest van de wereld) als buitenstaander in principe alleen beschik over de gepubliceerde jaarrekeningen.[12]

[12] In hoeverre het mogelijk is om TEMA modellen uitspraken te doen op basis van tijdreeksen met een

12.3.7 Van boekhouden naar rapporteren

Vergoossen & Van der Wel (2002, 565) stellen vast dat de roep groot is om een wereldstandaard voor de financiële verslaggeving van beursgenoteerde ondernemingen. Zij en ook Haller (2002, 181-2) menen dat de invoering van IFRS zal leiden tot de harmonisatie van de definitie van het winstbegrip, de activa en passiva en daardoor ook van nationale accountingsystemen, -regels en accounting gerelateerde belasting- en bedrijfswetgeving. Van der Tas (2003, 21) en Van Geffen (2004, 14) menen dat het effect hiervan niet beperkt blijft tot beursgenoteerde ondernemingen waar IFRS in eerste instantie wordt ingevoerd. Naast het gegeven dat de IASB werkt aan een IFRS *light* versie, speciaal voor SME's (small and Medium sized Enterprises) dat vermoedelijk door de overheden wordt overgenomen, zijn het met name verschillende indirecte effecten die kunnen leiden tot breder gebruik. Haller (2002, 181) en Van der Tas (2003, 21) veronderstellen dat financiers, zoals banken, ook van niet-beursgenoteerde ondernemingen verwachten dat zij de IFRS richtlijnen gaan gebruiken. Dit zal volgens Haller (2002, 183) een revolutionair effect hebben op de presentatie en onderlinge vergelijkbaarheid van financiële bedrijfsinformatie en dus ook op het analyseren hiervan met een nadrukkelijke verschuiving van de aandacht '...*from financial accounting to business reporting*.' Ik neem aan dat de toename van de onderlinge vergelijkbaarheid van de jaarrekening de relevantie van momentum accounting vergroot als methode om de snelheid van de positieverandering van een onderneming te rapporteren en te analyseren. Bij TEMA accounting worden immers dezelfde gegevens gebruikt uit de financiële administratie daarmee wordt daaraan wel een dynamisch perspectief toegevoegt.

12.4 Onderzoeksvraag, opzet & methoden

Zoals bij elke andere wetenschappelijke theorie geldt ook voor accounting dat de onderliggende veronderstellingen toetsbaar dienen te zijn aan de hand van feiten. De accounting theorie is echter minder makkelijk objectief te toetsen dan, bijvoorbeeld, een natuurkundige theorie. Sociale en economische processen en systemen zijn namelijk niet los te beschouwen van de context waarin zij zich afspelen en functioneren. Ook laten gecontroleerde laboratoriumexperimenten over, bijvoorbeeld, besluitvorming door managers zich moeilijk vertalen naar de praktijk en lijken soms zelfs in strijd te zijn met de gangbare economische theorie, zie bijvoorbeeld de bevindingen van Tversky & Kahneman (1986). De ontwikkeling en toetsing van accounting theorie wordt daarmee beperkt tot een formele analyse van casuïstiek. Naar ik hoop geeft dit voldoende uitsluitsel om met enige zekerheid uitspraken te doen over de geldigheid van aannames en proposities van het TEMA raamwerk.

12.4.1 Onderzoeksvraag

De onderzoeksvraag die in deze studie wordt beantwoordt is: heeft TEMA verklarend en voorspellend vermogen? Het antwoord wordt gezocht door de associatie te onderzoeken tussen accountingvariabelen uit het TEMA raamwerk die zijn betrokken op snelheid (momentum) en snelheidsverandering (force) van zowel de vermogensaanwas als de vermogenssamenstelling (wealth). FIGURE 160 en FIGURE 161 tonen de samenhang tussen de dimensies van het TEMA raamwerk voor zowel de meting van de vermogensaanwas als de vermogenssamenstelling.

kortere tijdspanne, bijvoorbeeld een maand, week of wellicht zelfs op dagbasis, moet blijken uit vervolgonderzoek op basis van interne gegevensbronnen. Wellicht wordt het mogelijk om te onderzoeken in hoeverre niet-financiële gegevensbronnen een plaats hebben in het TEMA raamwerk als force- en momentummeting.

Naast de hiervoor genoemde kritiek van Fraser op momentum accounting meent hij ook dat het ook niet mogelijk is de 'contemporary commercial reality' weer te geven onder de conventie van historische kosten die ten grondslag ligt aan de jaarrekening (Fraser 1993, 153). Daarom is het volgens hem in theorie niet mogelijk om de geldigheid te toetsen van driedimensionaal boekhouden. Zijn redenatie is dat tweedimensionaal (dubbel) boekhouden niets voorspelt en niets verklaart maar uitsluitend de gematerialiseerde effecten beschrijft van in het verleden afgesloten markttransacties (Id. 155, 157). Als dit inderdaad het geval is, dan is de uitgangspositie voor deze studie tamelijk ontmoedigend. Echter, ik ben het hiermee niet eens. Ik meen dat het mogelijk moet zijn om met empirisch onderzoek objectief toetsbare feiten aan te dragen om daarmee aan te tonen dat dergelijke verbanden wel degelijk traceerbaar zijn tussen de accountingvariabelen in alle temporele dimensies van het accounting systeem, dus zowel twee- als drie-dimensioneel. Overigens is met *canonical correlation analysis* eerder econometrisch bewijs geleverd voor dergelijke associaties tussen balansvariabelen door Stowe *et al.* (1980).

12.4.2 Onderzoeksdoelstelling

Het doel van dit onderzoek is om het verklarend en het voorspellend vermogen te toetsen van driedimensionaal boekhouden en momentum accounting, zoals voorgesteld door Yuji Ijiri (1982, 1984, 1986, 1987, 1988 en 1989), alsmede om hiervan de relevantie aan te tonen. Fraser (1993) verwerpt Ijiri's momentum accounting theorie op grond van het ontbreken van een duidelijk gebruiksdoel, onduidelijke voordelen, mogelijke gebruiksproblemen, ontoereikende interne logica en een geringe slaagkans om de stelling te valideren dat een algemene relatie bestaat tussen inkomen, vermogen en momentum. Daarbovenop komt zijn kritiek dat '...nuttige informatie waarschijnlijk eerder het resultaat zal zijn van toeval dan door ontwerp [van het systeem]' (Id. 157). Naar Fraser's mening is het niet mogelijk om empirisch de algemene relatie aan te tonen omdat de financiële administratie uitsluitend administreert op basis van historische kosten. Uitgezonderd de kas, debiteuren en crediteu-ren, beschrijven rekeningen niet, in zijn woorden, een 'hedendaagse commerciële realiteit.' Om op basis van de financiële administratie uitspraken te doen over de ontwikkeling van een onderneming in de toekomst is in de ogen van Fraser volstrekt zinloos.

12.4.3 Onderzoeksmethode

Om het tegendeel te bewijzen heb ik de jaarrekeningen van aan de AEX en de DOW genoteerde ondernemingen onderzocht met als doel om nieuwe kennis te verwerven over de relevantie en de empirische geldigheid van het TEMA raamwerk. Acht studies zijn in deze dissertatie besproken in twee delen. De eerste vier studies behandelen de informationele relevantie van de accounting variabelen uit het TEMA raamwerk. Om business momentum te kunnen bestuderen en om op de toekomst gerichte accounting informatie te ontsluiten, heeft Ijiri aanbevolen om gebruik te maken van ARIMA tijdreeksmodellen als alternatief voor een volledige implementatie van een driedimensionele boekhouding. Het tweede deel van deze dissertatie exploreert met deze onderzoeksmethode dezelfde ondernemingen en bestaat uit vier studies. Hierin wordt met econometrische modellen het verklarend en voorspellend vermogen getoetst van accounting variabelen uit het TEMA raamwerk.

12.5 De relevantie van TEMA

Accounting informatie is relevant, volgens Epstein & Mirza (1997, 54) als: '...het de mogelijkheid biedt om een verschil te maken voor de beslissingen van investeerders, crediteuren, of andere gebruikers.' Deze studie volgt een formele benadering om vast te stellen of accounting informatie relevant is binnen het TEMA raamwerk. Traditionele prestatiemetingen zijn vergeleken met een door mij ontwikkelde nieuwe momentummeting in hoofdstuk 3. Informatiemetingen ontwikkeld door Lev en Ijiri om relevante veranderingen vast te stellen in de samenstelling van de jaarrekening zijn door mij vergeleken met momentum en force metingen in hoofdstuk 4. Decompositie-analyse met Spectramap is toegepast in hoofdstuk 5 om de statische structuur tussen variabelen zichtbaar te maken en te vergelijken in de informationele TEMA dimensies: wealth, momentum en force. Hieruit blijkt dat de associatie tussen balansvariabelen, in het gebruikte voorbeeld van 3M, stand houdt in alle drie dimensies hetgeen ook is bevestigd met statistische correlatie-analyse. Accounting informatie tussen balansvariabelen op een meer gedetailleerd niveau is gevisualiseerd met behulp van Spectramap biplots en kleurcodering in hoofdstuk 6. De volgende paragrafen vatten de bevindingen samen van dit eerste deel van deze studie.

12.5.1 Prestatiemeting

In hoofdstuk 3 zijn traditionele prestatie indicatoren vergeleken met de momentummeting van het eigen vermogen. Uit het bestudeerde voorbeeld, Robert Half International Inc., is duidelijk geworden dat gedurende bepaalde perioden de verandering van het eigen vermogen anders verloopt dan de winstmarge of die van financiële ratios zoals *return on total assets*. Ik heb een nieuwe financial accounting ratio geïntroduceerd die gebruikt kan worden om de verandering in de samenstelling te onderzoeken van TEMA variabelen: de *common size format momentum* of *force ratio*. Aan de hand van het bestudeerde voorbeeld, Robert Half International Inc., werd duidelijk dat gedurende een periode van 19 jaar zowel de winstmarge als de *return on assets ratios* aanzienlijk fluctueert. Hetzelfde is het geval met de ruwe gegevens van het net wealth momentum. Echter, de common size format ratio van net wealth momentum is stabiel voor en na de zogeheten 'dotcom crash' gedurende vele jaren. Derhalve concludeer ik dat de common size format momentum ratio mogelijk nieuw inzicht oplevert hoe we de structurele aspecten van het financiële resultaat van een onderneming moeten kwalificeren. Daarom kan het niet bestuderen van momentummetingen om de prestatie van een onderneming te beoordelen leiden tot de onjuiste indruk dat de realisatie van het inkomen 'ongeveer' gelijk is als in een vorige periode terwijl de samenstelling van het eigen vermogen juist dramatisch wijzigt. Dergelijke dynamiek moet de aandacht hebben van het management van de onderneming, investeerders en analysten zowel op micro-economisch als op macro-economisch niveau (De Groot *et al.* 2004).

12.5.2 Informatiemetingen

In hoofdstuk 4 is aangetoond dat analyse met de decompositiemetingen van Baruch Lev alleen mogelijk zijn voor wealth variabelen uit het TEMA raamwerk. De disaggregatiemeting van Ijiri geeft vergelijkbare resultaten voor wealth variabelen. Ook is het hiermee mogelijk om momentum en force metingen te analyseren. Dit is niet mogelijk met de decompositiemetingen van Lev omdat deze negatieve waarden niet kunnen verwerken. In het voorbeeld van 3M blijkt voor wealth dat de decompositie- en disaggregatiemeting structurele veranderingen niet signaleren van de balans. Bij zowel momentum als force levert de disaggregatiemeting wel nadrukkelijk signalen op dat de structuur zowat elk tijdstip wijzigt. De informatiesignalen van wealth lijken

te lijden aan 'onder-signalering' terwijl die van momentum en force mogelijk lijden aan 'over-signalering' en hiermee zijn beiden mogelijk misleidend. Als zodanig sturen informatiemetingen de aandacht naar de econometrische eigenschappen van de TEMA tijdreeksen. Echter, als onderscheidend hulpmiddel voor de gebruikers van jaarrekeningen lijken de bestudeerde TEMA informatiemetingen weinig richting te geven bij de vraag of bij (het ontbreken van) een structurele verandering nadere inspectie van financiële variabelen op detailniveau rechtvaardigt of niet. Overeenkomstig Babich (1975) en Blommaert (1995A, 1996), lijkt het mij daarom raadzaam om de toepassing te ontmoedigen van zowel de decompositiemetingen van Lev als de disaggregatiemeting van Ijiri.

12.5.3 Balansdecompositie

De verandering in de samenstelling van de balans is onderzocht in twee studies van een van de 30 DOW bedrijven: 3M. In hoofdstuk 5 wordt de eerste studie besproken waarbij de trend is onderzocht in de verhouding tussen vijf balansvariabelen, dat wil zeggen op een hoog aggregatieniveau. De statische associatie is gevisualiseerd met behulp van Spectramap decompositie naar drie factoren met een cumulatief verklaarde variantie van 100% (Lewi 1982). Dit blijkt mogelijk in alle drie dimensies van het TEMA raamwerk: wealth, momentum en force. De visuele analyse van wealth, momentum en force met Spectramap biplots toont de mate en richting van de associatie tussen TEMA variabelen. Op detail niveau, besproken in hoofdstuk 6, zijn 14 accounting variabelen succesvol gereduceerd naar vijf factoren met Spectramap decomposition met een cumulatief verklaarde variantie van ongeveer 95%. Met kleurcodering van de balansposten en de meetpunten in de tijd zijn de scores van de twee laatste factoren gebruikt om zinvolle informatie te visualiseren over het contrast tussen activa en passiva. Met Spectramap decompositie is de visuele illustratie mogelijk van de associatie tussen balansvariabelen. Visuele analyse van wealth, momentum en force tijdreeksen maakt in dit voorbeeld duidelijk dat sprake is van associatie tussen balansvariabelen in alle drie dimensies van het TEMA raamwerk. Dit voorbeeld suggereert dat sprake is van een structurele relatie tussen momentum en force van het totale vermogen en de gedisaggregeerde vermogensrekeningen in deze dimensies. Het lijkt, naar mijn mening, dat de associatie tussen de dynamiek van de geaggregeerde en de gedisaggregeerde vermogensrekeningen aanwezig is voor momentum en force van de balanssamenstelling. Dit resultaat is relevant voor de ontwikkeling van econometrische TEMA modellen.

12.5.4 Directional change

De zogeheten *directional change* in de tijd van TEMA variabelen is onderzocht bij ondernemingen genoteerd aan de AEX en de DOW volgens de door Pahud de Mortanges & van Riel voorgestelde methode (2003, 524). De gemiddelde parallel directional change is bij het operationeel inkomen versus het eigen vermogen momentum ongeveer 74% voor de AEX en 80% voor de DOW. Voor de force metingen van deze variabelen is het ongeveer 71% voor de AEX en 63% voor de DOW. Het gemiddelde parallelle directional change is bij het total vermogen momentum versus het eigen vermogen momentum ongeveer 78% voor de AEX en 74% voor de DOW. Voor de force metingen van deze variabelen is het ongeveer 61% voor de AEX en 63% voor de DOW. Deze resultaten zijn een indicatie van de mogelijke temporele associatie tussen de TEMA variabelen. Dit wordt inderdaad bevestigd met het onderzoek naar het verklarend en voorspellend vermogen van econometrische TEMA modellen in deze studie.

12.5.5 Kleurcodering

Hering heeft voorgesteld dat voor de menselijke waarneming het volstaat om met drie paar tegengestelde kleursensaties te coderen (Judd & Wyszecki 1975, Nassau 1998). Het instituut voor colorimetrische standaarden, de Commission Internationale de l'Eclairage (CIE), heeft de normen bepaald voor de zogeheten CIELAB uniforme kleurenruimte voor reflecterende lichtbronnen. Kleuren zijn in de CIELAB kleurenruimte geordend naar metrische afstanden. De kleurwaarneming van mensen volgt de Weber-Fechner wet die een logaritmische relatie impliceert tussen de geometrische progressie van verschillende stimuli en de daarmee corresponderende waarneming die een arithmetische progressie vertoont. Recente studies suggereren dat bepaalde cognitieve en perceptueel-sensorische voorstellingen in het menselijk bewustzijn dezelfde fundamentele mechanismes en neurale coderingschema's delen voor zowel getallen als kleuren. De implicatie is dat mensen getallen waarnemen als continue grootheden hetgeen het mogelijk maakt om een integraal analytisch systeem te ontwerpen op basis van numerositeit, geometrie en colorimetrie. De kleurgecodeerde spectramap biplot is een dergelijk systeem waarmee een gedecomposeerde multivariate tabel met zes dimensies kan worden gevisualiseerd, drie van de geometrie en drie van de colorimetrie.[13] In hoofdstuk 2 is een door mij nieuw ontwikkelde methode besproken voor het coderen van informatie met het CIELAB kleursysteem (COLOR FIGURE 1–6, pag. 307-309). Kleurcodering werd door mij toegepast in verschillende studies om:

1. de informationele signaalsterkte te visualizeren van decompositie- en disaggregatiemetingen met een achromatische naar chromatische verlopende kleurenschaal (hoofdstuk 4, pagina 111, COLOR FIGURE 7);
2. de directionele signaalsterkte te visualizeren van momentum en force tiidreeksen met twee schalen van tegengestelde kleuren (hoofdstuk 4, pagina 112, COLOR FIGURE 8);
3. het aantal dimensions te verhogen om een spectramap biplot mee te tekenen met die van de CIELAB kleurenruimte (hoofdstuk 6, pagina 146, COLOR FIGURE 10–14);
4. de tijdsvertraging en associatierichting te bepalen van onafhankelijke variabelen ten opzichte van een afhankelijke variabele (hoofdstuk 10, pag. 230, COLOR FIGURE 15–16);
5. het structurele contrast te visualizeren tussen een afhankelijke variabele en alle onafhankelijke variabelen in tijdreeksregressie (hoofdstuk 10, pag. 232, COLOR FIGURE 17–20).

Op een lager aggregatieniveau wordt in hoofdstuk 6 besproken hoe 14 balansvariabelen succesvol met spectramap zijn gedecomposeerd naar vijf factoren met een cumulatief verklaarde variantie van ongeveer 95%. Met het coderen van informatie volgens het CIELAB kleursysteem blijkt het mogelijk om zinvolle informatie zichtbaar te maken. Het beeld dat hieruit volgt van de samenhang tussen balansvariabelen en hun meetpunten maakt een grondiger analyse mogelijk. Hiervoor zijn de waarden (scores) gebruikt van de laagste twee factoren (uit vijf). Het gebruik van op CIELAB gebaseerde kleurcodering maakt het mogelijk om de visualisatie van informatie uit te breiden van het gebruikelijke maximum van drie dimensies voor de x, y en z-as naar in totaal zes dimensies, inclusief de drie dimensies van het CIELAB kleursysteem. Het blijkt mogelijk objecten te plaatsen in een Cartesiaans coördinaten stelsel en deze te voorzien van een betekenisvolle kleur die wordt bepaald vanuit de driedimensionale CIELAB kleurenruimte.

[13] Data betrekt ons op de numerositeit van informatie (inzake fenomenen) en is onderwerp van een meer fundamenteel onderzoek naar onze perceptie en het kwantificeren daarvan (e.g. Lewi 1999).

12.6 Verklarend & voorspellend vermogen van TEMA

Vier econometrische studies bevestigen dat voorwaarts gerichte accounting informatie kan worden geleverd met variabelen van de informationele dimensies van het TEMA raamwerk. Zowel het verklarend vermogen als het voorspellend vermogen van de ARIMA modellen van de force van het operationeel inkomen en het totale vermogen blijken buitengewoon significant te zijn (H 7_a). In twee studies, besproken in hoofdstuk 7 en 8, is de trend van de accounting variabele eigen vermogen verklaard en voorspeld voor ondernemingen genoteerd aan de AEX en de DOW zowel met de individuele accounting variabelen totaal vermogen (dat wil zeggen de boekwaarde) en het operationeel inkomen als met hun combinatie. In de derde studie, besproken in hoofdstuk 9, is de dynamische relatie vastgesteld tussen de balansvariabelen van 3M in de informationele dimensies wealth en momentum van het TEMA raamwerk. Hiervoor is gebruik gemaakt van econometrische regressiemodellen voor tijdreekssimulatie met spectramap gedecomposeerde factoren. De modellen verklaren en voorspellen de tijdreeksen correct in ongeveer 92% van de factor scores voor het balansmomentum maar ook voor wealth als geaggregeerde factor score. Het resultaat gevisualiseerd in een driedimensionele biplot laat zien dat de voorspelde factor scores nauwkeurig genoeg naast het tijdpad te liggen om bruikbaar te zijn (FIGURE 130, pagina 208). In de vierde studie, besproken in hoofdstuk 10, omvat de empirische context de 30 ondernemingen genoteerd aan de DOW en de geaggregeerde resultaatmeting in de vorm van de trend van de DOW index. Het momentum model verklaart en voorspelt met modellen waarin gedecomposeerde spectramap factoren van het totaal vermogen momentum en operationeel inkomen zijn toegepast als onafhankelijke variabelen. S*tandardized* P*rincipal* C*omponents* A*nalysis* (SPCA) is gebruikt om vast te stellen welke vertraging van de factor variabelen noodzakelijk is om de de DOW Jones index te kunnen verklaren en te voorspellen. Het resultaat van deze vier studies levert empirisch bewijs voor de voornaamste onderzoekshypothese dat accounting variabelen van de drie informationele dimensies beschikken over verklarend en voorspellend vermogen in het TEMA raamwerk.

12.7 Conclusie

Meer inzicht in de bedrijfseconomische trends bij een onderneming alsook de mogelijkheid om deze te vergelijken met die in de markt lijkt mij nuttig voor alle gebruikers van financiële rapportages. Ook bij de besturing van de onderneming en het bepalen van de beloning van het management bestaat behoefte aan meer toekomstgerichte informatie. Op basis van dit onderzoek trek ik drie conclusies:

1. Het TEMA raamwerk is door mij getoetst met empirisch onderzoek van aan de AEX en de DOW genoteerde ondernemingen en dit levert nuttige informatie op.
2. Het gebruik van modellen op basis van het TEMA raamwerk blijkt niet beperkt tot de performance meting van een individuele onderneming maar kan ook worden toegepast voor beursindex analyse.
3. Econometrische accounting modellen op basis van het TEMA raamwerk kunnen de besluitvorming faciliteren gegeven de hoge succes score.

Gomaa *et al.* (2008) bestudeerden het effect van een beslissingsondersteunend instrument en de aanwezigheid van druk om resultaat te leveren en concluderen dat met een toename van de betrouwbaarheid van het instrument, besluitvormers dit vaker willen gebruiken. Opvalled is de observatie dat wanneer een beslissingsondersteunend instrument een betrouwbaarheid heeft van meer dan 80% dat dit dan zal worden gebruikt in circa 60% van de gevallen met slechts

één drukfactor om resultaat te leveren. Echter, dit percentage neemt tot circa 80% bij vier drukfactoren. Bovendien, als een beslissingsondersteunend instrument een betrouwbaarheid heeft van meer dan 90% dan zijn besluitvormers bereid om in 90% van de gevallen dit te gebruiken onafhankelijk van het aantal drukfactoren. Het succespercentage van de statische simulatievoorspellingen van mijn TEMA modellen ligt tussen 78%–90% voor de trend van het eigen vermogen van de DOW genoteerde ondernemingen en tussen 75%–83% voor de DOW Jones index. Daarom meen ik dat modellen gebaseerd op het TEMA raamwork besluitvormers kunnen ondersteunen.

12.7.1 Additional disclosure

Zoals eerder besproken, Kaplan & Norton (1996) zijn van mening dat financiële cijfers beter niet gebruikt kunnen worden voor strategische besluitvorming over onderwerpen gericht op de toekomst omdat het *lagging performance indicators* zijn. Met deze studie toon ik aan dat TEMA variabelen over eigenschappen beschikken die hen wel degelijk geschikt maken om te worden gebruikt als *leading performance indicators* van een onderneming (net wealth) of een markt (stock index). Ik heb aangetoond dat het mogelijk is om de trend te verklaren van het eigen vermogen (equity) *ex post* met twee TEMA variabelen: *total wealth force* en *operating income force*, als proxy van de samenstellingsdynamiek van het vermogen en die van de bedrijfsdynamiek. Bovendien blijkt het mogelijk om met TEMA modellen *ex ante* het eigen vermogen in vele voorbeelden correct te voorspellen meerdere kwartalen in de toekomst. Met dezelfde methode blijkt het mogelijk de trend van een beursindex te verklaren en te voorspellen. De vraag in hoeverre TEMA modellen met meer gedetailleerde financiële of operationele variabelen dit resultaat repliceren wordt niet beantwoord in dit onderzoek. Nadere studies moeten aantonen in welke mate de associatie tussen accounting variabelen zoals door mij vastgesteld bij de AEX en de DOW ondernemingen ook in andere voorbeelden aanwezig is dan wel met andere tijdreeksen en zo mogelijk ook met niet-financiële variabelen.[14] Net als Blommaert (1994A), beveel ik aan om de (te publiceren) jaarrekening uit te breiden met force en momentum metingen met inbegrip van de wijziging in de samenstelling van de balans. Dit is, bijvoorbeeld, goed mogelijk met de *common size format momentum* of *force ratio*, zoals voorgesteld in deze dissertatie. Het is relatief eenvoudig te berekenen en niet bijzonder ingewikkeld om te begrijpen voor degene die al gewend is om te werken met *common size format* jaarrekeningen.

12.7.2 Een boekhouding van force & momentum

De methodologie van Ijiri biedt mogelijkheden om te voorzien in een accounting informatiesysteem dat het management in staat stelt om in 'control' te zijn. Zijn redenering is dat de toepassing van driedimensionaal boekhouden de bruikbaarheid van accounting informatie vergroot (de gegevens zijn immers in principe al voorhanden) en dat ook de effectiviteit van de financiële administratie verbetert (zie ook: Bell *et al.* 1997). Het management kan dan als het ware de gordijnen opzij schuiven die hangen voor het venster op de toekomst. Ijiri neemt hiermee wel een stap over de grens van *financial accounting* naar *management accounting*. Het vergt niet veel voorstellingsvermogen om in te zien dat driedimensionaal boekhouden naar intentie en methode breekt met de strikte definitie van financial accounting. Hij neemt met TEMA een initiatief tot vernieuwing van het boekhouden in theorie èn praktijk. Ijiri streeft naar de administratie van economische feiten met een historische betekenis èn (zo mogelijk) hun

[14] In een verkennende studie naar TEMA segmentmodellen bleek het mogelijk om de trend van het eigen vermogen te verklaren en te voorspellen op basis van slechts één uit vier segmenten.

toekomstige betekenis voor de financiële positie van de onderneming. De relevantie van TEMA blijft in dat geval niet beperkt tot alleen het domein van de financiële administratie en rapportage.

12.7.3 Beursanalyse

Keil *et al.* (2004) toonden aan dat de voorspellingen van beursanalisten van het bedrijfsresultaat niet perfect zijn gecorreleerd het uiteindelijke resultaat. Zij concluderen op basis van hun onderzoek van de schattingen van meer dan 100 analysten: '...een statistische consequentie is dat de meest optimistische en de meest pessimistische voorspellingen gewoonlijk te optimistisch en te pessimistisch zijn. De nauwkeurigheid kan worden verbeterd door de voorspellingen af te zwakken in de richting van het gemiddelde.' Zij menen hiermee het succes van tegensgestelde investeringsstrategiën deels te kunnen verklaren. Mijn studie had niet tot doel om het vermogen te testen van het TEMA raamwerk om het bedrijfsresultaat te voorspellen of de beurskoers van ondernemingen. Mijn doel was om de algemene relatie tussen variabelen in het TEMA raamwerk empirisch te onderbouwen. Ik heb wel spectramap factor decompositie toegepast op momentum metingen van de 30 bedrijven die deel uitmaken van de DOW Jones index. Met de gedecomposeerde factoren bleek het mogelijk om de trend van DOW te verklaren en te voorspellen. Daarnaast maakte de visuele analyse van spectramap biplots met zes dimensies duidelijk dat slechts één van 30 bedrijven is gepositioneerd nabij het barycenter en zich derhalve beweegt als het gemiddelde van de DOW Jones index: Exxon Mobil (XOM). Vervolgens, bleek het TEMA model met uitsluitend Exxon Mobil TEMA variabelen in staat om de trend van de DOW Jones index correct te voorspellen voor vier kwartalen (FIGURE 123, page 205).

12.7.4 Consequenties voor toekomstig onderzoek

Het lijkt zinvol om de samenstellingen van jaarrekeningen uit te breiden met momentum en force metingen. De analyse hiervan zou niet beperkt moeten blijven tot de ontwikkeling van het eigen vermogen maar ook naar die van de samenstellende delen van de balans.

Het lijkt goed mogelijk om op basis van het resultaat van dit onderzoek ook te onderzoeken welke mate van associatie is vast te stellen tussen TEMA variabelen van beursgenoteerde ondernemingen en de beurswaarde van hun aandeel als een alternatief voor modellen gebaseerd op inkomen gerelateerde variabelen (Barniv & Myring 2006, Bird *et al.* 2001, Damant 2001). Mogelijk is een tweede onderzoekslijn de studie naar de slaagkans van TEMA modellen in vergelijking met alternatieve waarderingsmodellen van het bedrijfsresultaat (Jenkins 2003, Richardson & Tinaikar 2004). Een derde onderzoekslijn is die naar de toepassing van spectramap factor decompositie en visualisatie voor investerings portfolio management. Afgezien van de identificatie van ondernemingen met beursgemiddeld gedrag kan het localiseren van ondernemingen met contrasterende posities in biplots nuttig zijn om portfolio's te balanceren (Haensley 2003). Nader onderzoek naar de verklarende en de voorspellende waarde van TEMA modellen bij andere markt indices lijkt daarom nuttig maar zullen wellicht beperkt moeten blijven tot sub-panels van industrie segmenten.

12.7.5 Managen met modellen?

Volgens Wouter Bos, minister van Financiën, mag '…de schijnnauwkeurigheid van een modelwerkelijkheid met veel cijfers achter de komma … nooit reden zijn om het gezond verstand uit te schakelen. *Better roughly right than exactly wrong*.'[15] Ofschoon Bos reageert naar aanleiding van kritiek op zijn beleid is zijn reactie exemplarisch voor menigeen die zich geconfronteerd zien met het resultaat van econometrische modellen.[16] Elke inspanning tot het modelleren van sociale fenomenen resulteert per definitie in een model waarmee de 'werkelijkheid' aanzienlijk wordt vereenvoudigd. Vanzelfsprekend moeten modellen met 'gezond verstand' worden gehanteerd, ergo, een belangrijk doel van modelleren is juist om het rationeel vermogen aan te scherpen. Bos maakt bij zijn redenering eigenlijk twee fouten. De eerste fout is dat bij het econometrisch modelleren wel degelijk rekening wordt gehouden met de kans dat een bepaalde uitkomst juist danwel onjuist is. Elk modelresultaat is 'roughly right' en hierbij wordt aangegeven welke foutmarge acceptabel is. Dit heeft niets te maken met het aantal 'cijfers achter de komma' maar alles met de kwaliteit van het model. De tweede fout is dat een model geen doel op zich is maar een instrument om te komen tot inzicht over de kwantificeerbare aspecten van een bepaald (economisch) fenomeen.

Vanuit het door het gebruik van modellen verdiept inzicht kan de discussie worden gevoerd over micro- of macro-economisch beleid, Echter, het beperkte kader van econometrische modellen wordt al te vaak overschreden door beleidsmakers die menen dat een modelwerkelijkheid veel, zo niet alle, aspecten van de bedrijfshuishouding of de economie kan omvatten. Juist dit baart Heertje (2006, 37) grote zorgen: '…vooral bedrijfseconomen en accountants, die de blik uitsluitend richten op de calculeerbare werkelijkheid … dragen bij tot het misverstand … dat economisch op één lijn staat met financieel.' Heertje stelt dat de *subjectieve* welvaart en *objectieve* schaarste behoren tot de kern van de economie. Verwarring ontstaat met de poging om met financiële waarde de welvaart te objectiveren terwijl de schaarste wordt gesubjectiveerd.

Waar Bos terecht op wijst is het gegeven dat de *intuïtie* achter een model moet aansluiten op wat het 'gezond verstand' als acceptabel aanvaart. Maar hiervoor hanteert de wetenschap strenge normen. Het is niet moeilijk om een model in elkaar te 'schroeven' dat statistisch geldige resultaten genereert maar economisch gezien wankelt. Daarom de eis dat het theoretisch uitgangspunt *vooraf* wordt uitgesproken *voordat* een model wordt ontwikkeld. Pas als de modelresultaten in overeenstemming zijn met het theoretisch kader mogen we spreken in termen van 'right' maar liever nog: 'roughly right.'

12.7.6 Blik op de toekomst!

Momentum accounting biedt de mogelijkheid om vast te stellen in welke mate accountingvariabelen beschikken over een verklarend èn voorspellend vermogen. Hiermee is het belangrijkste punt of kritiek van Fraser (1993, 157) naar mijn mening verworpen, namelijk dat bij TEMA '…nuttige informatie eerder door toeval ontstaat dan door ontwerp.' TEMA levert informatie op vanuit een dynamische perspectief die besloten ligt in de jaarrekening. Tussen de temporele dimensies van het driedimensionele TEMA raamwerk is sprake van een structurele samenhang: *winstkracht (force)* aggregeert naar *momentum* en dit aggregeert naar *vermogen (wealth)*. Uit

[15] Wouter Bos, 'Niet alles is in modellen te vatten.' *De Volkskrant*, dinsdag 2 oktober 2007, 11.

[16] Drie lezenswaardige boeken ter introductie zijn: Franses (2002), Gowers (2002) en Langenberg *et al.* (2001). Franses (1998B) bespreekt diepgaand dergelijke kritiek op de econometrie in het algemeen.

deze studie blijkt dat het mogelijk is om econometrische modellen op te stellen van variabelen uit het driedimensionele raamwerk en causale verbanden zichtbaar en toetsbaar te maken, zowel ex post als ex ante. Dit levert empirisch bewijs dat het eigen vermogen zich ontwikkelt gegeven een bepaalde trend bij aan de AEX en de DOW genoteerde ondernemingen. Het is opmerkelijk dat de financieel-economische dynamiek van het bedrijfseconomisch systeem is te traceren en te modelleren op basis van informatie uit de financiële administratie.

In deze studie is het theoretisch uitgangspunt het driedimensioneel TEMA raamwerk van de accounting theory van Yuji Ijiri. Dit onderzoek staaft op basis van empirisch onderzoek de geldigheid van de algemene relatie assumptie van driedimensionaal boekhouden en TEMA. Met onderzoek van jaarrekeningen van bedrijven die deel uitmaken van de AEX en de DOW is gepoogd om verbanden te ontsluiten tussen accountingvariabelen in het TEMA raamwerk. Hierbij is de structuur in beeld gebracht met spectramap decompositie en in tijd met ARIMA tijdreeksmodellering. Daarnaast is op basis van econometrische modellen de trend in de ontwikkeling van het eigen vermogen ex post verklaard en ex ante voorspeld van aan de AEX en de DOW genoteerde ondernemingen. Hiermee is de geldigheid onderbouwd van de algemene relatie tussen accounting variabelen uit de informationele dimensies van het TEMA raamwerk van Yuji Ijiri.

Administratie van winstkrachten kan deel uitmaken van het instrumentarium om de ontwikkeling van de onderneming vanuit een holistisch systeemperspectief te monitoren en voortdurend de vraag te stellen of het momentum van variabelen stabiel is, of het afneemt of dat het toeneemt. Dit onderzoek is een pleidooi om het TEMA raamwerk uit de accounting theorie van Yuji Ijiri in te zetten om meer toekomstgerichte informatie te verstrekken op basis van gegevens uit de financiële administratie voor de analyse en besluitvorming inzake de bedrijfsvoering en bedrijfsbeoordeling.

Appendix

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Papers & Posters
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Color Figures

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[1] Prof. Dr. K.J. Rothmann kindly presented this book to me as a gift. I can recommend it to every student who strives to walk in the footsteps of Student.

Papers & Posters

The following papers and posters were presented during this study:

- 'Dynamic business modeling for management control and accounting.' Paper, *44th World Congress of the International Society for the System Sciences*, July 2000, Toronto, Canada.
- 'The foundation of dynamic simulation for management accounting.' Paper, *24th Annual Congress of the European Accounting Association*, April 2001, Athens, Greece.
- 'Matrix modeling method for discrete dynamic business simulation.' Paper, *4th International Congress Eurosim*, June 2001, Delft, The Netherlands.
- 'Time and the dimensions of the economic accounting system: A mereological exploration.' Paper, *2nd International Conference in General Accounting Theory*, June 2004, Warsaw, Poland.
- 'A time series analysis of proportional change of wealth accounts.' Paper, *ARNN Conference*, October 2004, Tilburg University, Tilburg, The Netherlands.
- 'A time series analysis of 3M financial accounts.' Paper, *ARNN Conference*, September 2005, RSM Erasmus University, Rotterdam, The Netherlands.
- 'The financial accounting model from a System Dynamics' perspective.' Poster, *System Dynamics Society Annual Conference*, July 2006, Nijmegen, The Netherlands.
- 'From data to scores.' Paper, *5th VfCM Annual Conference*, September 2007, Berlin, Germany.
- 'Common size format momentum ratios for financial statement analysis.' Research Forum Paper, 31st Annual Congress of the European Accounting Association, April 2008, RSM Erasmus University, Rotterdam, The Netherlands.

Curriculum Vitae

Eric Melse was born on the 4th of July 1956 in Voorburg, Zuid Holland, the Netherlands. He is married with Ellen K. Hoogeveen and lives together with their son, Alarik.

Eric obtained his secondary school diploma at Noctua, The Hague. He attended the Rotterdam School of Arts for two years. He received his masters degree in art history, formal logic and epistemology at the Vrije Universiteit, Amsterdam. At the Rijksuniversiteit Utrecht he received a post doctoral degree in information science & management. He also received a Masters degree in Business Administration from Bradford/Nimbas University, Utrecht.

From 1984 he worked as a self-employed entrepreneur and consultant for numerous companies. In 1990 he joined KPMG management consultants and was engaged with workflow management systems, information system development and prototyping. From 1995 he was managing director at Oasis (now Ordina Vision Works). He was co-founder of the Norwegian company Paradigm A.S. in 1996 and managed for three years their Dutch subsidiary. At Paradigm he managed the development of dynamic business and accounting simulators and various consultancy projects. From 1999 he worked for three years as director ICT and knowledge management at Randstad Special Products, now YACHT. Next, Eric worked as ICT strategy consultant at the Dutch Ministry of Education, Culture and Science. After that position, he was director for three years of the Centrale Automatiserings-Groep (now Careyn ICT). During that period, with his team of professionals, four WAN-infrastructures were migrated to a single, role defined, fault tolerant client-server architecture in compliance with NEN-7510, the Dutch information security standard for health care organizations. Currently he is assistant professor business intelligence at Nyenrode Business Universiteit, Breukelen, the Netherlands.

Besides his regular work, Eric has been active as executive trainer, management consultant, teacher and writer. He wrote a course on color theory, design and application for the Leidse Onderwijsinstellingen (LOI) and teached it for over a decade. In 1992, in Berlin, he won the *Karl Miescher-Stiftung Preis zur Farbenlehre* with his study on trichromatic color mixing. He lectured on subjects in information technology, management accounting and business intelligence at Hogeschool InHolland Rotterdam & Alkmaar, Hogeschool Utrecht-FEM Connect, Hogeschool Fontys, Erasmus University and Nimbas University. For the Vereniging Voor Credit Management (VVCM) he lectures dynamic business simulation at their degree program Certified Credit Practitioner. Eric wrote numerous publications, in newspapers, in public and professional journals. He writes columns for RTLZ, the Dutch business television channel and for *f.inc*, the business magazine of the firm Conquaestor, finance professionals, consultants and interim management.

Color figures

The objective of color coding is to facilitate the exploratory and visual analysis of decomposed multivariate (accounting) data with three additional dimensions. This appendix has the color figures of this thesis. Color Figure 10 to Color Figure 14 and Color Figure 17 to Color Figure 20 are spectramap biplots where the Cartesian coordinate system is used in combination with cielab based color coding (Color Figure 1–6). Color coding is discussed in more detail in Chapter 2, page 73.

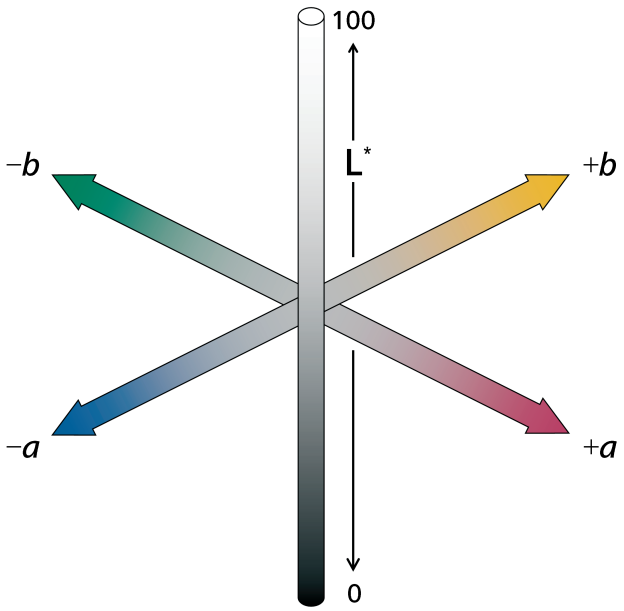
The combined use of the Cartesian coordinate system (x,y,z) and the equidistant perceptual colometric coordinate system (L,a,b) of reflective colors provides a new visual analytics method that truly is six-dimensional. The first three dimensions of the Cartesian system are used to position the table column items as cubes or squares by their Spectral Map Analysis factor loadings and, likewise, the table row items as globes or circles by their factor scores in a three-dimensional double centered biplot, called spectramap. The three dimensions of the cielab system are used to 'paint' all these items on the basis of some quantitative measure. In this study various applications of color coding are discussed in Chapter 4, 6 and 10. By increasing the number of dimensions in visual analysis also the amount of information visualized increases in the statistical interpretation of variance. The success rate of the decomposition of multivariate data tables is measured by the percentage of variance explained with the solution factors. Spectral Map Analysis that is employed in this thesis was developed by Lewi (1976, 1982, 1989) and is discussed in more detail in Chapter 2, page 71.

In the title of the color figures the amount of variance visualized with a color coded spectramap biplot is reported as R^2 measures with four percentages as follows: A|B [C+D], e.g. for Color Figure 20:

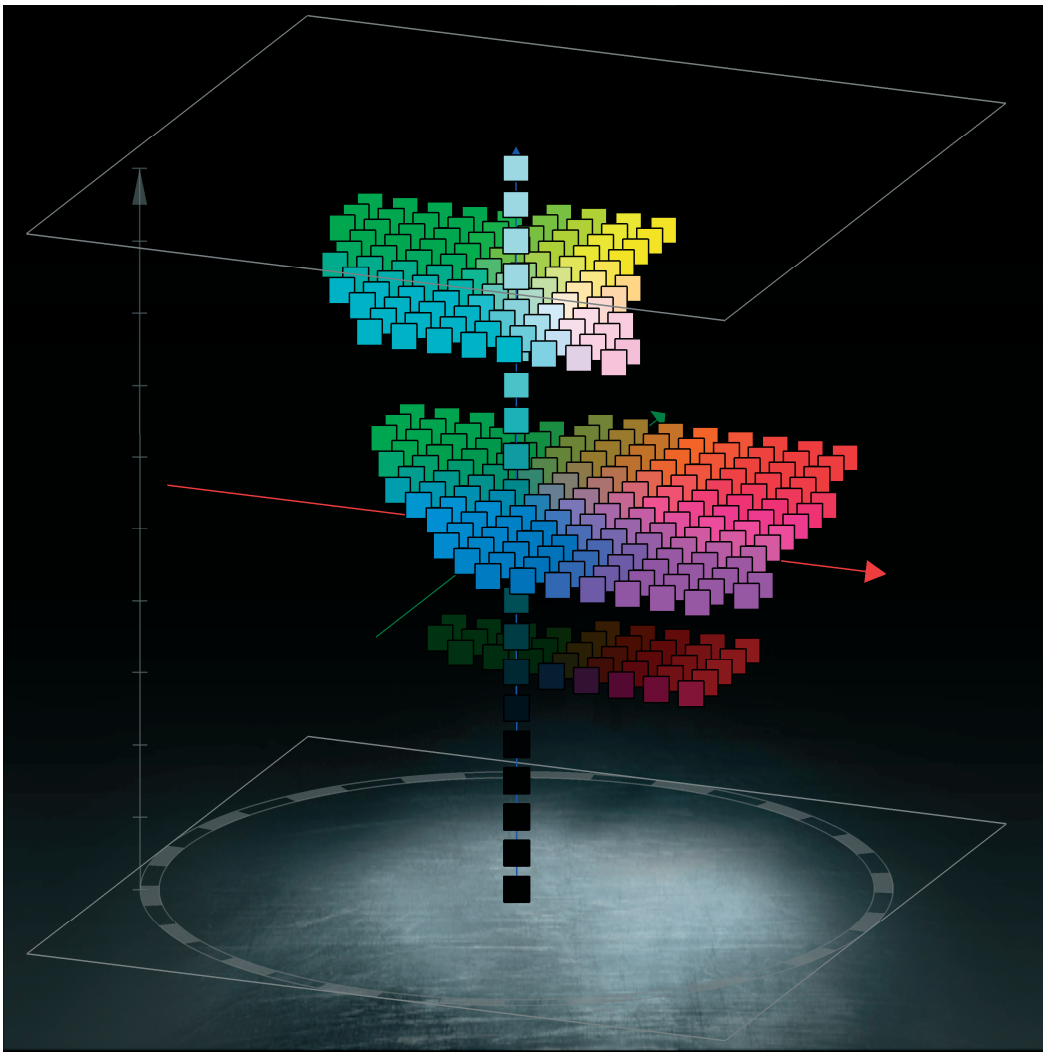
$$R^2 = 73.89|60.96\ [33.57+27.38].$$

The first percentage (A), before the bar, is the total variance visualized in the spectramap biplot, including color coding and independent of the rotation of the data space (x,y,z). The percentage after the bar excludes the variance expressed by the depth dimension (d) of the spectramap biplot (i.e. perpendicular to the projection plane (h,v): 73.89-60.96=12.93%. Depth is indicated in the twodimensional plots with the outline thickness object symbols. The more thick an outline is, the higher above the plane of projection a particular item is positioned. Conversely, the thinner the outline, the lower below the plane of projection a particular item is positioned. The percentages between straight brackets report the total variance (B) visualized in the plane of projection by object position (C: h,v = 33.57%) and by color coding of all objects (D: 27.38%). Thus: B=C+D.

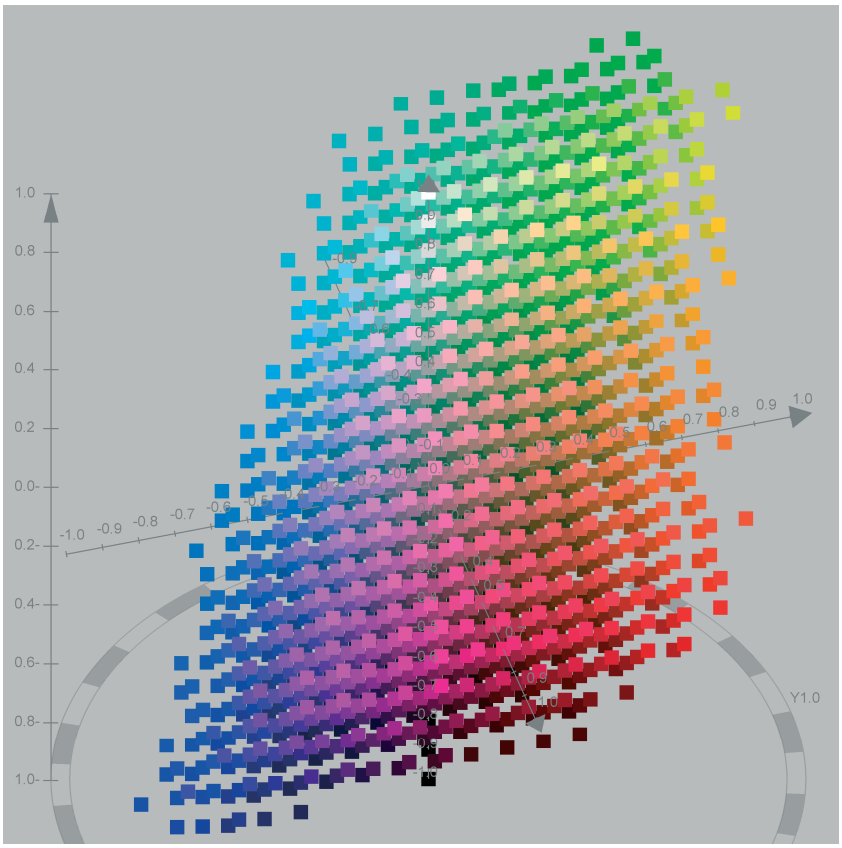
Observe that cielab based color coding does not necessarily create equidistant colors flawlessly due to limitations of the equidistant color space vis-à-vis the data scales of a particular analysis (although the applied algorithm seeks to optimize it). Therefore, the percentage of correctly coded colors is also reported as a percentage. Color printing limits equidistant color reproduction to some extent. Colorimetric research showed that cielab color differences are metrically more equidistant when color differences are small. However, these limitations have little impact on the visual analytics objective of this thesis.



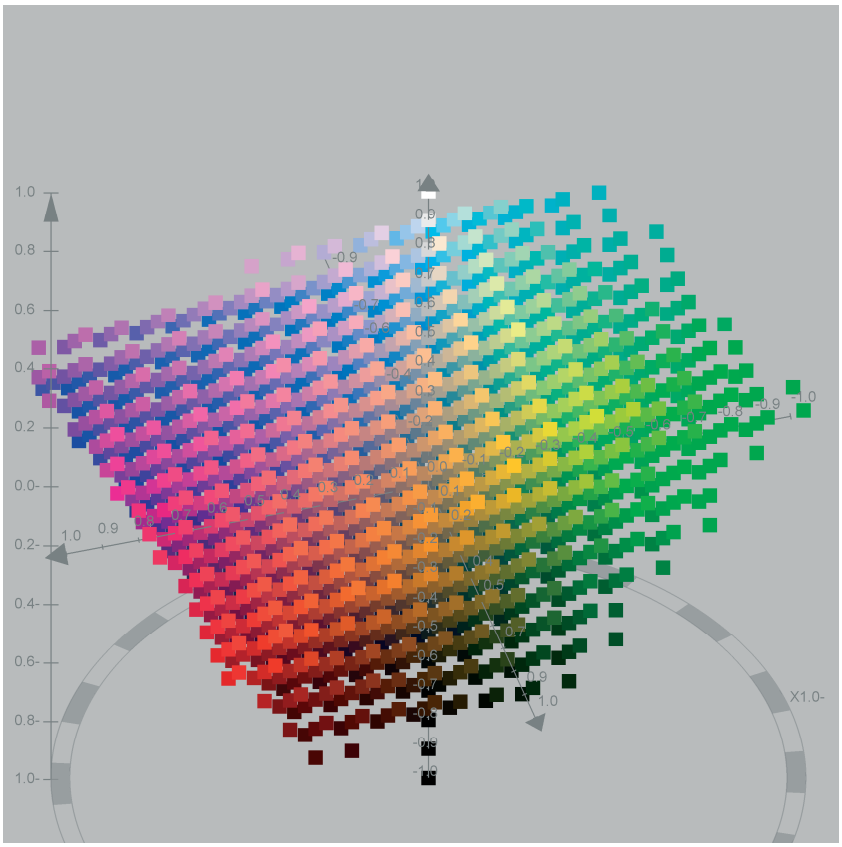
Color Figure 1 CIELAB color space dimensions with their opponent colors.



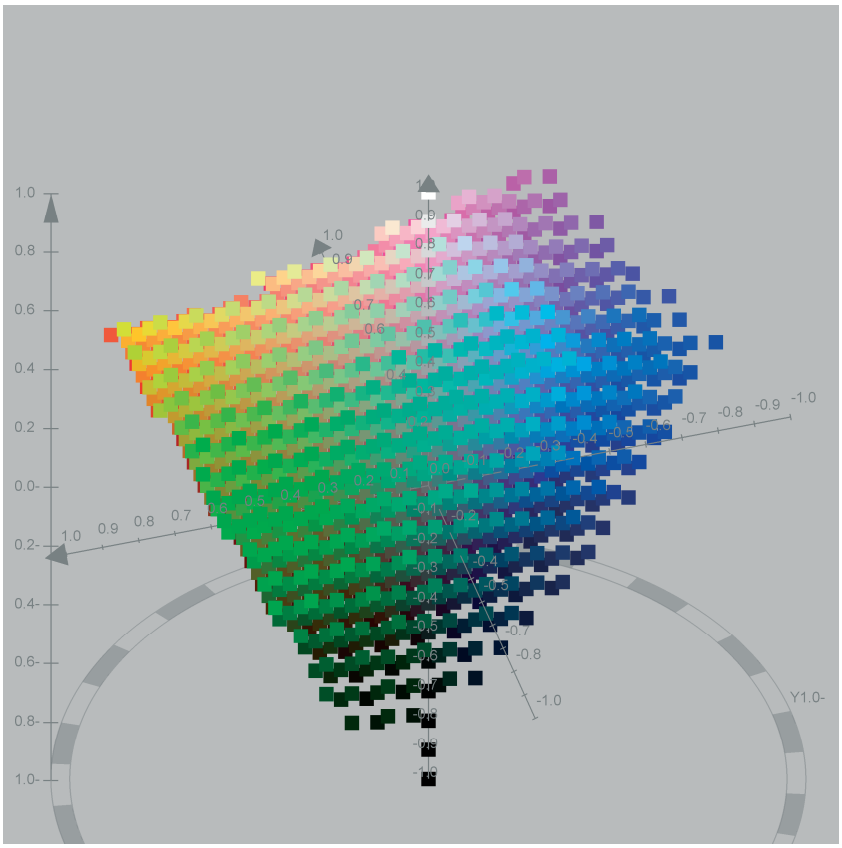
Color Figure 2 Artistic impression of the CIELAB color space dimensions with their opponent colors and equidistant colors at L*=80, 55 and 30.



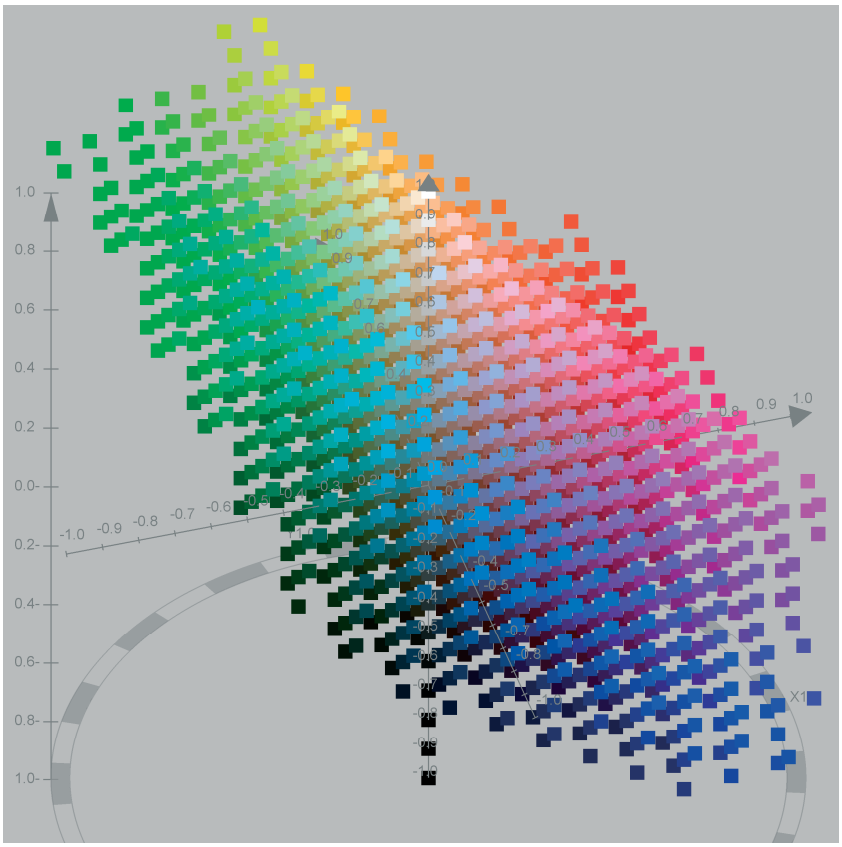
Color Figure 3 Artistic impression of the metric CIELAB-based color solid with equidistant colors for color coding.



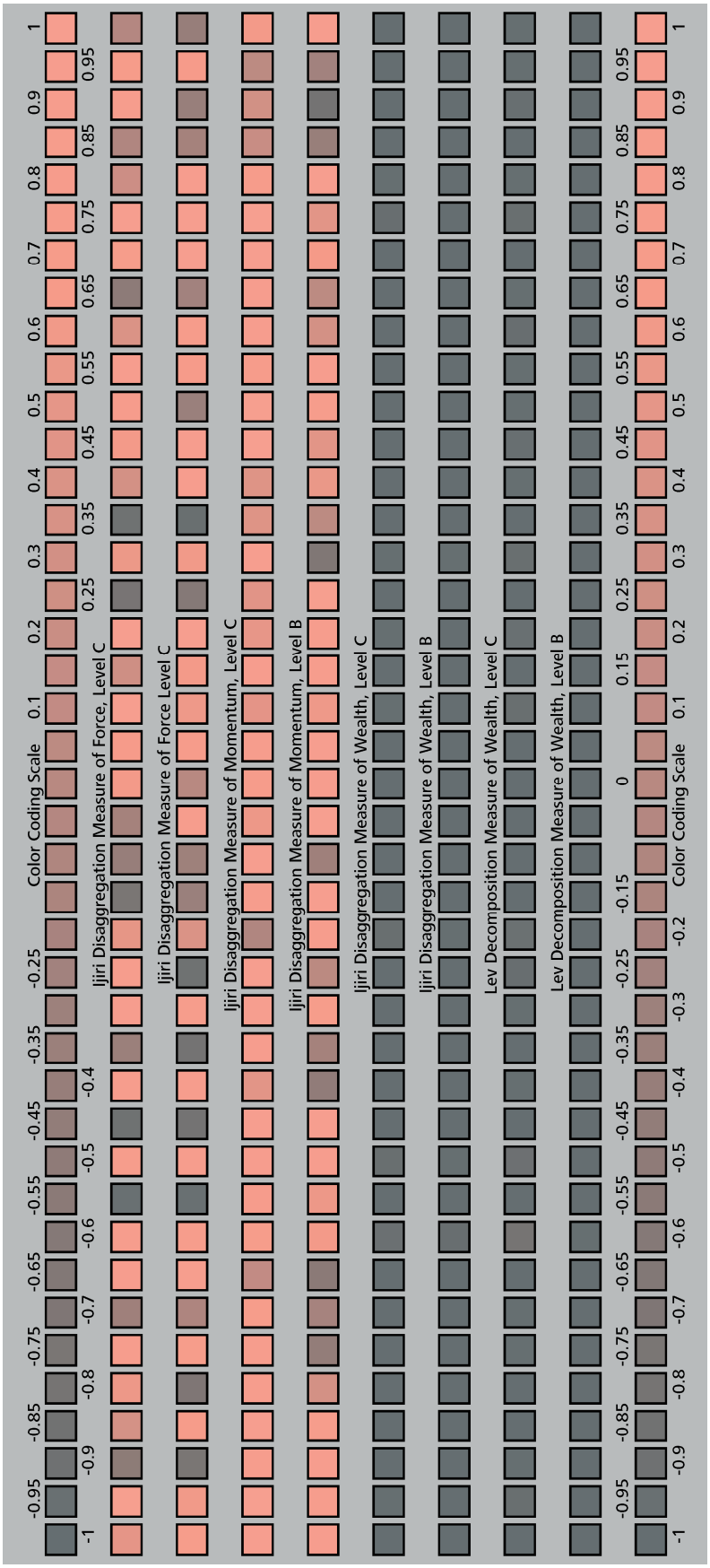
Color Figure 4 Same as Color Figure 3 but 90° rotated.



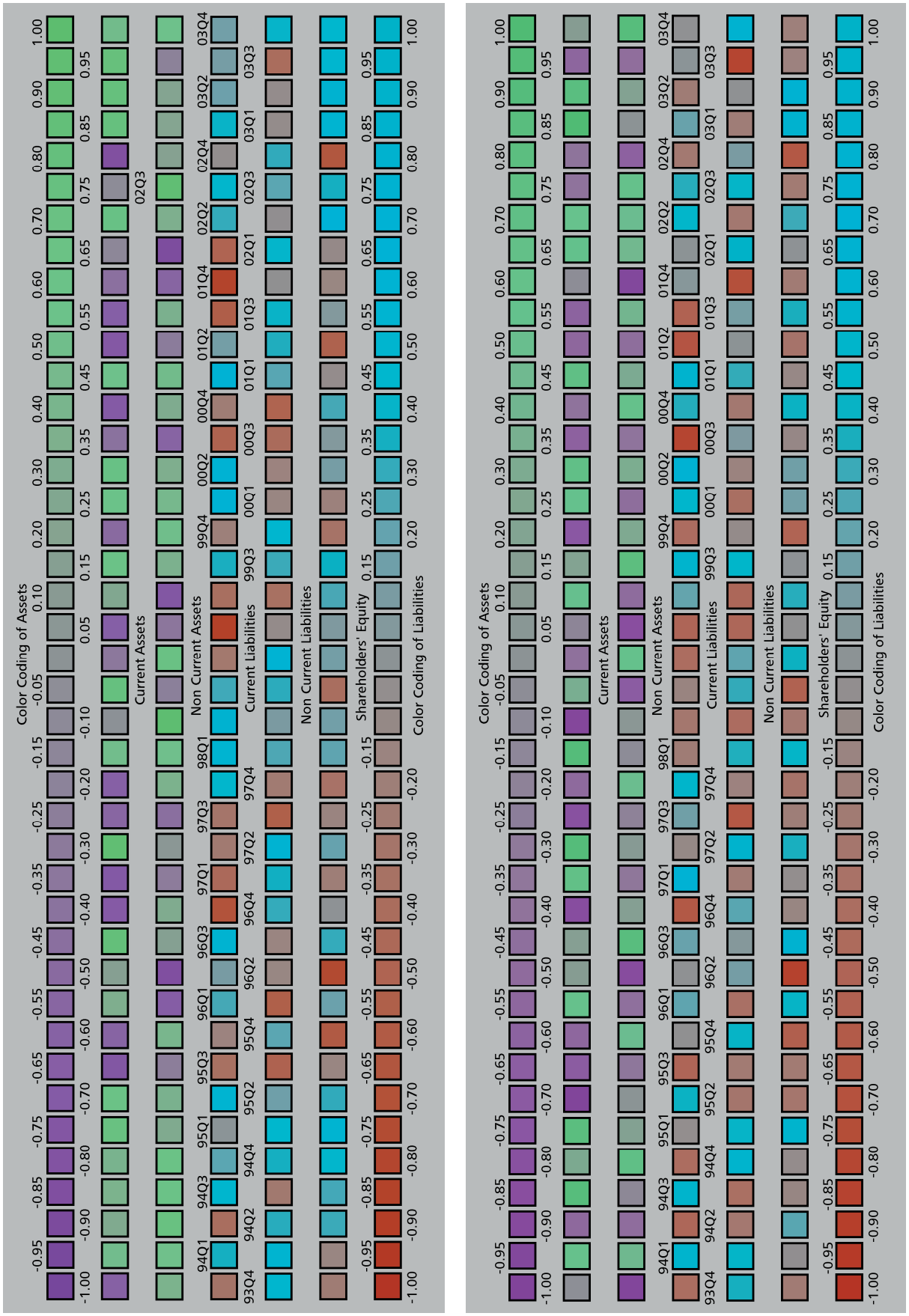
Color Figure 5 Same as Color Figure 4 but 90° rotated.



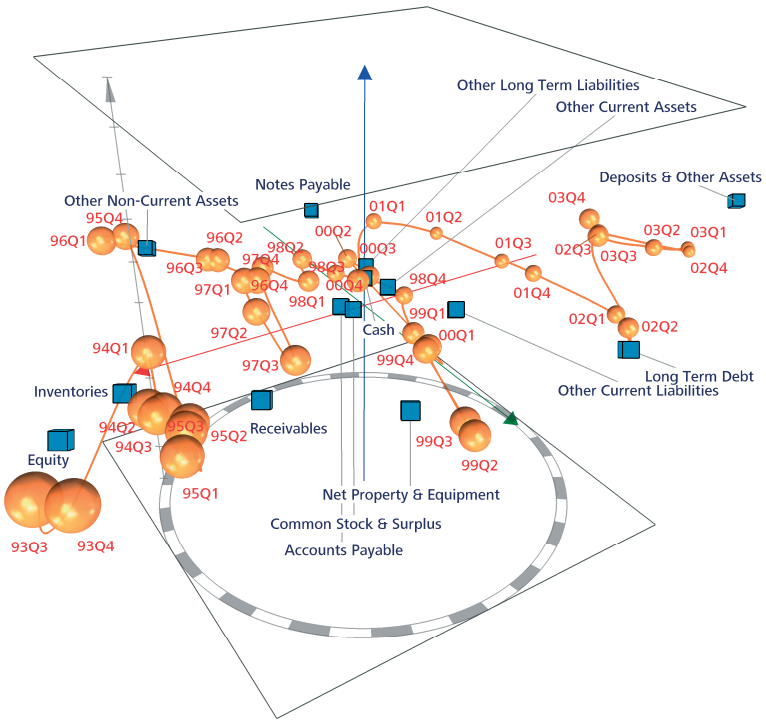
Color Figure 6 Same as Color Figure 5 but 90° rotated.



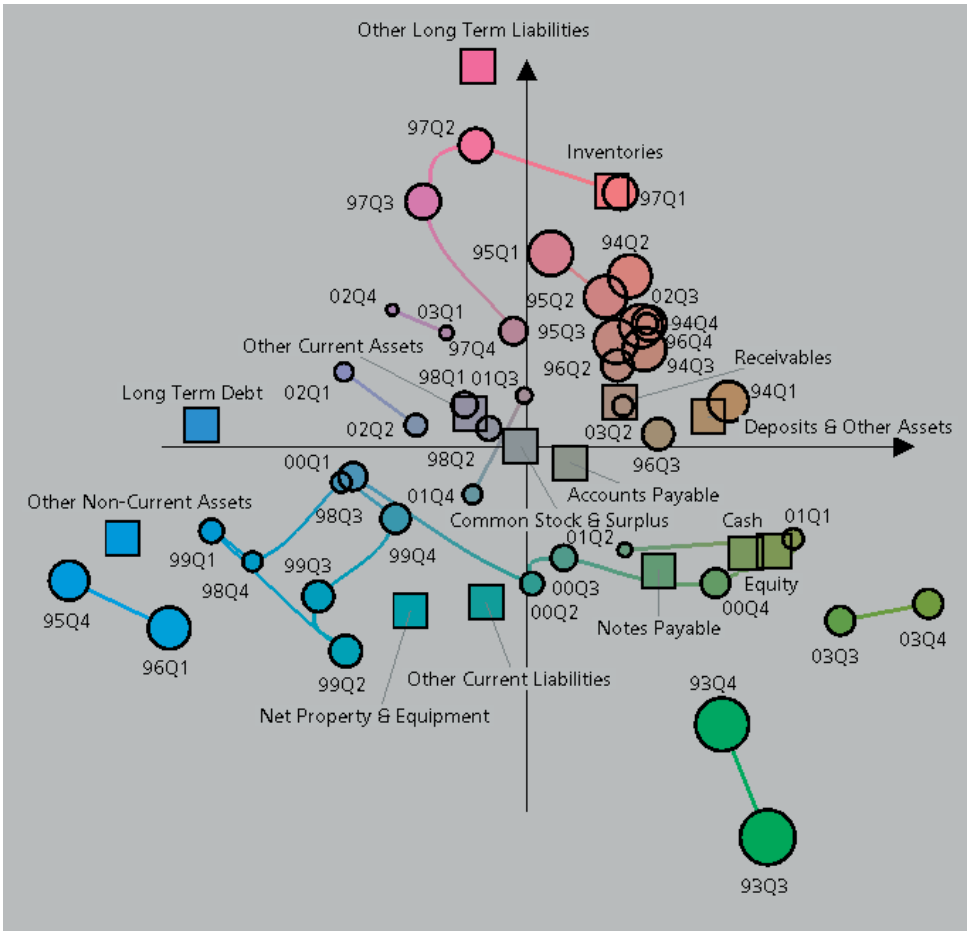
Color Figure 7 3M. Decomposition and disaggregation measures of wealth, momentum and force, 1993Q4-2003Q4. 100% correctly coded colors.



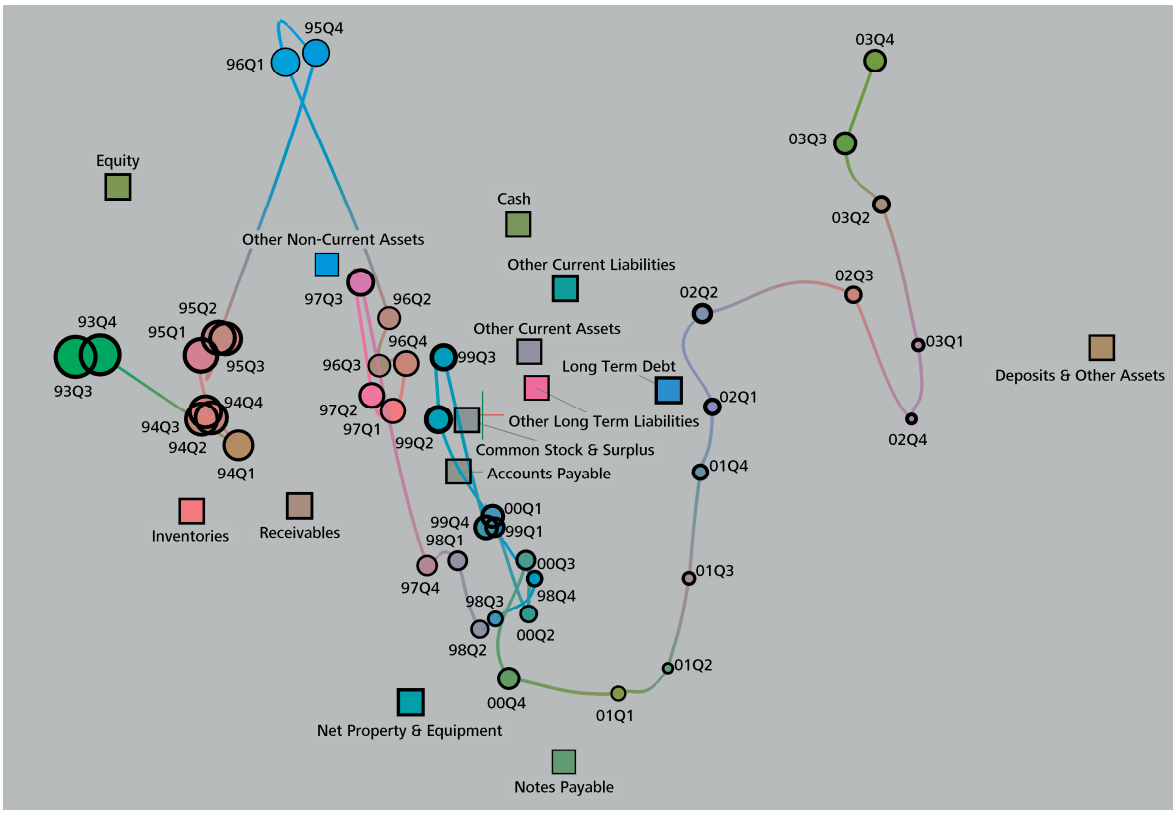
Color Figure 8 3M. Color coded time series. Level B, 1993Q4-2003Q4. Left: momentum. Right: force. Left: 99% correct coded colors. Right: 98.6% correctly coded colors.



Color Figure 9 Spectramap double space decomposition of 3M wealth accounts (level C, 1993Q3-2003Q4). Three dimensional biplot visualization of accounts & time points (by factor 1, 2 & 3, tilted).

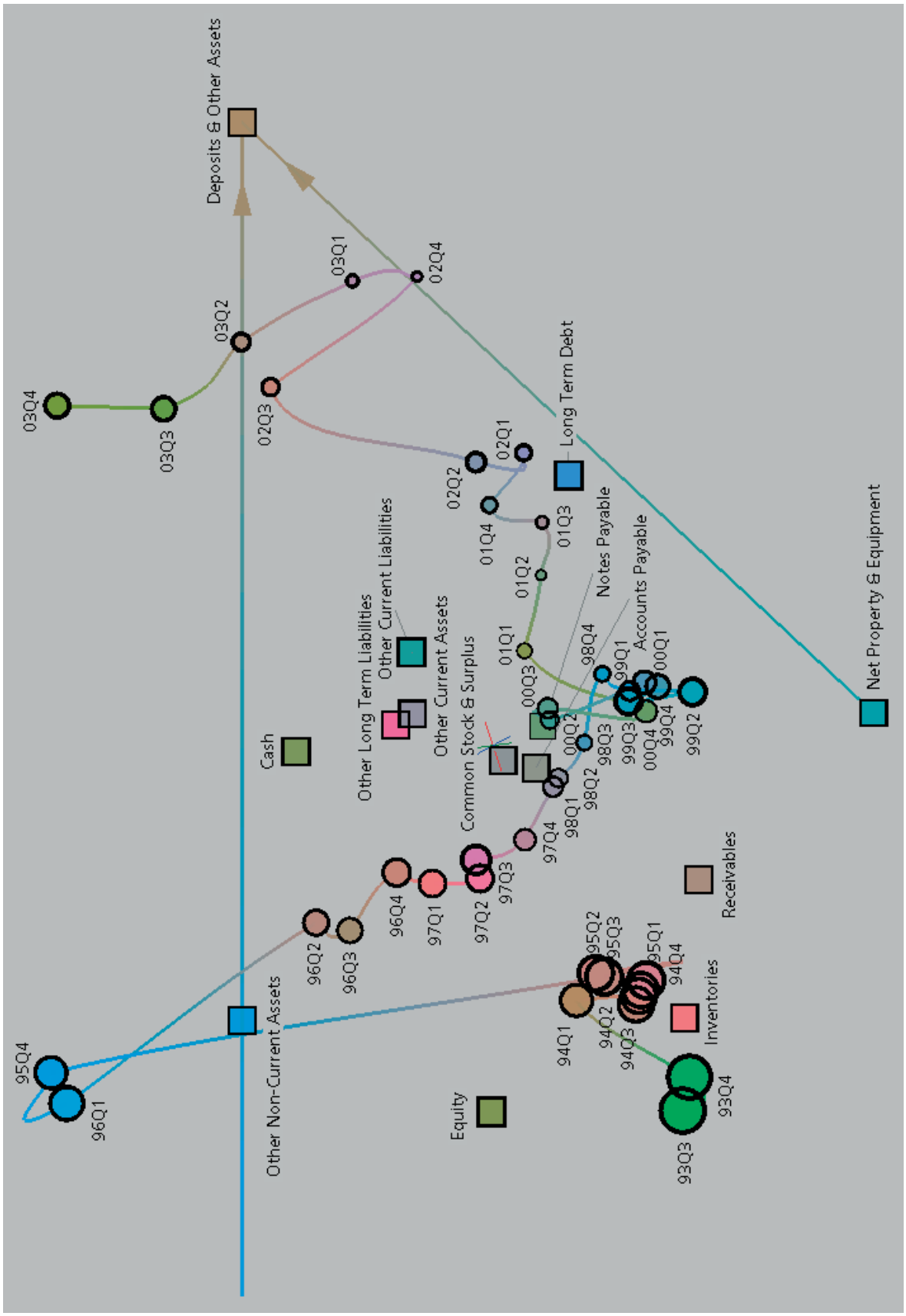


Color Figure 10 Geometry and color coding by factor 4 and 5. R^2 = 9.00|9.00 [9.00]. 92.9% correctly coded colors. Spectramap double space decomposition of 3M wealth accounts (level C, 1993Q3-2003Q4).

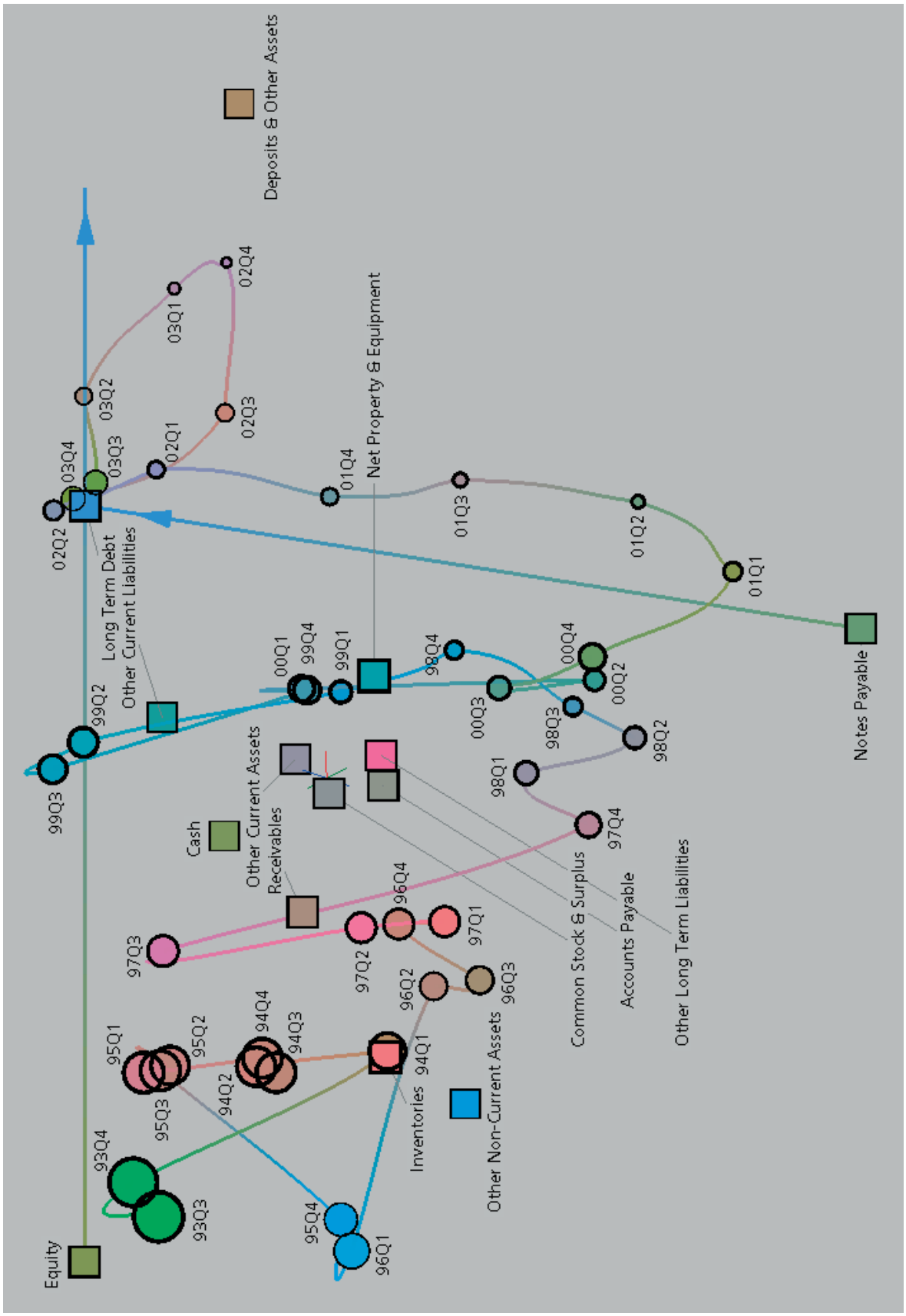


Color Figure 11 Geometry by factor 1, 2 & 3. Color coding by factor 4 & 5. R^2 = 94.79|86.03 [77.04+9.00]. Spectramap double space decomposition of 3M wealth accounts (level C, 1993Q3-2003Q4).

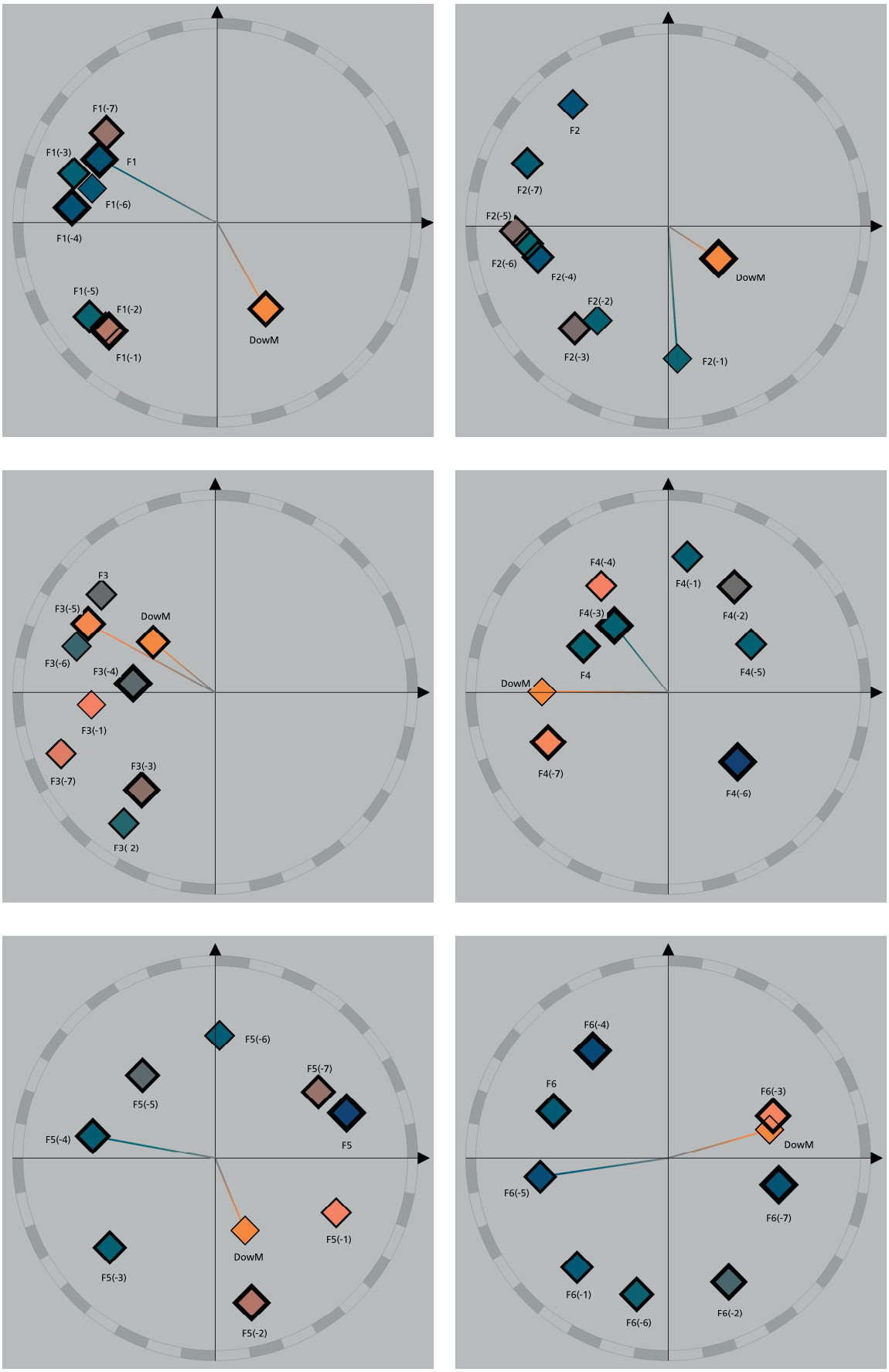
Color Figure 12 Geometry by factor 1, 2 & 3. Color coding by factor 4 & 5. R^2 = 94.79|86.03 [77.04+9.00]. Sequential links based on Color Figure 10 with 92.9% correctly coded colors.



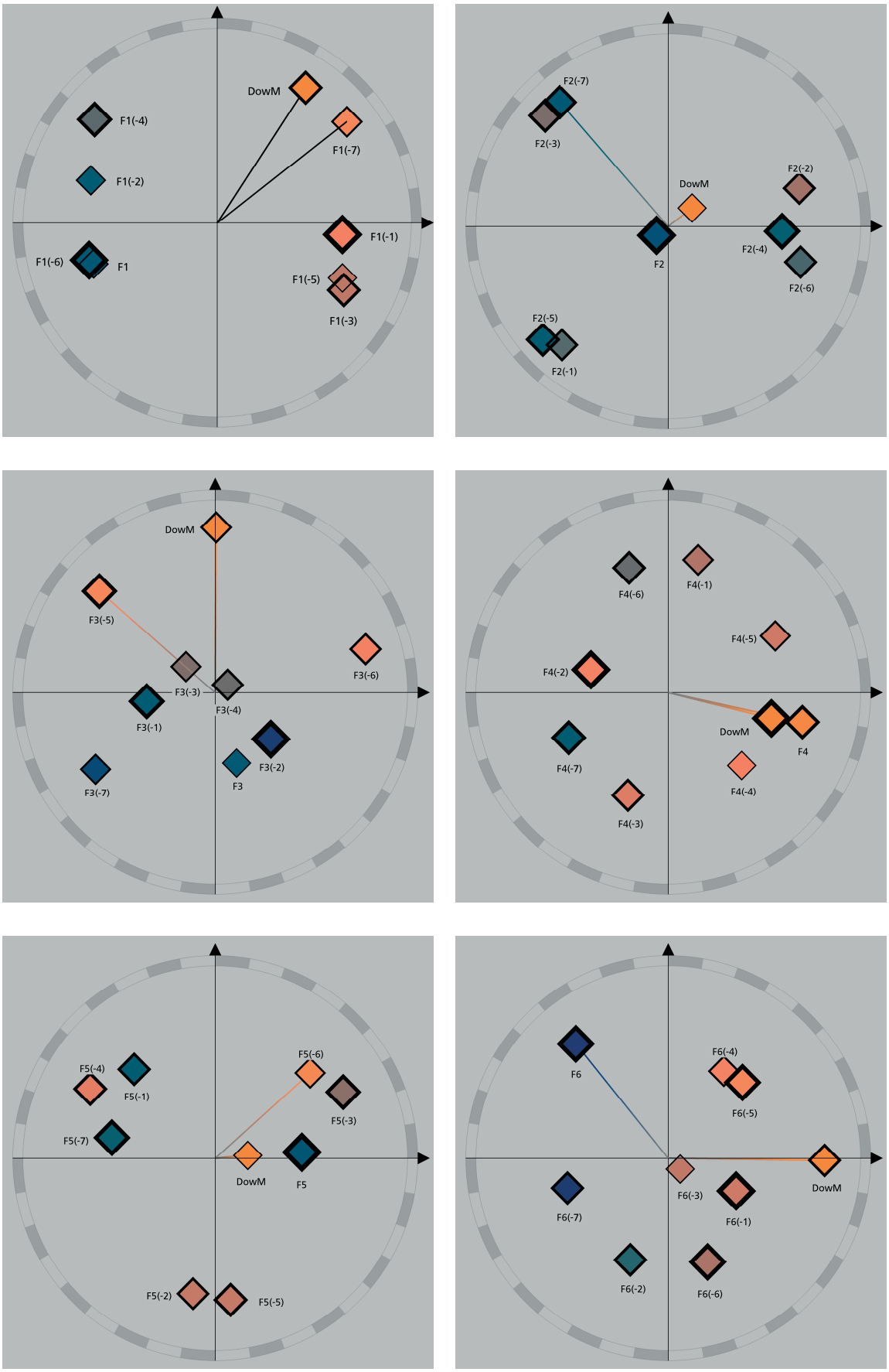
Color Figure 13 Color coded Spectramap, rotated, assets plane. R^2 = 94.79|86.89 [77.89+9.00] with 92.9% correctly coded colors.



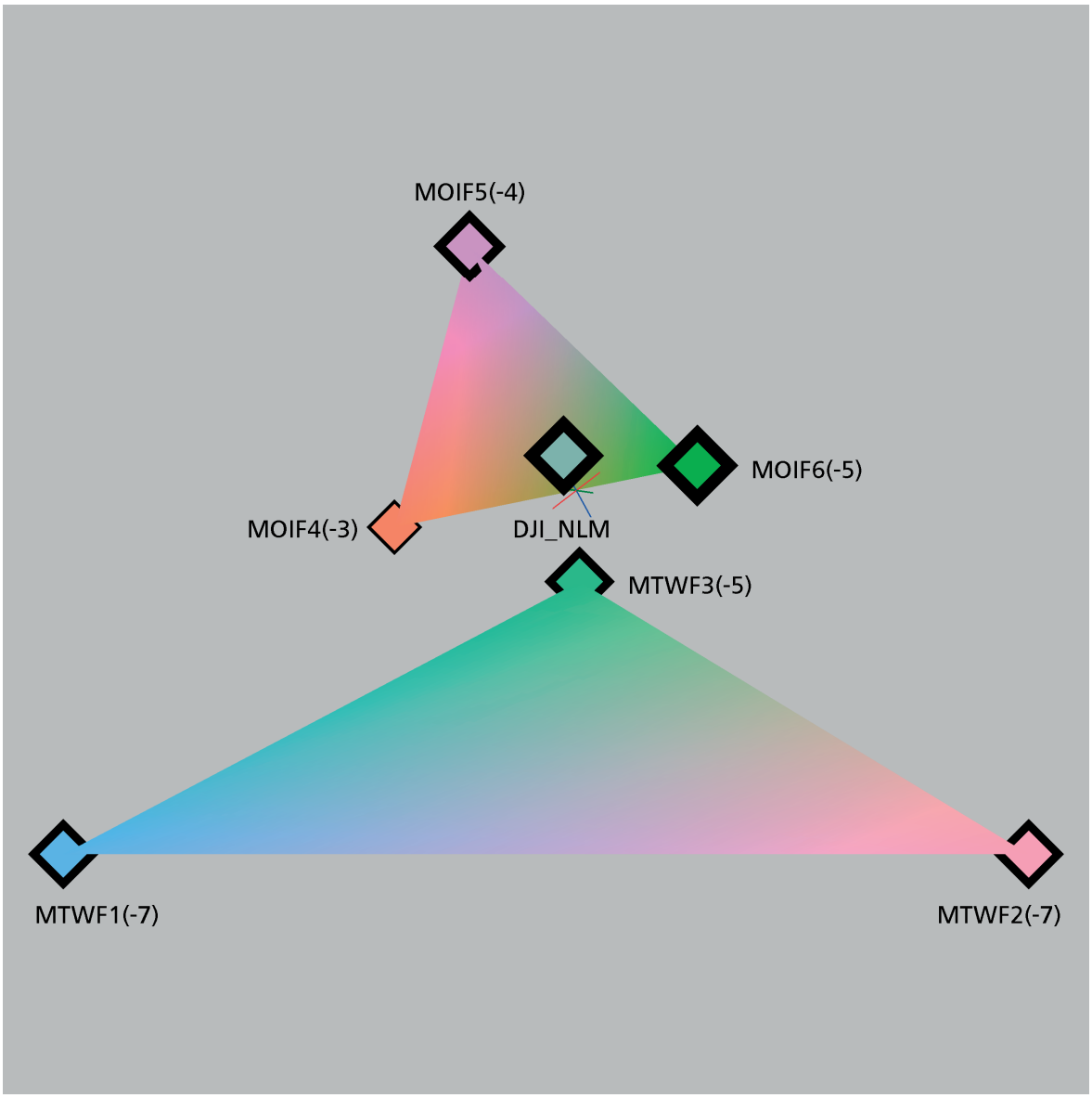
Color Figure 14 Color coded Spectramap, rotated, liabilities plane. R^2 = 94.79|83.16 [74.16+9.00] with 92.9% correctly coded colors.



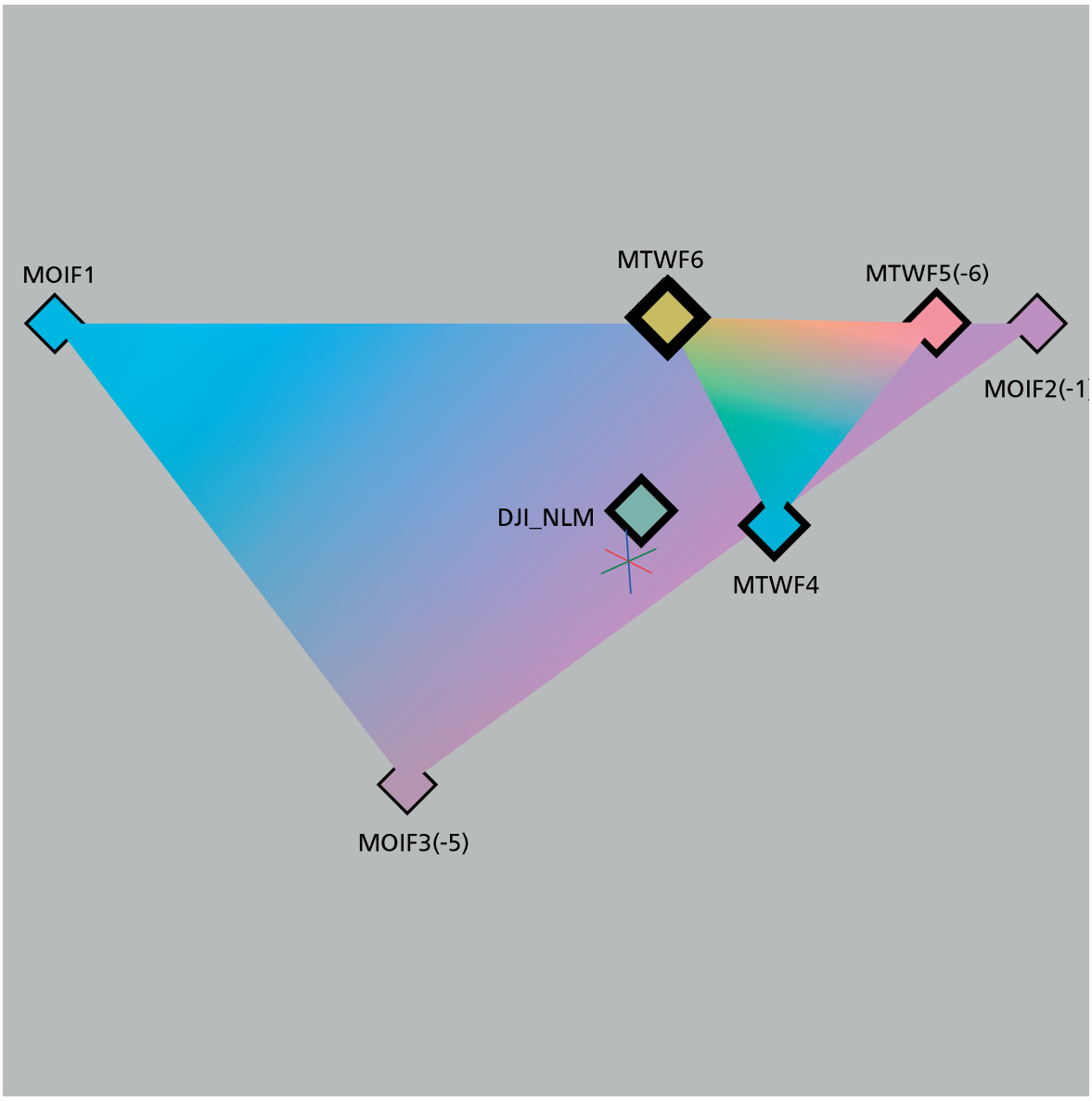
Color Figure 15 Association between the Dow and lagged factors of operating income by angle & coded color. From top left to bottom right, respectively, factor 1 to 6).



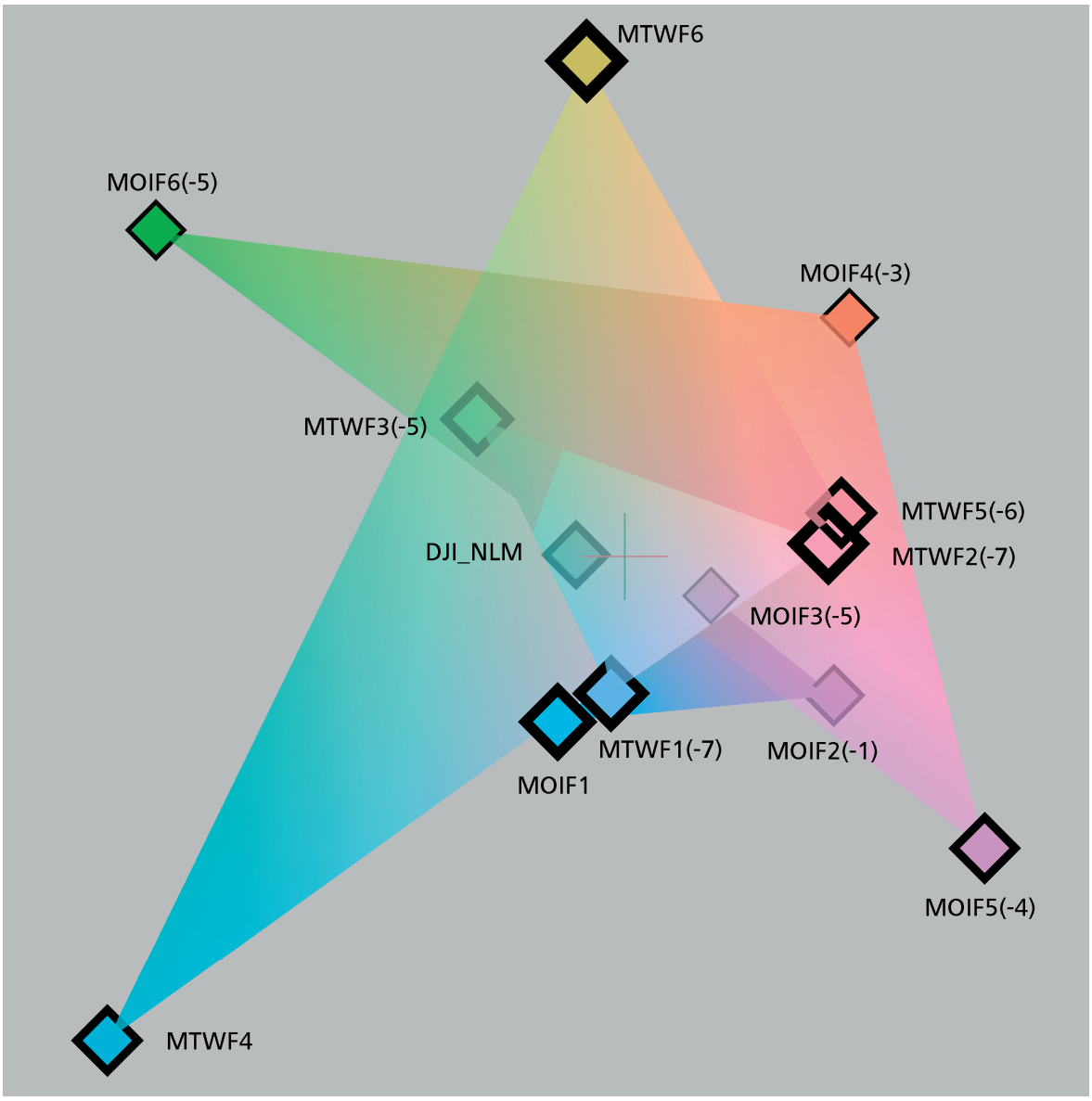
Color Figure 16 Association between the Dow and lagged factors of total wealth momentum by angle & coded color. From top left to bottom right, respectively, factor 1 to 6).



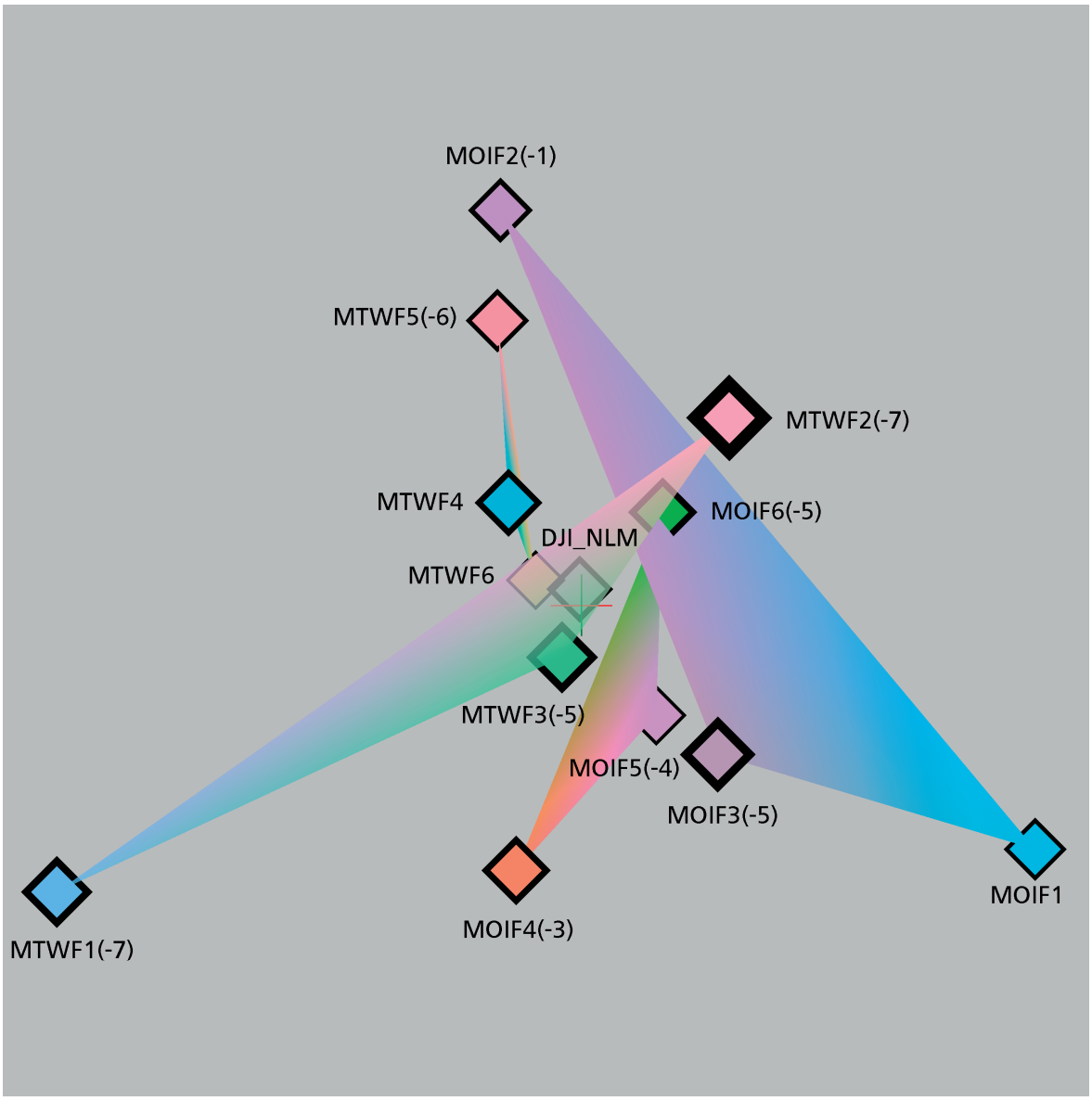
Color Figure 17 Spectramap of total wealth momentum factors projection plane. Geometry by factor 1, 2 & 3. Color coding by factor 4, 5 & 6. R^2 = 73.89|63.69 [36.58+27.38]. 93.7% correctly coded colors.



Color Figure 18 Spectramap of operating income factors projection plane. Geometry by factor 1, 2 & 3. Color coding by factor 4, 5 & 6. R^2 = 73.89|64.87 [37.49+27.38]. 93.7% correctly coded colors.



Color Figure 19 Spectramap of the Dow momentum joint model variables. Geometry and color coding by factor 4, 5 & 6. R^2 = 27.38|19.42 [27.38]. 93.7% correctly coded colors.



Color Figure 20 Spectramap of the Dow momentum joint model variables. Geometry by factor 1, 2 & 3. Color coding by factor 4, 5 & 6. R^2 = 73.89|60.96 [33.57+27.38]. 93.7% correctly coded colors.