The dynamics of innovation and firm performance: an econometric panel data analysis

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The Dynamics of Innovation and Firm Performance
An Econometric Panel Data Analysis

Proefschrift

ter verkrijging van de graad van doctor
aan de Universiteit Maastricht,
op gezag van Rector Magnificus,
Prof. mr. G.P.M.F. Mols
volgens het besluit van het College van Decanen,
in het openbaar te verdedigen
op donderdag 3 mei 2007 om 14.00 uur

door

Wladimir Raymond

To gran Clarisse and papa Lyn

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"I LOVE YOU".

Wladimir Raymond
Maastricht, March 2007

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CHAPTER 1

Introduction

1.1 Motivation

Technological innovation is recognized as being a key factor as both a creative force in the growth of enterprises and as a destructive force making those same enterprises prone to competition (Utterback, 1994). In the knowledge-based economy, innovation is also shown to play a positive role in firms' survival (Cefis and Marsili, 2005). New products and new processes keep being introduced into the market and force firms to adjust if they want to stay in the game. In order to stimulate economic growth, employment and environmental sustainability, governments are increasingly concerned about promoting firms' innovation but do not always have the right recipe to achieve their goal. It is hence very important to understand what makes firms innovative, how long it takes for innovation incentives to work out, how long it takes for R&D, trial production and first product launchings to become successful, and finally how long it takes between first product appearances and improvements of firm economic performance. Among the difficulties encountered by policy-makers in the past is the measurement of innovation. Early studies frequently use R&D activities (e.g. Hall and Hayashi, 1989) usually linked to productivity (e.g. Griliches and Mairesse, 1984; Mairesse and Sassenou, 1991), or patents (see Table 4.1) or both (e.g. Pakes and Griliches, 1984; Hall et al., 1986). In the 1980s scholars and statisticians in innovation felt growingly dissatisfied with the mere existence of R&D surveys or patent data to analyze innovation. Indeed, the

use of the sole R&D or patent data omits important aspects of the innovation process in that R&D is only one of various innovation inputs and some types of technology are not patentable.¹ Hence, under the auspices of OECD, the Oslo manual was written to guide a new kind of survey, the innovation survey also known in Europe as the Community Innovation Survey (CIS). In this survey, respondents are asked to give information about the input, the output and the behavioral and organizational dimensions of their innovations. On the input side, data on R&D expenditures and on other innovation expenditures besides R&D (such as product design, trial production, training of employees, and market analysis) are collected. On the output side, various market-based innovation indicators (unlike patents) are available, namely the declaration of whether an enterprise has introduced a new product or process, the percentage of sales due to incrementally or significantly improved or new products, and the share in sales of innovative products new to the enterprise or new to the industry. On the other dimensions of innovation, we have binary data on whether R&D is done continuously and in cooperation with others, and categorical data on the sources of knowledge, the reasons for innovating, the perceived obstacles to innovation, and the perceived strength of various appropriability mechanisms.

Several waves of the CIS have been launched since the first edition of the Oslo manual in 1992 making the use of panel data possible when analyzing the innovation process. The purpose of this thesis is to study the dynamics of innovation in Dutch manufacturing using firm data from three waves of the CIS pertaining to the periods 1994-1996, 1996-1998, and 1998-2000.² More specifically, the thesis seeks to answer questions related to the dynamics of innovation hitherto rarely examined when using the CIS such as the persistence of innovation considered on both the input and the output side, the effect of past R&D investments on current R&D investments, the effect of past share in total sales of innovative sales on current share in total sales of innovative sales, and the role of firm heterogeneity in the innovation process. Hence, the hypotheses of “success breeds success” (Mansfield, 1968), “dynamic economies of scales” and existence of *sunk costs* in firms’ innovation activities can be tested. The thesis also seeks to develop empirical models that can be applied to other types of

¹The limitations of R&D and patents are stressed in detail in the studies by Kleinknecht et al. (2002) and Griliches (1990) respectively.

²In The Netherlands, an additional survey pertaining to the period 1986-1988 was conducted prior to the first wave of the CIS (1990-1992). These two surveys could not be included in the thesis as they were conducted in a different manner. Furthermore, CIS 3.5 and CIS 4 pertaining to the periods 2000-2002 and 2002-2004 were not available at the time the research was being carried out.

economic panel data that have similar characteristics to the CIS data, hence contributing to the growing econometric literature on (dynamic) panel data.

1.2 Literature

As stated earlier, it is of great concern for policy-makers to understand the driving forces behind innovation and its socioeconomic consequences, hence the need for a model of the innovation process. A great deal of models that describe the innovation process exist in the literature. They range from the “naive” *linear models* to more realistic and more complex nonlinear models. The former also known as *pipeline* or *stage models* describe the innovation process as a series of stages assumed isolated from one another (Utterback, 1971), and the latter identify interrelationships between the various stages of the process (Kline and Rosenberg, 1986). Because of the complexity of the innovation process, no universal theoretical innovation model exists in the literature as it should include a myriad of factors that enter the process (Forrest, 1991). However, any model that describes the innovation process should account for the following critical factors identified by Forrest. Firstly, the model should be nonlinear in that the various stages of the innovation process are interrelated, and dynamic in that the process evolves over time. For instance, Utterback and Abernathy (1975) develop a nonlinear dynamic model of process and product innovation where the nature of the innovation process changes over time from new product development to process optimization and cost reduction. Secondly, the model should include both inputs and outputs of innovation so as to determine the effectiveness of the innovation process. Thirdly, the model should be of use with both product and process innovations, and must account for the effects of demand pull, technology push and “strategic alliances” (using Forrest’s terms) on the innovation process.³ Finally, firm heterogeneity should be accounted for due the dynamic feature of the innovation process. Indeed, firms have different innovative behavior because of different experience acquired from past innovative behavior. We are able to test empirically the relevance of those factors to the innovation process by including, in the specification of the models considered in the thesis, the above-mentioned variables which are available in the CIS.

³“Strategic alliances” include among others R&D cooperation with universities and research institutes. See Forrest (1991) for more details.

1.2.1 Theoretical explanations of the dynamics of innovation

Since the main issue of the thesis is the dynamics of innovation, it is worthwhile to stress its theoretical explanations.

On the input side, the persistence of R&D activities is usually explained by the hypothesis of *sunk costs*. For instance, Scherer (1967) argues that R&D is time dependent in that it is a heuristic process that involves significant uncertainties about feasible solutions. The *knowledge accumulation* theory (see for instance Hall and Hayashi, 1989; Klette, 1996) predicts that there is complementarity between current R&D effort and already acquired knowledge, hence R&D is a cumulative dynamic process. On the output side, Flaig and Stadler (1994) develop a stochastic dynamic optimization model where firms maximize their present value of profits over an infinite time horizon by choosing an optimal path of innovation activity. They allow for dynamic spillover effects and past innovation success, which reflects Mansfield's "success breeds success", i.e. past innovation success increases technological opportunities making future innovation success more likely. Finally, Stein (1997) develops a theoretical competition model that explains the dynamics of innovation by the *learning-by-doing* hypothesis.

1.2.2 CIS-based empirical studies of innovation

Due to the richness of the CIS in terms of innovation indicators, CIS-based empirical studies give a broader description of innovation than studies based on the sole traditional R&D and patent data. For instance, Brouwer and Kleinknecht (1996) model the decision to engage in R&D and the impact on the amount of R&D investments, and the effect of R&D investments on the probability to innovate and the share of innovative sales.⁴ Crépon et al. (1998, CDM) study in a unified framework the decision to engage in R&D activities and the impact on the amount of R&D investments, the effect of R&D investments on the share of innovative sales, and the effect of the share of innovative sales on productivity. Janz and Peters (2002) and Lööf and Heshmati (2002a) study variants of the CDM model and consider both the share in sales of innovative products new to the enterprise (incremental innovative sales) and new to the market (radical innovative sales). Janz and Peters find that the larger the firm the larger the probability to introduce incremental innovations while firm size does not increase the probability to introduce radical innovations. Lööf and Heshmati's results suggest that innovation investments play a role only in incremental innovations which have a larger effect

⁴See also Mairesse and Molnen (2001).

on firm productivity than radical innovations. Klomp and van Leeuwen (2001) depart from the CDM model using Kline and Rosenberg's (1986) *chain-link model* as the base framework and study the input and output stages of the innovation process linked with firm sales and employment growth. Unlike the CDM model, they allow for feedback effects of sales growth on innovation input and output.

In spite of their richness in explaining the innovation process, those studies fail to account for two important features of the process identified by Forrest, namely dynamics and firm heterogeneity.⁵ With the exception of Mairesse and Mohnen (2001), all the studies listed in Tables 2.6 and 6.7 assume similar innovative behavior across industries in that the parameters of the model are equal across industries. Furthermore, with the exception of van Leeuwen (2002) who considers a dynamic model of innovation, all those studies are static and fail to answer questions such as the persistence of innovation,⁶ the dynamics of R&D investments and innovation output. The thesis makes a step in that direction.

1.3 Contribution

As stated earlier, the thesis seeks to study the dynamics of innovation, hitherto rarely examined when using the CIS, using dynamic panel data econometric techniques, hence contributing to both the empirical literature on innovation and the econometric literature on (dynamic) panel data.

The thesis contributes to the empirical literature on innovation in a number of ways. Firstly, it analyzes the persistence of innovation using other output measures than patents (see Table 4.1). Secondly, unlike the empirical studies listed in Tables 2.6 and 6.7, three waves of the CIS, pertaining to the Dutch manufacturing sector, are used for the first time to link the persistence of innovation (qualitative) to the dynamics of firms' R&D investments and technological performance (quantitative). The incidence and the intensity of innovation are jointly estimated allowing for a correlation between the processes governing the introduction of new or significantly improved products and/or processes, and the generation of innovative sales (cf. Chapter 4), or the processes governing the engagement in innovation activities, R&D investments, and the generation of innovative sales (cf. Chapter 6). Finally, the thesis

⁵See Tables 2.6 and 6.7.

⁶Two other CIS-based empirical studies that investigate the persistence of innovation are Duguet and Monjon (2002) and Peters (2005). However, only the incidence of innovation is explained in those studies (See Chapter 4).

always accounts for observed and unobserved firm heterogeneity in the innovation process.

As for the contribution to the econometric literature, the thesis provides a practical method to the problem of the maximum likelihood estimation of the parameters of panel data sample selection models in which random individual effects (possibly correlated with the explanatory variables) and the lagged dependent variable are included in the selection equation as well as in the regression equation. The selection rule may be either of the binary or of the censoring type, the most two considered in the literature (see Table 3.1). To handle the initial conditions problem, Wooldridge's (2005) (cf. Chapter 3) and Heckman's (1981b) (cf. Chapter 5) solutions to this problem in single equation dynamic nonlinear panel data models are extended to models with two equations. "Two-step" Gauss-Hermite quadrature is used to evaluate the resulting double integral. In short, the thesis proposes a simple method to implement the maximum likelihood estimator of dynamic panel data extensions of the type 2 and type 3 tobit models, according to Amemiya's (1984) terminology. Furthermore, the thesis reports on a Monte Carlo investigation into the behavior in finite samples of the proposed method that is extended to dynamic panel data sample selection models with two regression equations and a selection equation (cf. Chapter 6). In this latter case, "three-step" Gauss-Hermite quadrature is used to evaluate the resulting triple integral.

1.4 Thesis outline

Chapter 2 studies the degree of homogeneity of innovative behavior in order to determine empirically an industry categorization of Dutch manufacturing that can be used for policy purposes. For each of the eleven Dutch manufacturing industries defined at two-digit level, we estimate a two-limit tobit model with sample selection that explains the decision by enterprises to innovate and, for innovators, the intensity of innovation as measured by the share of innovative sales. By estimating the model separately for each industry, possible differences in innovative behavior across industries are accounted for. Furthermore, within industries, we account for unobserved heterogeneity by treating "differently" non-innovators, process-only innovators, product innovators and "large" product innovators. The hypothesis of homogeneity of innovative behavior across industries is tested using a likelihood ratio (LR) test that reveals three types of categories of industries in Dutch manufacturing, namely high-tech, low-tech and the wood industry that seems to be different from the remaining

industries.

Chapter 3 investigates by means of Monte Carlo simulation the behavior of the maximum likelihood estimator of dynamic panel data extensions of the type 2 and type 3 tobit models with unobserved individual effects (possibly correlated with the explanatory variables) in each equation. The individual effects are assumed to be random following a normal distribution, and are “integrated out” from the joint density function for the data and individual effects. The initial conditions problem is solved using Wooldridge’s (2005) “simple solutions” that consist in writing the individual effects, in each period, as linear functions of the strictly exogenous explanatory variables and the initial conditions. The resulting likelihood functions involve a two-dimensional indefinite integral that is evaluated using two successive Gauss-Hermite approximations. In the Monte Carlo experiments, the “two-step” Gauss-Hermite quadrature works well for a number of integration points as small as two. Hence, the maximum likelihood estimation of the parameters in a random-effects dynamic sample selection model is feasible and could conceivably be incorporated as a command in a general use software package such as Stata.

In Chapter 4, we apply the dynamic type 2 tobit studied in Chapter 3 to a model of innovation that investigates the persistence of innovation and the dynamics of the share of innovative sales in Dutch manufacturing. We find that the persistence of innovation is spurious in the sense that, when unobserved individual effects and the initial conditions are properly handled, the persistence of innovation vanishes. More specifically, being successful in past innovation activities does not increase the probability of being successful in current innovation activities. However, past share of innovative sales does condition, albeit to a small extent, current share of innovative sales.

Chapter 5 considers an alternative way of handling the initial conditions problem, which consists in specifying a model for the initial conditions given the individual effects and the strictly exogenous explanatory variables. This model is often assumed to be similar to the underlying model of the remaining process (Heckman, 1981b). We then apply the Heckman approach to estimating the dynamic type 2 tobit model specified as in Chapter 4, hence studying the sensitivity of the persistence of innovation to the treatment of the initial conditions. We find that the lack of persistence is robust to the (proper) treatment of the initial conditions. We also investigate jointly the dynamics of incremental and radical innovations using a dynamic type 3 tobit using both the Heckman and the Wooldridge treatment of the

initial conditions. We find that the two approaches yield similar results in terms of the coefficients of the strictly exogenous variables while some differences arise in the coefficients of the lagged dependent variables and the individual effects.

In Chapter 6 we extend the model of Chapter 4 by adding a third equation of R&D investments. More specifically, we jointly investigate the dynamics of the decision to engage in innovation activities, that of R&D intensity and the share of innovative sales. The model is a dynamic panel data version of the first- and second-stage of the CDM model with individual effects in each equation. We use the same estimation method as in Chapter 3 extended to a sample selection model with two regression equations and a selection equation. “Three-step” Gauss-Hermite quadrature is now required to evaluate the likelihood function. The results suggest the presence of dynamics in the innovation process. Furthermore, the decision to engage in innovation activities, R&D intensity and the share of innovative sales are correlated at least through the individual effects, and unobserved firm heterogeneity plays an important role in the innovation process.

Finally, Chapter 7 summarizes the main findings of the thesis and stresses the limitations and recommendations for future research.

CHAPTER 2

A classification of Dutch manufacturing based on a model of innovation

2.1 Introduction

In order to encourage R&D or innovation, governments are interested in supporting firms that are expected to behave in a manner conducive to its policy objectives. It is necessary, therefore, to be able to identify categories of such firms towards which the support may be targeted, lest individual firms from a multitude of heterogeneous firms have to be selected. From an efficiency standpoint, these categories should be homogeneous in the sense that, within a category, the proportion of target firms should be as large as possible. The objective of this chapter is to study the degree of homogeneity of innovative behavior in order to determine empirically an industry categorization of Dutch manufacturing that can be used for policy purposes.

The most widely used categorization of industries is the Organization for Economic Co-operation and Development (OECD, 1999) industry classification. There are actually two OECD industry classifications. The first one uses only the direct R&D intensity expressed as the ratio of R&D expenditures over either gross output or value-added and distinguishes three categories of industries, namely the high-technology, the medium-technology, and the low-technology industries.¹ The second indicator uses the overall R&D intensity, which is de-

¹Hatzichronoglou (1997) points out that using value-added on the one hand and gross output on the other

defined as the ratio of R&D expenditures plus technology embodied in intermediate and capital goods over gross output. The revised classification, which is currently used, consists of four categories of industries: the high-technology, the medium-high-technology, the medium-low-technology and the low-technology industries.² The important point, however, is that the OECD taxonomy is based on a single innovation input indicator, namely the R&D intensity. This is too narrow. There are many other innovation policy instruments besides R&D support. For instance, a few of the wide-ranging policy reforms suggested by the OECD (1998) are “improving the efficiency and the leverage of industrial R&D support”, or “strengthening technology diffusion mechanisms by encouraging more competition in product markets”.

At least two other well-known classification schemes exist in the literature. One is the famous Pavitt (1984) taxonomy of innovating firms based on similarities and differences among sectors with respect to the sources, nature and impact of innovations, and the characteristics of innovating firms. Pavitt’s classification consists of three categories, namely the “supplier-dominated”, the “production intensive” and the “science-based” categories. The middle category consists of two sub-categories: “scale intensive” and “specialized-suppliers”. The other approach followed by Hollenstein (1996) and Baldwin and Gellatly (2000) is based on a principal components analysis accounting for a number of innovation indicators, such as worker skills and technology use, that are commonly used to classify industries. Their framework constitutes a multidimensional approach to industry classification. They state that existing industry taxonomies have a unidimensional characteristic and are therefore too narrow and incomplete.

In line with the approaches in the previous paragraph we also take a multidimensional view towards industry categorization. The main contribution of our study is to test an industry categorization based on an econometric model that explains innovation behavior. A category is called homogeneous if the parameters of the model for each industry in that category are identical. The model describes the decision to innovate and its impact on the share of innovative sales. This type of model has been used in many other studies. It is estimated for each two-digit industry using the standard industrial classification (SBI) and for categories formed by grouping industries, and then it is tested whether industries included in a category are similar in terms of innovative behavior. Firm-level data are used stemming

leads to different classifications.

²Industries that belong to these categories are described in details in OECD (1999).

from three Dutch Community Innovation Surveys (CIS) pertaining to the periods 1994-96, 1996-98 and 1998-2000, merged with production survey data. A comparison of the model-based categorization with other typologies concludes the chapter.

The chapter is organized as follows. The model and the likelihood ratio (LR) test are explained in Section 2.2. In Section 2.3 we describe the data sources, the variables constructed from the data samples, and some descriptive statistics. Empirical results for the model and the industry classification resulting from the LR test, and its policy implications are presented and discussed in Section 2.5. In Section 2.6 we summarize and conclude.

2.2 The model

The model we consider in this study explains the decision by Dutch manufacturing enterprises to innovate and, for innovators, the intensity of innovation as measured by the share of innovative sales. Modeling the determinants of innovation strongly depends on the design of the CIS. In the CIS a technological product and process (TPP) innovator is defined as an enterprise that has implemented new or improved products, and/or new or improved processes during the period under review. We have more information about TPP innovators than about non-TPP innovators. Our model therefore consists of two equations, a selection equation that discriminates between TPP innovators and non-innovators, and a regression equation explaining the share of innovative sales for innovators. Formally, our model can be written as

$$y_1^* = \beta_1' \mathbf{x}_1 + \epsilon_1, \quad (2.1)$$

$$y_2^* = \beta_2' \mathbf{x}_2 + \epsilon_2, \quad (2.2)$$

where the dependent variable is defined as

$$y_2 = \begin{cases} 0 & \text{if } y_1^* \leq 0 \text{ (non-innovators)} \\ c_1 & \text{if } y_1^* > 0 \text{ and } y_2^* \leq c_1 \text{ (process-only innovators)} \\ y_2^* & \text{if } y_1^* > 0 \text{ and } c_1 < y_2^* \leq c_2 \text{ ("normal" product innovators)} \\ c_2 & \text{if } y_1^* > 0 \text{ and } y_2^* > c_2 \text{ ("large" product innovators).} \end{cases} \quad (2.3)$$

As it stands in equations (2.1), (2.2) and (2.3), our model is a combination of the two-limit tobit model and the generalized tobit model.³ More specifically, it is a two-limit tobit model with sample selection. It is different from the former in that it consists of two decisions (two latent variables), and from the latter in that it has two additional thresholds c_1 and c_2 .

The latent variable y_1^* captures the potential post-innovation return to innovation for all enterprises. It is a function of explanatory variables included in the vector $\mathbf{x}_1$. When y_1^* is sufficiently large, i.e. the expected return to innovation is high enough, an enterprise has enough incentive to innovate, then the observed y_1 equals one, meaning that the enterprise is a TPP innovator. Moreover ϵ_1 is the error term that captures the effects unaccounted for by the model, and β_1 is the vector of parameters to be estimated.⁴ The second equation pertains only to TPP innovating firms. The dependent variable is the share of innovative sales in total sales y_2 . It is expressed as the ratio of sales from new or improved products over total sales. This figure is directly reported by the surveyed enterprises. As the original share of innovative sales lies within the unit interval, we take the logit transformation that may take on any real value. In addition, the logit transform makes the distribution of the share of innovative sales more symmetric than the original distribution of the share of innovative sales.⁵ β_2 is the vector of parameters to be estimated, and ϵ_2 is the error term capturing the effects influencing the share of innovative sales unaccounted for by the model.

The thresholds c_1 and c_2

TPP innovators comprise product-only innovators, process-only innovators, and product-and-process innovators. As there is no quantitative measure for a process innovation in the CIS, process-only innovators have a zero share of innovative sales during the period under review. Therefore, the logit transform of the share of innovative sales cannot be applied to process-only innovators. Mairesse and Mohnen (2001) choose to substitute, for the zero shares of process-only innovators, the smallest positive value of the original share of innovative sales, namely 0.01. Klomp and van Leeuwen (2001) use a similar approach where the smallest positive value of the share of innovative sales is 0.001. In our model, we choose to censor the zero values for process-only innovators, by fixing a threshold c_1 to 0.001 and treat all the zero

³The two-limit tobit model is described in details in Maddala (1983) and Thomas (2000). A variant of this model is the so-called model of friction used by Rosett (1959).

⁴In order to simplify the notation, the enterprise and industry subscripts have been dropped.

⁵See Appendix 2.B.

values as values that belong to the censored region.⁶ The difference between our approach and that of Mairesse and Mohnen (2001), and Klomp and van Leeuwen (2001) is that, for observations with share of innovative sales below the smallest observed positive value, the probability that the share is below this value has been used rather than the value of the density function evaluated at this value. The same holds for the category of “large” product innovators, i.e. enterprises whose sales are almost exclusively innovative sales. By fixing the threshold c_2 to 0.95, which is the value of the largest observed share less than one, values equal to unity are censored. Again, the probability that the share is above 0.95 has been used rather than the value of the density function evaluated at a value close to 1.

A further reason to introduce the thresholds c_1 and c_2 is that, according to the Oslo manual (OECD, 1997), process-only innovators are to be treated differently from product innovators and non-innovators. They are not to be treated as non-innovators, given that they have implemented new or improved processes. Actually, they produce unchanged products with changed methods, as opposed to non-innovators that produce unchanged products with unchanged methods. They are different from product-innovators in the sense that they have not implemented new or improved products (during the period under review), but they might do so in the future. Finally, the category of “large” product innovators, as measured by the share of innovative sales, mostly consists of firms that got established during the period studied by the innovation survey. Again, according to the Oslo manual (1997), these firms are to be treated differently, as they may be different from the remaining firms in terms of innovation activities, objectives and characteristics.

Estimation

In order to estimate the model, for each industry, the error terms are assumed to follow a bivariate normal distribution with zero mean and covariance matrix Σ with the error variance of the selection equation being normalized to one. The model is estimated by the method of maximum likelihood. Furthermore, we assume the vectors of disturbances to be independent across industries such that, the log-likelihood function for the Dutch manufacturing sector is the sum of the log-likelihood functions for each industry in this sector. The disturbance covariance matrix Σ is allowed to be different across industries.⁷

⁶For the estimation, logit transforms of the thresholds c_1 and c_2 have been used.

⁷The likelihood function of the two-limit tobit model with sample selection is given in Raymond et al. (2004), and derived in Appendix 2.A.

A likelihood ratio (LR) test for homogeneity among industries

The empirical studies on the determinants of innovation mentioned earlier implicitly assume that all industries in manufacturing have the same innovative behavior (in terms of the parameters of the model) and different intercepts. The only exception is the study by Mairesse and Mohnen (2001) that allows firms in the high-R&D industries to have a different innovative behavior than firms in the low-R&D industries. In our study, we account for possible differences in innovative behavior across industries by estimating our model for each of the eleven two-digit Dutch manufacturing industries. We shall be referring to this as the unrestricted model. Let a category, for instance, consist of k industries. The null hypothesis is that the p parameters of the model, i.e. the slope parameters, the two intercepts and the two parameters of Σ , for each of the k industries are equal versus the alternative that at least for one industry a parameter is different from the corresponding parameters of the $k - 1$ other industries. The resulting test statistic must be compared to the critical value for a χ^2 distribution with $(k - 1)p$ degrees of freedom. In the case that we allow the two intercepts in the k industries to differ, the number of degrees of freedom is $(k - 1)(p - 2)$.

2.3 Data

The data used to implement the model are collected by the *Centraal Bureau voor de Statistiek* (CBS). They stem from three waves of the Dutch Community Innovation Survey, CIS 2, 2.5 and 3, merged with data from Production Survey (PS). Only enterprises in Dutch manufacturing (SBI 15-37) are included in the analysis. The population of interest consists of enterprises with at least ten employees and positive sales at the end of the period covered by the innovation survey.

The CIS data are collected at the enterprise level. A combination of a census and a stratified random sampling is used. A census is used for the population of large enterprises, while a stratified random sampling is used for small- and medium-size enterprises. The size of an enterprise is measured by the number of employees, and the stratum variables are the economic activity and the size of an enterprise, where the economic activity is given by the Dutch standard industrial classification (SBI 1993). The cut-off point used by CBS to choose between a census and a sampling is 100 employees.

Like in the CIS, the statistical unit of analysis within the Production Survey is the enter-

prise. A census is also used for large enterprises, and a stratified random sampling for small- and medium-size enterprises. The stratum variables and the cut-off points are the same as in the CIS. However, unlike the CIS, non-financial activities are not covered by the PS, implying that enterprises in the institutions of finance, insurance and pension funds (SBI 65-67) are not surveyed. The PS data included in this study replace the CIS equivalents and pertain to the periods 1996, 1998 and 2000. The corresponding CIS data have been removed from the CIS data base.

We now explain the construction of the variables included in this analysis.

Innovation dummy

In the innovation survey, an enterprise is asked (1) whether it has implemented at least one new or improved product, (2) whether it has implemented at least one new or improved process, and (3) whether it has ongoing or abandoned innovative projects during the period under review. TPP innovators are those enterprises that have responded positively to either (1) or (2) or both.

Intensity of innovation

The CIS questionnaire provides information regarding the share of innovative sales in total sales. This is the measure for the success of product innovation used in this study. A logit transformation of this measure is used for reasons mentioned earlier in the analysis. A non-TPP innovator has automatically a zero innovation output intensity. Because there is no quantitative measure of the success of process innovations in the innovation survey, some TPP innovators also have a zero innovation output intensity. They are called process-only innovators.⁸

Size

The size of an enterprise used in this study is measured by the number of employees. This variable stems from the PS and is log-transformed.

Relative size

This variable is defined as the ratio of the sales of an enterprise over the total sales of the industry that it belongs to. A log-transformation of this ratio is used.

⁸In fact enterprises that report to have implemented at least one new or improved product but report a zero value for the share of innovative sales in total sales are considered as non-product innovators in the analysis.

Because of the way the innovation survey is designed, very few explanatory variables are available for innovators and non-innovators. Size and relative size are the only two variables that are available for all enterprises.⁹ This is the reason why, except for industry dummies, these are the only two variables that have been included in the vector $\mathbf{x}_1$ in equation (2.1). The vector $\mathbf{x}_2$ in equation (2.2) comprises, besides industry dummies, the variables size, demand pull, technology push, subsidies, cooperation, R&D intensity, continuous R&D and non-R&D performer.

Demand pull

In the CIS questionnaire, an enterprise is asked about the importance of the objectives of innovation, “open-up new markets”, “extend product range” and “replace products phased out”, on the basis of a 0-3 Likert scale. A dummy variable proxying demand pull equals one for an enterprise if at least one of the above objectives of innovation is given the highest mark (i.e. very important), and zero otherwise.

Technology push

Other innovation indicators available in the CIS are the sources of innovation. They may be internal (from the enterprise or other enterprises within the enterprise group), from the market (e.g. clients or customers), from public or private institutions (e.g. universities) or from other locations. Technology push is proxied by a dummy variable constructed from the indicators stating the importance of the sources of innovation from public or private institutions. This proxy takes on the value one if at least one of these institutions are deemed to be important or very important to an enterprise (i.e. at least one of the sources of innovation stemming from public or private institutes is given the values 2 or 3), and zero otherwise.

Subsidies

If an enterprise answers that it has been granted at least a subsidy during the period under review, the variable subsidies takes on the value one and zero otherwise.

Innovation cooperation

The dummy variable innovation cooperation takes on the value one if the enterprise reports that it undertook its innovative activities in cooperation of any kind and zero otherwise.

⁹In the innovation survey enterprises report whether they belong to a group or not. This potentially important information was, however, not available in the data provided by CBS.

R&D intensity

R&D intensity is the ratio of total (intramural and extramural) R&D expenditures (from the CIS) over total sales. The logarithmic transform of this variable is used when the variable takes on a positive value.

Continuous R&D

The dummy variable continuous R&D takes on the value one if the enterprise reports that it performed intramural R&D continuously during the period under review and zero otherwise.

Non-R&D performer

The dummy variable non-R&D performer takes on the value one if the enterprise had no (intramural or extramural) R&D expenditures during the period under review and zero otherwise.¹⁰

2.4 A model-based industry classification

Our industry taxonomy stems from likelihood ratio tests performed on our model. Table 2.1 reports the relevant statistics to perform the likelihood ratio test. The unrestricted model consists of eleven sub-models, where the log-likelihood is the sum of the eleven log-likelihoods of the sub-models. The restricted model assumes that the parameters are identical for industries within the categories referred to as high-tech, low-tech and wood, respectively (allowing for different industry dummies), and allows differences across categories. The results of Table 2.1 show that the restricted model, i.e. the classification into three categories, is not rejected at the conventional 5% level of significance with a *p-value* ranging from almost 20% to almost 30%. When the industry of wood is classified into either the low-tech category or the high-tech category, the restricted model is rejected with *p-values* below 1%.

Hence, an analysis of the innovative behavior of the enterprises in the Dutch manufacturing sector during 1994-2000 reveals that this sector can be classified into three categories. The categories consist of the industries of i) chemicals, electrical, machinery and equipment

¹⁰In addition to the variable R&D intensity, the dummy variable non-R&D performer is included in the analysis to 'compensate' for the fact that the log transform of the original R&D intensity is set up to zero for observations with original R&D intensity equal to zero.

(M&E), plastic and vehicle (that we refer to as high-tech), ii) food, metals, non-metallic products, textiles, and products not elsewhere classified (that we refer to as low-tech); and iii) wood that seems to be different from the remaining industries in Dutch manufacturing. All the industries in each category have the same innovative behavior in the sense that, the parameters of the model for the industries in that category are identical with the exception of the intercepts.

Table 2.1: Likelihood ratio test results for the two-limit tobit model with sample selection: CIS 2, CIS 2.5, CIS 3 The Netherlands

Industry	#parameters	CIS 2	CIS 2.5	CIS 3
log-likelihood				
Chemicals (SBI 23-24)	14	-482.376	-465.442	-490.161
Electrical (SBI 30-33)	14	-579.374	-528.182	-359.803
Machinery & equipment(SBI 29)	14	-761.739	-808.456	-683.550
Plastic (SBI 25)	14	-344.978	-334.675	-257.036
Vehicle (SBI 34-35)	14	-429.351	-366.979	-217.786
Food (SBI 15-16)	14	-845.271	-733.758	-581.581
Metals (SBI 27-28)	14	-892.064	-997.108	-878.325
Non-metallic (SBI 26)	14	-285.001	-257.903	-166.512
NEC (SBI 36-37)	14	-374.764	-346.728	-468.495
Textile (SBI 17-19)	14	-408.923	-281.351	-163.174
Wood (SBI 20-22)	14	-1001.419	-1028.358	-813.283
Unrestricted model	154	-6405.260	-6148.940	-5079.706
High-tech (SBI 23-25, 29, 30-35)	22	-2625.407	-2529.387	-2038.133
Low-tech (SBI 15-19, 26-28, 36-37)	22	-2831.791	-2642.834	-2280.811
Wood (SBI 20-22)	14	-1001.419	-1028.358	-813.283
Restricted model	58	-6458.617	-6200.579	-5132.227
p-values				
Test restricted-unrestricted		0.214	0.287	0.248

We also test for homogeneity of the innovative behavior of the three categories across the three waves of innovation survey. Pooling the data of the three waves for each category, we are able to jointly test for equality of the parameters of the model for each category across waves, allowing for different industry and time intercepts. Assuming that the vector of disturbances are independent over time, we find that the innovative behavior of the three categories in CIS 2 is similar to that in CIS 2.5, with a $\chi^2(36) = 46.72$ and a $p\text{-value} = 0.109$; while the innovative behavior of the three categories in CIS 3 is different from that in CIS 2.5, with a $\chi^2(36) = 64.72$ and a $p\text{-value} = 0.002$.

In Table 2.2 the descriptive statistics are shown for the three categories based on the testing procedure described above. The difference in the percentage of innovators and the

Table 2.2: Descriptive statistics for the 3 categories, means and standard deviations in parentheses for continuous variables: CIS 2 CIS 2.5 CIS 3
3 The Netherlands

Variable	CIS 2			CIS 2.5			CIS 3		
	High-tech industries	Low-tech industries	Wood	High-tech industries	Low-tech industries	Wood	High-tech industries	Low-tech industries	Wood
Number of firms	1281	1472	541	1244	1421	555	1008	1241	472
Dependent variables									
Percentage of innovators	0.742	0.594	0.538	0.741	0.588	0.539	0.699	0.552	0.492
Intensity of innovation for innovators	0.351 (0.276)	0.248 (0.246)	0.226 (0.257)	0.347 (0.265)	0.241 (0.226)	0.210 (0.248)	0.351 (0.268)	0.255 (0.241)	0.218 (0.246)
Independent variables									
Demand pull for innovators	0.651	0.576	0.543	0.576	0.480	0.472	0.787	0.739	0.659
Technology push for innovators	0.229	0.220	0.124	0.206	0.167	0.114	0.241	0.187	0.142
Subsidies for innovators	0.635	0.529	0.234	0.648	0.476	0.288	0.662	0.480	0.228
Innovation cooperation for innovators	0.354	0.332	0.237	0.334	0.248	0.224	0.369	0.272	0.246
Size (in log)	4.165 (1.121)	4.023 (1.058)	4.039 (1.063)	4.087 (1.104)	3.984 (1.076)	3.982 (1.097)	4.250 (1.178)	4.225 (1.222)	4.028 (1.074)
Relative size (in log)	-6.725 (1.432)	-6.828 (1.554)	-7.234 (1.297)	-6.838 (1.489)	-6.957 (1.672)	-7.333 (1.348)	-6.577 (1.442)	-6.712 (1.563)	-7.051 (1.272)
Continuous R&D, if performing R&D	0.782	0.669	0.549	0.780	0.671	0.580	0.828	0.671	0.560
Non-R&D performers	0.127	0.209	0.405	0.178	0.250	0.435	0.190	0.304	0.461
R&D intensity, if performing R&D (in log)	-3.442 (1.389)	-4.156 (1.560)	-4.198 (1.603)	-3.454 (1.465)	-4.311 (1.600)	-4.291 (1.644)	-3.514 (1.405)	-4.563 (1.367)	-4.838 (1.224)

average intensities of innovation for innovators show up very clearly. Firms that belong to the high-tech category have on average larger intensities of innovation and larger R&D intensities, receive innovation subsidies more often and innovate more frequently than firms in the low-tech category and in the wood industry. The first category of firms also perform R&D more frequently and more often on a continuous basis. For the three CIS, the enterprises in the wood industry seem to be rather different from the enterprises in the manufacturing industries. These differences are particularly pronounced for the dependent variables, the R&D variables and the dummy for subsidies. One explanation for this is that the wood industry consists of a high percentage of process-only innovators. The percentage of TPP innovators in the wood industry that are granted a subsidy is roughly 30 per cent while this percentage is more than 50 per cent in total manufacturing (figures not shown in the tables). We can also note that in the wood industry, the percentage of R&D performers among TPP innovators, the percentage of continuous R&D performers among R&D performers, and the average R&D intensities are rather different from the equivalent figures for the other two categories. However, firms in the three categories on average do not differ significantly in terms of size and relative size.

Across the three waves of the CIS the characteristics and the activities of the enterprises in Dutch manufacturing are rather similar. The only variables that vary from one wave to another are demand pull, size and relative size as measured by the market share. The values of these variables show a decrease from CIS 2 to CIS 2.5 and an increase in CIS 3.

2.5 Parameter estimates and innovation policy implications

In order to derive possible innovation policies, we shall discuss the estimated coefficients of the explanatory variables which are to be understood as innovation policy instruments. In the wood industry, the reference group is an enterprise that performs R&D occasionally, having no innovation cooperation of any kind, for which neither demand pull nor technology push are important, and not being granted innovation subsidies. In the high-tech and low-tech categories, the reference group is an enterprise having the same characteristics as above, and that belongs to the industries of chemicals products and products not elsewhere classified respectively.

Table 2.3: Maximum likelihood estimation results: CIS 2 The Netherlands

Variable	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)
Intensity of innovation						
	High-tech		Low-tech		Wood	
Size (in log)	-0.195**	(0.071)	-0.691**	(0.116)	-1.194**	(0.289)
Demand pull	0.260 [†]	(0.137)	0.749**	(0.178)	1.083**	(0.395)
Technology push	-0.074	(0.162)	-0.089	(0.220)	-0.343	(0.611)
Innovation cooperation	0.261 [†]	(0.150)	0.275	(0.200)	0.992*	(0.505)
Non-R&D performers	-0.467	(0.311)	-1.344**	(0.371)	-0.275	(0.817)
Continuous R&D	0.830**	(0.176)	0.500*	(0.210)	0.448	(0.517)
R&D intensity (in log)	0.165**	(0.052)	0.170**	(0.065)	-0.040	(0.162)
Subsidies	0.451**	(0.154)	0.146	(0.203)	0.729	(0.512)
Electrical	0.811**	(0.220)	-	-	-	-
M&E	0.831**	(0.204)	-	-	-	-
Plastic	0.475 [†]	(0.249)	-	-	-	-
Vehicles	1.141**	(0.250)	-	-	-	-
Food	-	-	-0.376	(0.348)	-	-
Metals	-	-	-0.081	(0.339)	-	-
Non-metallic	-	-	-0.559	(0.433)	-	-
Textile	-	-	0.314	(0.394)	-	-
Intercept	-0.740	(0.452)	2.805**	(0.608)	4.566**	(1.341)
σ	2.190**	(0.080)	3.404**	(0.134)	5.571**	(0.390)
Probability to innovate						
Size (in log)	0.070	(0.086)	0.209**	(0.059)	0.092	(0.111)
Relative size (in log)	-0.207**	(0.067)	0.105**	(0.040)	0.071	(0.087)
Electrical	-0.371**	(0.141)	-	-	-	-
M&E	-0.393**	(0.145)	-	-	-	-
Plastic	-0.580**	(0.207)	-	-	-	-
Vehicles	-0.717**	(0.153)	-	-	-	-
Food	-	-	0.249 [†]	(0.146)	-	-
Metals	-	-	0.131	(0.121)	-	-
Non-metallic	-	-	0.119	(0.137)	-	-
Textile	-	-	-0.143	(0.118)	-	-
Intercept	2.195*	(0.857)	0.012	(0.448)	0.221	(1.051)
ρ	-0.668**	(0.071)	-0.881**	(0.023)	-0.960**	(0.013)
Number of firms	1281		1472		541	
Log-likelihood	-2625.407		-2831.791		-1001.419	

Significance levels : [†]: 10% *: 5% **: 1%

2.5.1 The selection equation

Size and Relative size

According to the Schumpeterian tradition, the size and relative size of an enterprise influence positively the decision by this enterprise to engage in innovation activities, e.g. R&D, as well as the probability to be a product innovator. It is often argued that larger firms have better access to finance. Therefore, they are more likely to engage in risky projects,

and benefit from economies of scale. All empirical studies in Table 2.6 find such an evidence. Either size or relative size (or both) positively and significantly affects the probability to innovate in our high-tech and low-tech categories. The effect of size is less evident for the wood industry (only for CIS 2.5 there is a significant effect of size). Size and relative size are always significant in the low-tech industry.

Table 2.4: Maximum likelihood estimation results: CIS 2.5 The Netherlands

Variable	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)
Intensity of innovation						
	High-tech		Low-tech		Wood	
Size (in log)	-0.214**	(0.071)	-0.785**	(0.109)	-0.410	(0.259)
Demand pull	0.741**	(0.131)	0.571**	(0.160)	1.102**	(0.369)
Technology push	0.038	(0.161)	0.316	(0.229)	0.767	(0.650)
Innovation cooperation	0.277†	(0.144)	0.418*	(0.201)	0.298	(0.485)
Non-R&D performers	-0.419	(0.280)	-0.565†	(0.312)	0.540	(0.758)
Continuous R&D	0.813**	(0.176)	0.834**	(0.203)	0.012	(0.515)
R&D intensity (in log)	0.126*	(0.051)	0.148**	(0.057)	-0.092	(0.146)
Subsidies	0.442**	(0.154)	0.305†	(0.182)	0.407	(0.466)
Electrical	0.220	(0.231)	-	-	-	-
M&E	0.381†	(0.211)	-	-	-	-
Plastic	0.087	(0.256)	-	-	-	-
Vehicles	0.724**	(0.258)	-	-	-	-
Food	-	-	-0.521	(0.345)	-	-
Metals	-	-	-0.547†	(0.327)	-	-
Non-metallic	-	-	-0.873*	(0.428)	-	-
Textile	-	-	-0.438	(0.415)	-	-
Intercept	-0.561	(0.425)	3.211**	(0.559)	0.935	(1.307)
σ	2.304**	(0.076)	3.315**	(0.121)	5.548**	(0.379)
Probability to innovate						
Size (in log)	0.005	(0.078)	0.204**	(0.061)	0.272**	(0.101)
Relative size (in log)	0.240**	(0.059)	0.135**	(0.041)	-0.093	(0.075)
Electrical	-0.102	(0.129)	-	-	-	-
M&E	-0.198	(0.122)	-	-	-	-
Plastic	-0.447*	(0.178)	-	-	-	-
Vehicles	-0.444**	(0.136)	-	-	-	-
Food	-	-	0.220	(0.150)	-	-
Metals	-	-	0.166	(0.127)	-	-
Non-metallic	-	-	-0.060	(0.140)	-	-
Textile	-	-	-0.193	(0.132)	-	-
Intercept	2.498**	(0.746)	0.253	(0.462)	-1.685†	(0.922)
ρ	-0.831**	(0.033)	-0.931**	(0.013)	-0.963**	(0.012)
Number of firms	1244		1421		555	
Log-likelihood	-2529.387		-2642.834		-1028.358	
Significance levels :	†: 10%	*: 5%	**:	1%		

Significance levels : †: 10% *: 5% **: 1%

Crépon et al. (1996) point out that controlling for technological opportunities and appropriability may render the size or relative size effect on the probability to innovate insignificant. In our case technological opportunities and appropriability are captured by industry dummies, in the sense that it is easier to innovate in some industries than in others and that the way of appropriability of innovation differs with different industries. A case in point may be our finding of no significant effects of size and relative size for the wood industry,

Table 2.5: Maximum likelihood estimation results: CIS 3 The Netherlands

Variable	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)
Intensity of innovation						
	High-tech		Low-tech		Wood	
Size (in log)	-0.343**	(0.082)	-0.659**	(0.117)	-1.040**	(0.310)
Demand pull	0.537*	(0.198)	1.400**	(0.235)	2.036**	(0.434)
Technology push	-0.177	(0.199)	0.378	(0.261)	0.698	(0.629)
Innovation cooperation	0.504**	(0.182)	0.424 [†]	(0.233)	0.512	(0.542)
Non-R&D performers	-1.165**	(0.439)	-1.640**	(0.557)	-2.454 [†]	(1.368)
Continuous R&D	0.053	(0.252)	0.060	(0.269)	-0.183	(0.616)
R&D intensity (in log)	0.220**	(0.070)	0.263**	(0.092)	0.303	(0.240)
Subsidies	0.360 [†]	(0.196)	0.115	(0.222)	-0.004	(0.538)
Electrical	0.810**	(0.277)	-	-	-	-
M&E	0.857**	(0.239)	-	-	-	-
Plastic	0.226	(0.301)	-	-	-	-
Vehicles	1.205**	(0.322)	-	-	-	-
Food	-	-	-0.437	(0.376)	-	-
Metals	-	-	-0.415	(0.353)	-	-
Non-metallic	-	-	-0.832	(0.531)	-	-
Textile	-	-	-0.269	(0.539)	-	-
Intercept	0.808	(0.602)	3.457**	(0.816)	5.891**	(1.879)
σ	2.463**	(0.103)	3.718**	(0.169)	5.724**	(0.475)
Probability to innovate						
Size (in log)	0.324**	(0.072)	0.165**	(0.044)	0.046	(0.088)
Relative size (in log)	-0.022	(0.059)	0.075*	(0.037)	0.076	(0.068)
Electrical	-0.170	(0.146)	-	-	-	-
M&E	-0.223 [†]	(0.121)	-	-	-	-
Plastic	-0.124	(0.186)	-	-	-	-
Vehicles	-0.415**	(0.156)	-	-	-	-
Food	-	-	0.086	(0.112)	-	-
Metals	-	-	0.111	(0.101)	-	-
Non-metallic	-	-	-0.150	(0.156)	-	-
Textile	-	-	-0.151	(0.161)	-	-
Intercept	-0.803	(0.711)	-0.115	(0.417)	0.306	(0.794)
ρ	-0.781**	(0.048)	-0.911**	(0.019)	-0.964**	(0.014)
Number of firms	1008		1241		472	
Log-likelihood	-2038.133		-2280.811		-813.283	
Significance levels :	†: 10%	*: 5%	**: 1%			

that in this interpretation is homogeneous with respect to technological opportunities and appropriability.

2.5.2 The intensity equation

Size

The literature on the determinants of innovation reveals that there is mixed evidence with regard to the effect of size on the share of innovative sales in total sales given that a firm is an innovator. Our finding is in accordance with Brouwer and Kleinknecht (1996) and Janz et al. (2004), i.e., for the three CIS and for each category (except for the wood industry in CIS 2.5), smaller enterprises are more innovation intensive than their larger counterparts. While size is good for getting firms onto the innovation bandwagon, at least in low-tech industries, it does not lead to large shares of innovative sales. This holds for all categories.

Demand pull

On the basis of the Schmookler tradition, many empirical studies on the determinants of innovation include the variable demand pull as an explanatory variable of innovation. Regardless of the proxy used for demand pull, a majority of these studies find a positive impact on innovation output intensity. Our finding is in accordance with these studies. In other words, for each category and during the three periods under review, the variable demand pull has a positive impact on the share of innovative sales.

Technology push

Schumpeter's tradition reveals that technology push enhances innovation. However, many empirical studies find no evidence with regard to the positive effect of technology push on innovation. Our finding is in accordance with these studies, i.e., technology push does not seem to play a role in the innovation output intensity. It is often argued that, when controlling for technological opportunities, appropriability and demand conditions, as we do using industry dummies, pro-Schumpeterian results turn out non-significant (Crépon et al., 1996).

Cooperation

Unlike the previous empirical studies in Table 2.6, we find some evidence with regard to the role of cooperation in innovation output intensity. In some cases, cooperating innovators

Table 2.6: Empirical findings from studies on the determinants of innovation in manufacturing using the Community Innovation Survey

Study	Size	Relative size	Demand	Technology	Cooperation	Performing R&D	R&D inten-	Continuous R&D	Subsidy
			pull	push			sity		
Innovation output: share of innovative sales									
Brouwer and Kleinknecht (1996)	- effect	n.a	+ effect	n.a	no effect	n.a	+ effect	+ effect	n.a
Crépon et al. (1998)	no effect	n.a	+ effect	+ effect	n.a	n.a	+ effect	n.a	n.a
Mairesse and Mohnen (2001)	+ effect	n.a	+ effect	no effect	no effect	+ effect	+ effect	+ effect	n.a
Mohnen and Dagenais (2001)	no effect	n.a	+ effect	n.a	no effect	n.a	no effect	+ effect	n.a
Janz and Peters (2002)	+/- effect [‡]	n.a	no effect	no effect	n.a	n.a	n.a	n.a	n.a
Janz et al. (2004)	- effect	n.a	no effect	no effect	no effect	n.a	n.a	n.a	no effect
This study	- effect	n.a	+ effect	no effect	+ effect [*]	+ effect ^{**}	+ effect [†]	+ effect [†]	+ effect [†]
Probability to innovate									
Brouwer and Kleinknecht (1996)	+ effect	n.a	+ effect	n.a	no effect	n.a	+ effect	+ effect	n.a
Crépon et al. (1998)	+ effect	+ effect	+ effect	+ effect	n.a	n.a	n.a	n.a	n.a
Mairesse and Mohnen (2001)	+ effect	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a
Mohnen and Dagenais (2001)	+ effect	n.a	+ effect	n.a	n.a	n.a	n.a	n.a	n.a
Janz and Peters (2002)	+ effect	no effect	n.a	n.a	n.a	n.a	n.a	n.a	n.a
Janz et al. (2004)	+ effect	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a
This study	+ effect	+ effect [†]	n.a	n.a	n.a	n.a	n.a	n.a	n.a

[‡]The relationship between innovation output and size is inverted U-shaped. ^{*}There is some evidence for the three categories: [†]Only for the high- and low-tech categories; ^{**}There is some evidence for the high- and low-tech categories; [†]Only for the high-tech category;

seem to be more successful than non-cooperating innovators with the same characteristics. This is particularly so for the high-tech category in the three waves of the CIS. However, generally speaking the estimates of the effect of cooperation are not very precise. Based on the argument that developing innovation in cooperation is relevant mostly to firms lacking knowledge ("weak" innovators) we would expect cooperation to be particularly important for the low-tech or the wood industry compared to high-tech industry.¹¹ This is not borne out by our results.

R&D

It is often argued that experience and knowledge accumulated from past R&D positively influences innovation output. The three variables pertaining to R&D usually have a positive and significant effect on innovation output intensity in previous studies. There is some evidence that, among the innovators in the low-tech and high-tech categories, non-R&D performers are less successful than R&D performers with the same characteristics. This dummy variable hardly matters for the wood industry. Furthermore, except for CIS 3, in both the high-tech and low-tech categories, innovators that perform R&D on a continuous basis are more successful than those that perform R&D occasionally with the same characteristics. Again, there is no apparent effect of performing R&D continuously in the wood industry. Finally, R&D intensity, as measured by total R&D expenditures over total sales, always plays a positive and significant role in the innovation output intensity for the high-tech and for the low-tech categories. This variable never matters for the wood industry. To stimulate innovation, R&D, in particular continuous R&D, should be encouraged in the high-tech and low-tech industries. The evidence for the wood industry is less persuasive in favor of this policy instrument.

Subsidy

We expect enterprises that receive subsidies to be more innovative, on the grounds that they do more R&D which may also be expected to positively affect innovation output. In the three waves of the CIS, innovators in the high-tech category that are granted subsidies are more successful than those that are not granted subsidies with the same characteristics. In the low-tech category and in the wood industry, innovation subsidies do not seem to make

¹¹See Brouwer and Kleiuknecht (1996) for details.

a difference. The results suggest a positive correlation between subsidies and innovation in high-tech industries. It may be, however, that subsidies are given primarily to firms in high-tech industries because they are known to be innovative (Lach, 2002).

2.6 Conclusion

The contribution of our study is to set up an industry categorization of Dutch manufacturing that is based on a model of economic behavior. We have considered a model of the determinants of innovation that explains the decisions by business enterprises to innovate, and the impact of these decisions on the share of innovative sales in total sales. We have estimated a two-limit tobit model with sample selection for each industry and performed likelihood ratio tests to classify industries into categories. Each category consists of industries for which the parameters of the model are identical. Our taxonomy suggests that industries in the Dutch manufacturing sector can be classified into three categories, namely the high-tech category, the low-tech category, and the wood industry. The high-tech category consists of the chemicals, electrical, M&E, plastic and vehicle industries. The food, metals, non-metallic products, textiles, and products not elsewhere classified (NEC) industries form the low-tech category. Our empirically-based industry categorization of Dutch manufacturing holds for the three Dutch Community Innovation Surveys.

Two main differences between our categorization and the OECD taxonomy are to be noted. The first one is that we place the plastic industry in the high-tech category, while it belongs to the low-tech category of the OECD taxonomy. The second one is that the wood industry cannot be classified into either the high- and low-tech category because the hypothesis that it has the same innovative behavior as the other industries in Dutch manufacturing had to be rejected. However, our classification could have been more different from the OECD classification had we used a finer industrial aggregation. The Pavitt and PCA taxonomy approaches circumvent this problem, but they are based on descriptive statistics and hence suffer from the absence of an empirical model. The OECD classification relies only on aggregate R&D within an industry. It can therefore lead to inefficient innovation policies because it ignores differences between enterprises within an industry. The PCA approach is firm-based but it relies on clustering of enterprises on the basis of a set of characteristics without modeling the interactions between these characteristics. The Pavitt classification is constructed

on *a priori* knowledge and assumptions about industry characteristics and interrelationships rather than on empirical findings regarding their innovative behavior. To illustrate our point, consider the effect of size. We have found that size is conducive to becoming an innovator but not necessarily to increasing the share of innovative sales. Therefore, a policy suggested on the basis of our categorization would be to stimulate non-innovating enterprises, for example by letting them grow, but not to favor large enterprises that are innovators. One shortcoming of our data is that we have little information about non-innovators.

Although our classification is rather robust, it is not to be seen as the ultimate one. The classification may be sensitive to the choice of the model and to the choice of the explanatory variables used in the model. Therefore, before being considered as definitive, our classification should be tested using other models of innovation. We have considered a static model estimated for three cross-sectional data sets. We have also assumed that R&D is determined exogenously, and the observed innovation input (R&D) and output (innovative sales) are measured at the same period of time, namely at the end of the period under review. But, more and more recent empirical studies assume that there is a decision to engage in R&D, hence endogenize R&D. These studies are the variants of the Crépon-Duguet-Mairesse (CDM, 1998) model. However, as far as we know, all these studies endogenize R&D in a static framework.¹² We believe that there may be a time lag between innovation input (e.g. R&D) and innovation output as measured by the share of innovative sales. A natural way to extend our model is to consider a dynamic panel data framework.

Finally, we have found some homogeneity in the innovative behavior across certain industries in the Dutch manufacturing sector. But, within the categories of industries it is likely that heterogeneity among firms exists that we have not captured.¹³ The argument of Baldwin and Gellatly (2000) that high-tech firms may be found in low-tech industries and vice versa is still valid. It would be worthwhile in future research to account for unobservable heterogeneity by considering, for instance, a model with panel data and individual effects.

¹²An exception is the study by van Leeuwen (2002) who considers a dynamic variant of the CDM model.

¹³Actually, we have accounted for some heterogeneity within the categories of industries by treating “differently”, in the estimation of the model, non-innovators, process-only innovators, product innovators and “large” product innovators. However, this is done in a non-standard way as opposed, for instance, to including individual effects.

Appendix 2.A The likelihood function of the two-limit tobit model with sample selection

Consider the model given in equations (2.1), (2.2) and (2.3). Suppose that the error terms ϵ_1 and ϵ_2 are jointly and normally distributed with mean zero and covariance matrix $\Sigma = \begin{pmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma^2 \end{pmatrix}$. The likelihood function can be written as

$$L = \prod_0 P(y_1^* \leq 0) \prod_{c_1} P(y_1^* > 0; y_2^* \leq c_1) \prod_{y_2^*} f(y_2|y_1^* > 0; c_1 < y_2 \leq c_2) P(c_1 < y_2 \leq c_2|y_1^* > 0) P(y_1^* > 0) \prod_{c_2} P(y_1^* > 0; y_2^* > c_2), \quad (2.4)$$

where $\prod_0$, $\prod_{c_1}$, $\prod_{y_2^*}$ and $\prod_{c_2}$ denote the products over non-innovators, process-only innovators, product innovators and “large” product innovators respectively. The contribution of a non-innovator to the likelihood function (first expression) is written as $\Phi_1(-\beta'_1 \mathbf{x}_1)$, where Φ_1 is the univariate standard normal cumulative distribution function. The contribution of a process-only innovator (second expression) involves the calculation of a double integral, i.e. $\int_{-\beta'_1 \mathbf{x}_1}^{\infty} \int_{-\infty}^{\frac{c_1 - \beta'_2 \mathbf{x}_2}{\sigma}} \phi_2(\epsilon_1, \frac{\epsilon_2}{\sigma}, \rho) d\epsilon_1 d\frac{\epsilon_2}{\sigma}$, where ϕ_2 is the bivariate standard normal density function. This latter expression can be written as $\Phi_1(\frac{c_1 - \beta'_2 \mathbf{x}_2}{\sigma}) - \Phi_2(-\beta'_1 \mathbf{x}_1, \frac{c_1 - \beta'_2 \mathbf{x}_2}{\sigma}, \rho)$, where Φ_2 is the bivariate standard normal cumulative distribution function. The third expression, corresponding to a not too “large” product innovator, is calculated as $\frac{f(y_2|y_1^* > 0)}{P(c_1 < y_2 \leq c_2|y_1^* > 0)} P(c_1 < y_2 \leq c_2|y_1^* > 0) P(y_1^* > 0)$ so that it becomes

$$L = f(y_2|y_1^* > 0) P(y_1^* > 0). \quad (2.5)$$

From the definition of a truncated distribution, we derive L as $\int_0^\infty f(y_2, y_1^*) dy_1^*$, where f is the bivariate normal density function. In order to make the computation easier, we write the bivariate density as a conditional multiplied with a marginal density so that

$$\int_0^\infty f(y_2, y_1^*) dy_1^* = f(y_2) \int_0^\infty f(y_1^*|y_2) dy_1^*. \quad (2.6)$$

Proposition 1 *If y is normally distributed with mean μ and variance σ^2 , then $\int_0^\infty f(y)dy = \Phi\left(\frac{\mu}{\sigma}\right)$.*

Proof. The density function of y is $\frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2\right]$ so that

$$\int_0^\infty f(y)dy = \frac{1}{\sigma} \int_0^\infty \phi_1\left(\frac{y-\mu}{\sigma}\right) dy = \frac{1}{\sigma\sqrt{2\pi}} \int_0^\infty \exp\left[-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2\right] dy.$$

Let $z = \frac{y-\mu}{\sigma}$ such that $dy = \sigma dz$, then

$$\int_0^\infty f(y)dy = \frac{1}{\sigma} \int_{-\frac{\mu}{\sigma}}^\infty \phi_1(z) \sigma dz. \quad (2.7)$$

Using the property of symmetry of the normal distribution, the integral (2.7) is finally written as:

$$\int_0^\infty f(y)dy = \int_{-\infty}^{\frac{\mu}{\sigma}} \phi_1(z) dz = \Phi_1\left(\frac{\mu}{\sigma}\right).$$

■

Applying the results of Proposition 1 to the conditional distribution of $y_1^*|y_2$ that is normal with mean $\mu_{y_1^*|y_2}$ and variance $\sigma_{y_1^*|y_2}^2$, we finally obtain the contribution to the likelihood function of one product innovator as $L = \frac{1}{\sigma_2} \phi_1\left(\frac{y_2 - \beta_2' \mathbf{x}_2}{\sigma_2}\right) \Phi_1\left(\frac{\mu_{y_1^*|y_2}}{\sigma_{y_1^*|y_2}}\right)$.¹⁴

Finally, the contribution of a “large” product innovator (fourth expression in (2.4)) also involves a double integral $\int_{-\beta_1' \mathbf{x}_1}^\infty \int_{\frac{c_2 - \beta_2' \mathbf{x}_2}{\sigma}}^\infty \phi_2(\epsilon_1, \frac{\epsilon_2}{\sigma}, \rho) d\epsilon_1 d\frac{\epsilon_2}{\sigma}$ which equals $1 - \Phi_1(-\beta_1' \mathbf{x}_1) - \Phi_1(\frac{c_2 - \beta_2' \mathbf{x}_2}{\sigma}) + \Phi_2(-\beta_1' \mathbf{x}_1, \frac{c_2 - \beta_2' \mathbf{x}_2}{\sigma}, \rho)$.

¹⁴If $(y_1, y_2)'$ follows a bivariate normal distribution with mean $(\mu_1, \mu_2)'$ and covariance matrix $\Sigma = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}$, then the conditional distribution of $y_1|y_2$ is normal the mean and variance of which are respectively

$$\mu_{y_1|y_2} = \mu_1 + \frac{\rho\sigma_1\sigma_2}{\sigma_2^2} (y_2 - \mu_2),$$

and

$$\sigma_{y_1|y_2}^2 = \sigma_1^2 - \frac{\rho^2\sigma_1^2\sigma_2^2}{\sigma_2^2} = \sigma_1^2(1 - \rho^2).$$

Appendix 2.B The distribution of the share of innovative sales

Figure 2.1: The distribution of the share of innovative sales of “normal” product innovators per CIS

Figure 2.2: The distribution of the logit transform of the share of innovative sales of “normal” product innovators per CIS

CHAPTER 3

The behavior of the maximum likelihood estimator of dynamic panel data sample selection models

3.1 Introduction

The ongoing development of the relevant econometric methodology for panel data has increased the choice for the applied researcher as to which model to choose in any given situation. Whereas this choice should be driven by the question which underlying assumptions are appropriate in the case at hand, optimality properties of the estimators are typically known only for large sample sizes. In order to have some guidance in the choice process it is important to know the implications, in terms of ease of computation and the robustness to deviations of the assumptions, of employing a particular method. In this chapter the behavior is investigated by means of Monte Carlo simulation of the maximum likelihood (ML) estimator in a general model that encompasses a wide set of models that have been considered in the literature. The generic form of the model consists of a regression equation, henceforth referred to as the equation of interest, and a selection equation. Both equations contain a lagged dependent variable and unobserved individual effects possibly correlated with the explanatory variables. The selection rule may be of the binary type or of the censoring type.¹ In terms of the Amemiya (1984) typology, the models considered in this paper are the dynamic

¹Following the literature the term censoring model will be used throughout the chapter although it would, in line with Wooldridge (2005), be preferable to speak of corner solution models since the lagged dependent variable considered in this paper is the observed - rather than the latent - variable.

panel data extensions of the type 2 and type 3 tobit models. Variants of these types of models have been widely used, mostly in labor economics but also in other areas (see Section 3.2).

This study contributes to the existing literature in two ways. Firstly, a practical method is provided to the problem of the maximum likelihood estimation of the parameters of a panel sample selection model in which random individual effects and the lagged dependent variable are included in the equation of interest as well as in the selection equation. The selection rule may be either of the binary or of the censoring type.² To handle the initial conditions problem, Wooldridge's (2005) solution to this problem in single equation dynamic nonlinear panel data models is extended to models containing more than one equation. Gaussian quadrature is used to evaluate the resulting multiple integral. Secondly, the paper reports on a Monte Carlo investigation into the behavior in finite samples of the proposed method. It is shown that using Wooldridge's solution to deal with the dependence between the initial conditions and the individual effects is successful in recovering the parameters of a process that generates the data according to a stationary process. It is also shown that incorrectly ignoring the individual effects, or the dependence between the initial conditions and the individual effects results in an overestimation of the coefficients of the lagged dependent variable in both equations. The likelihood functions of the dynamic panel data extensions of the type 2 and type 3 tobit models involve a two-dimensional indefinite integral. For the likelihood functions generated in the Monte Carlo experiments, Gaussian quadrature, implemented as two successive Gauss-Hermite approximations, works well for a number of evaluation points as small as two.³ Evidently, when using real data more than two evaluation points may be necessary to attain the required numerical accuracy. Nevertheless, the Monte Carlo results indicate that ML estimation of the parameters in a random-effects dynamic sample selection model is feasible and could conceivably be incorporated as a command in a general use software package such as Stata.

The remainder of the chapter is organized as follows. We discuss the most cited studies on panel data sample selection models in Section 3.2. Section 3.3 describes the model and Section 3.4 describes its maximum likelihood estimation. The small sample behavior of the estimator is studied in a Monte Carlo study in Section 3.5, and Section 3.6 concludes. The

²These are the types of selection rule that are mostly considered in the literature (see Table 3.1). Other types of selection rule are ordered, multinomial, and those based on multiple indices (Vella, 1998).

³The use of Gauss-Hermite quadrature, instead of simulated likelihood, is motivated by the finding of Guilkey and Murphy (1993) that, for the same accuracy, the former method is 5 times as fast as the latter (see also Greene, 2004b).

Gauss-Hermite quadrature is explained in Appendix 3.A.

3.2 Literature

Most of the studies on panel data sample selection models are static and of the type 2 or type 3 tobit (see the upper part of Table 3.1), which are estimated either by ML or two-step least squares (Heckman, 1979).

For instance, Hausman and Wise (1979) define a two-period model of attrition and estimate by ML the impact of attrition on earnings. Attrition is defined as the inability to observe the dependent variable of the equation of interest in the second period.⁴ Ridder (1990) generalizes the model of Hausman and Wise (1979) to allow for more than two periods and attrition to occur also in the first period. Hence Ridder's model can be used as a standard attrition or sample selection model. Nijman and Verbeek (1992) apply this model to study the effect of nonresponse on Dutch households' consumption. Verbeek (1990) assumes random and fixed individual effects in the selection and regression equations respectively, and estimates by ML a transformed model with a selection equation written in levels and a within-transformed equation of interest. Verbeek's model is criticized by Zabel (1992) who considers random individual effects correlated with the explanatory variables in both the selection equation and the equation of interest and estimates the resulting model by ML. As mentioned earlier, all these studies are of limited use to the applied researcher who wants to implement the ML estimator as they present only the general expression of the likelihood function which involves a multiple integral that is yet to be calculated. Our study makes a step in this direction.

The two-step Heckman type estimator consists, in a first step, in estimating the selection equation and constructing an estimate of a selection correction term that is included as a regressor in the equation of interest which, in a second step, is estimated using ordinary least squares (OLS) regression. Wooldridge (1995) estimates an augmented equation of interest written in levels by pooled OLS where estimates of the selection correction terms are obtained, in a first step, using a probit model for each period. Kyriazidou (1997) and Honoré and Kyriazidou (2000a) propose to estimate, by kernel-weighted least squares, a pairwise differenced equation of interest for individuals that are selected into the sample and have "the

⁴Attrition in the first period is usually referred to as sample selection.

same" selection equation index in two different periods. Under a *conditional exchangeability* assumption, the sample selection is time-invariant for such individuals so that differencing the equation of interest over time wipes out, not only the individual effects, but also the sample selection effect. In order to construct the kernel weights, the parameters of the selection equation are estimated, in a first step, using conditional logit or smoothed conditional maximum score. Rochina-Barrachina (1999) applies OLS to a pairwise differenced equation of interest augmented with two selection correction terms for individuals that are selected into the sample in two different periods. Estimates of these selection correction terms are obtained, in a first step, using a bivariate probit for each combination of time periods. The studies cited so far consider sample selection models with a binary selection rule (type 2 tobit).

Heckman and MaCurdy (1980) estimate by ML a fixed-effects type 3 tobit and apply it to a wage equation with a labor supply (the number of hours worked) equation as the selection equation. Ai and Chen (1992) and Honoré and Kyriazidou (2000a) estimate the same model using symmetrically trimmed least squares (STLS), and Wooldridge (1995) uses the same estimator as the one mentioned above where estimates of the selection correction terms are now obtained, in a first step, using a tobit model for each period. A Monte Carlo study comparing the estimators of Wooldridge (1995), Honoré and Kyriazidou (2000a) and a semiparametric first-difference estimator is provided by Lee (2001).

So far, all the mentioned studies on panel data sample selection models assume strict exogeneity of the explanatory variables in the equation of interest. Models with censored endogenous explanatory variables are studied by Vella and Verbeek (1999) and Askildsen et al. (2003), while Dustmann and Rochina-Barrachina (2000) and Semykina and Wooldridge (2005) study models with continuous endogenous explanatory variables. Vella and Verbeek (1999) estimate by OLS with selection bias correction (SBC) a wage equation where labor supply enters the set of explanatory variables, and where estimates of the selection correction terms are obtained, in a first step, using a dynamic tobit model of labor supply. Askildsen et al. (2003) estimate the wage elasticity of labor supply for Norwegian nurses using an instrumental variable (IV) version of the Kyriazidou (1997) method. Dustmann and Rochina-Barrachina (2000) and Semykina and Wooldridge (2005) estimate the effect of experience, which is assumed to be endogenous, on wages. The former study extends the Wooldridge (1995), Kyriazidou (1997) and Rochina-Barrachina (1999) estimators in order to account for

Table 3.1: *Studies on sample selection models with panel data*

Study	Selection rule	Dynamic or static	Individual effects	Estimation method*	Application	
					Selection	Equation(s) of interest
A selection equation and an equation of interest						
Hausman and Wise (1979)	binary	static	random	ML	attrition equation	earnings equation
Heckman and MaCurdy (1980)	censored	static	fixed	ML	labor supply equation	wage equation
Ridder (1990)	binary	dynamic**	random	ML: OLS with SBC	n.a.	n.a.
Verbeek (1990)	binary	static	hybrid [†]	ML	n.a.	n.a.
Ai and Chen (1992)	censored	static	fixed	STLS	n.a.	n.a.
Nijman and Verbeek (1992)	binary	dynamic**	random	ML: FGLS with SBC	nonresponse equation	consumption equation
Zabel (1992)	binary	static	random	ML	n.a.	n.a.
Wooldridge (1995)	binary: censored	static	fixed	pooled OLS with SBC	n.a.	n.a.
Kyriazidou (1997) [‡]	binary	static	fixed	kernel weighted LS	n.a.	n.a.
Rochina-Barrachina (1999) [‡]	binary	static	fixed	OLS with SBC	n.a.	n.a.
Vella and Verbeek (1999)	binary: censored	dynamic**	random	OLS with SBC; CML	labor supply equation	wage equation
Dustmann and Rochina-Barra-china (2000) [‡]	binary	static	fixed	MD with SBC; kernel weighted IV; IV and GMM with SBC	labor supply participation decision	wage equation
Honoré and Kyriazidou (2000a) [‡]	binary: censored	static	fixed	kernel weighted LS; STLS	n.a.	n.a.
Kyriazidou (2001) [‡]	binary	dynamic	fixed	kernel weighted GMM	n.a.	n.a.
Lee (2001) [‡]	censored	static	fixed	semiparametric FD	n.a.	n.a.
Askildsen et al. (2003) [‡]	binary	static	fixed	kernel weighted LS and IV	labor supply participation decision	labor supply equation
Gayle and Viauxoux (2007)	binary	dynamic	fixed	SIV; SMD	n.a.	n.a.
Semykina and Wooldridge (2005)	binary	static	fixed	fixed-effects and pooled 2SLS with SBC	labor supply participation decision	wage equation
A selection equation and two equations of interest						
Arellano et al. (1999)	binary	dynamic ^{††}	random	ALS	labor supply participation decision	labor supply and wage equations
Charlier et al. (2001) [‡]	binary	static	fixed	kernel weighted LS and IV	tenure choice between owning and renting	owners' and renters' budget share equations

*ML, OLS, SBC, STLS, FGLS, LS, ALS, CML, MD, IV, GMM, FD, SIV, SMD and 2SLS respectively stand for maximum likelihood, ordinary least squares, selection bias correction, symmetrically trimmed least squares, feasible generalized least squares, least squares, asymptotic least squares, conditional maximum likelihood, minimum distance, instrumental variable, generalized method of moments, first difference, sieve instrumental variable, sieve minimum distance and two-stage least squares. **Only the selection (or attrition) equation allows for dynamics. [†]The individual effects of the selection and the outcome equation are random and fixed respectively. ^{††}The selection equation is static. [‡]In these studies, the estimation is based on the pairwise differenced equation of interest.

endogeneity in the explanatory variables, while the latter uses a pooled and a fixed-effects two-stage least squares estimator with SBC. Finally, sample selection models that allow for dynamics in both the selection equation and the equation of interest are studied by Kyriazidou (2001) who uses a two-step kernel weighted general method of moments (GMM) estimator, and Gayle and Viauroux (2007) who use a sieve instrumental variable (SIV) and minimum distance (SMD) estimator.

Two rather different sample selection models are studied by Arellano et al. (1999) and Charlier et al. (2001). The former estimate a simultaneous equation second-order autoregressive model of labor supply and wages with selection using asymptotic least squares (ALS). The latter estimate a type 5 tobit, also known as endogenous switching regression, that explains the effect of Dutch households' tenure choice between owning and renting on owners' and renters' budget shares using kernel weighted IV.

3.3 The model

The dynamic panel data sample selection model studied in this chapter consists of two latent dependent variables d_{it}^* and y_{it}^* written as

$$d_{it}^* = \rho d_{i,t-1} + \delta' \mathbf{w}_{it} + \eta_i + \epsilon_{1it}, \quad (3.1)$$

$$y_{it}^* = \gamma y_{i,t-1} + \beta' \mathbf{x}_{it} + \alpha_i + \epsilon_{2it}, \quad (3.2)$$

with observed counterparts d_{it} and y_{it} , and $i = 1, \dots, N$; $t = 1, \dots, T$. Equation (3.1) is the selection equation that determines whether individual i is included in the sample on which the estimation of the equation of interest (eq. (3.2)) is based at period t . It is a function of past selection outcome ($d_{i,t-1}$), strictly exogenous explanatory variables ($\mathbf{w}_{it}$), time-invariant unobserved individual effects (η_i) and other time-variant unobserved variables (ϵ_{1it}). The scalar ρ and the vector δ' capture respectively the effects of past selection outcome and the explanatory variables on the current selection process, and are to be estimated. The equation of interest depends on its past outcome ($y_{i,t-1}$), strictly exogenous explanatory variables ($\mathbf{x}_{it}$), time-invariant unobserved individual effects (α_i) and other time-variant unobserved variables

(ϵ_{2it}) , and is observed only when d_{it}^* is positive, i.e.

$$y_{it} = 1[d_{it}^* > 0]y_{it}^*, \quad (3.3)$$

where $1[\dots]$ is the indicator function with value one if the expression between square brackets is true, and zero otherwise. The scalar γ and the vector β' capture respectively the effects of past outcome and explanatory variables on current outcome, and are to be estimated. Since a fully parametric approach is considered in this study, there is no exclusion restriction in the vector of explanatory variables. In other words, $\mathbf{w}_{it}$ and $\mathbf{x}_{it}$ may be the same, totally different or may have common explanatory variables.

Two types of selection rule are considered in this study, namely binary and censored. When the selection rule is binary, only the sign of the current selection process is observed and the current selection outcome is defined as

$$d_{it} = 1[d_{it}^* > 0], \quad (3.4)$$

while in the censored case, not only the sign but also the actual value of the current selection process is observed whenever it is positive and the current selection outcome is defined as

$$d_{it} = 1[d_{it}^* > 0]d_{it}^*. \quad (3.5)$$

Amemiya (1984) refers to the model described in equations (3.1), (3.2), (3.3) and (3.4) as type 2 tobit, and the one described in equations (3.1), (3.2), (3.3) and (3.5) as type 3 tobit. We now turn to the estimation technique.

3.4 Maximum likelihood estimation

Two difficulties arise when estimating dynamic panel data sample selection models, namely the presence of unobserved individual effects and the treatment of the initial observations.⁵

One way of handling the presence of unobserved individual effects is to create a dummy variable for each individual i and estimate the corresponding parameters η_i and α_i , together

⁵This study describes the difficulties that arise when estimating dynamic nonlinear panel data models and suggests solutions to them in a fully parametric framework. Details on how to handle the presence of unobserved individual effects and lagged dependent variables as regressors in a semiparametric framework are given in Arellano and Honoré (2001).

with the other parameters of the model, by maximum likelihood assuming a joint distribution for the error terms ϵ_{1it} and ϵ_{2it} . This approach is referred to as fixed-effects and has two shortcomings when the considered panel consists of a large N and a small T . The first one lies in the difficulty of computing the maximum likelihood estimator of the coefficients of possibly thousands of dummy variables. This computational problem can be overcome, for instance, by a two-step “zigzag” kind of likelihood maximization (Heckman and MaCurdy, 1980) or by “brute force” maximization (Greene, 2004a). These two computational methods cannot, however, solve the second problem of “incidental parameters” of the fixed-effects approach, namely the inconsistency of the maximum likelihood estimator of η_i and α_i when the number of periods T is small (Neyman and Scott, 1948). Unlike in the linear model, the inconsistency of the estimator of the individual effects carries over to the estimator of the slope parameters. Hence, the individual effects have to be conditioned out of the likelihood function so that the remaining parameters of the model can be consistently estimated by maximum likelihood. The resulting estimator is known as the conditional maximum likelihood estimator and is studied, for instance, by Chamberlain (1980) and Magnac (2004). The conditional likelihood approach is, however, restrictive for two reasons. First, there are very few nonlinear panel data models for which conditioning the individual effects out of the likelihood function is possible. They are surveyed in the study by Lancaster (2000). Secondly, the approach works only under the assumption of strict exogeneity of the explanatory variables, which rules out the inclusion of lagged dependent variables as explanatory variables. The above-mentioned shortcomings of the fixed-effects approach may justify the use of a random-effects approach, where η_i and α_i are assumed to have a joint distribution.

A computational (and methodological) difficulty that arises in the random-effects approach is the so-called initial conditions problem. Two assumptions are often made on the initial conditions in the literature, namely they are exogenous or the process is in equilibrium. Neither assumption is satisfactory Hsiao (2003). Two approaches of handling the initial conditions problem are proposed by Heckman (1981b) and Wooldridge (2005). The first approach specifies a model for the initial conditions given the individual effects and the strictly exogenous explanatory variables. In empirical work, this model is often assumed to be similar to the model underlying the remaining process. For instance, if the underlying model is a dynamic panel data probit, the model at the initial period is assumed to be standard probit.

A likelihood function that is marginal to both the individual effects and the initial conditions can be derived and maximized using standard numerical procedures. The second approach specifies the distribution of the individual effects conditional on the initial conditions and the strictly exogenous explanatory variables. In this case, the likelihood function is marginal to the individual effects but conditional on the initial conditions. Under the assumption of correct specification of the distribution of the errors, both approaches yield consistent estimates of the parameters of the model. The Heckman approach is fairly difficult to implement even more so when the model consists of more than one equation. The Wooldridge approach, on the other hand, is easy to implement and flexible in the sense that it applies to a wide range of nonlinear dynamic panel data models. Furthermore, the likelihood function derived in this approach has the same structure for both the dynamic and the static versions of the nonlinear model. This study extends this latter approach to models containing more than one equation. The approach is described as follows.

The individual effects are assumed, in each period, to be linear in the strictly exogenous explanatory variables and the initial conditions, i.e.

$$\eta_t = b_0^s + b_1^s d_{i0} + \mathbf{b}_2^{s'} \mathbf{w}_t + a_{1t}, \quad (3.6)$$

and

$$\alpha_t = b_0^r + b_1^r y_{i0} + \mathbf{b}_2^{r'} \mathbf{x}_t + a_{2t}, \quad (3.7)$$

where $\mathbf{w}_t' = (\mathbf{w}_{t1}', \dots, \mathbf{w}_{tT}')$, $\mathbf{x}_t' = (\mathbf{x}_{t1}', \dots, \mathbf{x}_{tT}')$, b_0^s , b_1^s , $\mathbf{b}_2^{s'}$, b_0^r , b_1^r and $\mathbf{b}_2^{r'}$ are to be estimated, and a_{1t} and a_{2t} are independent of $(d_{i0}, \mathbf{w}_t)$ and $(y_{i0}, \mathbf{x}_t)$ respectively.⁶ The scalars b_1^s and b_1^r capture the dependence of the individual effects on the initial conditions. The vectors $(\epsilon_{1t}, \epsilon_{2t})'$ and $(a_{1t}, a_{2t})'$ are assumed independent of each other, and independently and identically distributed over time and across individuals following a normal distribution with mean zero and covariance matrix

$$\Omega_{\epsilon_1 \epsilon_2} = \begin{pmatrix} \sigma_{\epsilon_1}^2 & \rho_{\epsilon_1 \epsilon_2} \sigma_{\epsilon_1} \sigma_{\epsilon_2} \\ \rho_{\epsilon_1 \epsilon_2} \sigma_{\epsilon_1} \sigma_{\epsilon_2} & \sigma_{\epsilon_2}^2 \end{pmatrix} \text{ and } \Omega_{a_1 a_2} = \begin{pmatrix} \sigma_{a_1}^2 & \rho_{a_1 a_2} \sigma_{a_1} \sigma_{a_2} \\ \rho_{a_1 a_2} \sigma_{a_1} \sigma_{a_2} & \sigma_{a_2}^2 \end{pmatrix} \quad (3.8)$$

respectively. The parameters of the covariance matrices are also to be estimated. Hence, the

⁶The vectors of explanatory variables $\mathbf{w}_t$ and $\mathbf{x}_t$, in order to be included in equations (3.6) and (3.7), must be sufficiently time-variant, otherwise a collinearity problem will arise.

likelihood function of individual i , starting from $t = 1$ and conditional on the regressors and the initial conditions, is written as

$$L_i = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \prod_{t=1}^T L_{it}(d_{it}, y_{it} | d_{i0}, d_{i,t-1}, \mathbf{w}_i, y_{i0}, y_{i,t-1}, \mathbf{x}_i, a_{1i}, a_{2i}) g(a_{1i}, a_{2i}) da_{1i} da_{2i}, \quad (3.9)$$

where $\prod_{t=1}^T L_{it}(d_{it}, y_{it} | d_{i0}, d_{i,t-1}, \mathbf{w}_i, y_{i0}, y_{i,t-1}, \mathbf{x}_i, a_{1i}, a_{2i})$ and $g(a_{1i}, a_{2i})$ denote respectively the likelihood function of individual i conditional on the individual effects, and the bivariate normal density function of (a_{1i}, a_{2i}) . Define

$$A_{it} = \rho d_{i,t-1} + \delta' \mathbf{w}_{it} + b_0^s + b_1^s d_{i0} + \mathbf{b}_2^{s'} \mathbf{w}_i \quad (3.10)$$

and

$$B_{it} = \gamma y_{i,t-1} + \beta' \mathbf{x}_{it} + b_0^r + b_1^r y_{i0} + \mathbf{b}_2^{r'} \mathbf{x}_i, \quad (3.11)$$

the individual likelihood function conditional on the individual effects is written as

$$\begin{aligned} & \prod_{t=1}^T \Phi \left[- \left(\frac{A_{it} + a_{1i}}{\sigma_{\epsilon_1}} \right) \right]^{(1-d_{it})} \left[\frac{1}{\sigma_{\epsilon_2}} \phi \left(\frac{y_{it} - B_{it} - a_{2i}}{\sigma_{\epsilon_2}} \right) \right. \\ & \times \left. \Phi \left(\frac{A_{it} + a_{1i} + \rho_{\epsilon_1 \epsilon_2} \frac{\sigma_{\epsilon_1}}{\sigma_{\epsilon_2}} (y_{it} - B_{it} - a_{2i})}{\sigma_{\epsilon_1} \sqrt{1 - \rho_{\epsilon_1 \epsilon_2}^2}} \right)^{d_{it}} \right], \end{aligned} \quad (3.12)$$

when the selection rule is binary and

$$\begin{aligned} & \prod_{t=1}^T \Phi \left[- \left(\frac{A_{it} + a_{1i}}{\sigma_{\epsilon_1}} \right) \right]^{(1-s_{it})} \left[\frac{1}{\sigma_{\epsilon_2}} \phi \left(\frac{y_{it} - B_{it} - a_{2i}}{\sigma_{\epsilon_2}} \right) \right. \\ & \times \left. \frac{1}{\sigma_{\epsilon_1} \sqrt{1 - \rho_{\epsilon_1 \epsilon_2}^2}} \phi \left(\frac{d_{it} - A_{it} - a_{1i} - \rho_{\epsilon_1 \epsilon_2} \frac{\sigma_{\epsilon_1}}{\sigma_{\epsilon_2}} (y_{it} - B_{it} - a_{2i})}{\sigma_{\epsilon_1} \sqrt{1 - \rho_{\epsilon_1 \epsilon_2}^2}} \right) \right]^{s_{it}}, \end{aligned} \quad (3.13)$$

when the selection rule is censored.⁷ In equations (3.12) and (3.13), ϕ and Φ denote respectively the univariate standard normal density and cumulative distribution functions, s_{it} is defined in the type 3 tobit as

$$s_{it} = \mathbf{1}[d_{it}^* > 0].^8 \quad (3.14)$$

⁷The individual likelihood function conditional on the individual effects is the product over time of individual cross-sectional likelihood functions. These latter functions are derived for the type 2 and 3 tobit models in Amemiya (1984).

⁸In the type 2 tobit model, equations (3.4) and (3.14) are equivalent so that $s_{it} = d_{it}$, and σ_{ϵ_1} cannot be identified and is set to 1 in equation (3.12).

The double integral in equation (3.9) can be approximated, along the lines of Butler and Moffitt (1982), by “two-step” Gauss-Hermite quadrature (see Appendix 3.A) so that the random-effects individual likelihood functions of the type 2 and type 3 tobit models become respectively

$$\begin{aligned}
 L_i \simeq & \frac{\sqrt{1 - \rho_{a_1 a_2}^2}}{\pi} \sum_{p=1}^P w_p \left\{ \prod_{t=1}^T \left[\frac{1}{\sigma_{\epsilon_2}} \phi \left(\frac{y_{it} - B_{it} - a_p \sigma_{a_2} \sqrt{2(1 - \rho_{a_1 a_2}^2)}}{\sigma_{\epsilon_2}} \right) \right]^{d_{it}} \right. \\
 & \times \sum_{m=1}^M w_m \left\{ e^{2\rho_{a_1 a_2} a_p a_m} \prod_{t=1}^T \Phi \left[- \left(A_{it} + a_m \sigma_{a_1} \sqrt{2(1 - \rho_{a_1 a_2}^2)} \right) \right]^{(1 - d_{it})} \right. \\
 & \left. \left. \times \Phi \left(\frac{N_{it} + \frac{\rho_{\epsilon_1 \epsilon_2}}{\sigma_{\epsilon_2}} (y_{it} - B_{it} - a_p \sigma_{a_2} \sqrt{2(1 - \rho_{a_1 a_2}^2)})}{\sqrt{1 - \rho_{\epsilon_1 \epsilon_2}^2}} \right)^{d_{it}} \right] \right\} \right\}
 \end{aligned} \quad (3.15)$$

and

$$\begin{aligned}
 L_i \simeq & \frac{\sqrt{1 - \rho_{a_1 a_2}^2}}{\pi} \sum_{p=1}^P w_p \left\{ \prod_{t=1}^T \left[\frac{1}{\sigma_{\epsilon_2}} \phi \left(\frac{y_{it} - B_{it} - a_p \sigma_{a_2} \sqrt{2(1 - \rho_{a_1 a_2}^2)}}{\sigma_{\epsilon_2}} \right) \right]^{s_{it}} \right. \\
 & \times \sum_{m=1}^M w_m \left\{ e^{2\rho_{a_1 a_2} a_p a_m} \prod_{t=1}^T \Phi \left[- \left(\frac{A_{it} + a_m \sigma_{a_1} \sqrt{2(1 - \rho_{a_1 a_2}^2)}}{\sigma_{\epsilon_1}} \right) \right]^{(1 - s_{it})} \right. \\
 & \left. \left. \times \left[\frac{1}{\sigma_{\epsilon_1} \sqrt{1 - \rho_{\epsilon_1 \epsilon_2}^2}} \phi \left(\frac{d_{it} - N_{it} - \rho_{\epsilon_1 \epsilon_2} \frac{\sigma_{\epsilon_1}}{\sigma_{\epsilon_2}} (y_{it} - B_{it} - a_p \sigma_{a_2} \sqrt{2(1 - \rho_{a_1 a_2}^2)})}{\sigma_{\epsilon_1} \sqrt{1 - \rho_{\epsilon_1 \epsilon_2}^2}} \right) \right]^{s_{it}} \right] \right\} \right\}.
 \end{aligned} \quad (3.16)$$

where w_m , w_p , a_m and a_p are respectively the weights and abscissas of the first- and second-step Gauss-Hermite quadrature with M and P being the first- and second-step total number of integration points, and N_{it} is written as

$$N_{it} = A_{it} + a_m \sigma_{a_1} \sqrt{2(1 - \rho_{a_1 a_2}^2)}. \quad (3.17)$$

The product over i of the approximate likelihood functions (3.15) and (3.16) can be maximized using standard numerical procedures to obtain estimates of the parameters of the dynamic type 2 and type 3 tobit models.

Our approach handles the estimation, by maximum likelihood, of a wide range of linear and nonlinear panel data models. Indeed, equations (3.15) and (3.16) encompass the likelihood functions of the models which are obtained by restricting the values of certain parameters of the dynamic sample selection models (see Table 3.8 of Appendix 3.B). For instance, if $\rho_{a_1 a_2} = \rho_{\epsilon_1 \epsilon_2} = 0$ and the remaining parameters are unrestricted, the likelihood

functions are the product of the likelihood functions of a dynamic random-effects probit and a dynamic random-effects linear regression (eq. (3.15)), and that of the likelihood functions of a dynamic random-effects type 1 tobit and a dynamic random-effects linear regression (eq. (3.16)). In other words, when there is no selection bias, estimating a dynamic type 2 (type 3) tobit amounts to estimating separately a dynamic probit (type 1 tobit) and a dynamic linear regression. The parameter restrictions listed in Table 3.8 can be tested using a standard likelihood ratio or Wald test.

We now present Monte Carlo simulations to study the small sample behavior of the maximum likelihood estimator of the type 2 and type 3 tobit models.

3.5 Monte Carlo study

The data are generated according to the following “true” model

$$d_{it}^* = \rho d_{i,t-1} + \delta w_{it} + \eta_i + \epsilon_{1it}, \quad (3.18)$$

$$y_{it}^* = \gamma y_{i,t-1} + \beta x_{it} + \alpha_i + \epsilon_{2it}, \quad (3.19)$$

where w_{it} and x_{it} are generated according to the standard normal distribution and are independent of each other, $(\epsilon_{1it}, \epsilon_{2it})$ is generated according to the bivariate normal distribution with mean zero and covariance matrix defined as in equation (3.8) (first matrix). The individual effects (η_i, α_i) are generated independently of $(\epsilon_{1it}, \epsilon_{2it})$ according to the bivariate normal distribution with mean (d_{i0}, y_{i0}) and covariance matrix defined as in equation (3.8) (second matrix). The dependent variables of the equation of interest and the selection rules are defined as in equations (3.3-3.5), i.e., both the type 2 and type 3 tobit are considered. The true parameter values are $\delta = \beta = 1$, $\sigma_{a_1} = \sigma_{a_2} = \sigma_{\epsilon_2} = 0.5$, $\sigma_{\epsilon_1} = 1$, $\rho_{a_1 a_2} = 0.5$, $\rho_{\epsilon_1 \epsilon_2} = 0.8$, and two sets of values are chosen for ρ and γ , namely $\rho = \gamma = 0$ when the model is static, and $\rho = \gamma = 0.5$ when the model is dynamic.

Given these values of the parameters, sample selection is not constant over time, i.e. the selection outcome d_{it} (or s_{it}) has a rather high within standard deviation (around 0.40) for the (dynamic and static) type 2 and type 3 tobit. Furthermore, the censoring rate over the whole period, for both models, is approximately 40% and 50% in the dynamic and the static settings respectively. Finally, the correlation between the individual effects and the initial

conditions for the type 2 and type 3 tobit is 0.70 and 0.80 in the selection equation, and 0.80 for both models in the equation of interest.

To summarize, the data generating process (DGP) at the initial period is standard type 2 (type 3) tobit while the remaining period DGP is dynamic type 2 (type 3) tobit with endogenous initial conditions correlated with the individual effects, and accounting for selection bias correction (SBC). The static DGP is obtained by setting the true values of ρ , γ to 0.

The estimation results of ρ , γ , δ , β , σ_{a_1} , σ_{a_2} , $\rho_{a_1a_2}$ and $\rho_{\epsilon_1\epsilon_2}$ based on 200 replications are shown in Tables 3.2-3.7 for the following sample sizes: $N = 500$ and $T = 4$, $N = 500$ and $T = 7$, and $N = 800$ and $T = 4$. We report the mean and standard deviation over the replications of these estimates.⁹ In each replication, the estimation is based on $T - 1$ periods, the first one being the initial period. We study the small sample behavior of the maximum likelihood estimator (MLE) of the above-mentioned parameters when the model is both correctly and incorrectly specified. More specifically, when the DGP is dynamic, misspecification includes a dynamic model with no individual effects but SBC; with individual effects, exogenous initial conditions and SBC; with individual effects, endogenous initial conditions but no SBC; and a static model with individual effects and SBC. When the DGP is static, misspecification includes a static model with no individual effects but SBC; with individual effects but no SBC; and a dynamic model with no individual effects but SBC, and with individual effects and endogenous initial conditions correlated with the individual effects and SBC.

We now discuss the Monte Carlo results.

3.5.1 The MLE behavior when the model is correctly specified

The mean and standard deviation of the MLE of ρ , γ , δ , β , σ_{a_1} , σ_{a_2} , $\rho_{a_1a_2}$ and $\rho_{\epsilon_1\epsilon_2}$, when the model is correctly specified, are reported in Table 3.2.

The MLE of δ and β in both the dynamic and static type 2 and type 3 tobit is biased *towards* zero. The bias does not exceed 2% and 0.7% for δ and β in the type 2 tobit, and 3.5% and 0.8% in the type 3 tobit. There is no clear pattern of bias reduction as either T or N increases. In all cases but the dynamic type 2 tobit with $N = 800$ and $T = 4$, the estimate of β is on average closer to the true value than that of δ . In both the type 2 and type 3 tobit, the estimates of δ and β are closer to the true values in the static case than in the dynamic case, except in the dynamic type 2 tobit with $N = 800$ and $T = 4$ where the pattern shows up

⁹We do not report the estimate results of σ_{ϵ_1} (for the type 3 tobit), σ_{ϵ_2} , and the additional parameters of equations (3.6) and (3.7).

the other way round in the estimate of δ . From this, we can conclude that it is more difficult to estimate accurately the coefficients of the strictly exogenous explanatory variables in both the selection equation and the equation of interest of dynamic panel data sample selection models than those of their static counterparts.

The MLE of ρ and γ is also biased *towards* zero in both the dynamic type 2 and type 3 tobit. The bias does not exceed 2% and 4.7% for ρ and γ in the type 2 tobit, and 3.5% and 4.2% in the type 3 tobit. Like δ and β , there is no clear pattern of bias reduction as either T or N increases, and the MLE bias of ρ and γ is overall larger than that of δ and β . As a result, we can state that it is more difficult to estimate accurately the coefficients of the lagged dependent variables than those of the strictly exogenous variables in both the selection equation and the equation of interest of dynamic panel data sample selection models.

In both models, σ_{a_1} and σ_{a_2} are much less accurately estimated than ρ , γ , δ and β , even though their bias remains *towards* zero. For both models, the bias is smaller in the static case than in the dynamic case. In all cases but, for σ_{a_1} when $N = 500$ and $T = 7$, the bias is smaller in the type 2 tobit than in the type 3 tobit. The two models exhibit different patterns in the bias reduction as T increases. Indeed, the type 2 tobit shows an increase in the MLE bias of σ_{a_1} and σ_{a_2} that is more pronounced for σ_{a_1} than it is for σ_{a_2} . The increase in the MLE bias of σ_{a_1} , as T increases, confirms the results by Rabe-Hesketh et al. (2005) that show that the MLE of the standard deviation of the individual effects in random-effects probit models is biased *away* from zero for large cluster size T , with a bias that ranges from 19% for T as small as 10 to 178% for T as large as 500. The type 3 tobit on the other hand shows a decrease in the bias of the MLE of σ_{a_1} and σ_{a_2} that is more pronounced for σ_{a_1} than it is for σ_{a_2} . As N increases, the bias reduction pattern is not clear cut, especially in the type 3 tobit.

Finally, in both models, the MLE of $\rho_{u_1a_2}$ is biased *away* from zero with a bias of about 25%, while that of $\rho_{\epsilon_1\epsilon_2}$ is biased *away* from zero in the type 2 tobit and *towards* zero in the type 3 tobit. This bias decreases only slightly as T increases, while there is no clear pattern of reduction as N increases.

To summarize, we can state that, when the model is correctly specified, the MLE bias of the parameters of panel data sample selection models is very small for a sample size as large as the one considered in the Monte Carlo study. The “two-step” Gauss-Hermite quadrature used to approximate the likelihood function works very well, even for a number of integration

Table 3.2: ML estimates based on 200 replications and 2-point Gauss-Hermite quadrature: Data generating process

(True value)*	Estimate	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Estimated model									
		Static type 2 tobit				Static type 3 tobit			
		N=500; T=4				Dynamic type 3 tobit			
$(\rho = 0.5)$	$\hat{\rho}$	-	-	0.480	(0.086)	-	-	0.474	(0.023)
$(\gamma = 0.5)$	$\hat{\gamma}$	-	-	0.541	(0.018)	-	-	0.540	(0.016)
$(\delta = 1.0)$	$\hat{\delta}$	0.991	(0.050)	1.016	(0.055)	0.997	(0.027)	1.024	(0.025)
$(\beta = 1.0)$	$\hat{\beta}$	1.001	(0.021)	1.007	(0.019)	1.002	(0.018)	1.008	(0.016)
$(\sigma_{a_1} = 0.5)$	$\hat{\sigma}_{a_1}$	0.521	(0.077)	0.557	(0.096)	0.434	(0.070)	0.412	(0.075)
$(\sigma_{a_2} = 0.5)$	$\hat{\sigma}_{a_2}$	0.448	(0.021)	0.409	(0.058)	0.421	(0.018)	0.371	(0.108)
$(\rho_{a_1 a_2} = 0.5)$	$\hat{\rho}_{a_1 a_2}$	0.278	(0.014)	0.283	(0.041)	0.256	(0.017)	0.236	(0.070)
$(\rho_{\epsilon_1 \epsilon_2} = 0.8)$	$\hat{\rho}_{\epsilon_1 \epsilon_2}$	0.682	(0.047)	0.603	(0.072)	0.709	(0.024)	0.740	(0.022)
N=500; T=7									
$(\rho = 0.5)$	$\hat{\rho}$	-	-	0.489	(0.058)	-	-	0.465	(0.015)
$(\gamma = 0.5)$	$\hat{\gamma}$	-	-	0.545	(0.012)	-	-	0.539	(0.011)
$(\delta = 1.0)$	$\hat{\delta}$	0.999	(0.041)	1.020	(0.043)	0.998	(0.021)	1.035	(0.018)
$(\beta = 1.0)$	$\hat{\beta}$	1.000	(0.014)	1.005	(0.013)	1.000	(0.011)	1.005	(0.009)
$(\sigma_{a_1} = 0.5)$	$\hat{\sigma}_{a_1}$	0.581	(0.053)	0.593	(0.065)	0.526	(0.052)	0.532	(0.054)
$(\sigma_{a_2} = 0.5)$	$\hat{\sigma}_{a_2}$	0.446	(0.014)	0.397	(0.058)	0.429	(0.013)	0.391	(0.014)
$(\rho_{a_1 a_2} = 0.5)$	$\hat{\rho}_{a_1 a_2}$	0.308	(0.014)	0.308	(0.045)	0.276	(0.016)	0.256	(0.021)
$(\rho_{\epsilon_1 \epsilon_2} = 0.8)$	$\hat{\rho}_{\epsilon_1 \epsilon_2}$	0.685	(0.038)	0.618	(0.054)	0.714	(0.017)	0.750	(0.013)
N=800; T=4									
$(\rho = 0.5)$	$\hat{\rho}$	-	-	0.480	(0.062)	-	-	0.477	(0.016)
$(\gamma = 0.5)$	$\hat{\gamma}$	-	-	0.541	(0.015)	-	-	0.542	(0.013)
$(\delta = 1.0)$	$\hat{\delta}$	0.986	(0.038)	1.005	(0.042)	0.993	(0.021)	1.020	(0.019)
$(\beta = 1.0)$	$\hat{\beta}$	1.000	(0.017)	1.006	(0.014)	0.999	(0.014)	1.008	(0.012)
$(\sigma_{a_1} = 0.5)$	$\hat{\sigma}_{a_1}$	0.516	(0.064)	0.542	(0.068)	0.437	(0.054)	0.407	(0.059)
$(\sigma_{a_2} = 0.5)$	$\hat{\sigma}_{a_2}$	0.447	(0.017)	0.409	(0.057)	0.419	(0.014)	0.387	(0.014)
$(\rho_{a_1 a_2} = 0.5)$	$\hat{\rho}_{a_1 a_2}$	0.280	(0.010)	0.287	(0.041)	0.256	(0.011)	0.248	(0.013)
$(\rho_{\epsilon_1 \epsilon_2} = 0.8)$	$\hat{\rho}_{\epsilon_1 \epsilon_2}$	0.680	(0.035)	0.604	(0.053)	0.707	(0.019)	0.740	(0.017)

* $\rho = \gamma = 0$ in the static data generating process.

points, in each step, as small as 2. However, the standard deviations of the individual effects and the sample selection terms are less accurately estimated than the remaining parameters of Table 3.2. Accuracy in the estimates can be gained by either increasing the number of integration points or using adaptive Gauss-Hermite quadrature in the spirit of Rabe-Hesketh et al. (2005).¹⁰

We now discuss the behavior of the MLE when the model is incorrectly specified.

3.5.2 The MLE behavior when the model is incorrectly specified

The mean and standard deviation of the MLE of ρ , γ , δ , β , σ_{a_1} , σ_{a_2} , $\rho_{a_1a_2}$ and $\rho_{\epsilon_1\epsilon_2}$, when the model is incorrectly specified, are reported in Tables 3.3-3.7. More specifically, we study the finite sample bias of the MLE when we fail to account for individual effects, when we assume exogenous initial conditions and when we fail to correct for selection bias. We also study the case where a static model is estimated under a dynamic DGP and vice versa.

No individual effects

Table 3.3 reports the mean and standard deviation of the MLE of ρ , γ , δ , β and $\rho_{\epsilon_1\epsilon_2}$ when the individual effects, while being present in the DGP, are ignored in the estimation of the model, i.e., σ_{a_1} , σ_{a_2} and $\rho_{a_1a_2}$ are all assumed to be zero.

The MLE of β remains biased *towards* zero in all cases. In other words, the MLE bias of the coefficient of the strictly exogenous explanatory variable in the equation of interest is unaffected if we fail to account for individual effects. This result holds regardless of the type of the selection rule, and regardless of whether the model is dynamic or static. The MLE of δ also remains biased *towards* zero in the type 3 tobit and in the static type 2 tobit with a larger bias than that of β . In the dynamic type 2 tobit, however, the MLE of δ is biased *away* from zero with a bias that is always larger than 15%. Hence, unlike β , when we fail to account for individual effects, the MLE behavior of the coefficient of the strictly exogenous explanatory variable in the selection equation differs according to the type of the selection rule and according to whether the model is dynamic or static.

In the dynamic version of the model, the MLE of ρ and γ is biased *away* from zero and *upwards* in all cases, with a bias that gets as large as 61% in the type 2 tobit, and 55% in the

¹⁰In the study by Rabe-Hesketh et al. (2005), adaptive Gauss-Hermite quadrature is shown to work better than normal Gauss-Hermite quadrature in static random-effects probit models when T or the equicorrelation is very large. The use of adaptive Gauss-Hermite quadrature can be generalized to sample selection models but is beyond the scope of this study.

Table 3.3: *ML estimates based on 200 replications and 2-point Gauss-Hermite quadrature: No individual effects*

(True value)*	Estimate	Estimated model									
		Static type 2 tobit					Dynamic type 3 tobit				
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
N=500; T=4											
($\rho = 0.5$)	$\hat{\rho}$	-	-	1.106	(0.061)	-	-	-	-	0.989	(0.019)
($\gamma = 0.5$)	$\hat{\gamma}$	-	-	1.046	(0.020)	-	-	-	-	1.047	(0.019)
($\delta = 1.0$)	$\hat{\delta}$	0.901	(0.042)	0.841	(0.045)	1.002	(0.026)	1.002	(0.026)	1.049	(0.036)
($\beta = 1.0$)	$\hat{\beta}$	1.002	(0.023)	1.002	(0.031)	1.001	(0.020)	1.001	(0.020)	1.002	(0.026)
($\rho_{\epsilon_1\epsilon_2} = 0.8$)	$\hat{\rho}_{\epsilon_1\epsilon_2}$	0.664	(0.031)	0.473	(0.065)	0.666	(0.021)	0.666	(0.021)	0.535	(0.028)
N=500; T=7											
($\rho = 0.5$)	$\hat{\rho}$	-	-	1.036	(0.040)	-	-	-	-	0.907	(0.015)
($\gamma = 0.5$)	$\hat{\gamma}$	-	-	0.963	(0.012)	-	-	-	-	0.963	(0.014)
($\delta = 1.0$)	$\hat{\delta}$	0.900	(0.034)	0.828	(0.035)	1.002	(0.021)	1.002	(0.021)	1.057	(0.025)
($\beta = 1.0$)	$\hat{\beta}$	1.000	(0.017)	1.000	(0.018)	1.001	(0.014)	1.001	(0.014)	1.002	(0.018)
($\rho_{\epsilon_1\epsilon_2} = 0.8$)	$\hat{\rho}_{\epsilon_1\epsilon_2}$	0.665	(0.025)	0.428	(0.052)	0.663	(0.017)	0.663	(0.017)	0.534	(0.023)
N=800; T=4											
($\rho = 0.5$)	$\hat{\rho}$	-	-	1.103	(0.043)	-	-	-	-	0.989	(0.014)
($\gamma = 0.5$)	$\hat{\gamma}$	-	-	1.046	(0.015)	-	-	-	-	1.048	(0.016)
($\delta = 1.0$)	$\hat{\delta}$	0.896	(0.033)	0.832	(0.036)	0.997	(0.021)	0.997	(0.021)	1.048	(0.029)
($\beta = 1.0$)	$\hat{\beta}$	1.001	(0.018)	1.000	(0.021)	0.999	(0.014)	0.999	(0.014)	1.002	(0.021)
($\rho_{\epsilon_1\epsilon_2} = 0.8$)	$\hat{\rho}_{\epsilon_1\epsilon_2}$	0.664	(0.024)	0.473	(0.049)	0.664	(0.018)	0.664	(0.018)	0.531	(0.022)

* $\rho = \gamma = 0$ in the static data generating process. The individual effects, while being present in the data generating process, are ignored in the estimation of the model.

type 3 tobit. This bias is reduced fairly substantially (by about 9%) as T increases but remains very high, and is unchanged as N increases. In other words, when estimating the dynamic version of the model and failing to account for individual effects, the coefficients of the lagged dependent explanatory variables, in both the selection equation and the equation of interest, are overestimated. In the dynamic panel data discrete choice model, this phenomenon is known as *spurious state dependence* (Heckman, 1981a), i.e. too much credit is attributed to past event as a determinant of current event if intertemporal correlation in the unobservables is not accounted for.

Finally, the MLE of $\rho_{\epsilon_1\epsilon_2}$ is biased *away* from zero with a bias of about 25% in the static case, and about 35% in the dynamic case. There is no clear pattern of bias reduction as either T or N increases.

Exogenous initial conditions

Table 3.4 reports the mean and standard deviation of the MLE of ρ , γ , δ , β , σ_{a_1} , σ_{a_2} , $\rho_{a_1a_2}$ and $\rho_{\epsilon_1\epsilon_2}$ when the initial conditions, while being endogenous and correlated with the individual effects in the DGP, are assumed to be exogenous, i.e., b_1^* and b_1^* are assumed to be zero.

In both the type 2 and type 3 tobit, the MLE bias of δ and β increases by about 6% with respect to the case of the DGP but remains fairly small, less than 9% in the type 2 tobit, and less than 11% in the type 3 tobit. As for the MLE of ρ and γ , their bias remains substantially large compared to the case where the individual effects are ignored. Accounting for individual effects but assuming exogenous initial conditions also results in a spurious state dependence situation.¹¹ Hence, we can state that, in order for the coefficients of the lagged dependent explanatory variables to be accurately estimated, the correlation between the initial conditions and the individual effects must be taken into account: controlling for individual effects only is not sufficient. As T increases, the MLE bias of ρ and γ , in both the type 2 and type 3 tobit, decreases by about 10% but remains substantially large, while, as N increases, the bias remains the same. Finally, the MLE bias of $\rho_{a_1a_2}$ and $\rho_{\epsilon_1\epsilon_2}$ is higher than in the DGP case, and that of σ_{a_1} and σ_{a_2} is comparable to that of the same parameters in the DGP case.

¹¹ Although the term spurious state dependence was used in the context of discrete choice models, we use it in our study to explain the overestimation of the coefficients of the lagged dependent explanatory variables in both the selection equation and the equation of interest.

Table 3.4: ML estimates based on 200 replications and 2-point Gauss-Hermite quadrature:

<i>Exogenous initial conditions</i>					
(True value)*	Estimate	Mean	Std. Dev.	Mean	Std. Dev.
Estimated model					
Dynamic type 2 tobit					
Dynamic type 3 tobit					
N=500; T=4					
$(\rho = 0.5)$	$\hat{\rho}$	1.115	(0.069)	0.924	(0.020)
$(\gamma = 0.5)$	$\hat{\gamma}$	0.967	(0.026)	0.973	(0.024)
$(\delta = 1.0)$	$\hat{\delta}$	0.923	(0.051)	1.086	(0.035)
$(\beta = 1.0)$	$\hat{\beta}$	1.062	(0.030)	1.071	(0.025)
$(\sigma_{a_1} = 0.5)$	$\hat{\sigma}_{a_1}$	0.571	(0.080)	0.583	(0.078)
$(\sigma_{a_2} = 0.5)$	$\hat{\sigma}_{a_2}$	0.458	(0.175)	0.482	(0.177)
$(\rho_{a_1 a_2} = 0.5)$	$\hat{\rho}_{a_1 a_2}$	0.229	(0.088)	0.214	(0.080)
$(\rho_{\epsilon_1 \epsilon_2} = 0.8)$	$\hat{\rho}_{\epsilon_1 \epsilon_2}$	0.411	(0.095)	0.560	(0.034)
N=500; T=7					
$(\rho = 0.5)$	$\hat{\rho}$	1.030	(0.045)	0.829	(0.017)
$(\gamma = 0.5)$	$\hat{\gamma}$	0.863	(0.016)	0.869	(0.019)
$(\delta = 1.0)$	$\hat{\delta}$	0.915	(0.040)	1.102	(0.024)
$(\beta = 1.0)$	$\hat{\beta}$	1.048	(0.017)	1.051	(0.016)
$(\sigma_{a_1} = 0.5)$	$\hat{\sigma}_{a_1}$	0.632	(0.058)	0.718	(0.075)
$(\sigma_{a_2} = 0.5)$	$\hat{\sigma}_{a_2}$	0.532	(0.076)	0.538	(0.159)
$(\rho_{a_1 a_2} = 0.5)$	$\hat{\rho}_{a_1 a_2}$	0.266	(0.041)	0.240	(0.073)
$(\rho_{\epsilon_1 \epsilon_2} = 0.8)$	$\hat{\rho}_{\epsilon_1 \epsilon_2}$	0.403	(0.080)	0.586	(0.027)
N=800; T=4					
$(\rho = 0.5)$	$\hat{\rho}$	1.113	(0.480)	0.924	(0.017)
$(\gamma = 0.5)$	$\hat{\gamma}$	0.968	(0.019)	0.974	(0.020)
$(\delta = 1.0)$	$\hat{\delta}$	0.914	(0.039)	1.085	(0.029)
$(\beta = 1.0)$	$\hat{\beta}$	1.060	(0.020)	1.071	(0.019)
$(\sigma_{a_1} = 0.5)$	$\hat{\sigma}_{a_1}$	0.563	(0.057)	0.587	(0.058)
$(\sigma_{a_2} = 0.5)$	$\hat{\sigma}_{a_2}$	0.487	(0.027)	0.503	(0.102)
$(\rho_{a_1 a_2} = 0.5)$	$\hat{\rho}_{a_1 a_2}$	0.247	(0.012)	0.224	(0.046)
$(\rho_{\epsilon_1 \epsilon_2} = 0.8)$	$\hat{\rho}_{\epsilon_1 \epsilon_2}$	0.406	(0.069)	0.557	(0.025)

*The initial conditions are endogenous and correlated with the individual effects in the data generating process, but assumed to be exogenous in the estimation of the model.

No selection bias correction

The mean and standard deviation of the MLE of ρ , γ , δ , β , σ_{a_1} and σ_{a_2} are reported in Table 3.5 when we do not correct for the selection bias, i.e., we assume $\rho_{a_1 a_2}$ and $\rho_{\epsilon_1 \epsilon_2}$ to be zero.

In both the type 2 and type 3 tobit and regardless of whether the model is dynamic or static, the MLE bias of the coefficients of the lagged dependent and strictly exogenous explanatory variables is unaffected. This result always holds for δ and β when the strictly exogenous explanatory variables in the selection equation and in the equation of interest are not at all or only slightly correlated. When they are highly correlated, Monte Carlo results

Table 3.5: *ML estimates based on 200 replications and 2-point Gauss-Hermite quadrature. No selection bias correction (True value)**

Estimate	Static type 2 tobit		Dynamic type 2 tobit		Static type 3 tobit		Dynamic type 3 tobit	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Estimated model								
N=500; T=4								
$(\rho = 0.5)$	-	-	0.475	(0.091)	-	-	0.415	(0.031)
$(\gamma = 0.5)$	-	-	0.547	(0.018)	-	-	0.545	(0.020)
$(\delta = 1.0)$	1.007	(0.051)	1.016	(0.057)	1.003	(0.033)	1.042	(0.033)
$(\beta = 1.0)$	1.001	(0.022)	1.008	(0.020)	1.001	(0.022)	1.007	(0.020)
$(\sigma_{a_1} = 0.5)$	0.709	(0.070)	0.714	(0.079)	0.711	(0.056)	0.737	(0.050)
$(\sigma_{a_2} = 0.5)$	0.463	(0.021)	0.372	(0.121)	0.460	(0.020)	0.398	(0.021)
N=500; T=7								
$(\rho = 0.5)$	-	-	0.486	(0.057)	-	-	0.408	(0.018)
$(\gamma = 0.5)$	-	-	0.550	(0.012)	-	-	0.548	(0.015)
$(\delta = 1.0)$	1.006	(0.042)	1.014	(0.048)	1.001	(0.024)	1.063	(0.025)
$(\beta = 1.0)$	1.000	(0.015)	1.006	(0.012)	1.000	(0.016)	1.006	(0.015)
$(\sigma_{a_1} = 0.5)$	0.710	(0.045)	0.713	(0.054)	0.708	(0.034)	0.770	(0.043)
$(\sigma_{a_2} = 0.5)$	0.459	(0.014)	0.370	(0.095)	0.461	(0.014)	0.388	(0.014)
N=800; T=4								
$(\rho = 0.5)$	-	-	0.478	(0.072)	-	-	0.416	(0.024)
$(\gamma = 0.5)$	-	-	0.546	(0.015)	-	-	0.548	(0.017)
$(\delta = 1.0)$	1.003	(0.041)	1.002	(0.045)	0.999	(0.028)	1.043	(0.025)
$(\beta = 1.0)$	1.000	(0.019)	1.006	(0.015)	1.000	(0.018)	1.007	(0.016)
$(\sigma_{a_1} = 0.5)$	0.704	(0.056)	0.710	(0.065)	0.711	(0.038)	0.739	(0.039)
$(\sigma_{a_2} = 0.5)$	0.461	(0.016)	0.380	(0.093)	0.459	(0.015)	0.396	(0.016)

* $\rho_{a_1 a_2} = 0.5$ and $\rho_{\epsilon_1 \epsilon_2} = 0.8$ in the data generating process but are assumed to be 0 in the estimation of the model.

not reported here show that the MLE of the coefficients in the equation of interest are biased *downwards* while that of the coefficients in the selection equation remains unaffected. The most notable change occurs in the MLE of σ_{a_1} which, in all cases, becomes biased *away* from zero, while that of σ_{a_2} remains, in all cases but in the dynamic type 2 tobit, biased *towards* zero.

Static model estimated under a dynamic DGP

The MLE of δ , β , σ_{a_1} , σ_{a_2} , $\rho_{a_1a_2}$ and $\rho_{\epsilon_1\epsilon_2}$ are reported in Table 3.6 when a static model is estimated under a dynamic DGP, i.e., ρ and γ are assumed to be zero.

Table 3.6: ML estimates based on 200 replications and 2-point Gauss-Hermite quadrature:
Static model estimated under a dynamic data generating process

(True value)*	Estimate	Mean	Std. Dev.	Mean	Std. Dev.
Estimated model					
Static type 2 tobit					
Static type 3 tobit					
N=500; T=4					
$(\delta = 1.0)$	$\hat{\delta}$	0.682	(0.047)	1.338	(0.072)
$(\beta = 1.0)$	$\hat{\beta}$	0.909	(0.057)	0.919	(0.060)
$(\sigma_{a_1} = 0.5)$	$\hat{\sigma}_{a_1}$	0.762	(0.102)	2.075	(0.193)
$(\sigma_{a_2} = 0.5)$	$\hat{\sigma}_{a_2}$	1.408	(0.075)	1.410	(0.079)
$(\rho_{a_1a_2} = 0.5)$	$\hat{\rho}_{a_1a_2}$	0.248	(0.016)	0.237	(0.018)
$(\rho_{\epsilon_1\epsilon_2} = 0.8)$	$\hat{\rho}_{\epsilon_1\epsilon_2}$	0.345	(0.115)	0.365	(0.077)
N=500; T=7					
$(\delta = 1.0)$	$\hat{\delta}$	0.688	(0.041)	1.381	(0.057)
$(\beta = 1.0)$	$\hat{\beta}$	0.921	(0.038)	0.931	(0.041)
$(\sigma_{a_1} = 0.5)$	$\hat{\sigma}_{a_1}$	0.865	(0.077)	2.509	(0.196)
$(\sigma_{a_2} = 0.5)$	$\hat{\sigma}_{a_2}$	1.541	(0.068)	1.583	(0.078)
$(\rho_{a_1a_2} = 0.5)$	$\hat{\rho}_{a_1a_2}$	0.279	(0.019)	0.266	(0.018)
$(\rho_{\epsilon_1\epsilon_2} = 0.8)$	$\hat{\rho}_{\epsilon_1\epsilon_2}$	0.389	(0.133)	0.423	(0.073)
N=800; T=4					
$(\delta = 1.0)$	$\hat{\delta}$	0.679	(0.034)	1.347	(0.054)
$(\beta = 1.0)$	$\hat{\beta}$	0.908	(0.044)	0.915	(0.047)
$(\sigma_{a_1} = 0.5)$	$\hat{\sigma}_{a_1}$	0.752	(0.086)	2.079	(0.142)
$(\sigma_{a_2} = 0.5)$	$\hat{\sigma}_{a_2}$	1.402	(0.057)	1.403	(0.056)
$(\rho_{a_1a_2} = 0.5)$	$\hat{\rho}_{a_1a_2}$	0.249	(0.013)	0.236	(0.015)
$(\rho_{\epsilon_1\epsilon_2} = 0.8)$	$\hat{\rho}_{\epsilon_1\epsilon_2}$	0.338	(0.105)	0.365	(0.063)

* $\rho = \gamma = 0.5$ in the data generating process but are assumed to be 0 in the estimation of the model.

In both the type 2 and type 3 tobit, the MLE of δ is biased *away* from zero, with a bias that is no less than 30%, while the MLE of β remains biased *towards* zero but with a larger bias than in the DGP case. Furthermore, the standard deviations of the individual effects are

overestimated and their MLE bias gets as large as 200% for σ_{a_1} , and 100% for σ_{a_2} . In other words, when past event is a determinant of current event and is left out of the explanatory variables, too much credit is attributed to the individual effects as a determinant of current event. This is the reverse phenomenon of the spurious state dependence. Finally, $\rho_{a_1a_2}$ and $\rho_{e_1e_2}$ are biased *away* from zero with a bias of approximately 25% and 45% respectively.

Dynamic model estimated under a static DGP

We estimate two types of dynamic models under a static DGP. The first one ignores the individual effects, and the second one accounts for individual effects that are correlated with endogenous initial conditions. In other words, the first type assumes σ_{a_1} , σ_{a_2} and $\rho_{a_1a_2}$ to be all zero while the second one makes no restriction assumptions on the parameters of the model. The mean and standard deviation of the MLE of ρ , γ , δ , β , σ_{a_1} , σ_{a_2} , $\rho_{a_1a_2}$ and $\rho_{e_1e_2}$ are reported in Table 3.7.

In both cases, the MLE of δ and β are biased *towards* zero in the type 2 and type 3 tobit. However, the bias for δ is larger when we do not account for the individual effects than when we account for them. The most notable difference between the two cases lies in the estimates of the coefficients of the lagged dependent explanatory variables. They are positive, around 0.10 for ρ and 0.15 for γ , and significantly different from zero when we do not account for the individual effects. In other words, ignoring the individual effects results in attributing credit to past event as a determinant of current event while the former does not condition at all the latter. This is an extreme case of the spurious state dependence mentioned earlier. When we account for individual effects that are correlated with endogenous initial conditions, these estimates become very close to zero, their true value, and the standard deviations of the individual effects are biased *towards* zero. Hence, when estimating a dynamic panel data model, regardless of whether the DGP is dynamic or static, the issues of properly accounting for the individual effects and treating the initial conditions must be taken care of. As for $\rho_{a_1a_2}$, it is biased *away* from zero in both the type 2 and type 3 tobit, while $\rho_{e_1e_2}$ is biased *away* from zero in the type 2 tobit, and in the type 3 tobit with no individual effects. When individual effects that are correlated with endogenous initial conditions are accounted for, $\rho_{e_1e_2}$ is biased *towards* zero in the type 3 tobit.

Table 3.7: ML estimates based on 200 replications and 2-point Gauss-Hermite quadrature: Dynamic model estimated under a static data generating process

(True value)	Estimate	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
generating process									
Estimated model									
Dynamic type 2 tobit									
with no individual effects					with individual effects and en-				
dogenuous initial conditions					dogenuous initial conditions				
N=500: T=4									
$(\rho = 0.0)$	$\hat{\rho}$	0.106	(0.050)	-0.001	(0.074)	0.099	(0.026)	0.019	(0.028)
$(\gamma = 0.0)$	$\hat{\gamma}$	0.158	(0.025)	0.043	(0.026)	0.147	(0.021)	0.050	(0.021)
$(\delta = 1.0)$	$\hat{\delta}$	0.910	(0.042)	1.004	(0.050)	0.985	(0.027)	0.994	(0.028)
$(\beta = 1.0)$	$\hat{\beta}$	1.001	(0.023)	1.005	(0.021)	1.001	(0.019)	1.007	(0.018)
$(\sigma_{a_1} = 0.5)$	$\hat{\sigma}_{a_1}$	-	-	0.537	(0.080)	-	-	0.430	(0.069)
$(\sigma_{a_2} = 0.5)$	$\hat{\sigma}_{a_2}$	-	-	0.405	(0.102)	-	-	0.393	(0.017)
$(\rho_{a_1 a_2} = 0.5)$	$\hat{\rho}_{a_1 a_2}$	-	-	0.255	(0.065)	-	-	0.243	(0.019)
$(\rho_{\epsilon_1 \epsilon_2} = 0.8)$	$\hat{\rho}_{\epsilon_1 \epsilon_2}$	0.659	(0.034)	0.660	(0.051)	0.664	(0.021)	0.709	(0.025)
N=500: T=7									
$(\rho = 0.0)$	$\hat{\rho}$	0.103	(0.031)	-0.002	(0.044)	0.097	(0.018)	0.010	(0.019)
$(\gamma = 0.0)$	$\hat{\gamma}$	0.155	(0.018)	0.045	(0.017)	0.146	(0.015)	0.051	(0.013)
$(\delta = 1.0)$	$\hat{\delta}$	0.908	(0.034)	1.010	(0.041)	0.986	(0.020)	1.000	(0.021)
$(\beta = 1.0)$	$\hat{\beta}$	1.000	(0.016)	1.004	(0.015)	1.001	(0.013)	1.004	(0.011)
$(\sigma_{a_1} = 0.5)$	$\hat{\sigma}_{a_1}$	-	-	0.593	(0.055)	-	-	0.528	(0.053)
$(\sigma_{a_2} = 0.5)$	$\hat{\sigma}_{a_2}$	-	-	0.414	(0.015)	-	-	0.400	(0.014)
$(\rho_{a_1 a_2} = 0.5)$	$\hat{\rho}_{a_1 a_2}$	-	-	0.293	(0.016)	-	-	0.263	(0.019)
$(\rho_{\epsilon_1 \epsilon_2} = 0.8)$	$\hat{\rho}_{\epsilon_1 \epsilon_2}$	0.661	(0.025)	0.664	(0.034)	0.664	(0.016)	0.714	(0.016)
N=800: T=4									
$(\rho = 0.0)$	$\hat{\rho}$	0.103	(0.040)	0.000	(0.061)	0.098	(0.019)	0.019	(0.023)
$(\gamma = 0.0)$	$\hat{\gamma}$	0.154	(0.012)	0.044	(0.021)	0.143	(0.016)	0.047	(0.017)
$(\delta = 1.0)$	$\hat{\delta}$	0.905	(0.034)	0.998	(0.043)	0.980	(0.021)	0.989	(0.021)
$(\beta = 1.0)$	$\hat{\beta}$	1.002	(0.018)	1.006	(0.017)	0.999	(0.014)	1.005	(0.013)
$(\sigma_{a_1} = 0.5)$	$\hat{\sigma}_{a_1}$	-	-	0.528	(0.072)	-	-	0.430	(0.054)
$(\sigma_{a_2} = 0.5)$	$\hat{\sigma}_{a_2}$	-	-	0.412	(0.041)	-	-	0.394	(0.014)
$(\rho_{a_1 a_2} = 0.5)$	$\hat{\rho}_{a_1 a_2}$	-	-	0.261	(0.034)	-	-	0.244	(0.013)
$(\rho_{\epsilon_1 \epsilon_2} = 0.8)$	$\hat{\rho}_{\epsilon_1 \epsilon_2}$	0.661	(0.025)	0.654	(0.042)	0.663	(0.017)	0.707	(0.018)

3.6 Conclusion

We have proposed a simple method to implement the maximum likelihood estimator of dynamic panel data sample selection models. The method consists in writing the likelihood function conditional on the individual effects which are then “integrated out” with respect to their joint normal distribution. We have handled the double integral involved in the likelihood function using “two-step” Gauss-Hermite quadrature, and solved the initial conditions problem using the approach of Wooldridge (2005). The resulting likelihood function encompasses a wide range of likelihood functions of panel data models whose estimation can be achieved by simply making restriction assumptions on the parameters of the dynamic panel data sample selection model. These assumptions can be tested using a standard likelihood ratio or Wald test.

In order to assess the quality of the Gauss-Hermite quadrature, and hence that of the maximum likelihood estimator, we have conducted a Monte Carlo study and obtained the following results. First, under the data generating process, the maximum likelihood estimator works very well, even for a number of integration points, in each step of the Gauss-Hermite quadrature, as small as 2. The estimator bias of the coefficients of the lagged dependent and strictly exogenous explanatory variables, as well as that of the standard deviations of the individual effects is very small for a sample size as large as the one considered in the Monte Carlo study. The sample selection terms, however, are less accurately estimated when the number of integration points is very small. Secondly, too much credit is attributed to the lagged dependent variables as a determinant of the current dependent variables when either the individual effects or the correlation between the initial outcome and the individual effects are not taken into account. Thirdly, the selection bias really matters when the explanatory variables in the selection equation and the equation of interest are highly correlated, otherwise it can be safely ignored. Fourthly, when the lagged dependent variables condition the current dependent variables and are left out of the explanatory variables, too much credit is attributed to the individual effects as a determinant of the current dependent variables. Finally, when estimating a dynamic panel data model, regardless of whether the true model is dynamic or static, the individual effects and the correlation between the initial outcome and the individual effects must be taken into account, otherwise a situation of spurious state dependence will arise even under its extreme form. In this latter case, credit is attributed to the lagged

dependent variables as a determinant of the current dependent variables while the former do not condition at all the latter.

Our approach can be, in a straightforward manner, extended to estimate by maximum likelihood panel data sample selection models with more than two equations, that include a lagged dependent explanatory variable and individual effects in each equation. For instance, our approach can handle the estimation of dynamic panel data type 4 and type 5 tobit models with individual effects.

Appendix 3.A “Two-step” Gauss-Hermite quadrature

Consider the dynamic panel data type 2 tobit model defined by equations (3.1-3.4) and (3.6-3.7), and consider expressions (3.10) and (3.11). Assume that the vectors $(\epsilon_{1it}, \epsilon_{2it})'$ and $(a_{1i}, a_{2i})'$ are independent of each other, and independently and identically distributed over time and across individuals following a normal distribution with mean zero and covariance matrix given in equation (3.8). The likelihood function of individual i , starting from $t = 1$ and conditional on the regressors and the initial conditions, is obtained by “integrating out” the individual effects (equation (3.9)). The likelihood function of individual i conditional on the individual effects is written in equation (3.12) with σ_{ϵ_1} being normalized to 1 for identification reasons. The expression of the bivariate normal distribution of a_{1i} and a_{2i} is written as

$$g(a_{1i}, a_{2i}) = (2\pi\sigma_{a_1}\sigma_{a_2})^{-1} (1 - \rho_{a_1a_2}^2)^{-\frac{1}{2}} e^{-\frac{1}{2(1-\rho_{a_1a_2}^2)} \left(\frac{a_{1i}^2}{\sigma_{a_1}^2} - 2\rho_{a_1a_2} \frac{a_{1i}}{\sigma_{a_1}} \frac{a_{2i}}{\sigma_{a_2}} + \frac{a_{2i}^2}{\sigma_{a_2}^2} \right)}. \quad (3.20)$$

Hence, equation (3.9) can be written as

$$L_i = \int_{-\infty}^{\infty} e^{-\frac{a_{2i}^2}{2\sigma_{a_2}^2(1-\rho_{a_1a_2}^2)}} \prod_{t=1}^T \left[\frac{1}{\sigma_{\epsilon_2}} \phi \left(\frac{y_{it} - B_{it} - a_{2i}}{\sigma_{\epsilon_2}} \right) \right]^{d_{it}} H(a_{2i}) da_{2i}, \quad (3.21)$$

where $H(a_{2i})$ is written as

$$\begin{aligned} H(a_{2i}) &= (2\pi\sigma_{a_1}\sigma_{a_2})^{-1} (1 - \rho_{a_1a_2}^2)^{-\frac{1}{2}} \int_{-\infty}^{\infty} e^{-\frac{a_{1i}^2}{2\sigma_{a_1}^2(1-\rho_{a_1a_2}^2)}} e^{-\frac{1}{2(1-\rho_{a_1a_2}^2)} \left(\rho_{a_1a_2} \frac{a_{1i}}{\sigma_{a_1}} \frac{a_{2i}}{\sigma_{a_2}} \right)} \\ &\quad \times \prod_{t=1}^T \Phi [-(A_{it} + a_{1i})]^{(1-d_{it})} \left[\Phi \left(\frac{A_{it} + a_{1i} + \frac{\rho_{\epsilon_1\epsilon_2}}{\sigma_{\epsilon_2}} (y_{it} - B_{it} - a_{2i})}{\sqrt{1 - \rho_{\epsilon_1\epsilon_2}^2}} \right) \right]^{d_{it}} da_{1i}. \end{aligned} \quad (3.22)$$

Equation (3.21) can be approximated using “two-step” Gauss-Hermite quadrature which states that

$$\int_{-\infty}^{\infty} e^{-z^2} f(z) dz \simeq \sum_{m=1}^M w_m f(a_m), \quad (3.23)$$

where w_m and a_m are respectively the weights and abscissas of the Gauss-Hermite quadrature, the tables of which are formulated in mathematical textbooks (e.g. Abramovitz and Stegun, 1964), and M is the total number of integration points. The larger M , the more accurate

the Gauss-Hermite quadrature. The “two-step” Gauss-Hermite quadrature consists, in the first step, in approximating equation (3.22) using equation (3.23). In the second step, a second approximation is applied to equation (3.21) where $H(a_{2i})$ is replaced by its first-step Gauss-Hermite approximation. The approach is described as follows.

Consider the variable change $z_{1i} = \frac{a_{1i}}{\sigma_{a_1} \sqrt{2(1-\rho_{a_1 a_2}^2)}}$ so that $da_{1i} = dz_{1i} \sigma_{a_1} \sqrt{2(1-\rho_{a_1 a_2}^2)}$.

Equation (3.22) is then written as

$$H(a_{2i}) = \frac{\sqrt{2}}{2\pi\sigma_{a_2}} \int_{-\infty}^{\infty} e^{-z_{1i}^2} e^{\frac{1}{1-\rho_{a_1 a_2}^2} \left(\rho_{a_1 a_2} z_{1i} \sqrt{2(1-\rho_{a_1 a_2}^2)} \frac{a_{2i}}{\sigma_{a_2}} \right)} \times \prod_{t=1}^T \Phi \left[- \left(A_{it} + z_{1i} \sigma_{a_1} \sqrt{2(1-\rho_{a_1 a_2}^2)} \right) \right]^{(1-d_{it})} \times \left[\Phi \left(\frac{A_{it} + z_{1i} \sigma_{a_1} \sqrt{2(1-\rho_{a_1 a_2}^2)} + \frac{\rho_{\epsilon_1 \epsilon_2}}{\sigma_{\epsilon_2}} (y_{it} - B_{it} - a_{2i})}{\sqrt{1-\rho_{\epsilon_1 \epsilon_2}^2}} \right) \right]^{d_{it}} dz_{1i} \quad (3.24)$$

and can be approximated using equation (3.23) by

$$H(a_{2i}) \simeq \frac{\sqrt{2}}{2\pi\sigma_{a_2}} \sum_{m=1}^M w_m \left\{ e^{\frac{1}{1-\rho_{a_1 a_2}^2} \left(\rho_{a_1 a_2} a_m \sqrt{2(1-\rho_{a_1 a_2}^2)} \frac{a_{2i}}{\sigma_{a_2}} \right)} \times \prod_{t=1}^T \Phi \left[- \left(A_{it} + a_m \sigma_{a_1} \sqrt{2(1-\rho_{a_1 a_2}^2)} \right) \right]^{(1-d_{it})} \times \left[\Phi \left(\frac{A_{it} + a_m \sigma_{a_1} \sqrt{2(1-\rho_{a_1 a_2}^2)} + \frac{\rho_{\epsilon_1 \epsilon_2}}{\sigma_{\epsilon_2}} (y_{it} - B_{it} - a_{2i})}{\sqrt{1-\rho_{\epsilon_1 \epsilon_2}^2}} \right) \right]^{d_{it}} \right\}, \quad (3.25)$$

where w_m and a_m are the weights and abscissas of the first-step Gauss-Hermite quadrature with M being the total number of integration points.

Consider the second variable change $z_{2i} = \frac{a_{2i}}{\sigma_{a_2} \sqrt{2(1-\rho_{a_1 a_2}^2)}}$ so that $da_{2i} = dz_{2i} \sigma_{a_2} \sqrt{2(1-\rho_{a_1 a_2}^2)}$.

Replacing equation (3.25) into equation (3.21) yields

$$L_i \simeq \frac{\sqrt{1-\rho_{a_1 a_2}^2}}{\pi} \int_{-\infty}^{\infty} e^{-z_{2i}^2} \prod_{t=1}^T \left[\frac{1}{\sigma_{\epsilon_2}} \phi \left(\frac{y_{it} - B_{it} - z_{2i} \sigma_{a_2} \sqrt{2(1-\rho_{a_1 a_2}^2)}}{\sigma_{\epsilon_2}} \right) \right]^{d_{it}} \times \sum_{m=1}^M w_m \left\{ e^{2\rho_{a_1 a_2} z_{2i} a_m} \prod_{t=1}^T \Phi \left[- \left(A_{it} + a_m \sigma_{a_1} \sqrt{2(1-\rho_{a_1 a_2}^2)} \right) \right]^{(1-d_{it})} \times \left[\Phi \left(\frac{A_{it} + a_m \sigma_{a_1} \sqrt{2(1-\rho_{a_1 a_2}^2)} + \frac{\rho_{\epsilon_1 \epsilon_2}}{\sigma_{\epsilon_2}} (y_{it} - B_{it} - z_{2i} \sigma_{a_2} \sqrt{2(1-\rho_{a_1 a_2}^2)})}{\sqrt{1-\rho_{\epsilon_1 \epsilon_2}^2}} \right) \right]^{d_{it}} \right\} dz_{2i} \quad (3.26)$$

which can be approximated using again equation (3.23) by

$$\begin{aligned}
 L_i \simeq & \frac{\sqrt{1-\rho_{a_1a_2}^2}}{\pi} \sum_{p=1}^P w_p \left\{ \prod_{t=1}^T \left[\frac{1}{\sigma_{\epsilon_2}} \phi \left(\frac{y_{it} - B_{it} - a_p \sigma_{a_2} \sqrt{2(1-\rho_{a_1a_2}^2)}}{\sigma_{\epsilon_2}} \right) \right]^{d_{it}} \right. \\
 & \times \sum_{m=1}^M w_m \left\{ e^{2\rho_{a_1a_2} a_p a_m} \prod_{t=1}^T \Phi \left[- \left(A_{it} + a_m \sigma_{a_1} \sqrt{2(1-\rho_{a_1a_2}^2)} \right) \right]^{(1-d_{it})} \right. \\
 & \times \left. \left. \Phi \left(\frac{A_{it} + a_m \sigma_{a_1} \sqrt{2(1-\rho_{a_1a_2}^2)} + \frac{\rho_{\epsilon_1\epsilon_2}}{\sigma_{\epsilon_2}} (y_{it} - B_{it} - a_p \sigma_{a_2} \sqrt{2(1-\rho_{a_1a_2}^2)})}{\sqrt{1-\rho_{\epsilon_1\epsilon_2}^2}} \right)^{d_{it}} \right] \right\} \right\}, \tag{3.27}
 \end{aligned}$$

where w_p and a_p are the weights and abscissas of the second-order Gauss-Hermite quadrature with P being the total number of integration points.

Using equations (3.9), (3.13), (3.14) and (3.20), the random-effects individual likelihood function of the type 3 tobit can be derived similarly to yield equation (3.16).

Appendix 3.B Panel data models encompassed in the dynamic type 2 and type 3 tobit models

Table 3.8: Panel data models encompassed in the dynamic type 2 and type 3 tobit models

Restricted model	Parameter restrictions		
	Individual effects*	Initial conditions**	Sample selection
The general model is dynamic type 2 (type 3) tobit [†]			
Dynamic ^{††} type 2 (type 3) tobit	$\sigma_{a_1} \neq 0; \sigma_{a_2} \neq 0;$ present	$b_1^s = b_1^r = 0;$ exogenous	$\rho_{\epsilon_1 \epsilon_2} \neq 0; \rho_{a_1 a_2} \neq 0;$ selection bias correction
Dynamic type 2 (type 3) tobit	$\sigma_{a_1} = \sigma_{a_2} = 0;$ absent	$b_1^s = b_1^r = 0;$ exogenous	$\rho_{\epsilon_1 \epsilon_2} \neq 0; \rho_{a_1 a_2} \neq 0;$ selection bias correction
Dynamic probit (type 1 tobit) + dynamic linear regression	$\sigma_{a_1} \neq 0; \sigma_{a_2} \neq 0;$ present	$b_1^s \neq 0; b_1^r \neq 0;$ endogenous	$\rho_{\epsilon_1 \epsilon_2} = \rho_{a_1 a_2} = 0;$ no selection bias correction
Dynamic probit (type 1 tobit) + dynamic linear regression	$\sigma_{a_1} \neq 0; \sigma_{a_2} \neq 0;$ present	$b_1^s = b_1^r = 0;$ exogenous	$\rho_{\epsilon_1 \epsilon_2} = \rho_{a_1 a_2} = 0;$ no selection bias correction
Dynamic probit (type 1 tobit) + dynamic linear regression	$\sigma_{a_1} = \sigma_{a_2} = 0;$ absent	$b_1^s = b_1^r = 0;$ exogenous	$\rho_{\epsilon_1 \epsilon_2} = \rho_{a_1 a_2} = 0;$ no selection bias correction
Static ^{††} type 2 (type 3) tobit	$\sigma_{a_1} \neq 0; \sigma_{a_2} \neq 0;$ present	n.a.	$\rho_{\epsilon_1 \epsilon_2} \neq 0; \rho_{a_1 a_2} \neq 0;$ selection bias correction
Static type 2 (type 3) tobit	$\sigma_{a_1} = \sigma_{a_2} = 0;$ absent	n.a.	$\rho_{\epsilon_1 \epsilon_2} \neq 0; \rho_{a_1 a_2} \neq 0;$ selection bias correction
Static probit (type 1 tobit) + static linear regression	$\sigma_{a_1} \neq 0; \sigma_{a_2} \neq 0;$ present	n.a.	$\rho_{\epsilon_1 \epsilon_2} = \rho_{a_1 a_2} = 0;$ no selection bias correction
Static probit (type 1 tobit) + static linear regression	$\sigma_{a_1} = \sigma_{a_2} = 0;$ absent	n.a.	$\rho_{\epsilon_1 \epsilon_2} = \rho_{a_1 a_2} = 0;$ no selection bias correction

*The individual effects, when present, may be correlated ($\mathbf{b}_2^s \neq 0; \mathbf{b}_2^r \neq 0$) or uncorrelated ($\mathbf{b}_2^s = \mathbf{b}_2^r = 0$) with the explanatory variables. **When the model is static ($\rho = \gamma = 0$) the initial conditions problem is not an issue, so $b_1^s = b_1^r = 0$. [†]The general model contains individual effects and the initial conditions are endogenous and correlated with the individual effects. ^{††}“Hybrid” models with a static selection and a dynamic equation of interest (and vice versa) can also be estimated using our approach.

CHAPTER 4

Persistence of innovation in Dutch manufacturing: Is it spurious?

4.1 Introduction

This chapter examines, at the firm level, the dynamics of the innovation process in Dutch manufacturing using three waves of the Community Innovation Survey (henceforth CIS) pertaining to the periods 1994-1996, 1996-1998 and 1998-2000. More specifically, we attempt to answer two questions. First, does being successful in past innovation activities increase the probability of being successful in current innovation activities? Secondly, does past innovation output, as measured by the share in total sales of innovative sales,¹ generate current innovation output?

The first research question relates to the literature on the persistence of innovation which, at the micro level, plays an important role in the context of endogenous growth models (Romer, 1990; Aghion and Howitt, 1992). It also helps to understand industrial economics phenomena such as the persistence of profitability (Roberts, 2001) and total factor productivity (TFP) growth (Geroski, 1989). Several theoretical explanations of the persistence of innovation (at the firm level) exist in the literature. In one approach the persistence of innovation is explained by the existence of *sunk costs*: in order to build and maintain an R&D department, R&D expenditures are regular. In the *linear model* of innovation, as opposed to the *chain-link model*, a direct relationship between a firm's R&D expenditures and its

¹This chapter considers products that are new to the firm, not necessarily new to the market.

innovations is postulated such that the persistence of innovation coincides with that of R&D expenditures. A second explanation of the persistence of innovation pertains to the *financial constraints* that a firm may face in funding R&D activities, which makes it dependent on retained earnings as a source of funds. Innovations that have met a commercial success in the past generate profits that may be invested in current innovation activities and hence “success breeds success” (Mansfield, 1968). Finally an explanation of the persistence of innovation is given by the *learning-by-doing* model. It predicts that the production of innovations is subject to *dynamic economies of scale*. In other words, knowledge that has been used to produce past innovations can be used, assuming that the depreciation rate of innovative abilities is small, to produce current and even future innovations. In Schumpeterian terms, the three theoretical explanations of the persistence of innovation can be referred to as “creative accumulation”, as opposed to “creative destruction”, where the latter term is used to explain the absence of persistence in innovation activities.

The dynamics of innovation output, investigated by the second research question, plays a crucial role in understanding the dynamics of firms’ technological performance (e.g. innovative sales) and economic performance (e.g. profits). Since the empirical work by Crépon et al. (1998), a great number of empirical studies focus on the relationship between innovation output and firm performance, the latter variable being measured, for instance, by sales per employee, value-added per employee, export per employee, growth rates of sales, total employment growth and so on. The main finding of these studies is that, regardless of how performance is measured, innovation output positively and significantly affects firm performance, with the exception of the study by Klomp and van Leeuwen (2001) that finds a negative but insignificant effect of innovation output on employment growth.² For instance, innovation output has a positive and significant effect on value-added per employee of French firms (Crépon et al., 1998), sales per employee of German firms (Janz et al., 2004), sales growth of Dutch firms (Klomp and van Leeuwen, 2001), and labor productivity (value-added per employee) growth of Swedish firms (Löf and Heshmati, 2002a). Löf and Heshmati (2002b) perform a sensitivity analysis using, besides the previously-mentioned ones, three additional measures of firm performance, namely, sales margin, profit before and after depreciation (in level and growth rates), and find the same pattern of positive and significant

²The relationship between innovation and employment is not a clear-cut one. Empirical studies identify both a positive and a negative effect of the former on the latter. The sign of the relationship depends, e.g., on the type of the data, the time-period and the level of analysis (firm versus industry level) (Pianta, 2004).

effect of innovation output on firm performance. Because of this close relationship between innovation output and firm performance, the dynamics of the former is expected to explain that of the latter. In other words, our second research question can help us address the issue of the persistence of firm performance (Cefis, 2003b; Cefis and Ciccarelli, 2005).

This study contributes to the empirical literature on innovation in a number of ways. Firstly, it analyzes persistence using other output measures than patents. Secondly, unlike the aforementioned empirical studies on firm performance, three waves of the CIS, pertaining to the Dutch manufacturing sector, are used for the first time to link the persistence of innovation (qualitative) to the dynamics of firms' technological performance (quantitative). We estimate a dynamic panel data type 2 tobit model accounting for unobserved individual effects and handling the initial conditions problem encountered when estimating dynamic panel data models. The incidence and the intensity of innovation are jointly estimated allowing for a correlation between the processes governing the introduction of new or significantly improved products and/or processes, and the generation of innovative sales. We use estimation techniques suggested by Wooldridge (2005), and extended in Chapter 3, and find that being successful in past innovation activities does not increase the probability of being successful in current innovation activities, and that past innovation output does condition, albeit to a small extent, current innovation output.

Section 4.2 summarizes the findings of the empirical literature on the persistence of innovation and firm performance. Section 4.3 presents the model that is estimated in Section 4.4. We describe the data used to implement the model in Section 4.5, present and discuss estimation results in Section 4.6, and conclude in Section 4.7.

4.2 Literature

This section summarizes the findings of the empirical literature on the persistence of innovation. Two types of studies are identified according to whether patent or other data are used (see Table 4.1). We explain the importance of the type of data that are used to measure innovation activities when persistence is analyzed. We also describe the findings of the rather few empirical studies on the relationship between the persistence of innovation output and that of firm performance.

4.2.1 The persistence of innovation

The studies on the persistence of innovation are motivated by testing the Schumpeter Mark I and II hypotheses. In other words, authors seek to know whether innovation activities are subject to “creative destruction” or “creative accumulation”. The hypotheses of whether innovation activities are subject to “dynamic economies of scales” or whether “success breeds success” are also tested in these studies. Finally, industry and country differences in the persistence of innovation are investigated.

Patent data

Innovation activities are captured in these studies by the number of patents that are either applied for or granted by the European Patent office (henceforth EPO) or the United States Patents and Trademarks Office (henceforth US PTO). Table 4.1 shows that, with the exception of Crépon and Duguet (1997), all the studies on the persistence of innovation that use patent data conclude more or less alike regardless of the methodology: there is no clear-cut evidence of strong persistence in innovation activities. In fact, those studies share a common drawback, namely, the type of data used to analyze persistence. The limitations of patent data are well-known (Griliches, 1990), and the inability to obtain unequivocal empirical results using such data is therefore not surprising. Indeed, in order for a firm to be properly accounted for in a patent data set, it has to be the first to apply for a patent. Hence, when analyzing the persistence of innovation using patent data, one is unwittingly analyzing the persistence of “winning the patent race”, which is unlikely to be strong (Duguet and Monjon, 2002). As a result, other types of data should be used to investigate the persistence of innovation activities.

Major innovation, R&D, CIS and other innovation survey data

Major innovation, R&D, CIS and other innovation survey data are also used to analyze the persistence of innovation activities. The first type of data yields results that are similar to those of studies using patent data. Duguet and Monjon (2002) point out that persistence is also likely to be low when using major innovation data. Indeed, since a major innovation is one that meets a commercial success, innovators are likely to be innovation or commercial leaders, which is unlikely to persist over a long period of time. Thus, major innovation data are as demanding as patent data when analyzing the persistence of innovation. On the other

hand, R&D and CIS data are seen as less demanding as persistence can be analyzed at the firm level without mentioning the patenting or market leadership status of the firm. In this case, regardless of the methodology, persistence in innovation activities is found to be high, whether input measures (Máñez Castillejo et al., 2004; Peters, 2005) or output measures (Duguet and Monjon, 2002) of innovation are used. Using data stemming from an innovation survey similar to the CIS and collected by the IFO-Institute in Munich, Flaig and Stadler (1994) also find high persistence in realizing product and/or process innovations.

4.2.2 The dynamics of innovation output and firm performance

All the empirical studies mentioned in Section 4.1 on the relationship between innovation output and firm performance are cross-sectional, whereas this one is based on panel data.³ Hence, they cannot analyze the dynamics of the innovation process and that of firm performance. Little is known about the relationship between the dynamics of innovation and that of firm performance. Two instances of studies that investigate this relationship are Cefis (2003b) and Cefis and Ciccarelli (2005). Both studies use patent data and find that persistent innovators have profits that are and remain higher than those of non-persistent innovators, hence the persistence of innovation and that of firm performance are closely related to each other.

Our study attempts to give a first insight into the dynamics of the innovation process in Dutch manufacturing using three waves of the CIS. We consider a model of innovative behavior in a “true” dynamic panel data framework, i.e. accounting for unobserved individual effects and handling the initial conditions problem. We estimate a dynamic panel data type 2 tobit model, according to Amemiya’s (1984) terminology, which encompasses the cross-sectional type 2 tobit model studied, for instance, by Brouwer and Kleinknecht (1996) and Mairesse and Mohnen (2001).

4.3 Econometric model

The model explains the achievement by Dutch manufacturing enterprises of technological product and/or process (TPP) innovations and the impact of these innovations on the share

³To the best of our knowledge, van Leeuwen’s (2002) study is the only one that analyzes the dynamics of innovation input (R&D expenditures/total sales) and output (innovative sales/total sales), and links innovation output to firm performance. However, his analysis is not done in a “true” panel data framework in that individual effects are not accounted for.

Table 4.1: Empirical studies on the persistence of innovation

Study	Country and (Time-period)	Innovation activities	Methodology	Measure of persistence	Result
Patent data					
Crépon and Duguet (1997)	France (1984-1989)	patents applied for to EPO	GMM on dynamic count panel data model	effects of lagged patents	high persistence
Geroski et al. (1997)	UK (1969-1988)	patents granted by US PTO	duration dependence Weibull model	length of innovation spell	low persistence
Cahagnols et al. (1999)	France (1969-1985)	patents granted by US PTO	duration dependence Weibull model	length of innovation spell	low persistence
Malerba and Orsenigo (1999)	France, Germany, Italy, Japan, UK, US (1978-1991)	patents applied for to EPO	descriptive analysis	duration of patenting after entry	low persistence
Cefis and Orsenigo (2001)	France, Germany, Italy, Japan, UK, US (1978-1993) [†]	patents applied for to EPO	TPM used in 1 st and 2 nd order Markov chains	probability of remaining in the same state of patenting	bimodality* and low persistence
Cefis (2003a)	UK (1978-1991)	patents applied for to EPO	TPM used in 1 st and 2 nd order Markov chains	probability of remaining in the same state of patenting	bimodality* and low persistence
Major innovation, R&D, CIS and other innovation survey data					
Flaig and Stadler (1994)	West Germany (1979-1986)	produce product and/or process innovations	Heckman ML estimation on RE dynamic probit with panel data	lagged product and/or process innovations	high persistence
Geroski et al. (1997)	UK (1945-1982)	produce at least one major innovation	duration dependence Weibull model	length of innovation spell	low persistence
Duguet and Monjon (2002)	France (1986-1996) ^{††}	produce product and/or process innovations (CIS)	ML estimation on dynamic probit with no individual effects	lagged product and/or process innovations	high persistence
Mañez Castillejo et al. (2004)	Spain (1990-2000)	engage in R&D activities	SML on SICM dynamic probit with panel data [†]	lagged R&D activities	high persistence
Peters (2005)	Germany (1994-2002)	engage in innovation activities (CIS)	Wooldridge ML estimation on RE dynamic ^{††} probit with panel data	lagged innovation activities	high persistence

*Bimodality means that the probability to remain in the polar states (with zero and at least 6 patents) is very high, but the other probabilities are low, leading to low persistence in general. [†]The period is 1978-1991 for the UK; TPM means transition probability matrix. ^{††}1993 information is missing.

[†]SML and SICM mean simulated maximum likelihood and stationary intertemporal covariance matrix respectively. ^{††}RE means random-effects.

of innovative sales. Formally, it is written as

$$d_{it} = 1 [\rho d_{i,t-1} + \delta' \mathbf{w}_{it} + \eta_i + \epsilon_{1it} > 0] \quad (4.1)$$

$$y_{it} = \begin{cases} \gamma y_{i,t-1} + \beta' \mathbf{x}_{it} + \alpha_i + \epsilon_{2it} & \text{if } d_{it} = 1, \\ 0 & \text{if } d_{it} = 0, \end{cases} \quad (4.2)$$

with $t = 1, \dots, T$; $i = 1, \dots, N$.

Equation (4.1) models the current decision of enterprise i to innovate as a latent function of its past innovation achievement ($d_{i,t-1}$), its observable characteristics ($\mathbf{w}_{it}$)⁴, time-invariant unobserved individual effects (η_i) and other time-variant unobserved variables (ϵ_{1it}) uncorrelated with $\mathbf{w}_{it}$. The expression in square brackets represents the incentive to innovate. If the incentive is sufficiently high, enterprise i is a TPP innovator in which case d_{it} is observed to be 1. The scalar ρ and the vector δ' capture respectively the effects of past innovation achievement and firm characteristics on current innovation achievement, and are to be estimated. A positive and statistically significant estimate of ρ identifies the presence of persistence in innovation which may occur for two reasons: because of state dependence or because of unobserved effects or left-out variables that are correlated over time (through serially-correlated errors or individual effects). Heckman (1981a; 1981c) refers to the first phenomenon as *true state dependence* and the second one as *spurious state dependence*. True state dependence states that past innovation achievement increases positively and significantly the probability of current innovation achievement (true persistence).⁵ In order to distinguish it from spurious state dependence, unobserved effects that are correlated over time and the initial conditions must be properly accounted for when estimating eq. (4.1).

Equation (4.2) models the current share of innovative sales (y_{it}) of innovator i ($d_{it} = 1$) as being determined by its past share of innovative sales ($y_{i,t-1}$), its characteristics ($\mathbf{x}_{it}$), time-invariant unobserved individual effects (α_i) and other time-variant unobserved variables (ϵ_{2it}) uncorrelated with $\mathbf{x}_{it}$. This share is zero if enterprise i is not an innovator, and the full set of regressors included into $\mathbf{x}_{it}$ are only available when enterprise i is an innovator. The scalar γ and the vector β' capture respectively the effects of past share of innovative sales and firm characteristics on current share of innovative sales, and are to be estimated.

⁴ $\mathbf{w}_{it}$ could also include market specific characteristics if they were observable.

⁵When the term persistence is used in this study without any further explanation, it is to be understood as true persistence which occurs in the case of true state dependence.

Equations (4.1) and (4.2) are jointly estimated allowing for a correlation between the processes governing the introduction of TPP innovations and the generation of innovative sales.

We now turn to the estimation technique.

4.4 Maximum likelihood estimation

This section explains how to estimate the dynamic panel data type 2 tobit model accounting for individual effects and handling the initial conditions problem. It is shown in the econometric literature that the coefficient associated with the lagged dependent variable can be overestimated if these two problems are not properly accounted for. Estimation techniques that properly handle these problems are known in the econometric literature (Heckman, 1981b; Wooldridge, 2005).

Kyriazidou (2001) suggests a “semi-parametric fixed-effects” approach, i.e., the individual effects η_i and α_i are assumed to be fixed, and derives moment restrictions (along the lines of Ahn and Schmidt (1995)) that are exploited to construct two-step GMM-type estimators. In the first step, the parameters of eq. (4.1) are consistently estimated, e.g., by methods suggested by Honoré and Kyriazidou (2000b). In the second step, these estimates are used to construct kernel weights that are larger for individuals whose sample selection effect is small. Under appropriate assumptions, the derived kernel-weighted GMM estimators are shown to be consistent and asymptotically normal. These estimators, however, cannot be applied in this study because of data limitations. First, the fixed-effects approach requires data that show a lot of variation over time (within variation), otherwise they are wiped out when time-differencing. This is hardly the case in our data since most of the variables are qualitative, and the continuous ones exhibit little within variation. For instance, the approach does not identify the effects of industry dummies which are assumed to capture technological opportunities. Secondly, the estimators are effective when the number of time periods is fairly large ($T \geq 4$), which is not the case in our study either. Indeed, the moment equations require time-differencing resulting in a loss of information in the data, and the remaining information must be sufficient to estimate the model, which is not feasible when T is too small.

In order to cope with the limitations of our data, we consider a random-effects approach

and make distributional assumptions on the individual effects. We use estimation techniques suggested by Wooldridge (2005), and extended in Chapter 3. More specifically, we estimate the model by maximum likelihood using “two-step” Gauss-Hermite quadrature to evaluate the likelihood function.⁶ The same number of integration points ($P = M = 5$) is used in this study, although P need not be equal to M . Equations (4.1) and (4.2) are correlated through the individual effects ($\rho_{a_1 a_2} \neq 0$) and the idiosyncratic errors ($\rho_{\epsilon_1 \epsilon_2} \neq 0$), and the “total” correlation between the two equations is calculated as

$$\rho_{tot} = \frac{\rho_{a_1 a_2} \sigma_{a_1} \sigma_{a_2} + \rho_{\epsilon_1 \epsilon_2} \sigma_{\epsilon_1} \sigma_{\epsilon_2}}{\sqrt{(\sigma_{a_1}^2 + 1)(\sigma_{a_2}^2 + \sigma_{\epsilon_2}^2)}}. \quad (4.3)$$

4.5 Data

To implement the model, we use the same data as in Chapter 2 collected by the *Centraal Bureau voor de Statistiek* (CBS). They stem from three waves of the Dutch Community Innovation Survey, CIS 2 (1994-1996), CIS 2.5 (1996-1998) and CIS 3 (1998-2000), merged with data from the Production Survey (PS). Only enterprises in Dutch manufacturing (SBI 15-37) are included in the analysis. The population of interest consists of enterprises with at least ten employees and positive sales at the end of the period covered by the innovation survey. We consider enterprises that existed in 1994, survived (at least) until 2000 and took part in the three innovation surveys, resulting in a balanced panel of 861 enterprises.

Descriptive statistics and the definition of the variables are shown in Table 4.2. The dependent variable in equation (4.1) is binary indicating whether enterprise i is a TPP innovator. 71% of such enterprises exist in our panel. Besides being a past TPP innovator, the probability of being a current TPP innovator is explained by lagged size and relative size,⁷ and industry dummies (according to SBI) that capture technological opportunities and appropriability, the measurements of which are available for both TPP and non-TPP innovators. The dependent variable in equation (4.2) is the ratio of sales from new or improved prod-

⁶The approach considered in equations (3.6) and (3.7) allows the individual effects to be correlated with the regressors. However, because of the lack of variation over time (within variation) in our data, a more restricted approach is considered in this analysis where the individual effects are assumed to be correlated only with the initial conditions.

⁷In the innovation survey, firms are asked whether they have product and/or process innovations, or incomplete and abandoned innovation activities during the whole period under study, while size and sales are measured only at the end of the period. Hence, all the cross-sectional studies on the determinants of innovation have this unsatisfactory feature of explaining the probability of being a TPP innovator or being innovative (during the whole period) by size or relative size (at the end of the period). Taking lagged size or relative size as an explanatory variable in the panel data context overcomes this problem.

Table 4.2: Descriptive statistics

Variable	Description	Overall Mean	Overall Std. Dev.	Between Std. Dev.	Within Std. Dev.
Dependent variables					
TPP innovator	1 if product and/or process innovator	0.714	0.452	0.350	0.287
Intensity of innovation*	innovative sales/total sales, for TPP innovators	0.290	0.258	0.218	0.147
Explanatory variables					
Demand pull	1 if product-oriented innovation objectives are very important, for TPP innovators	0.640	0.480	0.370	0.337
Technology push	1 if innovation sources are from universities or other institutes, for TPP innovators	0.213	0.410	0.298	0.271
Innovation cooperation	1 if there is any type of cooperation, for TPP innovators	0.349	0.477	0.379	0.293
Non-R&D performers	1 if not performing R&D, for TPP innovators	0.196	0.397	0.380	0.214
Continuous R&D performers	1 if performing continuous R&D, for R&D performers	0.754	0.431	0.399	0.247
Subsidies	1 if being subsidized at least once, for TPP innovators	0.577	0.494	0.424	0.284
R&D intensity**	R&D expenditures/total sales, for R&D performers	0.046	0.078	0.064	0.037
Size [†]	number of employees	209.962	539.248	534.722	71.292
Relative size ^{††}	total sales/sales of industry	0.006	0.020	0.020	0.004
Number of observations		2583			

*A logit transformation; ** $\ln(\text{R\&D}/\text{total sales})$; [†] $\ln(\text{number of employees})$; ^{††} $\ln(\text{total sales}/\text{sales of industry})$ are used in the estimation.

ucts (innovative sales) over total sales. This variable is logit-transformed in order to make it lie within the set of real numbers.⁸ The average share of innovative sales is rather small (29%) in our panel. Besides lagged size, the current share of innovative sales is explained by past share of innovative sales and dummy variables capturing demand pull, technology push, innovation cooperation, non-R&D performers, continuous R&D performers, subsidies, and lagged R&D intensity. The characteristics of TPP innovators and R&D performers are as follows. Product-oriented innovation objectives are deemed important to 64% of TPP innovators, only 21% of them use innovation sources from public or private institutions (e.g. universities).⁹ About 35% of TPP innovators have some kind of cooperation, 58% receive at

⁸The share of innovative sales takes on the values 0 for process-only innovators, and 1 for innovators that are newly established. They are replaced respectively by 0.0001 and 0.9999 in the logit transformation.

⁹More detailed explanations about the construction of the variables are given in Section 2.3 of Chapter 2.

least one subsidy and 80% are R&D performers who spend on average 5% of their total sales in R&D, and of which 75% perform R&D continuously.

As mentioned earlier, most of the variables are qualitative and show little variation over time. The few continuous variables typically vary more “between” enterprises than “within” enterprises over time. This is in part due to the rather small number of time periods ($T = 3$) of the panel.

Table 4.3: Transition probability: Persistence in innovation and innovation intensity

CIS 2	CIS 3			CIS 2.5	CIS 3		
	Non-TPP (%)	TPP (%)	Total		Non-TPP (%)	TPP (%)	Total
Non-TPP	63.16	36.84	228	Non-TPP	64.50	35.50	231
TPP	21.64	78.36	633	TPP	20.95	79.05	630
Total	281	580	861	Total	281	580	861

CIS 2	Innov. intens. in CIS 3			CIS 2.5	Innov. intens. in CIS 3		
	< avg. (%)	> avg. (%)	Total		< avg. (%)	> avg. (%)	Total
< average	73.81	26.19	565	< average	73.01	26.99	552
> average	28.38	71.62	296	> average	31.72	68.28	309
Total	501	360	861	Total	501	360	861

Table 4.3 reports transition probabilities for innovation activities. 63% of non-TPP innovators and 78% of TPP innovators in CIS 2 remain in their initial state in CIS 3. The same holds for the two sub-periods. As regards innovation intensity, 73% of the innovators with below average intensity in CIS 2 remain below average in CIS 2.5 and CIS 3, and about 70% are always above average. The general pattern in the figures of Table 4.3 is that innovation activities are persistent which may occur, as mentioned earlier, for two reasons namely true and spurious state dependence. In order to distinguish the former from the latter, we estimate eqs. (4.1) and (4.2) using estimation techniques described in subsection 3.4 of Chapter 3.

We now present the estimation results.

4.6 Results

By simultaneous estimation of equations (4.1) and (4.2) an answer is sought to the two research questions taken jointly. As product-life cycle and R&D intensity vary across industries, the persistence of innovation and R&D intensity may be expected to be industry-specific (Malerba and Orsenigo, 1999; Cefis and Orsenigo, 2001). In first instance, a test was performed on the equality of the industry persistence parameters (coefficients of the lagged

dependent variables) and industry intercepts. The joint null hypothesis that the industry persistence parameters and the industry intercepts are equal could not be rejected. In Table 4.4 the results are presented of the model in which the industry persistence parameters and industry intercepts are restricted to be equal. In order to show the importance of accounting for individual effects and handling the initial conditions problem, we present the estimation results of the dynamic type 2 tobit model without accounting for individual effects in the second pair of columns in Table 4.4, and those of the same model in which individual effects have been taken into account but the initial conditions have been assumed exogenous in the third pair of columns. These results are to be contrasted with the estimates in the fourth pair of columns resulting from estimation of the dynamic type 2 tobit model in which both individual effects have been taken into account and the initial conditions have been treated as endogenous. The estimation results on the persistence of innovation, i.e., the estimates of the parameters in equation (4.1), are presented in the upper part of Table 4.4 and discussed in subsection 4.6.1. The estimation results on the dynamics of innovation output, i.e., the estimates of the parameters in equation (4.2), are presented in the middle part of Table 4.4 and discussed in subsection 4.6.2. Finally, the outcomes of some sensitivity analyses are reported on in subsection 4.6.3.

4.6.1 The persistence of innovation

No individual effects and individual effects with exogenous initial conditions

The estimation results of the dynamic type 2 tobit model assuming the absence of individual effects and, alternatively, accounting for individual effects and assuming the initial conditions to be exogenous are very similar.¹⁰ The persistence parameter is positive and highly significant and lagged size affects positively and significantly the probability to innovate. As mentioned earlier, the persistence of innovation may be spurious. The existence of true persistence in innovation may be ascertained by verifying that, after accounting for individual effects and properly handling the initial conditions problem, the effect of the lagged dependent variable is, economically and statistically, relevant.

Individual effects and endogenous initial conditions

¹⁰Exogenous initial conditions imply that being successful in achieving TPP innovations at the initial period does not affect the probability to innovate later on.

Table 4.4: Dynamic type 2 tobit estimates with 5-point Gauss-Hermite quadrature: Innovation output

Table 4.4: <i>Dynamic type 2 count estimates with 3-point Gauss-hermite quadrature: innovation deep</i>								
Variable	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)
	No selection bias correction				Selection bias correction			
	Unobserved individual effects				Unobserved individual effects			
	Endogenous initial conditions				Exogenous initial conditions			
	No unobserved individual effects				Endogenous initial conditions			
Estimation assumption	Current TPP innovation (d_{it})							
Past TPP innovation ($d_{i,t-1}$)	0.223	(0.221)	0.867**	(0.133)	0.856**	(0.137)	0.212	(0.193)
Lagged size (in log)	0.231**	(0.087)	0.143*	(0.060)	0.144*	(0.061)	0.162*	(0.072)
Lagged relative size (in log)	0.057	(0.062)	0.066	(0.041)	0.066	(0.042)	0.080	(0.051)
Intercept	-0.949	(0.761)	-0.296	(0.519)	-0.284	(0.529)	-0.448	(0.630)
	Current share of innovative sales (y_{it} in logit)							
Past share of innovative sales ($y_{i,t-1}$)	0.155**	(0.042)	0.249**	(0.025)	0.240**	(0.031)	0.109*	(0.043)
Lagged size (in log)	0.001	(0.123)	0.252*	(0.127)	0.252*	(0.128)	0.264*	(0.133)
R&D intensity (in log)	0.339**	(0.101)	0.335**	(0.096)	0.334**	(0.096)	0.340**	(0.099)
Non-R&D performers	-1.944**	(0.648)	-2.213**	(0.615)	-2.205**	(0.617)	-2.295**	(0.621)
Continuous R&D performers	0.679*	(0.342)	0.688*	(0.324)	0.707*	(0.326)	0.749*	(0.328)
Demand pull	1.145**	(0.248)	1.263**	(0.240)	1.252**	(0.241)	1.180**	(0.238)
Technology push	0.577*	(0.283)	0.580*	(0.270)	0.588*	(0.271)	0.589*	(0.273)
Cooperation in innovation	0.294	(0.262)	0.237	(0.250)	0.240	(0.251)	0.274	(0.254)
Subsidies	0.338	(0.276)	0.518*	(0.263)	0.517†	(0.264)	0.487†	(0.265)
Intercept	-1.218	(0.798)	-3.676**	(0.801)	-3.709**	(0.810)	-3.626**	(0.831)
Extra parameters								
Initial TPP innovation (d_{i0})	1.159**	(0.199)	-	-	-	-	0.984**	(0.181)
Initial share of innovative sales (y_{i0})	0.074*	(0.036)	-	-	-	-	0.144**	(0.037)
σ_{a_1}	0.654**	(0.195)	-	-	0.142	(0.288)	0.536*	(0.224)
σ_{a_2}	1.214**	(0.297)	-	-	0.674	(0.675)	1.539**	(0.337)
σ_{ϵ_2}	3.478**	(0.117)	4.212**	(0.111)	4.156**	(0.155)	3.900**	(0.138)
$\rho_{a_1\epsilon_2}$	-	-	-	-	0.458	(0.282)	0.411*	(0.168)
$\rho_{\epsilon_1\epsilon_2}$	-	-	0.823**	(0.024)	0.831**	(0.030)	0.914**	(0.081)
Number of observations	1722							
Log-likelihood	-3502.862	-3490.671	-3490.559	-3459.922				
Significance levels :	*: 5%	**: 1%						

Once the two typical problems of individual effects and initial conditions are properly handled, the hypothesis that the persistence parameter, i.e., the coefficient of the lagged dependent variable, is equal to zero can no longer be rejected. This result contrasts with that of Dugnet and Monjon (2002) who find strong persistence in achieving TPP innovations in French manufacturing. However, they do not account for individual effects, and their finding of persistence may well be due to spurious state dependence. Furthermore, lagged size positively and significantly affects the probability to innovate.

4.6.2 The dynamics of innovation output

No individual effects and individual effects with exogenous initial conditions

The estimates of the parameters of equation (4.2) are also similar in the dynamic type 2 tobit model without individual effects and in the model with individual effects and exogenous initial conditions. The persistence parameter is positive and highly significant. Furthermore, lagged size, R&D intensity, performing R&D on a continuous basis, demand pull, technology push and subsidies positively affect the current share of innovative sales and, *ceteris paribus*, non-R&D performers are less successful than R&D performers.

Individual effects and endogenous initial conditions

The results suggest that, even after accounting for individual effects and handling the initial conditions problem, the persistence parameter remains significant at 5% level of significance, suggesting that past innovation output generates in part current innovation output. As for the other regressors, the results mentioned above remain valid.

Both the model that assumes the absence of individual effects and the one that accounts for individual effects but assumes exogenous initial conditions are rejected using a likelihood ratio test at 1% level of significance. Hence, the full model is the preferred one where equations (4.1) and (4.2) are jointly estimated allowing for a correlation between the processes governing the introduction of TPP innovations and the generation of innovative sales. Both cross-equation individual effects and cross-equation idiosyncratic parts are found to be correlated and the “total” correlation (eq. (4.3)) between the two equations is calculated *ex post* to be 0.821.

4.6.3 Robustness analysis

When no correlation is assumed between the decision to be a TPP innovator and the share of innovative sales, consistent and efficient estimators of the parameters of the type 2 tobit model may be obtained by separately estimating equations (4.1) and (4.2), which is equivalent to setting both $\rho_{a_1 a_2}$ and $\rho_{\epsilon_1 \epsilon_2}$ to zero.¹¹ When estimating equations (4.1) and (4.2) separately, estimation techniques by Heckman (1981b) (eq. (4.1)) and Anderson and Hsiao (1981; 1982) (eq. (4.2)) can also be used.¹² The estimation results from separate estimations reveal the same pattern: similar to the results in Table 4.4, persistence in achieving TPP innovations vanishes when individual effects and the initial conditions are dealt with, while inertia shows up in the share of innovative sales. Hence, the lack of persistence in achieving TPP innovations is a rather robust result.

Also the sensitivity of the model to using R&D input rather than output measures has been investigated. The dynamic type 2 tobit has been estimated using the incidence of engaging in R&D activities rather than that of being a TPP innovator as dependent variable in equation (4.1) and using R&D intensity rather than the share of innovative sales as dependent variable in equation (4.2).¹³ The results of this analysis show the same pattern as that of Table 4.4, with the exception of the probit persistence parameter that remains significant also in the preferred model accounting for individual effects and the endogeneity of the initial conditions. More specifically, the magnitude of the persistence parameters in both equations lessens when accounting for individual effects and assuming endogenous initial conditions. In this analysis the full model is also shown to be the preferred one: the restrictions imposed in the model without individual effects on the one hand, and those imposed in the model with individual effects and exogenous initial conditions, on the other hand, are - as in Table 4.4 - rejected using a likelihood ratio test.

4.7 Conclusion

This study gives first insights into the persistence of innovation and the dynamics of innovation output in Dutch manufacturing using three waves of the CIS. We answer the questions jointly by estimating a dynamic type 2 tobit and find that there is no evidence of persistence

¹¹See the first pair of columns in Table 4.4.

¹²See sub-appendices 4.A.1 and 4.A.2 respectively.

¹³See sub-appendix 4.A.3.

in achieving TPP innovations, while past shares of innovative sales condition, albeit to a small extent, current shares of innovative sales. The lack of persistence of innovation contrasts with the results by Flaig and Stadler (1994) and Duguet and Monjon (2002) who find evidence of strong persistence of innovation in West German and French manufacturing respectively. Hence, unlike these studies, our results do not support the “success breeds success” hypothesis. Once the individual effects and the initial conditions are allowed for, they seem to take over the role of persistence. This phenomenon is even more plausible when the panel is short because, the shorter the panel the higher the correlation between the initial conditions (d_{i0}) and the lagged dependent variable ($d_{i,t-1}$). The fact that the same phenomenon does not take place in the regression equation (eq. (4.2)) indicates that the lack of persistence found cannot be attributed only to the shortness of the panel. This issue remains a topic of future research. The results on the sensitivity of the model to using R&D input rather than output measures indicate that there is evidence of persistence in engaging in R&D activities and in the share of R&D expenditures in total sales. The former result is in accordance with Máñez Castillejo et al. (2004) who find evidence of persistence by Spanish manufacturing firms in engaging in R&D activities, and Peters (2005) who finds persistence by German manufacturing and services firms in engaging in innovation activities. Hence, the hypothesis of existence of *sunk costs* in firms’ R&D activities is supported by our results. They suggest that there is evidence of true persistence of innovation when considered on the input side and spurious persistence when taken on the output side. The idea is that persistent R&D performers may not be guaranteed to persistently achieve TPP innovations.

The main caveat of this study is the data we use to implement the model. First, the panel is rather short ($T = 3$) which may explain in part the lack of true persistence in achieving TPP innovations. Secondly, there is one-year overlap between two consecutive waves of the Dutch CIS. Hence, to the extent that respondents answer this survey consistently, the overlap would tend to bias the results towards persistence in being a TPP innovator. As no evidence of persistence is found in the preferred model, it may be concluded that the effect of the overlapping year is not important.

Appendix 4.A The results of the robustness analysis

When estimating equations (4.1) and (4.2) separately, estimation techniques by Heckman (1981b) (eq. (4.1)) and Anderson and Hsiao (1981; 1982) (eq. (4.2)) can also be used. They are described as follows.

4.A.1 Dynamic probit: The persistence of innovation

Heckman (1981b) suggests that the initial conditions be approximated by a probit model

$$d_{i0} = 1[\delta'_0 \mathbf{w}_{i0} + \lambda \eta_i + \epsilon_{1i0} > 0], \quad (4.4)$$

where the vector δ'_0 and the scalar λ are to be estimated. $\delta'_0 \mathbf{w}_{i0}$ and λ capture respectively the mean of the process at the initial period and the dependence of the initial conditions on the individual effects, ϵ_{1i0} is the idiosyncratic error at the initial period. If we denote the error term in equation (4.4) by $\varsigma_{i0} = \lambda \eta_i + \epsilon_{1i0}$, the correlation between the initial conditions and the individual effects is shown to be $\rho_{\varsigma\eta} = \frac{\lambda \sigma_\eta}{\sqrt{\lambda^2 \sigma_\eta^2 + 1}}$, where $\sqrt{\lambda^2 \sigma_\eta^2 + 1}$ is the standard deviation of the error term of the probit model at the initial period.

Table 4.5: Dynamic probit estimates: The persistence of innovation

Variable	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)
Estimation method	Unobserved individual effects					
	No unobserved individual effects		Exogenous initial conditions		Endogenous initial conditions	
Current TPP innovation (d_{it})						
Past TPP innovation	1.044**	(0.074)	1.015**	(0.075)	0.256	(0.174)
Lagged size (in log)	0.154*	(0.061)	0.164**	(0.063)	0.280**	(0.087)
Lagged rel. size (in log)	0.081 [†]	(0.045)	0.081 [†]	(0.047)	0.091	(0.059)
Intercept	-0.497	(0.539)	-0.540	(0.552)	-0.134	(0.711)
Extra parameters						
Initial size (in log)	-	-	-	-	0.072	(0.121)
Initial rel. size (in log)	-	-	-	-	0.169 [†]	(0.088)
Intercept	-	-	-	-	1.742 [†]	(1.056)
σ_η	-	-	0.173**	(0.007)	0.885**	(0.171)
$\rho_{\varsigma\eta}$	-	-	-	-	0.769**	(0.052)
Number of observations	1722					
Log-likelihood	-881.888		-859.232		-1355.599	
Significance levels : [†] : 10% *: 5% **: 1%						

Once the initial conditions problem is handled, the model as specified in equations (4.1) and (4.4) can be estimated by maximum likelihood. The likelihood function of individual i ,

starting from $t = 0$ and conditional on the regressors, is written as

$$L_i(d_{i0}, d_{i1}, \dots, d_{iT} | d_{i,-1}, \mathbf{w}_{it}) = \int_{-\infty}^{\infty} \Phi[(2d_{i0} - 1)(\delta'_0 \mathbf{w}_{i0} + \lambda \eta_i)] \times \prod_{t=1}^T \Phi[(2d_{it} - 1)(\rho d_{i,t-1} + \delta'_t \mathbf{w}_{it} + \eta_i)] \frac{1}{\sigma_\eta} \phi\left(\frac{\eta_i}{\sigma_\eta}\right) d\eta_i, \quad (4.5)$$

where ϕ and Φ denote respectively the probability distribution function (pdf) and the cumulative distribution function (cdf) of the standard normal distribution. Using the Gauss-Hermite approximation in equation (3.23), the individual likelihood function is written as

$$L_i(d_{i0}, d_{i1}, \dots, d_{iT} | d_{i,-1}, \mathbf{w}_{it}) \simeq \frac{1}{\sqrt{\pi}} \sum_{m=1}^M w_m \Phi[(2d_{i0} - 1)(\delta'_0 \mathbf{w}_{i0} + \lambda a_m \sigma_\eta \sqrt{2})] \times \prod_{t=1}^T \Phi[(2d_{it} - 1)(\rho d_{i,t-1} + \delta'_t \mathbf{w}_{it} + a_m \sigma_\eta \sqrt{2})]. \quad (4.6)$$

The product over i of the approximate likelihood function (4.6) can be maximized using standard numerical procedures to obtain estimates of the parameters of the dynamic probit model.

Table 4.5 reports the estimates of the dynamic probit (eq.(4.1)).¹⁴ The results reveal the same pattern as in Table 4.4, i.e., persistence in achieving TPP innovations vanishes when individual effects and the initial conditions are dealt with. Hence, the lack of persistence in achieving TPP innovations is a rather robust result.

4.A.2 Dynamic linear regression: The dynamics of innovation output

Anderson and Hsiao (1981: 1982) make the following assumptions about the individual effects, the idiosyncratic error and the regressors of equation (4.2):

$$E\alpha_i = E\epsilon_{2it} = E\alpha_i \epsilon_{2it} = 0, \quad E\alpha_i \mathbf{x}'_{it} = \mathbf{0}',$$

$$E\alpha_i \alpha_j = \begin{cases} \sigma_\alpha^2 & \text{if } i = j \\ 0 & \text{otherwise,} \end{cases} \quad (4.7)$$

$$E\epsilon_{2it} \epsilon_{2js} = \begin{cases} \sigma_{\epsilon_2}^2 & \text{if } i = j, t = s \\ 0 & \text{otherwise.} \end{cases}$$

¹⁴ The last two pairs of columns in Table 4.5 are obtained by maximizing an approximate likelihood function using 5-point Gauss-Hermite quadrature.

Like in the dynamic probit, the initial conditions problem is also of great issue in the dynamic linear regression model. The idea is the same as before, i.e., a relationship that models the dependence of the initial conditions on the individual effects must be specified. Anderson and Hsiao (1981; 1982) distinguish various cases depending on different assumptions made on the initial conditions. The most relevant case to our study is the one where the initial conditions are assumed to be random with mean $\mu_{y_{i0}}$ and standard deviation $\sigma_{y_{i0}}$. Formally,

$$y_{i0} = \mu_{y_{i0}} + \nu_i, \quad (4.8)$$

where ν_i is randomly distributed with mean zero and standard deviation $\sigma_{y_{i0}}$. Furthermore, the initial outcome is assumed to be correlated with the individual effects. The intuition is that, the initial outcome affects all future outcomes through its correlation with the individual effects. Denoting by $\tau\sigma_{y_{i0}}^2$ the covariance between the initial outcome and the individual effects, the correlation between them is shown to be $\rho_{y_{i0}\alpha_i} = \frac{\tau\sigma_{y_{i0}}}{\sigma_{\alpha_i}}$. Under the assumption of normal distributions of ϵ_{2it} , α_i and ν_i , the likelihood function of individual i , starting from $t = 0$ and conditional on the regressors, is written as

$$\begin{aligned} L_i(y_{i0}, y_{i1}, \dots, y_{iT} | y_{i,t-1}, \mathbf{x}_{it}) &= (2\pi)^{-\frac{T}{2}} (\sigma_{\epsilon_{2it}}^2)^{-\frac{(T-1)}{2}} (\sigma_{\epsilon_{2it}}^2 + Tc)^{-\frac{1}{2}} \\ &\times \exp \left\{ -\frac{1}{2\sigma_{\epsilon_{2it}}^2} \sum_{t=1}^T [y_{it} - \gamma y_{i,t-1} - \beta' \mathbf{x}_{it} - \tau(y_{i0} - \mu_{y_{i0}})]^2 \right. \\ &\quad \left. + \frac{c}{2\sigma_{\epsilon_{2it}}^2 (\sigma_{\epsilon_{2it}}^2 + Tc)} \left[\sum_{t=1}^T [y_{it} - \gamma y_{i,t-1} - \beta' \mathbf{x}_{it} - \tau(y_{i0} - \mu_{y_{i0}})] \right]^2 \right\} \\ &\times (2\pi\sigma_{y_{i0}}^2)^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} \frac{(y_{i0} - \mu_{y_{i0}})^2}{\sigma_{y_{i0}}^2} \right\}, \end{aligned} \quad (4.9)$$

where $c = \sigma_{\alpha}^2 - \tau^2\sigma_{y_{i0}}^2$. The likelihood function in equation (4.9) is the product of the joint density of the outcomes, starting from $t = 1$ conditional on the initial outcome, and the marginal density of the initial outcome. The product over i of the likelihood function (4.9) can be maximized using standard numerical procedures to obtain estimates of the parameters of the dynamic linear regression model.

Table 4.6 reports the estimates of the dynamic linear regression (eq.(4.2)). The results reveal the same pattern as in Table 4.4, i.e., inertia shows up in the share of innovative sales of TPP innovators, even after accounting for individual effects correlated with endogenous

initial conditions.

Table 4.6: Dynamic linear regression estimates: The dynamics of innovation output

Table 4.6: Dynamic linear regression estimates: The dynamics of innovation						
Variable	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)
	Unobserved individual effects					
Estimation assumption	No unobserved individual effects		Exogenous initial conditions		Endogenous initial conditions	
	Current share of innovative sales (y_{it} in logit)					
Past share of innov. sales	0.179**	(0.026)	0.128**	(0.034)	0.078**	(0.027)
Lagged size (in log)	-0.009	(0.124)	-0.010	(0.131)	-0.008	(0.128)
R&D intensity (in log)	0.285**	(0.103)	0.270*	(0.107)	0.272**	(0.105)
Non-R&D performers	-1.604*	(0.656)	-1.564*	(0.668)	-1.511*	(0.659)
Continuous R&D perf.	0.746*	(0.346)	0.861*	(0.349)	0.822*	(0.343)
Demand pull	1.268**	(0.254)	1.216**	(0.253)	1.232**	(0.251)
Technology push	0.591*	(0.301)	0.646*	(0.306)	0.627*	(0.301)
Cooperation in innovation	0.444 [†]	(0.269)	0.464 [†]	(0.272)	0.454 [†]	(0.269)
Subsidies	0.131	(0.279)	0.163	(0.282)	0.126	(0.279)
Intercept	-1.395 [†]	(0.802)	-1.638 [†]	(0.841)	-1.629*	(0.818)
	Extra parameters					
σ_{α}	-	-	1.634**	(0.333)	1.152**	(0.032)
σ_{ϵ_2}	4.058**	(0.082)	3.728**	(0.147)	3.777**	(0.066)
$\mu_{y_{i0}}$	-	-	-	-	-1.561**	(0.165)
$\sigma_{y_{i0}}$	-	-	-	-	4.401**	(0.116)
$\rho_{y_{i0}\alpha_i}$	-	-	-	-	0.305**	(0.029)
Number of observations	1210					
Log-likelihood ¹⁵	-3411.795		-3408.794		-5471.718	
Significance levels : †: 10% *: 5% **: 1%						

4.A.3 The persistence of engaging in R&D and the dynamics of R&D investments

In order to investigate the sensitivity of the model to using R&D input rather than output measures, we estimate the dynamic type 2 tobit using the incidence of engaging in R&D activities rather than that of being a TPP innovator as dependent variable in equation (4.1) and using R&D intensity rather than the share of innovative sales as dependent variable in equation (4.2).

Table 4.7 reports the estimation results of the dynamic type 2 tobit that reveal the same pattern as that of Table 4.4, with the notable exception of the probit persistence parameter that remains significant also in the preferred model accounting for individual effects and

¹⁵Unlike in Table 4.4, the models in the first and second pair of columns of Tables 4.5 and 4.6 are not nested in the model in the third pair of columns. Hence the log-likelihood of the first two models cannot be compared to that of the third model. The model in the first pair of columns is, however, nested in the one in the second pair of columns.

Table 4.7: Dynamic type 2 tobit estimates with 5-point Gauss-Hermite quadrature: R&D investments

Variable	Coefficient (Std. Err.)		Coefficient (Std. Err.)		Coefficient (Std. Err.)	
	Unobserved individual effects					
Estimation assumption	No unobserved individual effects		Exogenous initial conditions		Endogenous initial conditions	
Engaging in current R&D activities (d_{it})						
Past R&D activities	1.503**	(0.120)	1.419**	(0.126)	0.580**	(0.148)
Lagged size (in log)	0.072	(0.081)	0.084	(0.085)	0.078	(0.113)
Lagged rel. size (in log)	0.071	(0.055)	0.065	(0.059)	0.096	(0.078)
Intercept	-0.198	(0.674)	-0.180	(0.716)	-0.107	(0.938)
Current R&D intensity (y_{it} in log)						
Past R&D intensity	0.429**	(0.021)	0.369**	(0.029)	0.077**	(0.024)
Size (in log)	-0.059	(0.040)	-0.061	(0.042)	-0.070	(0.046)
Demand pull	0.264**	(0.080)	0.264**	(0.079)	0.223**	(0.072)
Technology push	0.210*	(0.087)	0.225*	(0.088)	0.196*	(0.085)
Innovation cooperation	0.114	(0.083)	0.118	(0.083)	0.111	(0.079)
Subsidies	0.452**	(0.086)	0.455**	(0.087)	0.365**	(0.083)
Intercept	-2.590**	(0.228)	-2.804**	(0.255)	-2.520**	(0.260)
Extra parameters						
Initial R&D activities	-	-	-	-	1.293**	(0.233)
Initial R&D intensity	-	-	-	-	0.326**	(0.024)
σ_{a_1}	-	-	0.241 [†]	(0.137)	0.811**	(0.170)
σ_{a_2}	-	-	0.523**	(0.089)	0.832**	(0.048)
σ_{e_2}	1.182**	(0.034)	1.036**	(0.055)	0.817**	(0.034)
$\rho_{a_1a_2}$	-	-	-0.519**	(0.151)	0.369**	(0.125)
$\rho_{e_1e_2}$	0.617**	(0.061)	0.660**	(0.085)	0.581**	(0.126)
Number of observations	1087					
Log-likelihood	-1781.256		-1774.923		-1731.572	
Significance levels :	†: 10%	*: 5%	**: 1%			

the endogeneity of the initial conditions. Furthermore, the magnitude of the persistence parameters in both equations lessens when accounting for individual effects and assuming endogenous initial conditions.

CHAPTER 5

Modeling the initial conditions in dynamic panel data sample selection models

5.1 Introduction

When dealing with dynamic panel data models, a computational and methodological difficulty that arises, besides the unobserved individual effects, is the so-called initial conditions problem. In a random-effects approach, Anderson and Hsiao (1981; 1982) show that the consistency of the maximum likelihood estimator (MLE) of the dynamic linear regression depends on the treatment of the initial conditions. In nonlinear dynamic panel data models, the initial conditions problem is more difficult to solve, and the literature identifies various ways of treating the initial conditions.

A first approach is to assume that the initial conditions are exogenous. For instance, Nijman and Verbeek (1992) estimate the effect of nonresponse on Dutch households' consumption, where the nonresponse equation is modeled as a dynamic probit and the initial nonresponse is assumed to be exogenous. This treatment of the initial conditions is unsatisfactory because it assumes no correlation between the initial conditions and the unobserved individual effects.

A better approach is to allow for endogenous initial conditions correlated with the unobserved individual effects by specifying a distribution for the initial conditions conditional on the individual effects and the strictly exogenous explanatory variables. The difficulty of

this approach lies in the specification of this distribution. Some authors claim that the distribution of the initial conditions represent a steady-state distribution that is shown, in the literature, to exist in very special cases (Wooldridge, 2005). Heckman (1981b) circumvents this problem by “approximating” the initial conditions of a dynamic panel data probit, given the individual effects and the strictly exogenous regressors, by a simple probit. Although Heckman’s solution to the initial conditions problem is shown to perform fairly well in Monte Carlo results for a dynamic panel data discrete choice model, very few empirical studies adopt his approach. Two exceptions are Vella and Verbeek (1998) who estimate a dynamic (probit) model of unionism and the effects of unions on wage, and Vella and Verbeek (1999) who estimate a dynamic (tobit) model of weekly hours worked and their impact on hourly wage rate. The former approximate the model of the initial conditions by a standard probit, while the latter use a standard tobit for the initial conditions.

Finally, an alternative solution to handling the initial conditions is advocated by Pickles and Davies (1991) and more recently by Wooldridge (2005). It consists in specifying a distribution for the individual effects conditional on the initial conditions. In the former study, a dynamic panel data probit model is considered where the distribution of the individual effects consists of two different sets of parameters according to whether the initial conditions take on the value zero or one. The latter study considers any nonlinear dynamic panel data model with one equation, and the distribution of the individual effects given the initial conditions consists of one set of parameters. More and more recent empirical studies adopt the Wooldridge approach because of its flexibility, i.e., it applies in the same manner to a broad range of nonlinear dynamic panel data models. For instance, Kaiser and Kongsted (2004) estimate a dynamic panel data logit to study the persistence of West German firms’ exporting behavior, Contoyannis et al. (2004) estimate a dynamic panel data ordered probit to study the dynamics of British households’ health, and Peters (2005) estimates a dynamic panel data probit to study the persistence of engaging in innovative activities in the German manufacturing and services sectors. All these studies consider a single equation nonlinear dynamic model, and the Wooldridge approach is extended in Chapter 3 to nonlinear dynamic models with two equations.

The contribution of this chapter is to extend the Heckman approach of treating the initial conditions to dynamic panel data sample selection models. Since it is shown that the treatment of the initial conditions affects the estimates of nonlinear dynamic panel data

models (see Chapter 3 and Fotouhi, 2005) we investigate the sensitivity of the persistence of innovation to the treatment of the initial conditions. We estimate a dynamic type 2 tobit with the same specification as in Chapter 4 using the Heckman approach of treating the initial conditions and find that the lack of persistence is robust to the (proper) treatment of the initial conditions. Furthermore, we study the dynamics of incremental and radical innovations by estimating a dynamic type 3 tobit using both the Heckman and the Wooldridge approach of handling the initial conditions. We find that the two approaches yield similar results in terms of the coefficients of the strictly exogenous variables while some differences arise in the coefficients of the lagged dependent variables and the individual effects.

Section 5.2 describes the Heckman approach in the context of dynamic panel data sample selection models and the resulting maximum likelihood estimation. Section 5.3 presents an economic application, Section 5.4 discusses the estimation results, and Section 5.5 concludes.

5.2 Modeling the initial conditions and estimation

The Heckman approach consists in specifying a model for the initial conditions given the individual effects and the strictly exogenous explanatory variables. This model is often assumed to be similar to the underlying model of the remaining process. For instance, if the process under study is dynamic probit, the model of the initial conditions given the individual effects and the strictly exogenous regressors is assumed to be standard probit. The model of the initial conditions uses pre-sample information that affects the initial outcome of the process and takes account of the correlation between the initial conditions and the individual effects. We use this approach of handling the initial conditions problem to estimate the dynamic type 2 and type 3 tobit described in Chapter 3.

5.2.1 Dynamic type 2 tobit

Consider the dynamic type 2 tobit model defined in equations (3.1), (3.2), (3.3) and (3.4) of Chapter 3. Modeling the initial conditions consists in writing the latent variables at the initial period as

$$d_{i0}^* = \delta_0' \mathbf{w}_{i0} + \lambda_1 \eta_i + \epsilon_{1i0}, \quad (5.1)$$

$$y_{i0}^* = \beta_0' \mathbf{x}_{i0} + \lambda_2 \alpha_i + \epsilon_{2i0}, \quad (5.2)$$

where λ_1 and λ_2 capture the dependence of the initial conditions on the individual effects in the selection equation and in the equation of interest respectively, and δ'_0 and β'_0 , as well as λ_1 and λ_2 , are to be estimated. Assuming a type 2 tobit model for the initial conditions given the individual effects and the strictly exogenous regressors yield

$$d_{i0} = \mathbf{1}[d_{i0}^* > 0] \quad (5.3)$$

for the observed dependent variable of the selection equation and

$$y_{i0} = \mathbf{1}[d_{i0}^* > 0]y_{i0}^* \quad (5.4)$$

for the observed dependent variable of the equation of interest.

The vectors $(\epsilon_{1it}, \epsilon_{2it})'$ and $(\eta_i, \alpha_i)'$ are assumed independent of each other, and independently and identically distributed over time and across individuals following a normal distribution with mean zero and covariance matrix

$$\Omega_{\epsilon_{1\epsilon_2}} = \begin{pmatrix} 1 & \rho_{\epsilon_1\epsilon_2}\sigma_{\epsilon_2} \\ \rho_{\epsilon_1\epsilon_2}\sigma_{\epsilon_2} & \sigma_{\epsilon_2}^2 \end{pmatrix} \text{ and } \Omega_{\eta\alpha} = \begin{pmatrix} \sigma_{\eta}^2 & \rho_{\eta\alpha}\sigma_{\eta}\sigma_{\alpha} \\ \rho_{\eta\alpha}\sigma_{\eta}\sigma_{\alpha} & \sigma_{\alpha}^2 \end{pmatrix} \quad (5.5)$$

respectively. Let us denote by $\varsigma_{1i0} = \lambda_1\eta_i + \epsilon_{1i0}$ the error term of the initial conditions in the selection equation, and $\varsigma_{2i0} = \lambda_2\alpha_i + \epsilon_{2i0}$ that of the initial conditions in the equation of interest. The correlation between the initial conditions and the individual effects is shown to be $\rho_{\varsigma_1\eta} = \frac{\lambda_1\sigma_{\eta}}{\sqrt{\lambda_1^2\sigma_{\eta}^2 + 1}}$ in the selection equation and $\rho_{\varsigma_2\alpha} = \frac{\lambda_2\sigma_{\alpha}}{\sqrt{\lambda_2^2\sigma_{\alpha}^2 + \sigma_{\epsilon_2}^2}}$ in the equation of interest, where $\sqrt{\lambda_1^2\sigma_{\eta}^2 + 1}$ is the standard deviation of the error term of the initial conditions in the selection equation and $\sqrt{\lambda_2^2\sigma_{\alpha}^2 + \sigma_{\epsilon_2}^2}$ is that of the initial conditions in the equation of interest. We can then derive the likelihood function of individual i , starting from $t = 0$ and conditional on the regressors as

$$L_i = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} L_{i0}(\dots|\dots, \eta_i, \alpha_i) \prod_{t=1}^T L_{it}(y_{it}, d_{it}|d_{i0}, d_{i,t-1}, \mathbf{w}_{it}, y_{i0}, y_{i,t-1}, \mathbf{x}_{it}, \eta_i, \alpha_i) g(\eta_i, \alpha_i) d\eta_i d\alpha_i,$$

where $\prod_{t=1}^T L_{it}(y_{it}, d_{it}|d_{i0}, d_{i,t-1}, \mathbf{w}_{it}, y_{i0}, y_{i,t-1}, \mathbf{x}_{it}, \eta_i, \alpha_i)$ denotes the likelihood function of individual i conditional on the individual effects, $L_{i0}(\dots|\dots, \eta_i, \alpha_i)$ is the likelihood function of the initial conditions given the individual effects and the strictly exogenous regressors at the

initial period, and $g(\eta_i, \alpha_i)$ is the bivariate normal density function of (η_i, α_i) . The expression of the individual likelihood function conditional on the individual effects is given in equation (3.12) of Chapter 3 for the type 2 tobit, and the conditional likelihood function of the initial conditions is written as

$$L_{i0}(\dots|\dots, \eta_i, \alpha_i) = \Phi \left[-(\delta'_0 \mathbf{w}_{i0} + \lambda_1 \eta_i) \right]^{(1-d_{i0})} \left[\frac{1}{\sigma_{\epsilon_2}} \phi \left(\frac{y_{i0} - \beta'_0 \mathbf{x}_{i0} + \lambda_2 \alpha_i}{\sigma_{\epsilon_2}} \right) \right]^{d_{i0}} \times \Phi \left(\frac{\delta'_0 \mathbf{w}_{i0} + \lambda_1 \eta_i + \frac{\rho_{\epsilon_1 \epsilon_2}}{\sigma_{\epsilon_2}} (y_{i0} - \beta'_0 \mathbf{x}_{i0} + \lambda_2 \alpha_i)}{\sqrt{1 - \rho_{\epsilon_1 \epsilon_2}^2}} \right)^{d_{i0}}. \quad (5.6)$$

Hence, using the results of Appendix 3.A, the individual likelihood function, starting from $t = 0$ and conditional on the regressors can be approximated using “two-step” Gauss-Hermite quadrature by

$$L_i \simeq \frac{\sqrt{1 - \rho_{\eta\alpha}^2}}{\pi} \sum_{p=1}^P w_p \left\{ \left[\frac{1}{\sigma_{\epsilon_2}} \phi \left(\frac{y_{i0} - \beta'_0 \mathbf{x}_{i0} + \lambda_2 a_p \sigma_\alpha \sqrt{2(1 - \rho_{\eta\alpha}^2)}}{\sigma_{\epsilon_2}} \right) \right]^{d_{i0}} \times \prod_{t=1}^T \left[\frac{1}{\sigma_{\epsilon_2}} \phi \left(\frac{y_{it} - B_{it} - a_p \sigma_\alpha \sqrt{2(1 - \rho_{\eta\alpha}^2)}}{\sigma_{\epsilon_2}} \right) \right]^{d_{it}} \times \sum_{m=1}^M w_m \left\{ e^{2\rho_{\eta\alpha} a_p a_m} \Phi \left[-(\delta'_0 \mathbf{w}_{i0} + \lambda_1 a_m \sigma_\eta \sqrt{2(1 - \rho_{\eta\alpha}^2)}) \right]^{(1-d_{i0})} \times \Phi \left(\frac{\delta'_0 \mathbf{w}_{i0} + \lambda_1 a_m \sigma_\eta \sqrt{2(1 - \rho_{\eta\alpha}^2)} + \frac{\rho_{\epsilon_1 \epsilon_2}}{\sigma_{\epsilon_2}} (y_{i0} - \beta'_0 \mathbf{x}_{i0} + \lambda_2 a_p \sigma_\alpha \sqrt{2(1 - \rho_{\eta\alpha}^2)})}{\sqrt{1 - \rho_{\epsilon_1 \epsilon_2}^2}} \right)^{d_{i0}} \times \prod_{t=1}^T \Phi \left[-\left(A_{it} + a_m \sigma_\eta \sqrt{2(1 - \rho_{\eta\alpha}^2)} \right) \right]^{(1-d_{it})} \times \Phi \left(\frac{A_{it} + a_m \sigma_\eta \sqrt{2(1 - \rho_{\eta\alpha}^2)} + \frac{\rho_{\epsilon_1 \epsilon_2}}{\sigma_{\epsilon_2}} (y_{it} - B_{it} - a_p \sigma_\alpha \sqrt{2(1 - \rho_{\eta\alpha}^2)})}{\sqrt{1 - \rho_{\epsilon_1 \epsilon_2}^2}} \right)^{d_{it}} \right\} \right\} \quad (5.7)$$

whose product over i can be maximized using standard numerical procedures to obtain estimates of the parameters of the dynamic type 2 tobit.

5.2.2 Dynamic type 3 tobit

When the underlying model of the process is dynamic type 3 tobit, as defined in equations (3.1), (3.2), (3.3) and (3.5) of Chapter 3, the model of the initial conditions is assumed to be type 3 tobit. The latent variables at the initial period are written as in equations (5.1) and

(5.2), and their observed counterparts are given by

$$d_{i0} = \mathbf{1}[d_{i0}^* > 0]d_{i0}^* \quad (5.8)$$

and equation (5.4) respectively. In this case, the likelihood function of the initial conditions given the individual effects and the initial strictly exogenous explanatory variables is written as

$$L_{i0}(\dots|\dots, \eta_i, \alpha_i) = \Phi \left[- \left(\frac{\delta_0' \mathbf{w}_{i0} + \lambda_1 \eta_i}{\sigma_{\epsilon_1}} \right) \right]^{(1-s_{i0})} \left[\frac{1}{\sigma_{\epsilon_2}} \phi \left(\frac{y_{i0} - \beta_0' \mathbf{x}_{i0} + \lambda_2 \alpha_i}{\sigma_{\epsilon_2}} \right) \right]^{s_{i0}} \times \frac{1}{\sigma_{\epsilon_1} \sqrt{1 - \rho_{\epsilon_1 \epsilon_2}^2}} \phi \left(\frac{d_{i0} - \delta_0' \mathbf{w}_{i0} - \lambda_1 \eta_i - \rho_{\epsilon_1 \epsilon_2} \frac{\sigma_{\epsilon_1}}{\sigma_{\epsilon_2}} (y_{i0} - \beta_0' \mathbf{x}_{i0} - \lambda_2 \alpha_i)}{\sigma_{\epsilon_1} \sqrt{1 - \rho_{\epsilon_1 \epsilon_2}^2}} \right) \quad (5.9)$$

where s_{i0} is given by

$$s_{i0} = \mathbf{1}[d_{i0}^* > 0].^1$$

Using again the results of Appendix 3.A, the approximated individual likelihood function, starting from $t = 0$ and conditional on the regressors is given by

$$L_i \simeq \frac{\sqrt{1 - \rho_{\eta\alpha}^2}}{\pi} \sum_{p=1}^P w_p \left\{ \left[\frac{1}{\sigma_{\epsilon_2}} \phi \left(\frac{y_{i0} - \beta_0' \mathbf{x}_{i0} + \lambda_2 a_p \sigma_\alpha \sqrt{2(1 - \rho_{\eta\alpha}^2)}}{\sigma_{\epsilon_2}} \right) \right]^{s_{i0}} \times \prod_{t=1}^T \left[\frac{1}{\sigma_{\epsilon_2}} \phi \left(\frac{y_{it} - B_{it} - a_p \sigma_\alpha \sqrt{2(1 - \rho_{\eta\alpha}^2)}}{\sigma_{\epsilon_2}} \right) \right]^{s_{it}} \times \sum_{m=1}^M w_m \left\{ e^{2\rho_{\eta\alpha} a_p a_m} \Phi \left[- \left(\frac{\delta_0' \mathbf{w}_{i0} + \lambda_1 a_m \sigma_\eta \sqrt{2(1 - \rho_{\eta\alpha}^2)}}{\sigma_{\epsilon_1}} \right) \right]^{(1-s_{i0})} \times \left[\frac{1}{\varpi} \phi \left(\frac{d_{i0} - \delta_0' \mathbf{w}_{i0} - \lambda_1 a_m \sigma_\eta \sqrt{2(1 - \rho_{\eta\alpha}^2)} - \rho_{\epsilon_1 \epsilon_2} \frac{\sigma_{\epsilon_1}}{\sigma_{\epsilon_2}} (y_{i0} - \beta_0' \mathbf{x}_{i0} - \lambda_2 a_p \sigma_\alpha \sqrt{2(1 - \rho_{\eta\alpha}^2)})}{\varpi} \right) \right]^{s_{i0}} \times \prod_{t=1}^T \Phi \left[- \left(\frac{A_{it} + a_m \sigma_\eta \sqrt{2(1 - \rho_{\eta\alpha}^2)}}{\sigma_{\epsilon_1}} \right) \right]^{(1-s_{it})} \times \left[\frac{1}{\varpi} \phi \left(\frac{d_{it} - A_{it} - a_m \sigma_\eta \sqrt{2(1 - \rho_{\eta\alpha}^2)} - \rho_{\epsilon_1 \epsilon_2} \frac{\sigma_{\epsilon_1}}{\sigma_{\epsilon_2}} (y_{it} - B_{it} - a_p \sigma_\alpha \sqrt{2(1 - \rho_{\eta\alpha}^2)})}{\varpi} \right) \right]^{s_{it}} \right\} \right\}, \quad (5.10)$$

¹In the type 3 tobit, σ_{ϵ_1} is identifiable and is to be estimated. Furthermore, the correlation between the initial conditions and the individual effects becomes $\frac{\lambda_1 \sigma_\eta}{\sqrt{\lambda_1^2 \sigma_\eta^2 + \sigma_{\epsilon_1}^2}}$ in the selection equation.

where $\varpi = \sigma_{\epsilon_1} \sqrt{1 - \rho_{\epsilon_1 \epsilon_2}^2}$. The product over i of equation (5.10) can be maximized using standard numerical procedures to obtain estimates of the parameters of the dynamic type 3 tobit.

5.3 Application

We investigate the sensitivity of the persistence of innovation to the treatment of the initial conditions. More specifically, we estimate a dynamic type 2 tobit with the same specification as in Chapter 4 using the Heckman approach of treating the initial conditions. In other words, we model the initial conditions as a type 2 tobit explaining the initial decision to be a TPP innovator and, for initial innovators, the initial share of innovative sales. The initial decision to be a TPP innovator and the initial share of innovative sales are explained by the same initial strictly exogenous regressors as for the remaining process.

We also study the dynamics of incremental and radical innovations by estimating a dynamic type 3 tobit using both the Heckman and the Wooldridge approach of handling the initial conditions. Innovation surveys distinguish two types of product innovations, those new to the firm (incremental) and those new to the market (radical). The importance of each type of product innovation is measured by the share in total sales of innovative sales. But from the way the questionnaire of the survey is formulated, we only observe the latter if we observe the former. Equation (3.1) of Chapter 3 determines whether enterprise i is an incremental product innovator at period t ($d_{it}^* > 0$). In this case, the actual share of sales of incremental product innovations (eq. (3.5)) is positive, and the share of sales of radical product innovations (eq. (3.3)) and the full set of regressors included in the vector $\mathbf{x}_{it}$ are observed. When enterprise i is not an incremental product innovator, the shares of sales of incremental (d_{it}) and radical (y_{it}) product innovations are equal to zero, and only the set of regressors included in the vector $\mathbf{w}_{it}$ is observed. The average share of sales of radical innovations is very small (6.5%) in our panel. Like that of incremental innovations, the share of sales of radical innovations is logit-transformed in the estimation of the model.² The specification of the model is similar to that of Section 4.5, except that the share of incremental innovative sales is the dependent variable of the selection equation, and the share of radical innovative sales is the dependent variable of the regression equation. In the Heckman approach, we

²The share of sales of radical product innovations takes on the values 0 for some incremental product innovators. They are replaced by 0.0001 in the logit transformation.

model the initial conditions as a type 3 tobit explaining the initial share of incremental and, for incremental innovators, the initial share of radical innovative sales.

5.4 Estimation results

We discuss the results of the sensitivity of the persistence of innovation to the treatment of the initial conditions in subsection 5.4.1 and those of the dynamics of incremental and radical innovations in subsection 5.4.2.³

5.4.1 The sensitivity of the persistence of innovation to the treatment of the initial conditions

Table 5.1 reports the estimation results of the dynamic type 2 tobit where we correct for sample selection bias and allow for unobserved individual effects correlated with endogenous initial conditions specified as a type 2 tobit. The results suggest a similar pattern to that of Table 4.4. More specifically, there is no evidence of true persistence of innovation while past share of innovative sales of innovators conditions, albeit to small extent, current share of innovative sales. To the extent that innovation is not persistent, we interpret the latter result as a rather lengthy enjoyment by innovators of their old innovations. The probability to innovate is positively and significantly affected by lagged size, while lagged relative size hardly plays a role. The share of innovative sales of innovators is positively and significantly affected by lagged size, R&D intensity, performing R&D continuously, demand pull, technology push, subsidies while, *ceteris paribus*, non-R&D performers are less successful than R&D performers. Unobserved heterogeneity plays a highly significant role in both the probability to innovate and the share of innovative sales as suggested by the highly significantly estimated standard deviations of the individual effects. Furthermore, in both equations, the correlation between the initial conditions and the individual effects is statistically and significantly estimated to be 0.591 and 0.506 respectively. Hence, the assumptions of absence of unobserved individual effects and exogenous initial conditions can be rejected using a likelihood ratio at 1% level of significance, which corroborates the results of Section 4.6. Finally, like in Section 4.6, cross-equation individual effects and cross-equation idiosyncratic parts are found to be correlated, indicating the presence of sample selection.

³In order to save space, the parameter estimates of the model of the initial conditions are not reported. They can be obtained upon request.

Table 5.1: Dynamic type 2 tobit estimates with 5-point Gauss-Hermite quadrature and the Heckman approach of handling the initial conditions: Innovation output

Variable	Coefficient	(Std. Err.)
Estimation assumption	Selection bias correction with unobserved individual effects and endogenous initial conditions	
Current TPP innovation (d_{it})		
Past TPP innovation ($d_{i,t-1}$)	0.263	(0.160)
Lagged size (in log)	0.154*	(0.078)
Lagged relative size (in log)	0.093 [†]	(0.054)
Intercept	0.477	(0.672)
Current share of innovative sales (y_{it} in logit)		
Past share of innovative sales ($y_{i,t-1}$)	0.123**	(0.037)
Lagged size (in log)	0.306*	(0.138)
R&D intensity (in log)	0.371**	(0.098)
Non-R&D performers	-2.373**	(0.615)
Continuous R&D performers	0.854**	(0.321)
Demand pull	1.202**	(0.237)
Technology push	0.590*	(0.271)
Cooperation in innovation	0.304	(0.253)
Subsidies	0.532*	(0.264)
Intercept	-4.256**	(0.848)
Extra parameters		
σ_η	0.768**	(0.083)
σ_α	1.727**	(0.259)
σ_{ϵ_2}	4.002**	(0.103)
$\rho_{\eta\alpha}$	0.516**	(0.064)
$\rho_{\epsilon_1\epsilon_2}$ ⁴		0.950
$\rho_{\varsigma_1\eta}$	0.591**	(0.062)
$\rho_{\varsigma_2\alpha}$	0.506**	(0.044)
Number of observations	1722	
Log-likelihood	-5571.588	
Significance levels : † : 10% * : 5% ** : 1%		

5.4.2 The dynamics of incremental and radical innovations

Table 5.2 reports the estimation results of the dynamic type 3 tobit where we correct for sample selection bias and allow for unobserved individual effects correlated with endogenous initial conditions. In the first pair of columns, the initial conditions problem is solved according to the Heckman approach, i.e., a type 3 tobit model is specified for the initial conditions given the individual effects and the strictly exogenous regressors. In the second pair of columns, we handle the initial conditions problem using the Wooldridge approach, i.e., the individual effects are specified as a linear function of the initial conditions and the

⁴The estimate value of $\rho_{\epsilon_1\epsilon_2}$ tended to approach 1. Hence $\rho_{\epsilon_1\epsilon_2}$ has been fixed to 0.950.

*Table 5.2: Dynamic type 3 tobit estimates with 5-point Gauss-Hermite quadrature:
Incremental and radical innovation output*

Variable	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)
Estimation assumption				
Selection bias correction with unobserved individual effects and endogenous initial conditions				
Treatment of the initial conditions				
The Heckman approach The Wooldridge approach				
Current share of sales of incremental product innovations (d_{it} in logit)				
Past share of incremental innov. sales ($d_{i,t-1}$)	0.167**	(0.030)	0.113**	(0.033)
Lagged size (in log)	0.323*	(0.157)	0.354*	(0.159)
Lagged relative size (in log)	0.116	(0.116)	0.066	(0.117)
Intercept	-1.930	(1.374)	-2.172	(1.395)
Current share of sales of radical product innovations (y_{it} in logit)				
Past share of radical innov. sales ($y_{i,t-1}$)	0.155**	(0.049)	0.120*	(0.060)
Lagged size (in log)	0.101	(0.107)	0.057	(0.105)
R&D intensity (in log)	0.216*	(0.087)	0.193*	(0.087)
Non-R&D performers	-1.179*	(0.560)	-1.010†	(0.563)
Continuous R&D performers	0.817**	(0.294)	0.797**	(0.298)
Demand pull	0.676**	(0.218)	0.688**	(0.219)
Technology push	-0.131	(0.246)	-0.104	(0.247)
Cooperation in innovation	0.537*	(0.222)	0.530*	(0.223)
Subsidies	0.590*	(0.236)	0.555*	(0.237)
Intercept	-5.867**	(0.768)	-5.165**	(0.726)
Extra parameters				
Initial share of incremental innov. sales (d_{i0})	-	-	0.123**	(0.030)
Initial share of radical innov. sales (y_{i0})	-	-	0.125*	(0.050)
$\rho_{\epsilon, \eta}$	0.310**	(0.075)	-	-
$\rho_{\epsilon, \phi}$	0.392**	(0.072)	-	-
$\sigma_{\epsilon, 1}$	-	-	-	-
$\sigma_{\epsilon, 2}$	-	-	1.102**	(0.243)
σ_{η}	-	-	0.597	(0.681)
σ_{ϕ}	0.983**	(0.253)	-	-
$\sigma_{\epsilon, 3}$	0.720**	(0.331)	-	-
$\sigma_{\epsilon, 4}$	3.316**	(0.078)	3.283**	(0.098)
$\rho_{\epsilon, \sigma_4}$	3.159**	(0.084)	3.179**	(0.142)
ρ_{η, σ_4}	-	-	0.137	(0.337)
ρ_{ϕ, σ_4}	0.353**	(0.169)	-	-
$\rho_{\epsilon, \sigma_4}$	0.103**	(0.028)	0.101**	(0.037)
Number of observations	1722			
Log-likelihood	-9046.237			
Significance levels: †: 10% *: 5% **: 1%	-5904.049			

time-varying strictly exogenous regressors.

In both cases, the results suggest that past share of incremental and radical innovative sales affect positively and significantly current share of incremental and radical innovative sales respectively. Similarly to incremental innovators, to the extent that radical innovation is not persistent, radical innovators seem to profit for a fairly long time period from their old

radical innovations. The estimated coefficients associated with the lagged dependent variables in both the selection equation and the equation of interest are larger when using the Heckman approach (around 0.160) than when using the Wooldridge approach (around 0.120). Lagged size affects positively and significantly the current share of sales of incremental innovations. The current share of sales of radical innovations is positively and significantly affected by R&D intensity, performing R&D continuously, demand pull, innovation cooperation, subsidies while, *ceteris paribus*, non-R&D performers are less successful than R&D performers in terms of generating innovative sales from radical innovations. Both approaches of handling the initial conditions yield fairly similar estimates of the coefficients of the strictly exogenous explanatory variables. Accounting for unobserved individual effects matters in the estimation of the model (at least in the selection equation), and the individual effects are found to be correlated with the initial conditions as the coefficients associated with the initial conditions, in the Wooldridge approach, and $\rho_{\zeta_1\eta}$ and $\rho_{\zeta_2\alpha}$, in the Heckman approach, are significantly estimated. Hence, the assumptions of absence of unobserved individual effects and exogenous initial conditions can be rejected using a likelihood ratio at 1% level of significance. Finally, sample selection is present and operates only through the idiosyncratic errors in the Wooldridge case, and through the individual effects and the idiosyncratic errors in the Heckman case.

5.5 Conclusion

We have extended the Heckman approach of treating the initial conditions to dynamic panel data sample selection models. A model similar to the underlying model of the remaining process was specified for the initial conditions given the individual effects and the strictly exogenous explanatory variables. More specifically, the initial conditions were specified as a type 2 tobit when the underlying model of the remaining process is dynamic type 2 tobit, and a type 3 tobit was specified for the initial conditions when the underlying model of the remaining process is dynamic type 3 tobit.

We have investigated the sensitivity of results of Chapter 4 on the persistence of innovation and the dynamics of innovation output to the treatment of the initial conditions. We have contrasted the estimate results of the dynamic type 2 tobit when modeling the initial conditions (the Heckman approach) with those of the same model when conditioning on the

initial conditions (the Wooldridge approach). Regardless of the (proper) treatment of the initial conditions, there is no evidence of true persistence of innovation in Dutch manufacturing while, for innovators, past share of innovative sales conditions, albeit to a small extent, current share of innovative sales. The latter result is interpreted as a rather lengthy enjoyment by innovators of their old innovations. We have also studied the dynamics of incremental and radical innovations by estimating a dynamic type 3 tobit. The estimation results of the model when using the Heckman approach were contrasted with those of the same model when using the Wooldridge approach. We found that past share of sales of incremental and radical product innovations conditions current share of sales of incremental and radical product innovations respectively. Similarly to incremental innovators, radical innovators seem to have a rather lengthy enjoyment of their old radical innovations. The estimation results of the dynamic type 3 tobit when using both the Heckman and the Wooldridge approach are fairly similar, especially the estimates of the coefficients of the strictly exogenous explanatory variables. One notable difference is the coefficients associated with the lagged dependent variables that are somehow overestimated in the former case with respect to the latter. Furthermore, unobserved individual effects play a significant role in the two equations when using the Heckman approach, while they are significant only in the selection equation when using the Wooldridge approach. Finally, sample selection is present and operates only through the idiosyncratic errors when using the Wooldridge approach, and through the individual effects and the idiosyncratic errors when using the Heckman approach.

CHAPTER 6

Joint modeling of the dynamics of innovation activities, R&D investments and innovative sales

6.1 Introduction

This chapter studies, at the firm level, the dynamics of the interrelationship between the decision to engage in innovation activities, innovation input investments measured as R&D expenditures over total sales, and innovation output measured by the share of innovative sales using three waves of the Dutch Community Innovation Survey. We extend the model studied in Chapter 4 by adding a third equation with R&D intensity as the dependent variable.

Economic theory suggests that technological innovation is a nonlinear complex process. For instance, Kline and Rosenberg (1986) define a *chain-link model*, as opposed to the *linear model*, where five levels, from the “central chain of innovation” (first level) to the connection between innovation output and science (fifth level), are identified and where “innovation determines and is determined by the market” and R&D is essential to building up a knowledge base. Crépon et al. (1998, CDM) define a three-stage model of R&D activities, innovation output (patent or innovative sales) and productivity.¹ More specifically, in the first stage, firms decide whether or not to engage in R&D activities and choose the amount that is invested in R&D. In the second stage, innovation output is related to R&D and other determinants.

¹The term “stage” is usually used in linear models of innovation where the stages of the innovation process are assumed isolated from one another. In the CDM model, however, there is interrelationship between the various stages of the process.

Finally, an augmented Cobb-Douglas production function relates productivity to innovation output and other factors.

Technological innovation is also a dynamic process for which various explanations are given by economic theory. On the input side, the decision to engage in R&D activities is shown to be persistent because of *sunk costs* (Máñez Castillejo et al., 2004). Van Leeuwen (2002) derives a dynamic R&D intensity equation from an adaptation of the *knowledge accumulation* theory along the lines of Hall and Hayashi (1989) and Klette (1996) and relates it to a dynamic share of innovative sales equation. Further, on the output side, Flaig and Stadler (1994) explain the dynamics of product and process innovation by a “success breeds success” hypothesis (Mansfield, 1968) derived from a stochastic dynamic optimization model of innovation activity. Finally, Stein (1997) develops a theoretical competition model where *learning-by-doing* explains the dynamics of the innovation process.

A third important aspect of the innovation process is that it involves heterogeneous firms in that they face different technological opportunities and appropriability conditions (Blundell et al., 1995, 1999) which, together with “the cumulativeness of technical advances and properties of the knowledge base” form what Malerba and Orsenigo (1996) and Breschi et al. (2000) call a *technological regime*. Firms’ heterogeneity can also be interpreted as their difference in ability to carry out and achieve innovations (Labeaga and Martínez-Ros, 2005).

The contribution of this chapter is that we consider the three aspects of the innovation process in a unified framework. More specifically, we study a three-equation nonlinear dynamic model of innovation accounting for unobserved firm heterogeneity by including individual effects. The model is a dynamic panel data version of the first and second stage of the CDM model where we jointly investigate the dynamics of the decision to engage in innovation activities, that of R&D intensity and the share of innovative sales.² We estimate the model by maximum likelihood assuming random individual effects that are “integrated out” using “three-step” Gauss-Hermite quadrature and handling the initial conditions using the Wooldridge (2005) approach. The results suggest the presence of dynamics in the innovation process. Furthermore, the decision to engage in innovation activities, R&D intensity and the share of innovative sales are correlated at least through the individual effects, and firm heterogeneity plays an important role in the innovation process.

²The relationship between innovation and productivity considered in the CDM model is beyond the scope of this chapter.

We describe the model in Section 6.2, explain the estimation procedure in Section 6.3, present the data and report descriptive statistics in Section 6.4, discuss the estimation results in Section 6.5 and conclude in Section 6.6. The likelihood function of the three-equation nonlinear dynamic model using “three-step” Gauss-Hermite quadrature is derived in Appendix 6.A.

6.2 A three-equation nonlinear dynamic model of innovation

The model explains jointly the probability of engaging in innovation activities, the percentage of total sales invested in R&D and the share of innovative sales generated by R&D investments and other innovation activities. Formally it is written as

$$y_{1it} = 1 [\gamma_1 y_{1i,t-1} + \beta'_1 \mathbf{x}_{1it} + \alpha_{1i} + \epsilon_{1it} > 0] \quad (6.1)$$

and

$$y_{2it} = \begin{cases} \gamma_2 y_{2i,t-1} + \beta'_2 \mathbf{x}_{2it} + \alpha_{2i} + \epsilon_{2it} & \text{if } y_{1it} = 1, \\ 0 & \text{if } y_{1it} = 0, \end{cases} \quad (6.2)$$

$$y_{3it} = \begin{cases} \gamma_3 y_{3i,t-1} + \beta'_3 \mathbf{x}_{3it} + \alpha_{3i} + \epsilon_{3it} & \text{if } y_{1it} = 1, \\ 0 & \text{if } y_{1it} = 0, \end{cases} \quad (6.3)$$

with $t = 1, \dots, T$; $i = 1, \dots, N$.

Equation (6.1) models the current decision of enterprise i to engage in innovation activities as a latent function of its past engagement in innovation activities ($y_{1i,t-1}$), strictly exogenous explanatory variables ($\mathbf{x}_{1it}$), time-invariant unobserved individual effects (α_{1i}) and other time-variant unobserved variables (ϵ_{1it}) uncorrelated with $\mathbf{x}_{1it}$. The latent function can be interpreted as an incentive to engage in current innovation activities with the observed counterpart y_{1it} being 1, in which case enterprise i undertakes innovation activities, if the incentive is sufficiently high, or else y_{1it} is observed to be 0. The scalar γ_1 and the vector β'_1 capture respectively the effects of past innovation activities and firm and market characteristics on current innovation activities and are to be estimated. If γ_1 is positively and significantly estimated, there is persistence in engaging in innovation activities. However, the existence of true persistence may be ascertained by verifying that, after accounting for

individual effects and properly handling the initial conditions problem, γ_1 is positive and statistically significant.

Equations (6.2) and (6.3) model respectively current R&D intensity (y_{2it}) and the current share of innovative sales (y_{3it}) of an innovative enterprise i ($y_{1it} = 1$) as being determined by its past R&D intensity ($y_{2i,t-1}$) and its past share of innovative sales ($y_{3i,t-1}$), strictly exogenous explanatory variables ($\mathbf{x}_{2it}$ and $\mathbf{x}_{3it}$), time-invariant unobserved individual effects (α_{2i} and α_{3i}) and other time-variant unobserved variables (ϵ_{2it} and ϵ_{3it}) uncorrelated with $\mathbf{x}_{2it}$ and $\mathbf{x}_{3it}$. R&D intensity and the share of innovative sales are zero if enterprise i is not innovative, and the full set of regressors included into $\mathbf{x}_{2it}$ and $\mathbf{x}_{3it}$ are only available when enterprise i is innovative. The scalars γ_2 and γ_3 capture respectively the effects of past R&D intensity and past share of innovative sales on current R&D intensity and current share of innovative sales and are to be estimated. The vectors β'_2 and β'_3 capture the effects of firm and market characteristics on current R&D intensity and current share of innovative sales and are also to be estimated.

Equations (6.1), (6.2) and (6.3) are jointly estimated so that we allow for a correlation between the processes governing the engagement in innovation activities and R&D investments, the processes governing the engagement in innovation activities and the generation of innovative sales, and the processes governing R&D investments and the generation of innovative sales. We now discuss the estimation technique.

6.3 Maximum likelihood estimation

Estimating the three-equation dynamic tobit-type model with panel data is a complicated task to achieve. The individual effects have to be handled and the initial conditions problem has to be solved. The use of the within or first-difference transformation to get rid of the individual effects is not feasible because of the nonlinearity of the model, neither is a fixed-effects conditional likelihood approach as there is no sufficient statistic such that, conditional on it, the likelihood function depends only on the slope parameters (Lancaster, 2000). Furthermore, no GMM-type estimator is known for the three-equation dynamic tobit-type model. Hence we use a random-effects approach and make distributional assumptions on the individual effects. The problem of initial conditions is handled using Wooldridge's (2005) "simple solutions" that consist in writing the individual effects, in each period, as linear functions of

the strictly exogenous explanatory variables and the initial conditions. Formally,

$$\alpha_{1i} = b_0^{r1} + b_1^{r1} y_{1i0} + \mathbf{b}_2^{r1} \mathbf{x}_{1i} + a_{1i}, \quad (6.4)$$

$$\alpha_{2i} = b_0^{r2} + b_1^{r2} y_{2i0} + \mathbf{b}_2^{r2} \mathbf{x}_{2i} + a_{2i}, \quad (6.5)$$

$$\alpha_{3i} = b_0^{r3} + b_1^{r3} y_{3i0} + \mathbf{b}_2^{r3} \mathbf{x}_{3i} + a_{3i}, \quad (6.6)$$

where $\mathbf{x}_{ji}' = (\mathbf{x}_{ji1}', \dots, \mathbf{x}_{jiT}')$, b_0^{rj} , b_1^{rj} , $\mathbf{b}_2^{rj}$ ($j = 1, 2, 3$) are to be estimated, and a_{1i} , a_{2i} and a_{3i} are independent of $(y_{1i0}, \mathbf{x}_{1i})$, $(y_{2i0}, \mathbf{x}_{2i})$ and $(y_{3i0}, \mathbf{x}_{3i})$ respectively.³ The scalars b_1^{r1} , b_1^{r2} and b_1^{r3} capture the dependence of the individual effects on the initial conditions. The vectors $(\epsilon_{1it}, \epsilon_{2it}, \epsilon_{3it})'$ and $(a_{1i}, a_{2i}, a_{3i})'$ are assumed independent of each other, and independently and identically distributed over time and across individuals following a normal distribution with mean zero and covariance matrix

$$\Sigma_\epsilon = \begin{pmatrix} 1 & \rho_{\epsilon_1 \epsilon_2} \sigma_{\epsilon_2} & \rho_{\epsilon_1 \epsilon_3} \sigma_{\epsilon_3} \\ \rho_{\epsilon_1 \epsilon_2} \sigma_{\epsilon_2} & \sigma_{\epsilon_2}^2 & \rho_{\epsilon_2 \epsilon_3} \sigma_{\epsilon_2} \sigma_{\epsilon_3} \\ \rho_{\epsilon_1 \epsilon_3} \sigma_{\epsilon_3} & \rho_{\epsilon_2 \epsilon_3} \sigma_{\epsilon_2} \sigma_{\epsilon_3} & \sigma_{\epsilon_3}^2 \end{pmatrix}, \quad \Sigma_a = \begin{pmatrix} \sigma_{a_1}^2 & \rho_{a_1 a_2} \sigma_{a_1} \sigma_{a_2} & \rho_{a_1 a_3} \sigma_{a_1} \sigma_{a_3} \\ \rho_{a_1 a_2} \sigma_{a_1} \sigma_{a_2} & \sigma_{a_2}^2 & \rho_{a_2 a_3} \sigma_{a_2} \sigma_{a_3} \\ \rho_{a_1 a_3} \sigma_{a_1} \sigma_{a_3} & \rho_{a_2 a_3} \sigma_{a_2} \sigma_{a_3} & \sigma_{a_3}^2 \end{pmatrix} \quad (6.7)$$

respectively. The parameters of the covariance matrices are also to be estimated. Hence, the likelihood function of individual i , starting from $t = 1$ and conditional on the regressors and the initial conditions, is written as

$$L_i = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \prod_{t=1}^T L_{it}(\mathbf{y}_{it} | \mathbf{y}_{i0}, \mathbf{y}_{i,t-1}, \mathbf{x}_i, a_{1i}, a_{2i}, a_{3i}) g(a_{1i}, a_{2i}, a_{3i}) da_{1i} da_{2i} da_{3i}, \quad (6.8)$$

where $\mathbf{y}_{it} = (y_{1it}, y_{2it}, y_{3it})$, $\mathbf{y}_{i0} = (y_{1i0}, y_{2i0}, y_{3i0})$, $\mathbf{y}_{i,t-1} = (y_{1i,t-1}, y_{2i,t-1}, y_{3i,t-1})$ and $\mathbf{x}_i = (\mathbf{x}_{1i}, \mathbf{x}_{2i}, \mathbf{x}_{3i})$, and $\prod_{t=1}^T L_{it}(\mathbf{y}_{it} | \mathbf{y}_{i0}, \mathbf{y}_{i,t-1}, \mathbf{x}_i, a_{1i}, a_{2i}, a_{3i})$ and $g(a_{1i}, a_{2i}, a_{3i})$ denote respectively the likelihood function of individual i conditional on the individual effects and the trivariate normal density function of (a_{1i}, a_{2i}, a_{3i}) . Define

$$A_{it} = \gamma_1 y_{1i,t-1} + \beta_1' \mathbf{x}_{1it} + b_0^{r1} + b_1^{r1} y_{1i0} + \mathbf{b}_2^{r1} \mathbf{x}_{1i}, \quad (6.9)$$

$$B_{it} = \gamma_2 y_{2i,t-1} + \beta_2' \mathbf{x}_{2it} + b_0^{r2} + b_1^{r2} y_{2i0} + \mathbf{b}_2^{r2} \mathbf{x}_{2i}, \quad (6.10)$$

³The vectors of explanatory variables $\mathbf{x}_{1i}$, $\mathbf{x}_{2i}$ and $\mathbf{x}_{3i}$, in order to be included in equations (6.4), (6.5) and (6.6), must be sufficiently time-variant, otherwise a collinearity problem will arise.

$$C_{it} = \gamma_3 y_{3i,t-1} + \beta_3' \mathbf{x}_{3it} + b_0^{r3} + b_1^{r3} y_{3i0} + \mathbf{b}_2^{r3} \mathbf{x}_{3it}, \quad (6.11)$$

the individual likelihood function conditional on the individual effects is shown (in sub-appendix 6.A.1) to be

$$\begin{aligned} & \prod_{t=1}^T \Phi[-(A_{it} + a_{1i})]^{1-y_{1it}} \left[\frac{1}{\sigma_{\epsilon_3}} \phi\left(\frac{y_{3it} - C_{it} - a_{3i}}{\sigma_{\epsilon_3}}\right) \right. \\ & \times \frac{1}{\sigma_{\epsilon_2} \sqrt{1 - \rho_{\epsilon_2 \epsilon_3}^2}} \phi\left(\frac{y_{2it} - B_{it} - a_{2i} - \rho_{\epsilon_2 \epsilon_3} \frac{\sigma_{\epsilon_2}}{\sigma_{\epsilon_3}} (y_{3it} - C_{it} - a_{3i})}{\sigma_{\epsilon_2} \sqrt{1 - \rho_{\epsilon_2 \epsilon_3}^2}}\right) \\ & \left. \times \Phi\left(\frac{A_{it} + a_{1i} + \frac{\rho_{12,3}}{\sigma_{\epsilon_2}} (y_{2it} - B_{it} - a_{2i}) + \frac{\rho_{13,2}}{\sigma_{\epsilon_3}} (y_{3it} - C_{it} - a_{3i})}{\sqrt{1 - R_{1,23}^2}}\right) \right]^{y_{1it}}, \end{aligned} \quad (6.12)$$

where ϕ and Φ denote respectively the univariate standard normal density and cumulative distribution functions, and the expressions of $R_{1,23}^2$, $\rho_{12,3}$ and $\rho_{13,2}$ are given in sub-appendix 6.A.1. The triple integral in equation (6.8) can be approximated using “three-step” Gauss-Hermite quadrature described in sub-appendix 6.A.2 so that the random-effects individual likelihood function of the three-equation dynamic tobit-type model becomes

$$\begin{aligned} L_i \simeq & \Lambda_3 \sum_{q=1}^Q w_q \left\{ \prod_{t=1}^T \left[\frac{1}{\sigma_{\epsilon_3}} \phi\left(\frac{y_{3it} - C_{it} - \frac{a_q \sigma_{a_3} \sqrt{2}}{\sqrt{A_{33}}}}{\sigma_{\epsilon_3}}\right) \right]^{y_{1it}} \sum_{p=1}^P w_p \left\{ e^{-\left(A_{23} \frac{a_p \sqrt{2}}{\sqrt{A_{22}}} \frac{a_q \sqrt{2}}{\sqrt{A_{33}}}\right)} \right. \right. \\ & \times \prod_{t=1}^T \left[\frac{1}{\sigma_{\epsilon_2} \sqrt{1 - \rho_{\epsilon_2 \epsilon_3}^2}} \phi\left(\frac{y_{2it} - B_{it} - \frac{a_p \sigma_{a_2} \sqrt{2}}{\sqrt{A_{22}}} - \rho_{\epsilon_2 \epsilon_3} \frac{\sigma_{\epsilon_2}}{\sigma_{\epsilon_3}} (y_{3it} - C_{it} - \frac{a_q \sigma_{a_3} \sqrt{2}}{\sqrt{A_{33}}})}{\sigma_{\epsilon_2} \sqrt{1 - \rho_{\epsilon_2 \epsilon_3}^2}}\right) \right]^{y_{1it}} \\ & \times \sum_{m=1}^M w_m \left\{ e^{-\left(A_{12} \frac{a_m \sqrt{2}}{\sqrt{A_{11}}} \frac{a_p \sqrt{2}}{\sqrt{A_{22}}} + A_{13} \frac{a_m \sqrt{2}}{\sqrt{A_{11}}} \frac{a_q \sqrt{2}}{\sqrt{A_{33}}}\right)} \prod_{t=1}^T \Phi\left[-\left(A_{it} + \frac{a_m \sigma_{a_1} \sqrt{2}}{\sqrt{A_{11}}}\right)\right]^{1-y_{1it}} \right. \\ & \left. \left. \times \left[\Phi\left(\frac{A_{it} + \frac{a_m \sigma_{a_1} \sqrt{2}}{\sqrt{A_{11}}} + \frac{\rho_{12,3}}{\sigma_{\epsilon_2}} (y_{2it} - B_{it} - \frac{a_p \sigma_{a_2} \sqrt{2}}{\sqrt{A_{22}}}) + \frac{\rho_{13,2}}{\sigma_{\epsilon_3}} (y_{3it} - C_{it} - \frac{a_q \sigma_{a_3} \sqrt{2}}{\sqrt{A_{33}}})}{\sqrt{1 - R_{1,23}^2}}\right) \right]^{y_{1it}} \right] \right\} \right\}. \end{aligned}$$

The expressions of Λ_3 and A_{jk} ($j, k = 1, 2, 3$ and $A_{jk} = A_{kj}$) are given in sub-appendix 6.A.2; w_m , w_p and w_q are the weights of the first-, second- and third-step Gauss-Hermite quadrature; a_m , a_p and a_q are the corresponding abscissas, and M , P and Q are the first-, second- and third-step total number of integration points. The product over i of the approximated likelihood function L_i can be maximized using standard numerical procedures to obtain estimates of the parameters of the three-equation dynamic tobit-type model.

6.4 Data

We implement the model using data from three waves of the Dutch Community Innovation Survey (CIS) merged with data from the Production Survey collected at the enterprise level by the *Centraal Bureau voor de Statistiek* (CBS). More specifically, the data pertain to Dutch manufacturing during the periods 1994-1996 (CIS 2), 1996-1998 (CIS 2.5) and 1998-2000 (CIS 3). The target population consists of enterprises with at least ten employees and positive sales at the end of the period covered by the innovation survey.¹ We estimate a cross-sectional version of the model using each CIS separately, then we form a balanced panel that is used to estimate a dynamic panel data version of the model ignoring and accounting for individual effects. The panel consists of enterprises that existed in 1994, survived (at least) until 2000 and took part in the three innovation surveys considered in this study. Descriptive statistics of the variables that are included in the estimation of the model are reported in Table 6.1 for the three categories of industries defined in Chapter 2 and each CIS separately, and in Table 6.2 for the balanced panel.

6.4.1 The cross-sectional model specification

The dependent variable of equation (6.1) is binary with value 1 if an enterprise engages in innovation activities, i.e. reports positive total innovation expenditures, and 0 otherwise. An innovative enterprise may be a product innovator, a process innovator, or may have unsuccessful or incomplete innovation activities. About 70% of the enterprises are innovative in the high-tech category, 60% in the low-tech category and 50% in the wood industry for CIS 2 and CIS 2.5. The corresponding percentages for CIS 3 are respectively 66%, 50% and 40%. On the grounds of Schumpeter's tradition, we explain the decision to be innovative by size, as measured by the number of employees (in log), and relative size defined as firms' total sales over sales of industry (in log). For the high-tech and low-tech categories, we also include sectoral dummies that are assumed to capture technological opportunities and appropriability. The industry of chemical product is the reference sector in the high-tech category and the not elsewhere classified (NEC) industry is the reference sector in the low-tech category. These explanatory variables are available for both innovative and non-innovative enterprises, unlike those included into vectors $\mathbf{x}_2$ and $\mathbf{x}_3$.

¹More details about the data can be found in Section 2.3 of Chapter 2.

Table 6.1: Descriptive statistics per category of industries and CIS: Means and standard deviations in parentheses for continuous variables

Variable	Description	CIS 2			CIS 2.5			CIS 3		
		High-tech	Low-tech	Wood	High-tech	Low-tech	Wood	High-tech	Low-tech	Wood
		Dependent variables								
Innovative firm	1 if firm engages in innovation activities	0.744	0.582	0.516	0.723	0.559	0.505	0.658	0.495	0.422
R&D intensity [†]	R&D expenditures over total sales, or innovative firms	0.077 (0.429)	0.048 (0.445)	0.013 (0.027)	0.061 (0.234)	0.023 (0.071)	0.013 (0.027)	0.069 (0.149)	0.019 (0.040)	0.014 (0.044)
Share of innovative sales ^{††}	innovative sales over total sales for innovative firms	0.336 (0.279)	0.238 (0.243)	0.216 (0.259)	0.341 (0.269)	0.235 (0.229)	0.199 (0.242)	0.340 (0.268)	0.253 (0.242)	0.221 (0.245)
		Explanatory variables								
Demand pull	1 if product-oriented innovation objectives are very important, for innovative firms	0.647	0.574	0.559	0.587	0.494	0.500	0.775	0.746	0.673
Technology push	1 if innovation sources are from universities or other institutes for innovative firms	0.235	0.230	0.133	0.218	0.181	0.121	0.264	0.207	0.146
Innovation cooperation	1 if there is any type of cooperation, for innovative firms	0.362	0.340	0.251	0.350	0.269	0.254	0.383	0.298	0.276
Continuous R&D performers	1 if performing continuous R&D, for innovative firms	0.702	0.557	0.366	0.674	0.546	0.379	0.747	0.541	0.377
Subsidies	1 if being subsidized at least once, for innovative firms	0.647	0.553	0.254	0.671	0.514	0.307	0.716	0.529	0.266
Size [†]	number of employees	147.067 (361.866)	116.688 (356.673)	108.765 (176.572)	131.202 (324.565)	115.11 (358.861)	107.829 (190.13)	166.73 (401.888)	171.279 (457.99)	109.163 (199.155)
Relative size ^{††}	total sales/sales of industry	0.004 (0.013)	0.003 (0.009)	0.002 (0.004)	0.004 (0.015)	0.004 (0.010)	0.002 (0.004)	0.005 (0.020)	0.004 (0.011)	0.002 (0.005)
Number of firms		1281	1472	541	1244	1421	555	1008	1241	472

[†]ln(R&D/total sales); ^{††}A logit transformation: ln(number of employees); ln(total sales/sales of industry) are used in the estimation.

The explained variable of equation (6.2) is R&D intensity as measured by total R&D expenditures over total sales. This figure ranges from 6% (CIS 2.5) to 8% (CIS 2) in the high-tech category, from 2% (CIS 2.5 and CIS 3) to 5% (CIS 2) in the low-tech category and is about 1% (for the three CIS) in the wood industry. The percentage of total sales invested in R&D is zero for non-innovative enterprises. However, some innovative enterprises do not have R&D investments. There are about 15% of such firms in the three CIS. Since a natural logarithmic transformation of R&D intensity is used in the estimation, we replace the zero values for innovative firms by ε that is taken smaller than the smallest positive observed value of R&D intensity. Besides size and the sectoral dummies, we explain R&D intensity by indicators of demand pull, technology push, innovation cooperation and subsidies described in Table 6.1. The decision to engage in innovation activities and the actual percentage of total sales invested in R&D are allowed to be correlated in the estimation.

Finally, the dependent variable of equation (6.3) is the share of innovative sales measured as the ratio of sales of new or improved products over total sales.⁵ This figure is about 34% and 24% (for the three CIS) in the high-tech and low-tech category respectively and ranges from 20% (CIS 2.5) to 22% (CIS 2 and CIS 3) in the wood industry. We use the same regressors as in equation (6.2) and an indicator of continuous R&D performers to explain the share of innovative sales which takes on the value zero for non-innovative and some innovative enterprises, namely the process-only innovators and/or the unsuccessful innovative firms. These last two categories of enterprises represent 14% of the innovative firms. Furthermore, in the three CIS about 3% of the innovative firms, the new established ones, report a value 1 for the share of innovative sales. Since a logit transformation of the share of innovative sales, to make it lie within the set of real numbers, is used in the estimation, we use the same procedure as in Section 4.5 of Chapter 4 to deal with the zero and one values of the innovative firms. The actual share of innovative sales is allowed to be correlated with the decision to engage in innovation activities and R&D intensity in the estimation.

6.4.2 The panel data model specification

In the panel data specification of the model, we include in each equation the lagged dependent variable as an explanatory variable. More specifically, the current probability of engaging in innovation activities, current R&D intensity and the current share of innovative sales are

⁵Like in Chapter 4, we consider products new to the firm not necessarily new to the market.

explained by past engagement in innovation activities, past R&D intensity and past share of innovative sales respectively. The remaining regressors are the same as in the cross-sectional case, except that lagged size and relative size are considered because of the timing problem mentioned in Chapter 4. Furthermore, we account for unobserved firm heterogeneity by including individual effects in each equation of the model so that separate estimation for the three categories of industries is no longer needed.⁶ We still allow for different industry intercepts by including sectoral dummies in the three equations of the model with the wood industry being the reference.

Table 6.2: Descriptive statistics for the balanced panel

Variable	Overall Mean	Overall Std. Dev.	Between Std. Dev.	Within Std. Dev.
Dependent variables				
Innovative firm	0.688	0.463	0.370	0.280
R&D intensity [‡]	0.040	0.075	0.061	0.035
Share of innovative sales ^{‡‡}	0.284	0.259	0.215	0.149
Explanatory variables				
Demand pull	0.646	0.478	0.367	0.339
Technology push	0.223	0.416	0.303	0.278
Innovation cooperation	0.363	0.481	0.382	0.298
Continuous R&D performers	0.656	0.475	0.426	0.260
Subsidies	0.607	0.489	0.420	0.285
Size [†]	209.962	539.248	534.722	71.292
Relative size ^{††}	0.006	0.020	0.020	0.004
Number of observations	2583			

[‡] $\ln(\text{R\&D}/\text{total sales})$; ^{‡‡}A logit transformation: $\ln(\text{number of employees})$;

^{††} $\ln(\text{total sales}/\text{sales of industry})$ are used in the estimation.

Due to the sampling design of the Dutch CIS, firms' size is larger (on average) in the balanced panel than in each CIS taken separately. Indeed, for each wave of the CIS, a census is used by CBS for the population of enterprises with at least 100 employees (large enterprises), while a stratified random sampling is used for the population of enterprises with less than 100 employees (small- and medium-size enterprises). The remaining firm characteristics in the balanced panel are comparable to those of each single CIS. We now present the estimation results.

⁶Wald tests not reported in the chapter suggest that, when accounting for individual effects in the dynamic panel data model, we could not reject the joint null hypothesis that the industry slope parameters are equal.

6.5 Estimation results

Tables 6.3-6.5 report maximum likelihood (ML) estimation results of the cross-sectional version of the model for the three categories of industries in each CIS taken separately.⁷

Table 6.3: ML estimation results of the cross-sectional model: CIS 2 The Netherlands

Variable	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)
	High-Tech		Low-Tech		Wood	
Innovation activities						
Size (in log)	0.396**	(0.076)	0.210**	(0.058)	0.101	(0.112)
Relative size (in log)	-0.026	(0.057)	0.179**	(0.040)	0.111	(0.088)
Intercept	-1.252 [†]	(0.734)	0.457	(0.435)	0.416	(1.063)
R&D intensity (in log)						
Size (in log)	-0.041	(0.062)	0.064	(0.079)	-0.111	(0.150)
Demand pull	0.476**	(0.126)	0.438**	(0.142)	0.505 [†]	(0.273)
Innovation cooperation	0.632**	(0.136)	0.202	(0.156)	0.756*	(0.323)
Technology push	0.383**	(0.147)	0.403*	(0.169)	0.752 [†]	(0.396)
Subsidies	1.461**	(0.131)	1.366**	(0.147)	1.557**	(0.314)
Intercept	-5.256**	(0.349)	-5.875**	(0.117)	-6.305**	(0.762)
Share of innovative sales (in logit)						
Size (in log)	0.609**	(0.161)	0.991**	(0.184)	0.757*	(0.378)
Continuous R&D	1.961**	(0.389)	0.944**	(0.350)	0.236	(0.689)
Demand pull	0.792**	(0.297)	1.603**	(0.307)	1.770**	(0.546)
Innovation cooperation	0.233	(0.321)	0.770*	(0.333)	2.708**	(0.669)
Technology push	-0.028	(0.351)	-0.123	(0.361)	0.610	(0.799)
Subsidies	1.186**	(0.323)	0.920**	(0.324)	1.386*	(0.649)
Intercept	-8.717**	(0.881)	-10.722**	(0.913)	-13.133**	(1.768)
Extra parameters						
σ_{ϵ_2}	1.833**	(0.043)	1.953**	(0.047)	2.201**	(0.105)
σ_{ϵ_3}	5.522**	(0.151)	5.451**	(0.180)	6.838**	(0.487)
$\rho_{\epsilon_1\epsilon_2}$	-0.117	(0.084)	0.030	(0.079)	-0.213	(0.149)
$\rho_{\epsilon_1\epsilon_3}$	0.893**	(0.016)	0.852**	(0.022)	0.930**	(0.033)
$\rho_{\epsilon_2\epsilon_3}$	-0.014	(0.048)	0.055	(0.053)	-0.020	(0.109)
Number of firms	1281		1472		541	
Log-likelihood	-5339.998		-5115.745		-1782.251	
Significance levels : †: 10% *: 5% **: 1%						

The results are different across categories of industries suggesting different technological opportunities and innovation appropriability, hence the presence of firm heterogeneity in the innovation process, and across waves of the CIS. Overall, they are in accordance with most of the cross-sectional empirical studies on the interrelationship between the decision to engage in innovation activities, innovation input investments and innovation output reported in Table 6.7. A few exceptions are worth noting though. First, the negative and significant effect of

⁷In order to save space, we do not report in Tables 6.3-6.6 the coefficients of the industry dummies.

Table 6.4: ML estimation results of the cross-sectional model: CIS 2.5 The Netherlands

Variable	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)
	High-Tech		Low-Tech		Wood	
Innovation activities						
Size (in log)	0.237**	(0.078)	0.282**	(0.068)	0.249*	(0.123)
Relative size (in log)	0.126*	(0.059)	0.161**	(0.048)	-0.033	(0.097)
Intercept	0.625	(0.752)	0.087	(0.526)	-1.236	(1.178)
R&D intensity (in log)						
Size (in log)	0.012	(0.070)	0.008	(0.097)	-0.055	(0.140)
Demand pull	0.687**	(0.137)	0.428**	(0.146)	0.690*	(0.270)
Innovation cooperation	0.216	(0.147)	0.169	(0.170)	0.614 [†]	(0.320)
Technology push	0.817**	(0.163)	0.293	(0.189)	1.189**	(0.430)
Subsidies	1.682**	(0.450)	1.054**	(0.455)	0.784*	(0.312)
Intercept	-6.321**	(0.383)	-5.718**	(0.533)	-6.506**	(0.807)
Share of innovative sales (in logit)						
Size (in log)	0.649**	(0.140)	0.833**	(0.178)	0.972**	(0.322)
Continuous R&D	1.621**	(0.342)	2.030**	(0.347)	0.729	(0.711)
Demand pull	0.868**	(0.265)	0.959**	(0.277)	1.736**	(0.523)
Innovation cooperation	0.408	(0.283)	0.122	(0.320)	0.425	(0.621)
Technology push	-0.204	(0.316)	0.904*	(0.356)	1.718*	(0.849)
Subsidies	1.112**	(0.320)	0.730*	(0.304)	1.447*	(0.622)
Intercept	-8.181**	(0.727)	-8.729**	(0.927)	-13.521**	(1.659)
Extra parameters						
σ_{ϵ_2}	1.964**	(0.047)	2.001**	(0.050)	2.288**	(0.116)
σ_{ϵ_3}	4.581**	(0.136)	4.439**	(0.180)	6.262**	(0.507)
$\rho_{\epsilon_1\epsilon_2}$	0.120	(0.095)	-0.041	(0.118)	-0.236	(0.174)
$\rho_{\epsilon_1\epsilon_3}$	0.815**	(0.026)	0.716**	(0.053)	0.895**	(0.049)
$\rho_{\epsilon_2\epsilon_3}$	0.044	(0.050)	-0.030	(0.062)	-0.195	(0.120)
Number of firms	1244		1421		555	
Log-likelihood	-5022.059		-4718.722		-1803.266	
Significance levels : [†] : 10% *: 5% **: 1%						

size on R&D (or innovation input) intensity of innovative firms found in the literature is not supported by our cross-sectional results. Secondly, unlike the empirical literature, we do find evidence of positive and significant effect of cooperation on R&D intensity of innovative firms especially in the high-tech category (except for CIS 2.5) and the wood industry. There is also some evidence of positive and significant effect of cooperation on the share of innovative sales of innovative firms. Finally, size affects positively and significantly the share of innovative sales of innovative firms, while no significant effect of the former on the latter is found in the literature.

Table 6.6 reports ML estimation results of the dynamic panel data version of the model. In the first pair of columns, the model ignores unobserved individual effects, while they are accounted for as well as endogenous initial conditions in the second pair of columns. In the

Table 6.5: *ML estimation results of the cross-sectional model: CIS 3 The Netherlands*

Variable	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)
	High-Tech		Low-Tech		Wood	
Innovation activities						
Size (in log)	0.327**	(0.060)	0.070	(0.044)	0.222*	(0.094)
Relative size (in log)	0.012	(0.048)	0.259**	(0.037)	-0.038	(0.070)
Intercept	-0.815	(0.575)	1.281**	(0.412)	-1.395†	(0.838)
R&D intensity (in log)						
Size (in log)	-0.062	(0.070)	-0.109	(0.083)	0.119	(0.177)
Demand pull	-0.005	(0.181)	0.545**	(0.188)	0.197	(0.330)
Innovation cooperation	0.570**	(0.167)	0.638**	(0.182)	1.027**	(0.365)
Technology push	0.573**	(0.175)	0.363†	(0.199)	0.826†	(0.441)
Subsidies	1.513**	(0.172)	1.288**	(0.168)	0.846*	(0.374)
Intercept	-5.083**	(0.426)	-6.054**	(0.563)	-7.854**	(1.040)
Share of innovative sales (in logit)						
Size (in log)	0.830**	(0.173)	0.881**	(0.184)	0.935*	(0.445)
Continuous R&D	0.808†	(0.458)	0.795*	(0.382)	0.605	(0.819)
Demand pull	3.705**	(0.392)	4.134**	(0.370)	4.316**	(0.661)
Innovation cooperation	0.738*	(0.351)	0.776*	(0.363)	0.225	(0.773)
Technology push	-0.174	(0.377)	0.275	(0.390)	1.460†	(0.858)
Subsidies	0.541	(0.383)	0.707*	(0.341)	0.975	(0.787)
Intercept	-11.464**	(0.986)	-13.612**	(1.094)	-16.225**	(2.159)
Extra parameters						
σ_{ϵ_2}	1.881**	(0.053)	1.962**	(0.060)	2.198**	(0.124)
σ_{ϵ_3}	5.559**	(0.189)	5.685**	(0.218)	7.421**	(0.538)
$\rho_{\epsilon_1\epsilon_2}$	-0.144†	(0.088)	-0.174†	(0.104)	0.194	(0.190)
$\rho_{\epsilon_1\epsilon_3}$	0.918**	(0.014)	0.904**	(0.016)	0.939**	(0.020)
$\rho_{\epsilon_2\epsilon_3}$	-0.041	(0.060)	-0.068	(0.072)	0.162	(0.144)
Number of firms	1008		1241		472	
Log-likelihood	-3816.298		-3770.194		-1331.220	
Significance levels : †: 10% *: 5% **: 1%						

latter case, the likelihood function was maximized using 6-point Gauss-Hermite quadrature in each step of the procedure as described in sub-appendix 6.A.2. We discuss the results in detail for the full dynamic panel data model.

Dynamic effect

We find evidence of presence of dynamics in the innovation process. Indeed, in each equation, the lagged dependent variable affects significantly the current dependent variable. There is persistence in engaging in innovation activities and, for innovative firms, past R&D investments affect negatively and significantly current R&D investments and past share of innovative sales affect positively and significantly the current share of innovative sales. The first result supports the hypothesis of existence of *sunk costs* in innovation activities. This

Table 6.6: ML estimation results of the dynamic panel data model

Variable	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)
Estimation assumption	No individual effects		Individual effects with endogenous initial conditions	
Current innovation activities (y_{1it})				
Past innovation activities ($y_{1,it-1}$)	2.050**	(0.121)	0.922**	(0.192)
Lagged size (in log)	0.173 [†]	(0.090)	0.236 [†]	(0.129)
Lagged relative size (in log)	0.130 [†]	(0.067)	0.156	(0.096)
Intercept	-1.614 [†]	(0.839)	-2.707*	(1.206)
Current R&D intensity (y_{2it} in log)				
Past R&D intensity ($y_{2,it-1}$)	0.430**	(0.027)	-0.107*	(0.047)
Lagged size (in log)	0.014	(0.054)	0.028	(0.062)
Demand pull	0.385**	(0.109)	0.218*	(0.099)
Innovation cooperation	0.076	(0.114)	0.068	(0.107)
Technology push	0.381**	(0.123)	0.339**	(0.116)
Subsidies	0.685**	(0.119)	0.475**	(0.118)
Intercept	-1.158**	(0.361)	-1.481**	(0.426)
Current share of innovative sales (y_{3it} in logit)				
Past share of innovative sales ($y_{3,it-1}$)	0.295**	(0.029)	0.117**	(0.052)
Lagged size (in log)	0.174	(0.133)	0.164	(0.142)
Continuous R&D	1.057**	(0.315)	1.158**	(0.326)
Demand pull	1.824**	(0.259)	1.651**	(0.261)
Innovation cooperation	0.542*	(0.266)	0.523 [†]	(0.269)
Technology push	0.654*	(0.287)	0.698*	(0.292)
Subsidies	0.511 [†]	(0.284)	0.447	(0.288)
Intercept	-6.211**	(0.810)	-5.960**	(0.851)
Extra parameters				
Initial innovation activities ($y_{1,i0}$)	-	-	2.266**	(0.327)
Initial R&D intensity ($y_{2,i0}$)	-	-	0.459**	(0.047)
Initial share of innovative sales ($y_{3,i0}$)	-	-	0.143**	(0.047)
σ_{a1}	-	-	0.814**	(0.145)
σ_{a2}	-	-	1.333**	(0.096)
σ_{a3}	-	-	1.653**	(0.301)
ρ_{a1a2}	-	-	0.336**	(0.095)
ρ_{a1a3}	-	-	0.342*	(0.169)
ρ_{a2a3}	-	-	0.271**	(0.108)
$\sigma_{\epsilon2}$	1.597**	(0.038)	1.076**	(0.050)
$\sigma_{\epsilon3}$	3.985**	(0.112)	3.627**	(0.141)
$\rho_{\epsilon1\epsilon2}$	0.242**	(0.072)	-0.019	(0.134)
$\rho_{\epsilon1\epsilon3}$	0.606**	(0.067)	0.715**	(0.106)
$\rho_{\epsilon2\epsilon3}$	0.090*	(0.038)	-0.032	(0.053)
Number of observations	1564			
Log-likelihood	-5211.746		-5116.672	
Significance levels : [†] : 10% *: 5% **: 1%				

finding is in accordance with Máñez Castillejo et al. (2004) and Peters (2005) who estimate a dynamic probit and find evidence of persistence by Spanish manufacturing firms in engaging in R&D activities, and by German manufacturing and services firms in engaging in innovation

activities respectively. The second result is somewhat surprising as we would expect past R&D investments of innovative firms to affect positively current R&D investments. The positive effect identified in the dynamic panel data model without individual effects seems to be taken over by the initial R&D investments.⁸ Hence, a negative effect arises when we estimate the full dynamic panel data model accounting for unobserved individual effects and endogenous initial conditions. We are unable to identify a positive effect of both past and the initial (through its correlation with the individual effects) R&D investments on current R&D investments.⁹ This phenomenon might be due to the shortness of the panel in which case past and the initial R&D investments are highly correlated. Finally, the third result corroborates the finding of Chapter 4 and is also in accordance with van Leeuwen (2002). The coefficient of the lagged share of innovative sales in the dynamic model without individual effects is very similar to that of van Leeuwen's study which does not account for individual effects.

Size and relative size

Lagged size affects positively and significantly the probability to engage in innovation activities, although its significance lessens when technological opportunities and appropriability, through sectoral dummies, are controlled for (Crépon et al., 1996). This finding is in accordance with the empirical literature (see Table 6.7) and in particular with Cohen and Klepper's (1996) stylized fact 1.¹⁰ Like Crépon et al. (1998), we find no correlation between R&D intensity and firm size. This finding is at variance with the empirical literature which identifies a negative relationship between R&D intensity and firm size. Our results also suggest that firm size does not significantly affect the share of innovative sales, which is in accordance with the empirical literature and at variance with Cohen and Klepper's stylized fact 4.¹¹ The positive and significant effect of size on the share of innovative sales found in the cross-sectional version of the model vanishes when dynamics is allowed for.

⁸The coefficient of the lagged R&D intensity of the model without individual effects is very similar to that of the study by van Leeuwen (2002).

⁹At first, the "three-step" Gauss-Hermite quadrature was thought to be the main reason why past R&D investments affect negatively current R&D investments because of inaccuracy that might result from the use of too few integration points. We later increased the number of integration points, in each step of the procedure, to 12 and found similar results. Furthermore, the negative effect is confirmed when estimating a dynamic linear regression model of R&D investments, accounting for individual effects and endogenous initial conditions, using the subsample of innovative firms. In this latter case, no Gaussian quadrature is needed to evaluate the likelihood function the expression of which is given in equation (4.9) of sub-appendix 4.A.2.

¹⁰Cohen and Klepper's stylized fact 1 states that: "The likelihood of a firm reporting positive R&D effort rises with firm size and approaches one for firms in the largest size ranges."

¹¹Cohen and Klepper's stylized fact 4 states that: "Among R&D performing firms, the number of patents and innovations per dollar of R&D decreases with firm size and/or the level of R&D, and among all firms, smaller firms account for a disproportionately large number of patents and innovations relative to their size."

As for relative size, there is mixed evidence in the literature with regard to its role in the probability to engage in innovation activities. Like Janz and Peters (2002) and van Leeuwen (2002) we find no significant effect of relative size on the probability to engage in innovation activities.

Demand pull and technology push

The results suggest that demand pull and technology push affect positively and significantly both R&D investments and the share of innovative sales. In line with Cohen and Levinthal's (1989) "absorptive capacity", the coefficient of technology push is larger and more significant than that of demand pull in the R&D intensity equation. Conversely, demand pull affects more significantly the share of innovative sales than technology push. This finding is in accordance with the literature which shows a larger and more significant impact of technology push on R&D investments than demand pull, while demand pull is shown to have a larger and more significant impact on the share of innovative sales than technology push.

Innovation cooperation

The positive and significant effect of innovation cooperation on R&D intensity found in the cross-sectional version of the model vanishes in the dynamic specification of the model with panel data. Other things being equal cooperative enterprises do not seem to invest more in R&D than non-cooperative enterprises, which is in accordance with the empirical literature. However, unlike the empirical literature, we find evidence of positive correlation between cooperation and the share of innovative sales.

Continuous R&D

Like Klomp and van Leeuwen (2001) and van Leeuwen (2002) we find that, *ceteris paribus*, continuous R&D performers are more successful in terms of share of innovative sales than temporary R&D performers. This finding is in accordance with the empirical literature which identifies a positive and highly significant impact of doing R&D continuously on the share of innovative sales (see also Brouwer and Kleinknecht, 1996; Mairesse and Mohnen, 2001; Mohnen and Dagenais, 2001).

Subsidy

The empirical literature identifies two types of relationship, at the firm level, between subsidies and R&D investments. More specifically, subsidized and private R&D investments are *complements* if R&D investments increase with subsidies, otherwise subsidized and private R&D investments are *substitutes* in which case the former “crowd out” the latter (Lach, 2002; Almus and Czarnitzki, 2003). Our results suggest that subsidized firms have on average larger R&D investments than non-subsidized counterparts. Since we only observe whether or not an enterprise receives R&D subsidies, we can conclude that the hypothesis of complete “crowding out” effects is not supported by our results although some substitution between subsidized and private R&D investments may still exist (Czarnitzki and Fier, 2002). As for the share of innovative sales, the positive and significant effect of subsidy found in the cross-sectional specification of the model vanishes in the dynamic version of the model.

Firm heterogeneity and interrelationship

Firm heterogeneity is shown in the literature to be an important feature of the innovation process and ignoring it results in misleading inference about the process (see for instance Blundell et al., 1995, 1999). We account for observed heterogeneity in the cross-sectional specification by separately estimating the model for the three categories of industries. Furthermore, the industries of the high- and low-tech categories are allowed to have different intercepts by including sectoral dummies. Tables 6.3-6.5 suggest that the three categories of industries differ in their innovation behavior, hence the presence of heterogeneity in the innovation process. The dynamic panel data specification models both observed and unobserved heterogeneity including sectoral dummies and individual effects respectively. Table 6.6 suggests that the model assuming the absence of individual effects (see the first pair of columns) is rejected using a likelihood ratio test at 1% level of significance, hence the presence of unobserved firm heterogeneity in the innovation process. Indeed, in each equation of the model the standard deviation of the individual effects is significantly (at 1% level) estimated. Furthermore, the engagement in innovation activities, R&D intensity and the share of innovative sales at the initial period affect positively and significantly, through their correlation with the individual effects, the current engagement in innovation activities, current R&D intensity and the current share of innovative sales respectively.

Table 6.6 also shows that the decision to engage in innovation activities, the amount of R&D investments and the share of innovative sales are correlated through the idiosyncratic

Table 6.7: Empirical findings from studies on the interrelationship between innovation activities, innovation input and innovation output

Study	Dynamics	Size	Relative size	Demand	Technology	Cooperation	Continuous	Subsidy
Engaging in innovation activities								
Crépon et al. (1998) [†]	n.a	+ effect	+ effect	+ effect	+ effect	n.a	n.a	n.a
Klomp and van Leeuwen (2001) [‡]	n.a	- effect	+ effect	n.a	n.a	n.a	+ effect	n.a
Janz and Peters (2002) [‡]	n.a	+ effect	no effect	n.a	n.a	n.a	n.a	n.a
Lööf and Heshmati (2002a) [†]	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a
Lööf and Heshmati (2002b) [‡]	n.a	+ effect	n.a	n.a	n.a	n.a	n.a	n.a
van Leeuwen (2002) [†]	n.a	+ effect	no effect	n.a	n.a	n.a	n.a	n.a
Janz et al. (2004) [‡]	n.a	+ effect	n.a	n.a	n.a	n.a	n.a	n.a
This study [†]	+ effect	+ effect	no effect	n.a	n.a	n.a	n.a	n.a
Innovation input: R&D or total innovation investments								
Crépon et al. (1998) [†]	n.a	no effect	+ effect	+ effect	+ effect	n.a	n.a	n.a
Klomp and van Leeuwen (2001) [‡]	n.a	- effect	n.a	n.a	+ effect	no effect	no effect	+ effect
Janz and Peters (2002) [‡]	n.a	-/+ effect*	n.a	n.a	n.a	n.a	n.a	+ effect
Lööf and Heshmati (2002a) [†]	n.a	- effect	n.a	+ effect	n.a	+ effect	n.a	n.a
Lööf and Heshmati (2002b) [‡]	n.a	- effect	n.a	n.a	n.a	n.a	n.a	n.a
van Leeuwen (2002) [†]	+ effect	- effect	+ effect	no effect	+ effect	no effect	+ effect	no effect
Janz et al. (2004) [‡]	n.a	- effect	n.a	n.a	n.a	no effect	+ effect	no effect
This study [†]	- effect	no effect	n.a	+ effect	+ effect	no effect	n.a	+ effect
Innovation output: Innovative sales over total sales or innovative sales per employee ²								
Crépon et al. (1998) [†]	n.a	no effect	n.a	+ effect	- effect	n.a	n.a	n.a
Klomp and van Leeuwen (2001) [‡]	n.a	no effect	n.a	+ effect	no effect	no effect	+ effect	n.a
Janz and Peters (2002) [‡]	n.a	+/- effect [‡]	n.a	no effect	no effect	n.a	n.a	n.a
Lööf and Heshmati (2002a) [†]	n.a	no effect	n.a	n.a	n.a	- effect	n.a	n.a
Lööf and Heshmati (2002b) [‡]	n.a	no effect	n.a	n.a	+ effect	no effect	n.a	n.a
van Leeuwen (2002) [†]	+ effect	no effect	n.a	+ effect	no effect	no effect	+ effect	n.a
Janz et al. (2004) [‡]	n.a	- effect	n.a	no effect	no effect	no effect	n.a	no effect
This study [†]	+ effect	no effect	n.a	+ effect	+ effect	+ effect	+ effect	no effect

[†]These studies consider R&D investments as innovation input. [‡]These studies consider total innovation investments as innovation input. ^{*}The relationship between innovation input and size is U-shaped. [‡]The study by Lööf and Heshmati (2002b) uses innovative sales per employee. ²The relationship between innovation output and size is inverted U-shaped.

errors, when the model ignores the individual effects, and mostly through the individual effects when they are accounted for by the model. This finding rejects the hypothesis of *linearity* of the innovation process where the various stages of the process are assumed isolated from one another, and is in accordance with the empirical studies of Table 6.7.

6.6 Conclusion

We have studied the innovation process by modeling three important features of the process, namely it is nonlinear, dynamic and involves heterogeneous firms. More specifically, we considered a three-equation dynamic tobit-type model, accounting for individual effects in each equation, where the dynamics of the decision to engage in , that of R&D intensity and the share of innovative sales were jointly investigated. The model was estimated by maximum likelihood and “three-step” Gauss-Hermite quadrature was used to evaluate the likelihood function. The results are summarized as follows.

The nonlinearity of the innovation process as well as the presence of dynamics and firm heterogeneity are confirmed by the estimation results of the model. Firstly, the decision to engage in innovation activities, R&D intensity and the share of innovative sales are correlated, mostly through the individual effects. Secondly, engaging in innovation activities is persistent and, for innovative firms, past R&D investments affect negatively and significantly current R&D investments and past share of innovative sales affect positively and significantly the current share of innovative sales. Thirdly, the individual effects play a significant role in the decision to engage in innovation activities, R&D investments and the share of innovative sales. The results also suggest that size affects positively and significantly the probability to engage in innovative activities and plays no role in either the amount of R&D investments or the share of innovative sales. Demand pull and technology push affect positively and significantly both R&D investments and the share of innovative sales. Cooperative enterprises do not seem to invest more in R&D than non-cooperative counterparts, while there is evidence of positive correlation between cooperation and the share of innovative sales. Other things being equal, continuous R&D performers are more successful in terms of share of innovative sales than temporary R&D performers. Finally, subsidized firms invest more in R&D but are not more successful than non-subsidized counterparts.

The main caveat of this study is the shortness of the panel, which may explain why we

were unable to identify a positive effect of past R&D investments on current R&D investments when we accounted for individual effects and endogenous initial conditions. The fact that the same phenomenon does not take place in the other two equations indicates that the negative effect found cannot be attributed only to the shortness of the panel. This issue remains a topic of future research. Furthermore, the equations of R&D and the share of innovative sales were assumed to be correlated only through the individual effects and the idiosyncratic errors. A natural extension is to include R&D intensity in the set of explanatory variables of the equation of the share of innovative sales and vice versa, hence allowing for a direct effect of R&D investments on innovation output and a feedback effect of innovation output on R&D investments. Finally, the model ignored the relationship between innovation and firms' economic performance (e.g. productivity). This relationship can be studied by including, in the spirit of Crépon et al. (1998), a fourth equation of economic performance. However, estimating the resulting model allowing for dynamics and unobserved individual effects is a formidable task to achieve.

Appendix 6.A The random-effects likelihood function of the three-equation tobit-type model

6.A.1 The likelihood function conditional on the individual effects

Consider the three-equation dynamic tobit-type model defined in equations (6.1-6.3) with individual effects defined in equations (6.4-6.6), and expressions (6.9-6.11). Assume that the vectors $(\epsilon_{1it}, \epsilon_{2it}, \epsilon_{3it})'$ and $(a_{1i}, a_{2i}, a_{3i})'$ are independent of each other, and independently and identically distributed over time and across individuals following a normal distribution with mean zero and covariance matrix given in equation (6.7). Denote by y_{1it}^* the latent function in square brackets in equation (6.1). The likelihood function of individual i conditional on the individual effects, denoted by $\prod_{t=1}^T L_{it}(\mathbf{y}_{it}|\mathbf{y}_{i0}, \mathbf{y}_{i,t-1}, \mathbf{x}_i, a_{1i}, a_{2i}, a_{3i})$, is written as

$$\begin{aligned} \prod_{t=1}^T L_{it}(\mathbf{y}_{it}|\mathbf{y}_{i0}, \mathbf{y}_{i,t-1}, \mathbf{x}_i, a_{1i}, a_{2i}, a_{3i}) &= \prod_{t=1}^T [P(y_{1it}^* \leq 0)]^{1-y_{1it}} [f(y_{2it}, y_{3it}|y_{1it}^* > 0)P(y_{1it}^* > 0)]^{y_{1it}} \\ &= \prod_{t=1}^T [P(y_{1it}^* \leq 0)]^{1-y_{1it}} \left[\int_0^\infty f(y_{1it}^*, y_{2it}, y_{3it}) dy_{1it}^* \right]^{y_{1it}}, \end{aligned} \quad (6.13)$$

where $\mathbf{y}_{it} = (y_{1it}, y_{2it}, y_{3it})$, $\mathbf{y}_{i0} = (y_{1i0}, y_{2i0}, y_{3i0})$, $\mathbf{y}_{i,t-1} = (y_{1i,t-1}, y_{2i,t-1}, y_{3i,t-1})$, $\mathbf{x}_i = (\mathbf{x}_{1i}, \mathbf{x}_{2i}, \mathbf{x}_{3i})$ and $f(y_{1it}^*, y_{2it}, y_{3it})$ is the density function of the trivariate normal distribution of $(y_{1it}^*, y_{2it}, y_{3it})$. The trivariate density function can be written as the product of three univariate normal density functions $f(y_{1it}^*|y_{2it}, y_{3it})$, $f(y_{2it}|y_{3it})$ and $f(y_{3it})$ the expressions of which are given respectively by

$$\begin{aligned} f(y_{1it}^*|y_{2it}, y_{3it}) &= \frac{1}{\sqrt{1-R_{1,23}^2}} \phi \left(\frac{y_{1it}^* - A_{it} - a_{1i} - \frac{\rho_{12,3}}{\sigma_{\epsilon_2}}(y_{2it} - B_{it} - a_{2i}) - \frac{\rho_{13,2}}{\sigma_{\epsilon_3}}(y_{3it} - C_{it} - a_{3i})}{\sqrt{1-R_{1,23}^2}} \right), \\ f(y_{2it}|y_{3it}) &= \frac{1}{\sigma_{\epsilon_2} \sqrt{1-\rho_{\epsilon_2\epsilon_3}^2}} \phi \left(\frac{y_{2it} - B_{it} - a_{2i} - \rho_{\epsilon_2\epsilon_3} \frac{\sigma_{\epsilon_2}}{\sigma_{\epsilon_3}}(y_{3it} - C_{it} - a_{3i})}{\sigma_{\epsilon_2} \sqrt{1-\rho_{\epsilon_2\epsilon_3}^2}} \right), \\ f(y_{3it}) &= \frac{1}{\sigma_{\epsilon_3}} \phi \left(\frac{y_{3it} - C_{it} - a_{3i}}{\sigma_{\epsilon_3}} \right). \end{aligned} \quad (6.14)$$

$R_{1,23}^2$ denotes the multiple correlation of ϵ_{1it} with ϵ_{2it} and ϵ_{3it} , $\rho_{12,3}$ is the partial correlation between ϵ_{1it} and ϵ_{2it} given ϵ_{3it} , $\rho_{13,2}$ is the partial correlation between ϵ_{1it} and ϵ_{3it} given ϵ_{2it} , and ϕ is the univariate standard normal density function. The expressions of the multiple

and partial correlations are given by

$$R_{1,23}^2 = \frac{\rho_{\epsilon_1\epsilon_2}^2 + \rho_{\epsilon_1\epsilon_3}^2 - 2\rho_{\epsilon_1\epsilon_2}\rho_{\epsilon_1\epsilon_3}\rho_{\epsilon_2\epsilon_3}}{1 - \rho_{\epsilon_2\epsilon_3}^2}, \quad \rho_{12,3} = \frac{\rho_{\epsilon_1\epsilon_2} - \rho_{\epsilon_1\epsilon_3}\rho_{\epsilon_2\epsilon_3}}{1 - \rho_{\epsilon_2\epsilon_3}^2} \text{ and } \rho_{13,2} = \frac{\rho_{\epsilon_1\epsilon_3} - \rho_{\epsilon_1\epsilon_2}\rho_{\epsilon_2\epsilon_3}}{1 - \rho_{\epsilon_2\epsilon_3}^2}. \quad (6.15)$$

Equation (6.13) then becomes

$$\begin{aligned} & \prod_{t=1}^T \Phi[-(A_{it} + a_{1i})]^{1-y_{1it}} \left[\frac{1}{\sigma_{\epsilon_3}} \phi\left(\frac{y_{3it} - C_{it} - a_{3i}}{\sigma_{\epsilon_3}}\right) \right. \\ & \times \frac{1}{\sigma_{\epsilon_2} \sqrt{1 - \rho_{\epsilon_2\epsilon_3}^2}} \phi\left(\frac{y_{2it} - B_{it} - a_{2i} - \rho_{\epsilon_2\epsilon_3} \frac{\sigma_{\epsilon_2}}{\sigma_{\epsilon_3}} (y_{3it} - C_{it} - a_{3i})}{\sigma_{\epsilon_2} \sqrt{1 - \rho_{\epsilon_2\epsilon_3}^2}}\right) \\ & \times \left. \int_0^\infty \frac{1}{\sqrt{1 - R_{1,23}^2}} \phi\left(\frac{y_{1it}^* - A_{it} - a_{1i} - \frac{\rho_{12,3}}{\sigma_{\epsilon_2}} (y_{2it} - B_{it} - a_{2i}) - \frac{\rho_{13,2}}{\sigma_{\epsilon_3}} (y_{3it} - C_{it} - a_{3i})}{\sqrt{1 - R_{1,23}^2}}\right) dy_{1it}^* \right]^{y_{1it}}. \end{aligned} \quad (6.16)$$

Applying the results of Proposition 1 of Chapter 2 to $(y_{1it}^* | y_{2it}, y_{3it})$ that is normal with mean $A_{it} + a_{1i} + \frac{\rho_{12,3}}{\sigma_{\epsilon_2}} (y_{2it} - B_{it} - a_{2i}) + \frac{\rho_{13,2}}{\sigma_{\epsilon_3}} (y_{3it} - C_{it} - a_{3i})$ and variance $1 - R_{1,23}^2$, we obtain $\int_0^\infty f(y_{1it}^* | y_{2it}, y_{3it}) = \Phi\left(\frac{A_{it} + a_{1i} + \frac{\rho_{12,3}}{\sigma_{\epsilon_2}} (y_{2it} - B_{it} - a_{2i}) + \frac{\rho_{13,2}}{\sigma_{\epsilon_3}} (y_{3it} - C_{it} - a_{3i})}{\sqrt{1 - R_{1,23}^2}}\right)$ so that equation (6.16) becomes

$$\begin{aligned} & \prod_{t=1}^T \Phi[-(A_{it} + a_{1i})]^{1-y_{1it}} \left[\frac{1}{\sigma_{\epsilon_3}} \phi\left(\frac{y_{3it} - C_{it} - a_{3i}}{\sigma_{\epsilon_3}}\right) \right. \\ & \times \frac{1}{\sigma_{\epsilon_2} \sqrt{1 - \rho_{\epsilon_2\epsilon_3}^2}} \phi\left(\frac{y_{2it} - B_{it} - a_{2i} - \rho_{\epsilon_2\epsilon_3} \frac{\sigma_{\epsilon_2}}{\sigma_{\epsilon_3}} (y_{3it} - C_{it} - a_{3i})}{\sigma_{\epsilon_2} \sqrt{1 - \rho_{\epsilon_2\epsilon_3}^2}}\right) \\ & \times \left. \Phi\left(\frac{A_{it} + a_{1i} + \frac{\rho_{12,3}}{\sigma_{\epsilon_2}} (y_{2it} - B_{it} - a_{2i}) + \frac{\rho_{13,2}}{\sigma_{\epsilon_3}} (y_{3it} - C_{it} - a_{3i})}{\sqrt{1 - R_{1,23}^2}}\right) \right]^{y_{1it}}. \end{aligned} \quad (6.17)$$

The random-effects individual likelihood function of the three-equation dynamic tobit-type model is obtained by “integrating out” the individual effects using their trivariate normal density function whose expression is given by

$$g(a_{1i}, a_{2i}, a_{3i}) = \Lambda e^{\frac{-1}{2} \left(A_{11} \frac{a_{1i}^2}{\sigma_{a_1}^2} + 2A_{12} \frac{a_{1i}}{\sigma_{a_1}} \frac{a_{2i}}{\sigma_{a_2}} + 2A_{13} \frac{a_{1i}}{\sigma_{a_1}} \frac{a_{3i}}{\sigma_{a_3}} + 2A_{23} \frac{a_{2i}}{\sigma_{a_2}} \frac{a_{3i}}{\sigma_{a_3}} + A_{22} \frac{a_{2i}^2}{\sigma_{a_2}^2} + A_{33} \frac{a_{3i}^2}{\sigma_{a_3}^2} \right)}. \quad (6.18)$$

The constant term Λ equals $(\sigma_{a_1} \sigma_{a_2} \sigma_{a_3})^{-1} (2\pi)^{\frac{-3}{2}} (\Delta)^{\frac{-1}{2}}$, and the expressions of Δ and A_{jk} ($j, k = 1, 2, 3$ and $A_{jk} = A_{kj}$) are given by

$$\Delta = 1 - \rho_{a_1 a_2}^2 - \rho_{a_1 a_3}^2 - \rho_{a_2 a_3}^2 + 2\rho_{a_1 a_2} \rho_{a_1 a_3} \rho_{a_2 a_3},$$

$$A_{11} = \frac{1 - \rho_{a_2 a_3}^2}{\Delta}, \quad A_{22} = \frac{1 - \rho_{a_1 a_3}^2}{\Delta}, \quad A_{33} = \frac{1 - \rho_{a_1 a_2}^2}{\Delta},$$

$$A_{12} = \frac{\rho_{a_1 a_3} \rho_{a_2 a_3} - \rho_{a_1 a_2}}{\Delta}, \quad A_{13} = \frac{\rho_{a_1 a_2} \rho_{a_2 a_3} - \rho_{a_1 a_3}}{\Delta}, \quad A_{23} = \frac{\rho_{a_1 a_2} \rho_{a_1 a_3} - \rho_{a_2 a_3}}{\Delta}.$$

Hence, equation (6.8) can be written as

$$L_i = \int_{-\infty}^{\infty} \exp \left[\frac{-1}{2} \left(A_{33} \frac{a_{3i}^2}{\sigma_{a_3}^2} \right) \right] \prod_{t=1}^T \left[\frac{1}{\sigma_{\epsilon_3}} \phi \left(\frac{y_{3it} - C_{it} - a_{3i}}{\sigma_{\epsilon_3}} \right) \right]^{y_{1it}} H(a_{3i}) da_{3i}, \quad (6.19)$$

where the function $H(a_{3i})$ is written as

$$H(a_{3i}) = \int_{-\infty}^{\infty} e^{\frac{-1}{2} \left(A_{22} \frac{a_{2i}^2}{\sigma_{a_2}^2} \right)} e^{-\left(A_{23} \frac{a_{2i}}{\sigma_{a_2}} \frac{a_{3i}}{\sigma_{a_3}} \right)} \times \prod_{t=1}^T \left[\frac{1}{\sigma_{\epsilon_2} \sqrt{1 - \rho_{\epsilon_2 \epsilon_3}^2}} \phi \left(\frac{y_{2it} - B_{it} - a_{2i} - \rho_{\epsilon_2 \epsilon_3} \frac{\sigma_{\epsilon_2}}{\sigma_{\epsilon_3}} (y_{3it} - C_{it} - a_{3i})}{\sigma_{\epsilon_2} \sqrt{1 - \rho_{\epsilon_2 \epsilon_3}^2}} \right) \right]^{y_{1it}} G(a_{2i}, a_{3i}) da_{2i}, \quad (6.20)$$

and the function $G(a_{2i}, a_{3i})$ is written as

$$G(a_{2i}, a_{3i}) = \Lambda \int_{-\infty}^{\infty} e^{\frac{-1}{2} \left(A_{11} \frac{a_{1i}^2}{\sigma_{a_1}^2} \right)} e^{-\left(A_{12} \frac{a_{1i}}{\sigma_{a_1}} \frac{a_{2i}}{\sigma_{a_2}} + A_{13} \frac{a_{1i}}{\sigma_{a_1}} \frac{a_{3i}}{\sigma_{a_3}} \right)} \prod_{t=1}^T \Phi \left[- (A_{it} + a_{1i}) \right]^{1-y_{1it}} \times \left[\Phi \left(\frac{A_{it} + a_{1i} + \frac{\rho_{123}}{\sigma_{\epsilon_2}} (y_{2it} - B_{it} - a_{2i}) + \frac{\rho_{132}}{\sigma_{\epsilon_3}} (y_{3it} - C_{it} - a_{3i})}{\sqrt{1 - R_{1,23}^2}} \right) \right]^{y_{1it}} da_{1i}. \quad (6.21)$$

6.A.2 “Three-step” Gauss-Hermite quadrature

In the spirit of Chapter 3, the “three-step” Gauss-Hermite quadrature consists, in the first step, in approximating equation (6.21) using the Gauss-Hermite quadrature as defined in Butler and Moffitt (1982). In the second step, equation (6.20) is approximated similarly after replacing $G(a_{2i}, a_{3i})$ by its first-step Gauss-Hermite approximation. In the third step, we apply the same approximation to equation (6.19) where $H(a_{3i})$ is replaced by its second-step Gauss-Hermite approximation.

Consider the variable change $z_{1i} = \frac{a_{1i} \sqrt{A_{11}}}{\sigma_{a_1} \sqrt{2}}$ so that $da_{1i} = \frac{\sigma_{a_1} \sqrt{2}}{\sqrt{A_{11}}} dz_{1i}$. Equation (6.21) can then be written as

$$G(a_{2i}, a_{3i}) = \Lambda_1 \int_{-\infty}^{\infty} e^{-z_{1i}^2} e^{-\left(A_{12} \frac{z_{1i} \sqrt{2}}{\sqrt{A_{11}}} \frac{a_{2i}}{\sigma_{a_2}} + A_{13} \frac{z_{1i} \sqrt{2}}{\sqrt{A_{11}}} \frac{a_{3i}}{\sigma_{a_3}} \right)} \prod_{t=1}^T \Phi \left[- \left(A_{it} + \frac{z_{1i} \sigma_{a_1} \sqrt{2}}{\sqrt{A_{11}}} \right) \right]^{1-y_{1it}} \times \left[\Phi \left(\frac{A_{it} + \frac{z_{1i} \sigma_{a_1} \sqrt{2}}{\sqrt{A_{11}}} + \frac{\rho_{123}}{\sigma_{\epsilon_2}} (y_{2it} - B_{it} - a_{2i}) + \frac{\rho_{132}}{\sigma_{\epsilon_3}} (y_{3it} - C_{it} - a_{3i})}{\sqrt{1 - R_{1,23}^2}} \right) \right]^{y_{1it}} dz_{1i}$$

which can be approximated using Gauss-Hermite quadrature by

$$G(a_{2i}, a_{3i}) \simeq \Lambda_1 \sum_{m=1}^M w_m \left\{ e^{-\left(A_{12} \frac{a_m \sqrt{2}}{\sqrt{A_{11}}} \frac{a_{2i}}{\sigma_{a_2}} + A_{13} \frac{a_m \sqrt{2}}{\sqrt{A_{11}}} \frac{a_{3i}}{\sigma_{a_3}} \right)} \prod_{t=1}^T \Phi \left[- \left(A_{it} + \frac{a_m \sigma_{a_1} \sqrt{2}}{\sqrt{A_{11}}} \right) \right]^{1-y_{1it}} \right. \\ \left. \times \left[\Phi \left(\frac{A_{it} + \frac{a_m \sigma_{a_1} \sqrt{2}}{\sqrt{A_{11}}} + \frac{\rho_{123}}{\sigma_{\epsilon_2}} (y_{2it} - B_{it} - a_{2i}) + \frac{\rho_{132}}{\sigma_{\epsilon_3}} (y_{3it} - C_{it} - a_{3i}) \right)}{\sqrt{1 - R_{1,23}^2}} \right]^{y_{1it}} \right\}, \quad (6.22)$$

where Λ_1 equals $(2\sigma_{a_2}\sigma_{a_3})^{-1} (\pi)^{\frac{-3}{2}} (1 - \rho_{a_2 a_3}^2)^{\frac{-1}{2}}$, and w_m and a_m are the weights and abscissas of the first-step Gauss-Hermite quadrature with M being the total number of integration points.

Consider the second variable change $z_{2i} = \frac{a_{2i}\sqrt{A_{22}}}{\sigma_{a_2}\sqrt{2}}$ so that $da_{2i} = \frac{\sigma_{a_2}\sqrt{2}}{\sqrt{A_{22}}} dz_{2i}$. Replacing equation (6.22) into equation (6.20) yields

$$H(a_{3i}) \simeq \Lambda_2 \int_{-\infty}^{\infty} e^{-z_{2i}^2} e^{-\left(A_{23} \frac{z_{2i} \sqrt{2}}{\sqrt{A_{22}}} \frac{a_{3i}}{\sigma_{a_3}} \right)} \\ \times \prod_{t=1}^T \left[\frac{1}{\sigma_{\epsilon_2} \sqrt{1 - \rho_{\epsilon_2 \epsilon_3}^2}} \phi \left(\frac{y_{2it} - B_{it} - \frac{z_{2i} \sigma_{a_2} \sqrt{2}}{\sqrt{A_{22}}} - \rho_{\epsilon_2 \epsilon_3} \frac{\sigma_{\epsilon_2}}{\sigma_{\epsilon_3}} (y_{3it} - C_{it} - a_{3i})}{\sigma_{\epsilon_2} \sqrt{1 - \rho_{\epsilon_2 \epsilon_3}^2}} \right) \right]^{y_{1it}} \\ \sum_{m=1}^M w_m \left\{ e^{-\left(A_{12} \frac{a_m \sqrt{2}}{\sqrt{A_{11}}} \frac{z_{2i} \sqrt{2}}{\sqrt{A_{22}}} + A_{13} \frac{a_m \sqrt{2}}{\sqrt{A_{11}}} \frac{a_{3i}}{\sigma_{a_3}} \right)} \prod_{t=1}^T \Phi \left[- \left(A_{it} + \frac{a_m \sigma_{a_1} \sqrt{2}}{\sqrt{A_{11}}} \right) \right]^{1-y_{1it}} \right. \\ \left. \times \left[\Phi \left(\frac{A_{it} + \frac{a_m \sigma_{a_1} \sqrt{2}}{\sqrt{A_{11}}} + \frac{\rho_{123}}{\sigma_{\epsilon_2}} (y_{2it} - B_{it} - \frac{z_{2i} \sigma_{a_2} \sqrt{2}}{\sqrt{A_{22}}}) + \frac{\rho_{132}}{\sigma_{\epsilon_3}} (y_{3it} - C_{it} - a_{3i}) \right)}{\sqrt{1 - R_{1,23}^2}} \right]^{y_{1it}} \right\} dz_{2i}$$

which can be approximated again using Gauss-Hermite quadrature by

$$H(a_{3i}) \simeq \Lambda_2 \sum_{p=1}^P w_p \left\{ e^{-\left(A_{23} \frac{a_p \sqrt{2}}{\sqrt{A_{22}}} \frac{a_{3i}}{\sigma_{a_3}} \right)} \right. \\ \times \prod_{t=1}^T \left[\frac{1}{\sigma_{\epsilon_2} \sqrt{1 - \rho_{\epsilon_2 \epsilon_3}^2}} \phi \left(\frac{y_{2it} - B_{it} - \frac{a_p \sigma_{a_2} \sqrt{2}}{\sqrt{A_{22}}} - \rho_{\epsilon_2 \epsilon_3} \frac{\sigma_{\epsilon_2}}{\sigma_{\epsilon_3}} (y_{3it} - C_{it} - a_{3i})}{\sigma_{\epsilon_2} \sqrt{1 - \rho_{\epsilon_2 \epsilon_3}^2}} \right) \right]^{y_{1it}} \\ \sum_{m=1}^M w_m \left\{ e^{-\left(A_{12} \frac{a_m \sqrt{2}}{\sqrt{A_{11}}} \frac{a_p \sqrt{2}}{\sqrt{A_{22}}} + A_{13} \frac{a_m \sqrt{2}}{\sqrt{A_{11}}} \frac{a_{3i}}{\sigma_{a_3}} \right)} \prod_{t=1}^T \Phi \left[- \left(A_{it} + \frac{a_m \sigma_{a_1} \sqrt{2}}{\sqrt{A_{11}}} \right) \right]^{1-y_{1it}} \right. \\ \left. \times \left[\Phi \left(\frac{A_{it} + \frac{a_m \sigma_{a_1} \sqrt{2}}{\sqrt{A_{11}}} + \frac{\rho_{123}}{\sigma_{\epsilon_2}} (y_{2it} - B_{it} - \frac{a_p \sigma_{a_2} \sqrt{2}}{\sqrt{A_{22}}}) + \frac{\rho_{132}}{\sigma_{\epsilon_3}} (y_{3it} - C_{it} - a_{3i}) \right)}{\sqrt{1 - R_{1,23}^2}} \right]^{y_{1it}} \right\}, \quad (6.23)$$

where Λ_2 equals $(2\sigma_{a_3})^{-1}(\pi)^{\frac{-3}{2}}[(1-\rho_{a_1a_3}^2)(1-\rho_{a_2a_3}^2)]^{\frac{-1}{2}}(2\Delta)^{\frac{1}{2}}$, and w_p and a_p are the weights and abscissas of the second-step Gauss-Hermite quadrature with P being the total number of integration points.

Finally, consider the third variable change $z_{3i} = \frac{a_{3i}\sqrt{A_{33}}}{\sigma_{a_3}\sqrt{2}}$ so that $da_{3i} = \frac{\sigma_{a_3}\sqrt{2}}{\sqrt{A_{33}}}dz_{3i}$. Replacing equation (6.23) into equation (6.19) yields

$$\begin{aligned} L_i \simeq & \Lambda_3 \int_{-\infty}^{\infty} e^{-z_{3i}^2} \prod_{t=1}^T \left[\frac{1}{\sigma_{\epsilon_3}} \phi \left(\frac{y_{3it} - C_{it} - \frac{z_{3i}\sigma_{a_3}\sqrt{2}}{\sqrt{A_{33}}}}{\sigma_{\epsilon_3}} \right) \right]^{y_{1it}} \sum_{p=1}^P w_p \left\{ e^{-\left(A_{23} \frac{a_p\sqrt{2}}{\sqrt{A_{22}}} \frac{z_{3i}\sqrt{2}}{\sqrt{A_{33}}} \right)} \right. \\ & \times \prod_{t=1}^T \left[\frac{1}{\sigma_{\epsilon_2}\sqrt{1-\rho_{\epsilon_2\epsilon_3}^2}} \phi \left(\frac{y_{2it} - B_{it} - \frac{a_p\sigma_{a_2}\sqrt{2}}{\sqrt{A_{22}}} - \rho_{\epsilon_2\epsilon_3} \frac{\sigma_{\epsilon_2}}{\sigma_{\epsilon_3}} \left(y_{3it} - C_{it} - \frac{z_{3i}\sigma_{a_3}\sqrt{2}}{\sqrt{A_{33}}} \right)}{\sigma_{\epsilon_2}\sqrt{1-\rho_{\epsilon_2\epsilon_3}^2}} \right) \right]^{y_{1it}} \\ & \sum_{m=1}^M w_m \left\{ e^{-\left(A_{12} \frac{a_m\sqrt{2}}{\sqrt{A_{11}}} \frac{a_p\sqrt{2}}{\sqrt{A_{22}}} + A_{13} \frac{a_p\sqrt{2}}{\sqrt{A_{11}}} \frac{z_{3i}\sqrt{2}}{\sqrt{A_{33}}} \right)} \prod_{t=1}^T \Phi \left[- \left(A_{it} + \frac{a_m\sigma_{a_1}\sqrt{2}}{\sqrt{A_{11}}} \right) \right]^{1-y_{1it}} \right. \\ & \times \left. \left[\Phi \left(\frac{A_{it} + \frac{a_m\sigma_{a_1}\sqrt{2}}{\sqrt{A_{11}}} + \frac{\rho_{123}}{\sigma_{\epsilon_2}} \left(y_{2it} - B_{it} - \frac{a_p\sigma_{a_2}\sqrt{2}}{\sqrt{A_{22}}} \right) + \frac{\rho_{132}}{\sigma_{\epsilon_3}} \left(y_{3it} - C_{it} - \frac{z_{3i}\sigma_{a_3}\sqrt{2}}{\sqrt{A_{33}}} \right)}{\sqrt{1-R_{1,23}^2}} \right) \right]^{y_{1it}} \right\} \left. \right\} \end{aligned}$$

which can be approximated by

$$\begin{aligned} L_i \simeq & \Lambda_3 \sum_{q=1}^Q w_q \left\{ \prod_{t=1}^T \left[\frac{1}{\sigma_{\epsilon_3}} \phi \left(\frac{y_{3it} - C_{it} - \frac{a_q\sigma_{a_3}\sqrt{2}}{\sqrt{A_{33}}}}{\sigma_{\epsilon_3}} \right) \right]^{y_{1it}} \sum_{p=1}^P w_p \left\{ e^{-\left(A_{23} \frac{a_p\sqrt{2}}{\sqrt{A_{22}}} \frac{a_q\sqrt{2}}{\sqrt{A_{33}}} \right)} \right. \right. \\ & \times \prod_{t=1}^T \left[\frac{1}{\sigma_{\epsilon_2}\sqrt{1-\rho_{\epsilon_2\epsilon_3}^2}} \phi \left(\frac{y_{2it} - B_{it} - \frac{a_p\sigma_{a_2}\sqrt{2}}{\sqrt{A_{22}}} - \rho_{\epsilon_2\epsilon_3} \frac{\sigma_{\epsilon_2}}{\sigma_{\epsilon_3}} \left(y_{3it} - C_{it} - \frac{a_q\sigma_{a_3}\sqrt{2}}{\sqrt{A_{33}}} \right)}{\sigma_{\epsilon_2}\sqrt{1-\rho_{\epsilon_2\epsilon_3}^2}} \right) \right]^{y_{1it}} \\ & \times \sum_{m=1}^M w_m \left\{ e^{-\left(A_{12} \frac{a_m\sqrt{2}}{\sqrt{A_{11}}} \frac{a_p\sqrt{2}}{\sqrt{A_{22}}} + A_{13} \frac{a_p\sqrt{2}}{\sqrt{A_{11}}} \frac{a_q\sqrt{2}}{\sqrt{A_{33}}} \right)} \prod_{t=1}^T \Phi \left[- \left(A_{it} + \frac{a_m\sigma_{a_1}\sqrt{2}}{\sqrt{A_{11}}} \right) \right]^{1-y_{1it}} \right. \\ & \times \left. \left[\Phi \left(\frac{A_{it} + \frac{a_m\sigma_{a_1}\sqrt{2}}{\sqrt{A_{11}}} + \frac{\rho_{123}}{\sigma_{\epsilon_2}} \left(y_{2it} - B_{it} - \frac{a_p\sigma_{a_2}\sqrt{2}}{\sqrt{A_{22}}} \right) + \frac{\rho_{132}}{\sigma_{\epsilon_3}} \left(y_{3it} - C_{it} - \frac{a_q\sigma_{a_3}\sqrt{2}}{\sqrt{A_{33}}} \right)}{\sqrt{1-R_{1,23}^2}} \right) \right]^{y_{1it}} \right\} \left. \right\} \left. \right\}, \end{aligned}$$

where Λ_3 equals $\Delta(\pi)^{\frac{-3}{2}}[(1-\rho_{a_1a_2}^2)(1-\rho_{a_1a_3}^2)(1-\rho_{a_2a_3}^2)]^{\frac{-1}{2}}$, and w_q and a_q are the weights and abscissas of the third-step Gauss-Hermite quadrature with Q being the total number of integration points.

Appendix 6.B The dynamics of R&D investments of innovative firms

We report in Table 6.8 estimation results of a dynamic linear regression model of R&D investments of innovative firms (eq. (6.2)), in which case the amount of R&D investments is assumed to be uncorrelated with the decision to engage in innovation activities and the share of innovative sales. Anderson and Hsiao (1981; 1982) suggest to estimate the dynamic linear regression by maximum likelihood assuming random individual effects and endogenous initial conditions correlated with the individual effects ($\rho_{y_{2,0}\alpha_2}$). The initial conditions are assumed normal with mean $\mu_{y_{2,0}}$ and standard deviation $\sigma_{y_{2,0}}$. No Gauss-Hermite quadrature is required to evaluate the likelihood function and the estimation results suggest that the positive effect of past R&D intensity on current R&D intensity becomes negative when individual effects and endogenous initial conditions are accounted for.¹²

Table 6.8: ML estimation results of the dynamic linear regression model of R&D investments of innovative firms

Variable	Coefficient	(Std. Err.)	Coefficient	(Std. Err.)
Estimation assumption	No individual effects		Individual effects with endogenous initial conditions	
Current R&D intensity (y_{2it} in log)				
Past R&D intensity ($y_{2,it-1}$)	0.417**	(0.027)	-0.072†	(0.043)
Lagged size (in log)	-0.027	(0.053)	-0.005	(0.065)
Demand pull	0.372**	(0.110)	0.274**	(0.100)
Innovation cooperation	0.073	(0.116)	0.092	(0.111)
Technology push	0.401**	(0.124)	0.352**	(0.120)
Subsidies	0.676**	(0.121)	0.515**	(0.119)
Intercept	-3.781**	(0.345)	-6.107**	(0.431)
Extra parameters				
σ_{α_2}	-	-	1.553**	(0.100)
σ_{ϵ_2}	1.581**	(0.036)	1.121**	(0.045)
$\mu_{y_{2,0}}$	-	-	-4.534**	(0.091)
$\sigma_{y_{2,0}}$	-	-	2.144**	(0.063)
$\rho_{y_{2,0}\alpha_2}$	-	-	0.612**	(0.030)
Number of observations	992			
Log-likelihood	-1862.153		-3036.110	
Significance levels : †: 10% *: 5% **: 1%				

¹²The likelihood function has a closed-form expression which is given in equation (4.9) of sub-appendix 4.A.2.

CHAPTER 7

Conclusion

This chapter summarizes the main findings of the thesis and discusses the limitations and recommendations for future research.

7.1 Summary

We have studied the dynamics of innovation in Dutch manufacturing using three waves of the Community Innovation Survey, and found persistence of innovation when considered on the input side and a lack of persistence when considered on the output side. In other words, firms that have persistent innovation or R&D activities may not be guaranteed to persistently introduce new or improved products and/or processes into the market. Hence, the hypothesis of existence of *sunk costs* in firms' innovation or R&D activities is supported by the results, while Mansfield's (1968) hypothesis of "success breeds success" is rejected. Furthermore, while there is strong evidence of dynamics of R&D investments, the sign of the effect of past R&D investments on current R&D investments does not seem to be well-determined. Indeed the positive effect identified in Chapter 4 seems to contradict the negative effect found in Chapter 6. Finally, past share of sales of incremental and radical product innovations conditions current share of sales of incremental and radical product innovations. To the extent that innovation output is not persistent, we interpret this result as a rather lengthy enjoyment by innovators of their old innovations.

We have also studied the role of firm observed and unobserved heterogeneity in the innovation process. In Chapter 2, we have found that the high-tech and low-tech categories of industries, and the wood industry have different innovative behavior, and that the industries in each category have the same innovative behavior in the sense that, the parameters of the model for the industries in that category are identical with the exception of the intercepts. Unobserved individual effects play a significant role in the probability of introducing new or improved products and/or processes into the market, and in the share of sales of incremental and radical product innovations (cf. Chapters 4 and 5). In Chapter 6, the individual effects are shown to have a significant role in the decision to engage in innovation activities, in the amount of R&D investments and in the share of innovative sales of innovative firms.

Finally, we have found evidence of nonlinearity in that the different stages of the process are interrelated. The decision to introduce new or improved products and/or processes into the market and the share of sales of incremental and radical product innovations are interrelated (cf. Chapters 2, 4 and 5). There is also interrelationship between the decision to engage in innovative activities, the amount of R&D investments and the share of innovative sales (cf. Chapter 6). The interrelationship operates mostly through the individual effects.

As for the econometric results, the Monte Carlo investigation with regard to the behavior in finite samples of the method proposed in Chapter 3 shows that using Wooldridge's (2005) solution to deal with the dependence between the initial conditions and the individual effects is successful in recovering the parameters of a process that generates the data according to a stationary process. It is also shown that incorrectly ignoring the individual effects, or the dependence between the initial conditions and the individual effects results in an overestimation of the coefficients of the lagged dependent variables. This phenomenon was confirmed when studying the persistence of innovation output. When the individual effects were ignored or exogenous initial conditions (assuming no correlation between the individual effects and the initial conditions) were assumed, we found strong persistence of innovation output which then vanished when we accounted for the individual effects and endogenous initial conditions. However, we still found persistence in engaging in R&D or innovation activities after accounting for the individual effects and endogenous initial conditions. Hence, there is *spurious* persistence of innovation when considered on the output side and *true* persistence when considered on the input side. Finally, when estimating the dynamic type 3 tobit model of incremental and radical innovations using both the Heckman (1981b) and

the Wooldridge (2005) approach of handling the initial conditions, we found that the two approaches yield similar results in terms of the coefficients of the strictly exogenous variables while some differences arise in the coefficients of the lagged dependent variables and the individual effects.

7.2 Limitations and further research

The first limitation of the thesis is that we have little information about non-innovative firms, resulting in a very restricted set of explanatory variables of the likelihood of engaging in innovative activities or in achieving product and/or process innovations. Secondly, the panel is rather short ($T = 3$) which may explain in part the lack of true persistence in achieving product and/or process innovations in Chapter 4, and why we were unable to identify a positive effect of past R&D investments on current R&D investments when we accounted for individual effects and endogenous initial conditions. Third, there is one-year overlap between two consecutive waves of the Dutch CIS which was not taken into account. Hence, to the extent that respondents answer this survey consistently, the overlap would tend to bias the results towards persistence in being a product and/or process innovator. As no evidence of persistence is found, it may be concluded that the effect of the overlapping year is not important. Fourth, in the model of Chapter 6, R&D intensity and the share of innovative sales were assumed to be correlated only through the individual effects and the idiosyncratic errors. A natural extension is to include R&D intensity in the set of explanatory variables of the equation of the share of innovative sales and vice versa, hence allowing for a direct effect of R&D investments on innovation output and a feedback effect of innovation output on R&D investments. A next step to the three-equation dynamic tobit-type model would be to include R&D intensity as a regressor in the innovation equation. Finally, the model could be extended so as to link the dynamics of the innovation process to that of an economic performance (e.g. productivity) along the lines of Crépon et al. (1998). However, estimating the resulting model allowing for dynamics and unobserved individual effects is a formidable task to achieve.

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Samenvatting

Technologische innovatie wordt erkend als een factor zeer belangrijke in de groei van ondernemingen, zowel als creatieve kracht voor de groei en als vernietigende kracht die diezelfde ondernemingen aan de concurrentie blootstelt. In de kenniseconomie, innovatie speelt ook een positieve rol in de overleving van bedrijven. Nieuwe producten en nieuwe processen worden voortdurend op de markt gebracht en dwingen bedrijven om zich aan te passen als zij in het spel willen blijven. Om de economische groei te bevorderen, werkgelegenheid en milieuduurzaamheid, de overheden zijn meer en meer bezorgd over het bevorderen van de innovatie van firma's maar hebben niet altijd het juiste recept om hun doel te bereiken. Het is vandaar zeer belangrijk om te begrijpen wat bedrijven innovatief maakt, hoe lang het duurt voordat innovatiestimulans hun vruchten afwerpen, hoe lang het duurt voor O&O, proef productie en eerste lancering van nieuwe producten om succesvol te worden, en ten slotte hoe lang het duurt tussen eerste verschijning van producten op de markt en de verbeteringen van economische prestaties in de ondernemingen. Een van de moeilijkheden die door beleidsvormers in het verleden werden ondervonden is de meting van innovatie. In de jaren '80 voelden de geleerden en de statistici in innovatie een groeiende ontevredenheid met het zuivere bestaan van O&O- of octrooigegevens om innovatie te analyseren. Het gebruik van de van O&O of van het octrooi gegevens alleen laat immers belangrijke aspecten van het innovatieproces weg omdat O&O slechts één van diverse innovatie-inputs is en sommige soorten technologie niet patenteerbaar zijn. Vandaar, onder bescherming van OESO, werd het handboek van Oslo geschreven om een nieuw soort onderzoek te leiden, het innovatieonderzoek dat in Europa bekend staat als CIS. In dit onderzoek, de ondervraagden worden gevraagd om informatie te geven over de

input, de output en de gedrags- en organisatorische dimensies van hun innovaties. Voor de inputkant, gegevens over de uitgaven van O&O en over andere innovatieuitgaven naast O&O (zoals productontwerp, proef productie, opleiding van werknemers, en de marktanalyse) worden verzameld. Voor de outputkant, diverse marktinnovatieindicatoren (in tegenstelling tot octrooien) zijn beschikbaar, namelijk de verklaring of een onderneming een nieuw product of een proces heeft geïntroduceerd, het percentage verkoop toe te schrijven aan stapsgewijs of beduidend betere of nieuwe producten of het aandeel van de opbrengsten van innovatieve producten die nieuw zijn voor de onderneming of zelfs voor de industrie. Op de andere dimensies van innovatie hebben wij binaire gegevens op of R&D ononderbroken en in samenwerking met anderen is gedaan en categorische gegevens op de bronnen van kennis, de redenen tot het vernieuwen, de waargenomen belemmeringen naar innovatie en de waargenomen kracht van verschillende mechanismen om zich de voordelen van innovatie toe te eigenen.

Verscheidene golven van de CIS werden gelanceerd sinds de eerste uitgave die van het handboek van Oslo in 1992 en maken het gebruik van paneelgegevens mogelijk bij het analyseren van het innovatieproces. Het doel van deze thesis is de dynamica van innovatie in Nederlandse bewerkingsbedrijven te bestuderen met bedrijfsgegevens van drie golven van de CIS betreffende de periodes 1994-1996, 1996-1998, en 1998-2000. Meer specifiek, deze thesis heeft tot doel om vragen te beantwoorden met betrekking tot de tot nu toe zelden onderzochte dynamica van innovatie met gebruikmaking van de CIS, zoals de persistentie van innovatie die aan zowel de input als de outputkant wordt bekeken, het effect van de afgelopen investeringen van O&O op de huidige investeringen van O&O, het effect van afgelopen aandeel in totale verkoop van innovatieve verkoop op huidig aandeel in totale verkoop van innovatieve verkoop, en de rol van bedrijvenheterogeniteit in het innovatieproces. Vandaar, de hypothesen van “succes kweekt succes”, de “dynamische schaalvoordelen” en het bestaan van “sunk-costs” in de innovatieactiviteiten van firma's kunnen worden getest. De thesis heeft ook tot doel om empirische modellen te ontwikkelen die op andere types van economische paneelgegevens kunnen worden toegepast die gelijkaardige kenmerken als de CIS- gegevens hebben, vandaar bijdragen tot de groeiende econometrische literatuur over (dynamische) paneelgegevens.

Hoofdstuk 2 bestudeert de graad van homogeniteit van innovatief gedrag om empirisch de industrie- categorisatie van Nederlandse bewerkingsbedrijven te bepalen die voor beleidsdoeleinden kan worden gebruikt. Voor elk van de elf Nederlandse verwerkende industrie die op niveau met twee cijfers wordt bepaald, wij schatten twee-grens tobit model met steekproef-

selectie die het besluit tot innovatie door ondernemingen verklaart en, voor vernieuwers, de intensiteit van innovatie, gemeten door het aandeel innovatieve verkopen. Door het model voor elke industrietak afzonderlijk te schatten, mogelijke verschillen in het innovatiegedrag tussen verschillende bedrijfstakken kunnen worden verklaard. Verder, binnen die bedrijfstakken, verklaren wij onopgemerkte heterogeniteit door “niet-vernieuwers”, “proces-alleen vernieuwers”, productvernieuwers en “grote” productvernieuwers anders te behandelen. En de hypothese van homogeniteit van vernieuwend gedrag over industrieën is getest met een waarschijnlijkheid verhouding test die drie soorten categorieën van industrieën in Nederlandse productiebedrijven aan het licht brengt, namelijk high-tech, laag-technologie en de hout industrie die schijnen verschillend te zijn van de overige industrieën.

Hoofdstuk 3 onderzoekt door middel van een Monte Carlo simulatie het gedrag van de maximale waarschijnlijkheid schatter van dynamische panelen gegevensuitbreidingen van het type 2 en type 3 tobit modellen met ongemerkte individuele effecten (misschien gecorreleerde met de verklarende variabelen) in elk vergelijking. De individuele resultaten worden aangenomen willekeurig te zijn en een normale distributie te volgen, zijn “uit geïntegreerd” van de gezamenlijke dichtheidsfunctie voor de gegevens en individuele effecten. En het beginvoorwaarden probleem is opgelost met gebruik van recente “eenvoudige oplossingen” die erin bestaat de individuele effecten van elk periode te schrijven als een lineaire functie van de strikt exogene verklarende variabelen en de beginvoorwaarden. De resulterende waarschijnlijkheidsfunctie bevat een twee-dimensionale onbepaalde integraal die geëvalueerd kan worden met gebruik van twee opeenvolgende Gauss-Hermite benaderingen. In de Monte Carlo experimenten, de “twee-stappen” Gauss-Hermite kwadratuur werkt goed voor een aantal integratiepunten zo klein als twee. Daarom de maximale waarschijnlijkheid schatting van de parameters in een willekeurige-effecten dynamische steekproef model is mogelijk en zou denkbaar geïntegreerd kunnen worden als een commando in een algemeen gebruikt softwarepakket zoals Stata.

In Hoofdstuk 4 passen wij het dynamische type toe dat 2 tobit van Hoofdstuk 3 op een model van innovatie dat de persistent van innovatie en de dynamica van het aandeel van innovatievee verkopen in Nederlandse productiebedrijven onderzoekt. Wij vinden dat de persistentie van innovatie onecht is in de zin dat, wanneer ongemerkte individuele effecten en de beginvoorwaarden op de juiste manier behandeld zijn, de persistente van innovatie verdwijnt. Meer bepaald, succesvol zijn in voorgaande innovatieactiviteiten heeft geen verhogende invloed op de waarschijnlijkheid van de succes in huidige innovatieactiviteiten. Nochtans, voor-

gaand aandeel van innovatieve verkoop beïnvloedt huidig aandeel van innovatieve verkoop, hoewel maar in beperkte mate.

Hoofdstuk 5 beschouwt een alternatieve weg van behandeling van het van de beginvoorwaarden, die in het specificeren een model voor de eerste voorwaarde bestaat, met gegeven individuele voorwaarden en de strikt exogene verklarende variabelen. Dit model wordt dikwijls aangenomen als gelijkwaardig met het onderliggende model van het blijvende proces te zijn. Wij passen dan de benadering toe om het dynamische type 2 tobit model te schatten dat als in Hoofdstuk 4 wordt gespecificeerd. Vandaar studeren we daarom de gevoeligheid van de persistentie van innovatie naar de behandeling van de beginvoorwaarden. Wij vinden dat het ontbreken van persistentie robuust is op het (gepast) behandeling van de beginvoorwaarde.

In Hoofdstuk 6 verlengen wij het model van Hoofdstuk 4 door het toevoegen van een derde vergelijking van O&O investeringen. Meer bepaald onderzoeken wij gezamenlijk de dynamica van de beslissing om te investeren in innovatieactiviteiten, dat van O&O intensiteit en het aandeel van innovatieve verkopen. Wij gebruiken dezelfde schattingsmethode als in Hoofdstuk 3 uitgebreid tot een steelproef selectie model met twee regressie vergelijkingen en een selectie vergelijking. De "drie-stappen" Gauss-Hermite kwadratuur wordt nu vereist om de waarschijnlijkheid functie te evalueren. De resultaten wijzen op de aanwezigheid van een dynamiek in het innovatieproces. Verder zijn de beslissing om zich bezig te houden met innovatieactiviteiten, R&D intensiteit en het aandeel van innovatieve verkopen gecorreleerd, op zijn minst door de individuele effecten. Ten slotte, ongemerkte bedrijfsheterogeniteit speelt een belangrijke rol in het vernieuwing proces.

Curriculum vitae

Wladimir Raymond was born on May the 20th 1978 in Jacmel, Haiti. He attended secondary education at Centre Culturel Alcibiade Pommayrac, one of the two French high schools of the country. In 1997, he obtained a scholarship and went to Strasbourg, France, where he studied mathematics and economics. In 2002, he obtained his MSc in Economic Analysis, and later that year, joined the Quantitative Economics Department of Maastricht University where he started his PhD. Wladimir is currently employed as post-doc at the Department of Quantitative Economics, Maastricht.