The role of firm life cycle in the functioning of capital markets

THE ROLE *of*
FIRM LIFE CYCLE
in the FUNCTIONING *of* CAPITAL MARKETS

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1 INTRODUCTION

Whereas firm life cycle has been a widely investigated topic in the organizational literature, it has only recently received increased attention in the finance and accounting literature. So far, prior studies have mainly focused on how firm life cycle affects firm policies, including its financing, investment, dividend, and compensation policies. Nevertheless, given increased firm dynamics and the associated decrease in the informativeness of financial information, it is – more than ever – important to adopt a dynamic view of the firm in capital markets research rather than treating the firm as a static entity. In my dissertation I shed light on how firm life cycle affects the functioning of capital markets.

> *"Like people and plants, organizations have a life cycle. They have a green and supple youth, a time of flourishing strength, and a gnarled old age. But organizations differ from people and plants in that their life cycle isn't even approximately predictable. An organization may go from youth to old age in two or three decades, or it may last for centuries. More important, it may go through a period of stagnation and then revive. Organizations need not stagnate. Organizations can renew themselves continuously."*

\- John W. Gardner (1965)[2]

1.1. Firm Life Cycle

The organizational literature has since long recognized that a firm is a dynamic entity that evolves over time through distinct stages of development (Quinn and Cameron 1983; Miller and Friesen 1984; Mueller 1972). The chain of consecutive life cycle stages that a firm moves through from its birth to its eventual death is known as the firm life cycle. According to Miller et al. (1984, p. 1161):

> "*[…] each [life cycle] stage would manifest integral complementarities among variables of environment ("situation"), strategy, structure and decision making methods… [O]rganizational growth and increasing environmental complexity would cause each stage to exhibit certain significant differences from all other stages along these four classes of variables…*".

As such, each life cycle stage is a multifaceted construct that captures a unique combination of organizational characteristics. Furthermore, transitions between different stages could arise due to changes in both internal factors (i.e., strategy, structure, and decision making methods) and external factors (i.e., environment).

[2] In "How to Prevent Organizational Dry Rot", *Harper's Magazine* (October, 1965). An excerpt from the original article is retrieved on August 15, 2016 from: https://scholarship.rice.edu/handle/1911/45418

Prior literature has generally distinguished five life cycle stages: Introduction, growth, maturity, shake-out, and decline (Dickinson 2011; Gort and Klepper 1982; Miller et al. 1984).[3] In the *introduction stage*, firms try to establish a viable position in the market by the introduction of new products or services (Miller et al. 1984). Since these firms often lack legitimacy and financial resources, their success is critically dependent on their ability to obtain external support (Cameron and Whetten 1981; Freeman, Carroll and Hannan 1983; Grabowski and Mueller 1975; Quinn et al. 1983). Moreover, in generating a competitive advantage over potential competitors extensive (technological) innovation plays a crucial role (Gort et al. 1982; Mansfield 1962; Miller et al. 1984). Flexibility in decision making is one of the main criteria of effectiveness in this stage as it facilitates the necessary innovation and proactive behavior (Miller et al. 1984; Quinn et al. 1983). Nevertheless, firms in this stage are also more likely to fail than established firms – a phenomenon labeled as "the liability of newness" - as a consequence of, for instance, their limited legitimacy or difficulties faced in competing with established firms (Freeman et al. 1983; Hannan and Freeman 1984; Jovanovic 1982).

If the initial introduction of a new product or service is successful, then the firm could progress to a stage that is characterized by rapid growth and expansion, the *growth stage*. The abundant profitable opportunities lead to substantial investments, which are financed by reinvesting the internally generated cash flows and raising additional external capital (Grabowski et al. 1975; Mueller 1972). These substantial investments may also help firms in creating barriers of entry and can improve firms' relative market positions *vis-à-vis* its current and future competitors (Spence 1977, 1979, 1981; Wernerfelt 1985). More specifically, substantial investments in the production process can facilitate learning – resulting in cost advantages – and excess capacity enables the firm to expand production in response to an increased threat of entry (Spence 1977, 1981). As the complexity of the operating environment increases, the organizational structure becomes less centralized and more attention is paid to the coordination and cooperation among the different departments (Miller et al. 1984; Smith, Mitchell and Summer 1985).

Increased competition, saturation of the market, and a reduction in the available investment opportunities can lead to a decline in the return on investment (Grabowski et al. 1975; Mueller 1972). In the *mature stage*, operating performance stabilizes and the focus shifts to organizational efficiency (Cameron et al. 1981; Miller et al. 1984; Quinn et al. 1983; Smith et al. 1985). The accumulation of internal funds in combination with the decline in profitable investment opportunities increase the likelihood that excess funds are distributed to shareholders in form of dividend payouts or share repurchases (DeAngelo, DeAngelo and Stulz 2006; Grabowski et al. 1975). Whereas firms in the introduction and growth stage tend to act proactively, mature firms are more conservative and rather respond to actions of

[3] It should be noted however that there do exist differences in the number of stages and the labeling of these life cycle stages. For instance, Miller et al. (1984) label the shake-out stage as "revival", which implicitly suggests that firms are generally successful in their efforts to grow rapidly again after a period that has been characterized by slow growth or weak operating performance (i.e., a second growth stage). In accordance with, for instance, Dickinson (2011), I prefer to use the more neutral term "shake-out" as it encompasses not only firms that might be successful in their efforts to return to more profitable stages but also firms that fail to do so. Additionally, Quinn et al. (1983) indicate that some life cycle models only include the stages from introduction to maturity as the further development of the firm may be less predictable (see, for instance, Smith et al. 1985).

competitors (Miller et al. 1984). The stability of mature firms is also reflected in the formalization of rules, procedures and organizational goals (Cameron et al. 1981; Quinn et al. 1983). Yet, innovation still plays an important role, especially in environments that are characterized by intense rivalry among the incumbents (Chen, Katila, McDonald and Eisenhardt 2010; Hambrick 1983). In contrast to the major technological innovations in the introduction stage, however, the innovation in mature firms is more likely to arise from firms' accumulated experience over time (Gort et al. 1982).

Firms that are not able to maintain their competitive position in the market due to, for instance, weak operating efficiency or a failure to remain innovative could end up in the *shake-out stage* (Jovanovic 1982; Jovanovic and MacDonald 1994). Based on insights derived from monitoring the external environment, firms may still be able to reverse the negative trend in their operating performance by strategic renewal, diversification, or both (Quinn et al. 1983). As the institutionalization and formalization of mature firms could have restricted the necessary responsiveness to environmental changes (i.e., structural inertia), a renewed focus on flexibility is key to the success of the restructuring process in the shake-out stage (Hannan et al. 1984; Quinn et al. 1983).

Ultimately, if the firm is not able to get out of the downward spiral of performance, it may enter the *decline stage*. Additionally, this stage can also include firms that failed to establish a viable position in their introduction stage as a consequence of their "liability of newness" or firms from other life cycle stages that were less efficient than their competitors (Freeman et al. 1983; Jovanovic 1982). Firms are trapped in a vicious circle of poor performance arising from their stagnant business models and difficulties in attracting and retaining customers (Miller et al. 1984). Eventually, the inability to return to profitability could force the firm to exit the market, leading to their demise.

1.2. Measuring Firm Life Cycle

Even though the life cycle theory clearly indicates that firms move through distinct life cycle stages, the challenge remains to find a measure that can effectively classify a firm into one of the five stages that have been identified. Ideally, this measure is able to capture the life cycle features that are theorized – and found – in prior literature on firm life cycle. First, the empirical literature indicates that firms develop over the life cycle in a non-deterministic sequence (Miller et al. 1984). That is, firms do not necessarily move from the introduction stage to the decline stage in a predictable way but are more likely to move back and forth along the life cycle continuum. Second, firms do not have to proceed through every life cycle stage (Gort et al. 1982). The "liability of newness" phenomenon, for instance, relates to a scenario in which firms move immediately from the introduction stage to the decline stage without reaching one of the other life cycle stages (Freeman et al. 1983; Hannan et al. 1984). Third, the time spent in the different life cycle stages varies both within and across firms (Quinn et al. 1983; Lippitt and Schmidt 1967). For instance, some firms in the introduction and shake-out stage advance or return quicker to more stable stages as a result of successful innovative and restructuring efforts, and the time firms spend in the growth and mature stage increases with the strength of their competitive position in the market. Finally, the number of firms that reside in a life cycle stage varies across stages, being maximized in the growth and mature stage (Gort et al. 1982; Jovanovic et al. 1994). Overall, the insights that emerge from the life cycle literature suggest that substantial variation exists in firm life cycle across firms.

Common proxies that have been used in the prior literature to measure firm life cycle are firm size and age (e.g. Chen, DeFond and Park 2002; Klein and Marquardt 2006; Wasley and Wu 2006). However, these proxies implicitly assume that firms move monotonically and homogeneously through their life cycles and, consequently, do not capture the substantial variation in firm life cycle across firms (Dickinson 2011). In addition, by relying on size and age it is difficult to distinguish among the distinct life cycle stages. Another life cycle proxy that has been employed in prior studies and that does assign firms to different life cycle stages – albeit in equally large groups – is a composite score of firm age, net capital transactions, capital expenditures, and sales growth (Anthony and Ramesh 1992; Black 1998; Hribar and Yehuda 2015). While the inclusion of firm age assumes some monotonicity in firm life cycle, this assumption is relaxed to some extent by the inclusion of the other variables. Nevertheless, this proxy forces a uniform distribution on the number of firms that resides in each life cycle stage and hence still does not capture all features of firm life cycle.

Dickinson (2011) proposes and validates a life cycle proxy that is based on the pattern in firms' cash flows. Since operating, investing and financing policies evolve over the firm life cycle in a predictable way, the pattern observed in the cash flows from operating, investing and financing activities allows for the classification of firms into the different life cycle stages (Dickinson 2011; Faff, Kwok, Podolski and Wong 2016). While the cash flows of operating activities are still negative in the introduction stage as it takes time before sales outpace the investments in working capital related to the introduction of new products, these become positive in the growth and mature stage after the products have been successfully introduced to the market. In the shake-out stage, the cash flows of operating activities level off as a consequence of, for instance, saturation of the market or inefficient operations. The operating losses that characterize the decline stage are reflected in negative operating cash flows.

The substantial investments in new capital and innovation that are necessary to exploit the profitable investment opportunities in the introduction and growth stage are captured by a negative sign on the cash flow of investing activities. Whereas the cash flows of investing activities are still negative in the mature stage, they gradually become positive as the firm enters the shake-out and decline stage due to the asset disposals associated with the significant restructuring in these stages. However, the limited accumulation of internal funds in the introduction and growth stage necessitates external financing, reflected in a positive sign on the cash flow of financing in these stages. As the firm matures, it has retained enough earnings to become largely self-financing and it can start repaying part of its debt. As such, the sign on cash flow of financing activities is negative for mature firms. This process continues in the shake-out and decline stage, even though the restructuring could require some additional external financing. The cash flow classification of Dickinson (2011) as a proxy for firm life cycle is summarized in Table 1.1.

In contrast to the other life cycle proxies that have been used before, Dickinson's (2011) life cycle proxy exhibits all essential life cycle features identified in prior research. More specifically, as cash flow patterns vary both within and across firms over time, the flexibility in this life cycle proxy (1) allows firms to move back and forth along the life cycle continuum; (2) does not require a firm to proceed through all life cycle stages; (3) allows the time spent in every life cycle stage to vary across and within firms; and (4) does not impose a uniform distribution on the number of firms across life cycle stages. Given the superior features of Dickinson's (2011) life cycle proxy, I mainly rely on this measure to classify firm-year observations into life cycle stages throughout my dissertation.

TABLE 1.1

Life Cycle Classification: Cash Flow Mapping

	Life Cycle Stages							
	Introduction	***Growth***	***Mature***	***Shake-Out***			***Decline***	
Cash Flow Type	1.	2.	3.	4.	5.	6.	7.	8.
Operating Activities	-	+	+	-	+	+	-	-
Investing Activities	-	-	-	-	+	+	+	+
Financing Activities	+	+	-	-	+	-	+	-

Retrieved from: Dickinson 2011 (p. 1974).

1.3. Illustrative Examples

To illustrate the use of cash flows patterns to classify firms into life cycle stages, Figure 1.1 depicts the life cycle of a number of firms over the period 1988 to 2015. Panel A plots the life cycles of Walmart and Costco. Walmart is today's largest company based on revenues and has already been ranked among the top three largest companies in the Fortune Global 500 since 2000 (Fortune 2016). After expanding its chain of stores across the US until the 1980s, the introduction of Walmart's Supercenter concept in 1988 and its first move across borders by engaging in a joint venture with Cifra, a Mexican retailer, fueled rapid growth in the 1990s (Business Insider 2012; Walmart 2016). In accordance with Walmart's developments over the past two decades, Panel A indicates that Walmart was in the growth stage from the late 80s till the mid-90s and has been in the mature stage since then.

The life cycle evolvement of Costco resembles the pattern observed for Walmart, albeit with some lag. The time series of Costco starts in 1993 with the merger between the Costco Wholesale Corporation and the Price Company. According to analysts, this merger "would offer an intriguing marriage of strengths and personalities" by combining the superior productivity of Price stores with the open management style at Costco (The New York Times 1993a). In the years following the merger, Costco entered the European and Asian markets and broadened its business activities by, for instance, opening its first gas station in 1995 (Costco 2016). This diversification and the synergies that Costco derived from its merger with Price can be considered as the main drivers of the company's substantial growth around the turn of the 21st century before it entered the mature stage, as reflected in Panel A.

Figure 1.1, Panel B, plots the life cycle development of the two largest US car manufacturers, General Motors (GM) and Ford. The graphs in Panel B show the differential impact of the crisis in the US car industry (2008-2010) on the two companies. While GM was forced to obtain government funding to stay in business and eventually filed for Chapter 11 bankruptcy in 2009, Ford was able to survive the crisis without government assistance (The

Economist 2009; Time 2009a). The billions of dollars that Ford borrowed in anticipation of a potential recession in 2006 provided the company with the financial means to avoid a government bail-out (The New York Times 2009; Time 2009b). Despite the negative impact of the crisis in the US car industry on Ford's operating performance, analysts and credit rating agencies were optimistic about its future based on its strong competitive position (Time 2009a, 2009b). This optimism was justified as Ford achieved "one of the biggest turnarounds in American business history", which can be attributed to its innovative efforts and strong management (Forbes 2014). Panel B indicates that the cash flow classification is able to capture the revival of Ford after the crisis. Specifically, since 2012 Ford has been classified into the growth stage.

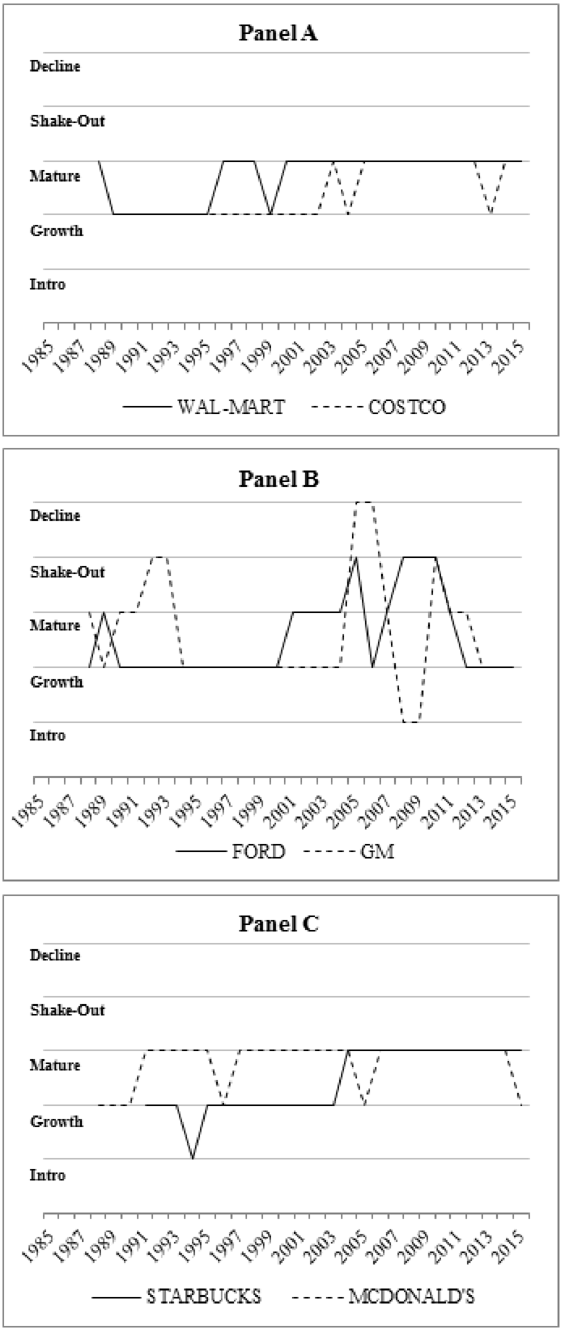
Given substantial operating losses, the bankruptcy of its biggest supplier, and its poorly performing finance subsidiary, GM was described as "a weird and painfully scarred combination of businesses" already at the beginning of 2006 (Fortune 2006). As such, there were already clear indications for GM's bankruptcy before the onset of the crisis in 2008. Consistent with the poor financial condition of GM, the company is assigned to the decline stage in 2005 and 2006. After GM was significantly restructured during the crisis period, in which it is classified into the introduction stage, it successfully undertook the biggest initial public offering (IPO) in US history (Reuters 2010). In the years following the IPO, GM slowly returned to the growth stage. In 2013, the US Treasury sold its final stake in the company and GM's decision to start with a major overhaul of its product range helped the company back into the growth stage (Bloomberg 2013; The Economist 2013). Finally, the classification of GM into the shake-out stage in the years 1992-1993 corresponds to a period in the aftermath of the Gulf War in which the company downsized its operations and reported the largest operating loss in its business history up until that time (The New York Times 1991, 1993b).

The life cycles of Starbucks and McDonald's, two successful US franchise companies, are shown in Figure 1.1, Panel C. After its IPO in 1992, Starbucks underwent tremendous growth throughout the 1990s and the beginning of the 2000s by rapidly expanding its coffee chain: In 1996, for instance, the company expanded internationally by opening its first store in Japan and until 2007 it opened on average two new stores each day (Entrepreneur 2008; The Guardian 2015). Yet, Starbucks also experienced fierce competition in the coffee market -also known as the "coffee wars" - over the past decade (The Economist 2008). Even though Starbucks focused on the higher segment of the market in contrast to its main competitors, its aim to grow rapidly in a mature market has led to overexpansion and commoditization (Forbes 2013; The Economist 2008). The gradual transformation of Starbucks from a growth firm in the 1990s and early 2000s to a mature firm in the wake of increased competition is captured by its life cycle development in Panel C.

McDonald's already witnessed substantial growth in the 1960s by riding the baby-boomer trend and in the 1970s to 1980s by riding the globalization trend (Forbes 2013). While McDonald's might have tried to act as a growth company over the past decades, analysts and shareholders have already indicated for some time that it is "a mature company in a much more competitive market that should be run for cash" (The Economist 2003). Despite competitive pressures, McDonald's has been able to keep up with its main competitors by broadening its product portfolio and benefiting from its

FIGURE 1.1

Illustrative Examples of Dickinson's (2011) Life Cycle Classification



sound franchise business model (Forbes 2013; The Economist 2015). Consistent with the company's business developments over the past three decades, McDonald's life cycle indicates that the company transferred from the growth stage to the mature stage in 1991 and has largely remained in the mature stage since then.

Overall, the examples above provide some anecdotal evidence that Dickinson's (2011) cash flow classification is able to capture firms' developments over their life cycle. As the examples illustrate, the life cycle stage in which a firm resides is the outcome of the interactions between internal strategic choices (e.g., international expansion and financing decisions) and the external operating environment (e.g., competitive pressures and macro-economic conditions). In addition, the examples show that these factors do not necessarily lead to a monotonic evolution through the firm life cycle but rather induce firms to move back and forth along the life cycle continuum.

1.4. The Role of Firm Life Cycle in the Functioning of Capital Markets

Well-functioning capital markets are of crucial importance for the efficient allocation of household savings to firms that need resources to fund their investment opportunities (Healy and Palepu 2001). The allocation of the financial resources across the available investment alternatives is determined by security prices (Kothari 2001). Security prices capture the market's assessment of the present value of the future net cash flows the firm will generate, i.e., the firm's intrinsic value. The (financial) information provided by firms to capital market participants via financial statements is an important input in the valuation process. The importance of financial statements in the valuation process is also reflected in the objective of general purpose financial reporting as stated in the conceptual framework of the International Accounting Standards Board (IASB) (2010, A23-A24):

> *"The objective of general purpose financial reporting is to provide financial information about the reporting entity that is useful to existing and potential investors, lenders and other creditors in making decisions about providing resources to the entity. [...] Investors', lenders' and other creditors' expectations about returns depend on their assessment of the amount, timing and uncertainty of (the prospects for) future net cash inflows to the entity. Consequently, existing and potential investors, lenders and other creditors need information to help them assess the prospects for future net cash inflows to an entity. [...] [However,] financial reports are not designed to show the value of a reporting entity; but they provide information to help existing and potential investors, lenders and other creditors to estimate the value of the reporting entity."*

The usefulness of financial information critically hinges on its relevance, that is, the ability to affect the decisions made by capital market participants (IASB, 2010). Starting with Ball and Brown (1968), a large body of capital markets research has concluded that financial reports provide relevant information to capital markets based on the significant association between accounting numbers and stock returns (Healy et al. 2001; Kothari 2001). Yet, over the past decades multiple studies have observed a decline in the value relevance of financial information (Core, Guay and Van Buskirk 2003; Healy et al. 2001; Lev and Zarowin 1999; Srivastava 2014; Zimmerman 2015). The deterioration of the usefulness of financial reports has been attributed to a variety of factors, including rapid advances in information technology and technological innovation (Core et al. 2003; Zimmerman 2015); increased competition in a global playing field (Lev et al. 1999; Irvine and Pontiff 2009); the transition from an industrial economy to a more knowledge-based economy (Srivastava 2014; Zimmerman 2015); and substantial changes in the fundamentals of publicly listed firms (Fama and French 2004). More specifically, as current reporting standards do not adequately capture the impact of changes in firms' operating environment on their financial performance, the aforementioned factors could have contributed to a decline in the relevance of financial information (Healy et al. 2001; Lev et al. 1999; Zimmerman 2015).

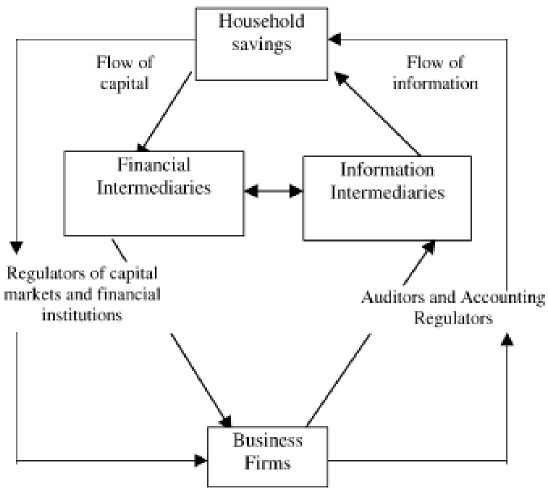
Another consequence of the substantial developments in the economy is a significant change in firm dynamics. Increased competition and the fast rate of technological innovation, for instance, force firms to respond instantly to changes in business conditions if they want to maintain their *status quo*. Where mature firms can act conservatively and benefit from economies of scale in stable markets, they have to act proactively and remain innovative in markets that are characterized by high rivalry to protect their established position in the industry (Chen et al. 2010; Gu 2016; Hambrick 1983; Miller et al. 1984). If mature firms fail to respond adequately to the changes in their business environment, they could lose their *status quo* and end up in either the shake-out or the decline stage (Jovanovic et al. 1994). In addition to the impact of the rapidly changing business environment on existing firms, newly listed firms also exhibit lower survival rates as a consequence of poor performance (Fama et al. 2004). Overall, the changing economic landscape has led to less stable business models for both new and existing firms (Owens, Wu and Zimmerman 2016; Zimmerman 2015), suggesting an increased importance of firm life cycle in capital markets.

Given the limited ability of current reporting standards to adequately capture the fundamental changes in the economic landscape and the substantial impact these changes have on firm dynamics, it is important to examine whether, and if so how, capital market participants incorporate firm life cycle information. In efficient markets, all available information is fully reflected in security prices and hence resources are allocated optimally among the available investment alternatives (Fama 1970; Kothari 2001). Early research on the value relevance of performance measures at the different stages of the firm life cycle (Anthony et al. 1992; Black 1998) suggests that investors do incorporate life cycle information into security prices. In contrast, the mispricing of securities across the firm life cycle observed in more recent studies casts substantial doubt on investor's understanding of the differential impact of firm life cycle on performance (Dickinson 2011; Hribar et al. 2015). These contradicting findings can again be attributed to the changes in the nature of firms and firm dynamics over the past decades (Fama et al. 2004; Srivastava 2014; Zimmerman 2015). The results of Core et al. (2003), for instance, indicate that although the coefficients on traditional financial variables in explaining equity values have remained stable, the explanatory power of these variables has declined. In other words, a larger proportion of the variance in equity values remains unexplained, suggesting an increase in the information asymmetries between the firm and investors attributable to managers' superior information about the firm's prospects.

In reducing the mispricing over the firm life cycle due to information asymmetries between the firm and investors and investors' lack of sophistication, information intermediaries and financial intermediaries could play an important role. Instead of investing resources directly, investors could also opt to invest their savings indirectly through financial intermediaries like banks. In addition, information intermediaries, such as financial analysts, can help investors in assessing firm value by means of their forecasts of future firm performance and stock recommendations. Whereas some financial intermediaries have access to private information that is not included in the financial reports, information intermediaries could reveal part of this "private" information by the use of their expertise and sophisticated forecasting models (Healy et al. 2001). As such, both financial intermediaries and information intermediaries could assist investors in overcoming the difficulties that arise as a consequence of firms' development over their life cycle. Figure 2 presents a schematic overview of capital and information flows among capital market participants (Healy et al. 2001, p. 408).

FIGURE 1.2

Financial and Information Flows in a Capital Market Economy



Retrieved from: Healy et al. 2001 (p. 408).

Even though more recent studies in the finance and accounting literature have acknowledged the importance of firm life cycle, these studies tend to focus on how firm life cycle affects firms' decision making and corporate policies. Examples include the impact of firm life cycle on dividend policies (DeAngelo et al. 2006); investment, financing, and cash policies (Faff et al. 2016); compensation policies (Drake and Martin 2015); and acquisition behavior (Arikan and Stulz 2016). In this dissertation, I extend the firm life cycle concept to a capital market setting by examining whether and, if so, how the behavior of various capital market participants differs across life cycle stages. More specifically, the first study adds to the literature on investors' understanding of firm life cycle by investigating the impact of firm life cycle on stock price crash risk. Consistent with the insights that emerge from recent research (Dickinson 2011; Hribar et al. 2015), the findings of the first study indicate that investors have difficulties in incorporating firm life cycle in their valuation models. The natural question arises whether information intermediaries respond to the difficulties investors face in understanding firm life cycle. Hence, the second study investigates the behavior of one of these financial intermediaries – sell-side financial analysts – over the firm life cycle. Specifically, this study examines how analyst following and the properties of analyst forecasts differ across life cycle stages. The third and final study examines the role of firm life cycle in the functioning of debt markets. As a consequence of the lack of internal funds, early-stage firms have to obtain external financing to exploit (profitable) investment opportunities.[4] Yet, the substantial growth opportunities of these firms also complicate lenders' assessment of borrowers' future value. The final study sheds light on the issues that arise in debt contracting over the firm life cycle by investigating how the source of lending and debt contract design vary by life cycle stage.

1.5. Firm Life Cycle and Stock Price Crash Risk

The substantial welfare losses investors faced during the recent financial crisis have led to an increased interest in the determinants of (firm-specific) stock price crash risk, i.e., the risk of a large decline in a firm's share price.[5] The general mechanism underlying stock price crashes is the accumulation of bad news and – once a certain tipping point has been reached – its sudden release to the stock market (Chen, Hong and Stein 2001; Hutton, Marcus and Tehranian 2009). While recent studies have mainly focused on managerial opportunistic behavior as the most important driver of stock price crash risk, firm life cycle is expected to affect crash risk via two different channels: Heterogeneity in investor beliefs and investors' misinterpretation of accounting information across life cycle stages.

Concerning heterogeneity in investor beliefs, the substantial value that firms derive from their growth opportunities in the introduction and growth stage is likely to contribute to a wide variation in investors' assessments of firm value. Bad news is initially not fully incorporated into stock prices and may only enter the market when optimistic investors revise their beliefs downwards, resulting in a stock price crash (Chen et al. 2001; Hong and Stein 2003). The unconditional conservatism inherent in accounting standards contributes to this effect as it limits the extent to which future growth opportunities are captured in the financial statements. Regarding investors' misinterpretation of accounting information, the lower future stock returns of early-stage firms observed by Dickinson (2011) suggest that at least some investors are too optimistic about the (future) operating performance of these firms. Irrespective of the channel via which firm life cycle affects stock price crash risk, however, crash risk is expected to be highest in the introduction and growth stage.

We test this hypothesis by investigating a sample of 62,004 firm-year observations in the period 1990-2013.[6] The data in this sample are retrieved from the Compustat and CRSP databases. After controlling for other variables that have been found to affect stock price crash risk and alternative measures of firm development, we find that stock price crash risk is

[4] I use the term "early-stage" throughout this dissertation to refer to firms in the introduction and growth stage. While this term may hint at a fixed chronological sequence of life cycle stages, I also use this term to label firms that have returned to the introduction and growth stage after spending time in one of the other life cycle stages.
[5] In terms of one of the empirical proxies used to measure firm-specific crash risk, "substantial" is defined as a weekly return that is more than 3.2 standard deviations below the average firm-specific return in a given year.
[6] Throughout this dissertation, I use "we" to refer to co-authored papers.

indeed highest for firms in the introduction and growth stage. Consistent with the expected impact of future growth opportunities, we find that this effect is significantly stronger for firms with an above-median market-to-book ratio. Additionally, as short selling constraints hinder the extent to which bad news is incorporated into stock prices, we find that crash risk is significantly higher in growth firms *without* short interest. To disentangle the two channels via which firm life cycle can affect stock price crash risk, we also split the sample based on the median operating performance in each life cycle stage. Although we do find evidence that crash risk is more pronounced for high-performing growth firms, investors' fixation on reported earnings growth cannot fully explain the higher crash risk for early-stage firms on a standalone basis.

The findings in this study are robust to the use of different measures of crash risk, a different life cycle proxy, and the inclusion of additional control variables for firm performance and other determinants of stock price crash risk. Moreover, further analysis indicates that our findings cannot be attributed to the inherent riskiness of early-stage firms as we do not find that these firms are also more likely to experience stock price jumps.

This study makes several contributions to the literature. First, it contributes to the life cycle literature by showing that heterogeneity in investor beliefs, as reflected in higher stock price crash risk, varies predictably over the firm life cycle. As such, firm life cycle does not only affect the level of returns but also its distribution. Relatedly, the findings in the first study also add to the literature investigating the determinants of stock price crash risk. While recent studies have focused on managerial opportunistic behavior as the main driver of stock price crash risk, the results in this study provide evidence of alternative explanations for increased crash risk (i.e., heterogeneity in investor beliefs and investors' misinterpretation of financial information). The frequent use of tail risk in risk management models and the impact it has on firms' cost of capital highlight the importance of raising awareness of the various factors driving stock price crash risk.

1.6. Firm Life Cycle and Analyst Forecast Behavior

Based on the first study and prior studies investigating investors' understanding of firm life cycle, it appears that investors generally lack the ability to efficiently incorporate life cycle information in their valuation models (Dickinson 2011; Hribar et al. 2015). These difficulties increase investor demand for analyst services, especially in early-stage firms. Specifically, given the sophistication of their private analyses, these financial intermediaries can help investors in valuing firms by means of their forecasts of future firm performance and investment recommendations (Schipper 1991; Healy et al. 2001). An additional factor that contributes to an increased demand for analyst services are firms' visibility concerns at the far ends of the life cycle continuum. That is, analyst coverage can help firms to overcome the costs related to the limited visibility of firms in these stages as a consequence of, for instance, a small investor base (Bushee et al. 2012; Merton 1987). Nevertheless, the same factors that contribute to investors' difficulties in processing life cycle information also increase forecasting difficulty and firms' limited visibility could reduce the benefits that analyst can derive from following these firms. Therefore, it is not clear *ex ante* whether analysts respond to the varying needs for their services over the firm life cycle.

In addition to its potential impact on analyst coverage decisions, firm life cycle is expected to affect analyst forecast properties. The relatively unstable operating environment of non-mature firms, for instance reflected in less persistent earnings, also increases the complexity of forecasting future firm performance and the effort analysts have to exert (Dickinson 2011; Donelson and Resutek 2015). The forecasting difficulty of non-mature firms – when compared to mature firms – is expected to reduce analyst forecast accuracy. However, analysts may be able to overcome these forecasting difficulties if they can make use of their industry expertise, which is considered as their most valuable attribute by themselves and investors (Bradshaw 2015; Brown, Call, Clement and Sharp 2015). Industry expertise is expected to be most valuable when there is life cycle alignment between the firm and its industry, for instance, because industry peers provide better benchmarks. In contrast to the potential positive effects of life cycle alignment, life cycle changes are expected to lead to a decrease in forecast accuracy. More specifically, analysts may need time to incorporate the changes in the earnings generating process following a firm's transition between life cycle stages (Markov and Tamayo 2006).

To test the developed hypotheses, we retrieve data on analyst forecast behavior from the I/B/E/S database at both the individual analyst and consensus level for the period 1994-2012. Consistent with analysts responding to investor needs, we find that analyst following is highest in early-stage firms. While analyst forecasts are generally less accurate for non-mature firms than for mature firms, their forecasts are most accurate for growth firms. Yet, the superior forecasting accuracy for growth firms is concentrated in firms whose life cycle is aligned with the industry life cycle, reflecting the greater extent to which analysts can benefit from their industry expertise. A similar beneficial effect of life cycle alignment on forecast accuracy is also found in other life cycle stages. Finally, we find that life cycle changes are followed by a decrease in forecast accuracy. This suggests that analyst fail to incorporate changes in the earnings generating process immediately after a life cycle shock.

Further analyses provide evidence that analyst indeed *respond* to an increased demand for their services. In addition, analyst following is higher for early-stage firms for which there is more heterogeneity in investor beliefs and firms at the far ends of the life cycle spectrum with a weaker financial position and a smaller investor base. These cross-sectional analyses provide support for the assertion that analysts incorporate the demand for their services in their coverage decisions. Finally, the findings in the main analysis are robust to the use of an alternative life cycle proxy and estimation of the empirical models at the consensus level.

With this study, we make several contributions to the literature. Whereas prior studies on the role of firm life cycle in capital markets focused on investors, this study shows that firm life cycle also affects analyst forecast behavior. Specifically, the findings in this study show that analyst do respond to the varying need for their services over the firm life cycle despite the associated costs. Second, we provide evidence on when analyst forecasts are most accurate, i.e. when there is life cycle alignment between the firm and its industry. Nonetheless, the findings also indicate that analysts need time to incorporate the implications of life cycle changes for forecasting future firm performance.

1.7. Debt Contracting over the Firm Life Cycle

Prior studies in the finance literature have generally observed a negative association between growth opportunities and leverage (Billett, King and Mauer 2007; Johnson 2003; Myers 1977; Smith and Watts 1992). Contrary to this common observation, the lack of internal funds in combination with the abundant investment opportunities in early-stage firms could necessitate firms to access the debt markets. Indeed, a recent study by Faff et al. (2016) indicates that net debt issuance is highest for early-stage firms. One explanation for these seemingly contradicting results is that the conflicts of interests between shareholders and debtholders, which are commonly used to explain the negative association between leverage and growth opportunities, play a relatively minor role in early-stage firms. Nevertheless, there still exists substantial uncertainty concerning the borrower's future value. As a consequence of this uncertainty, both lenders and borrowers face trade-offs that affect both the source of lending and the debt contract design.

First, with respect to the source of lending, borrowers have to trade off the costs and benefits related to the differences in monitoring and renegotiation flexibility of private versus public lenders. While the closer monitoring, access to private information, and the greater ease with which private lenders can renegotiate the terms of debt contracts could provide the borrower with the necessary flexibility in its investing decisions ("*Monitoring hypothesis*"), these firms are also more vulnerable to potential information rent extraction by private lenders ("*Rent Extraction hypothesis*") (Bharath, Sunder and Sunder 2008; Denis and Mihov 2003; Rajan 1992). As such, the preferred source of lending depends on whether the costs of potential rent extraction outweigh the benefits of more flexibility or *vice versa*.

Second, regarding debt contract design, lenders can adjust multiple contract features to incorporate the uncertainty concerning the future value of early-stage firms, including the maturity, interest spread and covenant design (Aghion and Bolton 1992; Demerjian 2015). Consistent with the findings in prior research (Bharath et al. 2008; Johnson 2003; Demerjian 2015), I expect that the debt contracts of early-stage firms have higher interest spreads, shorter maturities, and more covenants than firms in other life cycle stages. However, the relative importance of the different contract terms is likely to depend on the source of lending. Given the difference in renegotiation costs faced by the two types of lenders, I expect, on the one hand, that public lenders are more likely than private lenders to adjust the interest spread and maturity of the debt contract (cf. Bharath et al. 2008). Public lenders, on the other hand, are expected to rely more on covenants in designing debt contracts for early-stage firms.

Data on private loans and public bond issues are retrieved from, respectively, the LPC Dealscan database and Mergent FISD for the period 1989-2012. After reaffirming the importance of debt financing in early-stage firms, I find that firms in the introduction and growth stage prefer public debt to private debt. This finding is in accordance with the "*Rent Extraction hypothesis*", suggesting that the costs of banks' potential rent extraction outweigh the benefits of contractual flexibility for early-stage firms. Controlling for the endogenous choice of lending, I further find differences in how the two types of lenders incorporate the uncertainty concerning the future value of early-stage borrowers. Even though both public lenders and private lenders generally set more stringent price terms for these firms, private lenders include more covenants in the debt contracts of growth firms where public lenders rather use shorter maturities.

Additional analyses provide evidence that both public and private lenders adjust the covenant design to incorporate borrowers' needs and the different informativeness of performance measures across life cycle stages. Specifically, bond contracts include less investment-related covenants for early-stage firms than for mature firms. Furthermore, the loan contracts of most non-mature firms include less performance covenants; for firms in the growth stage, most performance covenants are based on EBITDA rather than net income. The results in the main analysis are robust to estimating the empirical models at various levels of analysis and the inclusion of the individual cash flow components.

This study contributes to the existing literature in several ways. Where prior research on firm life cycle has examined its role in equity markets, the findings in this study show that firm life cycle also affects both the source of lending and debt contract design. Although one could argue that the substantial investment activities of early-stage firms require more intense monitoring of private lenders, the findings in this study suggest that these firms prefer public debt instead to avoid information rent extraction. In addition, the different types of lenders seem to understand the different firm dynamics across life cycle stages since they adjust debt contracts accordingly. Whereas the covenant design of bond contracts tends to be rather standardized (De Franco, Vasvari, Vyas and Wittenberg-Moerman 2015), the findings in this study provide additional evidence that these contracts do incorporate borrowers' needs over the firm life cycle (Nash, Netter and Poulsen 2003). Finally, while earlier studies on debt contracting predominantly focused on debtholder-shareholder conflicts, the findings in this study add to recent findings that uncertainty concerning borrowers' future value also affects debt contract design when agency costs play a minor role (Demerjian 2015).

1.8. Outline of the Dissertation

The remainder of my dissertation is organized as follows. Chapter 2 presents the first study on the impact of firm life cycle on stock price crash risk. Chapter 3 covers the second study that investigates how firm life cycle affects analyst forecast behavior. In chapter 4, the third study examines debt contracting over the firm life cycle. Finally, chapter 5 concludes.

2 FIRM LIFE CYCLE AND STOCK PRICE CRASH RISK[7,8]

ABSTRACT – We examine the relation between firm life cycle and stock price crash risk. Firm life cycle reflects a firm's evolvement arising from changes in observable and unobservable factors and affects, among others, a firm's decisions and the level and persistence of its profitability. Recently, the rate of business change has increased dramatically, suggesting a bigger role for life cycle in the valuation process. At the same time, the recent financial crisis and the resulting losses that were incurred, have spurred additional interest in understanding the determinants of crash risk. We link these two important concepts and find that crash risk is highest in the introduction and growth stage. We argue that both heterogeneity in investor beliefs and investor overoptimism are driving these results. Supporting this argumentation, we find that the relation is stronger for firms without short interest, firms deriving more value from future growth opportunities, and high-performing growth firms.

2.1. Introduction

In this study, we investigate how a firm's stock price crash risk evolves over the corporate life cycle. Firm life cycle represents a firm's evolvement arising from changes in internal factors, such as its strategic choices, and external factors, such as the competitive pressures it faces (Dickinson 2011). Firm life cycle is recognized to have a substantial impact on firm decision making, the properties of accounting measures, and the dynamics of firm profitability. For example, whereas prior studies provide evidence of mean-reversion in firm profitability (Fama and French 2000; Fairfield, Sweeney, and Yohn 1996) and show that industry-level analysis does not have incremental relevance in forecasting profitability (Fairfield, Ramnath, and Yohn 2009), Dickinson (2011) shows that spreads in profitability across life cycle stages are substantial and persist for up to five years after the initial classification. Other studies have used life cycle theory to explain a firm's dividend policy (Grullon, Michaely, and Swaminathan 2002; DeAngelo, DeAngelo, and Stulz 2006), corporate acquisitions and diversification (Arikan and Stulz 2016), and the value relevance of accounting measures as well as accrual behavior (Anthony and Ramesh 1992; Black 1998; Hribar and Yehuda 2006, 2015).

As the above studies indicate, the importance of firm life cycle is not limited to within-firm decision making, but also extends to a capital market setting. For example, for investors it is of crucial importance to recognize that (valuation) approaches that are suitable for one

[7] This chapter is based on a working paper co-authored with Annelies Renders and Patrick Vorst.

[8] **Acknowledgements**: We would like to thank Judson Caskey (CFEA discussant), Gus De Franco, Naomi Soderstrom, Ayung Tseng (FARS discussant), Franco Wong, and seminar participants at Maastricht University, University of Toronto, the 2015 Conference on Financial Economics and Accounting at Rutgers University, and the 2016 FARS Mid-Year Meeting, for their helpful comments and suggestions.

life cycle stage may not transfer directly to other life cycle stages with the same rate of success. Despite the importance of firm life cycle, the life cycle concept has received only scant attention in the accounting literature to date. This stands in stark contrast to the management, organization, and strategy literatures where life cycle has since long been recognized as a topic of interest (e.g., Miller and Friesen 1983, 1984; Jawahar and McLaughlin 2001; Mueller 1972; Smith and Miner 1983). Yet, incorporating life cycle is important as firms are dynamic entities that can move back and forth along the life cycle continuum. Moreover, evidence in Lev and Zarowin (1999) suggests that recently firm life cycle may have gained importance as the rate of business change has increased dramatically.

Similarly, firm-specific stock price crash risk has gained importance as the recent financial crisis has shown that investors can suffer substantial welfare losses as a result of extreme negative events, thereby raising their concerns about the probability of such extreme events. This has spurred additional interest in understanding the drivers of tail risk. A number of studies have investigated factors that can be used to forecast firm-specific stock price crash risk. Whereas some studies have focused on managerial opportunistic behavior as a driver of crash risk (Hutton et al. 2009; Kim et al. 2011a, 2011b), others have linked heterogeneity in investor beliefs to crash risk (Chen et al. 2001; Hong and Stein 2003).

We expect firm life cycle to affect crash risk via several re-enforcing mechanisms. First, as firms move through the different life cycle stages, investors face different levels of uncertainty regarding fundamental values. These differences arise as a consequence of changes in the relative importance of the two components of firm value over the life cycle: The value of a firm's assets in place and the present value of its future growth opportunities. For firms whose value depends to a greater extent on future growth opportunities, uncertainty is greater and through an increase in heterogeneity in investor beliefs, this can result in increased crash risk (Hong and Stein 2003). Furthermore, this effect is exacerbated by the limited ability of accounting measures to capture these growth opportunities. For example, current accounting standards require the expensing of all research and development (R&D) outlays despite the fact that these investments positively impact firm value and investors value these as an asset (Joos and Plesko 2005). This does not only reduce the usefulness of accounting income as a measure of company performance, but also increases the divergence between book and market values, which limits the usefulness of book values as an anchor for firm valuation (Ohlson 2005).[9] In short, this first mechanism arises from the greater uncertainty associated with future growth opportunities which, coupled with a lack of appropriate accounting information, increases heterogeneity in investor beliefs. As growth opportunities likely play a bigger role for firms in the early life cycle stages, we expect crash risk to be more pronounced for firms in the introduction and growth stage.

A second mechanism relates to the misinterpretation of accounting information by investors over the life cycle stages. Dickinson (2011) shows that life cycle has important implications for (forecasting) the level and persistence of firm profitability. As such, firm life cycle can be seen as a fundamental, inherent, time-varying factor that affects the financial

[9] The starting point in any residual income/abnormal earnings valuation model is the firm's current book value. If all assets are recognized at fair value there would be no difference between a firm's market value and a firm's book value, book values would be fully informative about firm value, and firms would not earn residual income (Penman 2013).

performance of firms. More importantly, Dickinson (2011) provides evidence that investors have difficulties in assessing and understanding the implications of firm life cycle for firm profitability and valuation. Whereas firms in the introduction and growth stage earn lower future stock returns, firms in the mature, shake-out, and decline stage experience higher future returns. Coupled with the higher persistence in profitability of mature firms and the greater improvement in profitability of firms in the decline stage, this suggests that investors are overoptimistic of the growth prospects of early-stage firms.[10] Consistent with this argumentation, Hribar and Yehuda (2015) provide evidence that accruals convey different information at different life cycle stages and that investors misprice the growth component of accruals for firms in the growth stage. In the other life cycle stages, where the main role of accruals is to adjust operating cash flows for timing differences, accrual mispricing is subsumed by the mispricing of cash flows. Overall, these findings indicate overoptimistic expectations for early-stage firms, potentially driven by the issues discussed in the previous paragraph, and form a second mechanism by which crash risk is expected to be higher for firms in the introduction and growth stage.

We investigate the impact of firm life cycle on stock price crash risk for a sample of 62,004 firm-year observations over the period 1990-2013. Following Dickinson (2011), we use cash-flow patterns to classify firms into five life cycle stages: Introduction, growth, mature, shake-out, and decline. To measure firm-specific crash risk, we employ three measures commonly used in the literature: (i) An indicator variable that indicates whether a firm experiences a sudden and substantial decline in its stock price in the next year, (ii) negative conditional return skewness, and (iii) down-to-up volatility. After controlling for detrended share turnover, financial reporting opaqueness, alternative measures that capture a firm's development over time, the firm-specific information environment, and other control variables commonly included in prior studies, our findings provide strong evidence that firms are more crash-prone in the introduction and growth stage compared to the other three life cycle stages. Crash risk in the introduction and growth stage is, respectively, 8 and 6 percent higher than crash risk of mature firms.[11]

We also perform a number of analyses where we investigate how the effect of firm life cycle varies cross-sectionally. For heterogeneity in investor beliefs to affect stock price crash risk, Hong and Stein (2003) assume the presence of short selling constraints. Hence, we expect the effect of firm life cycle on stock price crash risk to be more pronounced for firms that are subject to short selling constraints. Using the presence of short interest at fiscal year-end as a proxy for short selling constraints, we find that growth-stage firms without short interest have higher crash risk than growth-stage firms with short interest.

One of the factors that contribute to the increase in heterogeneity in investor beliefs for high-growth firms is the limited ability of accounting standards to accurately capture the value of these growth opportunities. Hence, we expect the effect of firm life cycle on stock price crash risk to be more pronounced for high market-to-book firms. These firms do not only derive a large proportion of their value from future growth opportunities (Penman and Zhu 2014), but the divergence between their market and book values also suggests that book

[10] See for example Figure 1 in Dickinson (2011).

[11] Untabulated findings on the costliness of a crash reveal that the yearly return in crash-years is lower by on average 21 percent.

values capture these growth opportunities only to a limited extent as a consequence of the (unconditionally) conservative nature of accounting standards (Beaver and Ryan 2005). Our findings confirm that crash risk in the introduction and especially the growth stage is higher if firms also have high market-to-book ratios.

To test the relative importance of the second mechanism by which we expect firm life cycle to affect stock price crash risk, namely investor mispricing, we split the sample based on firms' return on net operating assets. Firm life cycle is not only an important determinant of the level of performance, but it also has a large impact on the persistence of, and future growth in, performance (Dickinson 2011). As investors are often too optimistic about the future performance of firms in the introduction and growth stage (Dickinson 2011), we hypothesize that the higher stock price crash risk in these stages is more pronounced for firms that currently perform best. Our findings confirm that, in the growth stage, this is indeed the case. However, even for low performing firms we continue to find evidence of higher crash risk for early-stage firms. This suggests that mispricing alone is not sufficient to explain the relation between life cycle and crash risk and that heterogeneity in investor beliefs still plays an important role.

Additional analyses reveal that the introduction and growth stage are not positively associated with stock price jumps, i.e., substantial increases in a firm's stock price, which suggests that the results obtained in the main analyses are not driven by the inherent riskiness of firms in the introduction and growth stage. Our inferences are also robust to alternative specifications of our empirical model, including an alternative proxy for firm life cycle and the inclusion of additional control variables for firm performance and other determinants of firm-specific crash risk.

Our study contributes to the literature by documenting that firm life cycle is an important determinant of firm-specific crash risk. Firm life cycle is a distinct combination of observable and unobservable, internal and external, firm, manager, and macro-economic characteristics. As such it is an inherent and time-varying factor that is able to predict stock price crash risk, and may do so in a non-linear fashion. The fact that many of these characteristics are unobservable and may act together, makes that life cycle is more than the sum of its determinants. As a result, its incremental relevance exceeds that of its underlying components and we expect it to predict crash risk over and above studying variables, such as R&D intensity and sales growth, that are associated with life cycle. In addition, by including factors such as R&D intensity, one assumes that they influence crash risk in a linear fashion. In contrast, firm life cycle theory incorporates how R&D investments interact with other variables that capture a firm's development over time, recognizing that a given investment level may have different implications in each stage, and thus allowing each of these factors to contribute to crash risk in a non-linear fashion.

In addition, prior studies, mainly in the management, organization, and strategy literature, have recognized firm life cycle as an important factor that is able to explain firm decision making. However, only few studies have investigated the effects of firm life cycle from a capital market perspective, despite its potential importance for the fields of accounting and finance. From these few existing studies we know that life cycle has important implications for the level and persistence of firm performance (Dickinson 2011), the value-relevance of accounting disclosures (Anthony and Ramesh 1992; Black 1998), and accrual behavior (Hribar and Yehuda 2015). Their findings are consistent with the argument that firm life cycle has an important role to play in the firm valuation process.

Whereas prior studies have investigated the effect of firm life cycle on the level of a firm's returns (Dickinson 2011; Hribar and Yehuda 2015), in this study we link firm life cycle to the distribution of returns and investigate how it affects tail risk. The recent financial crisis and the substantial losses that were incurred have spurred additional interest in understanding the determinants of tail risk. Furthermore, the widespread use of risk management tools aimed at mitigating tail risk suggests that investors indeed care about the return distribution. In addition, recent research in the finance literature indicates that such tail risk may be priced and thus affect a firm's cost of capital. For example, in the cumulative prospect theory based asset pricing model in Barberis and Huang (2008), investors have preferences for firms with positively skewed returns and these firms should exhibit lower average returns, which is consistent with the firm's return distribution affecting its cost of capital. Zhang (2013) provides empirical evidence that is consistent with such an asset pricing model.

The remainder of this chapter is structured as follows. We review prior literature and develop the hypotheses in Section 2.2. In Section 2.3, we discuss our research design. We present and discuss the empirical results of our main model in Section 2.4. Additional analyses and robustness checks are included in Section 2.5 and Section 2.6 concludes.

2.2. Related Literature and Hypothesis Development

The underlying mechanisms of stock price crash risk that have been investigated by prior research can generally be assigned to two broad categories: Heterogeneity in investor beliefs concerning firms' fundamental values and managers' opportunistic behavior (Bleck and Liu 2006; Hong and Stein 2003; Jin and Myers 2006). A common element of the mechanisms underlying stock price crash risk is the presence and accumulation of bad news about firms' fundamental values and its eventual release to the stock market. Studies that focus on managers' opportunistic behavior argue that managers intentionally engage in bad news hoarding to avoid the adverse outcomes that may be associated with the release of bad news (Hutton et al. 2009; Jin and Myers 2006; Kim et al. 2011a, 2011b; Kothari et al. 2009). Eventually, once the hoarding of bad news reaches its tipping point, for instance because managers' willingness to withhold bad news has reached its limit, the sudden release of the accumulated bad news results in a stock price crash (Bleck and Liu 2007; Jin and Myers 2006).

In contrast, studies that focus on heterogeneity in investor beliefs as the underlying mechanism of crash risk argue that different (private) signals about a firm's fundamental value lead to investor disagreement (Hong and Stein 2003). In a multi-period model developed by Hong and Stein (2003), two investors who are subject to short selling constraints receive different signals about the firm's fundamental value. Even though both signals can be informative of the firm's fundamental value, an important assumption underlying the model of Hong and Stein (2003) is that investors, for instance due to overconfidence, only believe the signals they receive themselves (or at least do not fully incorporate the information that could be derived from signals the other investor receives), which leads to differences of opinion among investors. Under this scenario, bad news about the firm's fundamental value may not be fully revealed to the market immediately. Only when the investor who initially received an optimistic signal about the firm's fundamental value updates his beliefs in response to bad news, the bad news of the other investor, which was previously hidden, will be revealed to the market, leading to an increase in stock price crash risk (Chen et al. 2001; Hong and Stein 2003).[12]

We argue that differences in valuation uncertainty across firm life cycle stages are an important factor contributing to heterogeneity in investor beliefs. Following Myers (1977), firm value is determined by the sum of two components: The present value of the assets the firm has in place and the present value of the firm's future growth opportunities. The importance of these two components differs across firm life cycle stages: Whereas a firm has little assets in place during the introduction and growth stage and thus derives most of its value from its future growth opportunities, the importance of a firm's assets in place increases once the firm leaves these stages and the growth opportunities are depleted (Black 1998; Hribar and Yehuda 2015). The varying importance of these two components also has implications for the informativeness and value relevance of different accounting measures across the life cycle stages (Anthony and Ramesh 1992; Hribar and Yehuda 2015). For instance, Hribar and Yehuda (2015) find that the extent to which free cash flows and total accruals convey unique signals is largest during the growth stage. This finding is consistent with the notion that the investment component of total accruals, which is positively related to growth, and not the component of random fluctuation, is most important during this stage.

The large impact of future growth opportunities on firm value during the introduction and growth stage is expected to lead to more valuation uncertainty. During these life cycle stages, a firm's substantial investments in for instance new capital and R&D are not yet backed by positive earnings. Since the future payoffs of these investments are highly uncertain compared to the payoffs that can be derived from assets in place, heterogeneity in investor beliefs concerning firms' fundamental values will be more pronounced during the introduction and growth stage (Baker and Wurgler 2007). This is further exacerbated by the fact that accounting standards are not able to adequately capture the value of these future growth opportunities. According to the "differences-of-opinion" theory (Chen et al. 2001), this heterogeneity in investor beliefs could manifest itself as an increase in stock price crash risk.

In sum, the substantial impact that future growth opportunities have on firm value during the introduction and growth stage is expected to lead to differences of opinion among investors concerning fundamental values. Therefore, we posit that stock price crash risk is higher during the introduction and growth stage. More formally, we hypothesize that:

Hypothesis 1: The probability of firm-specific stock price crashes is greater for firms in the introduction and growth stage.

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[12] Assume that the signals that A and B receive about the firm's fundamental value (i.e., S_A and S_B) are such that

$$S_A < P_C < S_{B1},$$

in which P_C represents the market clearing price set by a group of rational arbitrageurs who do not face short-selling constraints. Based on the assumption that investors A and B only believe their own signals, investor A will sell all its shares and sit out the market (Chen et al. 2001). Under this scenario, the information of S_A will not be fully revealed to the market and consequently will not be fully incorporated in the market price. If investor B subsequently receives bad news (i.e. $S_{B2} < S_{B1}$), it is more likely that information about S_A, will be revealed to the market.

While we attribute the differential impact of firm life cycle on stock price crash risk to heterogeneity in investor beliefs, managers' opportunistic behavior may also vary over the firm life cycle. Specifically, Benmelech, Kandel, and Veronesi (2010) argue that, as a consequence of stock-based compensation, managers' incentive to hide bad news from investors is highest when firms' investment opportunities decline. Under the life cycle classification employed in this study, this decline in investment opportunities takes place at the beginning of the mature stage as the cash flows from investing activities become negative. Such managerial opportunistic behavior would manifest itself in higher crash risk in the mature stage and hence would bias against finding significant results on the introduction and growth stage.

A crucial aspect of the asset-pricing model in Hong and Stein (2003) is that investors are subject to short selling constraints. Combined with investors' overreliance on their own signals, the presence of short selling constraints makes that bad news about firm fundamental values is not fully revealed to the market immediately. In addition, the valuation uncertainty and the subsequent heterogeneity in investor beliefs also affect investors' ability to sell short (D'Avolio 2002; Duffie, Garleanu, and Pedersen 2002). Specifically, the short selling constraints faced by investors are increasing in investors' uncertainty concerning firm value (Baker and Wurgler 2006). Based on this argumentation, the effect of firm life cycle should be more pronounced when investors face short selling constraints. Hence, we hypothesize that:

Hypothesis 2: The higher probability of stock price crashes for introduction-stage and growth-stage firms is more pronounced in the presence of short selling constraints.

We argue that firms are more prone to crash risk in the introduction and growth stage of the firm life cycle due to heterogeneity in investor beliefs arising from the relatively large impact of future growth opportunities on firm value in these stages. Following this line of reasoning, stock price crash risk is likely to be more pronounced in these early stages for firms for which future growth opportunities have a larger impact on firm value. Firms that derive a larger proportion of their value from growth opportunities face more investor uncertainty regarding average profitability than firms whose value depends to a large extent on their assets in place (Penman and Zhu 2014).

However, the heterogeneity in investor beliefs associated with future growth opportunities does not only depend on the relative importance of this component in the determination of firm value but also on the extent to which future growth opportunities are captured in the firm's book value. One factor that may increase the divergence between book value and economic value is the unconditionally conservative nature of accounting standards, which creates a downward bias in book values (Beaver and Ryan 2005; Zhang 2000). This downward bias is likely to be more pronounced during the introduction and growth stage due to the substantial investments in for instance new assets and innovation. Unconditional conservatism is reflected in the accounting depreciation of fixed assets outpacing economic depreciation and the immediate expensing of R&D investments despite the benefits that can be derived from these investments. As a consequence, the potential future benefits and hence the economic value of these investments is not fully reflected in book value. Overall, we expect that the impact of the introduction and growth stage on stock price crash risk is more pronounced for firms that either derive a larger proportion of their value from future growth opportunities or face a relatively large downward bias in book value as a consequence of unconditional conservatism.

One measure that has been used in prior research to capture the relative impact of growth opportunities on firm value and the impact of unconditional conservatism in accounting standards is the market-to-book ratio (Beaver and Ryan 2005; Myers 1984; Roychowdhury and Watts 2007). More specifically, a higher market-to-book ratio suggests that a firm derives more value from its future growth opportunities relative to its assets in place (Myers 1984). Additionally, it reflects a larger downward bias in book value and more uncertainty regarding average profitability (Beaver and Ryan 2005; Pastor and Veronesi 2003; Roychowdhury and Watts 2007). Based on the reasoning above, we expect that firms in the introduction and growth stage with a relatively high market-to book ratio are even more prone to stock price crash risk. In other words, we hypothesize:

> *Hypothesis 3: The higher probability of stock price crashes for introduction-stage and growth-stage firms is more pronounced for high market-to-book firms.*

Another factor that may explain differences in crash risk across the life cycle stages is the fact that investors misinterpret the varying persistence of firm performance over the life cycle. The findings of Dickinson (2011) indicate that operating performance is highest and most persistent for mature firms, due to improvements in operating efficiency during the mature stage. Additional analyses reveal that mature firms earn positive abnormal returns suggesting that investors undervalue mature firms by not fully recognizing their performance persistence (Dickinson 2011). While Dickinson (2011) mainly focuses on the abnormal returns earned by mature firms, her findings also show that firms in the introduction and the growth stage earn negative abnormal returns. These findings imply that investors overvalue firms in these early life cycle stages. One explanation for this overvaluation could be that at least some investors are too optimistic about the future prospects of firms in the introduction and growth stage by fixating on their reported earnings growth (Dickinson 2011). The eventual release of bad news about future performance could then result in a stock price crash. We examine whether next to heterogeneity in investor beliefs, this mechanism also results in higher crash risk in the early life cycle stages, and we expect stock price crash risk of firms in the introduction and growth stage to be higher for the firms with the highest profitability. Hence, we state the following hypothesis:

> *Hypothesis 4: The higher probability of stock price crashes for introduction-stage and growth-stage firms is more pronounced for the best-performing firms.*

2.3. Research Design

2.3.1 Sample Selection

Our sample includes all firm-year observations at the intersection of Compustat and CRSP for the period 1988-2013. We delete firm-year observations that do not have sufficient data to calculate the crash risk measures. Specifically, we delete observations with less than 26 weekly return observations over the year. We further delete observations that do not have sufficient data available to calculate the life cycle proxies and firms with missing data on the control variables. The final sample consists of 62,004 firm-year observations over the period 1990-2013.

2.3.2. Model Specification

The main empirical model that is used to examine the first hypothesis is as follows:

$$\begin{aligned} CRASH\ RISK_{i,t+1} = \alpha_0 &+ \beta_1 INTRO_{it} + \beta_2 GROWTH_{it} + \beta_3 SHAKE\text{-}OUT_{it} + \beta_4 DECLINE_{it} \\ &+ \beta_5 OPAQUE_{it} + \beta_6 DTURNOVER_{it} + \beta_7 NCSKEW/DUVOL_{it} \\ &+ \beta_8 RETURN_{it} + \beta_9 SIGMA_{it} + \beta_{10} SIZE_{it} + \beta_{11} LEV_{it} + \beta_{12} MTB_{it} \\ &+ \beta_{13} ROA_{it} + \beta_{14} R\&D\_INT_{it} + \beta_{15} FIRM\_AGE_{it} + \beta_{16} INSTH_{it} \\ &+ \beta_{17} ANALYST_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

where subscript *i* denotes firms and *t* years. Consistent with prior research (Chen et al. 2001; Kim et al. 2011a; Kim and Zhang 2015), we measure the dependent variable, firm-specific crash risk ($CRASH\ RISK_{i,t+1}$), one year ahead of the explanatory variables included in the model. This model specification ensures that we forecast firms' stock price crashes rather than just examine the association between crash risk and the explanatory variables.

2.3.3. Crash Risk Measures

We employ three measures commonly used in prior studies on crash risk. Before we construct these measures, we first need to obtain firm-specific weekly returns by taking the natural logarithm of one plus the residual of the following model:

$$r_{i,t} = \alpha_i + \beta_1\, r_{m,t-2} + \beta_2\, r_{m,t-1} + \beta_3\, r_{m,t} + \beta_4\, r_{m,t+1} + \beta_5\, r_{m,t+2} + \varepsilon_{i,t} \tag{2}$$

where $r_{i,t}$ is firm *i*'s stock return at time *t*; $r_{m,t}$ is the market return, as measured by the CRSP value-weighted market index at time *t* (Kim et al. 2011a, 2011b); and $\varepsilon_{i,t}$ captures the proportion of firm *i*'s stock returns that is not driven by aggregate market movements. The model is estimated over a one-year period starting in the fourth month of the fiscal year and ending three months after fiscal year-end. Using these firm-specific weekly returns, we derive our crash risk measures following prior studies (Kim et al. 2011a, 2011b). The first measure of crash risk is an indicator variable, *CRASH*, that is equal to one if a firm experiences at least one weekly return that is more than 3.2 standard deviations below the mean firm-specific weekly return during the year, and zero otherwise. The second measure of crash risk is the negative conditional skewness of returns, *NCSKEW* (Kim and Zhang 2015). We calculate *NCSKEW* as follows:

$$NCSKEW_{it} = - [n(n-1)^{3/2} \sum r_{it}^3] / [(n-1)(n-2)(\sum r_{it}^2)^{3/2}] \quad (3)$$

where r_{it} is the firm-specific weekly return as specified above. The numerator represents the third moment of the firm-specific weekly returns during year *t* and the denominator is the standard deviation of these returns during the same year raised to the third power. Higher values indicate more negatively skewed returns.

Our third crash risk measure is down-to-up volatility, *DUVOL.* We calculate *DUVOL* by dividing the firm-specific weekly returns obtained from the estimation of equation (1) into two groups depending on whether they are above (up sample) or below (down sample) the yearly mean of the firm-specific weekly returns. Next, we calculate the standard deviations of firm-specific weekly returns in the up and down samples. *DUVOL* is then defined as the natural logarithm of the ratio of the standard deviation of firm-specific weekly returns in down weeks to the standard deviation of firm-specific weekly returns in up weeks. Higher values of *DUVOL* indicate higher crash risk.

2.3.4. Life Cycle Measure

To determine a firm's life cycle stage, we rely on the measure developed by Dickinson (2011), who assigns firms to five different life cycle stages: Introduction, growth, mature, shake-out, and decline. Dickinson's (2011) classification is based on a systematic cash flow pattern over the life cycle.[13] For instance, the substantial investments during the introduction and growth stage are associated with negative cash flows from investing activities in these stages. As the internal funds during these stages are relatively limited, firms have to rely more on external financing, resulting in positive cash flows from financing activities. Both the level of investments and the need for external financing decrease as firms move to the other life cycle stages. While the superior operating performance of firms in the growth and mature stage results in positive cash flows from operating activities, these are likely negative in the other stages.

Whereas studies that use other proxies for firm life cycle, such as age and size (Anthony and Ramesh 1992; Hribar and Yehuda 2015), implicitly assume that firms move monotonically through their life cycle stages, Dickinson's (2011) life cycle proxy allows firms to move across the stages in a non-sequential order. This is an important feature of the life cycle proxy since firms can have a portfolio of products that are each at different stages in their life cycle, rather than one product that drives the firm through its life cycle in the standard sequence (Dickinson 2011). Moreover, permitting a non-sequential order also allows for the possibility that life cycle is the outcome of strategic choices rather than a predetermined process (Dickinson 2011). Based on Dickinson's (2011) specification of firm life cycle, we create four indicator variables, *INTRO*, *GROWTH*, *SHAKE-OUT* and *DECLINE,* that are equal to one if firm *i* is in that particular stage at time *t*, and zero otherwise. The mature stage is treated as the reference category. Hypothesis 1 predicts positive coefficients on *INTRO* and *GROWTH*.

[13] See Table 1.1 (p. 5) for Dickinson's (2011) classification scheme.

2.3.5. Control Variables

We control for firms' opaqueness. A common view in the recent literature is that a firm's opaqueness provides managers with the opportunity to hide and accumulate bad news which will result in a stock price crash once the accumulated bad news comes out all at once (Hutton et al. 2009; Kim et al. 2011a). To rule out that our findings are driven by reporting opaqueness rather than investor uncertainty about firm fundamentals, we control for a firm's opaqueness in our empirical model. Following Hutton et al. (2009), we measure opaqueness (*OPAQUE*) as the three-year moving sum of the absolute value of discretionary accruals, estimated based on the performance-matched Modified Jones model. Consistent with prior research, we expect a positive coefficient on *OPAQUE*.

Prior studies on the role of investor uncertainty (Chen et al. 2001; Hong and Stein 2003) argue that trading volume is positively associated with differences in investors' opinions about fundamental values. To investigate whether the uncertainty associated with early life cycle stages is incremental to the uncertainty reflected by trading volume, we further include detrended share turnover.[14] *DTURNOVER* is measured as firm *i*'s share turnover over year *t*, calculated over the 12-month period starting in the fourth month of the fiscal year, minus the turnover over in year *t-1*. We expect a positive coefficient on *DTURNOVER*.

We further control for a set of variables commonly included in prior studies on stock price crash risk (Chen et al. 2001; Kim et al. 2011a, 2011b; Kim and Zhang 2015). First, we control for the negative conditional return skewness (down-to-up volatility) in the current year since firms with a higher negative conditional return skewness (down-to-up volatility) in the current year are expected to have higher negative conditional return skewness (down-to-up volatility) in the next year as well (Chen et al. 2001).[15] We also include the average firm-specific weekly return (*RETURN*) and the volatility of these returns (*SIGMA*) in the current year. Consistent with prior studies (Kim et al. 2011a, 2011b), we expect positive coefficients on *RETURN* and *SIGMA* since firms with higher average stock returns and firms with a higher volatility face a higher likelihood of future crashes. Next, we include *SIZE*, measured as the natural logarithm of total assets; *LEV*, measured as total debt divided by total assets; *MTB*, measured as market value of equity divided by book value of equity; and *ROA*, measured as income before extraordinary items divided by lagged total assets. We include current levels of *ROA* rather than future *ROA*, as done in most other studies on crash risk, since Dickinson (2011) shows significant differences in profitability across life cycle stages. As we want to rule out that the results are driven by differences in performance, we control for contemporaneous ROA instead.[16] Based on the findings in prior studies (Chen et al. 2001; Hutton et al. 2009), we expect positive coefficients for *SIZE* and *MTB*, but a negative coefficient for *LEV*. We have no *ex ante* expectation for the coefficient of *ROA*.

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[14] Consistent with our argumentation that heterogeneity in investor beliefs is greater in the introduction and growth stage, we find that both *INTRO* and *GROWTH* are positively associated with detrended share turnover. However, the fact that we still find an effect of firm life cycle indicates that firm life cycle captures an aspect of valuation uncertainty that is not captured by trading volume.

[15] In the regressions with *DUVOL* as the dependent variable, we control for *DUVOL* in the current year instead of *NCSKEW*.

[16] Since our aim is to forecast stock price crash risk in year *t+1* based on factors that are observable for investors in year *t*, we control for current *ROA* instead of future *ROA*. However, in Section 2.5 we include future *ROA* as a robustness test. Our inferences are robust to the inclusion of future *ROA*.

We also include two variables that are expected to capture a firm's development over time and that may be associated with investors' uncertainty about firms' fundamental values. The first variable is R&D intensity (*R&D_INT*), measured as the ratio of R&D expenses over sales. Despite the potential future benefits that firms can derive from their investments in R&D, these outlays are expensed immediately. Given the uncertainty associated with the future payoffs of R&D expenses, which are expected to be highest during the introduction and growth stage, we expect a positive coefficient on *R&D_INT*. The second variable is firm age (*FIRM_AGE*). Since more firm-specific information is available to investors and less uncertainty exists among investors about firms' reporting quality as firms grow older (Ecker et al. 2006), we expect a negative coefficient for *FIRM_AGE*.

Furthermore, we control for two measures of the firm-specific information environment that have been found in prior studies to have an impact on stock price crash risk and that may evolve over the life cycle: Institutional ownership (*INSTH*) and analyst following (*ANALYST*). Institutional ownership is calculated from the 13F filings reported in the Thomson Reuters Institutional Holdings Database. The level of institutional ownership is equal to the percentage of shares held by institutions in the calendar-quarter immediately preceding the end of the fiscal year. We measure analyst following as the natural logarithm of the number of analysts included in the I/B/E/S consensus forecast on the date closest to but not exceeding the end of the fiscal year (An and Zhang 2013; Callen and Fang 2013; Chen et al. 2001). Based on the findings in these prior studies, we expect positive coefficients on both *INSTH* and *ANALYST*. Finally, the empirical models include both year and industry fixed effects. All continuous, non-logged, non-return variables are winsorized at the 1% and 99% levels.[17]

2.4. Empirical Results

2.4.1. Descriptive Statistics

Table 2.1, Panel A, reports summary statistics for the variables included in model (1). The mean value of 0.169 for $CRASH_{t+1}$ indicates that 16.9% of the firm-year observations in our sample experience at least one stock price crash. This percentage is comparable to the percentage of stock price crashes observed in prior studies (Kim et al. 2011a, 2011b). The mean and median values we observe for $NCSKEW_{t+1}$ are higher than the values reported by, for instance, Chen et al. (2001) and Kim and Zhang (2015), but comparable to the values reported by Kim et al. (2011a, 2011b). One potential explanation is that the investigated sample in the former two studies excludes the most recent crisis period, whereas the latter two studies include at least part of this period in their sample as well. Concerning our life cycle proxy, the reported numbers are similar to those reported by Dickinson (2011). More specifically, most firm-year observations are assigned to the growth and mature stage while the lowest percentage of firm-year observations is assigned to the decline stage.

Similar to Dickinson (2011), Table 2.1, Panel B, provides an overview of the mean values for some of the explanatory variables included in the main model to validate the life cycle proxy. The observed patterns are generally consistent with Dickinson (2011).

[17] The results obtained in the main analyses are robust to the winsorization of all variables.

TABLE 2.1

Descriptive Statistics

Panel A: Descriptive Statistics						
Variable	**N**	**Mean**	**Std.Dev**	**P25**	**Median**	**P75**
$CRASH_{t+1}$	62,004	0.169	0.375	0.000	0.000	0.000
$NCSKEW_{t+1}$	62,004	-0.030	0.847	-0.467	-0.054	0.363
$DUVOL_{t+1}$	62,004	-0.078	0.371	-0.318	-0.087	0.15
INTRO	62,004	0.117	0.322	0.000	0.000	0.000
GROWTH	62,004	0.299	0.458	0.000	0.000	1.000
MATURE	62,004	0.413	0.492	0.000	0.000	1.000
SHAKE-OUT	62,004	0.107	0.308	0.000	0.000	0.000
DECLINE	62,004	0.065	0.246	0.000	0.000	0.000
NCSKEW	62,004	-0.027	0.810	-0.458	-0.055	0.353
DUVOL	62,004	-0.078	0.363	-0.315	-0.088	0.146
DTURNOVER	62,004	0.023	1.003	-0.280	-0.001	0.283
SIGMA	62,004	0.063	0.038	0.037	0.054	0.079
RETURN	62,004	-0.003	0.005	-0.003	-0.001	-0.001
OPAQUE	62,004	0.281	0.195	0.141	0.233	0.373
SIZE	62,004	5.855	2.246	4.192	5.768	7.359
MTB	62,004	2.750	3.698	1.085	1.833	3.192
LEV	62,004	0.215	0.202	0.034	0.178	0.332
ROA	62,004	0.000	0.188	-0.018	0.034	0.085
INSTH	62,004	0.433	0.308	0.139	0.419	0.699
ANALYST	62,004	1.339	1.046	0.000	1.386	2.197
R&D_INT	62,004	0.154	0.707	0.000	0.000	0.056
FIRM_AGE	62,004	2.682	0.689	2.079	2.639	3.178

Panel B: Firm Characteristics by Life Cycle Stages						
Variable	Pooled	*INTRO*	*GROWTH*	*MATURE*	*SHAKE-OUT*	*DECLINE*
SIGMA	0.06	0.09	0.06	0.05	0.07	0.09
SIZE	5.84	4.29	6.20	6.29	5.73	4.37
LEV	0.22	0.23	0.24	0.20	0.19	0.18
MTB	2.75	3.80	2.64	2.62	2.16	3.16
ROA	0.00	-0.21	0.04	0.06	0.01	-0.21
R&D_INT	0.15	0.56	0.05	0.03	0.08	0.84
FIRM _AGE	2.68	2.42	2.62	2.83	2.71	2.46
N	62,004	7,259	18,536	25,578	6,604	4,027
% TOTAL	100.00%	11.71%	29.89%	41.25%	10.65%	6.49%

Table 2.1 presents descriptive statistics and correlations for the variables included in the main analysis. The final sample consists of 62,004 firm-year observations over the period 1990-2013. Panel A (B) reports summary statistics for the full sample (by life cycle stage). The variables are defined as follows: $CRASH_{t+1}$ is an indicator variable that equals one if the firm experiences at least once a weekly return that is more than 3.2 standard deviations below the mean firm-specific weekly returns during the year *t+1*, and zero otherwise; $NCSKEW_{t+1}$ is the negative conditional skewness of the firm's returns for the year *t+1*; $DUVOL_{t+1}$ is the natural logarithm of the ratio of the standard deviation of firm-specific weekly returns during down-weeks (defined as weeks in which the firm-specific return is below the mean firm-specific weekly return) over the standard deviation of firm-specific weekly returns during up-weeks (defined as weeks in which the firm-specific return is above the mean firm-specific weekly return). *INTRO*, *GROWTH*, *MATURE*, *SHAKE-OUT*, and *DECLINE* are indicator variables that equal one if the firm is in the particular life cycle stage based on Dickinson's (2011) life cycle stage classification, and zero otherwise; *DTURNOVER* is the detrended share turnover calculated by subtracting the firm's share turnover in the previous year from its share turnover in the current year; *OPAQUE* is the three-year moving sum of the absolute value of discretionary accruals; *NCSKEW* is the lagged value $NCSKEW_{t+1}$; *RETURN* is the average firm-specific weekly return over the fiscal year; *SIGMA* is the volatility of firm-specific weekly returns over the fiscal year; *SIZE* is the natural logarithm of total assets; *LEV* is total debt divided by total assets;

Table 2.1 - Continued

MTB is market value of equity divided by book value of equity; *ROA* is income before extraordinary items divided by lagged total assets; *R&D_INT* is R&D expense divided by sales; *FIRM AGE* is the firm's age measured by the natural logarithm of the number of years that the company is in the CRSP database; *INSTH* is the percentage of institutional holdings; and *ANALYST* is the natural logarithm of the number of analysts included in the I/B/E/S consensus forecast for the firm on the date closest to but not exceeding the end of the fiscal year.

Specifically, size, age and operating performance are maximized in the mature stage, while the volatility of firms' stock prices is at its minimum during this stage. These patterns can be attributed to firms' stability and operating effectiveness in the mature stage. The market-to-book ratio and R&D intensity are highest in the introduction and decline stage, which is consistent with the importance of investments in innovation in these stages. Finally, leverage is highest in the introduction and growth stage and decreases once the firm leaves these stages, which is in line with the pecking order theory (Myers 1984).

2.4.2. Multivariate Analysis

To test the first hypothesis that crash risk is higher during the introduction and growth stage, we use probit and OLS regressions to estimate model (1) using $CRASH_{t+1}$, $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ as the dependent variables, respectively. All regression models include standard errors clustered at the firm level (Petersen 2009).[18]

Table 2.2, column (1), reports the results from estimating model (1) using a probit specification with $CRASH_{t+1}$ as the dependent variable. We observe significantly positive coefficients on both *INTRO* and *GROWTH,* which implies that firms are more prone to stock price crashes during the introduction and growth stage compared to the mature stage. The coefficient comparisons at the bottom of Table 3 show that besides the mature stage, the differences in crash risk are only significant when comparing the introduction and growth stage to the shake-out stage.

To examine the economic significance of our results, we calculate the marginal effects for the probit regression (untabulated). The marginal effects indicate that firms in the introduction and growth stage face a 1.5% and 1.1% higher probability of experiencing a stock price crash in the subsequent year, respectively. Given the unconditional crash risk probability of 16.9% based on the descriptive statistics in Table 2.2, these marginal effects suggest that crash risk is about 8.8% (0.015/0.169) and 6.6% (0.011/0.169) higher for firms in the introduction and growth stage, respectively. Similarly, comparing the marginal effects of financial reporting opaqueness and detrended share turnover to the unconditional crash risk probability suggests a substantial impact of firm life cycle. A one standard deviation increase in these variables leads to an increase in crash risk of about 3.9% for financial reporting opaqueness and 4.1% for detrended share turnover. This is half the size of the economic impact of the life cycle stages. The relatively large marginal effects of the introduction and growth stage provide additional evidence on the economic significance of the life cycle stages.

[18] The results obtained in our main analyses are robust to the inclusion of standard errors that are clustered at both firm and year level.

With regard to the control variables, all coefficients, except for the coefficients on *SIGMA, SIZE* and *LEV*, are significant and have the expected sign. More specifically, consistent with the studies of Chen et al. (2001) and Hutton et al. (2009), the significantly positive coefficients on *OPAQUE* and *DTURNOVER* indicate that, ceteris paribus, firms with more opaque reporting as well as firms that have higher abnormal trading volume face higher stock price crash risk in the subsequent year. Furthermore, the results in Table 2.2, column (1) also show that crash risk increases with R&D intensity, institutional holdings and analyst following but decreases with firm age, again in line with our expectations.[19] In combination with the results we observe for the life cycle indicator variables, these findings suggest that the higher crash risk during the introduction and growth stage cannot only be explained by firms' substantial investments in R&D, limited experience or bad news hoarding that could also lead to increased uncertainty among investors (An and Zhang 2013; Chen et al. 2001).[20]

Table 2.2, columns (2) and (3), report the OLS results obtained by estimating model (1) using $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ as the dependent variables. The coefficients on both *INTRO* and *GROWTH* are positive and significant at the 1% significance level, which indicates that crash risk is higher in these stages than in the mature stage. Furthermore, the coefficient comparisons at the bottom of Table 2.2 indicate that crash risk is not only significantly higher in the introduction and growth stage compared to the mature stage but also compared to the shake-out and decline stage. Finally, all coefficients on the control variables are significant in the expected direction.

Table 2.2, columns (4) and (5), shows the results using a firm fixed effects specification. Whereas one could argue that the inclusion of the lagged value of $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ in the previous models controls to some extent for unobserved firm effects, we estimate the fixed effects specification of model (1), excluding the lagged dependent variable, as a robustness check. The results in column (4) and (5) are consistent with the results in columns (2) and (3).

To test our second hypothesis that the positive relation between crash risk and the introduction and growth stage is more pronounced when investors face short selling constraints, we collect data on whether there is short interest in firm *i*'s stock at fiscal year-end. We obtain data on short interest from Compustat's Supplemental Short Interest File. We then split the sample based on the presence or absence of short interest at fiscal year-end. Table 2.3 presents the results.

[19] Following An and Zhang (2013) and Callen and Fang (2013), we also estimate model (1) after classifying institutional investors into three categories: transient, dedicated and quasi-indexer investors. Our inferences do not change. Consistent with the findings of An and Zhang (2013) and Callen and Fang (2013), the estimation results obtained using this classification of institutional investors reveal that the positive association between institutional ownership and stock price crash risk is mainly explained by transient investors.

[20] By using Dickinson's (2011) life cycle classification it is possible that a firm switches from one life cycle stage to another every year. One could argue however that it may take some time for the firm to move to another stage. To address this potential concern, we classify firms into the various life cycle stages based on the sum of the cash flows in year t and t-1. Our inferences hold for this alternative classification, expect for the coefficient on *INTRO*, which loses significance when estimating model (1) using the probit specification. This is probably due to the relatively transitory nature of the introduction stage (Dickinson 2011).

TABLE 2.2

The Impact of Firm Life Cycle on Stock Price Crash Risk

Variables	$CRASH_{t+1}$	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t+1}$	$DUVOL_{t+1}$
	(1)	(2)	(3)	(4)	(5)
INTRO	**0.061****	**0.048*****	**0.016*****	**0.042*****	**0.018*****
	(2.50)	**(3.63)**	**(2.84)**	**(2.71)**	**(2.65)**
GROWTH	**0.046*****	**0.047*****	**0.018*****	**0.042*****	**0.018*****
	(3.08)	**(5.75)**	**(5.07)**	**(4.67)**	**(4.55)**
SHAKE-OUT	-0.001	-0.015	-0.009*	-0.010	-0.007
	(-0.04)	(-1.27)	(-1.81)	(-0.76)	(-1.31)
DECLINE	0.013	-0.010	-0.010	-0.023	-0.013
	(0.43)	(-0.58)	(-1.43)	(-1.21)	(-1.56)
OPAQUE	0.137***	0.077***	0.026***	0.043*	0.017
	(3.68)	(3.57)	(2.85)	(1.65)	(1.53)
DTURNOVER	0.028***	0.021***	0.012***	0.024***	0.012***
	(4.58)	(6.17)	(7.71)	(6.75)	(7.51)
$NCSKEW_t$	0.043***	0.035***			
	(5.42)	(7.23)			
$DUVOL_t$			0.033***		
			(7.31)		
RETURN	9.182**	3.245*	-0.689	-3.071	-2.742**
	(2.12)	(1.66)	(-0.86)	(-0.98)	(-2.26)
SIGMA	0.344	0.525**	-0.422***	-0.842**	-0.752***
	(0.64)	(1.99)	(-3.83)	(-2.02)	(-4.54)
SIZE	-0.020***	0.014***	0.007***	0.076***	0.035***
	(-3.69)	(5.08)	(6.24)	(8.52)	(9.07)
LEV	0.061*	-0.088***	-0.046***	-0.101***	-0.060***
	(1.67)	(-4.03)	(-5.05)	(-2.70)	(-3.82)
MTB	0.004**	0.007***	0.003***	0.011***	0.005***
	(2.12)	(6.22)	(6.58)	(7.74)	(8.72)
ROA	0.383***	0.247***	0.139***	0.292***	0.161***
	(7.99)	(9.45)	(12.69)	(8.63)	(11.41)
R&D_INT	0.056***	0.042***	0.016***	0.034**	0.014***
	(4.99)	(5.15)	(5.15)	(2.46)	(2.80)

FIRM_AGE	-0.030***	-0.039***	-0.014***	-0.042**	-0.007
	(-2.76)	(-6.65)	(-5.66)	(-2.16)	(-0.82)
INSTH	0.316***	0.191***	0.087***	0.130***	0.069***
	(10.55)	(11.47)	(12.00)	(4.27)	(5.28)
ANALYST	0.058***	0.060***	0.027***	0.084***	0.039***
	(5.62)	(10.97)	(11.28)	(9.08)	(9.52)
Constant	-1.260***	-0.289***	-0.134***	-0.424***	-0.262***
	(-7.34)	(-3.02)	(-3.08)	(-5.41)	(-7.68)
Industry FE	YES	YES	YES	NO	NO
Year FE	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	YES	YES
Observations	61,997	62,004	62,004	62,004	62,004
(Pseudo) Adj. R^2	0.029	0.046	0.066	0.026	0.034
INTRO – GROWTH = 0	χ^2 = 0.37	F = 0.01	F = 0.10	F = 0.00	F = 0.00
	p = 0.542	p = 0.904	p = 0.758	p = 0.983	p = 0.954
INTRO – SHAKE-OUT =0	χ^2 = 4.81**	F = 16.59***	F = 14.56***	F = 8.53***	F = 10.77***
	p = 0.028	p = 0.000	p = 0.000	p = 0.004	p = 0.001
INTRO – DECLINE = 0	χ^2 = 2.40	F = 9.96***	F = 12.08***	F = 10.43***	F = 12.94***
	p = 0.122	p = 0.002	p = 0.005	p = 0.001	p = 0.000
GROWTH – SHAKE-OUT = 0	χ^2 = 4.39**	F = 25.95***	F = 26.72***	F = 14.56***	F = 18.39***
	p = 0.036	p = 0.000	p = 0.000	p = 0.000	p = 0.000
GROWTH – DECLINE = 0	χ^2 = 1.25	F = 10.84***	F = 15.31***	F = 11.25***	F = 13.89***
	p = 0.264	p = 0.001	p = 0.000	p = 0.001	p = 0.000
SHAKE-OUT – DECLINE = 0	χ^2 = 0.18	F = 0.08	F = 0.81	F = 0.43	F = 0.37
	p = 0.673	p = 0.782	p = 0.903	p = 0.510	p = 0.542

Table 2.2 presents the results of the effect of firm life cycle on stock price crash risk obtained using probit, OLS and fixed-effects regressions. The sample consists of 61,997 (62,004) firm-year observations over the period 1990-2013. The z-values (t-values) reported in parentheses are based on standard errors clustered by firm; *, **, and *** indicate statistical significance at the 10%, 5%, and 1% significance level, respectively. All non-logged, non-return variables are winsorized at 1% and 99% levels. The tests that are reported at the bottom of Table 2.2 are coefficient comparisons to examine whether the coefficient estimates differ significantly across firms' life cycle stages. Variable definitions can be found in Table 2.1.

The coefficients on *GROWTH* are significantly higher for firms with short selling constraints, i.e., those without any short interest. With regard to *INTRO*, we find no significant differences. Concerning the other life cycle variables, we do not find evidence that the coefficients are significantly higher for the subsample of firms without short interest. These findings provide partial support for our second hypothesis. More specifically, firms in the growth stage are generally more prone to crash risk when there are short selling constraints. We acknowledge that the existence of short interest is not only driven by the supply (i.e., the absence or presence of short selling constraints), but also by the demand for shorting (i.e., investors are more likely to short stocks they expect to perform badly). However, our results are consistent with the former explanation only. Dickinson (2011) shows that the stock returns of firms in the introduction and growth stage are lower than those of firms in the other stages. Hence, if anything, one would expect the demand for shorting to be higher for firms in these stages and under this demand hypothesis introduction and growth firms that are shorted should have higher crash risk. Thus, even though the demand for shorting is likely higher, our finding that crash risk is higher for growth firms that are not shorted is consistent with severe short selling constraints being an important driver of the positive relation between growth-stage firms and crash risk.

To test our third hypothesis that the effect of the introduction and growth stage on crash risk is more pronounced for firms with a high market-to-book ratio, we estimate our main model after splitting the sample based on the median value of firms' market-to-book ratios for each life cycle stage. Table 2.4 reports the results for this split-sample analysis.

Consistent with our third hypothesis, the coefficients on *INTRO* and *GROWTH* are significantly higher for firms with a high market-to-book ratio than for firms with a low market-to-book ratio at the 10% and 1% significant levels, respectively. Concerning the other life cycle variables, we find no evidence that the coefficients are significantly higher for the subsample that includes firms with a high market-to-book ratio. These findings provide support for our third hypothesis. More specifically, firms in the introduction and growth stage are generally more prone to crash risk when they derive more of their value from future growth opportunities or, alternatively, when their book values deviate more from their economic values.

TABLE 2.3

Split-Sample Analysis: Short Interest

	$NCSKEW_{t+1}$			$DUVOL_{t+1}$		
Variables	Short Interest (1)	No Short Interest (2)	High - Low (3)	Short Interest (4)	No Short Interest (5)	High - Low (6)
INTRO	**0.045****	**0.052*****	**$\chi^2 = 0.08$**	**0.019****	**0.013**	**$\chi^2 = 0.31$**
	(2.36)	**(2.79)**	**p = 0.781**	**(2.38)**	**(1.58)**	**p = 0.579**
GROWTH	**0.031*****	**0.069*****	**$\chi^2 = 4.79$*****	**0.012*****	**0.025*****	**$\chi^2 = 2.86$***
	(3.05)	**(5.01)**	**p = 0.029**	**(2.76)**	**(4.15)**	**p = 0.091**
SHAKE-OUT	-0.017	-0.007	$\chi^2 = 0.20$	-0.009	-0.007	$\chi^2 = 0.05$
	(-1.18)	(-0.34)	p = 0.654	(-1.47)	(-0.83)	p = 0.830
DECLINE	-0.011	-0.003	$\chi^2 = 0.06$	-0.008	-0.012	$\chi^2 = 0.09$
	(-0.46)	(-0.12)	p = 0.8088	(-0.77)	(-1.18)	p = 0.762
OPAQUE	0.124***	0.009		0.045***	-0.002	
	(3.94)	(0.34)		(3.42)	(-0.20)	
DTURNOVER	0.020***	0.022***		0.011***	0.012***	
	(4.35)	(4.10)		(5.51)	(5.00)	
$NCSKEW_t$	0.035***	0.023***				
	(5.69)	(3.11)				
$DUVOL_t$				0.034***	0.017**	
				(6.18)	(2.38)	
RETURN	8.207***	3.077		0.513	-0.545	
	(2.76)	(1.27)		(0.42)	(-0.55)	
SIGMA	0.506	0.995***		-0.523***	-0.189	
	(1.33)	(2.73)		(-3.27)	(-1.25)	
SIZE	0.015***	0.008		0.008***	0.005**	
	(4.56)	(1.58)		(5.41)	(2.04)	
LEV	-0.097***	-0.038		-0.051***	-0.023*	
	(-3.34)	(-1.17)		(-4.24)	(-1.67)	
MTB	0.005***	0.009***		0.002***	0.004***	
	(3.45)	(5.69)		(3.78)	(5.76)	
ROA	0.257***	0.223***		0.143***	0.127***	
	(6.24)	(7.03)		(8.50)	(9.09)	

R&D_INT	0.047***	0.034***		0.018***	0.013***
	(3.84)	(3.56)		(3.86)	(3.31)
FIRM_AGE	-0.036***	-0.028***		-0.013***	-0.009**
	(-5.02)	(-2.69)		(-4.16)	(-2.10)
INSTH	0.166***	0.278***		0.073***	0.139***
	(8.47)	(8.84)		(8.62)	(9.80)
ANALYST	0.051***	0.088***		0.023***	0.039***
	(7.61)	(9.65)		(8.06)	(9.37)
Constant	-0.282	-0.413***		-0.126	-0.193***
	(-1.63)	(-3.38)		(-1.52)	(-3.39)
Industry FE	YES	YES		YES	YES
Year FE	YES	YES		YES	YES
Firm FE	NO	NO		NO	NO
Observations	40,952	21,052		40,952	21,052
(Pseudo) Adj. R^2	0.038	0.066		0.052	0.084
INTRO – GROWTH = 0	F= 0.51	F = 0.71		F = 0.71	F = 2.21
	p = 0.474	p = 0.398		p = 0.399	p = 0.137
INTRO – SHAKE-OUT =0	F = 8.22***	F = 6.63**		F = 9.56***	F = 3.97**
	p = 0.004	p = 0.010		p = 0.002	p = 0.046
INTRO – DECLINE = 0	F = 4.34**	F = 5.48**		F = 6.03**	F = 6.12**
	p = 0.037	p = 0.019		p = 0.014	p = 0.013
GROWTH – SHAKE-OUT = 0	F = 10.40***	F = 13.84***		F = 11.09***	F = 12.90***
	p = 0.001	p = 0.000		p = 0.001	p = 0.000
GROWTH – DECLINE = 0	F = 3.07*	F = 8.96***		F = 4.01**	F = 12.99***
	p = 0.080	p = 0.003		p = 0.045	p = 0.000
SHAKE-OUT – DECLINE = 0	F = 0.06	F = 0.02		F = 0.03	F = 0.17
	p = 0.800	p = 0.890		p = 0.868	p = 0.680

Table 2.3 presents the results of the impact of firm life cycle stages on crash risk obtained using OLS after splitting the sample based on whether or not there is short interest in firm *i*'s shares at the end of the fiscal year. Short interest is obtained from Compustat's Supplemental Short Interest database. The full sample consists of 62,004 firm-year observations over the period 1990-2013. The t-values reported in parentheses are based on standard errors clustered by firm; *, **, and *** indicate significance at the 10%, 5%, and 1% significance level, respectively. All non-logged, non-return variables are winsorized at 1% and 99% levels. The tests reported in columns 3 and 6 indicate whether the coefficient estimates differ significantly across the two sub-samples. The tests that are reported at the bottom of Table 2.3 are coefficient comparisons to examine whether the coefficient estimates differ significantly across firms' life cycle stages. Variable definitions can be found in Table 2.1.

TABLE 2.4

Split-Sample Analysis: Assets in Place versus Growth Opportunities

	$NCSKEW_{t+1}$			$DUVOL_{t+1}$		
Variables	Low MTB (1)	High MTB (2)	High - Low (3)	Low MTB (4)	High MTB (5)	High - Low (6)
INTRO	**0.025**	**0.071*****	**χ^2 = 2.78***	**0.007**	**0.024*****	**χ^2 = 1.98**
	(1.45)	**(3.25)**	**p = 0.095**	**(0.99)**	**(2.63)**	**p = 0.160**
GROWTH	**0.021***	**0.069*****	**χ^2 = 8.55*****	**0.007**	**0.028*****	**χ^2 = 8.62*****
	(1.90)	**(5.84)**	**p = 0.004**	**(1.42)**	**(5.43)**	**p = 0.003**
SHAKE-OUT	-0.032**	-0.013	χ^2 = 0.63	-0.018**	-0.007	χ^2 = 1.08
	(-1.97)	(-0.75)	p = 0.427	(-2.53)	(-0.97)	p = 0.300
DECLINE	-0.033	0.009	χ^2 = 1.54	-0.022**	-0.001	χ^2 = 2.01
	(-1.48)	(0.35)	p = 0.215	(-2.30)	(-0.13)	p = 0.156
OPAQUE	0.043	0.070**		0.012	0.022*	
	(1.46)	(2.31)		(0.98)	(1.78)	
DTURNOVER	0.009	0.024***		0.007***	0.012***	
	(1.62)	(5.03)		(2.84)	(5.91)	
$NCSKEW_t$	0.038***	0.033***				
	(5.82)	(4.34)				
$DUVOL_t$				0.035***	0.030***	
				(5.78)	(4.44)	
RETURN	3.838	2.520		-0.752	-0.432	
	(1.59)	(0.84)		(-0.79)	(-0.31)	
SIGMA	0.677**	0.247		-0.415***	-0.433**	
	(2.05)	(0.59)		(-3.08)	(-2.31)	
SIZE	0.018***	0.013***		0.009***	0.008***	
	(5.23)	(3.07)		(5.49)	(4.34)	
LEV	-0.039	-0.149***		-0.023*	-0.075***	
	(-1.29)	(-4.65)		(-1.83)	(-5.39)	
MTB	-0.006	0.003**		-0.002	0.002***	
	(-1.18)	(2.57)		(-1.08)	(2.88)	
ROA	0.195***	0.253***		0.114***	0.141***	
	(4.52)	(7.42)		(6.20)	(9.96)	

R&D_INT	0.029**	0.040***		0.012**	0.015***	
	(2.00)	(4.04)		(2.15)	(3.92)	
FIRM_AGE	-0.024***	-0.048***		-0.008**	-0.018***	
	(-3.26)	(-5.37)		(-2.56)	(-4.75)	
INSTH	0.175***	0.192***		0.082***	0.087***	
	(7.71)	(8.09)		(8.23)	(8.51)	
ANALYST	0.051***	0.048***		0.022***	0.022***	
	(6.67)	(6.10)		(6.52)	(6.48)	
Constant	-0.268**	-0.242		-0.116**	-0.129*	
	(-2.21)	(-1.59)		(-2.21)	(-1.69)	
Industry FE	YES	YES		YES	YES	
Year FE	YES	YES		YES	YES	
Firm FE	NO	NO		NO	NO	
Observations	31,002	31,002		31,002	31,002	
(Pseudo) Adj. R^2	0.036	0.043		0.051	0.065	
INTRO – GROWTH = 0	F = 0.03	F = 0.01		F =0.00	F = 0.20	
	p = 0.856	p = 0.941		p = 0.964	p = 0.654	
INTRO – SHAKE-OUT =0	F = 7.33***	F = 12.16***		F = 7.71***	F = 9.53***	
	p = 0.007	p = 0.005		p = 0.006	p = 0.002	
INTRO – DECLINE = 0	F = 5.48**	F = 5.10**		F = 7.83***	F = 5.34**	
	p = 0.019	p = 0.024		p = 0.005	p = 0.021	
GROWTH – SHAKE-OUT = 0	F = 10.19***	F = 22.05***		F = 11.57***	F = 21.71***	
	p = 0.001	p = 0.000		p = 0.001	p = 0.000	
GROWTH – DECLINE = 0	F = 5.63**	F = 5.49**		F = 8.77***	F = 7.57***	
	p = 0.018	p = 0.019		p = 0.003	p = 0.006	
SHAKE-OUT – DECLINE = 0	F = 0.00	F = 0.61		F = 0.14	F = 0.24	
	p =0.962	p = 0.435		p = 0.711	p = 0.627	

Table 2.4 presents the results of the impact of firm life cycle stages on crash risk obtained using OLS after splitting the sample based on the median value of firms' market-to-book ratios by life cycle stage. The full sample consists of 62,004 firm-year observations over the period 1990-2013. The t-values reported in parentheses are based on standard errors clustered by firm; *, **, and *** indicate significance at the 10%, 5%, and 1% significance level, respectively. All non-logged, non-return variables are winsorized at 1% and 99% levels. The tests reported in columns 3 and 6 indicate whether the coefficient estimates differ significantly across the two sub-samples. The tests that are reported at the bottom of Table 2.4 are coefficient comparisons to examine whether the coefficient estimates differ significantly across firms' life cycle stages. Variable definitions can be found in Table 2.1.

Finally, we investigate the extent to which the effect of firm life cycle on stock price crash risk is driven by heterogeneity in investor beliefs and/or mispricing resulting from investors' failure to understand the intertemporal profitability patterns associated with firm life cycle. We investigate this by splitting the sample based on median firm profitability in each life cycle stage. As Dickinson (2011) shows that investors are too optimistic about the future performance of early-stage firms, we expect crash risk to be higher for the best-performing firms in the introduction and growth stage. Consistent with Dickinson (2011), we measure firm profitability by the return on net operating assets, *RNOA*.[21] Table 2.5 reports the results of this split-sample analysis.

In line with our expectations, crash risk is more pronounced for firms in the growth stage that have a relatively high operating performance in the current fiscal year. This finding is consistent with mispricing being a (partial) explanation for the effect of firm life cycle on stock price crash risk. However, the fact that early-stage firms exhibit higher crash risk even if their performance is weak, suggests that heterogeneity in investor beliefs still plays an important role. The coefficient on *DECLINE*, however, is significantly lower in the high-performance subsample. This finding is consistent with investors being pessimistic about the future prospects of well-performing decline firms, consistent with the higher returns for these firms as documented by Dickinson (2011).

Overall, the empirical results provide strong evidence in support of our hypothesis that crash risk is highest during the introduction and growth stage. The findings indicate that a firm's life cycle stage is an important determinant of stock price crash risk beyond factors commonly investigated in prior studies. In addition, the increased crash risk for firms in the growth stage is more pronounced for firms where investors face short selling constraints, for firms that derive a relatively large proportion of their value from future growth opportunities which are not reflected in their book value and for firms that have relatively strong operating performance in the current fiscal year. Moreover, the fact that these results hold while controlling for financial reporting opaqueness and other factors that are likely to be associated with a firm's development over time suggests that the higher crash risk during the introduction and growth stage cannot only be explained by financial reporting opaqueness but could also arise because of heterogeneity in investor beliefs regarding firms' fundamental values as well as investor mispricing.

[21] This is in contrast to our previous analyses in which we used ROA as our measure of operating performance. Since we derive our expectation from the results obtained by Dickinson (2011) we deem it more appropriate to use RNOA as our performance measure in this test. Nevertheless, the differences in crash risk across the subsamples are still significant for firms in the growth stage also when we use ROA instead.

TABLE 2.5

Split-Sample Analysis: Performance Persistence

	$NCSKEW_{t+1}$			$DUVOL_{t+1}$		
Variables	Low RNOA (1)	High RNOA (2)	High - Low (3)	Low RNOA (4)	High RNOA (5)	High - Low (6)
INTRO	**0.035***	**0.031**	**$\chi^2 = 0.02$**	**0.009**	**0.008**	**$\chi^2 = 0.00$**
	(1.80)	**(1.55)**	**p = 0.879**	**(1.03)**	**(0.99)**	**p = 0.979**
GROWTH	**0.028****	**0.058*****	**$\chi^2 = 3.21$***	**0.010****	**0.023*****	**$\chi^2 = 3.02$***
	(2.55)	**(4.83)**	**p = 0.073**	**(2.07)**	**(4.39)**	**p = 0.082**
SHAKE-OUT	-0.004	-0.031*	$\chi^2 = 1.34$	-0.005	-0.016**	$\chi^2 = 1.14$
	(-0.25)	(-1.83)	p = 0.247	(-0.70)	(-2.16)	p = 0.286
DECLINE	0.027	-0.072***	$\chi^2 = 8.52$***	0.003	-0.036***	$\chi^2 = 7.43$***
	(1.12)	(-2.90)	p = 0.004	(0.25)	(-3.46)	p = 0.006
OPAQUE	0.023	0.104***		0.003	0.035***	
	(0.82)	(3.17)		(0.24)	(2.60)	
DTURNOVER	0.023***	0.014***		0.013***	0.007***	
	(4.81)	(2.70)		(6.14)	(3.29)	
$NCSKEW_t$	0.033***	0.035***				
	(5.08)	(4.77)				
$DUVOL_t$				0.032***	0.030***	
				(5.28)	(4.59)	
RETURN	2.825	6.578		-1.032	1.263	
	(1.37)	(1.36)		(-1.18)	(0.69)	
SIGMA	0.487	1.089**		-0.485***	-0.071	
	(1.53)	(2.01)		(-3.57)	(-0.33)	
SIZE	0.020***	0.011***		0.009***	0.007***	
	(5.42)	(2.76)		(5.87)	(3.84)	
LEV	-0.050*	-0.107***		-0.022*	-0.062***	
	(-1.74)	(-3.19)		(-1.77)	(-4.48)	
MTB	0.005***	0.006***		0.002***	0.003***	
	(3.54)	(4.04)		(3.79)	(3.97)	
ROA	0.128***	0.205***		0.080***	0.122***	
	(3.88)	(3.57)		(5.69)	(5.33)	

R&D_INT	0.024***	0.057***		0.008**	0.023***	
	(2.70)	(3.51)		(2.35)	(3.78)	
FIRM_AGE	-0.035***	-0.040***		-0.013***	-0.014***	
	(-4.52)	(-4.70)		(-3.92)	(-3.86)	
INSTH	0.197***	0.174***		0.091***	0.078***	
	(8.62)	(7.39)		(9.15)	(7.68)	
ANALYST	0.047***	0.063***		0.020***	0.030***	
	(6.46)	(7.99)		(6.05)	(8.73)	
Constant	-0.375***	-0.218*		-0.172***	-0.104*	
	(-3.08)	(-1.76)		(-3.00)	(-1.96)	
Industry FE	YES	YES		YES	YES	
Year FE	YES	YES		YES	YES	
Firm FE	NO	NO		NO	NO	
Observations	30,957	30,961		30,957	30,961	
(Pseudo) Adj. R^2	0.041	0.043		0.060	0.057	
INTRO – GROWTH = 0	F = 0.11	F = 1.89		F = 0.03	F = 3.02*	
	p = 0.740	p = 0.169		p = 0.857	p = 0.082	
INTRO – SHAKE-OUT =0	F = 3.19*	F = 7.47***		F = 2.07	F = 6.40**	
	p = 0.074	p = 0.006		p = 0.150	p = 0.011	
INTRO – DECLINE = 0	F = 0.10	F = 15.53***		F = 0.36	F = 16.77***	
	p = 0.751	p = 0.000		p = 0.548	p = 0.000	
GROWTH – SHAKE-OUT = 0	F = 3.70*	F = 25.99***		F = 4.16**	F = 26.47***	
	p = 0.055	p = 0.000		p = 0.042	p = 0.000	
GROWTH – DECLINE = 0	F = 0.00	F = 27.52***		F = 0.55	F =32.15***	
	p = 0.959	p = 0.000		p = 0.458	p = 0.000	
SHAKE-OUT – DECLINE = 0	F = 1.40	F = 2.33		F = 0.45	F =3.11*	
	p = 0.238	p = 0.127		p = 0.503	p = 0.078	

Table 2.5 presents the results of the impact of firm life cycle stages on crash risk obtained using OLS after splitting the sample based on the median return on net operating assets by life cycle stage. The return on net operating assets is calculated as operating income after depreciation (OIADP) divided by net operating assets (book value of equity minus cash plus total debt; SEQ – CHE + DLC +DLTT). The full sample consists of 62,004 firm-year observations over the period 1990-2013. The t-values reported in parentheses are based on standard errors clustered by firm; *, **, and *** indicate significance at the 10%, 5%, and 1% significance level, respectively. All non-logged, non-return variables are winsorized at 1% and 99% levels. The tests reported in columns 3 and 6 indicate whether the coefficient estimates differ significantly across the two sub-samples. The tests that are reported at the bottom of Table 2.5 are coefficient comparisons to examine whether the coefficient estimates differ significantly across firms' life cycle stages. Variable definitions can be found in Table 2.1.

2.5 Additional Analyses and Robustness Tests

2.5.1. Stock Price Jumps

Heterogeneity in investor beliefs and investors' overoptimism leads to stock price crashes if negative news that was previously not fully incorporated into market prices is revealed to the market. Hence, our theory only predicts that the likelihood of stock price crashes should increase, but has no implications for the effect of firm life cycle on the likelihood of stock price jumps, i.e., extreme increases in firm-specific stock prices. If we do observe a positive effect of the introduction and growth stage on stock price jumps, this suggests that our results are driven by higher stock price volatility during the introduction and growth stage and thus that these firms are more risky compared to firms in the other life cycle stages.

To examine the impact of firm life cycle on stock price jumps, we run a probit regression with a binary variable, $JUMP_{t+1}$, as the dependent variable. Similar to $CRASH_{t+1}$, $JUMP_{t+1}$ is an indicator variable that is equal to one if firm *i* experiences at least one weekly return that is more than 3.2 standard deviations above the mean firm-specific weekly returns in the next year, and zero otherwise. The independent variables are the same as those included in the previous models. The findings in Table 2.6 show that there is no significant effect of *INTRO* on the likelihood of a stock price jump. In addition, the likelihood of a stock price jump is lower for firms in the growth stage than for mature firms. With regard to the majority of the control variables, the signs of the coefficients are, as one would expect, exactly opposite to the signs of the coefficients found in the previous analyses.

2.5.2. Alternative Life Cycle Measure

The patterns that can be derived from Table 2.1, Panel B, are generally in line with the patterns that one expects based on firms' development throughout their life cycle and hence provide support for using Dickinson's (2011) approach to classify firms into the various life cycle stages. However, since Dickinson's (2011) approach is based on cash flows, a potential concern with the use of these variables is that they are picking up firm performance and that this is driving our results. To rule out this alternative explanation, we also use a different life cycle classification which is less likely to be associated with firm performance. Consistent with Hribar and Yehuda (2015), we rank firms into three life cycle stages based on a composite score that is derived from the standardized values of sales growth, capital expenditures, net-capital transactions and firm age.[22]

Using this alternative life cycle stage classification, we replace the four indicator variables for the different life cycle stages in model (1) with *GROWTH* and *DECLINE* that are equal to one if firm *i* is classified into that particular stage at time *t* based on the composite life cycle score calculated based on Hribar and Yehuda (2015), and zero otherwise.

[22] Contrary to Dickinson (2011), Hribar and Yehuda (2015) do not use the introduction and shake-out stage in their life cycle classification. As Hribar and Yehuda (2015) argue in footnote 11, "the start-up stage is not considered in the analysis as our sample of firms includes only publicly traded companies with analyst following and thus is unlikely to capture the start-up phase."

TABLE 2.6

The Impact of Firm Life Cycle on Stock Price Jumps

Variables	$JUMP_{t+1}$
INTRO	**0.005**
	(0.23)
GROWTH	**-0.055*****
	(-3.76)
SHAKE-OUT	0.014
	(0.68)
DECLINE	0.066**
	(2.53)
OPAQUE	-0.098***
	(-2.80)
DTURNOVER	-0.029***
	(-4.78)
$NCSKEW_t$	-0.026***
	(-3.56)
RETURN	-0.913
	(-0.38)
SIGMA	0.666*
	(1.72)
SIZE	-0.053***
	(-10.34)
LEV	0.216***
	(6.25)
MTB	-0.011***
	(-6.32)
ROA	-0.201***
	(-4.91)
R&D_INT	-0.015
	(-1.44)
FIRM_AGE	0.040***
	(4.00)
INSTH	-0.085***
	(-2.95)
ANALYST	-0.091***
	(-9.13)
Constant	-0.385***
	(-2.59)
Industry FE	YES
Year FE	YES
Firm FE	NO
Observations	61,999
(Pseudo) Adj. R^2	0.033
INTRO – GROWTH = 0	χ^2=7.04***
	p =0.008
INTRO – SHAKE-OUT =0	χ^2=0.11
	p =0.739
INTRO – DECLINE = 0	χ^2=4.66**
	p =0.031
GROWTH – SHAKE-OUT = 0	χ^2=10.93***
	p =0.001

Table 2.6 - Continued

GROWTH – DECLINE = 0	χ^2=21.31***
	p = 0.000
SHAKE-OUT – DECLINE = 0	χ^2=3.26
	p =0.071

Table 2.6 presents the results of the effect of firm life cycle stages on stock price jumps obtained using a probit regression. The sample consists of 61,999 firm-year observations over the period 1990-2013. The dependent variable is an indicator variable that equals one if the firm experiences at least once a weekly return that is more than 3.2 standard deviations above the mean firm-specific weekly returns during the year *t*, and zero otherwise ($JUMP_{t+1}$). The z-values reported in parentheses are based on standard errors clustered by firm; *, **, and *** indicate significance at the 10%, 5%, and 1% significance level respectively. All non-logged, non-return variables are winsorized at 1% and 99% levels. The tests that are reported at the bottom of Table 2.6 are coefficient comparisons to examine whether the coefficient estimates differ significantly across firms' life cycle stages. Variable definitions can be found in table 2.1.

The mature stage is treated as the reference category. Since the alternative life cycle classification is partly determined by firm age and investments in R&D, we exclude these variables from the adjusted models but include cash flows from operations as an additional control. For brevity, we do not tabulate the results.

The results using this alternative measure are consistent with the results based on Dickinson's (2011) life cycle classification. Specifically, crash risk is highest during the growth stage and the coefficients on most control variables are significant and in the expected direction. Moreover, the results using $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ as dependent variables suggest that crash risk decreases as the firm moves towards the decline stage. One potential explanation is that the alternative classification assigns more mature firms to *DECLINE* since these firms tend to be older and experience relatively lower sales growth compared to other firms (Dickinson 2011). In short, our findings are robust to an alternative life cycle classification.

2.5.3. Firm Performance and Other Determinants of Crash Risk

Since Dickinson's (2011) life cycle classification is based on cash flow patterns, our results could be driven by firms' underlying cash flows and profitability. To mitigate this potential concern, we add future ROA (ROA_{t+1}), cash flow of operations (*CFO*), and an indicator variable (*LOSS*) that is equal to one if the firm has a loss, and zero otherwise, as control variables to our model.

In addition, we control for other factors that were found by prior studies to have a significant impact on crash risk. Following Kim and Zhang (2015) and Kim et al. (2011b), we include measures of firms' accounting conservatism (*CSCORE*) and the sensitivity of CFOs' compensation to stock price volatility (*CFO_VEGA*) as additional variables. The inclusion of these two additional determinants of firm-specific crash risk decreases our sample size substantially. The findings are reported in Table 2.7.

TABLE 2.7

The Impact of Firm Life Cycle on Stock Price Crash Risk –Additional Control Variables

Variables	$CRASH_{t+1}$ (1)	$NCSKEW_{t+1}$ (2)	$DUVOL_{t+1}$ (3)	$CRASH_{t+1}$ (4)	$NCSKEW_{t+1}$ (5)	$DUVOL_{t+1}$ (6)	$NCSKEW_{t+1}$ (7)	$DUVOL_{t+1}$ (8)	$NCSKEW_{t+1}$ (9)	$DUVOL_{t+1}$ (10)
INTRO	**0.072*****	**0.059*****	**0.023*****	**0.118**	**0.095****	**0.037***	**0.051*****	**0.023*****	**0.087***	**0.036**
	(2.60)	**(3.86)**	**(3.56)**	**(1.53)**	**(2.04)**	**(1.81)**	**(2.95)**	**(3.13)**	**(1.65)**	**(1.52)**
GROWTH	**0.041*****	**0.045*****	**0.017*****	**0.080****	**0.046****	**0.018****	**0.041*****	**0.018*****	**0.027**	**0.012**
	(2.77)	**(5.51)**	**(4.88)**	**(2.49)**	**(2.51)**	**(2.24)**	**(4.60)**	**(4.49)**	**(1.30)**	**(1.32)**
SHAKE-OUT	0.004	-0.009	-0.006	-0.018	0.006	0.001	-0.007	-0.006	0.015	0.006
	(0.17)	(-0.71)	(-1.05)	(-0.37)	(0.22)	(0.08)	(-0.55)	(-0.99)	(0.51)	(0.49)
DECLINE	0.017	0.001	-0.002	-0.111	-0.022	0.001	-0.018	-0.008	-0.056	-0.014
	(0.51)	(0.06)	(-0.32)	(-1.13)	(-0.41)	(0.02)	(-0.84)	(-0.89)	(-0.85)	(-0.45)
OPAQUE	0.119***	0.064***	0.020**	0.041	0.053	0.029	0.044*	0.017	0.061	0.031
	(3.19)	(2.97)	(2.23)	(0.44)	(0.90)	(1.16)	(1.70)	(1.54)	(0.81)	(0.95)
DTURNOVER	0.029***	0.021***	0.011***	0.025*	0.013	0.006*	0.024***	0.011***	0.022**	0.009**
	(4.72)	(5.99)	(7.38)	(1.65)	(1.50)	(1.66)	(6.57)	(7.23)	(2.41)	(2.31)
$NCSKEW_t$	0.041***	0.035***		0.023	0.009					
	(5.27)	(7.12)		(1.31)	(0.86)					
$DUVOL_t$			0.032***			0.005				
			(7.25)			(0.54)				
RETURN	9.429**	3.960**	-0.273	22.719	11.615***	2.741***	-2.465	-2.397**	2.122	-0.743
	(2.13)	(2.04)	(-0.34)	(0.94)	(7.21)	(3.57)	(-0.80)	(-2.02)	(0.84)	(-0.77)
SIGMA	0.183	0.584**	-0.368***	1.994	2.212***	0.363	-0.694*	-0.667***	-1.084	-0.745**
	(0.33)	(2.21)	(-3.33)	(0.99)	(3.82)	(1.44)	(-1.68)	(-4.07)	(-1.45)	(-2.28)
SIZE	-0.019***	0.015***	0.008***	-0.016	0.009	0.005	0.074***	0.034***	0.095***	0.038***
	(-3.41)	(5.54)	(6.69)	(-0.88)	(0.84)	(1.15)	(8.36)	(8.95)	(3.43)	(3.08)
LEV	0.061*	-0.085***	-0.044***	-0.050	-0.112*	-0.059**	-0.090**	-0.054***	-0.123	-0.072
	(1.66)	(-3.87)	(-4.79)	(-0.45)	(-1.77)	(-2.15)	(-2.38)	(-3.40)	(-1.16)	(-1.53)
MTB	0.004**	0.007***	0.003***	0.011	0.015***	0.007***	0.011***	0.005***	0.030***	0.014***
	(2.10)	(6.10)	(6.44)	(1.63)	(3.98)	(4.23)	(7.84)	(8.81)	(6.31)	(6.96)
ROA	0.533***	0.300***	0.147***	1.052***	0.657***	0.279***	0.247***	0.128***	0.571***	0.244***
	(7.22)	(7.69)	(8.92)	(4.24)	(4.91)	(4.62)	(5.56)	(6.92)	(3.68)	(3.42)
R&D_INT	0.043***	0.031***	0.011***	0.020	0.020	-0.003	0.022	0.009*	0.059	0.010
	(3.72)	(3.66)	(3.53)	(0.40)	(0.61)	(-0.18)	(1.60)	(1.81)	(1.09)	(0.49)

Table 2.7 - Continued

FIRM_AGE	-0.029***	-0.039***	-0.014***	-0.045*	-0.019	-0.007	-0.043**	-0.007	-0.119**	-0.035
	(-2.66)	(-6.59)	(-5.61)	(-1.90)	(-1.45)	(-1.16)	(-2.21)	(-0.86)	(-2.19)	(-1.35)
INSTH	0.321***	0.196***	0.088***	0.479***	0.296***	0.137***	0.131***	0.069***	0.114	0.065
	(10.69)	(11.75)	(12.23)	(5.43)	(6.02)	(6.43)	(4.29)	(5.22)	(1.26)	(1.60)
ANALYST	0.057***	0.058***	0.026***	-0.028	0.023*	0.016**	0.083***	0.038***	0.044*	0.023*
	(5.50)	(10.74)	(11.03)	(-1.09)	(1.66)	(2.51)	(8.98)	(9.40)	(1.67)	(1.89)
ROA_{t+1}	-0.479***	-0.315***	-0.130***	-0.883***	-0.578***	-0.204***	-0.275***	-0.112***	-0.423***	-0.142***
	(-9.99)	(-10.71)	(-10.56)	(-5.37)	(-6.14)	(-5.05)	(-8.34)	(-8.08)	(-3.87)	(-2.98)
CFO	0.195***	0.118***	0.058***	-0.018	0.175	0.094*	0.055	0.031	0.125	0.075
	(2.58)	(2.79)	(3.25)	(-0.08)	(1.47)	(1.75)	(1.10)	(1.43)	(0.85)	(1.10)
LOSS	-0.018	-0.049***	-0.028***	0.013	-0.013	-0.013	-0.066***	-0.035***	-0.016	-0.016
	(-0.89)	(-4.54)	(-5.98)	(0.24)	(-0.44)	(-1.01)	(-5.34)	(-6.63)	(-0.47)	(-1.07)
CSCORE				0.104	0.188	0.110*			-0.171	-0.045
				(0.43)	(1.35)	(1.80)			(-0.99)	(-0.60)
CFO_VEGA				0.001**	0.000*	0.000*			0.001**	0.000**
				(2.51)	(1.76)	(1.83)			(2.25)	(2.26)
Constant	-1.262***	-0.292***	-0.137***	-1.536**	-0.959***	-0.460***	-0.407***	-0.255***	-0.494*	-0.329**
	(-7.37)	(-3.02)	(-3.08)	(-2.19)	(-2.92)	(-2.91)	(-5.21)	(-7.50)	(-1.68)	(-2.09)
Industry FE	YES	YES	YES	YES	YES	YES	NO	NO	NO	NO
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES
Observations	61,938	61,945	61,945	11,692	11,700	11,700	61,945	61,945	11,700	11,700
(Pseudo) Adj. R^2	0.031	0.049	0.068	0.040	0.042	0.047	0.028	0.037	0.038	0.041
INTRO – GROWTH = 0	χ^2=1.27	F=0.88	F=0.83	χ^2=0.25	F=1.13	F =0.87	F=0.33	F=0.55	F=1.11	F=1.03
	p=0.260	p=0.349	p=0.363	p=0.619	p=0.287	p=0.352	p=0.566	p=0.486	p=0.293	p=0.310
INTRO – SHAKE-OUT =0	χ^2=5.28**	F=16.85***	F=16.50***	χ^2=2.71*	F=3.38*	F=2.88*	F=9.91***	F=13.12***	F=1.31	F=1.41
	p=0.022	p=0.000	p=0.000	p=0.100	p=0.066	p=0.090	p=0.002	p=0.000	p=0.253	p=0.236
INTRO – DECLINE = 0	χ^2=3.18*	F=9.82***	F=11.31***	χ^2=4.48**	F=3.46*	F=1.65	F=11.38***	F=13.46***	F=3.78*	F=2.19
	p=0.075	p=0.002	p=0.001	p=0.034	p=0.063	p=0.199	p=0.001	p=0.000	p=0.052	p=0.139
GROWTH – SHAKE-OUT = 0	χ^2=2.80*	F=19.07***	F=18.42***	χ^2=3.86**	F=2.03	F=1.98	F=12.70***	F=15.47***	F=0.09	F=0.18
	p=0.095	p=0.000	p=0.000	P=0.049	p=0.155	p=0.159	p=0.000	p=0.000	p=0.759	p=0.676

Table 2.7 - Continued

GROWTH – DECLINE = 0	χ^2=0.60	F=5.79**	F=6.65***	χ^2=3.80*	F=1.56	F=0.51	F=7.96***	F=8.41***	F=1.80	F=0.74
	p=0.439	p=0.016	p=0.010	p=0.051	p=0.211	p=0.475	p=0.005	p=0.004	p=0.180	p=0.389
SHAKE-OUT – DECLINE = 0	χ^2=0.15	F=0.25	F=0.14	χ^2=0.88	F=0.26	F=0.00	F=0.23	F=0.06	F=1.40	F=0.45
	p=0.703	p=0.614	p=0.709	p=0.348	p=0.610	p=0.987	p=0.629	p=0.809	p=0.237	p=0.503

Table 2.7 presents the results of the effect of firm life cycle stages on crash risk including additional control variables. The samples consist of firm-year observations over the period 1990-2013. ROA_{t+1} is the lead value of *ROA*; *CFO* is the firm's cash flow of operations; *LOSS* is an indicator variable that equals one if the firm has a loss (income before extraordinary items [IB] lower than zero), and zero otherwise; *CSCORE* is a measure for firms' accounting conservatism derived from Kim and Zhang (2015); and *CFO_VEGA* is a measure for the sensitivity of CFOs' stock option compensation to stock price derived from Kim et al. (2011b). The t-values reported in parentheses are based on standard errors clustered by firm; *, **, and *** indicate significance at the 10%, 5%, and 1% significance level respectively. All non-logged, non-return variables are winsorized at 1% and 99% levels. The tests that are reported at the bottom of Table 2.7 are coefficient comparisons to examine whether the coefficient estimates differ significantly across firms' life cycle stages. Variable definitions can be found in table 2.1.

Overall, the findings in Table 2.7 are consistent with the results found in our main analysis. The coefficients on both *INTRO* and *GROWTH* are positive and significant in most of the model specifications, and they are significantly different from most of the other life cycle stages as well. The results based on the sample that includes *CFO_VEGA* are weaker, especially in the firm fixed effects specification for two reasons: First, even though the coefficients on the other life cycle stages are generally close to zero or even negative, their large standard errors reduce the statistical significance of the life cycle comparisons. Second, this sample includes firms included in the S&P 1500 only. These firms are generally larger, more visible, less likely subject to short selling constraints, and less likely to be mispriced and hence the weaker results obtained in this subsample logically follow from our theory.[23] In sum, these findings indicate that our results are robust to the inclusion of these additional variables.

2.6. Conclusion

Firm life cycle reflects the evolvement of firms that results from changes in observable and unobservable factors. In addition, some of the factors, such as a firm's strategy and its managers, are internal to the firm, others, such as the industry-wide and macro-economic environment, are external to the firm. Whereas studies in the strategy, organization and management literature have long recognized the importance of firm life cycle and have used life cycle theory to explain a firm's development and practices, only recently it has gained increased attention in the accounting literature (Dickinson 2011; Hribar and Yehuda 2015; Drake and Martin 2015). Nevertheless, incorporating life cycle is important from an accounting perspective as well, given the impact of firm life cycle on the development of a firm's profitability and the usefulness of its accounting disclosures (Dickinson 2011; Anthony and Ramesh 1992).

In this study we link firm life cycle to firm-specific stock price crash risk. Investigating crash risk is important for several reasons. First, the recent financial crisis has revealed the severe losses that investors can incur as a result of sharp, sudden drops in a company's stock price. The widespread availability and use of tools and instruments to mitigate tail risk further illustrate the importance of (mitigating) such tail risk. Second, recent studies in the finance literature suggest that such tail risk may be priced. In the cumulative prospect theory based asset pricing model in Barberis and Huang (2008), investors have preferences for stocks with positively skewed returns and as a result they demand a lower return on such stocks. Hence, tail risk has direct implications for a firm's cost of capital.

We document that crash risk is highest in the introduction and growth stage of the life cycle. We argue that this effect is driven by heterogeneity in investor beliefs as well as overoptimism on part of investors about the future prospects of early-stage firms. Firms in the introduction and growth stage have few assets in place and a substantial part of the current value comes from their future growth opportunities. However, the informativeness of accounting numbers and their ability to accurately capture the value of these growth opportunities is limited (Lev and Zarowin 1999). This is also reflected in the large divergence

[23] Total assets in this subsample are equal to $4.7 billion compared to $3.1 billion for the other firms in the main sample. Also, 80 percent of the firms in this subsample have short interest, compared to only 62 percent of the other firms in the main sample.

between a firm's book and market values, which further illustrates the reduced usefulness of book values as an anchor for firm valuation. The uncertainty associated with future growth opportunities and the limited ability of accounting measures to resolve such uncertainty make that heterogeneity in investor beliefs peaks during the introduction and growth stage. Following the model of Hong and Stein (2003), the greater heterogeneity in investor beliefs increases crash risk for firms in the introduction and growth stage. Cross-sectional tests in which we show that the positive relation between early-stage firms and crash risk is greater for firms with short selling constraints and high market-to-book firms provide further support for this argumentation.

Dickinson (2011) shows that life cycle has important implications for (the development of) a firm's profitability. Furthermore, her findings suggest that investors are too optimistic about the growth and persistence in profitability of early-stage firms, compared to firms in the other life cycle stages. To the extent that investors are confronted with sudden negative news for these firms, investor overoptimism forms a second mechanism by which crash risk is higher for firms in the introduction and growth stage. When we split the sample based on current profitability levels, we find that crash risk is highest for introduction and growth firms when current profitability is high. However, the fact that we continue to find evidence of higher crash risk for these firms even when current profitability is low, suggests that investor overoptimism is only a partial explanation for the effects we observe, and that heterogeneity in investor beliefs continues to play an important role.

Overall, our study has implications for academics, investors, managers and regulators. As stated before, only a limited number of studies in the financial literature incorporate the life cycle concept into their empirical models (Anthony and Ramesh 1992). In line with recent studies (Dickinson 2011; Hribar and Yehuda 2015), our findings suggest that valuable insights can be derived by taking life cycle into account and thus treating a firm as a dynamic, rather than static, entity that evolves over time. This is in line with studies in the organization and strategy literature that show that life cycle theory can be used to explain firm decision making (Miller and Friesen 1983, 1984). In this study we take a capital market perspective and investigate how crash risk evolves over the life cycle. Given the substantial impact of firm life cycle on crash risk, this study also informs investors in their investment decisions. Finally, the insights derived from our study can also be used by managers in their communication with investors. As crash risk does not only arise as a consequence of managers' opportunistic behavior, but also from heterogeneity in investor beliefs and investor overoptimism, firms as well as regulators may reconsider the actions they can undertake to mitigate the valuation uncertainty that is associated with the introduction and growth stage of the firm life cycle and reduce future crash risk.

3 FIRM LIFE CYCLE AND ANALYST FORECAST BEHAVIOR[24,25]

ABSTRACT – This study examines how analyst forecast behavior varies over the firm life cycle. While mispricing by investors and firms' visibility concerns could increase both the supply and demand for analyst services in early-stage firms, forecasting difficulty and limited visibility could in contrast reduce analysts' incentives to follow these firms. Consistent with analysts responding to investor needs, we find that analyst following is higher for firms in the introduction and growth stage. With regard to forecast accuracy, we find that whereas analyst forecasts are less accurate in the introduction, shake-out and decline stage, analysts issue more accurate forecasts for firms in the growth stage. Additionally, forecast accuracy increases when there is life cycle alignment between the firm and its industry, reflecting the greater extent to which analysts can be benefit from their industry expertise under these circumstances. Yet, forecast accuracy decreases after life cycle changes, suggesting that analyst do not immediately incorporate changes in the earnings generating process after a life cycle shock.

"[S]killed analysts must view companies from a perspective that identifies where they stand in their life cycle, realizing that companies refusing to 'act their age' can destroy value."

- Aswath Damodaran (2016)[26]

3.1. Introduction

In this study, we investigate how firm life cycle affects analyst following and analyst forecast properties. Firm life cycle captures a firm's evolution through distinct stages of development over time due to changes in both inherent firm characteristics, including the firm's business strategy and its innovative efforts, and the firm's operating environment, including competitive pressure and macroeconomic conditions (Dickinson 2011). By excluding firm life cycle from their analyses, prior research in the financial literature implicitly assumes that

[24] This chapter is based on a working paper co-authored with Annelies Renders and Patrick Vorst.

[25] **Acknowledgements**: We would like to thank Edith Leung, Franco Wong, and seminar participants at Erasmus University Rotterdam, KU Leuven, Maastricht University, and the 2016 EAA Congress in Maastricht for their helpful comments and suggestions.

[26] As cited by P.M.J. Gross, in "Insights from India: Opportunities, Aging Gracefully, and Averting Crisis", *CFA Institute* (January, 2016). Retrieved on August 16, 2016 from: https://blogs.cfainstitute.org/investor/2016/01/26/insights-from-india-opportunities-aging-gracefully-and-averting-crises/

firms are stationary rather than dynamic entities that move through the life cycle spectrum contingent on the changes firms face. Yet, recent studies cast substantial doubt on the stationarity assumption as the rate of business change has increased tremendously over the past decades due to, for instance, changes in the fundamental characteristics of newly listed firms, which tend to be more rapidly growing and less profitable; increased product market competition; and changes in the real economy arising from the transition from an industrial to a more knowledge-based economy (Fama and French 2004; Irvine and Pontiff 2009; Lev and Zarowin 1999; Srivastava 2014). At the same time, the extent to which current reporting standards are able to capture the impact of change on firm fundamental performance is limited, reducing the usefulness of financial information and consequently increasing the difficulty for investors of determining firm fundamental value (Lev et al. 1999; Srivastava 2014).

In contrast to adopting a rather static view of the firm, which assumes that firm fundamentals remain fairly stable over time, the dynamic features of the life cycle concept acknowledge that firms are constantly subject to change and provide the opportunity to track the firm along its evolutionary path. As such, firm life cycle plays an important role in firm valuation since prior research shows that both the properties and value relevance of the components of earnings vary across the life cycle stages (Black 1998; Dickinson 2011; Hribar and Yehuda 2015). Despite its importance in the valuation process, the life cycle concept has received only limited attention in the accounting literature so far. Furthermore, prior studies on firm life cycle have focused on the extent to which investors incorporate life cycle information in determining firms' stock prices (Dickinson 2011; Hribar et al. 2015). According to early studies that examine investors' understanding of firm life cycle, investors seem to be aware of the differential informativeness of various accounting performance measures as the firm moves through its life cycle stages (Anthony and Ramesh 1992; Black 1998). Recent findings, however, suggest that investors do not fully incorporate the information they could derive from the firm life cycle in their valuations (Dickinson 2011). Mispricing occurs throughout the entire life cycle but is especially pronounced during the early stages when the signals conveyed by different performance measures are most distinct (Dickinson 2011; Hribar et al. 2015).

Based on the difficulties investors have in incorporating firm life cycle in their investment decisions, we expect the supply and demand for the services provided by financial analysts to vary across the life cycle stages too. This expectation is in line with prior studies on the intermediating role of financial analysts that show that the supply and demand for analyst services depends on investor needs (Barth, Kasznik and McNichols 2001; Lehavy, Li and Merkley 2011). In addition to investor needs, firms' visibility concerns could also contribute to changes in the demand for analyst services over the firm life cycle. These concerns may be especially relevant in the early life cycle stages as firm size is limited and the investor base may still be narrow (Bushee and Miller 2012). However, the same factors that contribute to investors' mispricing of firms over the firm life cycle also increase the cost of following firms, while the limited visibility of early-stage firms reduces the potential benefits that analyst can derive from covering these firms. As such, analysts have to trade off the costs and benefits associated with following firms at different stages of their firm life cycle. It therefore remains an empirical question how analyst following evolves over the firm life cycle.

Not only analyst following but also the properties of analyst forecasts are likely to differ across the life cycle stages. The difficulty analysts face in forecasting future earnings varies over the firm life cycle. Specifically, the earnings of mature firms are more persistent as a result of their operating stability and, hence, potentially easier to forecast than the future earnings of firms in the other life cycle stages (Dickinson 2011; Donelson and Resutek 2015). Given the increased forecasting difficulty that analysts face as a consequence of the uncertainty in the future earnings for non-mature firms, we hypothesize that analyst forecasts are less accurate for non-mature firms.

Nevertheless, analysts may be able to overcome the difficulties related to changes in the parameters underlying the earnings process over the firm life cycle if they are aware of firms' evolvement over time. Two important attributes that can reduce forecast errors are analyst industry expertise and analyst learning (Brown, Call, Clement and Sharp 2015; Kadan, Madureira, Wang and Zach 2012; Markov and Tamayo 2006). As analysts can benefit from their industry expertise (Brown et al. 2015; Kadan et al. 2012), we hypothesize that accuracy increases when the firm life cycle is aligned with the industry life cycle. In addition, we expect that accuracy decreases after a firm moves to another life cycle stage. This expectation is consistent with the reasoning that life cycle shocks could impede analyst learning if analysts do not anticipate changes in life cycle stage (Markov et al. 2006).

Using a sample of U.S. listed firms over the period 1994 to 2012, we find that both analyst following and analyst forecast accuracy vary over the firm life cycle while controlling for a variety of variables that have been associated with firm life cycle and forecasting difficulty in prior studies. Analyst following is higher for firms in the introduction and growth stage compared to firms in the other life cycle stages, reflecting the higher demand for analyst services in these stages. Concerning analyst forecast accuracy, individual analyst forecasts are less accurate for firms in the introduction, shake-out and decline stage relative to the forecasts issued for mature firms. Surprisingly, individual analyst forecasts are more accurate for firms in the growth stage. Nevertheless, we only observe more accurate forecasts for growth firms whose life cycle is aligned with the industry life cycle, suggesting that analysts benefit more from their industry expertise under this scenario. This positive effect of life cycle alignment on analyst forecast properties is also observed in other life cycle stages. Furthermore, we find that forecast accuracy decreases after a firm's transition to another life cycle stage, indicating that analysts do not fully incorporate the changes in the earnings generating process immediately following a life cycle shock.

Additional analyses provide support for the assertion that analysts respond to the varying need for their services over the firm life cycle and show that analyst following is higher in the early stages of the firm life cycle when there is a lot of disagreement among investors about firm fundamental value and at the far ends of the life cycle spectrum for firms with a weak financial position or a limited number of common shareholders. The latter findings can be attributed to the uncertainty that exists among investors with regard to firm survival and firms' visibility concerns, which are especially relevant in these life cycle stages and give rise to an increased need for analyst services. Finally, the findings of our main models are robust to the estimation of the models at the consensus level and the use of an alternative life cycle proxy. In short, our results suggest that firm life cycle is not only associated with the properties of analyst forecasts, analysts also respond to the varying need for their services over the firm life cycle stages.

We contribute to the evolving literature on the impact of firm life cycle on the functioning of capital markets by investigating the behavior of financial analysts over the firm life cycle. While firms may exhibit similar features at various life cycle stages, it is the joint effect of both observable and unobservable factors that makes firm life cycle a unique fundamental, yet dynamic firm characteristic. Only recently an increasing number of studies in the financial literature has started to recognize the importance of the life cycle concept in a capital market setting by linking it to the dynamics of performance measures (Dickinson, 2011; Hribar et al. 2015) and firm activity in the capital markets (Arikan and Stulz 2016; DeAngelo, DeAngelo, and Stulz 2006; Grullon, Michaely, and Swaminathan 2002). We add to this literature by providing insights on whether and how information intermediaries, in this case sell-side analysts, respond to the varying needs of firms and investors over the firm life cycle. In addition, our study also contributes to the analyst forecasting literature. Similar to investors, analysts appear to face difficulties in forecasting future firm performance for non-mature firms. Yet, our findings suggest that analysts can partly overcome these difficulties under scenarios in which they can benefit most from their industry expertise (i.e., when there is alignment between firm and industry life cycle). Finally, the results in this study also provide empirical evidence of a shock, namely a change in life cycle stage, to the earnings generating process that complicates analysts' forecasting processes.

This chapter proceeds as follows. Section 3.2 provides an overview of the related literature and develops the hypotheses. Section 3.3 discusses the research design and section 3.4 contains the empirical findings of our main analyses. Section 3.5 reports the findings of the additional analyses and robust checks. Section 3.6 concludes.

3.2. Related Literature and Hypotheses Development

Due to changing firm fundamentals as a firm evolves over time, firm life cycle has a substantial impact on the informativeness and value relevance of various accounting measures of performance (Anthony et al. 1992; Black 1997; Dickinson 2011). Yet, to date only few accounting studies have examined the role firm life cycle plays in the functioning of capital markets (Hribar et al. 2015). Early studies investigating the impact of firm life cycle on the value relevance of accounting information (Anthony et al. 1992; Black 1997) find that investors' reactions to various performance measures differ across the life cycle stages.

In contrast with these early studies, more recent studies (Dickinson 2011; Hribar et al. 2015; Hamers et al. 2016) indicate that investors fail to fully incorporate life cycle information in their assessments of firm value. The findings of Dickinson (2011), for instance, suggest that mispricing occurs throughout the firm life cycle as a consequence of investors' inability to fully recognize the differences in performance persistence arising from changes in firms' operating efficiency. In a study on the mispricing of accruals and cash flows over the firm life cycle, Hribar et al. (2015) observe that the mispricing of both accruals and cash flows is most pronounced during the growth stage which is consistent with the argumentation that the information conveyed by accruals and cash flows is most distinct during the early life cycle stages (Black 1997). Finally, Hamers et al. (2016) find that heterogeneity in investor beliefs, which manifests itself in stock price crash risk, is highest during the introduction and growth stage. Taken together, the findings of the aforementioned studies indicate that investors have difficulties in understanding the dynamics of firm life cycle, as reflected in both the mispricing of various accounting measures and heterogeneity in investor beliefs, especially during the introduction and growth stage.

The difficulties investors face in assessing firm fundamental value during the early life cycle stages is likely to give rise to an increase in the demand for analysts' services. Specifically, given their superior access to information, financial analysts can, in their role as information intermediaries, use their expertise to help investors in processing financial information by means of their forecasts of future firm performance (Schipper 1991; Healy and Palepu 2001). In addition, the benefits analysts derive from providing their services increase with valuation uncertainty as well (Barth et al. 2001; Lehavy et al. 2011). More specifically, the mispricing that arises in certain life cycle stages as a consequence of investors' limited ability to incorporate life cycle dynamics into their valuations increases the value of analysts' private analyses of firms and hence provides analysts with profitable opportunities (Lehavy et al. 2011; Schipper 1991). The empirical findings in prior literature are consistent with the argumentation that analyst following increases with investor uncertainty about firm fundamental value. Barth et al. (2001) for instance find that firms with substantial intangible assets are followed by more analysts, which reflects analysts' response to the uncertainty concerning the value of firms' intangible assets and the information asymmetry between investors and the firm.

An additional factor that could contribute to differences in the demand for analyst services over the firm life cycle are firms' visibility concerns. These are most pronounced at the far ends of the life cycle spectrum. Due to the lack of visibility-enhancing characteristics, including their relatively small size, firms in the introduction and growth stage may find it difficult to attract the attention of market participants (Bushee et al. 2012). Given the positive effect firm visibility has on the cost of capital and firm value (Lehavy and Sloan 2002; Merton 1987), firms can benefit from higher analyst coverage as it improves their visibility among capital market participants (Bushee et al. 2012). In short, both uncertainty about the firm fundamental value and firms' visibility concerns could lead to higher analyst following in the introduction and growth stage. This reasoning is in line with the findings in a recent survey of Brown et al. (2015) that client needs are the most important determinant of analysts' decisions to follow firms.

Nonetheless, there are also reasons why analysts are less likely to follow firms in these stages. The same factors that contribute to the mispricing by investors also increase forecasting difficulty and, consequently, increase the costs and effort for analysts in following early-stage firms. Furthermore, the limited visibility of firms in the introduction and growth stage may limit the benefits analysts can derive from covering these firms (Bushan 1989; Bushee et al. 2012).

Overall, combining the insights above it is unclear whether the benefits that analysts can derive from covering early-stage firms outweigh the associated costs. As such, it remains an empirical question whether analyst following differs across life cycle stages. Therefore, we hypothesize (in the null form):

Hypothesis 1 (H1): Analyst following does not vary over the firm life cycle.

As mentioned in the preceding paragraphs, the varying firm dynamics across the different life cycle stages do not only provide analysts with profitable opportunities, but also demand more effort from analysts and increase the complexity that analysts face in analyzing the firm (Dichev and Tang 2009; Donelson et al. 2014; Hribar and McInnis 2012). Prior studies suggest that there is an association between valuation uncertainty and the accuracy of analysts' forecasts (Hribar et al. 2012). After establishing a link between earnings volatility and earnings predictability, Dichev et al. (2009) find that analysts' forecast errors are persistently related to earnings volatility which indicates that analysts do not fully incorporate the impact of earnings volatility on earnings predictability in their analyses. In a related study, Donelson et al. (2015) suggest that the relationship between earnings volatility and analysts' forecast errors found by Dichev et al. (2009) can be attributed to the uncertainty in future earnings rather than to the time variation in earnings.

The uncertainty in future earnings evolves over the firm life cycle in a predictable fashion. As a result of their production efficiency, mature firms are able to maintain a stable level of performance for a longer period of time which is reflected in more persistent earnings than the earnings of firms in the other life cycle stages (Dickinson 2011). While analysts could help investors in assessing firm value by revealing information about earnings persistence across the life cycle stages, the uncertainty in future earnings that arises due the relatively limited persistence of earnings in the non-mature stages also increases forecast difficulty and, consequently, could lead to less accurate forecasts (Barth and Hutton 2004; Dichev et al. 2009; Dickinson 2011).

Based on the insights above, we argue that analysts' forecasts are less accurate for non-mature firms as a consequence of the relatively high uncertainty in future earnings during these stages. More formally, we hypothesize:

Hypothesis 2 (H2): Forecast accuracy is lower for non-mature firms than for mature firms.

Despite the increased forecasting difficulty associated with the relatively limited operating stability of non-mature firms, analysts should be able to reduce these difficulties if they can identify where the firm stands in its life cycle and understand the firm dynamics in each life cycle stage. Two important attributes that have been found in prior literature to improve analyst forecasts and that could help analysts in forecasting the future performance of non-mature firms are analyst industry expertise and analyst learning (Brown et al. 2015; Markov et al. 2006).

Concerning analyst industry expertise, industry analysis is deemed to be a crucial aspect in forecasting earnings and valuing firms and hence analysts' industry knowledge is often considered as the most valuable attribute of analysts by both investors and analysts themselves (Bradshaw 2015; Brown et al. 2015; Kadan et al. 2012). It is common for analysts to specialize in an industry and to benchmark firms' performance against their industry peers (Boni and Womack 2006; Hutton, Lee, and Shu 2012; Ramnath 2002). As both firm life cycle and industry membership affect current as well as future firm performance, the extent to which analysts can benefit from their industry expertise in forecasting firm performance over the firm life cycle depends on the alignment between a firm's life cycle stage and that of the entire industry (Cantrell and Dickinson 2015; Dickinson 2011; Soliman 2008). The benefit that analysts can derive from their industry expertise is expected to be highest when the firm life cycle is in line with the evolvement of the industry, for instance because the firm's industry peers provide more accurate performance benchmarks. In short, we anticipate that analysts issue more accurate forecasts when the firm life cycle is aligned with the industry life cycle. This reasoning results in the following hypothesis:

> *Hypothesis 3a (H3a - Industry Life Cycle Alignment): Forecast accuracy increases when the firm life cycle is aligned with the industry life cycle.*

In addition to industry expertise, prior research also finds that analyst forecasts improve with learning at both the individual analyst level and the consensus level (Clement, Koonce and Lopez 2007; Markov et al. 2006; Mikhail, Walter and Willis 1997). More specifically, Markov et al. (2006) find that analysts learn rationally about the parameters underlying the earnings process in the absence of any shocks to the environment generating the earnings. One example of an environmental shock that changes the parameters underlying the earnings generating process and consequently could impede analyst learning is a change in firm life cycle stage (Markov et al. 2006). Therefore, if analysts do not anticipate life cycle changes, we expect that analysts issue less accurate forecasts after a life cycle shock. As such, we hypothesize:

> *Hypothesis 3b (H3b - Life Cycle Shocks): Forecast accuracy decreases after a change in life cycle stage.*

3.3. Research Design

To investigate our hypotheses we collect data on analyst forecast behavior from I/B/E/S over the period 1994-2012 at both the consensus level and the individual analyst level. We match the data on analyst forecast behavior to financial data retrieved from Compustat and CRSP and exclude observations with missing data on the main variables included in our models. Our final samples consist of 90,775 and 559,230 observations at the consensus level and the individual analyst level, respectively.

In line with prior research on firm life cycle (Dickinson 2011; Gort and Klepper 1982), we distinguish five different life cycle stages to capture a firm's evolvement over time: Introduction, growth, mature, shake-out, and decline stage. Using these life cycle stages, we estimate the following empirical model to test the first hypothesis on analyst following over the firm life cycle:

$$\begin{aligned} ANALYST\ FOLLOWING_{it} = {} & \alpha_0 + \beta_1 * INTRO_{it} + \beta_2 * GROWTH_{it} + \beta_3 * SHAKE\text{-}OUT_{it} \\ & + \beta_4 * DECLINE_{it} + \Sigma_n \beta_n * CONTROLS_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

where i denotes the firm and t denotes the year. *INTRO*, *GROWTH*, *SHAKE-OUT* and *DECLINE* are indicator variables that are equal to one if firm i is in the respective life cycle stage in year *t,* and zero otherwise. The mature stage is treated as the benchmark stage. Based on hypothesis 1, we expect to find positive coefficients on *INTRO* and *GROWTH*.

We measure the dependent variable, *ANALYST FOLLOWING*, as the natural logarithm of the number of analysts issuing earnings forecasts for firm *i* included in the I/B/E/S consensus forecast on the date closest to but not exceeding the end of fiscal year *t*. The logarithmic transformation reduces the skewness in the raw variable that arises because analysts do not issue forecasts for a substantial number of firm-year observations covered by I/B/E/S. Additionally, by using the log transformation we take into account that the incremental value of an additional analyst is likely to be higher when initial analyst following is low (O'Brien and Bhushan 1990).[27]

Following Dickinson (2011), we assign firms to the different life cycle stages based on the systematic patterns in the cash flows from operating, investing and financing activities over the firm life cycle.[28] For instance, during the introduction and growth stage a firm's substantial investments in new capital and innovation lead to negative cash flows from investing. In addition, the firm has to rely on external sources of financing as a consequence of the limited availability of internal funds, resulting in positive cash flows from financing, while operating cash flows only become positive in the growth stage after the product has been successfully introduced into the market. In contrast to other life cycle proxies commonly used in prior literature (Anthony et al. 1992; Hribar et al. 2015), this classification does not assume that firms move through their life cycle in a predetermined sequence but allows firms to switch from one stage to another in a non-sequential order (Dickinson 2011). As such, the life cycle classification based on cash flow patterns recognizes a firm as a dynamic entity whose life cycle stage is contingent on the strategic initiatives it undertakes as well as external factors, including competitive pressures (Dickinson 2011).

To test the hypotheses concerning the accuracy of individual analyst forecasts, we estimate the following empirical model:

$$\begin{aligned} FORECAST\ ACCURACY_{ijt} = \alpha_0 &+ \beta_1 * INTRO_{it} + \beta_2 * GROWTH_{it} + \beta_3 * SHAKE\text{-}OUT_{it} \\ &+ \beta_4 * DECLINE_{it} + \beta_5 * ANALYST\ FOLLOWING_{it} \\ &+ \textstyle\sum_n \beta_n * CONTROLS_{it} + \varepsilon_{it} \qquad (2) \end{aligned}$$

where *i* denotes the firm, *j* denotes the analyst, and *t* denotes the year. The dependent variable, *FORECAST ACCURACY*, is measured as the negative of the absolute difference between the individual analyst forecast and the actual EPS (i.e., the forecast error) for firm *i* in year *t*, scaled by the share price at the end of the previous year (Hope 2003; Lang and Lundholm 1996):

[27] Nevertheless, our inferences in section 3.4 are robust to the estimations of model (1) using a tobit model and a negative binomial regression model that include the (non-transformed) number of analysts issuing an earnings forecast for firm *i* included in the I/B/E/S consensus forecast on the date closest to but not exceeding the end of fiscal year *t*.

[28] Table 1.1 (p. 5) provides an overview of Dickinson's cash flow classification that is employed to assign firms to the five life cycle stages.

$$ACCURACY_{it} = \frac{-\left|FORECASTED\ EPS_{it} - ACTUAL\ EPS_{it}\right|}{P_{i,t\text{-}1}} \tag{3}$$

By taking the negative of the forecast error in equation (3) a higher value for *ACCURACY* reflects a more accurate consensus forecast. For each individual analyst, *ACCURACY* is measured at the forecast date closest to but not exceeding the fiscal year end. The indicator variables for the different life cycle stages and *ANALYST FOLLOWING* are defined in the same way as in model (1). Hypothesis 2 predicts negative coefficients on *INTRO*, *GROWTH*, *SHAKE-OUT*, and *DECLINE*.

Next to the main variables of interest, we also control for potential confounding variables. The first variables are proxies for firm size (*SIZE*), measured as the natural logarithm of total assets, and firm performance (*ROA*), measured as income before extraordinary items divided by lagged total assets. Not only do firm size and performance evolve over the firm life cycle in a predictable way (Dickinson 2011), findings in prior research also show that these factors are important determinants of analyst following (Bhushan 1989; McNichols and O'Brien 1997; O'Brien et al. 1990).[29] Another factor that is often considered to be an important determinant of firm life cycle in prior studies is firm age (Anthony et al. 1992; Hribar et al. 2015). In addition, the findings of Ecker, Francis Kim, Olsson, and Schipper (2006) suggest that investor uncertainty about reporting quality is lower for older firms as a result of the availability of more firm-specific information and hence the need for analyst services may also decrease with firm age. Consistent with Ecker et al. (2006), firm age (*FIRM AGE*) is measured by the number of years that the firm has appeared in CRSP.

The substantial investments in R&D and advertising during the introduction and growth stage, the potential operating losses associated with these investments, and the extent to which firm value depends on the value of growth opportunities and the uncertain future benefits that can be derived from these investments could also contribute to investors' uncertainty about firm fundamental value (Barth et al. 2001; Joos and Plesko 2005). Hence, these factors are also likely to influence both analyst coverage and the properties of analyst forecasts. To control for the uncertainty related to operating losses, investments in intangibles and growth opportunities, we include a dummy variable (*LOSS*) that is equal to one if firm *i* has a negative operating income in year *t* and zero otherwise; the market-to-book ratio (*MTB*); advertising intensity (*ADV_INT*), calculated as the ratio of advertising expenses to lagged total assets; and R&D intensity (*R&D_INT*), calculated as the ratio of R&D expenses to lagged total assets.

We also include both return volatility (*STD_RET*), measured as the standard deviation of monthly stock returns over the past sixty months, and earnings volatility (*STD_ROA*), measured as the standard deviation in annual ROA over the past five years, in our analyses. Concerning the former, Bhushan (1989) argues that analyst coverage increases with return volatility since private information is more valuable for volatile stocks. With regard to earnings volatility, Dichev et al. (2009) find that analyst forecast errors are systematically

[29] Given the substantial effect of firm size on analyst following (Bhushan 1989; Hong, Lim, and Stein 2000), we also estimate model (1) by orthogonalizing analyst following with respect to firm size. Our inferences do not change when we use the orthogonalized measure.

related to earnings volatility suggesting that analysts do not fully incorporate the effect of earnings volatility on earnings predictability. The uncertainty associated with volatile stocks is however also likely to give rise to an increased need for analyst services.

Consistent with prior studies on analyst forecast behavior (Lehavy et al. 2011), we also include the percentage of institutional holdings (*INSTH)*, the natural logarithm of the number of business segments (*SEGMENTS*), and the number of management earnings forecasts issued by the firm during the current fiscal year (*MNG_FORECASTS*) as measures of business complexity and the availability of firm-specific information. The findings in prior research suggest that business complexity and the information environment do not only affect analyst following but also the properties of analyst earnings forecasts (Bhushan 1989; Lang et al. 1996; Lehavy et al. 2011).

In model (2), we also control for analyst following since prior research finds that the number of analysts following a firm has an impact on the properties of analyst forecasts (Hope 2003). Additionally, we include the number of forecasts issued by the analyst in year *t* (*NUM_FORECAST*) and the number of years the analyst has already followed the firm (*YRS_FOLLOW*) to control for individual analyst characteristics in model (2) as these have also been found to affect forecast accuracy (Clement 1999; Clement et al. 2007; Jacob, Lys and Neale, 1999).

Finally, all analyses include year and industry fixed effects to control for variation in valuation uncertainty over time and across industries. All variables are winsorized at the 1% and 99% levels.

3.4. Empirical Findings

3.4.1. Descriptive Statistics

Table 3.1, Panel A, reports the descriptive statistics for the variables included in the main empirical analyses. The summary statistics for the common set of control variables in models (1) and (2) are reported for the observations with non-missing values at the consensus level as multiple analysts may cover the same firm and, hence, the same firm would be included multiple times if we report these statistics at the individual analyst level. The median value of 1.10 for analyst coverage indicates that the median number of analysts following a firm included in the I/B/E/S consensus forecast is equal to two. The substantial number of zeros in the distributions of the analyst variables may be attributed to the limited number of firm-year observations covered by I/B/E/S for which a consensus forecasts is available.[30] The mean value for forecast accuracy is -0.02. A closer look at the actual difference rather than the

[30] Our inferences for model (1) remain unchanged if we estimate the model by including only firm-year observations with non-zero analyst following.

TABLE 3.1

Descriptive Statistics and Correlations

Panel A: Summary Statistics								
Variable	**N**	**Mean**	**St.Dev.**	**P5**	**P25**	**Median**	**P75**	**P95**
Analyst Variables								
ANALYST_FOLLOWING	90,775	1.25	0.99	0.00	0.00	1.10	2.08	2.94
ACCURACY	559,315	-0.02	0.08	-0.08	-0.01	0.00	0.00	0.00
Life Cycle Variables								
INTRO	90,775	0.15	0.36	0	0	0	0	1
GROWTH	90,775	0.31	0.46	0	0	0	1	1
MATURE	90,775	0.35	0.46	0	0	0	1	1
SHAKE	90,775	0.11	0.31	0	0	0	0	1
DECLINE	90,775	0.08	0.27	0	0	0	0	1
Control Variables								
SIZE	90,775	5.69	2.18	2.30	4.08	5.63	7.17	9.52
ROA	90,775	-0.03	0.24	-0.53	-0.05	0.02	0.08	0.19
FIRM AGE	90,775	2.32	0.88	0.69	1.61	2.40	2.94	3.71
LOSS	90,775	0.35	0.48	0	0	0	1	1
MTB	90,775	2.85	3.98	0.30	1.07	1.84	3.27	9.21
ADV_INT	90,775	0.01	0.03	0.00	0.00	0.00	0.00	0.07
R&D_INT	90,775	0.06	0.13	0.00	0.00	0.00	0.06	0.29
STD_RET	90,775	0.16	0.09	0.06	0.10	0.15	0.21	0.34
STD_ROA	90,775	0.14	0.47	0.00	0.02	0.05	0.12	0.47
INSTH	90,775	0.43	0.31	0.00	0.13	0.40	0.69	0.94
SEGMENTS	90,775	0.85	0.28	0.69	0.69	0.69	1.09	1.39
MNG_FORECASTS	90,775	1.08	2.35	0	0	0	1	7
NUM_FORECAST	559,315	15.20	9.39	3	10	14	19	31
YRS_FOLLOW	559,315	3.54	2.96	1	1	3	5	10

Panel B: Summary Statistics by Life Cycle Stage						
Variable	Pooled	*INTRO*	*GROWTH*	*MATURE*	*SHAKE-OUT*	*DECLINE*
ANALYST FOLLOWING	1.25	0.84	1.43	1.42	1.05	0.83
SIZE	5.69	4.19	6.18	6.29	5.67	4.13
ROA	-0.03	-0.28	0.04	0.06	-0.01	-0.27
FIRM AGE	2.32	1.96	2.24	2.59	2.42	2.06
MTB	2.85	3.84	2.71	2.65	2.17	3.19
R&D_INT	0.06	0.14	0.04	0.02	0.04	0.15
STD_RET	0.16	0.23	0.15	0.14	0.16	0.23
N	90,775	13,864	28,418	31,437	9,581	7,475
% TOTAL	100.00%	15.30%	31.30%	34.60%	10.60%	8.20%

Table 3.1 - Continued

Panel C: Correlation Matrix - Analyst Following (N=90,775)

	Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.
1.	*ANALYST FOLLOWING*																		
2.	*INTRO*	-0.17																	
		(0.00)																	
3.	*GROWTH*	0.12	-0.29																
		(0.00)	(0.00)																
4.	*MATURE*	0.13	-0.31	-0.49															
		(0.00)	(0.00)	(0.00)															
5.	*SHAKE*	-0.07	-0.15	-0.23	-0.25														
		(0.00)	(0.00)	(0.00)	(0.00)														
6.	*DECLINE*	-0.12	-0.13	-0.20	-0.22	-0.10													
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)													
7.	*SIZE*	0.62	-0.29	0.15	0.20	0.00	-0.22												
		(0.00)	(0.00)	(0.00)	(0.00)	(0.27)	(0.00)												
8.	*ROA*	0.23	-0.44	0.21	0.28	0.03	-0.30	0.37											
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)											
9.	*FIRM AGE*	0.12	-0.17	-0.06	0.22	0.04	-0.09	0.28	0.21										
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)										
10.	*LOSS*	-0.24	0.36	-0.20	-0.28	0.04	0.31	-0.35	-0.66	-0.20									
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)									
11.	*MTB*	0.11	0.11	-0.02	-0.04	-0.06	0.03	-0.08	-0.11	-0.06	0.03								
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)								
12.	*ADV_INT*	0.06	0.02	-0.03	0.04	-0.02	-0.02	-0.03	0.01	-0.01	-0.02	0.05							
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)							
13.	*R&D_INT*	-0.01	0.26	-0.10	-0.19	-0.05	0.22	-0.30	-0.54	-0.15	0.31	0.25	-0.04						
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)						
14.	*STD_RET*	-0.24	0.31	-0.14	-0.22	-0.01	0.22	-0.48	-0.43	-0.28	0.44	0.11	0.04	0.32					
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)					
15.	*STD_ROA*	-0.11	0.16	-0.09	-0.10	-0.01	0.13	-0.22	-0.35	-0.11	0.21	0.07	0.01	0.24	0.27				
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)				
16.	*INSTH*	0.64	-0.23	0.11	0.18	-0.03	-0.15	0.61	0.29	0.22	-0.28	0.03	0.02	-0.10	-0.33	-0.14			
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			
17.	*SEGMENTS*	0.11	-0.09	-0.03	0.14	-0.01	-0.07	0.29	0.12	0.27	-0.12	-0.04	-0.02	-0.16	-0.16	-0.06	0.15		
		(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		
18.	*MNG_FORECASTS*	0.36	-0.12	0.03	0.12	-0.02	-0.09	0.27	0.15	0.12	-0.16	0.02	0.07	-0.06	-0.12	-0.59	0.38	0.08	
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

Table 3.1 - Continued

Panel D: Correlation Matrix - Forecast Accuracy (N=559,315)

	Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.
1.	*ACCURACY*																					
2.	*INTRO*	-0.15																				
		(0.00)																				
3.	*GROWTH*	0.06	-0.22																			
		(0.00)	(0.00)																			
4.	*MATURE*	0.11	-0.25	-0.65																		
		(0.00)	(0.00)	(0.00)																		
5.	*SHAKE*	-0.04	-0.09	-0.23	-0.27																	
		(0.00)	(0.00)	(0.00)	(0.00)																	
6.	*DECLINE*	-0.16	-0.06	-0.16	-0.18	-0.07																
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)																
7.	*ANALYST FOLLOWING*	0.23	-0.16	0.01	0.15	-0.04	-0.14															
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)															
8.	*NUM_FORECAST*	0.02	-0.03	0.02	0.01	0.00	-0.03	0.03														
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)														
9.	*YRS_FOLLOW*	0.05	-0.10	-0.08	0.14	0.02	-0.05	0.18	0.18													
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)													
10.	*SIZE*	0.15	-0.23	-0.02	0.23	0.01	-0.21	0.59	0.04	0.27												
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)												
11.	*ROA*	0.29	-0.40	0.12	0.25	-0.02	-0.34	0.21	0.04	0.09	0.25											
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)											
12.	*FIRM AGE*	0.09	-0.18	-0.12	0.24	0.03	-0.11	0.28	0.08	0.35	0.48	0.19										
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)										
13.	*LOSS*	-0.29	0.32	-0.09	-0.25	0.05	0.32	-0.21	-0.05	-0.09	-0.26	-0.67	-0.21									
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)									
14.	*MTB*	0.06	0.02	-0.01	0.02	-0.04	-0.01	0.15	-0.03	-0.03	-0.05	0.09	-0.04	-0.06								
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)								
15.	*ADV_INT*	0.02	0.00	-0.05	0.07	-0.02	-0.03	0.05	-0.01	0.02	-0.04	0.06	0.01	-0.05	0.11							
		(0.00)	(0.97)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)							
16.	*R&D_INT*	-0.11	0.24	-0.04	-0.19	0.00	0.24	-0.07	-0.06	-0.10	-0.33	-0.45	-0.17	0.30	0.22	-0.04						
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)						
17.	*STD_RET*	-0.22	0.29	0.01	-0.27	0.01	0.24	-0.22	-0.12	-0.22	-0.47	-0.42	-0.41	0.44	0.03	0.01	0.35					
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)					
18.	*STD_ROA*	-0.16	0.17	-0.06	-0.12	0.01	0.18	-0.10	-0.05	-0.08	-0.22	-0.37	-0.16	0.25	0.04	0.01	0.27	0.35				
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)				
19.	*INSTH*	0.19	-0.18	0.02	0.13	0.00	-0.14	0.32	0.02	0.12	0.27	0.23	0.23	-0.20	0.03	0.02	-0.11	-0.21	-0.14			
		(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			
20.	*SEGMENTS*	0.06	-0.09	-0.07	0.16	-0.01	-0.07	0.12	0.02	0.15	0.36	0.09	0.35	-0.12	-0.05	-0.02	-0.18	-0.24	-0.08	0.06		
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		
21.	*MNG_FORECASTS*	0.10	-0.10	-0.04	0.13	-0.04	-0.08	0.18	-0.04	0.05	0.14	0.12	0.12	-0.13	0.03	0.10	-0.06	-0.08	-0.04	0.24	0.08	
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

Table 3.1 - Continued

Table 3.1 reports the descriptive statistics and the correlations for the variables included in the main empirical models. Panel A (B) presents the summary statistics for the overall sample (by life cycle stage). Panels C and D report the Pearson correlations among the variables included in models (1) and (2) respectively; p-values are in parentheses. The final sample at the consensus (individual) level consists of 90,775 (559,230) firm-year observations over the period 1994-2012 with non-missing values for the variables included in the models. The variables are defined as follows: *ANALYST FOLLOWING* is the natural logarithm of the number of analysts issuing an earnings forecast included in the I/B/E/S consensus forecast; *ACCURACY* is the negative of the absolute difference between the individual analyst forecast and the actual EPS scaled by the share price at the end of the previous fiscal year; *INTRO*, *GROWTH*, *MATURE*, *SHAKE*, and *DECLINE* are indicator variables that are equal to one if the firm is assigned to the particular stage based on Dickinson's (2011) life cycle classification, and zero otherwise; *SIZE* is the natural logarithm of total assets; *ROA* is the income before extraordinary items divided by lagged total assets; *FIRM AGE* is the natural logarithm of the number of years that the company is listed in the CRSP database; *LOSS* is an indicator variable that is equal to one if the firm has a negative operating income, and zero otherwise; *MTB* is the market value of equity divided by the book value of equity; *ADV_INT* is advertising expense divided by lagged total assets; *R&D_INT* is R&D expense divided by lagged total assets; *STD_RET* is the volatility in monthly returns over the past sixty months; *STD_ROA* is the volatility in ROA over the past five years; *INSTH* is the percentage of institutional holdings; *SEGMENTS* is the natural logarithm of the number of business segments; *MNG_FORECASTS* the number of management earnings forecasts issued during the current fiscal year; *NUM_FORECAST* is the number of forecasts issued by the analyst; and *YRS_FOLLOW* is the number of years the analyst has already followed the firm. *ANALYST FOLLOWING* and *ACCURACY* are measured on the forecast date closest to but not exceeding the end of the fiscal year.

absolute difference between the consensus forecast and the actual EPS indicates that the consensus forecast is, on average, higher than the actual EPS which is consistent with analyst optimism observed in prior research (Bradshaw 2015; Kothari 2001).

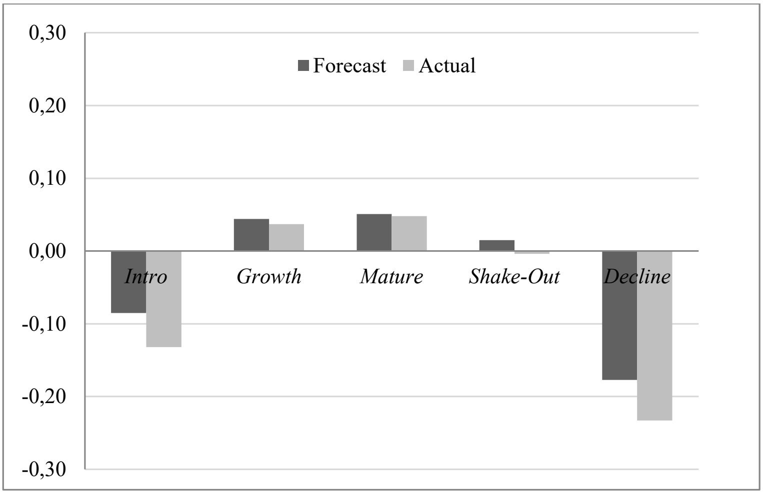
The descriptive statistics for the life cycle variables in Panel B are consistent with prior research that implements the cash flow classification to assign firms to the different life cycle stages (Dickinson 2011). Specifically, the majority of the firms is assigned to the growth and mature stage which is line with the relative stability of these stages (Dickinson 2011). An examination of the development of the variables by life cycle stage indicates that the average analyst following is highest in the growth and mature stage. The patterns observed for the other variables across life cycle stages provide support for the validity of Dickinson's (2011) life cycle proxy used in this study. Mature firms, for instance, tend to be older, larger and have a relatively stable operating performance compared to firms in the other stages.

Table 3.1, Panel C, reports the correlations among the variables included in model (1). While analyst following is significantly positively correlated with the growth and mature stage (ρ=0.12, p-value=0.00; and ρ=0.13, p-value=0.00 respectively), it is significantly negatively correlated with the other life cycle stages. Regarding the control variables, the correlations in Panel C indicate that analyst following is highly positively correlated with firm size and institutional holdings, which is consistent with firm size being one of the main determinants of analyst following (Bhushan 1989).

The correlation matrix in Table 3.1, Panel D, reports the correlations among the variables included in model (2). The reported correlations indicate that accuracy is significantly positively correlated with the growth and mature stage (ρ=0.06, p-value=0.00; and ρ=0.11, p-value=0.00 respectively). The opposite pattern can be observed for the other life cycle stages. These correlations imply that analyst forecasts are more accurate in the growth and mature stage than in the other life cycle stages. Although the observed correlation coefficients are generally in line with our expectation that forecast accuracy is lower for non-mature firms, the positive correlation between the growth stage and forecast accuracy contradicts this expectation. The other correlations in Panel C generally have the expected signs. Forecasts for instance appear to be less accurate for firms that have an operating loss, higher R&D intensity, higher return volatility and higher earnings volatility reflecting the forecasting difficulty that arises due to the valuation uncertainty associated with these factors.

FIGURE 3.1

Forecast Properties and Actual EPS by Life Cycle Stage



	INTRO	*GROWTH*	*MATURE*	*SHAKE-OUT*	*DECLINE*
FORECAST	-0.085	0.044	0.051	0.015	-0.177
ACTUAL	-0.132	0.037	0.048	-0.004	-0.233
FORECAST - ACTUAL (FE)	0.047	0.007	0.003	0.019	0.056

Figure 3.1 shows the averages of the individual analyst forecast of EPS and actual EPS at each stage of the firm life cycle. The individual forecast is obtained on the forecast date closest to but not exceeding the end of the fiscal year. Firm-year observations are assigned to the life cycle stages based on Dickinson's (2011) classification. See Table 3.1 for other variable definitions.

Figure 3.1 depicts the actual and forecasted EPS, both scaled by the share price at the end of the previous fiscal year, across the life cycle stages. The scaled analyst forecast is, on average, higher than the actual EPS suggesting that analysts tend to be optimistic in every life cycle stage. Yet, the observation that not only the actual EPS but also the forecast varies systematically over the life cycle stages provides an initial indication that analysts incorporate firm life cycle in their forecasts. The average difference between the forecasted and actual EPS (i.e., forecast accuracy) is largest for firms in the introduction and decline stage and smallest for firms in the growth and mature stage.[31] These observations again provide only

[31] One could argue that the observed patterns can at least partly be attributed to the scaling by share price at the end of the previous fiscal year since this measure could also vary systematically over the life cycle stages. To

partial support for our hypothesis concerning analyst forecast accuracy over the firm life cycle. Nevertheless, the preliminary insights that can be derived from the correlation matrices in Table 3.1, Panels C and D, and Figure 3.1 with respect to our hypotheses may be misleading since these univariate analyses do not take into account the presence of confounding factors that are associated with firm life cycle and analyst behavior. Therefore, further analysis is warranted.

3.4.2. Analyst Following and Forecast Properties over the Firm Life Cycle

We estimate models (1) and (2) using OLS regression analysis. All standard errors in the estimation models are clustered at the firm level (Petersen 2009).[32]

Table 3.2, column 1, reports the estimation results for model (1). The coefficients on *INTRO* (0.037; t-statistic = 3.37), *GROWTH* (0.075; t-statistic = 10.31), and *DECLINE* (0.081; t-statistic = 6.98) are all positive and significant, suggesting that, compared to mature firms, analyst coverage is higher during the introduction, growth and decline stage. More specifically, the coefficient estimates indicate that analyst following is 3.7, 7.5, and 8.1 percent higher in, respectively, the introduction, growth and decline stage than in the mature stage, holding all other factors constant. Furthermore, the coefficient comparisons at the bottom of Table 3.2 show that these coefficients are also significantly different from the coefficient on *SHAKE*, suggesting that analyst coverage is also higher in the introduction, growth and decline stage compared to the shake-out stage. Finally, there is no statistical difference between the coefficients on *GROWTH* and *DECLINE,* but both coefficients are significantly larger than the coefficient for *INTRO*. The significantly positive coefficients on *INTRO* and *GROWTH* are consistent with analysts responding to the difficulties investors have in valuing early-stage firms, as observed in prior research (Hamers et al. 2016; Hribar et al. 2015), and potential visibility concerns. One potential explanation for the finding that analyst following is also higher for decline firms is investor uncertainty about firm viability. Specifically, whereas firms in the decline stage could be able to move to another stage, the risk of financial distress as a consequence of deteriorating operations is high in this stage as well (Damodaran 2009).

Concerning the coefficient estimates for the control variables, the results are in line with those observed in prior research on analyst behavior (Lehavy et al. 2011). In general, the findings indicate that analyst following increases with firm size and valuation uncertainty as reflected in, for instance, the significantly positive coefficients on the market-to-book ratio, R&D and advertising intensity, and return and earnings volatility. In short, we find that analysts take firm life cycle into consideration in their coverage decisions beyond other factors that have been associated with valuation uncertainty in prior research.

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investigate this possibility, we also examine unscaled variables. Using unscaled variables does not alter our inferences.

[32] The analyses at the individual analyst level are robust to clustering the standard errors by analyst.

TABLE 3.2

Analyst Following Over the Firm Life Cycle

	ANALYST FOLLOWING	
Variable	(1)	(2)
INTRO	0.037***	0.069***
	(3.77)	(13.37)
GROWTH	0.075***	0.062***
	(10.31)	(18.44)
SHAKE-OUT	-0.007	-0.016***
	(-0.81)	(-3.50)
DECLINE	0.081***	-0.013**
	(6.98)	(-2.25)
ANALYST FOLLOWING$_{t-1}$		0.755***
		(203.93)
SIZE	0.257***	0.060***
	(53.51)	(30.89)
ROA	0.161***	0.126***
	(7.85)	(12.52)
FIRM AGE	-0.050***	-0.060***
	(-8.10)	(-28.67)
LOSS	-0.025***	-0.072***
	(-2.96)	(-17.76)
MTB	0.019***	0.010***
	(20.76)	(23.95)
ADV_INT	0.826***	0.315***
	(6.07)	(6.76)
R&D_INT	0.826***	0.361***
	(22.47)	(23.19)
STD_RET	0.416***	0.196***
	(7.57)	(9.50)
STD_ROA	0.034***	0.009***
	(5.23)	(3.04)
INSTH	0.999***	0.313***
	(43.70)	(38.08)
SEGMENTS	-0.268***	-0.053***
	(-12.03)	(-7.87)
MNG_FORECASTS	0.057***	0.014***
	(27.49)	(21.34)
CONSTANT	-0.279***	-0.049***
	(-4.07)	(-3.04)
Industry FE	YES	YES
Year FE	YES	YES
Observations	90,755	90,755
R-squared	62.1%	85.4%
INTRO - GROWTH = 0	p=0.0002***	p=0.2040
INTRO - SHAKE-OUT = 0	p=0.0000***	p=0.0000***
INTRO - DECLINE = 0	p=0.0000***	p=0.0000***
GROWTH - SHAKE-OUT =0	p=0.0000***	p=0.0000***
GROWTH - DECLINE = 0	p=0.5750	p=0.0000***
SHAKE-OUT - DECLINE = 0	p=0.0000***	p=0.6480

Table 3.2 – Continued
Table 3.2 reports the estimation results for model (1), obtained using OLS regression. The sample consists of 90,775 firm-year observations over the period 1994-2012. The t-values reported in parentheses are based on standard errors clustered by firm; *, **, ***, indicate significance at the 1%, 5%, and 10% level respectively. All continuous variables are winsorized at the 1% and 99% levels. The tests reported at the bottom of the table are coefficient comparisons to examine the significance of the differences in the coefficient estimates obtained for the indicator variables that capture the distinct life cycle stages. See Table 3.1 for variable definitions.

To assess the effect that potential omitted variables can have on the estimation results, we also estimate model (1) by including the lagged dependent variable. The estimation results in Table 3.2, column 2, show that the coefficients on *INTRO* and *GROWTH* are still positive and significant. Yet, the coefficient on *DECLINE* is now significantly negative, suggesting that the positive association between analyst coverage and the decline stage in column 1 can be biased as a consequence of omitted variables.

Table 3.3 reports the results obtained after estimating model (2) which investigates individual analyst forecast accuracy across the life cycle stages. Table 3.3, column 1, shows the results using forecast accuracy as the dependent variable. Consistent with our hypothesis, the significantly negative coefficients on *INTRO* (-0.005; t-statistic = -2.41), *SHAKE-OUT* (-0.006; t-statistic = -4.91), and *DECLINE* (-0.016; t-statistic = -4.46) indicate that forecast accuracy is lower for firms in the introduction, shake-out, and decline stage compared to mature firms. In contrast to our expectations, however, analyst forecast accuracy is higher for firms in the growth stage (*GROWTH* = 0.001; t-statistic = 2.21). In addition, the coefficient comparisons at the bottom of the table show that forecast accuracy is highest for growth firms and lowest for decline firms.

To provide additional insights into the accuracy of individual analyst forecasts, we also investigate the (signed) forecast error. According to the results in Table 3.3, column 2, analysts are, on average, more optimistic about the future performance of firms in the introduction and shake-out stage than that of mature firms. The optimism in analyst forecasts for growth firms does not significantly differ from the optimism in the other life cycle stages. Nevertheless, the results in Table 3.3, columns 3 and 4, suggest that the superior forecast accuracy for firms in the growth stage is driven by less pessimistic forecasts rather than less optimistic forecasts.[33]

The findings for the control variables generally support the notion that valuation uncertainty does not only provide profitable opportunities for analysts but also involves costs as a consequence of the increased complexity to analyze firms whose fundamental value is more uncertain. Analyst forecasts are, for instance, less accurate for firms with an operating loss and firms with higher volatility in earnings and returns. Increases in analyst following, institutional ownership and the number of management forecasts, on the contrary, are associated with more accurate analyst forecasts, reflecting the positive association between analyst performance and firms' information environments (Lang et al. 1996).

[33] We also estimate a logit model to examine the incidence of optimistic forecasts across life cycle stages, in which the dependent variable is an indicator variable that is equal to one if the forecast error is positive, and zero otherwise. The untabulated results reveal that analysts are more likely to issue optimistic forecast (i.e., more likely to make positive forecast errors) in the introduction, growth and shake-out stage than in the mature stage.

TABLE 3.3

Forecast Accuracy over the Firm Life Cycle

	FORECAST PROPERTY			
	(1)	(2)	(3)	(4)
Variable	ACCURACY	FORECAST ERROR (FE)	PESSIMISM (FE < 0)	OPTIMISM (FE > 0)
INTRO	-0.005**	0.003**	-0.003***	0.003
	(-2.41)	(2.10)	(-4.27)	(1.30)
GROWTH	0.001**	0.001	0.001***	-0.001
	(2.22)	(1.59)	(3.57)	(-1.37)
SHAKE-OUT	-0.006***	0.001**	-0.002***	0.008***
	(-4.91)	(1.97)	(-6.97)	(5.23)
DECLINE	-0.016***	-0.002	-0.009***	0.012***
	(-4.46)	(-1.12)	(-8.21)	(3.79)
FOLLOWING	0.019***	-0.008***	0.006***	-0.020***
	(17.36)	(-14.87)	(23.01)	(-17.98)
NUM_FORECAST	0.000***	-0.000**	0.000***	-0.000**
	(3.39)	(-2.06)	(5.95)	(-2.05)
YRS_FOLLOW	-0.000***	0.000***	-0.000***	0.000***
	(-5.61)	(3.23)	(-3.54)	(4.99)
SIZE	-0.003***	0.001***	-0.001***	0.004***
	(-6.15)	(3.75)	(-9.53)	(6.58)
ROA	0.049***	-0.034***	0.002*	-0.060***
	(7.91)	(-10.42)	(1.71)	(-9.90)
FIRM AGE	-0.003***	0.002***	-0.001***	0.004***
	(-5.35)	(5.50)	(-3.66)	(4.97)
LOSS	-0.022***	0.019***	-0.005***	0.028***
	(-12.31)	(17.74)	(-10.09)	(16.81)
MTB	0.000	0.000**	0.000***	-0.000**
	(0.60)	(2.45)	(3.57)	(-1.97)
ADV_INT	-0.011	0.019***	0.001	0.026
	(-0.83)	(2.75)	(0.26)	(1.41)
R&D_INT	0.012	-0.039***	-0.008***	-0.040***
	(1.19)	(-8.45)	(-3.69)	(-3.80)
STD_RET	-0.129***	0.017***	-0.046***	0.128***
	(-9.73)	(2.68)	(-15.21)	(9.18)
STD_ROA	-0.013***	0.002	-0.006***	0.008**
	(-3.57)	(0.97)	(-5.34)	(2.56)
INSTH	0.033***	-0.014***	0.007***	-0.033***
	(12.05)	(-11.39)	(10.81)	(-12.46)
SEGMENTS	0.003*	-0.002**	0.001**	-0.002
	(1.94)	(-2.18)	(2.19)	(-1.44)
MNG_FORECASTS	0.001***	-0.000	0.000***	-0.001***
	(4.42)	(-1.38)	(7.87)	(-3.47)
CONSTANT	-0.007	0.013	-0.008	0.265***
	(-0.00)	(.)	(-0.00)	(38.57)
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	559,315	559,315	338,183	221,132
R-squared	15.6%	8.4%	20.5%	22.8%

Table 3.3 - Continued

INTRO - GROWTH = 0	p=0.0023***	p=0.1050	p=0.0000***	p=0.0753*
INTRO - SHAKE-OUT = 0	p=0.8290	p=0.3600	p=0.6980	p=0.0547*
INTRO - DECLINE = 0	p=0.0032***	p=0.0132**	p=0.0000***	p=0.0044***
GROWTH - SHAKE-OUT = 0	p=0.0000***	p=0.3270	p=0.0000***	p=0.0000***
GROWTH - DECLINE = 0	p=0.0000***	p=0.1480	p=0.0000***	p=0.0000***
SHAKE-OUT - DECLINE = 0	p=0.0058***	p=0.0748*	p=0.0000***	p=0.2150

Table 3.3 reports the estimation results for model (2), obtained using OLS regression. The sample consists of 559,315 firm-year observations over the period 1994-2012. The t-values reported in parentheses are based on standard errors clustered by firm; *, **, ***, indicate significance at the 1%, 5%, and 10% level respectively. All continuous variables are winsorized at the 1% and 99% levels. The tests reported at the bottom of the table are coefficient comparisons to examine the significance of the differences in the coefficient estimates obtained for the indicator variables that capture the distinct life cycle stages. See Table 1 for variable definitions.

Firm life cycle thus appears to be associated with both analyst coverage decisions and the properties of analyst forecasts after controlling for various confounding factors that have been linked to analyst forecast behavior in previous research. The findings regarding analyst following over the firm life cycle provide support for the assertion that analysts respond to the increased need for their services in early-stage firms. Specifically, we find that analyst following is higher for firms in the introduction and growth stage compared to those in other life cycle stages.

Concerning individual analyst forecast accuracy over the firm life cycle, the results provide only partial support for the hypothesis. We find that analyst forecasts are less accurate for firms in the introduction, shake-out and decline stage when compared to the forecasts for mature firms, which provides some support for H2. These findings could be explained by the relatively unstable operating performance of non-mature firms, reflected in for instance less persistent earnings, which makes it more difficult for analysts to forecast future performance (Dichev et al. 2009; Dickinson 2011). More surprisingly and contrary to our hypotheses, the results also show that analyst forecasts are more accurate for firms in the growth stage compared to the forecasts for firms in the other life cycle stages. This finding can potentially be attributed to the analyst optimism generally observed in prior studies on analyst forecast behavior: While analysts tend to be too optimistic in every life cycle stage, analyst forecasts of firm performance may be more aligned with actual firm performance for firms in the growth stage given firms' development during this stage. Overall, analysts do not only appear to take firm life cycle into consideration in their coverage decisions, firm life cycle is also associated with the accuracy of individual analyst forecasts.

3.4.3. Industry Life Cycle Alignment and Life Cycle Changes

In line with our second hypothesis, the findings in the previous section indicate that firm life cycle does not only affect the level of analyst coverage but also the properties of analyst forecasts. As hypothesized, two important attributes that can contribute to the evolvement of analyst forecast properties over the firm life cycle are analyst industry expertise and analyst learning (Brown et al. 2015; Markov et al. 2006). More specifically, we expect that analysts can benefit most from their industry expertise in forecasting future firm performance when the firm life cycle is aligned with the industry life cycle while life cycle shocks have a negative effect on forecast accuracy if analysts do not (effectively) anticipate life cycle changes and its impact on the earnings generating process.

To examine the effect of the alignment between the firm and industry life cycle on the properties of analyst forecasts, we follow Cantrell et al. (2015) and determine the industry life cycle stage by taking the sum of the different cash flows types of its members and applying the life cycle classification scheme of Dickinson (2011). Firms are assigned to industries based on the two digit SIC code. After obtaining the industry life cycle, we estimate model (2) by splitting the sample based on whether the firm life cycle is aligned with the industry life cycle. The results of the analysis of the life cycle alignment between the firm and its industry are reported in Table 3.4.

Table 3.4, Panel A, reports the frequencies of firms across the industry life cycle.[34] While the majority of firms are aligned with the industry life cycle in the growth and mature stage (i.e., 52% and 64% respectively), there is little life cycle alignment for firms in the other stages. This can be explained by the fact that most industries, just like the individual firms, are classified as growth and mature. The estimation results in Table 3.4, Panel B, provide some evidence that is consistent with our hypothesis. Specifically, the higher accuracy of analyst forecasts for firms in the growth stage that we observe in our main analyses appears to be driven by those firms whose life cycle is aligned with the industry life cycle. We also observe the beneficial effect of life cycle alignment on analyst accuracy for firms in the introduction stage, but do not find a similar effect for firms in the shake-out and decline stage. Overall, we only find partial support for H3a.

TABLE 3.4

Forecast Accuracy – Industry Life Cycle Alignment

Panel A: Frequencies of Firm Life Cycle within Industries

Life Cycle		FIRM				
		INTRO	*GROWTH*	*MATURE*	*SHAKE-OUT*	*DECLINE*
INDUSTRY	*INTRO*	**196** **1%**	578 2%	211 1%	168 2%	72 1%
	GROWTH	6,506 47%	**14,870** **52%**	10,860 35%	4,017 42%	2,536 34%
	MATURE	6,971 50%	12,580 44%	**19,987** **64%**	5,078 53%	4,695 63%
	SHAKE-OUT	164 1%	375 1%	357 1%	**299** **3%**	146 2%
	DECLINE	27 0%	15 0%	22 0%	19 0%	**26** **0%**
Total		13,864	28,418	31,437	9,581	7,475

[34] The descriptive statistics in Table 4, panel A, again only include one observation per firm-year even if the firm is covered by multiple analysts in a given year.

Table 3.4 – Continued

Panel B: Regression Results – Industry Life Cycle Alignment			
	ACCURACY		
	(1)	(2)	
Variable	ALIGNMENT (FIRM_LC = IND_LC)	NO ALIGNMENT (FIRM_LC ≠ IND_LC)	(1) - (2)
INTRO	0.023**	-0.003	$\chi^2 = 6.24$
	(2.26)	(-1.06)	p = 0.013
GROWTH	0.003***	-0.001	$\chi^2 = 5.93$
	(3.48)	(-0.54)	p = 0.015
SHAKE-OUT	-0.034***	-0.003**	$\chi^2 = 15.25$
	(-4.36)	(-2.19)	p = 0.000
DECLINE	0.005	-0.012***	$\chi^2 = 0.11$
	(0.09)	(-3.45)	p = 0.738
FOLLOWING	0.013***	0.024***	
	(13.61)	(15.03)	
NUM_FORECAST	0.000*	0.000***	
	(1.79)	(3.33)	
YRS_FOLLOW	-0.000***	-0.001***	
	(-2.58)	(-5.28)	
SIZE	-0.003***	-0.004***	
	(-6.56)	(-5.00)	
ROA	0.016**	0.060***	
	(2.14)	(8.25)	
FIRM AGE	-0.001***	-0.005***	
	(-3.29)	(-4.46)	
LOSS	-0.025***	-0.021***	
	(-11.78)	(-9.46)	
MTB	-0.000	0.000	
	(-0.56)	(1.44)	
ADV_INT	-0.001	-0.012	
	(-0.07)	(-0.53)	
R&D_INT	0.020***	0.017	
	(3.08)	(1.29)	
STD_RET	-0.122***	-0.134***	
	(-8.91)	(-7.61)	
STD_ROA	-0.018**	-0.012***	
	(-2.50)	(-3.11)	
INSTH	0.020***	0.041***	
	(9.20)	(9.87)	
SEGMENTS	0.003***	0.003	
	(2.67)	(1.17)	
MNG_FORECASTS	0.000***	0.001***	
	(3.29)	(4.00)	
CONSTANT	-0.421***	-0.069	
	(-13.10)	(-1.00)	
Industry FE	YES	YES	
Year FE	YES	YES	
Observations	271,918	287,397	
R-squared	13.2%	15.9%	

Table 3.4 – Continued

Table 3.4 reports the findings of the analyses of the effect of the life cycle alignment on forecast accuracy. Panel A reports the distribution of firm life cycle stages within industries. Panel B presents the estimation results for model (2) after splitting the sample based on whether the firm life cycle is aligned with the industry life cycle, obtained using OLS regression. The sample consists of 559,315 firm-year observations over the period 1994-2012. Industries are assigned to the different life cycle stages based on Cantrell et al.'s (2015) cash flow classification. The t-values reported in parentheses are based on standard errors clustered by firm; *, **, ***, indicate significance at the 1%, 5%, and 10% level respectively. All continuous variables are winsorized at the 1% and 99% levels. The tests reported at the bottom of the table are coefficient comparisons to examine whether the coefficient estimates for the life cycle indicator variables differ significantly across the two split-samples. See Table 3.1 for other variable definitions.

To investigate the effect of life cycle changes on forecast accuracy, we estimate a first-difference specification of model (2), which can be written as follows:

$$\Delta FORECAST\ ACCURACY_{it} = \alpha_0 + \gamma_1 * \Delta LC\_STAGE_{it} + \Sigma_n \gamma_n * \Delta CONTROLS_{it} + \varepsilon_{it} \qquad (4)$$

The explanatory variable of interest, *ΔLC_STAGE*, is an indicator variable that is equal to one if firm *i* moved to another life cycle stage from year *t-1* to year *t*. If analysts do not immediately incorporate the effect of a life cycle shock on the earnings generating process, as we hypothesize, then we would expect a negative coefficient on *ΔLC_STAGE*. Table 3.5 reports the findings of the analysis of life cycle changes on the forecast accuracy of individual analysts.

The estimation results in Table 3.5 indicate that life cycle changes are indeed associated with a decrease in forecast accuracy (*ΔLC_STAGE* = -0.002; t-statistic = -4.98), providing support for H3b. This finding can be attributed to the detrimental effect of life cycle changes on analysts' ability to learn about the parameters underlying the earnings process at the various stages of the firm life cycle (cf. Markov et al. 2006).

Overall, the results in this section suggest that the favorable properties of analyst forecasts for growth firms can, at least partly, be explained by life cycle alignment between the firm and its industry, which should facilitate the use of analyst industry expertise.[35] In addition, analysts do not immediately incorporate life cycle shocks in forecasting future firm performance as forecast accuracy decreases following a firm's transition to another life cycle stage.

[35] Throughout the analyses in section 3.4, we have examined H2 and H3a by including indicator variables for all five stages separately. Nevertheless, the formulation of H2 and H3a suggest that we are mainly interested in comparing mature versus non-mature firms rather than all stages to each other. The results obtained after including a "non-mature" indicator variable in our models are as follows: The coefficient estimates on forecast accuracy, forecast error, pessimism, and optimism are -0.001 (p-value = 0.139); 0.001 (p-value = 0.021); -0.003 (p-value = 0.118); and 0.001 (p-value = 0.085). These results are only partially consistent with H2, which can be attributed to the higher forecast accuracy for growth firms. While the signed forecast error and analyst optimism are significantly higher for non-mature firms, the accuracy of non-mature firms is only significantly lower at the one-sided 10% significance level. Consistent with H3a, the accuracy for non-mature firms is significantly higher when the firm life cycle is aligned with the industry life cycle than when there is no such alignment (Non-mature – Aligned = 0.002;Non-mature – Non-Aligned = -0.002; Δ: χ^2 = 9.78 (p-value = 0.0018).

TABLE 3.5

Forecast Accuracy – Changes in Life Cycle Stage

Variable	ΔACCURACY (1)
ΔLC_STAGE	-0.002***
	(-4.98)
ΔFOLLOWING	0.025***
	(16.77)
ΔNUM_FORECAST	0.000***
	(12.24)
ΔSIZE	0.016***
	(9.23)
ΔROA	0.021***
	(3.67)
ΔFIRM AGE	-0.033***
	(-9.94)
ΔLOSS	-0.009***
	(-6.63)
ΔMTB	-0.000***
	(-3.74)
ΔADV_INT	-0.022
	(-0.90)
ΔR&D_INT	-0.013*
	(-1.67)
ΔSTD_RET	-0.224***
	(-11.02)
ΔSTD_ROA	-0.015**
	(-2.43)
ΔINSTH	0.023***
	(7.01)
ΔSEGMENTS	-0.001
	(-0.37)
ΔMNG_FORECASTS	0.000***
	(3.90)
CONSTANT	-0.027
	(-0.82)
Industry FE	YES
Year FE	YES
Observations	351,031
R-squared	5.9%

Table 3.5 reports the findings of the analysis of the effect of changes in life cycle stage on forecast accuracy. Panel A reports summary statistics of the length of the life cycle stages. Panel B presents the estimation results for model (4). *ΔLC_STAGE*, is an indicator variable that is equal to one if firm *i* moved to another life cycle stage from year *t-1* to year *t*. The sample consists of 351,031 firm-year observations (after first differencing) over the period 1994-2012. The t-values reported in parentheses are based on standard errors clustered by firm; *, **, ***, indicate significance at the 1%, 5%, and 10% level respectively. All continuous variables are winsorized at the 1% and 99% levels. See Table 3.1 for other variable definitions.

3.5. Additional Analyses and Robustness Checks

3.5.1. Changes in Analyst Following

In interpreting the results concerning analyst following, we assume that analysts *respond* to the varying demand for their services over the firm life cycle. That is, our reasoning suggests that investor uncertainty about firm fundamental value as well as firms' potential visibility concerns in the introduction and growth stage *cause* an increase in analyst following for firms in these stages. Following prior research (Lang et al. 1996; Lehavy et al. 2011), one way to shed further light on this assertion is to examine the association between changes in life cycle stage and lead changes in analyst following. More specifically, if analysts do indeed respond to changes in the demand for their services over the firm life cycle, we should observe the hypothesized effects by investigating the relation between current changes in life cycle stage and *future* changes in analyst following. If we already observe the hypothesized effects by examining changes in life cycle stage and *present* changes in analyst following, this could suggest that analyst already anticipate life cycle changes or that life cycle stage and analyst following are simultaneously determined by other exogenous variables (Lang et al. 1996).

We specify changes in life cycle stage by identifying all possible changes between the five life cycle stages, resulting in twenty possible changes in life cycle stage (i.e., a firm can move to four other stages from any of the identified five life cycle stages). The current (lead) change(s) in analyst following is (are) calculated as the difference(s) between analyst following at the end of the current fiscal year and analyst following at the end of the prior (next) fiscal year(s). When investigating the effect of current changes in life cycle stage and lead changes in analyst following (i.e., Δ_{t+1} and Δ_{t+2}), we require the firm to stay in the same life cycle stage as it moves to in the current fiscal year (i.e., year t). The estimation results for this alternative specification of model (1) are reported in Table 3.6.

Consistent with the results of our main analysis, we find significant positive relations between changes to the growth stage from any of the other life cycle stages and the lead change in analyst following. In addition, we also observe a significant positive relation between changes to the introduction stage from the shake-out and decline stage and the lead change in analyst following, but do not observe this pattern for firms that move from the growth or mature stage to the introduction stage. Moreover, the estimation results for the regression of changes in life cycle stage and the current change in analyst following suggest that the results of our main analyses are not driven by changes in analyst following that precede changes in life cycle stage as none of the coefficients is significantly positive. Finally, the findings in Table 3.6 indicate that it may take some time for analysts to respond to current changes in life cycle stage as most of the patterns that we observe for the one-year ahead change in analyst following can also be observed for the two-year ahead change in analyst following. Taken together, the results in this section are consistent with analysts responding to the varying need for their services over the life cycle and help to alleviate potential endogeneity concerns related to simultaneity bias.

TABLE 3.6

Changes in Analyst Following

	ΔANALYST FOLLOWING		
Variable	(1) ΔANALYST $FOLLOWING_t$	(2) ΔANALYST $FOLLOWING_{t+1}$	(3) ΔANALYST $FOLLOWING_{t+2}$
$INTRO_{t-1}$ to $GROWTH_t$	0.014	0.051***	0.024
	(1.46)	(3.02)	(0.99)
$INTRO_{t-1}$ to $MATURE_t$	-0.038***	-0.006	-0.018
	(-3.72)	(-0.31)	(-0.76)
$INTRO_{t-1}$ to SHAKE-OUT_t	-0.062***	-0.055*	-0.048
	(-4.12)	(-1.72)	(-0.95)
$INTRO_{t-1}$ to $DECLINE_t$	-0.030***	-0.082***	-0.156***
	(-3.10)	(-4.47)	(-4.98)
$GROWTH_{t-1}$ to $INTRO_t$	0.002	-0.035*	-0.075**
	(0.17)	(-1.78)	(-2.09)
$GROWTH_{t-1}$ to $MATURE_t$	-0.002	-0.013*	-0.009
	(-0.32)	(-1.86)	(-0.94)
$GROWTH_{t-1}$ to SHAKE-OUT_t	-0.012	-0.056***	-0.009
	(-1.44)	(-3.36)	(-0.29)
$GROWTH_{t-1}$ to $DECLINE_t$	-0.049***	-0.083***	-0.230***
	(-3.11)	(-2.82)	(-5.50)
$MATURE_{t-1}$ to $INTRO_t$	-0.020*	-0.010	0.060
	(-1.82)	(-0.38)	(1.17)
$MATURE_{t-1}$ to $GROWTH_t$	-0.011**	0.029***	0.050***
	(-2.14)	(3.51)	(4.02)
$MATURE_{t-1}$ to SHAKE-OUT_t	-0.029***	-0.016	-0.037
	(-3.92)	(-1.06)	(-0.91)
$MATURE_{t-1}$ to $DECLINE_t$	-0.033**	-0.066*	-0.162**
	(-2.09)	(-1.90)	(-2.17)
$SHAKE_{t-1}$ to $INTRO_t$	-0.046***	0.044*	-0.003
	(-3.34)	(1.72)	(-0.07)
$SHAKE_{t-1}$ to $GROWTH_t$	0.003	0.048***	0.042*
	(0.30)	(3.04)	(1.84)
$SHAKE_{t-1}$ to $MATURE_t$	0.008	0.002	0.031**
	(1.14)	(0.23)	(2.10)
$SHAKE_{t-1}$ to $DECLINE_t$	-0.075***	-0.018	-0.038
	(-5.34)	(-0.64)	(-0.80)
$DECLINE_{t-1}$ to $INTRO_t$	-0.011	0.078***	0.079***
	(-1.14)	(4.87)	(3.10)
$DECLINE_{t-1}$ to $GROWTH_t$	-0.019	0.071**	0.086**
	(-1.16)	(2.27)	(2.15)
$DECLINE_{t-1}$ to $MATURE_t$	-0.050***	-0.028	-0.088**
	(-2.86)	(-0.98)	(-2.49)
$DECLINE_{t-1}$ to SHAKE-OUT_t	-0.051***	-0.004	-0.021
	(-3.72)	(-0.12)	(-0.34)
ΔSIZE	0.204***	0.151***	0.008
	(34.24)	(17.46)	(0.65)
ΔROA	0.015	0.074***	0.034
	(1.12)	(3.59)	(1.21)
ΔFIRM AGE	0.003	-0.081***	-0.046*
	(0.23)	(-4.01)	(-1.86)

Table 3.6 - Continued

ΔLOSS	-0.026***	-0.020***	-0.004
	(-6.62)	(-3.26)	(-0.42)
ΔMTB	0.001***	0.005***	0.002**
	(3.27)	(7.20)	(2.53)
ΔADV_INT	0.173	0.078	-0.342*
	(1.43)	(0.50)	(-1.72)
ΔR&D_INT	-0.136***	0.088**	0.043
	(-5.16)	(2.38)	(0.85)
ΔSTD_RET	-0.391***	0.076	0.185**
	(-9.00)	(1.09)	(2.13)
ΔSTD_ROA	0.020***	-0.004	-0.003
	(3.51)	(-0.44)	(-0.29)
ΔINSTH	0.388***	0.185***	0.100***
	(23.90)	(8.65)	(4.21)
ΔSEGMENTS	-0.029**	-0.052***	-0.034
	(-2.49)	(-2.64)	(-1.10)
ΔMNG_FORECASTS	0.010***	0.001	-0.001
	(10.59)	(0.69)	(-0.54)
CONSTANT	-0.011***	-0.002	0.009**
	(-5.27)	(-0.53)	(2.33)
Industry FE	NO	NO	NO
Year FE	NO	NO	NO
Observations	77,662	32,536	16,395
R-squared	6.4%	3.7%	1.2%

Table 3.6 reports the estimation results for the analyses of current changes in life cycle stage on both current and lead changes in analyst following, obtained using OLS regression. The sample consists of firm-year observations over the period 1994-2012. The t-values reported in parentheses are based on standard errors clustered by firm; *, **, ***, indicate significance at the 1%, 5%, and 10% level respectively. All continuous variables are winsorized at the 1% and 99% levels. See Table 3.1 for variable definitions.

3.5.2. Heterogeneity in Investor Beliefs, Firm Viability and Visibility

In section 3.2 we argued that differences in the demand for analyst services over the firm life cycle could arise due to the difficulty for investors to assess firm fundamental value and firm's visibility concerns. To further substantiate the validity of our findings, we run some cross-sectional analyses.

The difficulty that investors have in assessing firm fundamental value is likely to be reflected in more disagreement among investors. Prior research already found that heterogeneity in investor beliefs is especially prevalent in the introduction and the growth stage, for instance, due to the relatively large impact of future growth opportunities on firm value (Hamers et al. 2016). If analysts indeed incorporate investor needs in their coverage decisions, we expect analyst following to be higher for those firms for which the intensity of disagreement among investors is relatively high.

One important factor that is expected to contribute to the valuation difficulties faced by investors over the firm life cycle is the financial viability of the firm. For firms at the far ends of the life cycle spectrum it is relatively uncertain whether the firm will be successful in its efforts to move forward or return to another, more stable life cycle stage or will go out of business. More specifically, uncertainty may exist regarding the successful implementation of new business ideas or firms' ability to cope with declining business opportunities for firms in the introduction, the shake-out, and the decline stage (Damodaran 2009). The uncertainty concerning firm viability is especially relevant for firms that face high distress risk. Since financially distressed firms are difficult to value and are more likely to be mispriced by investors (Baker and Wurgler 2006; Griffin and Lemmon 2002), the valuation uncertainty concerning firm viability leads to an increased need for analyst services, especially in the introduction, shake-out and decline stage. Hence, we expect that analyst following is higher for firms that face high financial distress risk in these stages.

With regard to firms' visibility concerns, firms that have relatively little visibility in the market may face lower valuations and a higher cost of capital than firms with a larger shareholder base (Lehavy et al. 2008; Merton 1987). These visibility concerns may again be especially relevant for firms at the far ends of the life cycle spectrum as these firms are most likely to lack visibility-enhancing characteristics (Bushee et al. 2012). One way in which firms can try to improve their visibility and, hence, overcome the negative effects associated with low visibility is to attract more analysts (Bushee et al. 2012). As such, if analysts respond to the increased demand for their services arising from firms' visibility concerns, we would expect that analyst following is higher for firms with low visibility.

To formally test these expectations, we conduct split-sample analyses using detrended share turnover as the proxy for heterogeneity in investor beliefs; the Altman Z-score as the proxy for financial distress risk; and the number of common shareholders as the proxy for firm visibility (Altman 1968; Armstrong, Core, Taylor and Verrecchia 2011; Chen, Hong and Stein, 2001; Grullon, Kanatas and Weston 2004).[36]

Firms are assigned to subsamples based on the median values for the detrended share turnover, the Z-score and the number of common shareholders in each life cycle stage.[37] Based on the reasoning above, we expect that analyst following is higher for firms with an above-median detrended share turnover; firms with a below-median Z-score; or firms with a below-median number of common shareholders. The results of these split-sample analyses are reported in Table 3.7.

[36] The Altman Z-score is calculated as follows (Altman 1968):

Altman Z-score = 1.2 (Net Working Capital/Total Assets) + 1.4 (Retained Earnings/Total Assets) + 3.3(EBIT/Total Assets) + 0.6 (Market Value Equity/Total Liabilities) + 0.999 (Sales/Total Assets).

[37] We use the median value for each separate life cycle stages in order to avoid the problems that may arise as a consequence of systematic differences in financial health and firm visibility across the various life cycle stages. However, the results are robust to the use of the full sample median.

TABLE 3.7

Split-sample Analysis – Heterogeneity in Investor Beliefs, Firm Viability and Visibility

	ANALYST FOLLOWING								
Variable	(1) Low Turnover	(2) High Turnover	(2) - (1)	(3) Low Z-Score	(4) High Z-Score	(4) - (3)	(5) Low Visibility	(6) High Visibility	(6) - (5)
$INTRO_t$	0.051***	0.069***	$\chi^2 = 2.95$	0.075***	0.032***	$\chi^2 = 13.21$	0.080***	0.056***	$\chi^2 = 5.00$
	(7.27)	(9.03)	p = 0.086	(7.98)	(4.39)	p = 0.000	(10.55)	(7.26)	p = 0.025
$GROWTH_t$	0.047***	0.071***	$\chi^2 = 14.71$	0.064***	0.062***	$\chi^2 = 0.02$	0.061***	0.051***	$\chi^2 = 2.03$
	(10.59)	(15.52)	p = 0.000	(11.48)	(12.71)	p = 0.8754	(11.94)	(10.40)	p = 0.154
$SHAKE\text{-}OUT_t$	-0.011*	-0.032***	$\chi^2 = 5.84$	0.000	-0.042***	$\chi^2 = 16.26$	-0.004	-0.036***	$\chi^2 = 10.68$
	(-1.75)	(-5.16)	p = 0.016	(0.05)	(-5.94)	p = 0.000	(-0.59)	(-5.21)	p = 0.001
$DECLINE_t$	-0.013	-0.025***	$\chi^2 = 0.99$	-0.008	-0.038***	$\chi^2 = 5.00$	-0.001	-0.020**	$\chi^2 = 2.33$
	(-1.62)	(-3.06)	p = 0.3196	(-0.77)	(-4.13)	p = 0.025	(-0.11)	(-2.30)	p = 0.127
$ANALYST\ FOLLOWING_{t-1}$	0.803***	0.804***		0.747***	0.732***		0.657***	0.766***	
	(211.24)	(191.60)		(130.04)	(126.50)		(120.56)	(143.23)	
$SIZE_t$	0.046***	0.042***		0.060***	0.078***		0.086***	0.066***	
	(23.61)	(19.43)		(21.07)	(24.67)		(29.73)	(23.87)	
ROA_t	0.073***	0.168***		0.023*	0.192***		0.141***	0.118***	
	(5.01)	(11.13)		(1.72)	(8.39)		(9.23)	(7.94)	
$FIRM\ AGE_t$	-0.008***	-0.030***		-0.050***	-0.072***		-0.105***	-0.051***	
	(-3.20)	(-11.65)		(-15.08)	(-22.58)		(-29.68)	(-17.27)	
$LOSS_t$	-0.069***	-0.055***		-0.062***	-0.052***		-0.068***	-0.081***	
	(-12.98)	(-9.46)		(-10.62)	(-7.01)		(-11.22)	(-13.39)	
MTB_t	0.009***	0.008***		0.006***	0.012***		0.012***	0.009***	
	(14.98)	(16.09)		(9.88)	(17.04)		(18.50)	(15.35)	
ADV_INT_t	0.134**	0.241***		0.248***	0.171***		0.389***	0.201***	
	(2.25)	(4.09)		(3.07)	(2.77)		(5.70)	(2.86)	
$R\&D\_INT_t$	0.306***	0.328***		0.273***	0.423***		0.407***	0.358***	
	(13.67)	(15.07)		(13.32)	(13.77)		(17.99)	(15.74)	
STD_RET_t	0.201***	0.249***		0.094***	0.373***		0.177***	0.198***	
	(7.25)	(8.09)		(3.16)	(10.39)		(5.69)	(6.33)	

STD_ROA$_t$	-0.003	0.008**	0.006	0.021**	0.008*	0.002
	(-0.68)	(1.97)	(1.64)	(2.04)	(1.89)	(0.43)
INSTH$_t$	0.254***	0.279***	0.318***	0.327***	0.404***	0.259***
	(26.08)	(27.53)	(24.39)	(27.09)	(29.96)	(21.93)
SEGMENTS$_t$	-0.030***	-0.047***	-0.064***	-0.051***	-0.064***	-0.041***
	(-3.83)	(-5.83)	(-6.17)	(-5.56)	(-5.92)	(-4.87)
MNG_FORECASTS$_t$	0.014***	0.009***	0.019***	0.012***	0.014***	0.011***
	(15.97)	(11.55)	(16.07)	(13.00)	(12.16)	(12.65)
CONSTANT	-0.172***	-0.089***	-0.096***	-0.093**	-0.094	-0.085**
	(-4.59)	(-3.00)	(-2.63)	(-2.52)	(-1.48)	(-2.23)
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	39,122	39,120	36,323	36,320	39,126	39,125
R-squared	88.0%	87.5%	84.3%	87.2%	83.3%	87.8%

Table 3.7 reports the estimation results for model (1) after splitting the sample based on the median value of detrended share turnover, the median value of firm's Altman Z-scores and the median number of common shareholders by life cycle stage, obtained using OLS regression. The sample consists of firm-year observations over the period 1994-2012. The t-values reported in parentheses are based on standard errors clustered by firm; *, **, ***, indicate significance at the 1%, 5%, and 10% level respectively. All continuous variables are winsorized at the 1% and 99% levels. The p-values presented alongside table 3.7 indicate whether the coefficient estimates for the life cycle indicator variables differ significantly across the two split-samples. See Table 3.1 for variable definitions.

First of all, the findings in Table 3.7 indicate that the coefficients on *INTRO* and *GROWTH* are positive and significant across all subsamples, suggesting that the investigated factors provide only partial explanations for the higher analyst following in the introduction and growth stage observed in the main analysis. Nevertheless, the findings in Table 3.7, columns 1 and 2, show that the analyst following is significantly higher in the introduction and growth stage for firms with a higher intensity of disagreement among investors as reflected in an above-median detrended share turnover. This finding provides support for our expectation that analyst following is higher for those firms for which investors find it more difficult to agree on firm value. In addition, the estimation results in Table 3.7, columns 3 to 6, show that analyst following is also significantly higher in the introduction, shake-out and decline stage when the firm has a below-median Z-score or a below-median number of ordinary shareholders in the introduction and shake-out stage. These findings are generally consistent with the notion that analyst following at the far ends of the life cycle spectrum is higher for financially distressed firms and firms with low visibility. As mentioned before, the finding that analyst following is higher for financially weak firms in the introduction, shake-out and decline stage can be attributed to investor uncertainty concerning firm survival. In these stages, analysts could, for instance, help investors to assess the likelihood of success of product (re)introductions, which is arguably more important if there are concerns about firm survival. Additionally, firms that reside at the far ends of the life cycle spectrum may attract analysts in order to enhance their visibility which is reflected in the higher analyst following for firms with a below-median number of common shareholders in the introduction and shake-out stage.

3.5.3. Forecast Properties at the Consensus Level

We also replicate our main results concerning forecast accuracy at the consensus level. Examining the consensus forecast provides us with the opportunity to investigate analyst dispersion, another variable that is used in prior research to capture the difficulty that analysts face in forecasting future firm performance (Lehavy et al. 2011). Forecast accuracy (*ACCURACY*) is measured as the negative of the absolute difference between the *consensus* forecast and the actual EPS (i.e., the forecast error) for firm *i* in year *t*, scaled by the share price at the end of the previous year. Forecast dispersion (*DISPERSION*) is computed as the volatility in the consensus forecast, scaled by the share price at the end of the previous year. Both *ACCURACY* and *DISPERSION* are measured at the forecast date closest to but not exceeding the fiscal year end. The results for the estimation of model (2) at the consensus level are reported in Table 3.8.

The findings in table 3.8 are consistent with the findings at the individual analyst level. Whereas forecast accuracy is lower for firms that reside in the introduction, shake-out, and decline stage, the consensus forecast is more accurate for growth firms compared to firms in the other life cycle stages. In addition, even though analyst forecasts are, in general, more dispersed for non-mature firms, reflecting again the forecasting difficulty faced by analysts, analyst forecasts are less dispersed for growth firms.

TABLE 3.8

Forecast Properties at the Consensus Level

	FORECAST PROPERTY	
	(1)	(2)
Variable	ACCURACY	DISPERSION
INTRO	-0.007*	0.002**
	(-1.93)	(2.03)
GROWTH	0.004***	-0.001*
	(3.51)	(-1.84)
SHAKE-OUT	-0.009***	0.001**
	(-3.82)	(2.52)
DECLINE	-0.021***	0.009***
	(-3.84)	(4.04)
FOLLOWING	0.022***	-0.004***
	(13.91)	(-6.67)
SIZE	-0.004***	0.001***
	(-4.66)	(3.20)
ROA	0.103***	-0.021***
	(9.91)	(-5.89)
FIRM AGE	-0.007***	0.001***
	(-5.66)	(3.44)
LOSS	-0.027***	0.005***
	(-9.14)	(5.66)
MTB	0.000*	-0.000
	(1.77)	(-0.22)
ADV_INT	-0.006	0.003
	(-0.21)	(0.38)
R&D_INT	0.043**	0.006
	(2.46)	(0.94)
STD_RET	-0.226***	0.039***
	(-10.36)	(6.34)
STD_ROA	-0.014***	0.002
	(-2.62)	(1.29)
INSTH	0.040***	-0.012***
	(9.99)	(-8.98)
SEGMENTS	0.001	-0.000
	(0.22)	(-0.59)
MNG_FORECASTS	0.000	-0.000***
	(0.79)	(-5.75)
CONSTANT	-0.157	0.004
	(-1.06)	(.)
Industry FE	YES	YES
Year FE	YES	YES
Observations	62,749	37,215
R-squared	12.2%	11.7%
INTRO - GROWTH = 0	p=0.0013***	p=0.0149**
INTRO - SHAKE-OUT = 0	p=0.5720	p=0.4680
INTRO - DECLINE = 0	p=0.0128**	p=0.0042***
GROWTH - SHAKE-OUT =0	p=0.0000***	p=0.0008***
GROWTH - DECLINE = 0	p=0.0000***	p=0.0000***
SHAKE-OUT - DECLINE = 0	p=0.0464**	p=0.0013***

Table 3.8 - Continued
Table 3.8 reports the findings of the analysis of forecast properties at the consensus level. The samples consist of firm-year observations over the period 1994-2012. *ACCURACY* is measured as the negative of the absolute difference between the consensus forecast and the actual EPS (i.e., the forecast error) for firm *i* in year *t*, scaled by the share price at the end of the previous year. *DISPERSION* is measured as the volatility in the consensus forecast, scaled by the share price at the end of the previous year. Both *ACCURACY* and *DISPERSION* are measured at the forecast date closest to but not exceeding the fiscal year end. The t-values reported in parentheses are based on standard errors clustered by firm; *, **, ***, indicate significance at the 1%, 5%, and 10% level respectively. All continuous variables are winsorized at the 1% and 99% levels. The tests reported at the bottom of the table are coefficient comparisons to examine the significance of the differences in the coefficient estimates obtained for the indicator variables that capture the distinct life cycle stages. See Table 3.1 for variable definitions.

3.5.4. Alternative Life Cycle Proxy

Even though prior research suggests that the cash flow pattern proxy for firm life cycle better captures firm dynamics across the different stages (Dickinson 2011), we examine the robustness of our results using an alternative life cycle proxy. Similar to Anthony et al. (1992) and Hribar et al. (2015), we group the firm-year observations into three equally large groups based on an aggregate score which we calculate by taking the sum of the standardized values of sales growth, capital expenditures, net-capital transactions and firm age. Following Hribar et al. (2015), we label these groups *GROWTH*, *MATURE*, and *DECLINE*. The results that we obtain after replacing the life cycle variables in models (1) and (2) by indicator variables based on the alternative life cycle classification are reported in Tables 3.9 and 3.10; the mature stage is treated as the reference stage.[38]

In line with the results found in the main analyses, analyst following is higher for firms in the growth stage compared to the mature stage. In addition, individual analyst forecasts appear to be more accurate in this stage. In contrast to our prior analyses, the properties of analyst forecasts do not differ significantly between firms in the mature and decline stage. The insignificant difference between firms in the mature and decline stage with regard to analyst forecast properties may be attributed to the uniform distribution of firm-year observations across the different firm life cycle stages imposed by the alternative life cycle proxy. As such, part of the mature firms may be assigned to the decline stage, making it more difficult to observe significant differences between these stages. Overall, though, our main results are generally robust to the use of an alternative life cycle proxy.

[38] Since the alternative life cycle partly depends on firm age, R&D intensity and advertising intensity, we exclude *FIRM AGE, R&D_INT* and *ADV_INT* as control variables from the analysis.

TABLE 3.9

Analyst Following over the Firm Life Cycle – Alternative Proxy

Variable	ANALYST FOLLOWING (1)
GROWTH	0.160***
	(19.11)
DECLINE	-0.057***
	(-5.08)
SIZE	0.254***
	(50.27)
ROA	-0.014
	(-0.66)
LOSS	-0.042***
	(-4.90)
MTB	0.024***
	(22.74)
STD_RET	0.412***
	(6.93)
STD_ROA	0.051***
	(4.77)
INSTH	1.053***
	(43.06)
SEGMENTS	-0.269***
	(-11.75)
MNG_FORECASTS	0.055***
	(25.58)
CONSTANT	-0.538***
	(-20.62)
Industry FE	YES
Year FE	YES
Observations	82,736
R-squared	62.9%

Table 3.9 reports the estimation results for model (1), obtained using OLS regression. The sample consists of 82,736 firm-year observations over the period 1994-2012. *GROWTH* and *DECLINE* are indicator variables that equal one if the firm is classified into the particular life cycle stage based on the life cycle classification of Hribar and Yehuda (2015), and zero otherwise. The t-values reported in parentheses are based on standard errors clustered by firm; *, **, ***, indicate significance at the 1%, 5%, and 10% level respectively. All continuous variables are winsorized at the 1% and 99% levels. See Table 3.1 for variable definitions.

TABLE 3.10

Forecast Properties over the Firm Life Cycle – Alternative Proxy

	FORECAST PROPERTY			
	(1)	(2)	(3)	(4)
Variable	ACCURACY	FORECAST ERROR (FE)	PESSIMISM (FE < 0)	OPTIMISM (FE > 0)
GROWTH	0.003**	-0.002***	0.000	-0.004***
	(2.51)	(-4.13)	(1.54)	(-3.13)
DECLINE	-0.001	0.000	0.000	0.001
	(-0.78)	(0.55)	(1.10)	(0.69)
FOLLOWING	0.018***	-0.008***	0.006***	-0.020***
	(15.86)	(-15.41)	(21.21)	(-17.38)
NUM_FORECAST	0.000**	-0.000	0.000***	-0.000
	(2.23)	(-0.69)	(5.40)	(-1.00)
YRS_FOLLOW	-0.000***	0.000***	-0.000***	0.000***
	(-6.05)	(2.85)	(-4.98)	(5.20)
SIZE	-0.004***	0.001***	-0.001***	0.004***
	(-6.50)	(5.44)	(-8.99)	(7.29)
ROA	0.055***	-0.030***	0.007***	-0.059***
	(7.16)	(-8.33)	(4.16)	(-8.42)
LOSS	-0.024***	0.019***	-0.006***	0.030***
	(-12.04)	(16.87)	(-11.11)	(16.44)
MTB	0.000	0.000	0.000**	-0.000**
	(0.68)	(0.61)	(2.46)	(-2.40)
STD_RET	-0.140***	0.018***	-0.052***	0.134***
	(-10.36)	(2.92)	(-15.56)	(9.57)
STD_ROA	-0.022***	0.000	-0.008***	0.016***
	(-3.83)	(0.23)	(-4.75)	(2.68)
INSTH	0.035***	-0.015***	0.008***	-0.036***
	(12.48)	(-11.46)	(11.59)	(-12.73)
SEGMENTS	0.001	-0.001	0.001	-0.001
	(0.91)	(-0.82)	(1.57)	(-0.50)
MNG_FORECASTS	0.001***	-0.000	0.000***	-0.000***
	(4.18)	(-0.40)	(8.10)	(-3.28)
CONSTANT	-0.033	0.010	-0.010	0.342***
	(-0.00)	(0.00)	(-0.00)	(52.79)
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	524,653	524,653	318,098	206,555
R-squared	16.0%	8.4%	20.1%	23.4%

Table 3.10 reports the estimation results for model (2), obtained using OLS regression. The investigated sample consists of 524,653 firm-year observations over the period 1994-2012. *GROWTH* and *DECLINE* are indicator variables that equal one if the firm is classified into the particular life cycle stage based on the life cycle classification of Hribar and Yehuda (2015), and zero otherwise The t-values reported in parentheses are based on standard errors clustered by firm; *, **, ***, indicate significance at the 1%, 5%, and 10% level respectively. All continuous variables are winsorized at the 1% and 99% levels. See Table 3.1 for variable definitions.

3.6. Conclusion

The purpose of this study is to examine how analyst forecast behavior differs over the firm life cycle. Investors' limited ability to incorporate firm life cycle information gives rise to an increased need for analyst services while the mispricing that arises as a consequence of the different firm dynamics across life cycle stages also provides profitable opportunities for analysts. In addition, firms in the introduction and growth stage may try to attract analysts in order to mitigate potential visibility concerns. Yet, the varying needs for their services over the firm life cycle do not only provide analysts with benefits, the relatively limited operating stability of non-mature firms may also increase the difficulty of forecasting future firm performance.

The findings in this study suggest that analysts do respond to the varying need for their services over the firm life cycle. Consistent with the increased need for their services due to uncertainty among investors and firms' potential visibility concerns, analyst following is higher for firms in the introduction and growth stage compared to firms in the other life cycle stages. Further analyses provide support for the assertion that analysts respond to changes in life cycle stages and show that analyst following is higher for firms that face more investor disagreement, whose future survival is more uncertain or that have a relatively small investor base, reflecting the increased need for analyst services in the presence of increased valuation difficulty and visibility concerns at the opposite ends of the life cycle spectrum. In line with the difficulty to forecast future firm performance for non-mature firms, the analyst forecasts for these firms are, in general, less accurate than the forecasts of mature firms. Surprisingly, however, analyst forecast accuracy appears to be superior for firms in the growth stage compared to the forecast accuracy for firms in the other life cycle stages.

Further analyses reveal that the superior forecast accuracy for growth firms can be attributed to firms whose life cycle is aligned with the industry life cycle, reflecting the greater extent to which analysts can benefit from their industry expertise. Even though we also observe some evidence of the beneficial effect of life cycle alignment in other life cycle stages, these results are mixed at best. One explanation for these mixed findings is the limited life cycle alignment between firm and industry for firms in the introduction, shake-out and decline stage as most industries are classified as growth or mature. Furthermore, our results also indicate that forecast accuracy decreases immediately after a firm moves to another life cycle stage, which indicates that analyst do not immediately incorporate the impact of life cycle shocks on the earnings generating process.

While interpreting these results, some potential caveats have to be taken into consideration. First, even though we control for a large set of potential confounding factors related to firm life cycle, valuation uncertainty, business complexity and the information environment, we cannot be fully certain that our results are not driven by unobservable factors associated with any of these components of the business environment. Nevertheless, the findings of our additional analyses provide us with some additional confidence in the results obtained in the main analyses. Another potential caveat relates to our life cycle proxy. Concerns may be raised regarding the difficulty to capture a fundamental concept as firm life cycle by relying on quantitative date. Yet, both the systematic development of various accounting measures across the life cycle stages that can be observed when using Dickinson's

(2011) cash flow classification and the finding that our results are generally robust to an alternative life cycle proxy used in prior studies may alleviate these concerns.

This study has implications for researchers, managers and investors. Although only a limited number of studies has included firm life cycle in the research design so far, this study provides additional evidence that firm life cycle is an important firm characteristic that can provide valuable insights to researchers investigating the functioning of capital markets. This study is also interesting for managers and investors as the findings suggest that analysts respond to the varying need for analyst services throughout the firm life cycle and, hence, could help in reducing investor uncertainty across the different life cycle stages.

4 DEBT CONTRACTING OVER THE FIRM LIFE CYCLE[39]

ABSTRACT – This study investigates the role of firm life cycle in debt markets. Both the source of lending and debt contract design are likely to differ across life cycle stages as a consequence of the trade-offs faced by borrowers and lenders that arise from uncertainty about borrowers' future values. Concerning the source of lending, I find that early-stage firms prefer public to private debt. This suggests that the costs of potential rent extraction by private lenders outweigh the benefits related to their superior monitoring abilities. With regard to debt contract design, both private and public lenders adjust contractual terms to incorporate uncertainty about the future value of early-stage borrowers. Yet, the way in which they do differs slightly, reflecting the differences in renegotiation costs between the two types of lenders. Specifically, while public lenders rely more on shorter maturities in the debt contracts of growth firms, private lenders rely on a higher covenant intensity instead. Additional analyses indicate that both types of lenders tailor the covenant design to borrower needs and the varying informativeness of accounting measures.

4.1. Introduction

In this study, I address how borrowers and lenders incorporate the dynamics in the uncertainty about borrowers' future values by examining how debt contracting evolves over the firm life cycle. Firms in the early stages of the firm life cycle need substantial funding to exploit the available investment opportunities, but the lack of internal sources of funding necessitates the reliance on external financing. When firms move to the other stages of the firm life cycle, the accumulation of profits in the mature stage and declining investment opportunities reduce the need to obtain additional financing from external capital providers (DeAngelo, DeAngelo and Stulz 2006; Dickinson 2011). Recent findings indeed show that both net equity issuance and net debt issuance increase in the introduction and growth stage of the firm life cycle but decrease as firms move to the other end of the life cycle spectrum (Faff, Kwok, Podolski and Wong 2016).

The combination of the large investment opportunity set of early-stage firms with their reliance on debt financing seems to contradict the common reasoning that a negative relation should exist between leverage and growth opportunities as a consequence of agency costs arising from conflicts of interest between shareholders and debtholders (Jensen and Meckling 1976; Myers, 1977; Smith and Warner 1979). Yet, the limited availability of (excess) cash flows and the need to make the right investment decisions to achieve operating stability contribute to a better alignment of the interests of the manager with those of the different

[39] **Acknowledgements**: This paper has benefited from discussions with Ole-Kristian Hope, Annelies Renders, Patrick Vorst, Dushyant Vyas, Franco Wong, course participants at University of Toronto and seminar participants at the 2016 DARC Conference in Rotterdam. Part of this study, including the data collection, was completed during a study visit at the Rotman School of Management, University of Toronto.

stakeholder groups in these stages. Even though agency costs may therefore play only a minor role in early-stage firms, a lot of uncertainty still remains about the borrower's future value given the significant value it derives from future growth opportunities in these early stages (Black 1998; Demerjian 2015). Consistent with this reasoning, evidence from the stock market indicates that heterogeneity in investor beliefs concerning firms' fundamental values is most pronounced in the introduction and growth stage (Hamers et al. 2016). This uncertainty is expected to affect both the source of lending (from the borrower's perspective) and the debt contract design (from the lender's perspective).

In deciding whether to obtain a bank loan or to issue bonds, borrowers, on the one hand, have to trade off the costs and benefits of the superior monitoring ability, information access and flexibility of private versus public debtholders (Bharath, Sunder, and Sunder 2008; Denis and Mihov 2003; Houston and James 1996; Rajan 1992). One the one hand, the higher monitoring intensity, access to private information and lower contract renegotiation costs could qualify private debt as the preferred source of lending as it may provide the borrower with the operating flexibility to effectively exploit its growth opportunities (*"Monitoring hypothesis"*). On the other hand, these characteristics of private lenders may also enable them to extract information rents from the borrower and, hence, borrowers may rather prefer public debt ("*Rent Extraction Hypothesis*"). Given these opposing views, the evolvement of the preferred choice of lending over the firm life cycle remains an empirical question.

Lenders, on the other hand, have to trade off the costs and benefits related to providing the borrower with the operating flexibility it needs to exploit the available investment opportunities. Potential lenders can incorporate the uncertainty about the borrower's future value by increasing the interest spread, shortening the maturity and including more covenants in debt contracts (Aghion and Bolton 1992; Bharath et al. 2008; Demerjian 2015; Smith et al. 1979). Accordingly, I expect that the debt contracts of early-stage firms have higher interest spreads, lower maturity and a higher covenant intensity in order to reduce the costs associated with this uncertainty. However, the relative importance of the investigated contract terms is likely to differ between the two types of lending due to differences in renegotiation costs. Specifically, based on the higher renegotiation costs faced by public lenders, I expect them to rely more on the interest spread and maturity but less on the covenant intensity compared to private lenders.

I investigate a sample of publicly traded US firms that issue public debt, private debt or both in the period 1989-2012. After reconfirming the importance of debt financing in early-stage firms (cf. Faff et al. 2016), I find that these firms prefer public over private debt. This finding provides support for the "*Rent Extraction hypothesis*". Concerning the debt contract design, lenders incorporate the varying credit risk over the firm life cycle by adjusting both the interest spread and the maturity of the debt contract. Furthermore, the higher covenant intensity in the debt contracts of early-stage firms suggests that covenants are also used to respond to the uncertainty about the borrower's future value in these stages. Although I do not find that the price terms are more stringent for bond contracts compared to loan contracts over the firm life cycle, the bond contracts of growth firms have a shorter maturity than loan contracts while the loan contracts of these firms have a higher covenant intensity instead.

Additional analyses provide evidence that the covenant design of debt contracts is tailored to the needs of the contracting parties and the evolvement of the performance measures over the firm life cycle. Specifically, where the bond contracts of early-stage firms include less investment-related covenant restrictions, loan contracts include less performance covenants at the far ends of the life cycle spectrum and include more EBITDA-based performance covenants for growth firms.

My study contributes to two streams of research. First, this study contributes to the research on the role of firm life cycle in the functioning of capital markets. Firm life cycle has only recently received increased attention in the financial literature (Dickinson, 2011; Hribar and Yehuda 2015). To date, this research has only examined the role of firm life cycle in equity markets. Nevertheless, as debt financing is the primary source of new external financing for US firms (Bharath et al. 2008; Elliott, Ghosh and Moon 2009), it is also important to obtain a better understanding of how firm life cycle affects debt markets. To the best of my knowledge, this study is the first to investigate how debt contracting evolves across life cycle stages. The findings in this study suggest that debtholders recognize a firm's position in its life cycle and adjust debt contracts accordingly. Second, this study contributes to the debt contracting literature. Whereas abundant research has already investigated how debt contracts are designed to mitigate conflicts of interest between shareholders and debtholders, few studies have examined the role of uncertainty about the borrower's future value in debt contract design (Demerjian 2015). By investigating uncertainty about borrowers' future value in a setting in which agency costs play a minor role (i.e., early-stage firms) I contribute to this stream of literature. Additionally, while the covenant design of public debt contracts tends to be standardized (De Franco, Vasvari, Vyas, and Wittenberg-Moerman 2015), I provide evidence on lenders – both private and public – incorporating borrowers' needs and the varying informativeness of performance measures in the covenant design (Christensen and Nikolaev 2012; Nash, Netter, and Poulsen 2003).

The remainder of this chapter proceeds as follows. Section 4.2 provides an overview of the related literature and develops the hypotheses. Section 4.3 describes the research design and section 4.4 presents the main empirical results. Section 4.5 discusses the findings from additional analysis and robustness tests. Section 4.6 concludes.

4.2. Related Literature and Hypotheses Development

Extant research has already examined the determinants of corporate borrowing and the financial contracting between the firm and its creditors (Aghion et al. 1992; Myers 1977; Smith et al. 1979; Smith and Watts 1992). The starting point of the majority of these studies is the conflict of interest that exists between stockholders and debtholders as a consequence of the differences in their payoff structures and seniority of their claims (Jensen et al. 1976; Smith et al. 1979; Christensen, Nikolaev, and Wittenberg-Moerman 2016). Specifically, in their lending decisions and the design of debt contracts, potential debtholders have to incorporate that firms acting in the interest of stockholders have incentives to expropriate wealth from debtholders via, for instance, dividend payments and suboptimal investments (Myers 1977; Smith et al. 1979; Nikolaev 2010). Consistent with the reasoning that debtholder-stockholder conflicts are especially pronounced in firms that have abundant growth opportunities, prior research generally finds a negative relation between leverage and growth opportunities, as reflected in the market-to-book ratio (Billett, King and Mauer 2007; Johnson 2003; Myers 1977; Smith et al. 1992).

In contrast to the intuition underlying these prior studies, recent findings indicate that firms issue more debt and have higher levels of leverage in the introduction and growth stage than in the other life cycle stages despite the major impact of future growth opportunities on firm value in early-stage firms (Black 1998; Dickinson 2011; Faff et al. 2016). These findings reflect the evolvement of both financing and investment needs over the firm life cycle: While substantial investments in new capital and innovation are necessary to benefit from the growth opportunities available to firms in the introduction and growth stage, the limited availability of internal funds in these stages increases the need for external financing to undertake these investments (Faff et al. 2016).

Arguably, however, the aforementioned debtholder-stockholder conflicts are relatively limited in the introduction and growth stage compared to the other life cycle stages. First of all, the interests of stockholders and debtholders are aligned in the introduction and growth stage as it is in the best interest of both the manager and *all* stakeholders that the firm makes the right investment decisions to successfully survive the introduction stage and, hence, underinvestment is not likely to occur. Benmelech, Kandel and Veronesi (2010) for instance find that stock-based compensation induces the CEO of maturing firms to follow suboptimal investment policies when there is a decline in the available investment opportunities. In addition, the limited availability of (excess) operating cash flows in the introduction and growth stage limit the firm's ability to overinvest in (risky) projects or to distribute an excessive amount of cash flows to stockholders in the form of dividends (Jensen 1986; Richardson 2006). In line with the latter argument, the findings of DeAngelo et al. (2006) suggest that dividend-paying firms tend to be mature firms that have accumulated enough retained earnings over time to distribute dividends to their shareholders in the absence of attractive investment opportunities.

Yet, despite the limited role that debtholder-stockholder conflicts may play in the early stages of the firm life cycle, Demerjian (2015) proposes another non-agency based contracting problem that could play an important role in debt contracting in these stages: Uncertainty about the borrower's future value. In designing the debt contract, potential lenders – who are mainly concerned about the firm's ability to generate future cash flows to make the fixed contractual payments (Easton, Monahan, and Vasvari 2009; Elliot, Ghosh, and Moon 2010) – have to trade off the costs and benefits that are associated with providing the borrower with the operating flexibility that is necessary to exploit its growth opportunities. More specifically, whereas operating flexibility allows the firm to undertake the necessary investments and, hence, could enhance the firm's ability to generate future cash flows, the future payoffs of these investments are uncertain. At the same time, borrowers have to trade off the advantages and disadvantages associated with the relative bargaining power and flexibility of private and public lenders in their choice of debt financing (Bharath et al. 2008; Diamond 1991; Rajan 1992). As such, the tradeoffs faced by lenders and borrowers are expected to affect both the choice of debt financing and the debt contract design over the firm life cycle.

First, concerning the *source of lending*, it is not clear *ex ante* how borrowers' choice between private debt (i.e., bank loans) and public debt (i.e., bonds) varies across the different life cycle stages. On the one hand, the superior monitoring ability, access to private information and, most importantly, flexibility of renegotiating the debt contract of private lenders compared to public lenders (Bharath et al. 2008; Denis et al. 2003; Houston et al. 1996; Rajan 1992) provides them with the means to deal with the uncertainty about the borrower's future value in the introduction and growth stage. Consistent with the informational advantages of private lenders, Krishnaswami, Spindt, and Subramaniam (1999) find that firms with more growth options in their investment opportunity set use higher proportions of privately placed debt to reduce contracting costs related to moral hazard. In addition, borrowers may have to rely on private lending in the early life cycle stages since they first have to obtain a reputable credit record before they can access the public debt market (Diamond, 1991). Following this reasoning, one would expect that firms rely more on private debt than on public debt in the introduction and growth stage ("*Monitoring hypothesis*").

On the other hand, due to the substantial growth opportunities of firms in the introduction and growth stage these firms are also more vulnerable to banks' bargaining power over firms' profits (Bharath et al. 2008; Houston et al. 1996; Rajan 1992). More specifically, while monitoring the firm, the bank has the ability to extract monopoly information rents based on its access to private information, especially when the future financing needs of the firm are high (Bharath et al. 2008; Rajan 1992). In line with the costs related to information rent extraction, Houston et al. (1996) find that for firms with a single bank lender the importance of growth opportunities is negatively related to the firm's reliance on bank debt. As such, one could also expect that firms prefer public debt to private debt to limit banks' information rent extraction during the introduction and growth stage ("*Rent Extraction hypothesis*"). Given these opposing views and the mixed findings in previous studies, it remains an empirical question how the source of lending varies across life cycle stages. In short, the reasoning above leads to the following hypothesis (in the null form):

Hypothesis 1 (H1): Firms are indifferent between private loans and public bonds in the introduction and growth stage.

Second, concerning the *debt contract design*, prior research suggests that lenders have multiple options to tailor the debt contract in order to mitigate the costs arising from the uncertainty about the borrower's future value, including debt covenant design, maturity of the debt contract and interest spread (Aghion et al. 1992; Demerjian 2015; Smith et al. 1979). According to Demerjian (2015), the solution for lenders to incorporate uncertainty about the borrower's future value into the debt contract design lies in the flexibility of debt contracts, as provided by contract renegotiations. Specifically, when *ex ante* uncertainty about a borrower's future value increases, so do the incentives for *ex post* contract renegotiations to reduce the impact of unforeseen future events. The main mechanism that Demerjian (2015) proposes to facilitate lender-initiated renegotiation is the inclusion of financial covenants in the debt contract. This provides the lender with the opportunity to renegotiate the contractual terms as soon as the covenant is triggered. Consistent with the beneficial effects of covenants in debt contract design, Billett et al. (2007) find that covenants attenuate the negative relation between leverage and growth opportunities observed in earlier studies. Additionally, the findings of Nini, Smith and Sufi (2009) suggest that the inclusion of capital expenditure restrictions in debt contracts reduces overinvestment, even in the absence of a covenant violation (cf. Chava and Roberts 2008). Nevertheless, the inclusion of covenants could also unduly restrict the firm's operating flexibility and, consequently, limit the ability to exploit wealth-increasing growth opportunities available to the firm (De Franco et al. 2015; Nash et al. 2003; Smith et al. 1979). Recognizing the costs of including restrictive covenants in debt contracts, Kahan and Yermack (1995) find that the number of covenants in bond contracts decreases with the growth opportunities of the firm, while the findings of Nash et al. (2003) indicate that the covenant structure of bond contracts mainly helps firms to maintain flexibility in their financing activities. In short, prior literature indicates that lenders have to trade off the costs and benefits of including restrictive covenants in debt contracts (Nikolaev, 2010; Smith et al. 1979).

In addition to the debt covenant design, lenders can also adjust the maturity of the debt contract and the interest spread in response to the uncertainty about the borrower's future value (Billett et al. 2007; Bharath et al. 2008; Johnson 2003). Regarding the maturity structure of debt contracts, short term debt can help lenders to mitigate the (agency) costs that arise as a consequence of the growth options in the firm's investment opportunity set and facilitates lenders' ability to negotiate new contractual terms (Barclay and Smith 1995; Demerjian 2015; Johnson 2003). Furthermore, prior research suggests that another way in which lenders incorporate the uncertainty about the future cash flows of the borrower is to set more stringent price terms, as reflected in a higher interest spread (Bharath et al. 2008; Francis, LaFond, Olsson, and Schipper 2005).

The optimal combination of the different terms in the debt contract in response to the uncertainty about the borrower's future value is likely to depend on the source of financing. More specifically, due to their access to private information and superior monitoring ability, banks face less renegotiation costs than dispersed bondholders who have to reach consensus about both price and non-price terms in case of renegotiations of the debt contract (Bharath et al. 2008). The higher renegotiation costs of public debt are for instance reflected in the covenant design of bond contracts which tends to be rather standardized (De Franco et al. 2015; Smith et al. 1979). Accordingly, the findings of Bharath et al. (2008) suggest that bondholders mainly adjust price terms to incorporate the conditions of the borrower rather than non-price terms as a consequence of the limited renegotiation flexibility. Following this line of reasoning, bondholders are therefore more likely to rely on the interest spread and the maturity structure of the debt contract than on the covenant design as covenants - once triggered – may require the need to renegotiate contractual terms.[40]

Combining the insights above, potential lenders can use various contractual features to incorporate the uncertainty about the borrower's future value in the debt contracts of early-stage firms, including higher interest spreads, shorter maturities and a higher covenant intensity. In addition, I would expect that whereas private debtholders are more likely to rely on debt covenants in incorporating uncertainty about the borrower's future value in the introduction and growth stage of the firm life cycle, public debtholders are more likely to

[40] This reasoning deviates from Bharath et al. (2008) to the extent that they argue that bondholders only rely on price terms instead of non-price terms – including both maturity and covenants. Yet, when compared to covenants, the maturity of the debt contract reduces the need to renegotiate after the initial features of the debt contract have been determined. That is, while covenants – once triggered – may require bondholders to renegotiate the contractual terms, bondholders could also choose to issue bonds with a shorter maturity in response to the uncertainty as to the borrower's future value.

adjust the maturity of the debt contract and the interest spread in these life cycle stages.[41] More formally, I hypothesize:

Hypothesis 2a (H2a): Firms in the introduction and growth stage face higher interest spreads, shorter debt maturity and a higher covenant intensity than firms in the other life cycle stages.

Hypothesis 2b (H2b): While public debtholders rely more on the interest spread and the maturity in the debt contracts for firms in the introduction and growth stage, private debtholders rely more on the covenant design.

4.3. Research Design

To investigate the effect of firm life cycle on the source of lending and the debt contract design, I collect data on private loans and public bonds from the Loan Pricing Corporation (LPC) DealScan database and Mergent Fixed Income Securities Database (FISD) respectively. Consistent with prior research (Bharath et al. 2008), private loans are included at the facility level rather than at the package level, which can contain multiple facilities, as loan characteristics vary per facility.[42] The sample includes US dollar-denominated loans and bonds obtained and issued by US borrowers; excludes loan contracts that do not use LIBOR as the base rate; excludes non-fund based facilities such as bridge loans, standby letters of credit and multi-option facilities; excludes private loans and public bonds of financial institutions; and excludes observations for which financial data, retrieved from Compustat and CRSP, are missing.[43] The final sample consists of 18,248 banks loans obtained by 3,451 firms and 7,756 bonds issued by 1,337 firms over the period 1989-2012.[44]

The empirical model that I estimate to examine the first hypothesis concerning the source of lending is as follows:

$$BOND_{d,i,t} = \alpha_0 + \beta_1{*}INTRO_{i,t} + \beta_2{*}GROWTH_{i,t} + \beta_3{*}SHAKE_{i,t} + \beta_1{*}DECLINE_{i,t} + \Sigma_n\beta_n{*}CONTROLS_{i,t-1} + \varepsilon_{d,i,t} \quad (1)$$

in which *d* denotes the debt issue, *i* the issuing firm and *t* the year of the debt issue. The dependent variable, *BOND*, is an indicator variable that is equal to one if firm *j* issues a bond in year *t*, and zero if the firm obtains a bank loan. To derive a firm's life cycle stage, I rely on Dickinson (2011) who assigns firms into five different life cycle stages (i.e., introduction, growth, mature, shake-out, and decline) based on their cash flow patterns that reflect

[41] Consistent with this reasoning, Demerjian (2015) for instance does not find a significant relation between borrower-level uncertainty and loan maturity.

[42] If a company enters into multiple loan arrangements (facilities) with a lender or syndicate of lenders on a particular date, these loan arrangements can be combined in a loan package. As such, a loan package can consist of multiple loan facilities.

[43] To merge the data retrieved from LPC Dealscan to the financial data retrieved from Compustat and CRSP, I use the link file of Chava et al. (2008). The latest version includes links for loan packages up to August 31, 2012.

[44] This final sample relates to the estimation model examining the source of lending over the firm life cycle. The number of observations included in the estimation model that investigates the debt contract design across the different life cycle stage is significantly lower, mainly as a consequence of the large number of missing values for the number of covenants included in the debt contracts (see, for instance, Christensen et al. 2012).

differences in operating performance, investment activities and financing needs across the different life cycle stages.[45] In contrast to other life cycle proxies that have been used in the prior literature (Anthony and Ramesh 1992; Hribar et al. 2015), classifying firms into the different life cycle stages based on their cash flow pattern does not impose a uniform distribution on the firms assigned to each life cycle stage and relaxes the assumption that a firm moves monotonically along the life cycle continuum (Dickinson 2011).[46] *INTRO*, *GROWTH*, *SHAKE*, and *DECLINE* are indicator variables that are equal to one if firm *j* is in the respective life cycle stage in year *t* based on Dickinson's (2011) life cycle classification, and zero otherwise. In model (1), the mature stage is the benchmark stage.

To examine *H2a* and *H2B* regarding the evolvement of the different features of debt contracts over the firm life cycle, I estimate the following empirical model:

$$FEATURE_{d,i,t} = \alpha_0 + \beta_1{*}INTRO_{i,t} + \beta_2{*}GROWTH_{i,t} + \beta_3{*}SHAKE_{i,t} + \beta_1{*}DECLINE_{i,t} + \Sigma_n\beta_n\,{*}CONTROLS_{i,t-1} + \varepsilon_{d,i,t} \quad (2)$$

where *d*, *i*, and *t* again denote the debt issue, firm and year respectively. *FEATURE* captures the investigated contractual features of debt contracts: Interest spread, maturity and covenant design. To measure the interest spread (*SPREAD*), I use the drawn all-in spread for loans, which is the spread between the borrower's drawn line of credits and LIBOR in basis points, and the basis point spread between the issue's offering yield and the yield of a treasury bond of similar maturity for bonds (Bharath et al. 2008). The maturity of the debt contract (*MATURITY*) is measured by the natural logarithm of the number of months between the initiation and the end of the debt contract for both loans and bonds. The covenant design (*COV_INT*) is calculated as the number of covenants included in the debt contract scaled by the maximum number of covenants (i.e., seven for loans and twenty-one for bonds).[47]

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[45] An overview of Dickinson's (2011) life cycle classification can be found in Table 1.1 (p. 5).

[46] Despite the favorable properties of Dickinson's (2010) life cycle proxy over alternative life cycle proxies, I also assess the robustness of the main results to the use of the life cycle classification of Hribar et al. (2015). Specifically, Hribar et al. (2015) assign firm-year observations to three equally large groups based on a composite score that aggregates the standardized values of firm age, sales growth, capital expenditures and net-capital transactions. The results in the main analysis do not hold when exmploying this alternative life cycle proxy, neither when the alternative life cycle proxy is calculated using data from the entire Compustat universe nor when I only impose a uniform distribution on the firms in the investigated subsample. There are however various explanations for the fact that the main results do not hold using this alternative life cycle proxy. First of all, whereas the number of firms assigned to the growth (decline) stage is relatively high (low) using Dickinson's (2011) life cycle classification – consistent with the importance of external financing in these stages (Faff et al. 2016) – the largest number of firms is classified as being in the decline stage using the proxy of Hribar et al. (2015) when calculated using the entire Compustat universe. This issue of imposing a uniform distribution on the investigated observations is further exacerbated when only using the firms included in the subsample of firms that are matched to LPC Dealscan and Mergent FISD. In addition, while one could argue that mature firms can become older and larger than other firms as a result of their operating stability, the alternative life cycle proxy rather assigns older firms to the decline stage (Dickinson 2011; Hribar et al. 2015). As a consequence, it can be more difficult to differentiate between mature and decline firms as some mature firms may be classified as being in the decline stage and vice versa. Overall, the reasoning above indicates that in this study the applicability of the life cycle classification of Hribar et al. (2015) is limited compared to Dickinson's (2011) cash flow classification.

[47] The scaling enhances the comparability of the covenant intensity of the debt contract across the two different sources of debt financing. Nevertheless, my inferences generally do not change if I use the unscaled measure instead. The only differences arise in the coefficient comparisons across models after estimating model (2) using

In addition to the indicator variables that capture the different life cycle stages, which are the main explanatory variables of interest, I control for a number of potential confounding factors that are associated with firm dynamics over the firm life cycle, the source of lending and debt contract design. First of all, I control for firm size (*SIZE*), proxied by the natural logarithm of total assets; firm profitability (*ROA*), calculated as the ratio of income before extraordinary items to lagged total assets; and firm age (*AGE*), calculated as the number of years that the firm has appeared in CRSP. These variables have been used to capture firm life cycle in prior studies and evolve over the firm life cycle in a curvilinear fashion, being maximized in the mature stage (Anthony et al. 1992; Dickinson, 2011; Hribar et al. 2015). Furthermore, based on their financial stability and longer operating history, firms that are larger, more profitable and older may have better access to the public debt market and could obtain debt contracts at more favorable contractual terms (Bharath et al. 2008; Denis et al. 2003; Krishnaswami et al. 1999). I also control for the borrowers' investment opportunity set and asset structure by including the market-to-book ratio (*MTB*), calculated as the ratio of the market value of equity to the book value of equity; R&D intensity (*R&D_INT*), calculated as the R&D expenses divided by lagged total assets; and tangibility (*TANGIB*), calculated as the net amount of PP&E divided by total assets. While prior research has found mixed results concerning the impact of the importance of growth opportunities on the source of lending, firms with more tangible assets tend to have better access to public debt markets (Denis et al. 2003; Houston et al. 1996).

To control for the debt capacity and creditworthiness of the firm, I include firm leverage (*LEV*), measured by the ratio of total debt to total assets; cash flow performance (*CF_OPR*), calculated by dividing the cash flow of operations by sales; the current ratio (*CUR_RAT*), measured by the ratio of current assets to current liabilities; the Altman Z-score (*ZSCORE*); and the S&P credit rating (*CR*), which is transformed into a numerical variable that ranges from one (D) to twenty-three (AAA) and is set equal to zero in case the company is not rated. Prior research indicates that the credit quality of the borrower is the most important determinant of the source of lending and that borrowers with higher credit quality can also benefit from more favorable terms in their debt contracts (Bharath et al. 2008; Denis et al. 2003). Additionally, I include stock price volatility (*STD_RET*), measured as the volatility in daily stock returns over the past fiscal year; earnings volatility (*STD_ROA*), measured as the volatility in quarterly ROA over the past five years; and accounting quality (*AQ*), measured as the performance-matched discretionary accruals derived from the modified-Jones model, to control for the degree of information asymmetry and the riskiness in the future performance of the borrower. The findings of Bharath et al. (2008) and Krishnaswami et al. (1999) for instance indicate that borrowers that are subject to a higher degree of information asymmetry find it more difficult to access the public debt market and have more stringent terms in their debt contracts. Consistent with prior research, I measure all control variables at the beginning of the fiscal year (Bharath et al. 2008).

Next to the common set of control variables, I also include an indicator variable (*CM_ACC*) in model (1) that is equal to one if the company has accessed the public debt

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an endogenous switching model (see section 4.5). However, these differences can be attributed to the variation in the maximum number of covenants between bond contracts and loan contracts.

market previously, and zero otherwise, as firms that have had a prior bond issue may find it easier to access the public debt market again (Bharath et al. 2008). In model (2), I also control for the other contractual features of the debt issue when examining the individual contract terms; the natural logarithm of the amount (in millions) of the loan or bond issue (*AMOUNT*); and I include an indicator variable (*SECURED*) that is equal to one if the debt issue is secured with collateral, and zero otherwise.[48] Prior research indicates that the use of different contractual features is interrelated (Bharath et al. 2008; Billett et al. 2007; Demiroglu and James 2010).

Finally, the analyses include both year and industry fixed effects to control for variation in debt contracting over time and across industries. All continuous variables, except for the number of covenants, are winsorized at the 1% and 99% levels to mitigate the detrimental effect of potential outliers on the statistical inferences.

4.4. Empirical Results

4.4.1. Descriptive Statistics

Table 4.1, Panel A, provides descriptive statistics concerning the choice of lending. The majority of the firms in the sample is classified as growth and mature firms, reflecting the relative stability of these firms (Dickinson, 2011). Comparing firms that obtain bank loans to firms that issue bonds across the different life cycle stages, growth and mature firms appear to rely more on the public market (i.e., $\text{Loans}_{\text{GROWTH}} - \text{Bonds}_{\text{GROWTH}} = -0.054$, p-value < 0.01; $\text{Loans}_{\text{MATURE}} - \text{Bonds}_{\text{MATURE}} = -\ 0.019$, p-value < 0.01). In contrast, firms in the other life cycle stages tend to obtain more banks loans to finance their operations when accessing the debt markets (i.e., $\text{Loans}_{\text{INTRO}} - \text{Bonds}_{\text{INTRO}} = 0.035$, p-value < 0.01; $\text{Loans}_{\text{SHAKE}} - \text{Bonds}_{\text{SHAKE}} = 0.024$, p-value < 0.01; $\text{Loans}_{\text{DECLINE}} - \text{Bonds}_{\text{DECLINE}} = 0.014$, p-value < 0.01). These univariate results suggest that firms at the ends of the life cycle continuum may find it more difficult to access the public debt market for instance because their poorer operating performance requires more intensive (bank) monitoring or more efficient renegotiation in case of financial distress (Denis et al. 2003), whereas growth firms may try to avoid potential rent extraction by banks through issuing bonds.

[48] While prior research has controlled for other contractual features in their models to account for the bi-directional relationships between these variables (Bharath et al. 2008), the inclusion of the other contractual features as control variables in the models in which they are not the dependent variable is open to discussion. Nevertheless, when excluding these variables, my inferences remain largely unchanged. Specifically, when using OLS, only the coefficient on *INTRO* in the model examining loan maturity loses its significance, while the coefficient on *INTRO* becomes positively significant in the model examining loan covenants. When using the endogenous switching model, the coefficient on *SHAKE* becomes positively significant in the model examining loan covenants and the coefficient comparisons indicate that covenant intensity is significantly higher for bond contracts than for loan contracts.

TABLE 4.1

Descriptive Statistics

Panel A: Descriptive Statistics - Choice of Debt Financing

	Full Sample			Loans			Bonds			Means Comparison	
Variable	**Mean**	**Median**	**StDev**	**Mean**	**Median**	**StDev**	**Mean**	**Median**	**StDev**	**Loans - Bonds**	**Test stat.**
INTRO	0.069	0.000	0.253	0.079	0.000	0.270	0.044	0.000	0.206	0.035	z = 10.113***
GROWTH	0.439	0.000	0.496	0.423	0.000	0.494	0.477	0.000	0.499	-0.054	z = -8.081***
MATURE	0.408	0.000	0.492	0.403	0.000	0.490	0.422	0.000	0.494	-0.019	z = - 2.809***
SHAKE	0.064	0.000	0.245	0.072	0.000	0.258	0.048	0.000	0.213	0.024	z = 7.211***
DECLINE	0.019	0.000	0.138	0.024	0.000	0.152	0.009	0.000	0.097	0.014	z = 7.668***
SIZE	7.327	7.334	1.856	6.826	6.775	1.748	8.506	8.588	1.543	-1.680	t = -73.395***
ROA	0.042	0.048	0.089	0.041	0.047	0.091	0.045	0.052	0.086	-0.004	t = -3.102***
AGE	2.780	2.773	0.910	2.664	2.639	0.886	3.051	3.178	0.909	-0.386	t = -31.922***
MTB	2.670	2.041	3.441	2.583	1.991	3.385	2.875	2.164	3.560	-0.292	t = -6.257***
R&D_INT	0.018	0.000	0.039	0.019	0.000	0.041	0.016	0.000	0.034	0.003	t = 6.044***
TANGIB	0.349	0.295	0.235	0.326	0.270	0.227	0.404	0.371	0.244	-0.078	t = -24.899***
LEV	0.319	0.293	0.198	0.311	0.285	0.202	0.337	0.310	0.186	-0.026	t = -9.731***
CF_OPR	0.115	0.090	0.137	0.104	0.082	0.129	0.142	0.108	0.150	-0.039	t = -20.995***
CUR_RAT	1.791	1.544	1.056	1.891	1.643	1.095	1.558	1.338	0.918	0.333	t = 23.517***
ZSCORE	1.294	1.073	0.994	1.385	1.148	1.046	1.080	0.927	0.821	0.305	t = 22.875***
RATED	0.598	1.000	0.490	0.494	0.000	0.500	0.842	1.000	0.364	-0.348	z =-52.387***
CR	8.485	10.000	7.478	6.741	0.000	7.227	12.589	14.000	6.373	-5.848	t = -61.787***
STD_RET	0.019	0.012	0.022	0.020	0.013	0.022	0.017	0.010	0.020	0.003	t = 11.366***
STD_ROA	0.029	0.025	0.014	0.030	0.027	0.015	0.026	0.022	0.013	0.005	t = 24.402***
AQ	0.076	0.053	0.076	0.080	0.056	0.078	0.068	0.048	0.069	0.012	t = 11.564***
CM_ACC	0.587	1.000	0.492	0.463	0.000	0.499	0.876	1.000	0.329	-0.413	z = -61.866***
#Firms		3,657			3,451			1,337			
N		26,004			18,248			7,756			

Table 4.1 – Continued

Panel B: Loan Characteristics

Variable	Loan Sample	Intro	Growth	Mature	Shake-Out	Decline
AMOUNT	18.62	17.80	18.68	18.78	18.60	17.89
MATURITY	3.79	3.73	3.85	3.75	3.70	3.54
SPREAD	187.86	232.48	186.77	171.60	206.86	266.12
COV_INT	0.35	0.38	0.36	0.33	0.35	0.33
SEC	62.8%	78.6%	66.4%	53.9%	63.6%	83.3%
N	11,086	918	4,941	4,247	729	251

Panel C: Bond Characteristics

Variable	Bond Sample	Intro	Growth	Mature	Shake-Out	Decline
AMOUNT	12.67	12.22	12.57	12.78	12.85	11.68
MATURITY	4.82	4.70	4.84	4.80	4.79	4.36
SPREAD	164.36	223.37	174.85	150.15	184.43	124.27
COV_INT	0.30	0.41	0.30	0.29	0.31	0.43
SEC	1.2%	7.5%	1.3%	0.7%	1.7%	27.2%
N	4,084	79	1,856	1,958	180	11

Table 4.1 presents the descriptive statistics for the variables included in the main empirical models. Panel A reports the summary statistics for the variables included in model (1). Panels B and C show the summary statistics for, respectively, the loan and bond characteristics across the life cycle stages. The final sample consists of 26,004 debt issues by 3,657 firms in the period 1989-2012 with non-missing values for the main variables included in model (1); the number of observations included in the analysis of model (2) depends on the availability of the investigated contract terms. The variables are defined as follows: *INTRO*, *GROWTH*, *MATURE*, *SHAKE*, and *DECLINE* are indicator variables that are equal to one if the firm is in the respective life cycle stage based on Dickinson's (2011) life cycle classification, and zero otherwise; *SIZE* is the natural logarithm of total assets; *ROA* is the ratio of income before extraordinary items to lagged total assets; *AGE is* the number of years that the firm has appeared in CRSP; *MTB* is the ratio of the market value of equity to the book value of equity; *R&D_INT* is the R&D expenses divided by lagged total assets; *TANGIB* is the net amount of PPE divided by total assets; *LEV is* the ratio of total debt to total assets; *CF_OPR* is the cash flow of operations divided by sales; *CUR_RAT* is the ratio of current assets to current liabilities; *ZSCORE* is the Altman Z-score (Altman, 1968); *CR* is the S&P credit rating, which is transformed into a numerical variable that ranges from one (D) to twenty-three (AAA) and is set equal to zero in case the company is not rated; *STD_RET* is the volatility in daily stock returns over the past fiscal year; *STD_ROA* is the volatility in quarterly ROA over the past five years; *AQ* is the performance-matched discretionary accruals derived from the modified-Jones model; and *CM_ACC* is an indicator variable that is equal to one if the company has accessed the public debt market previously, and zero otherwise. Regarding the debt characteristics in Panels B and C, *AMOUNT* the natural logarithm of the amount (in millions) of the debt issue; *MATURITY* is the natural logarithm of the number of months between the initiation and the end of the debt contract; *SPREAD is* the drawn all-in spread and the basis point spread between the issue's offering yield and the yield of a treasury bond of similar maturity for loans and bonds respectively; *COV_INT* is the number of covenants included in the debt contract scaled by the maximum number of covenants; and *SEC* is an indicator variable that is equal to one if the debt issue is secured with collateral, and zero otherwise.

Consistent with prior research, the univariate analysis concerning the control variables generally indicate that firms that are larger, older, more profitable, more creditworthy, and face a lower degree of information asymmetry are more likely to issue public debt than to obtain private loans (Bharath et al. 2008; Denis et al. 2003; Houston et al. 1996). Additionally, in line with the importance of obtaining a good credit reputation, firms that previously accessed the public market also tend to prefer issuing bonds to obtaining bank loans (Bharath et al. 2008; Diamond 1991).Panels B and C in Table 4.1 report the evolvement of different contractual features over the firm life cycle for loan contracts and bond issues, respectively. For both loan contracts and bond issues, the contract terms follow a curvilinear trend over the firm life cycle, being generally most favorable in the mature stage (i.e., highest amount, longest maturity, lowest spread, lowest covenant intensity and lowest proportion secured) and least favorable at the far ends of the life cycle spectrum. The favorable terms of the debt contracts of mature firms could be explained by the stable operating performance of these firms (Dickinson, 2011), suggesting that lenders face the lowest risk of borrower default in the mature stage.

Nevertheless, the validity of the initial insights derived from the univariate analysis above might be limited as the effect of potential confounding factors is not taken into consideration. Hence, further analysis is warranted to examine how debt contracting evolves over the firm life cycle.

4.4.2. Preliminary Analysis – Access to the Debt Market over the Firm Life Cycle

Before I continue with the multivariate analysis to more formally test the hypotheses, I first assess the reliance on debt financing over the firm life cycle. The main assumption underlying the hypothesis development is that debt financing plays especially an important role in the introduction and growth stage of the firm life cycle as a consequence of the lack of internal sources of financing. While Faff et al. (2016) already provide evidence that debt issuance is highest in the early stages of the firm life cycle, I further address the validity of this assumption by estimating the following empirical model:

$$\begin{aligned} \textit{DEBT MARKET ACCESS}_{i,t} = \alpha_0 &+ \beta_1 * \textit{INTRO}_{i,t} + \beta_2 * \textit{GROWTH}_{i,t} + \beta_3 * \textit{SHAKE}_{i,t} \\ &+ \beta_4 * \textit{DECLINE}_{i,t} + \Sigma_n \beta_n * \textit{CONTROLS}_{i,t-1} + \varepsilon_{i,t} \qquad (3) \end{aligned}$$

in which *it* denotes a firm-year observation. I employ two different measures to proxy for firm's *i* access to the debt market in year *t*. The first measure, *DEBT*, is an indicator variable that is equal to one if the firm appears in the debt market sample that is constructed by using the information available in the LPC DealScan database and Mergent FISD, and zero otherwise. Specifically, I keep one observation per firm-year in the debt market sample that indicates whether the firm obtained a bank loan, issued bonds or both and merge this variable to the Compustat universe. The second measure, *DEBT_ISSUED*, is the net debt issuance of firm *i* in year *t*, scaled by lagged total assets, which is derived from Faff et al. (2016) and mainly serves to replicate their results. While *DEBT* captures the frequency with which a firm accesses the debt market, *DEBT_ISSUED* relates to the amount obtained in the debt markets. The control variables included in model *(3)* are the same variables as those included in model *(1)* with the exception of *CM_ACC*. The estimation results for model *(3)*, that are obtained using logistic regression and OLS for the models in which, respectively, *DEBT* and *DEBT_ISSUED* are the dependent variables, are reported in Table 4.2.

TABLE 4.2

Debt Financing over the Firm Life Cycle

	DEBT MARKET ACCESS	
	(1)	(2)
Variable	DEBT	DEBT_ISSUED
INTRO	0.462***	0.111***
	(9.75)	(22.18)
GROWTH	0.754***	0.120***
	(25.63)	(39.60)
SHAKE	-0.037	-0.014***
	(-0.82)	(-4.41)
DECLINE	-0.080	0.012***
	(-1.10)	(2.78)
SIZE	0.366***	-0.003**
	(25.04)	(-2.27)
ROA	0.742***	0.032***
	(5.70)	(3.44)
AGE	0.075***	-0.012***
	(3.54)	(-4.80)
MTB	0.002	0.001***
	(0.65)	(2.85)
R&D_INT	-3.058***	-0.138***
	(-8.16)	(-7.34)
TANGIB	-0.475***	0.013
	(-4.46)	(1.18)
LEV	1.091***	0.228***
	(13.02)	(20.32)
CF_OPR	0.030	-0.002**
	(1.35)	(-2.33)
CUR_RAT	-0.091***	-0.005***
	(-8.37)	(-6.84)
ZSCORE	-0.003	-0.001*
	(-0.50)	(-1.80)
CR	0.028***	-0.002***
	(9.11)	(-4.62)
STD_RET	-7.715***	-0.605***
	(-7.93)	(-6.33)
STD_ROA	-0.211	-0.008
	(-0.41)	(-0.19)
AQ	0.079	0.012
	(0.55)	(0.94)
CONSTANT	-4.229***	0.025
	(-14.24)	(1.07)
Industry FE	YES	YES
Year FE	YES	YES
Observations	62,051	62,051
(Pseudo) R-Squared	0.2067	0.115
INTRO - GROWTH = 0	p=0.0000***	p=0.0986*
INTRO - SHAKE-OUT = 0	p=0.0000***	p=0.0000***
INTRO - DECLINE = 0	p=0.0000***	p=0.0000***
GROWTH - SHAKE-OUT =0	p=0.0000***	p=0.0000***
GROWTH - DECLINE = 0	p=0.0000***	p=0.0000***

Table 4.2 - Continued

SHAKE-OUT - DECLINE = 0	p=0.5975	p=0.0000***

Table 4.2 presents the estimation results for model (3). The sample includes firm-year observations in the period 1989-2012. *DEBT* is an indicator variable that is equal to one if the firm appears in the LPC DealScan database, Mergent FISD or both in year *t*, and zero otherwise. *DEBT_ISSUED*, is the net debt issuance of the firm in year *t*, scaled by lagged total assets. The t-values in parentheses are based on standard errors clustered by firm; *, **, and *** indicate significance at the 1%, 5% and 10% level respectively. All continuous variables are winsorized at the 1% and 99% levels. The tests reported at the bottom of the table are coefficient comparisons to examine the significance of the differences in the coefficients obtained for the life cycle variables. See Table 4.1 for other variable definitions.

The results in Table 4.2 indicate that firms in early stages of the firm life cycle both access the debt market more often and issue more debt than firms in the other stages. More specifically, the coefficients on *INTRO* (0.462, p-value < 0.01) and *GROWTH* (0.754, p-value < 0.01) in column (1) are positive and significant, suggesting that firms in the introduction and growth stage are more likely to issue debt to finance their operations than firms that reside in the mature stage. In addition, the coefficient comparisons at the bottom of the table indicate that the coefficients on *INTRO* and *GROWTH* are also significantly higher than the coefficients on *SHAKE* and *DECLINE*. Consistent with the findings of Faff et al. (2016), the findings in column (2) show that early stage firms also obtain larger amounts of financing, measured as a percentage of total assets, in the years that they access the debt markets. Based on the coefficients on *INTRO* (0.111, p-value < 0.01) and *GROWTH* (0.120, p-value < 0.01), the net debt issuance of firms in the introduction and growth stage is higher by, respectively, 11.1% and 12% of total assets than the net debt issuance of mature firms. Overall, these findings provide support for the assumed importance of debt financing for early-stage firms.

4.4.3. The Source of Lending over the Firm Life Cycle

To examine the hypotheses more formally, I conduct multivariate analysis to estimate the effect of firm life cycle on debt contracting while controlling for a wide set of variables that have been found by prior research to influence both the choice and the structure of firm borrowing. All multivariate estimation models include standard errors that are clustered at the firm-level (Petersen 2009).

Table 4.3 reports the estimation results for model (1), obtained using logistic regression, that examines the source of lending over the firm life cycle. Table 4.3, column (1), shows that the coefficients on *INTRO* (0.517, p-value < 0.01) and *GROWTH* (0.461, p-value < 0.01) are positive and significant, which implies that firms in the early life cycle stages prefer public debt financing (bonds) to private debt financing (loans) compared to mature firms. Firms in the shake-out stage, on the contrary, rather rely on private debt instead of public debt compared to mature firms, as reflected in a significantly negative coefficient (*SHAKE* = - 0.187, p-value < 0.05). However, I do not observe a significant difference in the debt choices of decline and mature firms (*DECLINE* = - 0.059, n.s.). The coefficient comparisons at the bottom of the table indicate that the preference for public debt is not only more pronounced for early-stage firms compared to mature firms, but also compared to the other life cycle stages. Furthermore, the marginal effects in column (2) suggest that the observed preference for public debt in early-stage firms is also economically significant. More specifically, given that the unconditional probability of accessing the public bond market is approximately 30% (i.e., 7,756 out of the 26,004 debt issues investigated are bonds), firms in the introduction and growth stage are, respectively, 30.2% (=0.09/0.298) and 26.8% (=0.08/0.298) more likely to issue bonds instead of obtaining a loan than mature firms. Overall, the obtained regression results for the life cycle variables are consistent with the "*Rent Extraction hypothesis*". That is, for firms in the introduction and growth stage the costs of potential information rent extraction outweigh the benefits of the superior renegotiating flexibility and monitoring skills of banks (Houston et al. 1996; Rajan 1992). In other words, firms that reside in the early stages of the firm life cycle prefer public debt to private debt to avoid banks' rent extraction in these stages.

The coefficient estimates on the control variables are generally consistent with the findings in previous studies (Bharath et al. 2008; Denis et al. 2003; Houston et al. 1996). For instance, firms that are larger and firms that have more tangible assets, more leverage, have a higher credit quality, and have accessed the public debt market previously prefer public debt to private debt financing. These results are consistent with the reasoning that firms that face lower information costs have better access to the public bond market (Bharath et al. 2008; Denis et al. 2003).

TABLE 4.3

The Choice of Debt Financing over the Firm Life Cycle

Variable	(1) BOND	(2) Marginal Effect
INTRO	0.517***	0.090***
	(4.88)	(0.253)
GROWTH	0.461***	0.080***
	(9.29)	(0.496)
SHAKE	-0.187**	-0.032**
	(-2.10)	(0.245)
DECLINE	-0.059	-0.010
	(-0.32)	(0.138)
SIZE	0.413***	0.071***
	(16.59)	(1.856)
ROA	-0.194	-0.034
	(-0.57)	(0.089)
AGE	-0.016	-0.003
	(-0.48)	(0.910)
MTB	0.013*	0.002*
	(1.94)	(3.441)
R&D_INT	0.431	0.075
	(0.51)	(0.039)
TANGIB	0.699***	0.121***
	(4.25)	(0.235)
LEV	0.478***	0.083***
	(2.86)	(0.198)
OCF	-0.177	-0.031
	(-0.67)	(0.137)
CUR_RAT	0.044	0.008
	(1.48)	(1.056)
ZSCORE	-0.014	-0.002
	(-0.36)	(0.994)
CR	0.029***	0.005***
	(4.66)	(7.478)
STD_RET	-2.650	-0.459
	(-1.07)	(0.022)
STD_ROA	2.347**	0.407**
	(1.97)	(0.014)
AQ	0.143	0.025
	(0.50)	(0.076)
CM_ACC	1.046***	0.181***
	(13.85)	(0.492)
CONSTANT	-5.979***	
	(-11.53)	
Industry FE	Yes	
Year FE	Yes	
Observations	26,004	
R-Squared	23.7%	
INTRO - GROWTH = 0	p=0.5961	
INTRO - SHAKE-OUT = 0	p=0.0000***	
INTRO - DECLINE = 0	p=0.0052***	

Table 4.3 - Continued

GROWTH - SHAKE-OUT =0	p=0.0000***
GROWTH - DECLINE = 0	p=0.0045***
SHAKE-OUT - DECLINE = 0	p=0.5255

Table 4.3 presents the estimation results for model (1). The sample includes 26,004 debt issues in the period 1989-2012, retrieved from the LPC Dealscan database (loans) and Mergent FISD (bonds). *BOND* is an indicator variable that is equal to one if the firm issues a bond in year t, and zero if the firm obtains a bank loan. The unconditional probability of issuing a bond is 29.8%. The t-values in parentheses are based on standard errors clustered by firm; *, **, and *** indicate significance at the 1%, 5% and 10% level respectively. All continuous variables are winsorized at the 1% and 99% levels. The tests reported at the bottom of the table are coefficient comparisons to examine the significance of the differences in the coefficients obtained for the life cycle variables. See Table 4.1 for other variable definitions.

4.4.4. Debt Contract Design over the Firm Life Cycle – OLS

So far, the analyses show that firm life cycle affects both firms' access to the debt markets and the source of lending. Specifically, despite the uncertainty about the borrower's future value, which is likely to be most pronounced in the early stages of the firm life cycle, firms in the introduction and growth stage access the debt market more often and are able to obtain larger amounts of debt financing while preferring public debt to private debt financing. Given the importance of debt financing for early-stage firms, the question arises how lenders incorporate the uncertainty about the borrower's future value in the terms of the debt contract.

To examine H2a regarding the use of the different features in the debt contract design, I estimate model (2) using OLS. Table 4.4 reports the estimation results for the regressions on the different debt contract terms for loans and bonds separately.

Columns (1) and (2) of Table 4.4 report the findings for the interest spread across the different life cycle stages for loans and bonds respectively. Regarding the interest spread for loans, the spread is consistently higher in the non-mature stages as reflected in the significantly positive coefficients on *INTRO*, *GROWTH*, *SHAKE*, and *DECLINE*. This finding can be attributed to the superior operating stability of mature firms (Dickinson 2011), which reduces the credit risk faced by lenders. Consistent with the pattern observed in the univariate analysis, the loan spread evolves in a curvilinear fashion over the firm life cycle based on the coefficient comparisons at the bottom of column (1). Similar findings are obtained for the bond spread, which is the dependent variable in column (2) of Table 4. More specifically, the coefficients on *GROWTH* (22.252, p-value < 0.01) and *SHAKE* (20.855, p-value < 0.01) are again positive and significant. Surprisingly, however, the coefficient on *DECLINE* (-131.925, p-value < 0.01) is significantly negative, indicating that firms in the decline stage are able to issue bonds at more favorable interest terms. Nevertheless, the reliability of this result is questionable given the limited number of firms in the decline stage for which there are non-missing values on all contract terms and control variables (i.e., 11 out of 4,084 firms that issue bonds).

Concerning the maturity of loans (columns (3) and (4) in Table 4.4), the significantly negative coefficients on *INTRO*, *SHAKE*, and *DECLINE* in column (3) indicate that the loans of non-mature firms, except for firms in the growth stages, have a shorter maturity than mature firms. This finding suggests that the maturity of the loan is an alternative mechanism to incorporate the credit risk of non-mature firms. For bond issues, I only find limited evidence that the maturity differs across the various life cycle stages. Only the maturity of bond issues by firms in the decline stage is shorter than that of firms in the other life cycle stages, given the significantly negative coefficient on *DECLINE* (-0.376, p-value < 0.01) and the reported coefficient comparisons. Additionally, with respect to the covenant structure (columns (5) and (6) in Table 4.4), loans have more covenants for firms in the growth stage (*GROWTH* = 0.015, p-value < 0.01) but less covenants for firms in the decline stage (*DECLINE* = -0.050, p-value < 0.01). The covenant structure does not seem to play a differential role in the contract design of bond issues over the firm life cycle, as none of the indicator variables for the life cycle stages is significant nor is any of the coefficient comparisons at the bottom of column (6) significant.

With regard to the control variables, the coefficient estimates indicate that firms with a better operating performance can issue debt at more favorable price terms. In addition to benefiting from more favorable interest spreads, firms with a higher credit rating also have fewer covenants in their debt contracts. On the contrary, the debt contracts of firms that are more highly leveraged have higher interest spreads, lower maturity and more covenants. Finally, the interest spread is increasing while (loan) maturity is decreasing in the information costs faced by the firm.

Overall, the findings above suggest that both private and public debt contracts incorporate the varying degree of uncertainty about the borrower's future value over the firm life cycle by adjusting the contract terms, albeit in different ways. Whereas the interest spread plays an important role in both loans and bonds, loans also include more covenants for growth firms – potentially allowing them to increase the maturity of the loan for growth stage firms (cf. Demerjian 2015). These findings provide only partial support for H2a. Nevertheless, two caveats have to be taken into account that could impede the accuracy of the inferences above. First, as mentioned before, the reliability of the findings for the bond contract design of firms in the introduction and decline stage may be limited as a consequence of the relatively low number of observations for these stages that are included in the analysis. Second, the OLS method does not adjust for the potential endogeneity bias in the debt contract design over the firm life cycle as the source of lending also depends on the firm life cycle stage and prevents the possibility to assess the differential importance of the investigated contract terms across the different sources of lending.

TABLE 4.4

Debt Contract Design over the Firm Life Cycle (OLS)

	CONTRACT TERMS					
	SPREAD		MATURITY		COV_INT	
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	LOAN	BOND	LOAN	BOND	LOAN	BOND
INTRO	29.725***	9.414	-0.041*	-0.037	0.010	0.041
	(6.51)	(0.37)	(-1.72)	(-0.56)	(1.35)	(1.47)
GROWTH	16.400***	20.164***	0.022*	-0.030	0.015***	0.002
	(7.26)	(4.20)	(1.76)	(-1.20)	(3.77)	(0.36)
SHAKE	12.895***	22.721**	-0.048**	0.011	0.002	0.007
	(2.93)	(2.29)	(-2.03)	(0.27)	(0.29)	(0.62)
DECLINE	40.065***	-122.161*	-0.135***	-0.376**	-0.050***	0.017
	(4.12)	(-1.80)	(-2.59)	(-2.10)	(-3.33)	(0.28)
SIZE	2.891*	-20.219***	-0.081***	0.012	-0.011***	-0.037***
	(1.79)	(-6.28)	(-8.84)	(0.67)	(-4.11)	(-8.69)
ROA	-134.262***	-215.437***	0.063	0.123	0.043*	-0.114*
	(-7.86)	(-3.89)	(0.83)	(0.75)	(1.70)	(-1.89)
AGE	-3.319**	0.221	-0.024***	0.024	-0.003	-0.001
	(-2.09)	(0.06)	(-2.61)	(1.33)	(-0.99)	(-0.22)
MTB	-0.988**	-1.216	-0.004*	-0.007**	-0.000	-0.004***
	(-2.32)	(-1.22)	(-1.94)	(-2.06)	(-0.00)	(-3.02)
R&D_INT	-23.838	-69.711	-0.640***	0.127	-0.105	-0.031
	(-0.62)	(-0.78)	(-3.27)	(0.26)	(-1.52)	(-0.28)
TANGIB	-10.541	42.343*	0.002	0.232**	-0.029**	-0.018
	(-1.30)	(1.85)	(0.05)	(2.24)	(-2.01)	(-0.63)
LEV	82.148***	103.435***	0.147***	-0.114	0.075***	0.139***
	(10.76)	(3.80)	(3.62)	(-1.28)	(5.35)	(5.03)
CF_OPR	-25.506*	-109.979***	0.074	0.076	0.005	0.052
	(-1.82)	(-3.04)	(1.02)	(0.52)	(0.19)	(0.93)
CUR_RAT	-2.801**	5.544	0.013**	0.047***	0.005**	0.009*
	(-2.36)	(1.40)	(2.05)	(2.71)	(2.42)	(1.76)
ZSCORE	-1.543	-2.033	-0.007	-0.010	-0.003	-0.000
	(-1.16)	(-0.45)	(-1.09)	(-0.55)	(-1.61)	(-0.05)
CR	-0.758***	-1.637***	-0.002*	0.000	-0.001***	-0.001**
	(-3.36)	(-3.29)	(-1.67)	(0.03)	(-3.52)	(-1.98)
STD_RET	1,218.383***	2,392.196***	-2.750***	-5.626***	-0.594***	2.320***
	(11.19)	(4.75)	(-4.76)	(-3.89)	(-3.22)	(4.92)
STD_ROA	241.362***	606.959***	-1.229***	-0.310	-0.265**	-0.467*
	(3.93)	(2.69)	(-4.27)	(-0.42)	(-2.38)	(-1.80)
AQ	13.139	69.240**	-0.197***	-0.064	-0.030	0.044
	(0.94)	(2.00)	(-2.69)	(-0.41)	(-1.28)	(1.21)
MATURITY	12.365***	11.496***			0.029***	-0.006*
	(6.19)	(4.97)			(9.20)	(-1.91)
COV_INT	107.354***	-27.957	0.469***	-0.142*		
	(11.62)	(-1.08)	(9.46)	(-1.95)		
SPREAD			0.001***	0.000***	0.000***	-0.000
			(5.95)	(4.30)	(11.50)	(-1.08)
AMOUNT	-13.382***	8.209**	0.138***	0.012	-0.002	0.015***
	(-10.48)	(2.11)	(17.02)	(0.39)	(-1.11)	(2.72)
SECURED	63.524***	21.167	0.140***	-0.069	0.040***	0.075**
	(25.04)	(0.65)	(9.42)	(-0.78)	(8.91)	(2.02)
CONSTANT	188.366***	-4.418	2.093***	4.516***	0.184***	0.180*
	(7.95)	(-0.07)	(14.97)	(10.79)	(3.92)	(1.71)

Table 4.4 - Continued

Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,086	4,084	11,086	4,084	11,086	4,084
#Firms	2,748	856	2,748	856	2,748	856
R-Squared	56.0%	49.6%	22.2%	8.8%	29.9%	31.3%
INTRO - GROWTH = 0	p=0.0027***	p=0.6700	p=0.0061***	p=0.9140	p=0.5270	p=0.1650
INTRO - SHAKE-OUT = 0	p=0.0040***	p=0.6230	p=0.8190	p=0.4980	p=0.4010	p=0.2530
INTRO - DECLINE = 0	p=0.3140	p=0.0675*	p=0.0782*	p=0.0704*	p=0.0001***	p=0.7040
GROWTH - SHAKE-OUT =0	p=0.4440	p=0.8080	p=0.0040***	p=0.3370	p=0.0795*	p=0.6550
GROWTH - DECLINE = 0	p=0.0144**	p=0.0362**	p=0.0026***	p=0.0546*	p=0.0000***	p=0.8030
SHAKE-OUT - DECLINE = 0	p=0.0085***	p=0.0339**	p=0.1170	p=0.0354**	p=0.0011***	p=0.8770

Table 4.4 presents the estimation results for model (2), obtained using OLS. The sample includes 11,086 loans and 4,084 bonds issued in the period 1989-2012. The unconditional probability of issuing a bond is 29.8%. The t-values in parentheses are based on standard errors clustered by firm; *, **, and *** indicate significance at the 1%, 5% and 10% level respectively. All continuous variables are winsorized at the 1% and 99% levels. The tests reported at the bottom of the table are coefficient comparisons to examine the significance of the differences in the coefficients obtained for the life cycle variables. See Table 4.1 for other variable definitions.

4.4.5. Debt Contract Design over the Firm Life Cycle – Endogenous Switching

To address the potential endogeneity bias in the debt contract design over the firm life cycle due to the non-random assignment of firms to either the loan or the bond sample, I employ an endogenous switching model (Bharath et al. 2008; Beatty, Liao and Weber 2010; Lokshin and Sajaia 2004; Maddala 1983). The endogenous switching model follows a two-step procedure: First, a selection equation sorts the firms based on the choice of lending (i.e., loans vs. bonds) in order to determine which regime the firm faces, followed by two equations for the contract terms under each of the two different sources of lending (Maddala 1983; Lokshin and Sajaia 2004). This model can be written as follows (see, for instance, Bharath et al. 2008, p. 20):

$$
\begin{array}{lll}
 & I_i\,(BOND) = 1 \text{ if } \gamma Z_i + u_i > 0; & \\
 & I_i\,(LOAN) = 0 \text{ if } \gamma Z_i + u_i \leq 0; & \\
\text{Regime 1 } (BOND)\text{:} & FEATURE_{BOND,i} = \beta_{BOND} X_{BOND,i} + \varepsilon_{BOND,i} & \text{if } I_i = 1\text{; and} \\
\text{Regime 2 } (LOAN)\text{:} & FEATURE_{LOAN,i} = \beta_{LOAN} X_{LOAN,i} + \varepsilon_{LOAN,i} & \text{if } I_i = 0
\end{array} \qquad (4)
$$

in which I_i represents the selection equation; Z_i is a vector of variables that determines the source of lending which consists of the explanatory variables in model (1); $FEATURE_{BOND,i}$ and $FEATURE_{LOAN,i}$ are the features of the debt contract under the two sources of debt financing; and $X_{BOND,i}$ and $X_{LOAN,i}$ are vectors of variables that relate to the debt contract design and consist of the explanatory variables in model (2). Each stage of the endogenous switching model includes one or more exogenous variables that are unique to the stage to enhance the reliability of the inferences. Following Bharath et al. (2008), the selection stage includes *CM_ACC*, which indicates whether the firm has issued bonds previously, while the equations on the different contract terms include the contract terms that are not investigated, the amount of debt issued (*AMOUNT*), and an indicator variable that indicates whether the debt issue is secured or not (*SECURED*). The results obtained after estimating the endogenous switching model are reported in Table 4.5.

The findings in Table 4.5 are generally consistent with the findings that were obtained after using OLS. Nevertheless, in addition to adjusting the interest spread to the uncertainty associated with early-stage firms, the findings obtained by estimating the endogenous switching model also indicate that growth firms issue bonds with a shorter maturity. Furthermore, the findings in Table 4.5, columns (5) and (6), also show that the number of covenants included in the debt contracts for firms in the introduction stage is significantly higher than the number of covenants included in the debt contracts of mature firms. While still limited, the insights that can be derived after investigating the debt contract design using an endogenous switching model are more consistent with H2a than those obtained after using OLS, underlining the importance of controlling for the endogeneity bias that may arise as a consequence of the non-random selection of the source of lending.

The coefficient comparisons alongside the columns provide insight into the relative importance of the various contract terms in loan versus bond contracts. Although the positive coefficients on *GROWTH* and *DECLINE* are larger in magnitude for bond contracts than for loan contracts, the differences in these coefficients are not significant. Additionally, the interest spread is significantly higher in loan contracts than in bond contracts for firms in the introduction and decline stage. Regarding the maturity of the debt contracts, the maturity of bonds issued by growth firms is significantly shorter than the maturity of the loans they obtain, while the opposite pattern is observed for firms in the shake-out stage. Finally, the loan contracts of growth firms have a significantly higher covenant intensity than their bond contracts, but firms in the decline stage face a significantly lower covenant intensity when they obtain a loan than when they issue bonds. Combined, these findings provide only limited support for H2b. Specifically, although I do find that private lenders rely more on the covenant design and public lenders are more likely to shorten the maturity for firms in the growth stage, I do not find similar results for firms in the introduction stage nor do I find that the price terms, as reflected in the interest rate spread, are more stringent in bond contracts than in loan contracts.

TABLE 4.5

Debt Contract Design over the Firm Life Cycle (Endogenous Switching)

	CONTRACT TERMS								
	SPREAD			MATURITY			COV_INT		
	(1)	(2)		(3)	(4)		(5)	(6)	
Variable	LOAN	BOND	(1) - (2)	LOAN	BOND	(3) - (4)	LOAN	BOND	(5)-(6)
INTRO	31.298***	9.513	$\chi^2 = 2.76$	-0.004	-0.032	$\chi^2 = 0.06$	0.016***	0.040***	$\chi^2 = 2.55$
	(10.34)	(0.75)	p = 0.097	(-0.19)	(-0.43)	p = 0.800	(3.03)	(2.65)	p = 0.111
GROWTH	17.932***	22.252***	$\chi^2 = 0.13$	0.058***	-0.107***	$\chi^2 = 29.85$	0.020***	0.004	$\chi^2 = 11.23$
	(10.48)	(5.98)	p = 0.7143	(4.94)	(-4.42)	p = 0.000	(7.13)	(0.81)	p = 0.001
SHAKE	10.930***	20.855**	$\chi^2 = 2.09$	-0.095***	0.107**	$\chi^2 = 10.95$	-0.005	0.006	$\chi^2 = 1.33$
	(3.50)	(2.53)	p = 0.1486	(-4.35)	(2.03)	p = 0.001	(-0.91)	(0.59)	p = 0.250
DECLINE	37.156***	-131.925***	$\chi^2 = 22.85$	-0.209***	-0.076	$\chi^2 = 0.26$	-0.059***	0.004	$\chi^2 = 3.78$
	(7.17)	(-4.13)	p = 0.000	(-5.55)	(-0.41)	p = 0.610	(-6.73)	(0.11)	p = 0.052*
SIZE	6.218***	-16.174***		0.029***	-0.098***		0.001	-0.033***	
	(6.10)	(-6.36)		(3.77)	(-6.64)		(0.51)	(-11.15)	
ROA	-132.750***	-211.215***		0.155**	0.023		0.045***	-0.108***	
	(-13.48)	(-6.87)		(2.23)	(0.12)		(2.71)	(-2.90)	
AGE	-1.318	1.718		0.026***	-0.025*		0.004**	0.000	
	(-1.32)	(0.73)		(3.80)	(-1.66)		(2.57)	(0.11)	
MTB	-1.012***	-1.266**		-0.004**	-0.004		-0.000	-0.004***	
	(-4.50)	(-2.26)		(-2.48)	(-1.01)		(-0.11)	(-5.66)	
R&D_INT	-17.523	-61.033		-0.448***	-0.360		-0.077**	-0.023	
	(-0.75)	(-0.90)		(-2.81)	(-0.84)		(-1.97)	(-0.28)	
TANGIB	-2.810	51.008***		0.146***	-0.021		-0.003	-0.010	
	(-0.55)	(3.80)		(4.52)	(-0.25)		(-0.31)	(-0.63)	
LEV	81.022***	105.414***		0.117***	-0.192**		0.074***	0.139***	
	(17.55)	(7.56)		(3.68)	(-2.22)		(9.52)	(8.26)	
CF_OPR	-25.126***	-110.212***		0.070	0.051		0.003	0.052**	
	(-3.05)	(-5.18)		(1.28)	(0.39)		(0.21)	(2.02)	
CUR_RAT	-2.782***	6.144**		0.012**	0.025		0.005***	0.009***	
	(-3.56)	(2.37)		(2.13)	(1.54)		(4.00)	(2.86)	

Table 4.5 - Continued

ZSCORE	-1.359	-1.701	0.001	-0.018	-0.003*	-0.000
	(-1.60)	(-0.59)	(0.09)	(-1.01)	(-1.92)	(-0.03)
CR	-0.386**	-1.070***	0.007***	-0.013***	-0.000	-0.001*
	(-2.43)	(-2.67)	(6.33)	(-5.46)	(-0.12)	(-1.74)
STD_RET	1,236.983***	2,276.258***	-2.752***	-1.727	-0.550***	2.211***
	(17.38)	(9.14)	(-5.61)	(-1.15)	(-4.60)	(7.35)
STD_ROA	247.803***	601.503***	-0.887***	0.353	-0.252***	-0.470***
	(6.67)	(4.99)	(-3.39)	(0.47)	(-4.05)	(-3.23)
AQ	16.542*	72.897***	-0.115*	-0.006	-0.019	0.047
	(1.68)	(2.74)	(-1.67)	(-0.04)	(-1.15)	(1.48)
MATURITY	10.936***	11.647***			0.023***	-0.005*
	(7.51)	(4.51)			(9.98)	(-1.74)
N_COV	14.627***	-1.468**	0.039***	-0.006		
	(17.64)	(-2.38)	(7.26)	(-1.62)		
SPREAD			0.000***	0.000***	0.000***	-0.000**
			(6.86)	(3.24)	(17.99)	(-2.29)
AMOUNT	-13.750***	7.782**	0.081***	0.002	-0.005***	0.015***
	(-14.79)	(2.29)	(12.38)	(0.08)	(-3.08)	(3.65)
SECURED	62.414***	19.800	0.094***	-0.017	0.039***	0.074***
	(34.04)	(1.26)	(8.20)	(-0.20)	(12.64)	(3.90)
CONSTANT	190.126**	249.244**	1.908***	6.426***	0.216	-0.311**
	(2.14)	(2.22)	(3.13)	(10.75)	(1.47)	(-2.21)
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	11,086	4,084	11,086	4,084	11,086	4,084
INTRO - GROWTH = 0	p=0.0000***	p=0.4402	p=0.0034***	p=0.3126	p=0.3617	
INTRO - SHAKE-OUT = 0	p=0.0000***	p=0.3153	p=0.0002***	p=0.1720	p=0.0019***	p=0.0548*
INTRO - DECLINE = 0	p=0.2477	p=0.0002***	p=0.0000***	p=0.5853	p=0.0000***	p=0.5498
GROWTH - SHAKE-OUT =0	p=0.0430**	p=0.5655	p=0.0000***	p=0.0003***	p=0.0000***	p=0.5934
GROWTH - DECLINE = 0	p=0.0001***	p=0.0000***	p=0.0000***	p=0.8682	p=0.0000***	p=0.7079
SHAKE-OUT - DECLINE = 0	p=0.0000***	p=0.0000***	p=0.0037***	p=0.2340	p=0.0000***	p=0.8184

Table 4.5 - Continued

Wald χ^2	12,369.72 (p = 0.00)	3,709.91 (p = 0.00)	3,537.78 (p = 0.00)
LR Test χ^2	29.06 (p = 0.00)	590.01 (p = 0.00)	396.71 (p = 0.00)

Table 4.5 presents the estimation results for model (4), obtained using an endogenous switching model. Model (1) is used as the selection model. The sample includes 11,086 loans and 4,084 bonds issued in the period 1989-2012. The unconditional probability of issuing a bond is 29.8%. The t-values in parentheses are based on standard errors clustered by firm; *, **, and *** indicate significance at the 1%, 5% and 10% level respectively. All continuous variables are winsorized at the 1% and 99% levels. The tests reported at the bottom of (alongside) the table are coefficient comparisons to examine the significance of the differences in the coefficients obtained for the life cycle variables within (across) columns. See Table 4.1 for other variable definitions.

4.5. Additional Analysis and Robustness Tests

4.5.1. Debt Covenant Design and Other Contract Features

The results of the main analyses suggest that lenders increase the covenant intensity of debt contracts for early-stage borrowers in response to the uncertainty about the borrowers' future value. While this finding is in line with the reasoning that covenants could facilitate the renegotiation of contract terms upon the occurrence of future events or conditions (Demerjian 2015), an increase in the covenant intensity can also hinder borrowers' ability to make value-increasing operating decisions by for instance limiting the possibility to obtain additional financing or restricting investments (Nash et al. 2003; Nikolaev 2010; Nini et al. 2009). To provide some insight in how lenders deal with the tradeoff between the costs and benefits of an increase in the covenant intensity for early-stage firms, I examine the covenant design of both bond and loan contracts in more detail. Whereas the main findings indicate that covenant intensity does not differ as much across the various life cycle stages for bond contracts as it does for loan contracts, reflecting the differences in renegotiation costs between these two types of debt financing (De Franco et al. 2015), prior research also shows that the bond covenant design is tailored to the financing and investment needs of the borrower (Kahan et al. 1995; Nash et al. 2003).

To classify the covenants into different categories, I rely on the classifications of Christensen et al. (2012) and Nikolaev (2010) for loan contracts and bond contracts respectively. First, concerning loan contracts, Christensen et al. (2012) distinguish between capital covenants (C-Covenants) and performance covenants (P-Covenants): Where C-Covenants mainly serve to achieve *ex ante* interest alignment between the contracting parties, P-covenants function as trip wires that enable *ex post* contract renegotiations. Even though it would seem evident based on the reasoning above to argue that the debt contracts of early-stage firms include more P-covenants, the effectiveness of P-covenants strongly depends on the informativeness of the underlying performance measure (Christensen et al. 2012). As the informativeness of earnings is relatively limited in the early stages of the firm life cycle as a consequence of the substantial investments in for instance new capital and innovation (Black 1998), potential lenders may therefore rather rely on C-covenants in these stages. Following Christensen et al. (2012), I examine the covenant mix by calculating the ratio of P-covenants to the total of P-Covenants and C-Covenants (*P_COV_INT*). To explore the role of P-covenants over the firm life cycle in more detail, I also split the P-covenants based on whether the covenants use net income as the underlying performance measure or EBITDA and calculate the ratio of EBITDA covenants to the total number of P-Covenants (*EBITDA_INT*). Especially in early-stage firms, the relatively large depreciation expenses associated with the investments in new capital put substantial downward pressure on net income, reducing its informativeness. If potential lenders incorporate the limited informativeness of the net income of early-stage firms when using P-covenants, then one would expect to observe a higher intensity of EBITDA-covenants.

Since the loan covenant classification of Christensen et al. (2012) mainly covers accounting-related covenants, I also investigate some additional covenants and other contractual features of loan contracts that relate to operating, financing and investing activities. Specifically, I include indicator variables that reflect whether the loan contract includes a performance pricing provision (*PERF_PRICING*); a restriction on dividend payouts (*DIV_RESTR*); or capital expenditures restrictions (*CAPEX_RESTR*). While the uncertainty about the borrower's future performance may limit its application for early-stage firms, performance pricing can be considered as a less costly alternative to debt covenants as it does not require *ex post* renegotiation but involves pre-determined interest rate changes that are contingent on realized outcomes (Demerjian 2015; Asquith, Beatty and Weber 2005). With regard to dividend restrictions, the findings of DeAngelo et al. (2006) suggest that early-stage firms are less likely to pay dividends given the limited availability of retained earnings to distribute and, hence, dividend restrictions may be redundant for these firms. On the other hand, however, dividend restrictions could also ensure that borrowers use the external financing they obtain solely for investing activities in the early stages of the firm life cycle. Finally, Nini et al. (2009) find that capital expenditure restrictions reduce the borrower's investing activities even in the absence of covenant violations, which makes them arguably less suitable for inclusion in the debt contracts of early-stage firms.

Second, regarding bond contracts, I follow Nikolaev (2010) and classify the bond covenants into five categories: pay-out related covenants (*DIV_COV*), investment-related covenants (*INV_COV*), financing-related covenants (*FIN_COV*), accounting-related covenants (*ACC_COV*), and other covenants (*OTH_COV*). All five variables that relate to the bond covenant design are measured by the number of covenants within a certain category divided by the total number of bond covenants. If bondholders recognize the importance of financing and investing flexibility in the early stages of the firm life cycle, I expect to observe lower intensities of investment-related and financing-related covenants for firms in the introduction and growth stage. Additionally, given the limited informativeness of performance measures for early-stage firms, as argued before, I would also expect to find a lower intensity of accounting covenants for these firms.

Given the results of the endogenous switching model in the previous section that underline the importance of controlling for the non-random selection of the source of lending and the fact that the different covenants and other contract features are only observed for either loans or bonds, I control for potential selection bias in the covenant design by including the inverse Mill's ratio. As the operationalization of the covenant design features differs across the two types of debt contracts and some of the features are measured by indicator variables, I cannot employ an endogenous switching model in examining the debt covenant design (Bharath et al. 2008). Hence, the inverse Mill's ratio is used as an alternative to correct for potential selection bias in the source of lending. The inverse Mill's ratio (λ) is calculated using the following formula (Heckman, 1979, p. 156):

$$\lambda_i = \frac{\phi\,(Z_i)}{1 - \Phi(Z_i)} \tag{5}$$

in which $\phi(.)$ represents the standard normal density function; $\Phi(.)$ represents the standard normal cumulative distribution function; and Z_i is the predicted value from model (1), which is used as the selection model.[49] In addition to the inverse Mills ratio, I also include the same set of control variables as used in model *(2)* when examining the covenant design over the firm life cycle. The estimation results for the regressions on debt covenant design are reported in Table 4.6.

Concerning loan covenant design, the findings in column (1) of Table 4.6, panel A, indicate that firms in the introduction, shake-out, and decline stage have a lower P-covenant intensity than firms in the mature and growth stage. While the lower intensity of P-covenants could limit lenders' ability to renegotiate the contract terms, this finding is in line with the reduced effectiveness of P-covenants at the far ends of the life cycle spectrum as a consequence of the limited informativeness of various performance measures, which tend to be negative in these stages (Dickinson, 2011; Christensen et al. 2012). Furthermore, the significantly positive coefficient on *GROWTH* (0.018, p-value < 0.05) in column (2) - in combination with the coefficient comparisons at the bottom of the table - shows that loan contracts for growth firms appear to include more P-covenants that are based on EBITDA than on net income compared to firms in the introduction and mature stage. This result suggests that private lenders are aware of the negative effect substantial investments could have on the net income of growth firms and therefore rather rely on EBITDA-based P-covenants. Regarding the other contractual features in columns (3) – (5), very few differences exist in the loan contract design across the various life cycle stages. Finally, the inverse Mills ratio is significant in four out of the five models, which indicates that it is important to control for selection bias while examining loan contract design.

Panel B reports the findings for the bond covenant design. The estimation results in column (2) indicate that bond issues by early-stage firms include less investment-related covenant restrictions than mature firms as reflected in the significantly negative coefficients on *INTRO* (-0.103, p-value < 0.01) and *GROWTH* (-0.019, p-value < 0.05). This finding suggests that bondholders provide early-stage firms with more flexibility in their investment activities that could help them to effectively exploit the available growth opportunities in these stages. In addition, bond contracts of firms in the introduction stage also include more restrictions on dividend payouts and accounting-related restrictions. While the latter finding seems surprising based on the foregoing expectations, the variable *ACC_COV* does not distinguish between capital covenants and performance covenants (cf. Christensen et al. 2012; Nikolaev 2010). However, after defining the accounting-related covenant restrictions in the bond contracts as either C-covenants or P-covenants, untabulated analyses reveal that the C-covenant intensity is significantly higher in the introduction stage compared to mature firms, which is in line with the earlier results on loan contract design in Panel A.[50]

[49] When investigating the covenant design of loans, I replace *BOND* by *LOAN* in the selection model. Similar to *BOND*, *LOAN* is an indicator variable that is equal to one if the firm obtains a loan, and zero otherwise.

[50] Following the intuition underlying the loan covenant classification of Christensen et al. (2012), I classify net_earnings_test_issuance, fixed_charge_coverage, and su_fixed_charge_coverage as performance covenants; and indebtness, su_indebtness, leverage_test, su_leverage_test, declining_net_worth, and maintenance_net_worth as capital covenants.

TABLE 4.6

Debt Covenant Design over the Firm Life Cycle

Panel A: Loan Covenant Design

Variable	(1) P_COV_INT	(2) EBITDA_INT	(3) PERF_PRICING	(4) DIV_RESTR	(5) CAPEX_RESTR
INTRO	-0.054***	-0.016	0.031	-0.148	0.126
	(-3.51)	(-1.02)	(0.26)	(-0.81)	(0.73)
GROWTH	0.010	0.018**	-0.024	0.100	-0.089
	(1.23)	(2.18)	(-0.35)	(1.15)	(-0.96)
SHAKE	-0.035**	-0.007	-0.039	-0.415***	0.055
	(-2.32)	(-0.41)	(-0.32)	(-2.61)	(0.35)
DECLINE	-0.091***	-0.017	-0.100	0.008	-0.199
	(-3.74)	(-0.51)	(-0.53)	(0.02)	(-0.73)
Inv. Mills Ratio	-0.284***	0.040	-0.369*	-1.813***	-1.188***
	(-7.63)	(1.10)	(-1.85)	(-5.74)	(-2.67)
CONSTANT	0.043	-0.280***	-4.513***	2.194	-2.587**
	(0.36)	(-2.59)	(-5.99)	(1.12)	(-2.32)
Controls	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	11,035	10,210	11,021	10,386	10,723
(Pseudo) R-Squared	19.8%	14.9%	14.5%	27.4%	30.9%
INTRO - GROWTH = 0	p=0.0000***	p=0.0239**	p=0.6230	p=0.1690	p=0.1950
INTRO - SHAKE-OUT = 0	p=0.3230	p=0.6490	p=0.6510	p=0.2400	p=0.7330
INTRO - DECLINE = 0	p=0.1610	p=0.9690	p=0.5140	p=0.7220	p=0.2700
GROWTH - SHAKE-OUT = 0	p=0.0042***	p=0.1420	p=0.9070	p=0.0018***	p=0.3790
GROWTH - DECLINE = 0	p=0.0000***	p=0.3020	p=0.6830	p=0.8240	p=0.6920
SHAKE-OUT - DECLINE = 0	p=0.0366**	p=0.7660	p=0.7680	p=0.3230	p=0.3830

Panel B: Bond Covenant Design

Variable	(1) DIV_COV	(2) INV_COV	(3) FIN_COV	(4) ACC_COV	(5) OTH_COV
INTRO	0.021**	-0.103***	0.023	0.040**	0.021
	(2.57)	(-3.85)	(1.52)	(2.26)	(0.70)
GROWTH	0.001	-0.019**	0.002	0.004	0.012
	(0.61)	(-2.00)	(0.31)	(0.90)	(1.54)
SHAKE	-0.001	0.008	-0.000	0.002	-0.010
	(-0.15)	(0.45)	(-0.03)	(0.26)	(-0.58)
DECLINE	0.032	0.050	-0.019	0.015	-0.078
	(1.28)	(0.65)	(-0.63)	(0.77)	(-1.57)
Inv. Mills Ratio	0.002	-0.068**	0.020	-0.003	0.050**
	(0.29)	(-2.49)	(1.64)	(-0.34)	(2.45)
CONSTANT	0.009	0.479***	-0.009	0.042	0.478***
	(0.25)	(2.72)	(-0.11)	(0.52)	(3.84)
Controls	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	4,068	4,068	4,068	4,068	4,068
R-Squared	39.6%	45.2%	23.7%	39.9%	35.6%

Table 4.6 - Continued

INTRO - GROWTH = 0	p=0.0168**	p=0.0013***	p=0.1590	p=0.0442**	p=0.7690
INTRO - SHAKE-OUT = 0	p=0.0191**	p=0.0004***	p=0.1840	p=0.0469**	p=0.3630
INTRO - DECLINE = 0	p=0.6600	p=0.0534*	p=0.1780	p=0.3190	p=0.0756*
GROWTH - SHAKE-OUT = 0	p=0.6900	p=0.1450	p=0.8360	p=0.8930	p=0.2010
GROWTH - DECLINE = 0	p=0.2190	p=0.3740	p=0.4850	p=0.5690	p=0.0704*
SHAKE-OUT - DECLINE = 0	p=0.1970	p=0.5980	p=0.5470	p=0.5490	p=0.1880

Table 4.6 presents the estimation results for the models investigating the loan covenant design (Panel A) and the bond covenant design (Panel B). The sample includes debt issues in the period 1989-2012. In Panel A, *P_COV_INT* is the ratio of P-covenants to the sum of P-covenants and C-Covenants (Christensen et al. 2012); *EBITDA_INT* is the ratio of P-covenants that is based on EBITDA to the total number of P-covenants; *PERF_PRICING*, *DIV_RESTR*, and *CAPEX_RESTR* are indicator variables that, respectively, reflect whether the loan contracts includes a performance pricing provision; a restriction on dividend payouts; or capital expenditures restrictions. In Panel B, *DIV_COV*, *INV_COV*, *FIN_COV*, *ACC_COV* and *OTH_COV* are the number of, respectively, pay-out related covenants, investment-related covenants, financing-related covenants, accounting-related covenants, and other covenants (Nikolaev, 2010), scaled by the total number of bond covenants. The inverse Mill's ratio is calculated using model (1) as the selection model. The t-values in parentheses are based on standard errors clustered by firm; *, **, and *** indicate significance at the 1%, 5% and 10% level respectively. All continuous variables are winsorized at the 1% and 99% levels. The tests reported at the bottom of the table are coefficient comparisons to examine the significance of the differences in the coefficients obtained for the life cycle variables. See Table 4.1 for other variable definitions.

Overall, the analyses on loan and bond covenant design above provide evidence that both private and public lenders incorporate the differences in contractibility or informativeness of performance measures as well as borrowers' needs when deciding which covenants to include in debt contracts at the various stages of the firm life cycle. More specifically, while loan contracts include fewer P-covenants for firms at the far ends of the life cycle continuum and more EBITDA-based P-covenants for growth firms, these contracts do not place more restrictions on investment activities for early-stage firms than for firms in the other life cycle stages. Additionally, despite the similarity in bond covenant design observed in prior studies, the bond contracts of early-stage firms include less investment-related covenant restrictions, reflecting borrowers' need for investment flexibility in these stages (De Franco et al. 2015; Nash et al. 2003).

4.5.2. Robustness Tests

The life cycle proxy of Dickinson (2011) used in this study to classify the observations into the different life cycle stages relies on the systematic pattern in firms' cash flows. Even though I already include the cash flow of operations – scaled by sales – to control for the borrower's ability to make the fixed contractual payments in the short run (Easton et al. 2009), it may still be the case that the results obtained in the main analysis are driven by the magnitude of borrowers' financing and investing activities rather than the evolving pattern in the different types of firm activities over the firm life cycle. To address this potential concern, I also include the cash flows from investing and financing activities, both scaled by sales, in the estimation models. Untabulated findings show that the inferences are robust to the inclusion of the different types of cash flows and, hence, suggest that the life cycle indicator variables do not simply capture the magnitude of the *individual* cash flows in each category but reflect the *combination* of firm activities at each stage of the firm life cycle.

As an additional robustness test, I also run the analyses including the loan observations at the package level rather than at the facility level in which the interest rate spread, maturity and amount are measured as the average of these loan characteristics across the facilities included in the same loan package. In the main analysis, the loan sample retrieved from Dealscan consists of observations at the facility level since the interest spread and the maturity of the loan contracts can vary by credit facility (Bharath et al. 2008). Yet, the number of covenants included in the loan contract does not differ among the facilities included in the same loan package and, hence, prior studies investigating loan covenants conduct their analyses at the package level (Christensen et al. 2012). Untabulated results reveal that the inferences derived from the main analyses remain largely unchanged when I estimate the models at the package level; only the coefficient on *GROWTH* in the OLS model examining the loan maturity is no longer significant at the one-sided 10% significance level.[51]

4.6. Conclusion

In sharp contrast to the negative relation between firms' investment opportunity sets and leverage generally observed in prior research, the combination of a lack of internally generated funds and the necessity to exploit the available growth opportunities to become and remain profitable increases the need for early-stage firms to access the debt markets to obtain external financing. Even though debtholder-shareholder conflicts may be relatively limited in early-stage firms as the incentives of the contracting parties are well-aligned, there still exists substantial uncertainty about the borrower's future value as a consequence of the large impact of growth opportunities on firm value in these stages. When incorporating this uncertainty, potential lenders have to trade off the costs and benefits associated with providing the borrower with the operational flexibility that is needed to make the necessary investments. At the same time, however, borrowers have to trade off the costs and benefits that arise due to the different characteristics of private versus public lenders. As such, both the source of lending and the debt contract design are likely to evolve over the firm life cycle.

After establishing that early-stage firms are more likely to access the debt markets and issue more debt than firms in the other life cycle stages, I find that firms in the introduction and growth stage prefer public debt to private debt while firms in the shake-out stage rely more on private debt. This finding is consistent with the "Rent Extraction hypothesis" which argues that early-stage firms prefer issuing bonds to avoid the extraction of information rents by banks (Rajan 1992; Houston et al. 1996). Concerning the debt contract design, both public and private lenders adjust the debt contract in response to the uncertainty about the borrower's future value, but they do so using different contract terms. After controlling for the potential non-random selection of the source of lending, I find that both types of lenders incorporate the varying credit risk over the firm life cycle by adjusting the interest spread. In addition, the debt contracts of firms in the introduction stage have a higher covenant intensity under both sources of lending. However, while public bondholders allow growth firms to issue bonds with a shorter maturity, private lenders rather rely on a higher covenant intensity.

[51] The coefficient on *INTRO* in the endogenous switching model examining the loan covenant design also loses some of its significance, but is still significant at the one-sided 10% significance level (p-value = 0.108).

Furthermore, additional analyses provide some evidence that the covenant design and the use of other contract features are tailored to the needs of the contracting parties.

However, as a consequence of potential caveats, some caution has to be taken in interpreting these results. First of all, I follow Demerjian (2015) in attributing the observed differences in debt contract design over the firm life cycle to uncertainty about the borrower's future value rather than to agency conflicts. In doing so, I argue that the interests of the manager are well-aligned with those of all stakeholders in the early stages of the firm life cycle. However, it is difficult to perfectly disentangle these two explanations for the observed differences in the debt contract design. Nevertheless, the analysis of the debt covenant design provides some indication that lenders provide early-stage borrowers with some operating flexibility instead of overly restricting investing and financing activities in response to potential agency conflicts in these stages. Second, the investigated sample only includes publicly traded firms which could limit the generalizability of the results. For instance, when compared to private firms, public firms may have obtained a strong credit reputation before going public. As such, whereas publicly traded firms in the introduction and growth stage are able to access the public debt markets, private firms in these stages could face more difficulties in issuing public debt. Finally, the number of observations for decline firms that issue bonds is relatively limited, which undermines the reliability of the associated estimates.

Overall, the insights that can be derived from this study shed additional light on the role of firm life cycle in the functioning of capital markets. While the scarce research on firm life cycle in the accounting literature has focused on the equity markets so far, the results of this study indicate that firm life cycle also has an important impact on debt contracting. In contrast to equity investors – who face difficulties in understanding life cycle dynamics according to recent research findings (Dickinson 2011; Hribar et al. 2015) – private and public lenders appear to respond to the varying firm dynamics across the life cycle stages in designing debt contracts. As such, the findings can provide useful information to both lenders and borrowers in their financing decisions.

5 CONCLUSION

In this dissertation I examine how the behavior of various market participants evolves over the firm life cycle. The life cycle concept provides a structured approach to capture firms' dynamic development through distinct stages over time. Overall, the three studies in this dissertation show that life cycle affects both the decisions by – and the interactions among – firms, investors, information intermediaries and financial intermediaries.

5.1. Summary and Implications

As a consequence of significant developments in the world economy over the past decades, including rapid technological advances and increased competition in a global playing field, firms have constantly been subject to change (Core, Guay and Van Buskirk 2003; Irvine and Pontiff 2009). Yet, the ability of accounting standards to adequately capture change in a timely manner is limited. This has contributed to a decrease in the value relevance of financial information over the same time period (Lev and Zarowin 1999; Srivastava 2014; Zimmerman 2015). While the increased firm dynamics and unstable business models call for a dynamic view of firms, studies in the financial literature have generally been executed from a cross-sectional perspective that often treats firms as static entities. Over the past few years, however, an increasing number of researchers in finance and accounting have started to adopt a dynamic perspective on firms by including firm life cycle in their analyses. Whereas these studies tend to focus on within-firm decision making, the studies in this dissertation examine how firm life cycle affects the behavior of other capital market participants.

In the first study (Chapter 2), we examine how stock price crash risk varies over the firm life cycle. The substantial value that early-stage firms derive from growth opportunities relative to assets-in-place is expected to lead to more heterogeneity in investor beliefs. In addition, investors can become overoptimistic about future firm performance if they do not acknowledge differences in earnings persistence across life cycle stages but rather fixate on realized earnings growth. Both heterogeneity in investor beliefs and investors' misinterpretation of earnings persistence can prevent bad news from being impounded in stock prices immediately. If the accumulated bad news is eventually released to the market all at once, the stock price of the firm declines significantly (i.e., a stock price crash). Stock price crash risk is expected to be further exacerbated by the unconditional conservatism inherent in accounting standards and short-selling constraints.

The findings in this study confirm our hypothesis that firm-specific stock price crash risk is highest for early-stage firms. Cross-sectional analyses also reveal that this result is more pronounced in firms with a higher market-to-book ratio and no short interest, providing additional support for the "heterogeneity-in-investor-beliefs" hypothesis. Regarding investor (over)optimism about future firm performance as an alternative explanation, crash risk is significantly higher for growth firms with above-median operating performance. Nevertheless, this mechanism provides only a partial explanation for the higher crash risk observed in early-stage firms. Furthermore, additional analysis shows that early-stage firms do not experience more stock price jumps. This implies that our results are not driven by the inherent riskiness of these firms.

Building on the findings in the first study which suggest that investors do not efficiently incorporate life cycle information into their valuations, the second study (Chapter 3) examines (1) whether analysts respond to the varying need for their services over the firm life cycle; and (2) how firm life cycle affects individual analyst forecasts. Given the intermediating role analysts can fulfill in helping investors analyze financial information, one could argue that investor demand for analyst services is higher for early-stage firms. Firms' visibility concerns at the far ends of the life cycle are another factor that can contribute to an increased demand for analyst coverage at the far ends of the life cycle spectrum. On the contrary, forecasting difficulty and limited visibility could also reduce analysts' incentives to follow non-mature firms. The difficulty in forecasting future firm performance of non-mature firms is likely to result in less accurate forecasts. Whereas analyst may overcome these forecasting difficulties if they can benefit more from their industry expertise, they may also face additional difficulties when there is a life cycle shock.

The empirical results in the second study indicate that analysts respond to investor needs since analyst following is highest in the introduction and growth stage. Concerning forecast accuracy, analyst forecasts indeed appear to be less accurate for most non-mature firms. To our surprise, analyst forecasts are *most* accurate for growth firms. The superior forecasting accuracy for growth firms is however concentrated in firms whose life cycle is aligned with the industry life cycle, reflecting the greater extent to which analysts can benefit from their industry expertise. Yet, as life cycle changes are followed by a reduction in forecast accuracy, analysts appear to have difficulties in immediately incorporating the implications of life cycle shocks in their forecasting models. Additional analyses provide further support for the assertion that analysts respond to the needs for their services and show that the forecasting difficulty associated with non-mature firms is also reflected in more dispersion at the consensus level.

Where the first two studies examine the role of firm life cycle in equity markets, the third study (Chapter 4) investigates how firm life cycle affects the interactions between borrowers and lenders in debt markets. Even though the shareholder-debtholder conflicts – which underlie most theoretical reasoning in prior studies on debt contracting – are arguably limited in early-stage firms, there still exists a lot of uncertainty concerning borrowers' future value in these stages. As the limited availability of internal funds increases the likelihood that early-stage firms access the debt markets, both lenders and borrowers have to incorporate this uncertainty in their decisions. Borrowers, on the one hand, face a trade-off between the costs and benefits related to private versus public lending. Specifically, even though private lenders can provide borrowers with more flexibility in investment decisions, their close monitoring could also enable them to extract informational rents. Lenders, on the other hand, have to trade off the costs and benefits of providing investment flexibility to the borrower in optimizing the likelihood that the borrower will (be able to) make the contractual payments.

The findings show that early-stage borrowers prefer public debt to private debt, suggesting that these borrowers try to avoid information rent extraction by private lenders. Both private and public lenders incorporate firm life cycle into debt contract design, albeit in different ways that reflect the differences in renegotiation flexibility between the two types of lenders. Specifically, while public lenders tend to rely on shorter maturities for growth firms, private lenders rather increase the covenant intensity for these firms. In addition to the aforementioned differences in debt contract design, both types of lenders generally set more stringent price terms for non-mature firms. Moreover, further analysis of the covenant design provides evidence that the different types of lenders take borrowers' needs and the varying informativeness of accounting measures into account.

Overall, the (combined) findings of the three studies have important implications for investors, firms, regulators, and researchers. First, the findings of the first study could inform investors in their investment decisions. Firm life cycle does not only affect the level of return but also its distribution. If investors are not aware of the higher tail risk of early-stage firms, they may suffer substantial welfare losses. In a similar vein as Dickinson (2011), the findings should also raise investor awareness of the differential persistence in accounting performance measures across life cycle stages. Investors' (over)optimism about the future performance of early-stage firms not only leads to overpricing of early-stage firms but could eventually also result in a stock price crash. On a more positive note, the findings in the second and third study imply that investors could overcome the valuation difficulties over the firm life cycle by relying more on financial and information intermediaries. For instance, investors can use the findings in the second study to derive conditions under which analyst forecast accuracy is higher (or lower).

Second, firms could use the results in this dissertation to help them in their communications with investors and their financing decisions. Despite the assistance information and financial intermediaries provide to investors in interpreting financial information over the firm life cycle, early-stage firms may provide investors with additional guidance in their external communications. Additional guidance to investors could mitigate the negative skewness in early-stage firms' stock returns and, in turn, could reduce their cost of capital. Furthermore, the findings in the third study can also inform firms in their financing decisions. More specifically, both public and private lenders appear to understand the varying borrowing needs over the firm life cycle, which provides firms more flexibility in their choice of the source of lending.

Third, regulatory accounting bodies can consider the insights that can be derived from this dissertation in their standard setting. As mentioned before, multiple studies have already recognized that current accounting standards do not adequately capture changing firm fundamentals in a timely manner (Lev et al. 1999; Srivastava 2014; Zimmerman 2015). The findings in the first and second study indicate that the associated difficulties in interpreting financial information may not only reduce investor welfare but can also negatively affect the performance of more sophisticated capital market participants (i.e., financial analysts in this case). Regulators could either give more attention to firm dynamics in future standard setting or – at least – make capital market participants more aware of the limitations of current accounting standards.

Fourth, the combined findings underline the importance of firm life cycle in capital markets. As such, the findings emphasize the need to adopt a more dynamic perspective on firms in finance and accounting research rather than the static stance that (implicitly) dominates in the current literature. Whereas researchers, for instance, generally control for time and industry effects in their empirical models, they could additionally control for life cycle effects to incorporate firm dynamics in their statistical analyses.

5.2. Limitations and Future Research

Despite the contributions of my dissertation, some potential caveats have to be taken into account while interpreting the findings of the three studies. First and foremost, the question arises how well an empirical proxy is able to capture a theoretical concept that is as inherently complex as firm life cycle. Like all other life cycle proxies employed in previous studies, for instance, the cash flow proxy of Dickinson (2011) is backward-looking in nature and, hence, may not be able to provide capital market participants with timely information. Yet, the validation of the life cycle proxy in Dickinson (2011) and the superior features of this life cycle proxy over the available alternatives – as discussed in Section 1.2. – provide the necessary confidence about its use in the empirical models throughout my dissertation.

Second, and related to the first caveat, the question arises what underlying information the life cycle proxy exactly captures, especially after controlling for a wide variety of other variables. The concern that firm life cycle *just* captures uncertainty or firms' growth opportunities has been raised multiple times during the writing process of this dissertation. Even though it is difficult to completely rule out these alternative explanations, there are multiple indications throughout this dissertation that firm life cycle captures more than merely uncertainty or growth opportunities. For instance, all empirical models control for variables that have often been used to measure firms' growth opportunities (i.e., market-to-book ratio) and uncertainty (i.e., stock price volatility and earnings volatility). Additionally, if firm life cycle only captures increased uncertainty in early-stage firms, then the findings of the first study would have shown a higher likelihood of stock price jumps in these stages as well. If anything, the opposite is true. Furthermore, cross-sectional analyses in the second study also show that firm life cycle could partly capture differences in firm visibility across stages; a factor that is not necessarily related to uncertainty. Finally, the robustness checks in the third study show that the results are not driven by the uncertainty that could arise as a consequence of negative operating cash flows but rather by the combined pattern in firm cash flows. All in all, it seems that each of the life cycle stage indeed captures distinct "*integral complementarities among variables*" that reflect the interplay among different firm activities and which cannot be measured by a single (or combination of) other variable(s) (Miller and Friesen 1984, p. 1161).

Third, the investigated samples only include publicly traded US firms. One could argue that it is unlikely to observe a publicly traded firm that is still in its introduction stage. Nonetheless, the product portfolio of firms can consist of multiple products that are at different stages in the product life cycle; the aggregate of the cash flows generated by the individual products then determines a firm's life cycle stage (Cox 1967; Dickinson 2011; Mueller 1972). While mature firms may be able to finance new products with internal funding, substantial product innovations that help a firm back into the growth stage are likely to require additional external financing. The example of General Motors in Section 1.3. (Figure 1.1., Panel B) also illustrates that bail-outs and the subsequent reorganization of companies can force firms back into the introduction stage.

The potential limitations discussed above do provide fruitful avenues for future research. Researchers could include private firms in their analyses and investigate how the impact of firm life cycle differs between private and public firms, for instance with respect to their financing decisions. Whereas early-stage firms that are publicly traded could have obtained the necessary credit reputation that allows them to access public bond markets, private firms may initially have to rely on private debt before they have established a reputable credit record in the debt markets (Diamond 1991). Nevertheless, private firms may also rely on other sources of external financing, like venture capitalists, to overcome the information problems in early stages (Zimmerman 2015).

Furthermore, even though this dissertation has examined how firm life cycle affects various capital market participants, there are still multiple ways in which the analyses can be extended. For instance, the studies in this dissertation have mainly focused on investors and the two types of capital market intermediaries in isolation without including their interactions with other capital market participants. While the findings in the second study, for instance, suggest that sell-side financial analysts respond to investor needs, it remains silent on how analyst forecasts affect investor mispricing at the various life cycle stages. Additionally, I do not examine how firms respond to the difficulties investors face in understanding firm life cycle. Prior studies (Chen, DeFond and Park 2002; Wasley and Wu 2006) already provide some indications that firms adjust their forecasting behavior accordingly but proprietary costs could play a significant role in early-stage firms as well. Relatedly, future research could investigate how the use and informativeness of non-GAAP earnings varies over the firm life cycle. Specifically, the provision of non-GAAP earnings may allow managers of early-stage firms to exclude some of the detrimental effects substantial investments have on GAAP earnings in these stages and, thus, could result in more informative performance metrics.

Another way in which the analyses in this dissertation can be extended is by examining other information intermediaries. Next to sell-side analysts, credit rating agencies and auditors are other information intermediaries that have been frequently investigated in prior research. Firm life cycle could also play an important role in their functioning. Extant research in the auditing literature has for instance examined the issuance of going-concern opinions (GCOs) to audit clients and the error rates in these GCOs (Carson, Fargher, Geiger, Lennox, Raghunandan, and Willekens 2013).[52] Based on their synthesis of auditing research on GCOs, Carson et al. (2013) indicate that 80-90 percent of firms that receive a GCO have been found to remain in business (i.e., a Type I error). If auditors do not fully understand where a firm stands in its life cycle, they may be more likely to falsely issue a GCO for early-stage firms based on their relatively weak operating performance despite the future growth potential of these firms.

Finally, the rapid advances in textual analysis can also turn out to be useful for research on firm life cycle. A closer examination and analysis of the text in annual reports, voluntary firm disclosures or financial press releases could result in a more timely and maybe even more accurate measure of firm life cycle.

[52] According to SAS no. 59 (AU Section 341, paragraph .02), an auditor has to issue a GCO if "there is substantial doubt about the entity's ability to continue as a going concern for a reasonable period of time, not to exceed one year beyond the date of the financial statements being audited" (AICPA 1988).

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VALORIZATION

According to Appendix 4 of the Regulation Governing the Attainment of Doctoral Degrees (Maastricht University 2013), knowledge valorization refers to the "process of creating value from knowledge, by making knowledge suitable and/or available for social (and/or economic) use and by making knowledge suitable for translation into competitive products, services, processes and new commercial activities" (adapted definition based on the National Valorization Committee 2011:8). Five questions are addressed in this valorization addendum: 1. Relevance – What is the social (and/or economic) relevance of the research results (i.e. in addition to the scientific relevance)? 2. Target groups – To whom, in addition to the academic community, are the research results of interest and why? 3. Activities – Into which concrete services, processes, activities or commercial activities can the results be translated and shaped? 4. Innovation – To what degree can the results be called innovative in respect to the existing range of services, processes, activities and commercial activities? 5. Schedule and Implementation – How will this/these plan(s) for valorization be shaped? What is the schedule, are there risks involved, what market opportunities are there and what are the costs involved?

1. **Relevance.** Over the past two decades, various developments – including rapid technological innovation, advances in information technology and globalization – have contributed to increased dynamics in capital markets. Hand in hand with these developments we have witnessed a decrease in the relevance of financial information – i.e., the extent to which financial information affects the decisions made by capital market participants. Combining the importance of financial information in the communication between firms and their stakeholders, as underlined by accounting standard-setters, with the limited ability of (current) accounting standards to adequately capture increased dynamics, the social and economic relevance of this dissertation are reflected in its investigation of how firm dynamics affect the behavior of various capital market participants. More specifically, in this dissertation I adopt a dynamic view of the firm – as captured by the firm life cycle – and examine to what extent various capital market participants incorporate and understand a firm's evolvement over time. Making capital market participants aware of their own and others' (mis)understanding of firm dynamics can help them to overcome the problems they face in incorporating life cycle information and, hence, to improve their future decisions.[53]
2. **Target groups**. Given the research questions addressed in this dissertation, the findings can inform capital market participants and regulatory bodies in their decision-making and standard setting, respectively. Specifically, the findings in Chapter 2 suggest that

[53] I do not claim that capital market participants are unaware that firms evolve over time. Yet, it is their understanding of the impact of firm life cycle on the informativeness of financial information that affects the quality of their decisions.

investors' limited understanding of firm life cycle can lead to substantial welfare losses as a consequence of stock price crashes. This finding is relevant for investors, managers and regulators. First of all, it makes investors aware of the costs related to the valuation difficulties of early-stage firms that arise due to the substantial impact of growth opportunities on firm value. As the problems investors face in valuing early-stage firms could also negatively affect firms, for instance in the form of higher costs of capital, managers may want to inform investors better of their current position in the firm life cycle to reduce these potential costs. Furthermore, regulators could put more effort in (further) increasing investors' awareness of the limitations of current accounting standards to mitigate a further decline in the relevance of financial information.

The findings in Chapter 3, which investigates the behavior of financial analysts over the firm life cycle, are relevant for both investors and financial analysts. For investors, the results not only indicate that analysts respond to their varying needs over the firm life cycle but also provide insights in when analyst forecasts are most accurate. For analysts, the findings could increase their awareness of the changes in the earnings generating process that relates to transitions between life cycle stages. Since life cycle changes appear to be followed by a decline in forecast accuracy, financial analysts fail to incorporate these changes in their forecasts immediately. More timely and adequate incorporation of life cycle changes could therefore improve their forecasts.

Finally, Chapter 4 examines how debt markets are affected by firm life cycle. The findings in this chapter are relevant for firms (borrowers) and investors (lenders). Specifically, the findings in Chapter 4 indicate that both public and private lenders incorporate firm life cycle information in the design of debt contracts while taking the varying needs of the borrower into account. Although prior research has found that bond contracts tend to be rather standardized, the implication of the findings in this study for borrowers is that bond contracts still have features that reflect the different needs over the firm life cycle and, hence, provide borrowers with the necessary flexibility. For lenders, the findings in this study inform them about firms' preferred source of lending across life cycle stages and suggest that they are able to incorporate firm dynamics in the debt contract design.

3. **Activities**. As suggested by the preceding paragraphs, different capital market participants can use the insights from this dissertation in their day-to-day activities. By increasing their awareness of how firm life cycle affects the behavior of (and interaction among) capital market participants, the findings in this dissertation can be used, for instance, by (1) investors to make better informed investment decisions; (2) financial analysts to improve their forecasts of future firm performance; (3) lenders when screening potential borrowers and designing debt contracts; (4) firms in the communication with their stakeholders; and (5) regulators in their standard setting.
4. **Innovation**. By excluding firm life cycle from their analyses, previous research in the accounting and finance literature has implicitly treated firms as rather static entities. The increased dynamics in capital markets and firms' business models, however, require the adoption of a more dynamic view of the firm. Under this dynamic view, the firm is treated as an entity that evolves back and forth through multiple stages of development over time. While recent studies have started to examine how firms' (internal) policies differ across

firm life cycle stages, limited research has investigated how the firm life cycle affects the behavior of capital market participants. As such, adopting a dynamic rather than a static view of the firm in this dissertation provides novel and innovative insights in how capital market participants are affected by firm dynamics that can help them to enhance their decision-making processes.

5. **Schedule and Implementation**. As mentioned before, increasing the awareness of firm life cycle among capital market participants could help them to make better informed decisions in the future and, as a result, could lead to a more efficient allocation of financial resources across the available investment opportunities. While it is relatively easy to derive a firm's current life cycle stage from publicly available financial statements based on Dickinson's (2011) life cycle classification, incorporating firm life cycle information in decision-making and regulation is not without limitations. Specifically, even if capital market participants are aware of the impact of firm life cycle on the relevance of financial information, the forecasting difficulties of firms across the various life cycle stages remains. Nevertheless, whereas the valuation of firms is never without risk, the insights in this dissertation can help capital market participants to better incorporate the risks related to firm dynamics in their analyses. Additionally, managers and regulators can try to further decrease the costs and risks involved in incorporating firm life cycle information by providing or requiring more information on firms' expected development (conditional on their life cycle stage). Yet, despite the managers' superior private information about the company, managers are also not able to perfectly foresee the future. Therefore, before disclosing or requiring additional information on firms' expected development, managers and regulators have to trade-off the benefits of a potential increase in the relevance of the information against the costs related to a potential loss in the reliability of these numbers. Furthermore, it is questionable whether the proprietary costs of information – that are arguably especially high for early-stage firms – offset the potential benefits that can be derived from additional disclosure.

SUMMARY IN DUTCH[54]
(*Nederlandse Samenvatting*)

Terwijl de levenscyclus van bedrijven een frequent onderzocht onderwerp is in de organisatieliteratuur, heeft dit concept slechts recent meer aandacht gekregen in accounting onderzoek. Voorgaande studies hebben zich met name gericht op de vraag hoe het (interne) beleid van bedrijven met betrekking tot financiering, investeringen, dividenden en beloningen verandert gedurende hun levenscycli. De levenscyclus van bedrijven beïnvloedt echter ook de communicatie tussen bedrijven en externe partijen. Door de sterk toegenomen bedrijfsdynamiek in de afgelopen decennia is de relevantie van de financiële informatie, die bedrijven aan externe partijen verstrekken, afgenomen. Gegeven deze tendens, is het – meer dan ooit - belangrijk om ook in de context van kapitaalmarkten de levenscyclus van bedrijven in acht te nemen in plaats van het statische perspectief te handhaven dat impliciet in voorgaand onderzoek is aangenomen. In mijn proefschrift verschaf ik inzicht in de rol die de levenscyclus van bedrijven heeft in het functioneren van kapitaalmarkten door het gedrag (en de interactie) tussen verschillende spelers op de kapitaalmarkten tijdens de verschillende levensfases van bedrijven te belichten.

Bedrijven zijn dynamische entiteiten die in de loop van de tijd verschillende ontwikkelingsfases doorlopen. De aaneenschakeling van ontwikkelingsfases die het bedrijf doorloopt van haar oprichting tot aan haar (mogelijke) faillissement, staat bekend als de levenscyclus van het bedrijf. Elke ontwikkelingsfase omvat een unieke combinatie van bedrijfskenmerken. Transities die bedrijven ondergaan tussen de verschillende fases van hun levenscycli worden veroorzaakt door zowel interne factoren, zoals bedrijfsstrategieën en -structuren, als externe factoren, zoals concurrentie en macro-economische ontwikkelingen.

Op basis van voorgaand onderzoek (Dickinson 2011; Gort en Klepper 1982; Miller en Friesen 1984) kan er een onderscheid worden gemaakt tussen vijf verschillende levensfases: *introductie*, *groei*, *volwassenheid*, *verzadiging*, en *verval*. Elk van deze levensfases wordt gekenmerkt door verschillen in financiële prestaties, investeringsgedrag en financieringsbehoeftes. Bedrijven die zich in de introductie- of groeifase bevinden, investeren veel in (de ontwikkeling van) nieuwe, creatieve projecten met veel winstpotentieel om een sterke positie in de markt te bemachtigen en groei te realiseren. Deze substantiële investeringen oefenen echter ook een neerwaartse druk uit op de winst van deze bedrijven. Hierdoor zijn de beschikbare financiële middelen om zelf te voorzien in de investeringen beperkt en is er een grotere vraag naar externe financiering. Indien bedrijven er in slagen hun producten in de markt te positioneren, zal de winstgevendheid van de producten toenemen. De

[54] **Dankwoord**: De Nederlandse samenvatting is mede tot stand gekomen dankzij de feedback en commentaren van Jo Hamers, Annelies Renders en Mark Vluggen.

stabiele financiële prestaties die volwassen bedrijven leveren, stellen hen in staat om zelf te voorzien in de financiering van projecten en leiden tot de mogelijkheid om de opgebouwde externe financiering af te bouwen. Ondanks de stabiliteit van volwassen bedrijven zullen zij waakzaam moeten zijn dat hun concurrentiepositie in de markt niet verslechtert. Mocht het bedrijven niet lukken om succesvol te concurreren met andere bedrijven en daarmee hun positie in de markt te behouden, kunnen zij in de verzadigingsfase belanden. Op basis van herstructureringen kunnen bedrijven in deze fase proberen om hun positie in de markt te behouden of te heroveren. Wanneer de pogingen om terug te keren naar een stabielere, meer winstgevende fase mislukken, kunnen bedrijven in verval geraken. In deze laatste fase van de levenscyclus zullen bedrijven proberen een dreigend faillissement af te wenden.

Welke levensfases bedrijven doorstaan, de volgorde daarvan, en de tijd die in de verschillende levensfases wordt doorgebracht, verschilt van bedrijf tot bedrijf. Zo zullen sommige bedrijven er niet in slagen om hun product succesvol in de markt te introduceren, waardoor deze bedrijven meteen in verval raken. Daarnaast zal de tijd die bedrijven doorbrengen in, bijvoorbeeld, de groei en volwassenheid sterk afhangen van de mate waarin zij hun concurrentiepositie in de markt kunnen verdedigen. Verder zal de mate waarin bedrijven succesvol zijn in hun herstructurering in de verzadigings- of vervalfase bepalen of zij terugkeren naar de introductie-, groei- of volwassen fase óf dichter bij een faillissement terecht komen. Tenslotte zal het aantal bedrijven niet gelijk over de vijf levensfases verdeeld zijn, maar zal het merendeel van de bedrijven zich in de groei of volwassenheid bevinden door de relatieve stabiliteit van deze fases.

Hoewel het moeilijk is om een maatstaf te vinden die de complexiteit en het unieke van elke levensfase van een bedrijf weet te omvatten, zal de optimale maatstaf – op basis van het bovenstaande – aan de volgende criteria moeten voldoen: de maatstaf (1) stelt bedrijven in staat om zich zowel voorwaarts als achterwaarts door de verschillende levensfases voort te bewegen; (2) vereist niet dat bedrijven elke levensfase doorlopen tijdens hun levenscyclus; (3) biedt de mogelijkheid om de tijd die bedrijven in de verschillende levensfases doorbrengen te laten variëren, zowel voor één bedrijf als tussen verschillende bedrijven; en (4) forceert geen gelijke verdeling van de bedrijven over de vijf levensfases. Veelvoorkomende maatstaven die in eerder onderzoek zijn gebruikt om de levenscyclus van bedrijven te meten, zoals de leeftijd en de grootte van bedrijven, zijn niet in staat om de complexiteit van de levenscyclus te omvatten. In tegenstelling tot deze veelgebruikte maatstaven, ontwikkelde en valideerde Dickinson (2011) een maatstaf op basis van het patroon in de drie soorten kasstromen van bedrijven – de operationele, de investerings-, en de financieringskasstroom – die wel voldoet aan de eerder genoemde criteria.[55] In mijn proefschrift is Dickinson's (2011) maatstaf dan ook gebruikt om per jaar te bepalen in welke levensfase bedrijven zich bevinden.

Zoals reeds aangegeven, is de levenscyclus van bedrijven geen onbekend begrip in voorgaand onderzoek. De toepassing van dit begrip in accounting onderzoek is echter beperkt, hetgeen vrij verrassend is gegeven de ontwikkelingen in de kapitaalmarkten gedurende de afgelopen decennia. Goedwerkende kapitaalmarkten zijn van cruciaal belang voor een efficiënte verdeling van het beschikbare (investeerders)kapitaal tussen bedrijven, die dit

[55] Zie tabel 1.1 (p. 7) voor een overzicht van Dickinson's (2011) maatstaf om bedrijven in te delen in de vijf levensfases op basis van het patroon in de operationele, investerings-, en financieringskasstromen.

kapitaal gebruiken om hun investeringen te financieren (Healy en Palepu 2001). Deze kapitaalallocatie vindt plaats op basis van effectenprijzen, die de verwachtingen van de toekomstige waarde van bedrijven weergeven (Kothari 2001). Bij de totstandkoming van deze prijzen speelt de financiële informatie, die bedrijven aan externe partijen verstrekken, een belangrijke rol. Ondanks de belangrijke rol van financiële informatie in het functioneren van kapitaalmarkten, hebben meerdere studies aangetoond dat de relevantie van deze informatie – d.w.z., de mate waarin de informatie beslissingen van spelers in de kapitaalmarkten beïnvloedt – is afgenomen gedurende de afgelopen decennia (zie bijvoorbeeld Lev en Zarowin 1999; Srivastava 2014; Zimmerman 2015).

De afname van de relevantie van financiële informatie wordt onder andere toegeschreven aan de snelle ontwikkelingen in de informatietechnologie en technologische innovatie (Core, Guay en Van Buskirk 2003); toegenomen concurrentie in een globaal speelveld (Irvine en Pontiff 2009); de overgang van een industriële economie naar een kennisgedreven economie (Srivastava 2014); en substantiële veranderingen in de fundamentele kenmerken van bedrijven (Fama en French 2004). De huidige boekhoudnormen beperken de mate waarin deze ontwikkelingen tijdig en adequaat in de financiële verslagen van bedrijven worden weergegeven. Daarnaast hebben de snelle ontwikkelingen in de (wereld)economie ook geleid tot een toename in de bedrijfsdynamiek. Zo zullen volwassen bedrijven door de toegenomen concurrentie – zowel nationaal als internationaal – en snelle technologische innovatie continu in staat moeten zijn om zich aan te passen aan het veranderende economische klimaat, willen zij hun verkregen status in de markt behouden. Samengevat, de toegenomen dynamiek in de kapitaalmarkten en de daaruit voortvloeiende consequenties onderstrepen het belang om bedrijven vanuit een dynamisch perspectief te beschouwen. Met behulp van de levenscyclus van bedrijven verschaf ik in de drie studies van mijn proefschrift inzicht in hoe deze bedrijfsdynamiek het gedrag van (en de interactie tussen) verschillende spelers op de kapitaalmarkten beïnvloedt.

In de eerste studie van mijn proefschrift (hoofdstuk 2) wordt de invloed van de levenscyclus van bedrijven op het risico op substantiële dalingen in aandelenprijzen, het zogenaamde "crashrisico", onderzocht. De grote verliezen op de aandelenportefeuilles van investeerders tijdens de recente financiële crisis hebben geleid tot meer aandacht voor de determinanten van het crashrisico van bedrijven. Over het algemeen wordt een hoger crashrisico toegeschreven aan een opeenstapeling van slecht nieuws en – wanneer een bepaalde drempel wordt bereikt – het daaropvolgende, plotselinge vrijkomen van dit slechte nieuws in de aandelenmarkten (Chen, Hong en Stein 2001; Hutton, Marcus en Tehranian 2009). Hoewel voorgaand onderzoek zich vooral heeft gericht op het opportunistische gedrag van managers als de voornaamste determinant van crashrisico, kan de levenscyclus van bedrijven dit risico ook via twee andere kanalen beïnvloeden: heterogeniteit in de verwachtingen van investeerders en misinterpretatie van bedrijfsinformatie gedurende de verschillende bedrijfsfases.

Met betrekking tot de heterogeniteit in de verwachtingen van investeerders wordt verwacht dat de grote invloed die de (toekomstige) groeimogelijkheden – in tegenstelling tot de waarde van de bestaande, materiële activa – hebben op de waarde van bedrijven in, met name, de introductie- en groeifase leidt tot grote verschillen in de verwachtingen over de actuele waarde van het bedrijf. Door de verschillende verwachtingen van investeerders over het groeipotentieel van deze bedrijven wordt slecht nieuws in eerste instantie niet volledig opgenomen in de aandelenprijs. Pas op het moment dat optimistische investeerders hun verwachtingen neerwaarts bijstellen, komt al het slechte nieuws ineens vrij in de aandelenmarkten wat kan leiden tot een 'crash' in de aandelenprijs. Conservatieve boekhoudnormen, die de mate waarin groeimogelijkheden in de financiële verslaggeving van bedrijven worden opgenomen beperken, dragen bij aan dit effect. Met betrekking tot de onjuiste interpretatie van bedrijfsinformatie suggereert voorgaand onderzoek dat sommige investeerders te zeer vasthouden aan de huidige prestaties van bedrijven in de introductie- en groeifase en daardoor té optimistisch zijn over hun toekomstige prestaties (Dickinson 2011). Ongeacht via welk kanaal de levenscyclus het crashrisico van bedrijven beïnvloedt, wordt dus verwacht dat dit risico het hoogst is voor bedrijven in de introductie- en groeifase.

Op basis van een steekproef van 62,004 bedrijf/jaar observaties over de periode 1990-2012 blijkt – in overeenstemming met de verwachting – dat het crashrisico van bedrijven inderdaad het hoogst is voor bedrijven in de introductie- en groeifase. Overeenkomstig de verwachte invloed van de (toekomstige) groeimogelijkheden van bedrijven, blijkt dit effect sterker te zijn voor bedrijven waarvan de marktwaarde meer afwijkt van de boekwaarde (een maatstaf voor het belang van groeimogelijkheden in de waarde van bedrijven). Daarnaast wordt de mate waarin slecht nieuws wordt opgenomen in aandelenprijzen, gehinderd door beperkingen op *short selling* – een investeringsstrategie waarin wordt geprofiteerd van dalende aandelenprijzen. De bevinding dat crashrisico hoger is voor groeibedrijven waarvoor er geen *short selling* is, kan dan ook worden toegeschreven aan de belemmerende rol van beperkingen op deze investeringsstrategie. Verder wordt de steekproef opgedeeld in twee groepen op basis van de huidige prestaties van de bedrijven (hoog versus laag) om zo een onderscheid te maken tussen de verschillende kanalen via welke de levenscyclus van bedrijven hun crashrisico kan beïnvloeden. Conform de verwachte rol die het (overmatige) optimisme van sommige investeerders speelt in het hogere crashrisico van bedrijven in de introductie- en groeifase, blijkt het crashrisico van deze bedrijven hoger te zijn wanneer zij beter presteren. De bevindingen in deze laatste analyse tonen echter ook aan dat de fixatie van sommige investeerders op de huidige prestaties van bedrijven niet in staat is om het hogere crashrisico van bedrijven in de introductie- en groeifase volledig te verklaren. Tenslotte toont verdere analyse aan dat de bevindingen in deze studie niet enkel toegeschreven kunnen worden aan het inherent hogere risico van bedrijven in de introductie- en groeifase.

Deze studie levert meerdere bijdrages aan de bestaande literatuur. Zo draagt de studie bij aan de literatuur over de levenscyclus van bedrijven door aan te tonen dat crashrisico zich op een voorspelbare manier ontwikkelt gedurende de levenscyclus. De levenscyclus heeft dus niet alleen een invloed op de hoogte van het verwachte rendement op aandelen, maar ook op de distributie van deze rendementen. De studie verschaft bovendien verder inzicht in de determinanten van crashrisico. Waar recente studies zich vooral richten op opportunistisch gedrag van managers, levert deze studie bewijs voor andere verklaringen voor een hoger crashrisico. De toename van het gebruik van staartrisico – het risico op extreme gebeurtenissen in de uiteinden van de rendementsdistributie – in risicobeheer en de invloed die dit risico heeft op de kapitaalkosten van bedrijven onderstrepen het belang om het bewustzijn van de verschillende factoren die bijdragen aan het crashrisico van aandelenprijzen te vergroten.

Op basis van de bevindingen in de eerste studie en eerder onderzoek op dit terrein, blijkt dat investeerders moeite hebben om de levenscyclus op een juiste manier in hun waarderingsmodellen op te nemen. In de tweede studie van mijn proefschrift (hoofdstuk 3) wordt onderzocht hoe het gedrag van financiële analisten, die functioneren als tussenpersonen in de communicatie tussen bedrijven en investeerders, wordt beïnvloed door de levenscyclus van bedrijven. De problemen die investeerders ondervinden in het verwerken van informatie met betrekking tot de levenscyclus, leidt tot een toename in de vraag naar de diensten van financiële analisten – vooral voor bedrijven in de introductie- en de groeifase. Dankzij hun geavanceerde analyses zijn financiële analisten vaak in staat om een deel van de "private" informatie van bedrijven (d.w.z., de informatie die niet onmiddellijk in de financiële verslaggeving zichtbaar is) bloot te leggen (Healy et al. 2001). Met behulp van de superieure bedrijfsinformatie die zij zo verkrijgen, kunnen zij investeerders helpen met hun investeringsadviezen en voorspellingen van toekomstige bedrijfsprestaties (Schipper 1991). Naast de vraag van investeerders, verandert ook de vraag vanuit bedrijven voor de diensten van financiële analisten gedurende de levenscyclus van bedrijven. Zo kunnen analisten bedrijven die zich aan de uiteinden van de levenscyclus bevinden, helpen om hun zichtbaarheid – die mogelijk beperkt is door bijvoorbeeld, het kleine aantal beleggers dat zij aantrekken – voor andere spelers op de kapitaalmarkten te vergroten (Bushee en Miller 2012). Dezelfde factoren die de analyse van investeerders tijdens de verschillende bedrijfsfases bemoeilijken, maken het echter ook voor analisten moeilijk om toekomstige bedrijfsprestaties te voorspellen. Daarnaast kan de beperkte zichtbaarheid van bedrijven leiden tot minder voordelen die analisten kunnen behalen in het volgen van deze bedrijven. Kortom, gegeven de verschillende kosten en baten van hun bedrijfsanalyses, is het niet duidelijk of analisten hun gedrag aanpassen aan de veranderende vraag voor hun diensten tijdens de levenscyclus van bedrijven.

Naast de mogelijke invloed die de levenscyclus van bedrijven heeft op de keuze van analisten om bepaalde bedrijven te volgen, kan deze ook de eigenschappen van de voorspellingen van analisten beïnvloeden. Naar verwachting maakt de relatieve instabiliteit van onvolwassen bedrijven het moeilijker voor analisten om toekomstige bedrijfsprestaties te voorspellen (Dickinson 2011; Donelson en Resutek 2015). Dit leidt waarschijnlijk tot minder accurate voorspellingen voor onvolwassen bedrijven. Echter, analisten kunnen beter met deze moeilijkheden omgaan wanneer zij in staat zijn gebruik te maken van hun industrie-expertise, de meest waardevolle eigenschap van analisten volgens henzelf en investeerders (Bradshaw 2015; Brown, Call, Clement en Sharp 2015). Analisten worden verwacht het meeste voordeel uit hun industrie-expertise te kunnen halen wanneer de bedrijfsfase overeenkomt met de levensfase waarin de industrie verkeert. In dit geval dienen branchegenoten als een beter referentiepunt voor het voorspellen van toekomstige bedrijfsprestaties. In tegenstelling tot de voordelen die overeenkomende levensfases van bedrijf en industrie kunnen opleveren, kunnen transities tussen bedrijfsfases tot problemen leiden voor analisten. Dit vanwege de tijd die het analisten mogelijk kost om de veranderingen, die deze transities met zich meebrengen, in hun voorspellingen te verwerken (Markov en Tamayo 2006).

In deze studie is gebruik gemaakt van een steekproef die informatie bevat over het gedrag van financiële analisten gedurende de periode 1994-2012. Conform de redenering dat analisten reageren op de behoeftes van investeerders, geven de resultaten aan dat bedrijven in de introductie- en groeifase door meer analisten worden gevolgd. In overeenstemming met de verwachtingen blijkt verder dat de voorspellingen van analisten minder accuraat zijn voor de meeste onvolwassen bedrijven, wanneer deze vergeleken worden met de voorspellingen voor volwassen bedrijven. Echter, de voorspellingen voor groeibedrijven blijken verrassend genoeg het meest accuraat te zijn. Verdere analyse geeft aan dat dit resultaat zich concentreert in groeibedrijven waarvan de bedrijfsfase overeenkomt met de levensfase van de industrie. Dit kan worden toegeschreven aan de grotere mate waarin analisten kunnen gebruik maken van hun industrie-expertise. Een soortgelijk positief effect van industrie-expertise wordt ook in andere levensfases aangetroffen. Tenslotte blijken transities tussen bedrijfsfases gevolgd te worden door een afname in de accuratesse van de voorspellingen van analisten. Dit suggereert dat analisten niet meteen in staat zijn om de veranderingen, die de transities met zich meebrengen, te verwerken.

Additionele analyses tonen aan dat analisten inderdaad *reageren* op een toename in de vraag naar hun diensten. Verder blijken analisten zowel meer introductie- en groeibedrijven te volgen waarvoor er meer heterogeniteit in de verwachtingen van investeerders is, als meer onvolwassen bedrijven met een zwakkere financiële positie en een kleiner aantal beleggers. De bevindingen van deze additionele analyses ondersteunen de bewering dat analisten de vraag van investeerders naar hun diensten in beschouwing nemen in hun keuze welke bedrijven te volgen.

Waar voorgaand onderzoek naar de rol van de levenscyclus van bedrijven in kapitaalmarkten zich met name heeft gericht op investeerders, geven de bevindingen in deze studie aan dat ook het gedrag van financiële analisten wordt beïnvloed door deze levenscyclus. Meer specifiek tonen de bevindingen aan dat analisten reageren op de veranderende behoeftes van investeerders gedurende de verschillende bedrijfsfases ondanks de daarbij behorende kosten. Daarnaast laat deze studie ook zien dat de voorspellingen van financiële analisten het meest accuraat zijn wanneer er overeenstemming is tussen de levenscycli van het bedrijf en de industrie tot welke zij behoort. De bevindingen tonen echter ook aan dat het enige tijd kost voordat analisten de gevolgen van veranderingen in bedrijfsfases hebben verwerkt in hun analyses.

Terwijl de eerste twee studies van mijn proefschrift zich richten op de invloed van de levenscyclus van bedrijven op de aandelenmarkt (d.w.z., investeerders in het eigen vermogen van bedrijven), onderzoek ik in de derde studie (hoofdstuk 4) hoe de levenscyclus de interactie tussen bedrijven en de verstrekkers van vreemd vermogen beïnvloedt. In voorgaand onderzoek in de financieringsliteratuur wordt over het algemeen gesproken over een negatief verband tussen de groeimogelijkheden van een bedrijf en de hoeveelheid vreemd vermogen in haar kapitaalstructuur (Myers 1977; Smith en Watts 1992). In schril contrast met deze algemene constatering, kan de combinatie van een gebrek aan intern gegenereerde financiële middelen met de ruime investeringsmogelijkheden in bedrijven in de introductie- en groeifase leiden tot een grotere vraag naar vreemd vermogen. Een recente studie, uitgevoerd door Faff, Kwok, Podolski, en Wong (2016), toont inderdaad aan dat de netto uitgifte en aantrekking van vreemd vermogen het hoogst is voor bedrijven in deze bedrijfsfases. Een mogelijke verklaring voor deze paradoxale bevindingen is dat de tegenstrijdige belangen van investeerders in het eigen vermogen en de verstrekkers van vreemd vermogen – die vaak worden aangehaald in het verklaren van het negatieve verband tussen groeimogelijkheden en vreemd vermogen – mogelijk een beperkte rol spelen in bedrijven in de introductie- en groeifase. Desondanks bestaat er nog steeds grote onzekerheid met betrekking tot de toekomstige waarde van het bedrijf in deze fases. Ten gevolge van deze onzekerheid moeten zowel de leners als de verstrekkers van het vreemd vermogen afwegingen maken die én de bron van het vreemd vermogen én de contractuele bepalingen in de overeenkomst tussen lener en verstrekker beïnvloeden.

Allereerst, wat betreft de bron van het vreemd vermogen, moeten de leners van vreemd vermogen een afweging maken tussen de kosten en baten die samenhangen met de verschillen in de controlemogelijkheden en flexibiliteit in heronderhandelingen tussen private (bijv. banken) en publieke (bijv. obligatiehouders) verstrekkers van vreemd vermogen. Hoewel de mogelijkheid tot scherpe controle, toegang tot private informatie, en het grotere gemak met welke private verstrekkers van vreemd vermogen de contractuele bepalingen kunnen heronderhandelen, leners bij hun investeringsbeslissingen van de nodige flexibiliteit kunnen voorzien ("*Controle hypothese*"), zijn deze bedrijven ook kwetsbaarder voor de mogelijke uitbuiting van private informatie door private verstrekkers van vreemd vermogen ("*Uitbuitingshypothese*") (Bharath, Sunder, en Sunder 2008; Rajan 1992). De geprefereerde bron van vreemd vermogen hangt in de introductie- en groeifase dus af van de afweging tussen de voordelen van de grotere flexibiliteit enerzijds en de nadelen van mogelijke uitbuiting door private verstrekkers van vreemd vermogen anderzijds.

Ten tweede, wat betreft de contractuele bepalingen, kunnen de verstrekkers van het vreemde vermogen meerdere onderdelen van het contract, zoals de looptijd, de interestvoet en convenanten, aanpassen om de onzekerheid over de toekomstige waarde van de lener op te nemen in de contractuele bepalingen (Aghion en Bolton 1992, Demerjian 2015). In overeenstemming met de bevindingen in eerder onderzoek (Bharath et al. 2008; Demerjian 2015), verwacht ik dat de leningsovereenkomsten tussen verstrekkers en bedrijven in de introductie- en groeifase hogere interestvoeten, kortere looptijden, en meer convenanten bevatten dan de leningsovereenkomsten van bedrijven in de andere bedrijfsfases. Echter, het belang van de verschillende contractuele bepalingen hangt hoogstwaarschijnlijk af van de bron van het vreemd vermogen. Gegeven het verschil in de flexibiliteit in het heronderhandelen van de contractuele bepalingen, verwacht ik dat publieke verstrekkers van vreemd vermogen meer geneigd zijn om de interestvoet en de looptijd van de leningsovereenkomst aan te passen. Private verstrekkers van vreemd vermogen maken daarentegen naar verwachting meer gebruik van convenanten in hun leningsovereenkomsten met bedrijven in de introductie- en groeifase.

Om de gestelde verwachtingen empirisch te testen, onderzoek ik een steekproef van private leningen en uitgegeven publieke obligaties in de periode 1989-2012. Nadat ik het belang van vreemd vermogen voor bedrijven in de introductie- en groeifase heb bevestigd, laat ik zien dat bedrijven in de introductie- en groeifase de uitgifte van publieke obligaties verkiezen boven het verkrijgen van private leningen. Dit resultaat is in overeenstemming met de "*Uitbuitingshypothese*", hetgeen suggereert dat de mogelijke kosten van de uitbuiting van private informatie door private verstrekkers van vreemd vermogen zwaarder wegen dan de contractuele flexibiliteit die zij kunnen verschaffen. Wanneer ik de (endogene) keuze voor de bron van vreemd vermogen in beschouwing neem, vind ik verder onderscheid in de manier waarop de twee types verstrekkers van vreemd vermogen de onzekerheid over de toekomstige waarde van bedrijven opnemen in hun leningsovereenkomsten. Waar beide verstrekkers van vreemd vermogen hogere interestvoeten voor bedrijven in de introductie- en groeifase hanteren, maken private verstrekkers van vreemd vermogen meer gebruik van convenanten voor groeibedrijven terwijl publieke verstrekkers van vreemd vermogen de voorkeur geven aan kortere looptijden.

Verdere analyses tonen aan dat zowel private als publieke verstrekkers van vreemd vermogen de keuze van de gebruikte convenanten aanpassen aan de behoeftes van de lener en de verschillen in de informatie die prestatiemaatstaven verstrekken gedurende de verschillende bedrijfsfases. Zo bevatten obligatieleningen, die uitgegeven worden door bedrijven in de introductie- en groeifase, minder convenanten die investeringen beperken dan de obligaties van volwassen bedrijven. Daarnaast bevatten de leningen die verstrekt worden aan de meeste onvolwassen bedrijven minder convenanten gebaseerd op prestatiemaatstaven. De convenanten van groeibedrijven worden eerder gebaseerd op de winst vóór interest, belastingen en de afschrijvingen op zowel materiële als immateriële activa (*EBITDA*) dan op de nettowinst.

Ook met deze laatste studie lever ik een aantal bijdragen aan de bestaande literatuur. Terwijl voorgaand onderzoek naar de rol van de levenscyclus van bedrijven in kapitaalmarkten vooral op de aandelenmarkt focust, tonen de bevindingen in deze studie aan dat de levenscyclus van bedrijven ook de keuze voor vreemd vermogen en leningsovereenkomsten beïnvloedt. Hoewel men kan redeneren dat de investeringspraktijken van bedrijven tijdens de introductie- en groeifase scherpe controle door private verstrekkers van vreemd vermogen vereist, suggereren de resultaten van mijn onderzoek dat deze bedrijven de voorkeur geven aan publieke obligaties om zo mogelijke uitbuiting van private informatie te voorkomen. Tevens houden de twee types verstrekkers van vreemd vermogen rekening met de dynamiek van bedrijven tijdens hun levenscycli, aangezien zij de contractuele bepalingen van leningsovereenkomsten aanpassen aan de kenmerken van de verschillende bedrijfsfases. Terwijl de convenanten in obligatieleningen meestal vrij gestandaardiseerd zijn (De Franco, Vasvari, Vyas en Wittenberg-Moerman 2015), blijken ook de convenanten in deze leningsovereenkomsten aangepast te worden aan de veranderende behoeftes van de lener gedurende de levenscyclus. Tot slot, terwijl eerdere studies naar de structuur van leningsovereenkomsten zich vooral hebben gericht op de tegenstrijdige belangen van investeerders in het eigen vermogen en de verstrekkers van vreemd vermogen, dragen de resultaten van mijn onderzoek bij aan recente bevindingen dat onzekerheid over de toekomstige waarde van de lener ook een belangrijke rol speelt in de structuur van leningsovereenkomsten.

CURRICULUM VITAE

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