Employment Dynamics, Firm Performance and Innovation Persistence in the Context of Differentiated Innovation Types: Evidence from Luxembourg

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When I look back only with nostalgia, those years remind me of a poem of Mark Strand: "The night would not end. Someone was saying the music was over and no one had noticed. Then someone said something about the planets, about the stars, how small they were, how far away." This journey is far more beautiful and fruitful than I could imagine.

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Alis grave nil.

Abstract

This doctoral dissertation examines the essential topics of employment dynamics, firm performance and innovation persistence comprehensively. In particular, this doctoral dissertation provides an assessment of the differentiated role of innovation strategies in employment, firm performance and innovation persistence.

After an introduction, the second chapter studies the dynamic relationship between technological innovation and employment using Luxembourgish firm level data pertaining to the non-financial corporate sector during the period 2003-2012. A simple theoretical model that distinguishes the employment effect of product innovation from that of process innovation is developed. The model is then estimated by two-step generalised method of moments using an unbalanced panel data stemming from the annual structural business survey merged with the biennial innovation survey.

The third chapter investigates the two-way relationship between technological innovation and firm performance at the firm level. In the framework of evolutionary economics, innovation is regarded as a highly cumulative process which exhibits positive feedback. This chapter aims at capturing the interdependent relationship and possible bidirectional causality between innovation and firm performance. Superior firm performance facilitates the emergence of innovations, innovation contributes to firm performance by gaining successful and sustainable competitive advantage, which forms a virtuous circle. A fully recursive simultaneous model is established where product and process innovation are explicitly distinguished. The system of simultaneous equations with mixed structure is estimated by full information maximum likelihood methods. The longitudinal firm-level data is applied over the 2003-2012 period by merging five waves of the Luxembourgish innovation survey with structural business surveys.

The fourth chapter explores innovation persistence at the firm level by means of dynamic nonlinear random effects models based on the estimator proposed by Albarrán et al. [2015]. It aims at capturing the true state dependence which indicates the causal relationship between innovation in one period and decision to innovate in the subsequent period. The Albarrán et al. [2015] method accounts for unobserved individual effects that are correlated with the initial conditions as well as the unbalanced structure of panel. Using five questionnaire waves of Luxembourgish Community Innovation Surveys (CIS) for the years 2002-2012, this study provides new insights on the differentiated patterns of persistence among product and process innovation.

This doctoral dissertation explicitly distinguishes different mechanisms of product and process innovation and reveals their distinct impacts on employment. Product innovation is found to exert a positive effect on employment where the process innovation does not exert a significant effect on the firm level of employment. This doctoral dissertation also reveals that enhanced firm performance facilitates process innovation and process innovation

improves firm performance, which forms a self-reinforcing virtuous circle. An opposite pattern is identified for the product innovation on the ground of cannibalization effect and inherent market risks associated with new products. Moreover, results highlight the relevance of innovation persistence for all types of innovation, particularly the highest level of persistence is found for product innovation. In addition, the state dependence of product innovation is mainly associated with sunk costs relevant to R&D expenditures, whereas the state dependence of process innovation can be attributed to other factors such as dynamic increasing returns and learning effect. The further differentiation of product innovator category reveals that the state dependence of incremental product innovation can be mainly attributed to sunk costs relevant to R&D expenditures. In contrast, the joint significance of average R&D intensity, intramural R&D share as well as the past realization of radical product innovation suggests the role of other factors such as dynamic increasing returns and learning effect in fostering state dependence for radical innovations.

This doctoral dissertation also appears to have far-reaching economic, managerial and policy implications. Policy makers should aim to encourage companies to undertake innovation activities, particularly, product innovations as a constant driver of national employment growth. This dissertation also emphasizes the self-reinforcing mechanism in determining the innovation-performance trajectory. Policy makers should implement support instruments and funding schemes to stimulate innovation and foster a virtuous circle between innovation and firm performance. In case of true state dependence of innovation persistence, innovation policy not only affects current innovation but also all future innovation activities. Therefore, it is crucial to spur the undertaking of the initial innovation activity and remove barriers to innovation for initial innovators.

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Chapter 1

Introduction

1.1 Introduction

Innovation is a key concept central to economic development. Innovation constitutes a primary source of sustained competitive advantage for firm's growth (Schumpeter [1934], Tushman et al. [1997]). Innovation develops dynamic capabilities which enable firms to learn, to adapt, to solve emerging new problems (Dosi and Marengo [2000]). Schumpeter [1939] regards innovation as both the creator and destroyer of corporations and entire industries. In light of the prominent role of innovation in fostering corporate sustainability and economic growth, public policies to promote firm-level innovation are high on the agenda in most EU countries. This doctoral dissertation examines the essential topics of employment dynamics, firm performance and innovation persistence comprehensively. In particular, this doctoral dissertation provides an assessment of the differentiated role of innovation strategies in employment, firm performance and innovation persistence.

There is a growing concern on the potential benefits of innovation on employment. The OECD Jobs Study (1994) regards technological development as a crucial force in determining employment growth in the long run. Foray and Lundvall [1998] point out postwar economic boom in Europe was built on the basis of factor accumulation and imitation. To transform into knowledge-based economies, it is crucial to invest in knowledge and innovation to stimulate economic growth.

The relationship between innovation and employment, albeit age-old, is at the center of the policy debate and no definite answer has been found. Both theoretical and empirical studies provide equivocal arguments on whether technological change creates or destroys jobs. The pessimism that prevails 19th century mostly manifests in the quote of [Ricardo, 1891, pp.275]: '[...] the opinion entertained by the labouring class, that the employment of machinery is frequently detrimental to their interests, is not founded on prejudice and error, but is conformable to the correct principles of political economy'. By contrast, a growing number of economists hold optimistic views that new technology creates more jobs than destroying jobs. Innovation may create jobs by introducing new products which expands the demand and increases the employment (*compensation effect*). Innovation may also destroy jobs by using less labour input in light of the labour-displacing technology (*displacement effect*). It is crucial to understand whether compensation effect prevails over adverse displacement effect induced by the innovation.

Looking for original answers often implies asking a different set of questions. I attempt to address these issues in this dissertation: will the differentiated types of innovation exert different effects on firm-level employment? Can we separate employment effect of process innovation from product innovation? Can we further identify the separate employment effects of old products, new-to-market products and new-to-firm products?

From a theoretical perspective, it is difficult to disentangle different sources of employment effects due to complex nature of the relationship between innovation and employment (Calvino and Virgillito [2017]). Nonetheless, we establish a theoretical model with endogenized product and process innovation which allows a separate identification of the employment effects of product and process innovation. The employment effect of product innovation is furthermore distinguished between radical and incremental innovation. The effect of product innovation on employment operates directly through the firm labour demand function. A theoretical link between the demand for labour and product innovation is directly established by decomposing output into sales of old or unchanged, new-to-the-firm and new-to-the-market products. The effect of process innovation mainly operates through the labour augmenting technology parameter of the production function. An empirical model of firm demand for employment is then estimated using several waves of yearly Luxembourgish Structural Business Statistics merged with biennial innovation survey data over the period 2003-2012. We apply the two-step system GMM estimator developed by Blundell and Bond [1998]. Product innovation is found to exert a positive effect on employment where the process innovation does not exert a significant effect on the firm level of employment.

The second essential component of this dissertation points to the analysis of interdependent relationship and possible bidirectional causality between innovation and firm performance. Schumpeter acknowledges the great impact of the successful introduction of product, process and organizational innovations on firm performance. Nelson and Winter [2009] emphasize the key role played by innovation as the most important weapon for firms to gain successful and sustainable competitive advantage in an economic and technological context.

Meanwhile, Schmooklerian hypothesis states that innovation activities are responsive to economic output, as increased sales imply that more financial resources can be allocated to innovation. Moreover, new sales may bring about new preferences and elevated standards. Accordingly, modifications and improvements upon the existing products will be implemented to satisfy the emerging new requirements from customers.

The link between innovation and firm performance is by no means one-way directional and mutually exclusive. The causal relationships between innovation and firm performance can operate two ways simultaneously. Nonetheless, the simultaneous relationship between firm performance and innovation output is seldom investigated in the literature. Luxembourg as one of the most dynamic economies of the EU-28, remains almost entirely undiscovered regarding this relationship on firm level, hence the motivation of this study. This dissertation aims to fill the research gap by understanding what stimulates innovation activities, how long it takes to translate innovation activities into improved firm performance, whether and to what extent differentiated innovation types affect firm performance differently, whether an interdependent relationship exists between innovation and firm performance which forms a self-reinforcing cycle. Given the cumulative and path-dependence nature of innovation, Cainelli et al. [2006] argue that it is likely that innovation capabilities and economic performances are interdependent and this mechanism will persist and reinforce over time. Acknowledging both effects, I adopt an evolutionary approach on technological change and firm dynamics by looking at the two-way relationship between innovation and economic performance.

In order to tackle these questions, a simultaneous structural model is established with the fully recursive form. The lagged latent innovation variable is dependent on the past firm performance, which further determines the current firm performance. A system of equations with mixed structure is estimated by full information maximum likelihood methods. The longitudinal firm-level data is applied over the 2003-2012 period by merging five waves of the Luxembourgish innovation survey with Structural Business Statistics. This dissertation finds out that superior firm performance facilitates the emergence of process innovations, and process innovation contributes to firm growth and performance by gaining successful and sustainable competitive advantage, which forms a virtuous circle. Nonetheless, we cannot identify an exact pattern for the product innovation on the ground of cannibalization effect and inherent market risks associated with new products.

The third eminent component of this doctoral dissertation involves the investigation of the state dependent characteristics at the firm level. Innovation persistence is a substantial topic from both theoretical and policy perspectives. The persistence of innovation is identified as the phenomenon that firms that have innovated during a given period innovate in the subsequent period. The examination of innovation persistence can shed light on the endogenous mechanism which triggers the innovation behavior and sustains the continuous undertaking of innovative activities. In addition, the assessment of characteristics and determinants of innovation persistence at the firm level has far-reaching implications for strategic management and public policy. To illustrate, if innovation exhibits true state dependence regardless of public financial support from local or regional authorities, government intervention on firms' innovative activity might be modified in terms of funding allocation. In order to foster innovation efficiently, government might give non-innovators a financial preference to encourage them to embark on an innovation journey, on the grounds that innovative firms are more likely to innovate in subsequent period in light of true state dependence.

This doctoral dissertation explores innovation persistence by means of dynamic nonlinear random effects models based on the estimator proposed by Albarrán et al. [2015]. Albarrán et al. [2015] method accounts for unobserved individual effects that are correlated with the initial conditions as well as the unbalanced structure of the panel. This empirical analysis is based on a longitudinal panel using five questionnaire waves of Luxembourgish Community Innovation Surveys (CIS) at the firm level for the years 2002-2012. In addition, this study provides a differentiated analysis on the persistence of different types of innovation indicators, as innovation is a highly differentiated phenomenon associated with diverse firm strategies (Pianta and Crespi [2008], Antonelli et al. [2012]). In view of the sunk-cost hypothesis we expect to find evidence of state dependence in particular for R&D based innovation activities. Finally, I explore whether persistence patterns vary across diverse types of product innovation, namely, radical and incremental product innovation. This analysis resembles Clausen and Pohjola [2013] in terms of a clear distinction between radical product innovation and incremental product innovation, where radical innovations (defined as new-to-market product innovation) open up new markets and fundamentally transform a firm's value chain. The determinants of persistence of radical and incremental product innovation can be distinctively constituted in light of positive feedback among knowledge, learning effect, dynamic capabilities as well as capacity to deliver radical innovations, the introduction of new market products may be characterized by major persistence even after accounting for sunk costs relevant to R&D.

Results highlight the relevance of innovation persistence for all types of innovation, particularly the highest level of persistence is found for product innovation. In addition, the state dependence of product innovation is mainly associated with sunk costs relevant to R&D expenditures, whereas the state dependence of process innovation can be attributed to other factors such as dynamic increasing returns and learning effect.

1.2 Literature

The empirical literature usually identifies a positive relationship between product innovation and employment. By contrast, the relationship between process innovation and employment tends to be inconclusive and ambiguous. For instance, Van Reenen [1997] finds that technological innovations have a positive and significant effect on employment, which persists over several years. This positive effect is confirmed by, among other studies, Lachenmaier and Rottmann [2011] for German manufacturing, Piva and Vivarelli [2005] for Italian manufacturing and Harrison et al. [2014] for manufacturing and services in France, Germany, Spain and the UK. Moreover, Hall et al. [2009] discover positive effects of new and old products and no evidence of displacement effect associated with process innovation. Benavente and Lauterbach [2008] suggest that product innovation affects employment positively and significantly, while no clear evidence is found for process innovations. Similar results are derived for Crespi and Tacsir [2011] which discover positive links between product innovation and employment growth at the firm level using micro data from innovation surveys in four Latin American countries (Argentina, Chile, Costa Rica and Uruguay).

The study on two-way relationship between innovation and firm performance can be compared with other innovation studies that follow a similar structural approach to assess the impact of innovation on firm performance (Klomp and Van Leeuwen [2001], Lööf and Heshmati [2002], Marsili and Salter [2005], Cainelli et al. [2006]). Moreover, this study is closely linked to Cainelli et al. [2006] which explores the two-way relationship between innovation and economic performance in services using the Italian Community Innovation Survey (CIS II). Cainelli et al. [2006] confirm the positive self-reinforcing mechanism between innovation and firm performance which forms a virtuous circle.

Another strand of literature investigates the impact of the differentiated innovation types. Jefferson et al. [2006] point out that product innovation does not necessarily improve firm performance as the decline of firms' sale existing products might occur with product innovation. Isogawa et al. [2012] examine the relationship between product innovation and firms' sales of a new product and of existing products. Isogawa et al. [2012] argue that the cannibalization effect is less for new-to-market product innovation than new-to-firm product innovation. Consequently, only a firm with new-to-market product innovation tends to achieve large sales from a new product. By and large, the cannibalization effect induced by product innovation is substantial and the net impact on total sales is unclear. Furthermore, Leiponen [2000] discovers the positive effect of process innovation and the negative effect of product innovation on profit, which is consistent with my findings. David [1990], Drazin [1990] and Brimm [1988] suggest that improved technology reduces cost per unit and improves the firm performance accordingly. Moreover, Yamin et al. [1997] find out that process innovation is the stronger predictor of firm performance in terms of return on investment than product innovation. Similarly, Prajogo [2006] demonstrates that process innovation shows a stronger positive impact on firm performance than product innovation in manufacturing sectors.

The third essential component of this dissertation involves analysis of innovation persistence. One strand of empirical studies focuses on innovation survey and provides insights on the existence and significance of innovation persistence (Peters [2009], Raymond et al. [2010b], Clausen et al. [2011], Antonelli et al. [2012]). Based on a German innovation panel data for the period 1994-2002, Peters [2009] discovers a strong innovation persistence at the firm level using the Wooldridge [2005] approach in the context of dynamic random effects discrete choice model. Raymond et al. [2010b] confirm the hypothesis of true state dependence in the high-tech industries using four waves of Community Innovation Survey of Dutch manufacturing firms over the period 1994-2002. Using corresponding innovation survey, a stream of empirical studies stresses the disparate impacts of differentiated types of innovation on innovation persistence. To illustrate, based on a sample of 451 Italian manufacturing firms during the years 1998-2006, Antonelli et al. [2012] provide new insights on the role of R&D investments in innovation persistence and analyze differentiated patterns of persistence across product and process innovation. The highest level of persistence is found for R&D-based innovation activities, particularly for product innovation. In addition, Clausen and Pohjola [2013] analyze the innovation persistence by distinguishing between incremental and radical innovation. Clausen and Pohjola [2013] confirm the distinct persistence patterns across types of innovations, particularly, a more prominent innovation persistence associated with radical innovation than incremental innovation.

The multifaceted function of innovation is closely linked to the innovation types. Utterback and Abernathy [1975] regard product and process innovation as crucial different firms strategies in response to different development state achieved in the production process, different environment and strategy for competition and growth. Product innovation refers to the introduction of new or significantly improved goods, (excluding the simple resale of new goods purchased from other enterprises and changes of a solely aesthetic nature) and new or significantly improved services during the period under review. A product innovation can be either new to the enterprise or new to the sector or market. Process innovation refers to the introduction of new or significantly improved methods of manufacturing or producing goods or services, new or significantly improved logistics, delivery or distribution methods for inputs, goods or services, or new or significantly improved supporting activities for processes, such as maintenance systems or operations for purchasing, accounting, or computing. Product and process innovation tend to associate with diverse competencies and organizational skills (Damanpour and Gopalakrishnan [2001], Leiponen [2000]). Product innovations are primarily market and customer driven, whereas process innovations are efficiency driven and focus on internal change (Utterback and Abernathy [1975], Damanpour and Gopalakrishnan [2001]). Product innovation consists of understanding customer needs, successfully designing, manufacturing the product to suit the needs. It also requires successful commercialization of final products. By contrast, process innovation necessitates the application of new technology to improve the efficiency of production and delivery of the outcome (Ettlie et al. [1984], Damanpour and Gopalakrishnan [2001]). Product innovation can be further distinguished between radical and incremental innovation (Dewar and Dutton [1986], Ettlie et al. [1984]). This dissertation aims to inclusively examine the essential topics of employment dynamics, firm performance and innovation persistence in the context of differentiated innovation types.

1.3 Contribution

This dissertation contributes to the prior literature on the topics of employment dynamics, firm performance and innovation persistence in manifold ways. Firstly, this dissertation analyzes essential innovation subjects and builds the analysis upon a longitudinal dataset of innovation survey. The previous study uses mostly R&D and patent data. Patents represent a crucial aspect of innovation. Nonetheless, patents are biased in favour of formalized types of R&D investments (Antonelli et al. [2012]). Secondly, many strategic decisions of enterprise such as innovation, subsidy, cooperation are largely endogenous thus correlate to an unobservable omitted third factor (Mairesse and Mohnen [2010]). The panel setting of five waves of the innovation survey enables us to deal with endogeneity issue and control for unobserved firm heterogeneity through individual fixed effects. Thirdly, in spite of theoretical difficulty to disentangle different sources of employment effects, this dissertation establishes a theoretical model with endogenized product and process innovation which allows a separate identification of the employment effects of product and process innovation. The employment effect of product innovation is furthermore distinguished between radical and incremental innovation. Fourthly, prior literature mostly focuses on the one-way directional link between innovation and firm performance and largely overlooks the simultaneous relationship. This dissertation captures a dynamic self-reinforcing two-way relationship between innovation and firm performance.

Fifthly, earlier research has largely ignored the differentiated pattern between innovation types and sorely focused on single type of innovation. Given the generic differences between innovation types which are differently determined and associated with different capabilities and skills, it is essential to recognize innovation types as different strategies of firms in response to different challenges in lieu of treating innovation strategies homogeneously in the context of universalistic theory. This doctoral dissertation aims at contributing to previous empirical work by explicitly distinguishing different mechanisms of product and process innovation and revealing their distinct impacts on firm performance. By and large, I discover that superior firm performance facilitates the emergence of process innovations, and process innovation contributes to firm performance by gaining successful and sustainable competitive advantage, which forms a virtuous circle. Nonetheless, an opposite pattern is identified for the product innovation as a result of cannibalization effect and inherent market risks associated with new products. Sixthly, this dissertation applies a brand new econometric approach to study innovation persistence at the firm level. The application of the Albarrán et al. [2015] method correctly accounts for unobserved individual effects that are correlated with the initial conditions as well as the unbalanced structure of panel. Most prior studies are based on the Wooldridge [2005] method which neglect the fact that the Wooldridge [2005] estimator is derived for the balanced panel. The unbalanced structure of panel cannot be overlooked for consistent estimation of dynamic models. Applying the Wooldridge [2005] method to unbalanced panels can lead to inconsistent coefficient estimates by ignoring the unbalancedness. This work is the first attempt to empirically analyze the true state dependence and the role of sunk costs in forming innovation persistence within the context of the Albarrán et al. [2015] framework. Seventhly, this dissertation evaluates the degree of innovation persistence at the firm level and explores whether persistence patterns vary across types of innovations. The results highlight differentiated patterns of persistence among product and process innovation. The state dependence of product innovation (particularly, incremental product innovation) is mainly associated with sunk costs related to R&D. By contrast, the state dependence of process innovations cannot be explained entirely by the sunk-cost hypothesis, which suggests that it can be further attributed to dynamic increasing returns and learning effect. To further look into the product innovation category, a significant state dependence is observed for the radical product innovation. By contrast, an analogous pattern cannot be identified for the incremental product innovation indicator after accounting for the sunk costs related to R&D. Last but not least, it is the first study using Luxembourgish micro data to examine the essential topics of employment dynamics, firm performance and innovation persistence comprehensively.

1.4 Data

1.4.1 Community Innovation Survey

There is a substantial body of literature using traditional measures such as R&D expenditures and patent data. R&D expenditures mainly measure the innovation inputs, whereas patent data is biased in favor of major innovations that are worth patent application (Antonelli et al. [2012]). Patent data may underestimate the persistence of innovation on the grounds that patent data measures the persistence of innovation leadership rather than innovation persistence (Duguet and Monjon [2004]). Moreover, Arundel and Kabla [1998] argue that firms tend to patent more product innovations than process innovations. In consequence, the patent data is biased in favor of product innovations (Duguet and Monjon [2004]).

Another strand of empirical studies focuses on innovation survey, which is known as the Community Innovation Survey (CIS). CIS is formalized and standardized in the Oslo Manual since 1992 (Mairesse and Mohnen [2010]). The microeconometric analysis in this dissertation relies fully on the Luxembourgish Community Innovation Survey (CIS) which consists of five questionnaire waves 2002-2004, 2004-2006, 2006-2008, 2008-2010, 2010-2012. The survey methodology and innovation definition of Luxembourgish CIS database are consistent with the Oslo Manual which produces internationally comparable data. CIS survey data provides us with a comprehensive outlook of innovation activities at the firm level. The innovation survey contains biennial information regarding the introduction of product innovation and process innovation during the reference period. It also includes information concerning the introduction of new market products and new firm products, the percentage of turnover from goods and services that are unchanged or only marginally modified, the percentage of employees with higher education and the degree of market competition. Information concerning innovation input is also provided such as the estimated amount of intramural and extramural R&D expenditures. Other firm-level characteristics are also available such as subsidy and innovation cooperation. The rich structure of data allows us to explore the dynamic relationship between different types of innovations, employment and firm performance. It also enables us to identify the role of R&D activities in explaining innovation persistence and differentiated patterns of persistence across diverse typologies of innovation outputs.

According to Luxembourgish CIS quality report published by National Institute of Statistics and Economic Studies of the Grand Duchy of Luxembourg (STATEC), CIS data are collected from a combination of a sample survey and a census. The census includes a number of enterprises known to be highly involved in R&D activities. Additionally, large enterprises (250 or more employees) are all included in the sample. The sample is drawn from the national business register. Missing values appear to be randomly distributed and no systematic patterns are identified for the missing data. According to the CIS 2008 quality report published by STATEC, the sampling scheme used is a stratified sample based on an optimal allocation approach. The sample can be broken down by the size of the enterprise (10-49, 50-249, 250 or more) and industry, which leads to the creation of 48 strata for CIS 2006-2008 data. For instance, the overall sample rate for CIS 2006-2008 data reaches 38.6%, the corresponding overall sample rate is 43.2% for CIS 2004-2006 data.

Although CIS data presents in waves of cross-sectional data, a common firm identifier allows us to merge five waves of Luxembourgish Community Innovation Survey to construct a panel. Many strategic decisions of enterprise such as innovation, subsidy, cooperation are largely endogenous thus correlate to an unobservable omitted third factor (Mairesse and Mohnen [2010]). The panel setting further enables us to deal with endogeneity issue and control for unobserved firm heterogeneity through individual fixed effects.

1.4.2 Structural Business Statistics

Structural Business Statistics (SBS) is an annual database which provides us with a rich range of information on firms activities and performances such as turnover, value-added, persons employed, gross investment in tangible goods and wages. Moreover, SBS allows us to take into account the sample selection issue as it encompasses both innovators and non-innovators. The annual Structural Business Statistics (SBS) can be further linked to Luxembourgish Community Innovation Survey through the common firm identifier. The availability of firm-level characteristics facilitates us to disentangle the actual determinants of employment, firm performance and innovation persistence for wider groups of innovators. Chapter 2 and Chapter 3 will discuss the challenge of merging yearly data from the Structural Business Statistics (SBS) with biennial data from the Community Innovation Survey (CIS) in detail.

Structural Business Statistics (SBS) are collected and processed by STATEC. According to the SBS methodology published by STATEC in 2003 [1], the business register covers all activities in Sections C-K and O of NACE Rev.1. It covers part of the activities in Sections A (agriculture), L (public administration), M (education), N (health and social work) and Q (extra-territorial organisations and bodies). Sections completely excluded are fishing and private households with employed persons. The Luxembourgish SBS also excludes information for the financial sector, which is rather unfortunate as this sector represents a sizable percentage of the CIS sample and exhibits larger shares of product and process innovators. In addition, all geographical areas are covered. The 2003 survey is based on a sample of units which have less than 50 employees or less than 7 million EUR turnover. The survey is exhaustive for units with 50 or more employees or turnover above 7 million EUR. The number of enterprises covered by the survey is limited to about 2,600. The sample is drawn according to the European commission's recommendations (3 April 1996) on the definitions of SMEs. The survey covers all enterprises falling into the medium-sized and large enterprise classes. Different sampling percentages are used for enterprises in the small size class. The response rate amounts to 87% for 2003 SBS data.

1.5 Thesis outline

Chapter 2 studies the dynamic relationship between technological innovation and employment using Luxembourgish firm-level data pertaining to the non-financial corporate sector during the period 2003-2012. A simple theoretical model that distinguishes the employment effect of product innovation from that of process innovation is developed. The model is then estimated by two-step generalised method of moments using an unbalanced panel data stemming from the annual Structural Business Statistics merged with the biennial innovation survey. We discover that product innovation exerts a positive effect on employment while process innovation does not have any significant effect on the firm level of employment.

Chapter 3 investigates the two-way relationship between technological innovation and firm performance at the firm level. In the framework of evolutionary economics, innovation is regarded as a highly cumulative process which exhibits positive feedback. This chapter aims at capturing the interdependent relationship and possible bidirectional causality

[1] Please refer to SBS report for more information on Structural Business Statistics methodology.

between innovation and firm performance. Superior firm performance facilitates the emergence of innovations; innovation contributes to firm performance by gaining successful and sustainable competitive advantage, which forms a virtuous circle.

A fully recursive simultaneous model is established where product and process innovation are explicitly distinguished. The system of simultaneous equations with mixed structure is estimated by full information maximum likelihood methods. The longitudinal firm-level data is applied over the 2003-2012 period by merging five waves of the Luxembourgish innovation survey with Structural Business Statistics. This chapter discovers that enhanced firm performance facilitates process innovation and process innovation improves firm performance, which forms a self-reinforcing virtuous circle. Nonetheless, we cannot identify an exact pattern for the product innovation as a result of cannibalization effect and inherent market risks associated with new products.

Chapter 4 explores innovation persistence at the firm level by means of dynamic nonlinear random effects models based on the estimator proposed by Albarrán et al. [2015]. It aims at capturing the true state dependence which indicates the causal relationship between innovation in one period and decision to innovate in the subsequent period. The Albarrán et al. [2015] method accounts for unobserved individual effects that are correlated with the initial conditions as well as the unbalanced structure of panel. Using five questionnaire waves of Luxembourgish Community Innovation Surveys (CIS) for the years 2002-2012, this study provides new insights on the differentiated patterns of persistence among product and process innovation. Results highlight the relevance of innovation persistence for all types of innovation, particularly the highest level of persistence is found for product innovation. In addition, the state dependence of product innovation is mainly associated with sunk costs relevant to R&D expenditures, whereas the state dependence of process innovation can be attributed to other factors such as dynamic increasing returns and learning effect. The further differentiation of product innovator category reveals that the state dependence of incremental product innovation can be mainly attributed to sunk costs relevant to R&D expenditures. By contrast, the joint significance of average R&D intensity, intramural R&D share as well as the past realization of radical product innovation suggests the role of other factors such as dynamic increasing returns and learning effect in fostering state dependence for radical innovations.

Finally, Chapter 5 summarizes the main findings of the dissertation, derives the managerial implications and discusses the limitations and directions for future research.

Chapter 2

Dynamics of technological innovation and employment: panel evidence from Luxembourg

2.1 Introduction

The endogenous growth models identify innovation, or more broadly technological change, as the main driver of a nation's productivity and income growth [Romer, 1990, Aghion and Howitt, 1992]. Furthermore, the preservation of employment in a capitalist economy requires a growing income, an idea that dates back at least to Karl Marx. For instance, between 1987 and 1990, an average growth rate of output of 3.4% was reached and accompanied by a growth rate of employment of 1.4% with annual productivity gains of 2% in the then EU-12 [see Drèze and Malinvaud, 1994]. The question whether technological change creates or destroys jobs, albeit age-old, is still debated today and no definite answer has been found. These contrasting views of job creation or destruction induced by technological change are termed optimistic or pessimistic and have evolved a lot over time.[1] For instance, whereas David Ricardo endorsed the optimistic view in the beginning of the 19th century, he later withdrew it as shown in his quote '[...] the opinion entertained by the labouring class, that the employment of machinery is frequently detrimental to

[1] In the pessimistic view case, economists also refer to 'technological unemployment', a term that was popularised by Keynes.

their interests, is not founded on prejudice and error, but is conformable to the correct principles of political economy' [Ricardo, 1821]. Furthermore, after being dominant among the economists during the second half of the 19th century, the 20th century and the first decade of the 21st century, the optimistic view is being seriously challenged nowadays by a growing number of economists.[2]

In order to predict the effect of technological change on employment, economic theory usually distinguishes between product and process innovation [see e.g. Stoneman, 1983]. Product innovation is expected to change upwards the demand curve for goods or services, which will raise the demand for labour (compensation effect). Evidently, if a firm produces multiple products, new goods may simply drive out old goods so this will reduce the overall expansion in labour demand. Process innovation, on the other hand, is expected to reduce production costs by increasing the productivity of labour or capital. Although the resulting required labour per unit of output is lower (displacement effect), technological progress that reduces the effective cost of labour will cause a firm to increase output. The net effect of process innovation on employment depends on which of these two effects dominates. Overall, product innovation is expected to have a positive net effect on employment whereas the net effect of process innovation is less clear-cut.

Against popular conceptions, the empirical literature usually identifies a positive relationship between technological innovation and employment. For instance, Meghir et al. [1996] find that, during booms, more jobs are created by technologically dynamic firms in the UK because they face lower adjustment costs in employment. Furthermore, technological innovators are more flexible and more capable of moving to their equilibrium levels of employment when faced with shocks. Using similar data and controlling for fixed effects, dynamics and endogeneity, Van Reenen [1997] finds that technological innovations have a positive and significant effect on employment, which persists over several years. This positive effect is confirmed by, among other studies, Lachenmaier and Rottmann [2011] for German manufacturing, Piva and Vivarelli [2005] for Italian manufacturing, Ciriaci et al. [2016] for Spanish firms in manufacturing and service sectors, Harrison et al. [2014] for manufacturing and services in France, Germany, Spain and the UK. Vivarelli [2014] and Calvino and Virgillito [2017] provide a critical survey of the most recent empirical findings at the firm and industry level. Particularly, Calvino and Virgillito [2017] discuss the operation of compensation mechanism at the firm level and conceptualize a number of stylized facts on the relationship between innovation and employment. In addition, there is a substantial body of literature which focuses on automation, digitalization and employment polarization (Freeman and Soete [1994], Brynjolfsson and McAfee [2012], David [2015], Arntz et al. [2016], Frey and Osborne [2017]). For example, Arntz et al. [2016] argue that automation and digitalization are unlikely to destroy large numbers of

[2]In a 2013 article in The New York Times entitled "Sympathy for the Luddites", the view of 2008 Nobel Prize winner, Paul Krugman, is that 'highly educated workers are as likely as less educated workers to find themselves displaced and devalued [...]'. Furthermore, at the 2014 Davos meeting, 80% of the 147 respondents of a survey agreed that technological change was driving unemployment.

jobs. However, low qualified workers are more susceptible to automation compared to highly qualified workers. Frey and Osborne [2017] also suggest a truncation towards labour market polarization, with computerization being principally confined to low-skill occupations. Another strand of literature investigates the relationship between innovation input and employment (Yang and Lin [2008], Coad and Rao [2011], Bogliacino et al. [2012]). Bogliacino et al. [2012] and Coad and Rao [2011] confirm the positive impact of R&D expenditures on employment. Moreover, Bogliacino and Pianta [2010] apply the Pavitt taxonomy for summarizing differences in the patterns of technological change and reveal the differentiated impact of innovation on employment across industry groups. Spiezia and Polder [2016] also confirm the positive relationship between ICT investments and employment.

In the context of Luxembourg economy, according to STATEC report, from the mid-1980s until 2000, the average growth rate of GDP reached a level more than 5% per year. The rate of GDP growth slowed down at the beginning of the decade and experienced a sharp slowdown after the 2008 financial crisis [3]. The OECD Review of Innovation Policy report (2015) points out that, Luxembourg still faces challenges of reducing unemployment, enhancing productivity growth and diversifying economy. Graph 2.1 presents the evolution of labour productivity growth, structural unemployment rate and potential GDP per capita growth in Luxembourg over the period 2000-2013. The unemployment rate has risen to 7% and the share of the long-term unemployment reaches 25% of total unemployment. [4] A long-term goal for Luxembourg is to achieve and maintain economic competitiveness and productivity growth. Recent OECD estimates indicate that trend labour productivity growth has declined after 2002 and was negative before the outbreak of the financial crisis. Along with the growing structural unemployment rate, innovation may serve as a key driver of sustainable productivity, employment growth and competitiveness for Luxembourg. Graph 2.2 suggests that the share of enterprises with technological innovation (product or process innovations) is rather stable over the period 2006-2012. Nonetheless, the composition of innovation types varies before and after the crisis. In particular, the share of product innovators declines while the share of process innovators increases after the crisis. As for Luxembourg, one of the most dynamic economies of the EU-28, we know nothing about the relationship between innovation and employment on firm level, hence the motivation of this study.

In this chapter, a simple theoretical model that clearly distinguishes the employment effect of product innovation from that of process innovation is developed. More specifically, we distinguish between the employment effects of unchanged or old products, products new to

[3] http://www.luxembourg.public.lu/en/investir/portrait-economie/conjoncture/index.html

[4] Source: The OECD Review of Innovation Policy report (2015).

[5] http://dx.doi.org/10.1787/888933198007

[6] Enterprises with 10 or more employees based on biennial data.
Source: http://www.statistiques.public.lu/stat/TableViewer/tableViewHTML.aspx?ReportId=13568IF$_{Language} = engMainTheme = 4FldrName = 9RFPath = 2224$

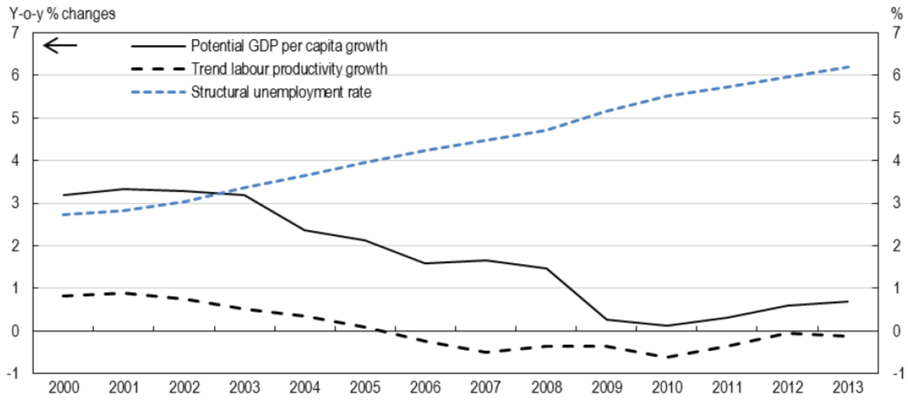


Figure 2.1: Trend in unemployment and productivity over the period 2000-2013.[5]
Source: OECD (2015), based on OECD (2014a).

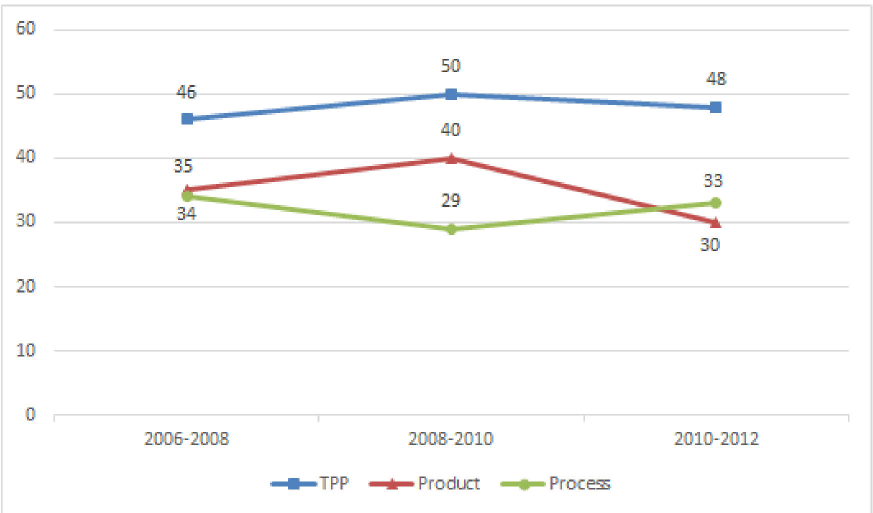


Figure 2.2: Innovations by types (in %) biennial data over the period 2006-2012.[6]
Source: Statec. Community Innovation Survey CIS2008, CIS2010, CIS2012.

the firm, products new to the market and new production or delivery methods. An empirical model is then estimated using several waves of yearly data from the Luxembourgish structural business survey merged with biennial data from the innovation survey and pertaining to the period 2003-2012. A search for the most appropriate estimation method suggests using the system GMM estimator [Blundell and Bond, 1998] with predetermined or endogenous innovation variables. The results indicate a positive and significant effect of product innovation on employment where the semi-elasticity of the latter with respect to the percentage of turnover from new product lies between 0.2% and 0.5%. Furthermore, we find some evidence of a significantly more sizable effect of radical innovation than incremental innovation. The differential in the employment effects between radical and incremental innovation is estimated to be 50%. Similarly, the employment level differential between product innovators and firms with unchanged products lies between 4% and 11%. Unlike product innovation, however, process innovation does not have any significant effect on the firm level of employment.

The remainder of this chapter is organised as follows. Section 2.2 presents the theoretical framework upon which the empirical model is based. Section 2.3 presents the resulting dynamic empirical model and discusses various methods of estimation of such models. Section 2.4 describes the data used in the estimation, discusses the challenge of merging yearly data from the structural business survey with biennial data from the innovation survey and presents descriptive statistics on the variables of interest. Section 2.5 discusses the search for the most appropriate estimation technique and the resulting estimation results. Section 2.6 summarises the results, emphasises the strengths and weaknesses of the study and concludes.

2.2 Theoretical framework

Our theoretical model is based upon Hamermesh [1996] and Cahuc and Zylberberg [2004]. As in their models, we claim that the volume of work is more adaptable than the stock of capital in the short run. Thus, under the assumption that the firm operates under a constant elasticity of substitution (CES) production function with capital and labour as factors of production, labour demand will depend on real wage and market power of the firm. Formally,

$$Y = \left[(\alpha L)^{\frac{\sigma-1}{\sigma}} + (\beta K)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\theta\sigma}{\sigma-1}} e^{\eta+\varepsilon},\ \theta,\sigma,\alpha,\beta > 0, \tag{2.2.1}$$

where Y denotes output, K and L are respectively capital and labour, θ and σ capture respectively the degree of homogeneity of the function and the elasticity of substitution between capital and labor, α and β are respectively labour-augmenting Harrod-neutral technology and capital-augmenting Solow-neutral technical change and measure the reaction of labour and capital to a technological shock, η denotes the unobserved time-invariant firm-specific fixed effects and ε denotes time-specific productivity shocks with $E(\varepsilon) = 0$.[7]The amount of labour is assumed flexible in the short run whereas the stock of capital is considered rigid on that horizon. Let us denote the inverse demand function as $P = P(Y)$ so that $\rho_Y^P = \frac{YP'(Y)}{P(Y)}$ is the inverse of the price elasticity of demand and $|\rho_Y^P|$ denotes the firm's market power. Thus, perfect competition is characterised by $\rho_Y^P = 0$. Given the model's assumptions, the firm's decision is to choose the level of employment so as to maximise profit

$$\pi(L) = P(Y)Y - WL, \tag{2.2.2}$$

where W denotes labour cost per capita (proxied by wage per capita). The first-order condition with respect to labour yields

$$Y'(L) = \frac{\nu W}{P}, \tag{2.2.3}$$

where ν is the markup, $\nu \geq 1$ and $\nu = \frac{1}{(1+\rho_Y^P)}$. Hence, the size of the mark-up depends on the price elasticity of demand. Equation (2.2.3) indicates that in the short run, the firm attains its maximum profit when marginal productivity of labour is equal to real wage multiplied by a markup ν. By derivating equation (2.2.1) and taking natural logarithm, the demand for labour equation becomes

$$\ln L = \frac{\theta\sigma - \sigma + 1}{\theta} \ln Y + (\sigma - 1)\ln\alpha - \sigma \ln\frac{W}{P} - \sigma\ln\nu + \sigma\ln\theta + \frac{\sigma - 1}{\theta}(\eta + \varepsilon). \tag{2.2.4}$$

If we use sales as a proxy for output and assume that

$$Y = Y_{old} + Y_{new} = Y_{old} + Y_{new\ firm} + Y_{new\ market} \tag{2.2.5}$$

where Y_{old} and Y_{new} denote respectively sales of old (or unchanged) and new products, the latter being the sum of sales of new-to-the-firm $(Y_{new\ firm})$ and new-to-the-market $(Y_{new\ market})$ products.[8] Using first-order Taylor expansion around $\frac{Y_{new}}{Y}$ (with $\frac{Y_{new}}{Y} < 1$) yields

$$\ln L \simeq \frac{\theta\sigma - \sigma + 1}{\theta}\left(\frac{Y_{new\ firm}}{Y} + \frac{Y_{new\ market}}{Y} + \ln Y_{old}\right) + (\sigma - 1)\ln\alpha - \sigma\ln\frac{W}{P} - \sigma\ln\nu$$
$$+ \sigma\ln\theta + \frac{\sigma - 1}{\theta}(\eta + \varepsilon).^{9} \tag{2.2.6}$$

[7]To keep the exposition simple, we discard for now firm and time subscripts and use a similar notation to Hamermesh [1996] and Cahuc and Zylberberg [2004].

[8]A product is to be interpreted as a good or a service.

[5]The condition $\frac{Y_{new}}{Y} < 1$ is necessary for first-order Taylor approximation. In our sample, this ratio is on average equal to 7.25% so that a higher order expansion is unnecessary. Nonetheless, in one of the specifications of the model, we use a quadratic term in the estimation which turns out insignificant. The results are not reported but can be obtained upon request. For more details on the Taylor expansion, see Appendix 2.A.

In equation (2.2.6) we explain the level of employment by incremental product innovation $\left(\frac{Y_{new\ firm}}{Y}\right)$, radical product innovation $\left(\frac{Y_{new\ market}}{Y}\right)$ and process innovation captured by the labour augmenting technology parameter α. The variables $\left(\frac{Y_{new\ firm}}{Y}\right)$ and $\left(\frac{Y_{new\ market}}{Y}\right)$ are readily available in the innovation survey and the unobserved parameter α is proxied by an indicator of process innovation also available in the innovation survey. We now explain the mechanisms through which product and process innovation affect employment.

The effect of product innovation

Product innovation refers to the introduction of new or significantly improved goods, (excluding the simple resale of new goods purchased from other enterprises and changes of a solely aesthetic nature) and new or significantly improved services during the period under review. A product innovation can be either new to the enterprise or new to the sector or market. The effect of product innovation on employment operates directly through the firm labour demand function. A theoretical link between the demand for labour and product innovation is directly established by decomposing output (in this case sales) into sales of old or unchanged, new-to-the-firm and new-to-the-market products. New products are expected to stimulate demand, which allows innovative firms to hire more workers, hence predicting a positive effect of product innovation on employment (compensation effect). It is important to distinguish between the employment effects of incremental and radical innovation as the literature identifies new market products as more essential for employment than incremental product innovations [see e.g. Falk, 1999]. Nonetheless, if a firm produces multiple products, new products may simply drive out old products, which will reduce the magnitude of the compensation effect if both old and new products are substitutes. As a result, the net employment effect of product innovation depends upon the degree of substitutability between existing and new products. The simple model presented here does not take into account this particular displacement effect of product innovation. However, in the empirical part, we control for the degree of substitutability between existing and new products by using as regressors market competition variables that measure how rapidly products are becoming old-fashioned or outdated.

The effect of process innovation

Process innovation refers to the introduction of new or significantly improved methods of manufacturing or producing goods or services, new or significantly improved logistics, delivery or distribution methods for inputs, goods or services, or new or significantly improved supporting activities for processes, such as maintenance systems or operations for purchasing, accounting, or computing. Economic theory suggests that process innovation is expected to have a displacement effect on employment by virtue of enhanced efficiency. In other words, process innovators produce more cheaply and hence tend to reduce employment. This effect operates through the technology parameter α of the production function.

However, process innovation may bring about compensation effect as well. By introducing a new technology, the process innovator will reduce marginal costs and the price of its products, which will stimulate demand for these products, hence the necessity to hire in order to meet this increased demand. The potential positive employment effect of process innovation depends upon the price elasticity of demand, which is incorporated in the markup parameter ν. If demand is elastic, a small change in price will result in significant demand expansion and higher employment, which may outweigh the direct displacement effect. This increase in demand is in theory higher for new-to-the-market products in comparison with new-to-the-firm products. Furthermore, in the case of labour-augmenting technological progress, labour is relatively more efficient than capital. This is translated into a higher elasticity of substitution σ, which makes firms more prone to substitute labour for capital, hence an increase in the level of employment. Finally, the market structure that the firm operates in also plays a role in the innovation-employment relationship. In a competitive market where entry is relatively easy, unit cost reduction (brought about by process innovation) is fully translated into a reduction in product price, which increases demand for the product and the level of employment, whereas closed markets tend to exhibit low price elasticity of demand [see Stoneman, 1983, Katsoulacos, 1984].

2.3 Empirical model and estimation

The empirical model derived from the theoretical framework is written as

$$\begin{aligned}\ln L_{it} = \; & \beta_1 \left[\frac{\left(Y_{new\ firm}\right)_{it}}{Y_{it}} \right] + \beta_2 \left[\frac{(Y_{new\ market})_{it}}{Y_{it}} \right] + \beta_3 \ln\left(Y_{old}\right)_{it} + \beta_4 Process_{it} \\ & + \beta_5 \ln\left(\frac{W}{P}\right)_{it} + \beta_6' \mathbf{Market}_{it} + \tau_t + \eta_i + \varepsilon_{it}, \qquad (2.3.1)\end{aligned}$$

where $\ln L_{it}$ is the logarithm of the level of employment of firm i at time t $(i = 1, ..., N; t = 1, ..., T_i)$,[10] $\frac{\left(Y_{new\ firm}\right)_{it}}{Y_{it}}$ is the share in total sales of products new to the firm, $\frac{(Y_{new\ market})_{it}}{Y_{it}}$ is the share of sales of products new to the market,[11] $\ln\left(Y_{old}\right)_{it}$ is the logarithm of sales of old or unchanged products, $Process_{it}$ refers to the dummy variable which takes the value 1 if the enterprise introduces new or significantly improved methods of manufacturing or producing goods or services, new or significantly improved logistics, delivery or distribution methods for inputs, goods or services, or new or significantly improved supporting activities for processes, such as maintenance systems or operations for purchasing, accounting, or computing. $\ln\left(\frac{W}{P}\right)_{it}$ is the logarithm of real wage, $\mathbf{Market}_{it}$ captures market competition

[10] Strictly speaking, the first value of t also varies across firms so that they enter or leave the sample at any time.

[11] In the estimation, we have multiplied both shares by 100 so as to have variables expressed in percentage points. Moreover, as products are expressed by values of sales, one can add up old and new products rather than treating them distinctively.

variables that measure how rapidly products are becoming old-fashioned or outdated, η_i denotes the unobserved time-invariant firm-specific fixed effects, τ_t denotes the full set of time dummies to control for the general macroeconomic demand shocks. $\varepsilon_{it} \sim iid(0, \sigma_\omega^2)$ denotes idiosyncratic disturbances that are independent across firms and over time. β_k $(k = 1, ..., 5)$ and β_6 are parameters to be estimated.

As Arellano and Bond [1991] point out, if firms endure a costly employment adjustment, the actual level of employment may in the short run deviate from the equilibrium. This is particularly true for European firms that experience high hiring and firing costs. This adjustment cost motivates the inclusion of autoregressive terms into equation (2.3.1). The empirical literature suggests a second-order autoregressive specification where the first lag captures adjustment costs in employment changes and the second lag is due to aggregation over skilled and unskilled workers [see e.g. Van Reenen, 1997]. Thus, an extended and more realistic version of the empirical model is written as

$$\ln L_{it} = \rho_1 \ln L_{i,t-1} + \rho_2 \ln L_{i,t-2} + \beta' \mathbf{X}_{it} + \tau_t + \underbrace{\eta_i + \varepsilon_{it}}_{v_{it}}, \tag{2.3.2}$$

where $\mathbf{X}$ encompasses other explanatory variables (besides the lagged employment regressors) such as output, innovation and wage, and ρ_1, ρ_2, and β are parameters to be estimated.

The ordinary least squares (OLS) estimator of equation (2.3.2) with v_{it} as the error term is biased and inconsistent for two reasons. Firstly, even if ε_{it} is serially uncorrelated, v_{it} is serially correlated because of the presence of the time-invariant firm-specific fixed effect η_i. Secondly, since $\ln L_{it}$ is a function of η_i, so are $\ln L_{i,t-1}$ and $\ln L_{i,t-2}$, which makes them correlated with the error term v_{it}. Some of the regressors of $\mathbf{X}_{it}$, e.g. innovation, may also be correlated with v_{it} through η_i. The OLS estimator ignores the correlation between the regressors (e.g. $\ln L_{i,t-1}$) and η_i, hence suffering from the omitted-variables bias. The within transformation that is used in the fixed-effects estimator accounts for this correlation by wiping out the firm-specific effect η_i. However, the within-transformed expression of $\ln L_{i,t-1}$, i.e. $\ln\left(L_{i,t-1} - \sum_{t=2}^{T_i} L_{i,t-1}/(T_i - 1)\right)$, is correlated with the within-transformed idiosyncratic error, i.e. $(\varepsilon_{it} - \sum_{t=1}^{T_i} \varepsilon_{it}/T_i)$. As a result, the fixed-effects estimator is also biased, which in the econometric literature is referred to as Nickell's [1981] bias, and its consistency depends on T_i being large. When T_i is small or moderate as in our case, to obtain consistent estimates after within-transforming equation (2.3.2), we would need to use an instrumental variables (IV) or generalised method-of-moments approach to account for the endogeneity of the regressors in the within-transformed equation. But, finding readily available (external) instruments to use in the transformed equation is not straightforward and alternative transformations that wipe out the firm-specific effect have to be found.

An alternative transformation that wipes out η_i is the first-difference transformation, i.e.,

$$\underbrace{\ln L_{it} - \ln L_{i,t-1}}_{\Delta \ln L_{it}} = \rho_1 \underbrace{(\ln L_{i,t-1} - \ln L_{i,t-2})}_{\Delta \ln L_{i,t-1}} + \rho_2 \underbrace{(\ln L_{i,t-2} - \ln L_{i,t-3})}_{\Delta \ln L_{i,t-2}} + \beta' \underbrace{(\mathbf{X}_{it} - \mathbf{X}_{i,t-1})}_{\Delta \mathbf{X}_{it}}$$
$$+ \underbrace{(\tau_t - \tau_{t-1})}_{\Delta \tau_t} + \underbrace{(\varepsilon_{it} - \varepsilon_{i,t-1})}_{\Delta \varepsilon_{it}}. \tag{2.3.3}$$

Applying OLS to the first-differenced equation also yields inconsistent estimates because $\Delta \ln L_{i,t-1}$ is correlated with $\Delta\varepsilon_{it}$, which stems from the fact that $\ln L_{i,t-1}$ and $\varepsilon_{i,t-1}$ are correlated (see equation (2.3.2)). Anderson and Hsiao [1981, 1982] suggest estimating equation (2.3.3) by the instrumental variables method using $\ln L_{i,t-2}$ or $\Delta \ln L_{i,t-2}$ as an instrument for $\Delta \ln L_{i,t-1}$, even though the use of $\ln L_{i,t-2}$ as an instrument is recommended in empirical work, see e.g. Baltagi [2008].[12] The resulting IV estimators are consistent but inefficient. More efficient estimators can be obtained if additional valid instruments are used in a GMM framework.

Difference GMM [Arellano and Bond, 1991]

Under the assumption of serially uncorrelated idiosyncratic errors conditional on η_i, i.e.

$$\mathbb{E}(\varepsilon_{it}|\eta_i) = \mathbb{E}(\varepsilon_{it}\varepsilon_{is}|\eta_i) = 0,\ \forall t \neq s, \tag{2.3.4}$$

Arellano and Bond [1991] show that $\ln L_{i,t-j}$, with $j = 2,...,t-1$ and $t = 4,...,T_i$, can be used as instruments for the endogenous variable $\Delta \ln L_{i,t-1}$ in equation (2.3.3). In other words, the linear moment restrictions of the difference GMM estimator are written as

$$\mathbb{E}\left(\Delta\varepsilon_{it} \ln L_{i,t-j}\right) = 0,\ j = 2,...,\ t-1;\ t = 4,...,T_i. \tag{2.3.5}$$

If $\mathbf{X}_{it}$ is a vector of strictly exogenous explanatory variables in equation (2.3.2), i.e. $\mathbb{E}(\mathbf{X}_{is}\varepsilon_{it}) = 0,\ \forall s,t$, then the first-differenced variables $\Delta\mathbf{X}_{it}$ can be used as their own instruments in equation (2.3.3). Similarly, since $\Delta \ln L_{i,t-2}$ is uncorrelated with $\Delta\varepsilon_{it}$, it is used as its own instrument in equation (2.3.3). If $\mathbf{X}_{it}$ consists of predetermined regressors, i.e. $\mathbb{E}(\mathbf{X}_{is}\varepsilon_{it}) = 0$ for $s \leq t$, then $\mathbf{X}_{i1},...,\mathbf{X}_{i,t-1}$ can be used to instrument to $\Delta\mathbf{X}_{it}$ in equation (2.3.3). Finally, if $\mathbf{X}_{it}$ is "endogenous" in the sense that $\mathbb{E}[\mathbf{X}_{it}(\eta_i + \varepsilon_{it})] = \mathbb{E}[\mathbf{X}_{it}\nu_{it}] \neq 0$, then second-order and earlier lagged values of $\mathbf{X}_{it}$ have to be used as instruments in equation (2.3.3), i.e. $\mathbf{X}_{i1},...,\mathbf{X}_{i,t-2}$.[13]

[12] Anderson and Hsiao [1981] approach assumes strict exogeneity for the vector of regressors $\mathbf{X}_{it}$, i.e. $\mathbb{E}(\varepsilon_{it} \mid \eta_i, \mathbf{X}_{i1},...,\mathbf{X}_{iT_i}) = 0$.

[13] if $\mathbf{X}_{it}$ is endogenous in the sense that $\mathbb{E}[\mathbf{X}_{it}\varepsilon_{it}] \neq 0$, then the lagged variables can no longer be used as internal instruments and one needs to find external instruments.

System GMM [Blundell and Bond, 1998]

When the first-order autoregressive coefficient, ρ_1, is large and the number of time periods, T_i, is small or moderate, Blundell and Bond [1998] show that the difference GMM estimator has large finite-sample bias and poor precision resulting from the weak instruments problem. Instead, they advocate the use of a system GMM estimator that consists in using lagged differences of the endogenous variables as instruments in the level equation (2.3.2) in addition to the moment conditions of equation (2.3.5). The additional linear moment conditions are written as

$$\mathbb{E}(\nu_{it}\Delta \ln L_{i,t-1}) \text{ for } t = 5, ..., T_i, \tag{2.3.6}$$

and the resulting system GMM estimator is shown to be consistent and to perform better than the difference GMM in finite samples in terms of bias and precision especially when ρ_1 is close to unity and T_i is moderately small.[14] If the explanatory variables $\mathbf{X}_{it}$ are strongly exogenous in the sense that $\mathbb{E}(\mathbf{X}_{is}\varepsilon_{it}) = 0$, $\forall s,t$, then $\mathbf{X}_{it}$ can be used as their own instruments in equation (2.3.2). If the regressors $\mathbf{X}_{it}$ are predetermined, i.e. $\mathbb{E}(\mathbf{X}_{is}\varepsilon_{it}) = 0$ for $s \leq t$, then $\Delta\mathbf{X}_{it}$ can be used as instruments in equation (2.3.2). Finally, if $\mathbf{X}_{it}$ is endogenous with respect to ν_{it}, then $\Delta\mathbf{X}_{i,t-1}$ can be used as instruments in equation (2.3.2).

2.4 Data

The data stem from five waves of the Luxembourgish community innovation survey (CIS) pertaining to all business sectors covered by the survey for the periods 2002-2004, 2004-2006, 2006-2008, 2008-2010 and 2010-2012,[15] and merged with data from the annual structural business survey (SBS) starting from 2003 until 2012. The merged CIS-SBS data is an unbalanced panel that consists of 1436 firms of which 42 enterprises (i.e. 3% of the sample) with no sales of old products are removed as they violate the Taylor expansion of Section 2.2.[16] Furthermore, some sectors are removed from the analysis because of missing SBS information (e.g. financial services) or insufficient observations (e.g. real estate activities), which results in a sample of roughly 1200 enterprises with at least 10 employees and positive output, turnover and wage over the 2003-2012 period.

[14]The system GMM estimator is shown to exploit information on the initial conditions while the difference GMM estimator does not. As a result, the system GMM is more efficient than the difference GMM, see Arellano and Bond [1991] and Blundell and Bond [1998] for more details on both estimators.

[15]For more details on the data collection procedure, see Raymond and Plotnikova [2015]. The sectors considered in this analysis are shown in Tables 2.2 and 2.3.

[16]These enterprises are more likely to be newly active in the market as in the case of start-ups with a different behaviour from that of 'traditional' enterprises. Thus, they deserve a special treatment and should be analysed separately.

The innovation survey contains biennial information regarding the introduction of new or improved products or processes. The new products are further classified into new-to-the-firm and new-to-the-market products whose contribution as a percentage of total turnover as well as the contribution of unchanged or old products are also provided. Biennial information on market competition, which explains the extent to which products are becoming old-fashioned or outdated, is also provided. Controlling for the market condition in the relation between innovation and employment is important, as we already argued in Section 2.2. As for the SBS, annual information on employment, wage and output (among others) is provided.

2.4.1 Merging CIS with SBS

When merging the CIS data with that of SBS, we face the challenge of merging two datasets with different periodicities. In other words, in the empirical model, we are regressing a yearly-available variable stemming from SBS, i.e. employment, on biennially-available innovation variables stemming from CIS. Two options then emerge.

The first option consists in using a yearly panel where the SBS variables are used as such and the CIS variables are repeated for each year of the period covered by the innovation survey. For instance, in 2005 and 2006, the yearly information on employment is used while a product innovator during the 2004-2006 period is treated as a product innovator in 2005 and 2006.[17] Similarly, new product turnover, as a percentage of total turnover, reported at the end of the CIS period is repeated for each year of the period. Thus, when explaining annual employment by innovation, the latter is to be understood as an 'average' innovation behaviour over the CIS period. The benefit of using a yearly panel is that it enables us to use as many observations as possible over the 2003-2012 period, which is a necessary condition to estimate accurately equation (2.3.2). Nonetheless, the approach also has two drawbacks related to the fact that the CIS is carried out biennially and pertains to 3-year periods. The first drawback is that the exact year of occurrence of innovation is unknown over each 3-year period. As a result, considering again the 2004-2006 example, it may well be the case that employment in 2005 is explained by innovation occurrence in 2004, 2005 or 2006 depending on the exact year of innovation occurrence. Whereas explaining employment in 2005 by innovation in 2004 or 2005 is reasonable, using innovation in 2006 as an explanatory variable of employment in 2005 is problematic. To tackle this problem, we also consider in some specifications of the empirical model lagged innovation variables as regressors. The second drawback is concerned with the overlapping year between two consecutive waves of the CIS. This is problematic in the yearly panel when the enterprise claims to be an innovator over a 3-year period and not an innovator in a subsequent period. In this case, the enterprise is assumed to be a non-innovator in the

[17] Since the regression to be estimated (equation 2.3.2) is a second-order autoregressive model, we automatically 'lose' two years of observation. As a result, the first observation of the dependent variable starts from 2005.

overlapping year, which seems a reasonable assumption. The overlapping year is less of a problem when the enterprise is an innovator or a non-innovator in two consecutive waves. The overlapping year is not an issue either for the continuous innovation variables since the values of these variables are reported at the end of each CIS period. In this case, the overlapping year takes on the current period values.[18]

The second option consists in using a biennial panel where only the last year of each CIS period is retained, namely 2004, 2006, 2008, 2010 and 2012. The advantage of this panel is that we no longer have this problem of explaining employment by future values of innovation, nor must we use ‘imputation’ to deal with the values of the overlapping year of two consecutive waves. However, the biennial panel consists of many fewer observations, which may render the estimation of equation (2.3.2) less accurate. We use both types of panel to estimate equation (2.3.2). The results are described in details for the yearly panel, those obtained with the biennial panel are included as a robustness check.

2.4.2 Descriptive statistics

Table 2.1 shows descriptive statistics on the non-transformed variables used in the empirical model. We present the distribution of the variables by showing their mean and standard deviation as well as their three quartiles. While the ‘average’ enterprise operating in Luxembourg between 2003 and 2012 is medium-sized, half of them are small and over three quarters of them (more precisely 90%) are small or medium-sized.[19] Similarly, whereas the enterprise turnover is about 65 million euros on average, it is roughly a tenth less for half of them. In other words, the mean value of total turnover is driven by the few large players’ turnover. Wage per capita on the other hand is more symmetrically distributed than employment and turnover, where the mean value is closer to the median, with fewer extreme outliers. The share of product innovators is similar in magnitude to that of process innovators over the period under study, i.e. both shares represent roughly one third of the sample. The percentage of turnover from an innovator’s new products is rather small on average, roughly 20%, and is larger than 30% for only one fourth of the sample. Furthermore, this percentage is split almost equally between incremental and radical innovation’s turnover. Finally, market competition as perceived by the enterprise is almost uniformly distributed across its four modalities.[20] In other words, one third of the sample perceives no competition at all, one third deems competition low, one fourth perceives competition as medium and the remaining 8% deem competition high.

[18] In our jargon, the overlapping year of two consecutive CIS periods, say 2004-2006 and 2006-2008, is 2006. The current period is 2004-2006, and 2006-2008 is referred to as the subsequent period.

[19] Small, medium-sized and large enterprises have respectively their employment headcounts belonging to [10, 49], [50, 249] and [250 and more]. The 90$^{\text{th}}$ percentile value of employment is equal to 233.

[20] Market competition measures the enterprise perception on how rapidly products are becoming old-fashioned or outdated.

Table 2.1: Descriptive statistics on employment, wage, innovation and market competition over the period 2003-2012 using the yearly panel†

Variable	Mean	Std. Dev.	Q_1	Median	Q_3
Employment	124.13	351.41	19.35	45	94
Wage per capita	42.56	17.94	31.06	38.43	49.48
Total turnover	65.25	570.31	2.53	7.07	22.76
Old product turnover	59.85	556.76	2.37	6.53	21.27
Product innovator	0.32	-	0	0	1
% of turnover from new products	6.78	14.74	0	0	5
Radical	3.29	9.20	0	0	0
Incremental	3.49	9.23	0	0	0
% of turnover from new products, if innov.	21.51	19.31	7	17	30
Radical, if innov.	10.44	13.93	0	5	15
Incremental, if innov.	11.07	13.66	0.13	5	15
Process innovator	0.27	-	0	0	1
Market competition					
None	0.30	-	0	0	1
Low	0.30	-	0	0	1
Medium	0.24	-	0	0	0
High	0.16	-	0	0	0
# observations			4689		

† The turnover variables and wage per capita are expressed respectively in millions and thousands of euros. The means of the binary variables represent shares of ones and their standard deviation has no real meaning.

Table 2.2 shows the various sectors being studied, their weight in the sample of analysis and, for each of them, descriptive statistics on employment and innovation over the period 2003-2012. Almost all corporate sectors of the Luxembourgish economy are analysed with the notable exception of the financial sector for which SBS information such as wage or turnover is not available.[21] One third of the industries under study account for three quarters of the sample of analysis. These industries are food, drinks and tobacco (NACE 10-12), metals (NACE 24-25), wholesale trade (NACE 46), transport and storage (NACE 49-53), information and communication (NACE 58-63) and professional, scientific and technical activities (NACE 69-74). The various industries consist mainly of small and medium-sized enterprises (SMEs), which reflects the whole economy as covered by CIS and SBS. Nonetheless, in the sectors of plastics and rubber (NACE 22) and computer and electronics (NACE 26) the ‘average’ enterprise is large. Moreover, one third of the enterprises that belong to the plastics and rubber industry and half of those that belong to the computer and electronic industry are large.[22] The manufacturing sector, as characterised

[21] The missing SBS information for the financial sector is rather unfortunate because this sector represents a sizable percentage of the CIS sample and exhibits larger shares of product and process innovators than those of the whole sample of analysis.

[22] In the latter case, this is explained by the fact that very few computer and electronics enterprises are covered by CIS and SBS, which increases the likelihood of covering mainly large enterprises.

Table 2.2: Descriptive statistics on employment and the share of innovators by sector of activity over the period 2003-2012†

Sector	NACE	% in sample		Employment		Share of innovators	
		CIS	SBS-CIS	Mean	Median	Product	Process
Mining & quarrying	08	0.67	0.85	44	26	0.13	0.08
Manufacturing	-	-	-	157	56	0.37	0.34
Food, drinks & tobacco	10-12	5.49	6.87	107	71	0.19	0.28
Textile & leather	13-15	0.82	1.04	:(c)	:(c)	0.45	0.51
Wood & paper	16-18	2.31	2.92	97	35	0.25	0.37
Chemicals	20	1.46	1.83	76	65	0.45	0.36
Plastics & rubber	22	2.04	2.52	449	117	0.60	0.43
Non-metallic products	23	1.64	2.07	234	89	0.41	0.31
Metals	24-25	7.39	8.91	142	40	0.23	0.28
Computer & electronics	26	0.64	0.81	:(c)	:(c)	0.87	0.61
Electrical equipment	27	1.04	1.30	75	60	0.33	0.25
Machinery & equip., NEC	28	2.65	3.35	211	86	0.76	0.41
Transport equipment	29-30	1.04	1.30	66	53	0.43	0.51
Other manufacturing	31-33	2.18	2.50	29	21	0.43	0.30
Utilities	-	-	-	90	42	0.14	0.20
Electricity, gas & water	35	1.46	1.86	115	42	0.09	0.16
Water supply & waste	36-38	2.01	2.09	68	43	0.17	0.23
Construction	41-43	0.50	0.64	98	46	0.07	0.13
Wholesale trade	46	13.36	16.04	75	35	0.26	0.25
Services	-	-	-	120	41	0.32	0.24
Transport & storage	49-53	15.94	17.21	163	45	0.15	0.22
Information & communic.	58-63	13.85	16.31	106	43	0.52	0.27
Financial sector	64-66	15.21	na	na	na	0.49	0.43
Professional activities	69-74	8.31	9.58	66	26	0.31	0.22
# observations		5971	4689		4689		

†The figures for employment and innovation are based upon the joint SBS-CIS data after merging both datasets. As SBS data is not available (na) for the financial sector, the share of innovators is based on the sole CIS data for that sector. In addition, :(c) indicates confidential data.

by the various industries shown in Table 2.2, exhibits significantly larger mean and median employment than the remaining sectors such as utilities and services among others. The share of product and process innovators is also significantly larger in the manufacturing sector as opposed to utilities and services. It is worth noting that most of the industries (mainly from manufacturing) that exhibit shares of product and process innovators that are larger than those of the whole economy under study also exhibit larger means and medians employment, even though these industries consist mainly of SMEs.

Table 2.3 shows descriptive statistics on the percentage of turnover from new products, incremental and radical. The industries with larger shares of product innovators (see Table 2.2) are also observed to exhibit larger percentages of turnover from new products (see

Table 2.3: Descriptive statistics on the percentage of turnover from new products, incremental and radical, by sector of activity over the period 2003-2012†

Sector	NACE	% of turnover from new products					
		total		radical		incremental	
		Mean	Median	Mean	Median	Mean	Median
Mining & quarrying	08	16	20	6	0	10	10
Manufacturing	-	22	18	11	5	11	8
Food, drinks & tobacco	10-12	15	10	6	0	9	5
Textile & leather	13-15	32	33	8	8	24	20
Wood & paper	16-18	15	10	4	0	11	8
Chemicals	20	23	20	10	10	13	10
Plastics & rubber	22	22	20	11	5	11	10
Non-metallic products	23	21	13	10	3	11	10
Metals	24-25	19	18	9	5	10	5
Computer & electronics	26	27	20	17	6	10	6
Electrical equipment	27	19	10	10	10	9	5
Machinery & equip., NEC	28	23	18	12	10	11	5
Transport equipment	29-30	25	30	11	10	14	15
Other manufacturing	31-33	27	25	17	15	10	8
Utilities	-	10	10	6	5	4	1
Electricity, gas & water	35	11	10	6	8	5	4
Water supply & waste	36-38	9	5	6	5	3	1
Construction	41-43	15	15	5	5	10	10
Wholesale trade	46	21	17	9	5	12	8
Services	-	22	19	11	5	11	5
Transport & storage	49-53	21	10	9	1	12	5
Information & communic.	58-63	24	20	13	10	11	5
Financial sector	64-66	20	10	8	3	12	7
Professional activities	69-74	19	10	7	3	12	5
# observations				4689			

†The figures are based on the joint SBS-CIS data after merging both datasets except for the financial sector where they are based upon the sole CIS data with number of observations equal to 5065. They are reported for product innovators.

Table 2.3), which is consistent with the fact that innovating SMEs are by definition more intensive in innovation output than larger counterparts.[23] The main observed pattern in the industry's mean and median percentage of turnover from new products is that they are either larger for incremental innovations or equally large for incremental and radical innovations with the exception of a few industries such as computer and electronics or manufacturing not elsewhere classified. As for the manufacturing sector as a whole, the mean and median percentage of turnover from new products are similar to those of

[23] An SME that introduces product innovations is more likely to achieve a large percentage of turnover from these innovations.

the wholesale trade and service sectors, unlike in Table 2.2 where we observe a larger share of innovators for the manufacturing sector. Furthermore, this percentage is equally distributed on average between radical and incremental innovations for both manufacturing and services. Finally, the construction industry and the utilities sector are observed to exhibit not only the lowest shares of innovators but also the lowest percentages of turnover from new products.

2.5 Estimation results

Tables 2.4, 2.5 and 2.6 show estimation results of the second-order autoregressive (AR(2)) specification of the model (equation (2.3.2)) estimated by ordinary least squares (OLS), the fixed-effects method, two-step difference GMM [Arellano and Bond, 1991] and two-step system GMM [Blundell and Bond, 1998] using the yearly unbalanced panel data. Table 2.7 shows estimation results obtained using the preferred estimation method, i.e. two-step system GMM, and the yearly panel where 2-year lagged output and innovation variables are used as regressors in lieu of current output and innovation. Table 2.8 shows as a robustness check two-step system GMM estimation results of a first-order autoregressive (AR(1)) model using the biennial panel.[24] Before discussing the results, it is worth noting that the model specified in equation (2.3.2) is dynamically stable as the sum of the coefficients associated with the lagged dependent variables is significantly different from 1 regardless of the estimation method. We also note that the presence of first-order autocorrelation in ε_{it} is rejected, as shown in Tables 2.5, 2.6 and 2.7.[25]

2.5.1 The search for the appropriate estimation method

As mentioned in Section 2.3, the OLS estimator suffers from the omitted-variables bias. More specifically, the coefficient of the AR(1) term, ρ_1, is shown in the econometric literature to be biased upwards while the coefficients of the other explanatory variables $\mathbf{X}_{it}$, i.e. β, are biased towards zero. These two results are reflected in the 'OLS' columns of Table 2.4 where the estimated value of ρ_1 is close to unity and where the estimated coefficients of old product turnover, wage per capita as well as those of the innovation variables are close to zero.

[24] We shall explain later in this section the reason why an AR(1) model is estimated when using the biennial data.

[25] First-order serial correlation in ε_{it} would invalidate some of the moment conditions of Section 2.3. Arellano and Bond [1991] suggest testing for it by checking for serial correlation in $\Delta\varepsilon_{it}$. By construction, $\Delta\varepsilon_{it}$ is serially correlated of order 1, and evidence of it is uninformative. Thus, a second-order serial correlation in $\Delta\varepsilon_{it}$ is indicative of first-order serial correlation in ε_{it}.

The fixed-effects estimator does not suffer from the omitted-variables bias as it within-transforms the data, hence wiping out the firm-specific effect, η_i. However, within-transforming the data induces a correlation between the within-transformed expression of $\ln L_{i,t-1}$ and that of the idiosyncratic error. Since the fixed-effects estimator suggests applying OLS after within-transforming equation (2.3.2), it is shown to be biased when the time dimension, T_i, is small or moderate as in our case. This bias, referred to as Nickell's [1981] bias, is shown to be negative for the AR(1) coefficient, ρ_1. The 'fixed-effects' columns of Table 2.4 show a rather small value for the estimated AR(1) coefficient, reflecting this downwards Nickell bias.

The biased results obtained using the OLS or the fixed-effects estimator, albeit economically irrelevant, are important in our search for the right specification and estimation method of the model. The fixed-effects and OLS estimated values of ρ_1 define respectively the lower and upper bounds of the AR(1) coefficient. Any estimation method that yields an AR(1) coefficient below the fixed-effects or above the OLS counterparts is inappropriate or signals misspecification. Thus, the two-step difference GMM estimates reported in Table 2.5 seem problematic as the AR(1) coefficient is below the lower bound and the coefficients associated with the innovation regressors are economically and statistically insignificant. Instrumenting the endogenous regressors of equation (2.3.3) by their second-order and earlier lagged values seems insufficient to make correct inference. The 'weak instruments' problem pointed out by Blundell and Bond [1998] seems present in our dataset. Therefore, our preferred estimation method is the two-step system GMM which yields the results reported in Tables 2.6 and 2.7.

2.5.2 Determinants of employment

In the 'strict exogeneity' columns of Tables 2.6 and 2.7, all regressors but the lagged dependent variables are treated as strictly exogenous. This assumption is clearly unsatisfactory and induces results that are sensitive to the model specification.[26] When yearly employment level is explained by the average innovation behaviour taken at the current CIS period,[27] the effects of old product turnover and wage are overestimated and take over the effect of innovation. When 2-year lagged innovation regressors are considered, i.e. taken in the previous CIS period, neither old product turnover nor the innovation variables are significant, and wage per capita is only weakly significant, i.e. at the 10% significance level. The much better and more robust results of the 'endogenous regressors' columns of the tables suggest treating output and innovation as endogenous or predetermined and wage as endogenous. This is logical as small, medium-sized and large enterprises have

[26] Repeating new product turnover for each year of the CIS period, while originally reported at the end of the period (see subsection 2.4.1), induces a correlation between this variable and the individual effects. As a result, innovation as well as old product turnover have to be treated as endogenous at least in the sense $\mathbb{E}[\mathbf{X}_{it} v_{it}] \neq 0$.

[27] See footnote 18 in subsection 2.4.1 for the explanation on the timing.

Table 2.4: OLS and fixed-effects estimates of the AR(2) regression using yearly data‡

Regressor	Dependent variable: employment$_t$, in log							
	OLS				Fixed-effects			
	Slope	(Std. Err.)	Slope	(Std. Err.)	Slope	(Std. Err.)	Slope	(Std. Err.)
Employment$_{t-1}$, in log	0.935**	(0.022)	0.935**	(0.022)	0.383**	(0.021)	0.383**	(0.021)
Employment$_{t-2}$, in log	0.004	(0.021)	0.005	(0.021)	-0.019	(0.023)	-0.019	(0.023)
Old product turnover$_t$, in log	0.037**	(0.005)	0.037**	(0.005)	0.141**	(0.014)	0.141	(0.014)
% of turnover from new products$_t$	0.000†	(0.000)	-	-	0.001**	(0.000)	-	-
Radical	-	-	0.000	(0.000)	-	-	0.002*	(0.001)
Incremental	-	-	0.000	(0.000)	-	-	0.001**	(0.001)
Process innovator$_t$	0.008	(0.010)	0.008	(0.010)	0.007	(0.011)	0.007	(0.011)
Wage per capita$_t$, in log	-0.052**	(0.014)	-0.052**	(0.014)	-0.181**	(0.037)	-0.181**	(0.037)
Market competition$_t$								
Low	-0.018†	(0.011)	-0.018†	(0.011)	-0.008	(0.013)	-0.008	(0.013)
Medium	-0.015	(0.011)	-0.015	(0.011)	-0.023†	(0.013)	-0.023†	(0.013)
High	-0.026†	(0.014)	-0.026†	(0.014)	-0.039*	(0.016)	-0.039*	(0.016)
Industry dummies	yes		yes		yes		yes	
Time dummies	yes		yes		yes		yes	
F-test, model significance	$F_{(18,2117)} = 4691.70^{**}$		$F_{(19,2116)} = 4443.09^{**}$		$F_{(17,1618)} = 56.87^{**}$		$F_{(18,1617)} = 53.68^{**}$	
F-test, all $\eta_i = 0$	-		-		$F_{(500,1618)} = 4.07^{**}$		$F_{(500,1617)} = 4.06^{**}$	
# observations	2136							

‡Industry dummies that do not vary over time are wiped out in the within transformation of the fixed-effects estimator.

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

Table 2.5: Two-step difference GMM estimates of the AR(2) regression using yearly data: Arellano and Bond (1991)[‡]

Regressor	Dependent variable: employment$_t$, in log							
	Strict exogeneity				Endogenous regressors			
	Slope	Windmeijer (Std. Err.)	Slope	Windmeijer (Std. Err.)	Slope	Windmeijer (Std. Err.)	Slope	Windmeijer (Std. Err.)
Employment$_{t-1}$, in log	0.241**	(0.084)	0.240**	(0.083)	0.300**	(0.063)	0.321**	(0.057)
Employment$_{t-2}$, in log	-0.003	(0.119)	-0.004	(0.119)	0.020	(0.107)	0.002	(0.109)
Old product turnover$_t$, in log	0.049	(0.035)	0.049	(0.035)	0.070**	(0.027)	0.073**	(0.026)
% of turnover from new products$_t$	0.000	(0.001)	-	-	0.000	(0.001)	-	-
Radical	-	-	0.000	(0.001)	-	-	0.000	(0.002)
Incremental	-	-	0.000	(0.001)	-	-	0.000	(0.001)
Process innovator$_t$	0.004	(0.014)	0.004	(0.014)	0.040†	(0.021)	0.043†	(0.025)
Wage per capita$_t$, in log	-0.085†	(0.049)	-0.085†	(0.050)	-0.163*	(0.079)	-0.206*	(0.094)
Market competition$_t$								
Low	-0.019	(0.019)	-0.019	(0.019)	-0.029†	(0.016)	-0.024	(0.016)
Medium	-0.012	(0.021)	-0.012	(0.021)	-0.055*	(0.0182)	-0.046*	(0.024)
High	-0.066*	(0.032)	-0.066*	(0.032)	-0.067**	(0.024)	-0.062*	(0.025)
Industry dummies	yes		yes		yes		yes	
Time dummies	yes		yes		yes		yes	
# instruments	38		39		181		216	
Hansen test	$chi2_{(21)}$= 27.53		$chi2_{(21)}$= 27.46		$chi2_{(164)}$= 150.06		$chi2_{(198)}$= 186.17	
AR(1) test, diff. residuals	z-stat = -2.05**		z-stat = -2.05**		z-stat = -2.17*		z-stat = -2.28*	
AR(2) test, diff. residuals	z-stat = -0.62		z-stat = -0.62		z-stat = -0.71		z-stat = -0.61	
# observations	2136							

[‡]In the "endogenous regressors" columns, innovation, output and wage are assumed endogenous.

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

Table 2.6: Two-step system GMM estimates of the AR(2) regression using yearly data: Blundell and Bond (1998)[‡]

Regressor	Dependent variable: employment$_t$, in log							
	Strict exogeneity				Endogenous regressors			
	Slope	Windmeijer (Std. Err.)	Slope	Windmeijer (Std. Err.)	Slope	Windmeijer (Std. Err.)	Slope	Windmeijer (Std. Err.)
Employment$_{t-1}$, in log	0.796**	(0.103)	0.796**	(0.102)	0.843**	(0.038)	0.854**	(0.034)
Employment$_{t-2}$, in log	-0.025	(0.031)	-0.026	(0.031)	-0.002	(0.021)	-0.002	(0.019)
Old product turnover$_t$, in log	0.142*	(0.068)	0.143*	(0.067)	0.112**	(0.022)	0.106**	(0.019)
% of turnover from new products$_t$	0.002†	(0.001)	-	-	0.002**	(0.000)	-	-
Radical	-	-	0.002	(0.001)	-	-	0.002**	(0.000)
Incremental	-	-	0.003*	(0.001)	-	-	0.002**	(0.000)
Process innovator$_t$	0.023	(0.020)	0.022	(0.019)	0.022	(0.015)	0.018	(0.016)
Wage per capita$_t$, in log	-0.179**	(0.070)	-0.179**	(0.070)	-0.120*	(0.050)	-0.141**	(0.046)
Market competition$_t$								
Low	-0.009	(0.018)	-0.009	(0.018)	-0.015	(0.011)	-0.019	(0.011)
Medium	-0.001	(0.019)	-0.001	(0.019)	-0.024	(0.016)	-0.023	(0.015)
High	-0.032	(0.021)	-0.032	(0.021)	-0.035*	(0.016)	-0.035*	(0.016)
Industry dummies	yes		yes		yes		yes	
Time dummies	yes		yes		yes		yes	
# instruments	45		46		220		263	
Hansen test	$\text{chi2}_{(26)} = 63.09^{**}$		$\text{chi2}_{(26)} = 62.70^{**}$		$\text{chi2}_{(201)} = 228.26$		$\text{chi2}_{(243)} = 265.40$	
AR(1) test, diff. residuals	z-stat = -2.99**		z-stat = -2.99**		z-stat = -3.13**		z-stat = -2.35*	
AR(2) test, diff. residuals	z-stat = -0.53		z-stat = -0.52		z-stat = -0.57		z-stat = -0.63	
# observations	2136							

[‡]In the "endogenous regressors" columns, innovation, output and wage are assumed endogenous.

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

Table 2.7: Two-step system GMM estimates of the AR(2) regression with lagged innovation as regressors using yearly data: Blundell and Bond (1998)‡

Regressor	Dependent variable: employment$_t$, in log							
	Strict exogeneity				Endogenous regressors			
	Slope	Windmeijer (Std. Err.)	Slope	Windmeijer (Std. Err.)	Slope	Windmeijer (Std. Err.)	Slope	Windmeijer (Std. Err.)
Employment$_{t-1}$, in log	0.743**	(0.216)	0.742**	(0.216)	0.935**	(0.028)	0.932**	(0.028)
Employment$_{t-2}$, in log	-0.194	(0.111)	-0.195	(0.112)	-0.062	(0.042)	-0.056	(0.040)
Old product turnover$_{t-2}$, in log	0.273	(0.193)	0.274	(0.193)	0.089**	(0.029)	0.089**	(0.029)
% of turnover from new products$_{t-2}$	0.005	(0.003)	-	-	0.002**	(0.000)	-	-
Radical	-	-	0.005	(0.004)	-	-	0.003**	(0.000)
Incremental	-	-	0.005	(0.003)	-	-	0.002**	(0.000)
Process innovator$_{t-2}$	0.031	(0.026)	0.031	(0.026)	-0.002	(0.018)	0.005	(0.022)
Wage per capita$_t$, in log	-0.237†	(0.132)	-0.238†	(0.070)	-0.104*	(0.040)	-0.112**	(0.039)
Market competition$_t$								
Low	-0.010	(0.025)	-0.009	(0.025)	-0.010	(0.010)	-0.013	(0.011)
Medium	-0.003	(0.025)	-0.003	(0.025)	-0.015	(0.013)	-0.020	(0.015)
High	-0.047	(0.031)	-0.047	(0.031)	-0.028†	(0.015)	-0.043*	(0.018)
Industry dummies	yes		yes		yes		yes	
Time dummies	yes		yes		yes		yes	
# instruments	45		46		172		199	
Hansen test	$\text{chi2}_{(26)} = 55.76^{**}$		$\text{chi2}_{(26)} = 55.63^{**}$		$\text{chi2}_{(153)} = 165.52$		$\text{chi2}_{(179)} = 189.01$	
AR(1) test, diff. residuals	z-stat = -3.04**		z-stat = -3.04**		z-stat = -3.37**		z-stat = -3.33*	
AR(2) test, diff. residuals	z-stat = 0.17		z-stat = 0.17		z-stat = -0.29		z-stat = -0.30	
# observations	2136							

‡In the “endogenous regressors” columns, output and innovation are assumed predetermined, and wage is assumed endogenous.

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

different capabilities of production and different bargaining power in wage determination. Furthermore, larger firms are found in the economic literature to have an unambiguously larger probability to achieve product or process innovation (see e.g. Raymond et al. [2006b],Raymond et al. [2010a]), and to achieve lower percentages of turnover from new products [see e.g. Brouwer and Kleinknecht, 1996, Janz et al., 2004]. Therefore, the results shown in the rightmost columns of Tables 2.6 and 2.7 will be used for discussion.

The role of technological innovation

When we account for the endogeneity of turnover, innovation and wage by controlling for the fact the firm innovation and production capabilities as well as its bargaining power in wage determination vary with its size, Tables 2.6 and 2.7 show a semi-elasticity of employment with respect to the rate of new product turnover of 0.2. In other words, *ceteris paribus* the firm employment level increases on average by 0.2% in each year of the CIS period upon increasing its rate of new product turnover by one percentage point over that period. This semi-elasticity is similar in magnitude and not statistically different for incremental and radical innovation whether innovation is considered at period t or $t-1$ (see Tables 2.6 and 2.7 respectively). The results also show that the effect of product innovation on employment operates with a certain time lag, which is rather common in the empirical literature [see e.g. Lachenmaier and Rottmann, 2011]. In order to fully and more accurately assess this lagged effect, yearly data on both employment and innovation is required so that models such as distributed lag regressions [Hall et al., 1986] or panel vector autoregressions [Holtz-Eakin et al., 1988] could be estimated.

Unlike product innovation, process innovation achievement does not seem to affect significantly firm employment. One explanation resides in the fact that firms that operate in Luxembourg consider process innovation as an intermediate stage towards achieving product innovation, the latter being their ultimate goal.[28] The positive effect of product innovation coupled with the insignificant effect of process innovation are in accordance with Van Reenen's [1997] results for UK manufacturing and at odds with those of Lachenmaier and Rottmann [2011] for German manufacturing. Both studies make use of a rather long yearly panel and uncover a lagged effect of technological innovation on employment. The positive effect of product innovation in Van Reenen [1997] study peaks after 6 years, which might also be the case for Luxembourg, hence the need for longer yearly innovation data.

[28] Process and product innovation are significantly correlated in our data. Furthermore, cross-dynamics between them suggests that process innovation Granger-causes product innovation while the reverse causality does not hold.

Other determinants

The dynamic feature of demand for employment reflecting among others adjustment costs shows in the results as current employment is positively and significantly affected by one-year lagged employment. The second-year negative lagged effect is not uncommon in the empirical literature [see e.g. Nickell and Wadhwani, 1991], although insignificant in our case. The firm output, measured by old product turnover, and wage per capita enter significantly the employment equation with the expected signs. In other words, firm output and wage per capita affect positively and negatively respectively the firm-level of employment with an elasticity of 0.1% in absolute value. Unfortunately, the effects of new and old product turnover on employment cannot be compared in magnitude as a semi-elasticity is estimated in one case while an elasticity is estimated in the other. However, estimation results of an alternative specification of the model where only dichotomous innovation regressors are considered show that *ceteris paribus* the employment level differential between product innovators and firms with unchanged products lies between 4% and 11% (see Table 2.B.3). Finally, we find that, *ceteris paribus,* an enterprise that perceives high market competition with respect to rapid product obsolescence tends to decrease its level of employment by about 4% compared to the one that perceives no competition, which is also consistent with the economic literature.[29]

2.5.3 Robustness analysis

We now present estimation results of the model using the biennial panel data. As explained in subsection 2.4.1, the main advantage of using the biennial panel is that we no longer need to resort to ‘imputation’ nor to repeated values of old and new product turnover to explain employment. As a result, the timing of the effect of innovation on employment is different and more precise than for the yearly panel. However, the biennial panel consists of less observations, hence suffers from degrees of freedom, and may yield larger standard errors of the estimates.

Table 2.8 shows two-step GMM estimates of an AR(1) specification of the model.[30] As expected, the standard errors of these estimates are larger than those of the corresponding estimates of Tables 2.6 and 2.7. The results obtained with the biennial panel are similar to those obtained with the yearly panel in terms of direction and significance of the coefficients but different in terms of magnitude. The AR(1) coefficient remains positive and significant suggesting the presence of dynamics in the firm demand for employment but is smaller in

[29] See for instance Konings and Walsh [2000] who analyse the relation between product market competition and employment in unionised and non-unionised UK firms. However, such a distinction cannot be made in our data.

[30] We have also estimated an AR(2) model, which decreased the number of observations of the biennial panel by 50%, and obtained an insignificant AR(2) coefficient like the yearly panel.

Table 2.8: Two-step system GMM estimates of an AR(1) specification of the model using biennial data‡

Regressor	Dependent variable: employment$_t$, in log							
	Endogenous output and innovation				Predetermined output and innovation			
	Slope	Windmeijer (Std. Err.)	Slope	Windmeijer (Std. Err.)	Slope	Windmeijer (Std. Err.)	Slope	Windmeijer (Std. Err.)
Employment$_{t-1}$, in log	0.553**	(0.140)	0.559**	(0.139)	0.549**	(0.168)	0.545**	(0.170)
Old product turnover, in log	0.283**	(0.085)	0.280**	(0.085)	0.260*	(0.106)	0.262*	(0.107)
% of turnover from new products	0.005**	(0.002)	-	-	0.005*	(0.002)	-	-
Radical	-	-	0.006**	(0.001)	-	-	0.006*	(0.003)
Incremental	-	-	0.004**	(0.001)	-	-	0.004*	(0.002)
Process innovator	0.035	(0.026)	0.034	(0.026)	0.027	(0.022)	0.028	(0.022)
Wage per capita$_t$, in log	-0.264**	(0.084)	-0.259**	(0.083)	-0.199*	(0.090)	-0.200*	(0.091)
Market competition$_t$								
Low	-0.014	(0.024)	-0.014	(0.023)	-0.017	(0.025)	-0.017	(0.025)
Medium	-0.003	(0.025)	-0.002	(0.024)	-0.006	(0.028)	-0.007	(0.028)
High	-0.052*	(0.025)	-0.054*	(0.025)	-0.067*	(0.030)	-0.067*	(0.030)
Industry dummies	yes		yes		yes		yes	
Time dummies	yes		yes		yes		yes	
# observations	1068							

‡In the ‘endogenous’ and ‘predetermined’ columns, output and innovation are taken at periods t and t-1 respectively. Wage per capita is assumed endogenous in the estimation.

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

size, which is logical as the time dimension t now refers to two years. Similarly, the effect of innovation on employment appears more sizable and the distinction between radical and incremental innovation is sharper where the semi-elasticities now vary between 0.4% and 0.6% as compared to 0.2% and 0.3% obtained with the yearly panel. In other words, a one percentage point increase in the percentage of turnover from incremental (or radical) innovation yields a 0.4% (or 0.6%) increase in the firm level of employment. Process innovation remains insignificant and wage per capita still has a negative and significant but more sizable effect on employment. Its elasticity of employment as well as the output elasticity of employment almost trebles. As with the yearly panel, the effect of old product turnover on employment cannot be compared with that of new product turnover. However, the differential in employment level between product innovators and firms with only old product turnover passes from 4% to 11% (see Table 2.B.3). Finally, the firm perception of a high market competition also has a more sizable negative impact on the firm demand for employment.

2.6 Conclusion and policy implications

The age-old and still debated question whether technological change creates or destroys jobs is tackled in this study. We develop a simple theoretical model with endogenized product and process innovation which allows a separate investigation of the employment effects of product and process innovation. The employment effect of product innovation is furthermore distinguished between radical and incremental innovation. An empirical model of firm demand for employment is then estimated using several waves of yearly structural business statistics merged with biennial innovation survey data and pertaining to the period 2003-2012. After searching for the appropriate estimation method, i.e. Blundell and Bond's [1998] two-step system GMM, we obtain the following results. Firstly, in order to uncover a significant causal relation from technological innovation to employment, we must account for the fact that larger firms are more likely to achieve technological innovation. Thus, product innovation is found to exert a positive effect on employment where the semi-elasticity of the latter with respect to the percentage of turnover from new product lies between 0.2% and 0.5%. This positive effect of product innovation on employment operates with a certain time lag. Secondly, we find some evidence of a significantly more sizable effect of radical innovation especially when we use the biennial panel with no imputed values of innovation. The differential in the employment effect between radical and incremental innovation is estimated to be 50%. Thirdly, while the effect of old product turnover on employment cannot be compared with that of new product turnover, the employment level differential between product innovators and firms with unchanged products lies between 4% and 11%. Fourthly, unlike product innovation, process innovation does not have any significant effect on the firm level of employment. Fifthly, the firm output and wage per capita have respectively the expected positive and negative effect on firm employment. Finally, a perception by the firm of a high market competition impacts negatively its level of employment.

Our empirical findings are consistent with the literature which emphasizes the positive impact of product innovation on employment, while a more subtle and ambiguous employment effect associated with process innovation (Entorf and Pohlmeier [1990], Brouwer et al. [1993], Smolny [1998], Audretsch and Thurik [1999], Greenan and Guellec [2000], Pianta [2003], Benavente and Lauterbach [2008], Hall et al. [2009], Crespi and Tacsir [2011], Vivarelli [2013], Vivarelli [2014], Harrison et al. [2014], Peters et al. [2014], Calvino and Virgillito [2017]). In particular, using data on Italian SMEs over the period 1995-2003, Hall et al. [2009] discover positive effects of new and old products and no evidence of displacement effect associated with process innovation. In line with our results, Hall et al. [2009] highlight the equal contribution of product innovation and sales of old products to employment growth. Using firm-level micro-data for the period 1998-2001 in Chile, Benavente and Lauterbach [2008] suggest that product innovation affects employment positively and significantly. On the other hand, no evidence is found that process innovations significantly affect employment dynamics after controlling for investment and sectoral patterns. Similar results are derived for Crespi and Tacsir [2011] which discover positive links between product innovation and employment growth at the firm level using micro data from innovation surveys in four Latin American countries (Argentina, Chile, Costa Rica, and Uruguay). By the same token, no significant effect of process innovation is identified. Moreover, Peters et al. [2014] find out positive employment growth for product innovators particularly during economics booms and limited impact of process innovations for 26 European countries over the period 1998-2010.

The assessment of the effect of technological change on employment at the firm level has far-reaching implications for policy makers. Luxembourg is an open small economy with the highest GDP in the OECD area and among the highest in the world. The OECD Review of Innovation Policy report (2015) points out that Luxembourg still faces challenges including reducing unemployment, strengthening productivity growth and diversifying the economy. The overall objective of Luxembourg innovation policy is to strengthen innovation as a driver of sustainable productivity, employment growth and competitiveness. Consistent with previous findings, our results highlight the substantial positive impact of product innovation on employment. The immediate economic implication calls for the support of product innovation. There is some evidence that the effect of radical innovation measured by the share of sales of products new to the market is more sizable than incremental innovation, measured by the share in total sales of products new to the firm. In this context, policy makers should aim to encourage companies to undertake innovation activities, particularly, radical innovations as a constant driver of national employment growth. Moreover, our results highlight the crucial contribution of sales of old products to employment growth. Consequently, managers should aim at minimizing the effects of cannibalization, further secure the sales of old products and corresponding market share. Managers may need to take into account the market position of existing products and introduce product innovation in light of the products life cycle phase.

Albeit very interesting, the results can hypothetically be improved on. Firstly, while the positive effect of technological product innovation on employment seems robust, we cannot assess accurately the time lag required for product innovation to translate into jobs. For this, we need yearly data on both innovation and employment that would be used in more advanced dynamic models such as distributed lag regressions or panel vector autoregressions. Secondly, our data does not allow us to discriminate between skilled and unskilled workers so that the ‘skilled-biased technological change’ hypothesis cannot be tested. Finally, the assumption of a short-run fixed capital stock can be released in the theoretical model so that a capital stock regressor is included in the empirical model. This assumption is motivated by the unavailability of capital stock in the data and by too few observations on which such a stock would be constructed. Nevertheless, we do not expect the inclusion of capital stock to change our main results on the relation between innovation and employment. If anything, controlling for capital in the regression is expected to alter the effect of wage reflecting greater substitution possibilities between capital and labour costs [Van Reenen, 1997].

To conclude, we believe that this study, being the first ever to investigate on firm level how technological change affects employment in the Luxembourgish non-financial corporate sector, can pave the way for additional studies on that subject while improving on its current shortcomings.

Appendix

2.A First-order Taylor expansion

Let

$$\ln Y = \ln\left(Y_{old} + Y_{new}\right). \tag{2.A.1}$$

Equation (2.A.1) can be written as

$$\begin{aligned}
\ln Y &= \ln\left(\frac{Y_{old}+Y_{new}}{Y_{old}}Y_{old}\right) = \ln\left(\frac{Y_{old}+Y_{new}}{Y_{old}}\right) + \ln Y_{old} \\
&= -\ln\left(\frac{Y_{old}}{Y}\right) + \ln Y_{old} = -\ln\left(\frac{Y-Y_{new}}{Y}\right) + \ln Y_{old} \\
&= -\ln\left(1-\frac{Y_{new}}{Y}\right) + \ln Y_{old}.
\end{aligned} \tag{2.A.2}$$

Using first-order Taylor expansion around $\frac{Y_{new}}{Y} < 1$ yields

$$\ln Y \simeq \frac{Y_{new}}{Y} + \ln Y_{old}. \tag{2.A.3}$$

Using the fact that $Y_{new} = Y_{new\ firm} + Y_{new\ market}$ yields

$$\ln Y \simeq \frac{Y_{new\ firm}}{Y} + \frac{Y_{new\ market}}{Y} + \ln Y_{old}. \tag{2.A.4}$$

2.B Variable definitions and additional results

Table 2.B.1: List of variables

Var. name	Definition	Type
Dependent variable		
L	Firm-level employment	Continuous
Independent variables:		
$\frac{(Y_{new\ firm})}{Y}$	The share in total sales of products new to the firm	Continuous
$\frac{(Y_{new\ market})}{Y}$	The share of sales of products new to the market	Continuous
Y_{old}	Sales of old or unchanged products	Continuous
Process	1 if process innovator	Binary
$\frac{W}{P}$	Real wage	Continuous
Market	Market competition variables that measure how rapidly products are becoming old-fashioned or outdated	Categorical
None	1 if not relevant	
Low	1 if low	
Medium	1 if medium	
High	1 if high	
τ	A full set of time dummies to control for the general macroeconomic demand shocks	Binary

Table 2.B.2: Cross-correlation table

Variables	Employment	Wage	Turnover	Old product	Product innovator	% sales of new	% sales of radical	% sales of incremental	Process innovator	Low	Medium	High
Employment	1.00											
Wage per capita	0.12	1.00										
Total turnover	0.31	0.19	1.00									
Old product turnover	0.27	0.18	0.99	1.00								
Product innovator	0.18	0.16	0.04	0.02	1.00							
% sales of new products	0.09	0.11	0.01	-0.01	0.67	1.00						
% sales of radical products	0.08	0.10	0.02	0.00	0.52	0.80	1.00					
% sales of incremental products	0.06	0.07	0.00	-0.01	0.55	0.80	0.28	1.00				
Process innovator	0.15	0.05	0.06	0.05	0.40	0.31	0.24	0.25	1.00			
Market competition												
Low	-0.01	-0.03	0.03	0.03	0.00	-0.03	-0.04	-0.01	0.01	1.00		
Medium	0.04	0.07	0.00	-0.00	0.11	0.09	0.12	0.02	0.07	-0.37	1.00	
High	0.00	-0.03	-0.02	-0.02	0.06	0.05	0.04	0.04	0.00	-0.28	-0.24	1.0

Table 2.B.3: Two-step system GMM estimates using dichotomous measures of innovation

Regressor	Dependent variable: employment$_t$, in log			
	Yearly panel		Biennial panel	
	Slope	Windmeijer (Std. Err.)	Slope	Windmeijer (Std. Err.)
Employment$_{t-1}$, in log	0.850**	(0.037)	0.589**	(0.144)
Employment$_{t-2}$, in log	-0.000	(0.020)	-	-
Old product turnover$_t$, in log	0.100**	(0.020)	0.224*	(0.087)
Product innovator$_t$	0.042**	(0.015)	0.107**	(0.041)
Process innovator$_t$	0.026	(0.020)	0.030	(0.023)
Wage per capita$_t$, in log	-0.133**	(0.046)	-0.175*	(0.080)
Market competition$_t$				
Low	-0.015	(0.011)	-0.017	(0.025)
Medium	-0.021	(0.010)	-0.008	(0.029)
High	-0.037*	(0.018)	-0.068*	(0.030)
Industry dummies	yes		yes	
Time dummies	yes		yes	
# observations	2136		1068	

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

Chapter 3

An evolutionary approach to the two-way relationship between innovation and firm performance: a firm-level panel analysis from Luxembourg

3.1 Introduction

Innovation is primarily regarded as a crucial source of sustainable competitive advantage for firm growth and performance. Innovation is closely associated with inner social and technological changes. At the level of individual invention, innovation could arise from "entrepreneurial fact" or innovative impetus which is the core of firms' competition and dynamic efficiency. According to Schumpeter [1934, pp.65]: "It is, however, the producer who as a rule initiates economic change, and consumers are educated by him if necessary; they are, as it were, taught to want new things, or things which differ in some respect or other from those which they have been in the habit of using..... To produce means to combine materials and forces within our reach. To produce other things, or the same things by a different method, means to combine these materials and forces differently. "

The "entrepreneurial fact" at the firm level is responsive to economic pressures and opportunities, induced by economic forces that predict the latent demand. The major innovations in an established industry lead to technological and product market spillovers. Endogenous growth theory acknowledges the importance of spillovers from firms at the technological frontier (Grossman and Helpman [1991], Aghion and Howitt [1990], Klette and Kortum [2002]). Schmookler [1962] points out that the incentive to innovate is affected by the excess of expected returns over expected cost. Scientific progress may reduce expected costs and increase the likelihood of delivering certain innovation. Innovation contributes to the long-run growth and socio-economic development at a broader level, which further facilitates the emergence of new innovations and underlying scientific discovery.

Schumpeter [1934, pp.65] wrote that: “It is not possible to explain economic change by previous economic conditions alone.” The most interesting economic issues are associated with changes either in terms of external market conditions or within the industry or firms. Evolutionary economics explicitly deals with this with the broad connotations of ‘evolutionary’ which imply a concern with long-term progressive changes (Nelson and Winter [2009]). Innovation is characterized by high uncertainty, high cumulativity and path dependency in an evolutionary framework. The exploration of a two-way interdependent relationship between innovation and firm performance is fully consistent with the approach of evolutionary economics.

The literature has mostly overlooked the simultaneous relationship between firm performance and innovation output. The extant literature which follows a structural modeling approach mainly emphasizes other relationships such as R&D and productivity. For instance, on studying the returns to R&D, Griliches [1979] recognizes the problem of simultaneity and proposes to establish a system of recursive equations, where future output depends on current R&D which further depends on past output. Focusing on the relationship between innovation and productivity, Crépon et al. [1998] form a nonlinear structural model to investigate the relationship among innovation input, innovation output and productivity levels. This study is closely linked to Cainelli et al. [2006] which explores the two-way relationship between innovation and economic performance in service sector using the Italian Community Innovation Survey. Cainelli et al. [2006] argue that, given the cumulative and path-dependence nature of innovation, it is likely that innovation capabilities and economic performances are interdependent and this mechanism will persist and reinforce over time. Cainelli et al. [2006] also endorse the positive self-reinforcing mechanism between innovation and firm performance which forms a virtuous circle.

In this chapter, I explore the two-way dynamic link between innovation and firm performance on a micro-level perspective. I employ the unique Luxembourgish longitudinal firm-level data based on the merged dataset of Community Innovation Survey and Structural Business Statistics over the period 2003 – 2012. These data are used to identify whether past firm performance affects product and process innovation, and the extent to which innovation has an impact on future firm performance. I establish a fully recursive simultaneous model which acknowledges the dynamic nature of the system. The lagged latent innovation variable is dependent on the past firm performance and further determines the current firm performance. More specifically, the contribution is characterized by several features:

- I aim at capturing a dynamic self-reinforcing two-way relationship between innovation and firm performance. To this purpose, I take full account of the simultaneity problem and endogeneity of firm performance and innovation of either kind.
- The empirical literature has mostly focused on single type of innovation and overlooked the differentiated pattern between innovation types. This chapter aims at contributing to previous empirical work by explicitly distinguishing different mechanisms of product and process innovation and their distinct impacts on firm performance.
- It is the first study using Luxembourgish micro data which aims at testing the presence of two-way relationship. The panel dataset has the advantage of capturing the true causality link between innovation and performance.

By and large, I discover that superior firm performance facilitates the emergence of process innovation, and process innovation contributes to firm performance by gaining successful and sustainable competitive advantage which forms a virtuous circle. Nonetheless, an opposite conclusion is reached for product innovation which results from market cannibalization and latent market risk associated with the initial stage of the product life cycle.

The analysis presented in this chapter is structured as follows. In Section 3.2 the key relationship is identified between innovation and economic performance. In particular, I stress different types of innovation and their diverse impacts on firm performance. Section 3.3 discusses the econometric model and relevant econometric background. Section 3.4 provides a summary of data construction and variables selection along with ‘ve statistics of the dataset. In Section 3.5, estimation results are shown for the model with latent product and process innovation combined with the model with both latent product and process innovation propensity to explain firm performance. Section 3.6 presents the analysis of robustness check. Section 3.7 synthesizes the main findings and concludes.

3.2 Firm performance and innovation

3.2.1 The impact of firm performance on innovation

Schumpeter emphasizes the costly, risky and uncertain nature of innovation activities. There is much debate centered on the Schmooklerian hypothesis whether innovation is responsive to market demand. Using industry-level data, Schmookler [1962] points out that variations in innovation are a consequence of economic conditions with which output is positively correlated. Schmookler [1962] argues that the expected profits from innovation, the ability to finance, and the dissatisfaction from customers which motivates the innovation are all likely to be associated with sales. Schmookler [1962] further explains the phenomenon in a similar fashion as Schumpeter concerning financial capability. When the industry's sales are high, more financial resources can be allocated to innovation than recession periods. Moreover, buyers will be more capable of supporting innovations financially. Innovation is also more likely to be delivered when a fixed percentage of sales are set for research budgets. In addition, Schmookler [1962] emphasizes the motivation to innovate from the demand side. Innovation may stem from dissatisfaction with existing products. Modifications and improvements in the products will be done to satisfy the burgeoning new requirements from customers. Moreover, new sales and new customers may bring about new preferences and elevated standards.

The empirical studies have derived less clear-cut findings on this front. For example, Brouwer and Kleinknecht [1999] and Geroski and Walters [1995] find empirical support for the Schmooklerian hypothesis. In particular, by examining cyclical patterns of innovative activity in the United Kingdom over the period 1948 – 1983, Geroski and Walters [1995] discover clear evidence of a long-term secular relation between the level of innovative activity and the level of economic activity. Fontana and Guerzoni [2008] argue that demand stimulates innovation by providing economic incentives and reducing uncertainty, particularly for process innovation. Nonetheless, Mensch [1979] argues that innovation is more likely to be counter-cyclical. In other words, innovation activities are in fact triggered by unfavorable economic conditions which oblige firms to invest more R&D efforts and resources in order to survive. Kleinknecht and Verspagen [1990] empirically support this idea and suggest a simultaneous relationship between demand and innovation. Scherer [1982] casts doubt on demand-pull theory when all manufacturing industry is investigated and when industrial materials inventions are the focus. Nemet [2009] points out that for non-incremental technological change, inventors of the most important inventions do not respond positively to strong demand-pull policies. Meanwhile, Artés [2009] argues that R&D intensity is not affected by monopoly power, but the probability of a firm being innovative increases with it.

In general, the funding of risky, long-term innovative projects calls for financial support. A healthy cash flow is central to implement innovation. Accordingly, it is widely accepted in the economic literature that large firms tend to have unambiguously larger probability to achieve product or process innovation (see e.g. Cohen and Klepper [1996], Raymond et al. [2006a], Raymond et al. [2010b]). For example, Cohen and Klepper [1996] imply an advantage to large firm size in conducting R&D based on R&D cost spreading. Mairesse et al. [1999] confirm that cash flow helps to determine future R&D in the firm. Piva and Vivarelli [2007] point out that exporting and liquidity-constrained firms, and firms not receiving public subsidies and not heading a business group are particularly sensitive to sales when deciding the amount of R&D expenditures. Furthermore, Cainelli et al. [2006] point out that the service sectors such as telecommunications, transports and finance are associated with the establishment of expensive technological infrastructures, which require better access to financial resource. Those sectors comprise a substantial part of Luxembourgish economy. Accordingly, past healthy economic performance might be particularly important to pave the way for innovative activities.

3.2.2 The impact of innovation on firm performance

Schumpeter acknowledges the great impact of successful introduction of product, process and organizational innovations on firm performance. Creative destruction is associated with dynamic efficiency rather than static efficiency. Dosi and Marengo [2000] argue that dynamic competencies refer to the abilities to learn, to adapt, to solve problems, in particular, to find new problems to solve.

In the framework of evolutionary economics, Nelson and Winter [2009] emphasize the key role played by innovation as the most important weapon for firms to gain successful and sustainable competitive advantage in an economic and technological context. Moreover, Nelson and Winter [2009] suggest the presence of assets such as knowledge accumulated over periods, a set of learned principles and routines which give rise to generic differences between firms. Firms cannot naturally preserve a superior competitive position based on the existing routines. Innovation involves upgrading existing routines or developing new routines. Firm's competitive position finally involves many factors such as the quality of firm's routines combined with the importance of knowledge inside the firm, organizational structure and R&D efforts.

There is a large body of literature which focuses on the relationship between innovation and productivity. This positive effect is confirmed, among other studies, by Crépon et al. [1998] for French manufacturing firms, Griliches [1987] for U.S. manufacturing corporations, Hall et al. [2009] for Italian SMEs, Cefis and Ciccarelli [2005] for UK manufacturing firms, and Marsili and Salter [2005] for Dutch manufacturing firms.

Another strand of literature focuses on the relationship between innovation and profit (Scherer [1965], Geroski et al. [1993], Geroski and Machin [1993], Leiponen [2000]). For example, Scherer [1965] finds out that corporate innovative activity has a favorable effect on profits by facilitating the growth of sales at constant profit margins. Moreover, business recessions appear to have an especially unfavorable impact on the sales and profits of highly inventive corporations.

Using a panel data covering 721 U.K. manufacturing firms observed over the period 1972-1983, Geroski et al. [1993] discover the positive effect of innovation on corporate profitability especially during recession. They identify the direct but transitory positive effect on profitability associated with product and process innovation. By contrast, the indirect effect of process of innovating exhibits a more important role in profitability which signals the transformation of a firm's internal capabilities. Moreover, Geroski et al. [1993] point out that the difference in terms of profitability is not closely timed with the introduction of specific innovation. In most cases, only a clear difference in profitability between non-innovators and innovators is evident at the end of period.

Likewise, Cefis and Ciccarelli [2005] discover a positive effect of innovation on profits that decreases over time using a panel data covering 267 UK manufacturing firms over the period 1988-1992. In addition, Leiponen [2000] investigates the impact of innovation on profitability using dynamic model based on a panel of Finnish manufacturing firms. This study is analogous to Leiponen [2000] in terms of clear distinction between product and process innovation. Furthermore, Leiponen [2000] discovers positive effect of process innovation and negative effect of product innovation on profit, which is consistent with our findings. Consistent with the literature on firm performance and innovation, for example,Klomp and Van Leeuwen [2001], Jefferson et al. [2006], Cainelli et al. [2006], Prajogo [2006], Artz et al. [2010], Isogawa et al. [2012], this chapter uses turnover to measure the overall economic performance of firms. Before proceeding to the two-way relationship, I may briefly illustrate the role of product and process innovation and their differentiated impacts on firm performance.

3.2.3 The differentiated role of product and process innovation

The distinction between a product and a process innovation has long been recognized as crucial different strategies of firms in response to different challenge (Utterback and Abernathy [1975]). It is crucial to distinguish between product and process innovation in view of their varied impacts on firm performance (Abernathy and Clark [1985] ,Ettlie et al. [1984], Yamin et al. [1997]). To the best of the author's knowledge, empirical works have given limited attention to identify the differentiated patterns associated with innovation types. Most studies on the relationship between innovation and firm performance are predominantly based on a single innovation type.

Nelson and Winter [2009] stress that Schumpeterian dynamics differ between a new product or a new process innovation. The distinction between product and process innovation is crucial as product and process innovation tend to associate with diverse competencies and organizational skills (Damanpour and Gopalakrishnan [2001], Leiponen [2000]). Product innovations are primarily market and customer driven, whereas process innovations are efficiency driven and focus on internal change (Utterback and Abernathy [1975], Damanpour and Gopalakrishnan [2001]). Product innovation requires the firm to understand customer needs and design, manufacture the product to suit the needs. It also requires successful commercialization of final products. Meanwhile, process innovation necessitates the application of new technology to improve efficiency of production and delivery of the outcome (Ettlie et al. [1984], Damanpour and Gopalakrishnan [2001]). Given the diversity of innovative activities, Damanpour [1991] points out that not all innovative activities relate to firm performance in the same way. In particular, Utterback and Abernathy [1975] reveal that innovation strategies vary systematically with differences in the development state achieved in the production process, firm's environment and strategy for competition and growth. For example, product innovations occur more frequently at an early stage of a company than process innovations. Accordingly, the impact on firm performance may vary based on the diverse types of innovation strategies adopted.

A product innovation is the introduction of a good or service that is new or has significantly improved characteristics or intended uses. Product innovation can exert both positive and negative impact on corporate performance. Product innovation leads to new products and new sales which change upward the demand curve for goods or services. Thus, product innovation contributes to an elevated temporary market position and competitive advantage (Petrin [2002]). By differentiating products from other competitors, firms can reap a price premium (Baines et al. [2009]). Montgomery [1995] argue that by launching a series of product innovations, firms can earn a continuum of monopoly profit. In this degree, product innovation brings about direct positive effect on sales. To illustrate, Artz et al. [2010] discover that product innovations are found to be positively related to firm performance measured as return on assets and sales growth. Hua and Wemmerlöv [2006] confirm that the rate of new product introduction for a PC firm is positively associated with market share and growth performance.

Nonetheless, product innovation can exert adverse impact on firms' sales. The new product is accompanied by cannibalization effect if a firm produces multiple products. Industrial organization elucidates various reasons which prevent innovative firms from staying innovative. An incumbent innovator may fear the cannibalization effect where new products may simply drive out old products or compete with firms existing products from previous innovations hence hurt the total sales (Schumpeter [1942]). Jefferson et al. [2006] also point out that innovation does not necessarily improve firm performance as the decline of firms' sale of existing products might occur with product innovation. Isogawa et al. [2012] examine the relationship between product innovation and firms' sales of a new product and of existing products. Isogawa et al. [2012] argue that the cannibalization effect is less for new-to-market product innovation than new-to-firm product innovation. Consequently, only a firm with new-to-market product innovation tends to achieve large sales from a new product. Accordingly, the cannibalization effect induced by product innovation is substantial and the net impact on total sales is unclear.

Moreover, product innovation contains more risk as the commercialization of the final results is not guaranteed. Nelson and Winter [2009] stress that for product innovation, the profitability to the firm depends strongly on the uncertain market reactions and potential consumers. By launching a new product, the initial introduction stage of new products is often associated with small or no market. It rarely occurs when a new product and fantastic marketing campaign create consumer demand straight away. In general, it takes time and effort before new products achieve the momentum. With the substantial marketing costs incurred by launching a new product, most firms earn negative profits for the initial stage of the product life cycle. The amount and duration of these negative profits vary from one market to another. In particular, firms in manufacturing sector could earn profit quite quickly whereas firms in other sectors could take years. In addition, it is also likely that all demand is satisfied due to prior innovations and there is no need for further product innovation (Peters [2009]). Firms which introduce new-to-firm product innovation may face severe competition as the product is already provided by other firms. By and large, the net effect of product innovation is determined by the difference in degree of positive and negative effects induced. In view of inherent risks associated with new product, in the short run, the influence of product innovation on firm performance is ambiguous.

A process innovation refers to the implementation of a new or significantly improved production or delivery method. Process innovation contributes substantially to the reduction of unit cost and improvement of the quality of products and services. The cost reduction results in a lower price which will expand demand by passing on to price advantage, which will stimulate demand for these products. Becker and Egger [2013] point out that process innovation helps to strengthen a firm's market position given the characteristics of its product supplied. David [1990], Drazin [1990] and Brimm [1988] suggest that improved technology reduces cost per unit and improves the firm performance accordingly. By investigating how firms capture the value from innovating in the manufacturing sector, Ettlie and Reza [1992] argue that successful adoption of process innovation requires simultaneous market-directed integration and integration directed at the Value-Added Chain, which further improves productivity and throughput capacity. Moreover, Yamin et al. [1997] find out that process innovation is the stronger predictor of firm performance in terms of return on investment than product innovation. Our descriptive statistics show that on average, 1.7% of unit cost is decreased due to process innovation launched in the reference period. Moreover, 60.7% of firms agree that the processes innovation introduced implies a significant improvement of the quality of products and services. Compared to the turnover without the improvement of the quality, on average, the turnover has increased 3.3% due to this improved quality in the reference period owing to the processes innovation. Therefore, in general, process innovation contributes substantially to the reduction of unit cost and improvement of the quality of products and services in the sample.

Moreover, process innovation involves less market uncertainty in comparison to product innovation. Nelson and Winter [2009] argue that the market constraints are more relaxed for process innovation, as process innovation does not alter the nature of the product, hence relates to less market uncertainty. Nelson and Winter [2009, pp266] state that "The firm can make an assessment of profitability by considering the effects on costs, with far less concern for consumer reaction." In addition, Nelson and Winter [2009] argue that product innovations usually arise from a firm's own R&D, which implies inherent risks associated with sunk cost. While process innovations often come from the R&D provided by suppliers and investment in machinery and equipment, which already fully embody the new technology. This further reinforces the difference between product and process innovation. [1] Accordingly, we expect process innovation exerts a positive impact on firm performance.

In addition, process innovation often implies a systemic transformation of firm, while the influence induced by product innovation is rather confined to the R&D department. Tornatzky et al. [1990] argue that the impact of process innovation is systemic and the adoption of process innovation often implies large aggregate of tools, machines, human resources and social systems, thus, more disruptive than product innovation. Geroski et al. [1993] acknowledge the prominent role of process of innovating on profitability which signals the transformation of a firms internal capabilities. Prajogo [2006] demonstrates that process innovation shows a stronger positive impact on firm performance than product innovation in manufacturing sectors. Product innovation is more open for imitation whereas process innovation is internal thus difficult for competitors to imitate (Prajogo [2006], Damanpour and Gopalakrishnan [2001]). Consistent with the resource-based view theory, resources which are difficult to imitate contribute to building up firms' competitive advantages (Barney [1991], Prajogo [2006]).

By and large, process innovations imply cost reduction and improved efficiency in production, prevalent transformation and less market uncertainty. Accordingly, we expect process innovation exerts a direct positive lasting effect on firm performance. By contrast, the impact of product innovation on firm performance is more ambiguous due to cannibalization effect and market uncertainty.

3.2.4 Two-way relationship

Evolutionary economics emphasizes the path-dependent and cumulative nature of technological advance. Nelson and Winter [2009, pp.256] argue that new technology today forms the basis of building blocks to be used tomorrow. The link between innovation and firm performance is by no means one-way directional and mutually exclusive. The causal relationships between innovation and firm performance could operate two ways simultaneously. Superior firm performance facilitates the emergence of product and process innovations, and innovation contributes to firm growth and performance by gaining successful and sustainable competitive advantage, which forms a virtuous circle. However,

[1] The missing information in the data in terms of R&D developer of product and process innovations is rather unfortunate. Our descriptive statistics show that 37.9% firms agree that the process innovation introduced implies a decrease in the unit cost of production.

the literature has largely ignored the two-way relationship between innovation and firm performance particularly in terms of firm-level analysis. Luxembourg as one of the most dynamic economies of the EU-28, remains almost entirely undiscovered in terms of this relationship on firm level, hence the motivation of this study.

This study can be compared with other innovation studies that follow a similar structural approach to assess the impact of innovation on firm performance. (Klomp and Van Leeuwen [2001], Lööf and Heshmati [2002], Marsili and Salter [2005], Cainelli et al. [2006]). In particular, Klomp and Van Leeuwen [2001] take into account the joint dependence of the different stages of the innovation process and overall firm performance using the second Community Innovation Survey for the Netherlands. Klomp and Van Leeuwen [2001] reveal that the implementation of process innovation contributes to a firm's overall sales performance and productivity. Moreover, the existence of feedback effect from a firm's overall performance to its innovation endeavor is verified, which strongly supports Schmookler's hypothesis. Moreover, this study is closely linked to Cainelli et al. [2006] which explores the two-way relationship between innovation and economic performance in services using the Italian Community Innovation Survey (CIS II). Cainelli et al. [2006] confirm the positive self-reinforcing mechanism between innovation and firm performance which forms a virtuous circle. Given the cumulative and path-dependence nature of innovation, it is likely that innovation capabilities and economic performances are interdependent and this mechanism will persist and reinforce over time (Cainelli et al. [2006]). Acknowledging both effects, I adopt an evolutionary approach on technological change and firm dynamics by looking at the two-way relationship between innovation and economic performance. More specifically, this chapter aims to test whether past superior firm performance facilitates innovation, while innovation exerts positive effects on firm performance, which forms a virtuous circle.

3.3 Econometric Modeling

A two-equation simultaneous structural model is established with the fully recursive form which involves underlying continuous unobservable variables. Equation (3.3.1a)-(3.3.1c) aim to test the presence of a two-way relationship between innovation and economic performance at the firm level. As discussed, we expect a virtuous circle between innovation and firm performance, meanwhile investigate whether just being an innovator suffices, or whether it is the type of innovation introduced that matters. Panel data enables us to control for unobserved firm heterogeneity through individual fixed effects. Moreover, sample selection is controlled for as not all firms implement innovation.

The simultaneous structural model can be expressed as follows:

$$Innov^*_{it-1} = \beta_{11} lnturn_{it-2} + \beta'_{12} X_{1it-1} + \tau_{1t} + \alpha_{1i} + \varepsilon_{1it-1}. \tag{3.3.1a}$$

$$Innov_{it-1} = 1\left[Innov^*_{it-1} > 0\right]. \tag{3.3.1b}$$

$$lnturn_{it} = \beta_{21} Innov^*_{it-1} + \beta'_{22} X_{2it} + \tau_{2t} + \alpha_{2i} + \varepsilon_{2it}. \tag{3.3.1c}$$

$$\left[\varepsilon_{1i,t-1}\varepsilon_{2it}\right]\left[\right] \begin{array}{l} X_{1i0},\ldots,X_{1iT} \\ X_{2i1},\ldots,X_{2iT} \\ \alpha_{1i},\alpha_{2i} \\ lnturn_{i,-1}, lnturn_{i,0},\ldots, lnturn_{i,t-1} \end{array} \sim i.i.d.N\left(0,\begin{bmatrix} 1 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2. \end{bmatrix}\right) \tag{3.3.2}$$

The first equation explains the probability that firm i implements product or process innovation. $Innov^*_{it-1}$ is the unobserved latent variable of innovation which represents the respective firm's propensity to innovate. $Innov_{it-1}$ is the observed counterpart at period $t-1$, a dichotomous variable which represents either product or process innovation. As indicator function (3.3.1b) denotes, if the unobserved incentive of firm i to innovate crosses the threshold zero, the firm is observed to be either a product or process innovator.

X_{1it-1} represents vectors of explanatory variables which are assumed to be strictly exogenous or predetermined. Many strategic decisions of enterprise such as innovation, subsidy, cooperation are largely endogenous thus correlate to an unobservable omitted third factor (Mairesse and Mohnen [2010]). The panel setting enables us to deal with endogeneity issue and control for unobserved firm heterogeneity through individual fixed effects. More specifically, X_{1it-1} includes log R&D intensity, the dummy variable for non-R&D performer, innovation subsidy and innovation cooperation, all in two-period lagged form to further avoid endogeneity issue. Additionally, X_{1it-1} includes tangible investment intensity (in the two-period lagged form) for process innovation alone. As suggested by Mairesse and Robin [2009], process innovation generally implies the purchase of new machines and equipments, in particular in the manufacturing industry. Moreover, the size dummies and full set of time dummies are added to control for the general macroeconomic demand shocks, inflation and economic growth. α_{1i} and α_{2i} denote time-invariant individual fixed effects. Time dummies are included in the innovation and performance equation and indicated by τ_{1t} and τ_{2t} respectively. The idiosyncratic errors $(\varepsilon_{1it-1}, \varepsilon_{2it})'$ are identically and independently distributed across individuals and over time, which follow a normal distribution with mean zero and a positive-definite symmetric covariance matrix.

In order to capture the dynamic feature of the system, the lagged latent innovation variable $Innov^*_{it-1}$ is dependent on the past firm performance, which further determines the current firm performance. The firm performance equation models the logarithm value of turnover as a function of past product or process innovation and a number of other control variables.

$lnturn$ is the observed continuous dependent variable which measures the firm performance. Other things equal, we might expect a different outcome for firm performance when $Innov^*_{it-1}$ is well below the threshold zero than when $Innov^*_{it-1}$ is marginally below the threshold. This effect is captured in equation (3.3.1c) by incorporating $Innov^*_{it-1}$ rather than the observed counterpart.

X_{2it} includes firm-specific and industry-specific variables: tangible investment intensity (in the one-period lagged form), logarithm value of the market share (in the one-period lagged form), concentration ratio, the interaction term between market share and concentration ratio, logarithm value of employment, logarithm value of wage, education level, market competition and time dummies.

Equation (3.3.1a)-(3.3.1c) form a simultaneous-equation model with mixed structures and individual effects in each equation. The building blocks of this simultaneous equation are a probit model and a linear model with latent variable, hence, a model with the mixed structure. This simultaneous model has the fully recursive structure. Fully recursive is defined in the sense that in case that $T = 2$, the initial firm performance ($lnturn_{i0}$) is determined first, then $lnturn_{i0}$ determines innovation activity ($Innov_{i1}$), whereby $Innov_{i1}$ and initial firm performance $lnturn_{i0}$ directly influence the firm performance $lnturn_{i2}$. In other words, the effect of initial firm performance ($lnturn_{i0}$) on current firm performance ($lnturn_{i2}$) is also captured in the effect of interaction term between the two variables on the probability of firm performance conditional on the initial firm performance and initial innovation activity. I adopt the fully recursive models as only fully recursive models can give a causal or structural interpretation (Maddala [1986]). Equation (3.3.1a)-(3.3.1b) should be distinguished from selection equations, on the grounds that a complete sample is observed in terms of turnover, which is independent of innovation indicator function. In other words, our sample encompasses both innovators and non-innovators. As no selection mechanism occurs, innovators and non-innovators only differ in the magnitude of the unobserved latent innovation variables which further influence the turnover level. Our model should also be distinguished from a switching regression model, where the sales equation relates to different coefficients depending on whether the latent innovation propensity is below or above the threshold.

In order to handle the firm unobserved heterogeneity, the individual dummies are included for each firm and the model can be rewritten as follows:

$$Innov^*_{it-1} = \beta_{11} lnturn_{it-2} + \beta'_{12} X_{1it-1} + \tau_{1t} + \sum_{i=2}^{N} \mu_{1i} d_i + \varepsilon_{1it-1}. \tag{3.3.3a}$$

$$Innov_{it-1} = 1 \left[Innov^*_{it-1} > 0 \right]. \tag{3.3.3b}$$

$$lnturn_{it} = \beta_{21} Innov^*_{it-1} + \beta'_{22} X_{2it} + \tau_{2t} + \sum_{i=2}^{N} \mu_{2i} d_i + \varepsilon_{2it}. \tag{3.3.3c}$$

where di is a dummy variable for the ith individual firm, $i = 2...,N$. [2]

The reduced form of the structural equations is derived by substituting equation 3.3.3a to 3.3.3c.

$$\begin{aligned} lnturn_{it} =& \beta_{11}\beta_{21}lnturn_{it-2} + (\beta_{21}\beta_{12}'X_{1it-1} + \beta_{22}'X_{2it}) + (\beta_{21}\tau_{1t} + \tau_{2t}) \\ &+ \beta_{21}\sum_{i=2}^{N}\mu_{1i}d_i + \sum_{i=2}^{N}\mu_{2i}d_i + \underbrace{\beta_{21}\varepsilon_{1it-1} + \varepsilon_{2it}}_{\xi_{2it}}. \end{aligned} \tag{3.3.4}$$

Since error terms $(\varepsilon_{1i,t-1}, \varepsilon_{2it})$ follow a bivariate normal distribution,

$$\left[\varepsilon_{1i,t-1}\varepsilon_{2it}\right] \sim i.i.d.N\left(0, \begin{bmatrix} 1 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix}\right). \tag{3.3.5}$$

The compound error term ξ_{2it} is the linear combination of $(\varepsilon_{1i,t-1}, \varepsilon_{2it})$, which follows the normal distribution $\xi_{2it} \sim N(0, \sigma_{\xi_{2it}}{}^2)$, where

$$\sigma_{\xi_{2it}}{}^2 = \beta_{21}{}^2 + \sigma_2^2 + 2\beta_{21}\sigma_{12}. \tag{3.3.6}$$

The individual likelihood function encompasses both innovators and non-innovators. It is effectively the probability density function of the compound error term ξ_{2it} of the reduced-form equation along with the contributions from the probit model, which can be written as:

$$\begin{aligned} L_i = \prod_{t=0_i+1}^{T_i} & \Phi(\beta_{11}lnturn_{it-2} + \beta_{12}'X_{1it-1} + \tau_{1t} + \sum_{i=2}^{N}\mu_{1i}d_i)^{Innov_{it-1}} \\ & (1-\Phi(\beta_{11}lnturn_{it-2} + \beta_{12}'X_{1it-1} + \tau_{1t} + \sum_{i=2}^{N}\mu_{1i}d_i))^{1-Innov_{it-1}} \frac{1}{\sqrt{2\pi\sigma_{\xi_{2it}}{}^2}} exp^{-\frac{\xi_{2it}{}^2}{2\sigma_{\xi_{2it}}{}^2}} \end{aligned} \tag{3.3.7}$$

where Φ denotes the cumulative distribution function of the normal distribution.

$$\begin{aligned} \xi_{2it} =& lnturn_{it} - \beta_{11}\beta_{21}lnturn_{it-2} - (\beta_{21}\beta_{12}'X_{1it-1} + \beta_{22}'X_{2it}) \\ &- (\beta_{21}\tau_{1t} + \tau_{2t}) - \beta_{21}\sum_{i=2}^{N}\mu_{1i}d_i - \sum_{i=2}^{N}\mu_{2i}d_i \end{aligned} \tag{3.3.8}$$

Since Amemiya [1974] first raises the issue of estimation of mixed-process models, the simultaneous models with the mixed structure (both limited and continuous dependent variables) have received increasing attention. Especially, Maddala and Lee [1976] discuss the estimation procedures and identification of the simultaneous equations model involving

[2]The first individual firm is omitted as by default it will serve as base or reference category.

underlying continuous unobservable variables for which the observed variables are qualitative. Nelson and Olson [1978] have discussed the estimation of simultaneous-equation models in which some or all endogenous variables are limited. In particular, they propose a simple two-equation model with one continuous and one limited dependent variable which is similar to our specification. The econometric literature used to focus on multi-stage estimation procedures which are less computationally demanding. At present, the powerful computers have made maximum likelihood estimation practical. In particular, Monte Carlo-type simulated likelihood methods facilitate estimation of integrals of multivariate normal distributions of dimension 3 and higher.

In this chapter, the command cmp proposed by Roodman [2009] is applied, which fits a large family of multi-equation, multi-level and mixed-process estimators. The current version of cmp is not restricted to the estimation of the recursive structure and fully observability of data. It allows for estimation of simultaneous equations as well as references to the unobserved linear functional of the binary dependent variable by using suffix. In other words, an endogenous dummy variable can be included in an equation as well as the hypothesized continuous latent variable within it. [3]

In order to achieve speeding convergence, the default Newton-Raphson method is applied which works well once ml has found a concave region. Davidon-Fletcher-Powell algorithm works better before a concave region is discovered. I use the combination of the two techniques and switch between the two methods every five steps.

3.4 Data

3.4.1 Data

The empirical analysis is based on an unbalanced longitudinal dataset over the period 2003-2012. This dataset is constructed by merging two different datasets, Community Innovation Survey (CIS) and Structural Business Statistics (SBS) of Luxembourg. The Luxemburgish CIS is a questionnaire collected biennially over the period 2002-2012. It consists of five waves of firm-level data which provides information regarding innovation

[3] Roodman [2009] has mentioned two requirements on the multi-equation model: recursivity and fully observability. Recursivity means that the matrix of coefficients of the endogenous variables in one anothers equations is triangular. Recursive models imply clearly defined stages. Fully observability means that endogenous variables enter subsequent stages only as observed. A dummy endogenous variable can be included in an equation, but the hypothesized continuous variable that is latent within it cannot appear on the right sides of equations directly.

It is worth noting that version 6 of cmp, introduced in 2013, can handle violations of both conditions. Please resort to detailed documentation of cmp help file. Based on Roodman et al. [2017], each equation's linear functional can appear on the right side of any equation, even when it is modeled as latent variable (not fully observed), and even if the equation system is simultaneous rather than recursive. According to Roodman et al. [2017], condition 2 is no longer required: models may refer to latent variables using suffix.

activities, in particular, product innovation and process innovation during the reference period. It also provides information regarding the introduction of new market products and new firm products, intramural and extramural R&D expenditure, subsidy, innovation cooperation, the percentage of employees with higher education and the degree of market competition. Structural Business Statistics (SBS) is an annual database which provides us with a rich range of information on firm's activities and performances such as turnover, employment level, gross investment in tangible goods and wages. [4] SBS can link to CIS data by means of common firm identifier.

Since Luxembourg earns the reputation as the European top tax haven where certain taxes are levied at a low rate, I remove firms with less than 10 employees to avoid abundant shell corporations. Moreover, firms with negative turnover and zero wage are further removed to avoid unreasonable estimates. To deal with the missing values, I replace the missing values of employment in SBS dataset by its counterpart from CIS. Our econometric model implicitly requires three consecutive time periods. Accordingly, only firms with at least three consecutive time periods remain in the estimation sample. This leads to a sample of roughly 497 enterprises with at least 10 employees and positive output, turnover and wage over the 2003-2012 period. Our estimation sample encompasses both innovators and non-innovators.

When merging the CIS data with SBS, we face the challenge of merging two datasets with different periodicities. In other words, in the empirical model, we are regressing a yearly-available variable stemming from SBS, i.e. turnover, on biennially-available innovation variables stemming from the CIS dataset. Two options then emerge.

The first option consists in using a yearly panel where the SBS variables are used as such and the CIS variables are repeated for each year of the period covered by the innovation survey. For instance, in 2005 and 2006, the yearly information on turnover is used while a product innovator during the 2004-2006 period is treated as a product innovator in 2005 and 2006. Thus, when explaining annual turnover by innovation, the latter is to be understood as an 'average' innovation behavior over the CIS period. The benefit of using a yearly panel is that it enables us to use as many observations as possible over the 2003-2012 period, which is a necessary condition to estimate equation (3.3.3a)- (3.3.3c) accurately. Nonetheless, the approach also has disadvantage related to the fact that the CIS is carried out biennially and pertains to 3-year periods.

[4] Data on structural business statistics (SBS) are collected and processed by STATEC. According to the structural business statistics methodology, the business register covers all activities in Sections C-K and O of NACE Rev. 1. It covers part of the activities in Sections A (agriculture), L (public administration), M (education), N (health and social work) and Q (extra-territorial organisations and bodies). The survey is based on a sample of units which have less than 50 employees or less than 7 million EUR turnover. For units with 50 or more employees or turnover above 7 million EUR, the survey is exhaustive. The number of enterprises covered by the survey is limited to about 2,600.

The exact year of occurrence of innovation is unknown over each 3-year period. Accordingly, we consider a recursive lagged structure in the simultaneous equation. In other words, lagged innovation variable is considered as regressor in the firm performance equation, and the innovation equation is explained by lagged firm performance. As a result, considering again the 2004-2006 example, it may well be the case that turnover in 2007 is explained by innovation occurrence in 2005 or 2006 depending on the exact year of innovation occurrence. For the innovation equation, innovation in 2005 or 2006 is explained by firm performance in 2005 depending on the exact year of innovation occurrence. The disadvantage resides in the fact that we cannot distinguish between the contemporaneous and lagged effects case. Nonetheless, it appears to be irrelevant as the original biennial data suffers from the same issue, as the fundamental obstacle resides in the absence of information regarding the exact year of occurrence of innovation over each 3-year period in the questionnaire.

As for the overlapping year between two consecutive waves of the CIS, this is problematic in the yearly panel when the enterprise claims to be an innovator over a 3-year period and non-innovator in a subsequent period. In other words, controversies only arise when one wave reports negative innovation activities proceeding with a positive response, as questions relevant to a three-year period. In this case, the enterprise is assumed to be a non-innovator in the overlapping year, which seems a reasonable assumption. To illustrate, firm innovates in the period 2002-2004 whereas no innovation is reported in the period 2004-2006, we make the assumption in such way that firm innovates in 2003, whereas no innovation is implemented in 2004, 2005 and 2006. The overlapping year is less of a problem when the enterprise is a non-innovator and an innovator in two consecutive waves. The overlapping year is not an issue either for the continuous innovation variables since the values of these variables are reported at the end of each CIS period. In this case, the overlapping year takes on the current period values.[5]

The second option consists in using a biennial panel where only the last year of each CIS period is retained, namely 2004, 2006, 2008, 2010 and 2012. The advantage is that we are not dependent on the 'imputation' for the absent values of the year 2003, 2005, 2007, 2009 and 2011. However, the biennial panel fails to exploit all the information contained in SBS and consists of less periods and observations, which may render the estimation inaccurate. In particular, short time periods may lead to incidental parameters problem with the probit model in the presence of fixed effects. Therefore, I focus on the imputed annual data for reliable estimates.

[5] The overlapping year of two consecutive CIS periods, say 2004-2006 and 2006-2008, is 2006. The current period is 2004-2006, and 2006-2008 refers to the subsequent period.

3.4.2 The selection of variables

The structural model consists of an innovation equation and a firm performance equation. The dependent variable for innovation equation is a binary variable which indicates whether or not an enterprise implements product or process innovation. Product innovator is the dummy variable which takes the value 1 if the enterprise introduces new or significantly improved goods, (excluding the simple resale of new goods purchased from other enterprises and changes of a solely aesthetic nature) and new or significantly improved services during the period under review. [6] A product innovation can be either new to the enterprise or new to the sector or market. It could be originally developed by the enterprise or by other enterprises. Process innovator is the dummy variable which takes the value 1 if the enterprise introduces new or significantly improved methods of manufacturing or producing goods or services, new or significantly improved logistics, delivery or distribution methods for inputs, goods or services, or new or significantly improved supporting activities for processes, such as maintenance systems or operations for purchasing, accounting, or computing. Ongoing, planed innovation activities and abandoned product and process innovation during the reference period are not considered as innovation. Accordingly, we focus on the measure of innovation output.

The second dependent variable is the firm performance indicator. Consistent with the literature on firm performance and innovation, for example,Klomp and Van Leeuwen [2001], Jefferson et al. [2006], Cainelli et al. [2006], Prajogo [2006], Artz et al. [2010], Isogawa et al. [2012], logarithm value of turnover is used to represent the overall economic performance of firms. [7] Some strands of literature on profit and innovation use gross operating surplus to measure profitability, which is defined as gross output less the cost of intermediate goods and services to give gross value added, and less compensation of employees. The variable gross operating surplus in the sample exhibits cyclical pattern which results in unsatisfactory estimates. Accordingly, I focus on the overall firm performance measured by turnover to derive reliable inference.

The probability of being a product innovator is explained by the past firm performance, log R&D intensity, subsidy, innovation cooperation, headquarter, firm size dummies, time dummies and firm-specific fixed effects [8]. As indicated by Mairesse and Robin [2009], process innovation generally implies the purchase of new machines and equipments, in particular in the manufacturing industry. Accordingly, apart from aforementioned explanatory variables, the measure of tangible investment intensity is included in the process innovation

[6]The use of continuous variable for product innovation could be an alternative approach. In this case, different econometric models are called for product than process innovation. The application of dummy variable for product and process innovation allows us to treat both innovation types uniformly in the econometric model, which avoids theoretical complexity.

[7]Turnover is not calculated at current prices deflated by the deflator of sales. But we include year dummies to account for inflation.

[8]Market share is excluded from the innovation equation as it is highly correlated with turnover.

equation. Total R&D expenditures measure the sum of intramural R&D expenditure, extramural R&D expenditure, acquisition of machinery expenditure and external knowledge expenditure. R&D intensity is measured by the ratio of R&D expenditures per employee. I use log transformation for enterprises with positive R&D expenditures and set the log R&D intensity to zero for enterprises with zero R&D expenditures. A dummy variable for non-R&D performer with zero R&D expenditure is included to compensate for this correction.We apply the log transformation as the distribution of R&D expenditures is highly right-skewed. Without log transformation the level estimate of R&D intensity leads to a minuscule coefficient which is close to zero. Subsidy is the dummy variable which takes the value 1 if the enterprise receives any public financial support for innovation activities from local or regional authorities, the European Union or the central government (including central government agencies or ministries). Innovation cooperation is the dummy variable which takes the value 1 if the enterprise cooperates for any of innovation activities with other enterprises or institutions. It focuses on active participation with other enterprises or non-commercial institutions on innovation activities.

Education is a dummy variable which takes value 1 if the firm has more than 25% highly educated employees (including post-secondary college diplomas and university graduates diplomas), and value 0 if the firm has less than 25% highly educated employees. [9] Headquarter is a dummy variable which takes value 1 for firms with headquarters located in Luxembourg.

Tangible investment intensity is defined as the share of gross investment in tangible goods per employee. [10] The distribution of tangible investment intensity is highly right-skewed. In order to obtain reasonable magnitude of coefficients, log transformation is applied to tangible investment intensity with positive gross investment in tangible goods. The log of tangible investment intensity is set to zero for enterprises with zero investment in tangible goods. A dummy variable for non-investor in tangible goods is included to compensate for this correction. As explained before, tangible investment intensity enters the process innovation equation exclusively. Moreover, log R&D intensity, non-R&D performer, subsidy, innovation cooperation and tangible investment intensity are included in two-period lagged form in order to avoid endogeneity issue.

The firm performance is explained by past innovation activities, tangible investment intensity, log of market share, concentration ratio, the interaction term of log of market share

[9] The survey contains a variable empud, a categorical variable which indicates the estimated percentage of employees that have a university degree. More specifically, it ranges from 0-6, which indicates 0% , 1% to 4% , 5% to 9%, 10% to 24%, 25% to 49%, 50% to 74%, 75% to 100%. As the median value of this variable is 3, a dummy variable is generated to indicate the firm with the level of highly educated employees above the median value 25%, or below the median value 25%.

[10] To be consistent with the definition of R&D intensity, tangible investment intensity is measured by the ratio of gross investment in tangible goods in proportion to employees rather than sales. Moreover, it is favorable to avoid sales dimension which may capture the spurious persistence.

and concentration ratio, firm employment, log of wage, education, market competition, time dummies and firm-specific fixed effects.

Market share is defined as the proportion of the firms' turnover to total turnover in the domestic 2-digit sector. Market share enters the firm performance equation in one-period lagged form in order to avoid endogeneity issue. Concentration ratio is the measure of the percentage of market share in an industry held by the three largest firms within that industry. Furthermore, it is favorable to control for the interaction term between market share and concentration ratio, suggested by Kwoka Jr and Ravenscraft [1986] and Geroski and Machin [1993]. [11] In other words, the slope of log of turnover against log of market share might vary with concentration ratio.

Market competition is a categorical variable which measures how fast products and services are rapidly old-fashioned or outdated. It is defined on a 0-3 scale where 0 indicating not relevant, 1 indicating low market competition and 3 indicating high market competition. Size class is a categorical variable defined on a 1-3 scale, where 1 indicating small enterprise, 2 indicating medium enterprise and 3 indicating large enterprise. The definition of SMEs is consistent with the definition of the European Commission. [12]

Tangible investment intensity is included in one-period lagged form in the firm performance equation in order to avoid endogeneity issue. It is worth noting that the industry dummies are not included in the innovation and firm performance equation as they are already captured by firm-specific fixed effect dummies. Moreover, market share is excluded from the innovation equation as it is highly correlated with the two-period lagged value of turnover, which raises the multicollinearity issue.

In both innovation and firm performance equation, I account for unobserved firm heterogeneity through individual fixed effects. Cross-equation correlations are also accounted for through the idiosyncratic errors.

3.4.3 Descriptive statistics

Table 3.1 presents the descriptive statistics on the non-transformed variables used in the empirical model. It shows the distribution of the variables in terms of mean, standard

[11] Concentration ratio can be treated as time-constant, as the within standard deviation equals to 0.06.

[12] According to the European Commission (Recommendation 2003/361/EC: SME Definition), there are three broad parameters which define small, medium and large enterprises:

- Micro-entities are companies with up to 10 employees.
- Small companies employ up to 50 workers.
- Medium-sized enterprises have up to 250 employees.
- Large enterprises have 250 or more persons employed.

deviation and three quartiles. In our estimation sample with at least 3 consecutive periods of non-missing values, there are 497 firms in total, out of which emerges 128 non-innovative firms and 210 firms implementing product and process innovation simultaneously. The sample is composed of 36% product innovators and 29% of process innovations. 75% of the firms' turnover lies below 34.88 millions of euros, the superlative mean value implies substantial influence from a few large enterprises. Likewise, 53% of the firms incur no R&D expenditures. The average value is driven upward by a few large firms with massive R&D expenditures.

Wage is more evenly distributed across firms where the median is close to the mean value. Although the average employment level is medium-sized, the comparison with the third quartile suggests that the mean value is largely driven up by a few large firms. In effect, the sample consists of 86.77% SMEs. Tabulation between firm size and innovation activities demonstrates that SMEs amounts to 79.23 % of innovators over the period 2003 to 2012. Large enterprises, in spite of their limited share, play the indispensable role in innovative activities. More specifically, 71.84 % of large firms implement either product or process innovation. It is consistent with the argument of Freeman and Soete [1997] which suggests that in the presence of barriers to entry and weak appropriability conditions, large firms with ex-ante monopolistic power might be more conducive to innovation than fully competitive markets populated by small firms.

Moreover, around 17.61% of the innovative firms claim no intramural R&D expenditure, extramural R&D expenditure, acquisition of machinery expenditure and external knowledge expenditure. According to the CIS survey, those firms may still incur cost such as training (internal or external training for personnel specifically for the development and/or introduction of new or significantly improved products and processes), cost of market introduction of innovations (activities for the market introduction of new or significantly improved goods and services, including market research and launch advertising), cost of other preparations procedures and technical preparations to implement new or significantly improved products and processes that are not covered elsewhere. Moreover, innovation could arise from information sources within enterprise or enterprise group, markets sources, institutional source and other sources. [13]

Table 3.2 shows the cross-tabulation result between sector and innovation groups. Column 2 and column 4 demonstrate the industry distribution among non-innovator and innovative firms. Innovative firms represent TPP innovator which implements either product or process innovation. Non-innovators refer to enterprises which introduce neither product nor process innovation. The sector of information & communication, transport & storage,

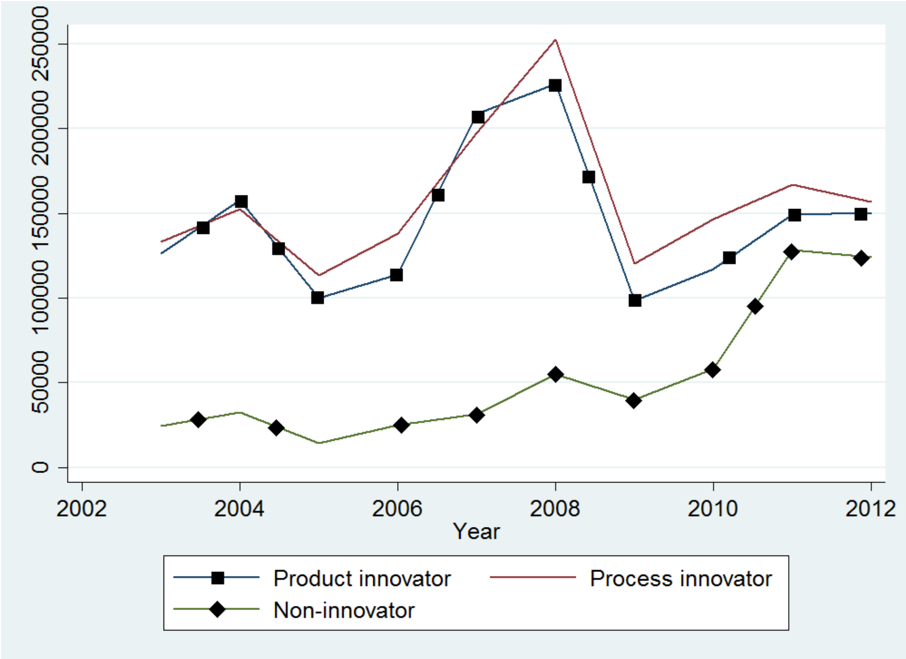
[13] Internal sources indicate knowledge within the enterprise or enterprise group. Markets sources include suppliers of equipment, materials, components, or software, clients or customers, competitors or other enterprises in the sector, consultants, commercial labs, or private R&D institutes. The institutional source includes universities or other higher education institutions, government or public research institutes. Other sources include conferences, trade fairs, exhibitions, scientific journals and trade/technical publications, and professional and industry associations.

Table 3.1: Descriptive statistics for the variables over the period 2003-2012 using the yearly panel[†]

	Mean	**Std.Dev.**	**Q1**	**Median**	**Q3**
Product innovator	0.36	–	0	0	1
Process innovator	0.29	–	0	0	1
Turnover	66.29	329.82	3.96	11.56	34.88
Total R&D expenditure	1236.33	8398.45	0	0	250
Non-R&D performer	0.53	–	0	1	1
Financial support, gvt. or EU	0.16	–	0	0	0
Innovation cooperation	0.17	–	0	0	0
Tangible investment	3479.39	21569.48	0	101.24	786.27
Non-investor in tangible goods	0.29	–	0	0	1
Market share	0.01	0.05	0	0	0
Concentration ratio	0.04	0.11	0	0.01	0.02
Employment	167.07	422.56	27.86	66	126
Wage	43.60	17.69	31.88	39.43	50.45
Education	0.37	–	0	0	1
Size class					
Small	0.39	–	0	0	1
Medium-sized	0.48	–	0	0	1
Large	0.13	–	0	0	0
Market competition					
None	0.29	–	0	0	1
Low	0.30	–	0	0	1
Medium	0.25	–	0	0	0
High	0.16	–	0	0	0
Headquarter	0.46	–	0	0	1
N	3113				

[†]The turnover variable is expressed in millions of euros. Wage per capita and innovation expenditure variable are expressed in thousands of euros. The means of the binary variables represent shares of ones and their standard deviation has no real meaning.

Figure 3.1: Turnover comparison among innovation groups over the period 2003-2012



wholesale trade exhibit highly innovative features and are regarded as the most innovative sectors in Luxembourg. [14] As Cainelli et al. [2006] point out, the service sectors such as telecommunications, transports and finance are associated with the establishment of expensive technological infrastructures, which require better access to large financial resource. Accordingly, past healthy economic performance might be more relevant as a basis for their overall financial commitment to innovation. The presence of large share of those sectors in the sample corroborates the importance of including past firm performance as a determinant of innovation. Moreover, the service sector is the main driving force behind the Grand Duchy's economy, which amounts to 50.50% of total sector. Most empirical studies explicitly focus on manufacturing sectors. The Luxembourgish sample allows us to explore the distinct feature of interdependent role between innovation and firm performance inclusive of service sectors.

Graph 3.1 compares the turnover among the product innovator, process innovator and non-innovator over the period 2003-2012. The major swings are similarly timed. The minor fluctuations in each trend seem to be duplicated in others with the different magnitude. In particular, product and process innovator show remarkably similar behavior. They all reach their all-peaks turnover in 2008 before the economic crisis, following a sharp, rapid

[14] The missing SBS information for the financial sector is rather unfortunate, as this sector represents the substantial percentage of the total economy and is regarded as one of the most innovative sectors.

Table 3.2: The cross-tabulation analysis between non-innovator, innovative firms and sector

	Non-innovator		Innovative firms		Total
	(1)	(2)	(3)	(4)	(5)
Chemicals	40.96	2.01	59.04	3.44	2.67
Computer & electronics	7.89	0.18	92.11	2.46	1.22
Construction	100	0.95	0	0	0.51
Elec., gas & water	75.90	3.73	24.10	1.40	2.67
Electrical equipment	55.38	2.13	44.62	2.04	2.09
Food, drinks & tobacco	66.06	8.65	33.94	5.26	7.10
Information & communication	41.62	12.80	58.38	21.26	16.67
M&E NEC	13.82	1.24	86.18	9.19	4.88
Metals	64.95	11.20	35.05	7.16	9.35
Mining & quarrying	83.33	1.78	16.67	0.42	1.16
Non-Metallic products	52.17	2.84	47.83	3.09	2.96
Other manufacturing	49.32	2.13	50.68	2.60	2.35
Plastics & rubber	25.49	1.54	74.51	5.33	3.28
Professional & scientific	58.98	8.95	41.02	7.37	8.22
Textile & leather	35.42	1.01	64.58	2.18	1.54
Transport & storage	73.11	17.71	26.89	7.72	13.14
Transport equipment	31.75	1.18	68.25	3.02	2.02
Water supply & waste	57.32	2.78	42.68	2.46	2.63
Wholesale trade	62.11	13.98	37.89	10.11	12.21
Wood & paper	56.25	3.20	43.75	2.95	3.08
Total	54.22	100	45.78	100	100
N	3113				

† Almost all corporate sectors of the Luxembourgish economy are analyzed with the exception of the financial sector for which SBS information such as turnover, wage, and tangible investment intensity is not available. Moreover, Service, NEC sector and Real estate sector are not reported due to insufficient observations.

plunge in sales, ensuing the slow recovery from 2009 to 2011. This prevalent similarity suggests the role of common external forces in shaping the course of turnover between product innovator and process innovator. In addition, graph 3.1 reveals that innovative firms surpass non-innovative firms in terms of turnover over the period 2003-2012. Moreover, process innovator outperforms product innovator over the period 2005 – 2012, whereas product innovator only temporarily overtakes process innovator around 2007. The superior performance associated with innovative firms, in particular with the process innovator, is consistent with the findings of Geroski et al. [1993], Leiponen [2000] and Cefis and Ciccarelli [2005]. Geroski and Machin [1993] stress that, although individual innovations have a positive effect on profitability and growth, the process (rather than results) of innovation seems to transform firms which gives rise to generic differences between innovators and non-innovators. Product innovations carried out by extramural R&D and acquisition of machinery, equipment and software may give rise to less pervasive generic difference. Nonetheless, empirical studies often suggest that innovating firms are much less sensitive to cyclical shocks than non-innovative firms, which appears to be irrelevant to Luxembourg. It provides interesting food for thought to identify the magnified gap of turnover between innovative and non-innovative firms after the crisis.

3.5 Estimation results

I now turn to the main estimation results of the model. The full information likelihood estimation results are presented in Table 3.3 for the model with latent product innovation propensity as a predictor of firm performance, and Table 3.4 for the model with latent process innovation propensity. The comparison between Table 3.3 and Table 3.4 reveals distinct features of the two-way relationship between innovation and firm performance based on different types of innovation.

3.5.1 The impact of past firm performance on technological innovation

By and large, the coefficient of log of turnover (-0.934) indicates that an increase in turnover decreases the predicted probability of product innovation. Nonetheless, past firm performance exhibits significantly positive effect on process innovation. This (surprising) estimation result suggests the absence of motivation to implement product innovation by virtue of the risky and uncertain nature associated with the product innovation. By contrast, process innovations do not change the nature of the product and need not to face the new and unfamiliar market reactions (Nelson and Winter [2009]). The healthy cash flow paves the way for financial commitment to process innovation by encouraging the purchase of new machines and equipments.

Other determinants do not differ remarkably across innovation types. Overall I find evidence of positive impact of lagged R&D intensity on innovation. Enterprises that declare undertaking R&D continuously during the previous year are more likely to be process innovators. The positive effect of a higher R&D intensity on innovation is stronger and more significant for process innovation than product innovation. The positive and significant coefficient of innovation cooperation suggests that cooperation leads to an increase in the predicted probability of being product innovator. Cohen and Klepper [1996] point out that R&D cooperation can reduce R&D costs per unit of output and enable firms to profit from R&D projects that they can not manage alone. The positive effect of innovation cooperation is stronger and more significant for product innovation than process innovation, which suggests that innovation cooperation is more crucial and relevant for product innovation.

Nonetheless, there is evidence that product and process innovation are differently determined. The negative and significant coefficient of dummy variable non-R&D performer suggests that being non-R&D performer last period leads to a decrease in the predicted probability of being product innovator. Product innovator exhibits a relatively higher persistence level than process innovators, which is consistent with the literature (Le Bas and Poussing [2014], Antonelli et al. [2012]). Antonelli et al. [2012] argue that the reason resides in the presence of important sunk costs for product innovators, which represents an essential motive for entering and adhering to a specific regime of R&D activity. Moreover, Nelson and Winter [2009] argue that product innovations usually arise from a firm's own R&D, whereas process innovations often come from the R&D provided by suppliers or investment in machinery and equipment which embodies new technology. This further reinforces the difference between product and process innovation. Moreover, many firms choose Luxembourg as their headquarters on the grounds of favorable legal and tax environment, which decreases their incentives to implement headquarters innovation. The negative and significant coefficient of headquarters in the product innovation equation corroborates it.

In addition, large enterprises tend to implement more product innovation and less process innovation. This is consistent with the findings of Raymond et al. [2015] for French manufacturing firms. The difference can be traced back to more favorable R&D research environment, better financing channels, higher risk-management capability and less chance of market failures for large firms. In general, the estimates are consistent with the findings of Leiponen [2000], which stress the different competencies associated with product and process innovation. Becker and Egger [2013] also point out that product innovation is a key factor for successful market entry in models of creative construction and Schumpeterian growth. Process innovation accordingly helps to strengthen a firm's market position given the characteristics of its product supplied.

3.5.2 The impact of technological innovation on firm performance

The separated effects of product and process innovation show that product innovation tends to have adverse effect on firm performance, whereas process innovation exerts positive and significant effects on firm performance. The estimate of the effect of product innovation (-0.079) indicates that for a representative firm, the introduction of product innovation will decrease the turnover by 7.9%. By contrast, the introduction of process innovation will increase the turnover by 15.4%. This discrepancy in estimation results suggests that there might be an endogenous mechanism which selects firms into product or process innovations.

First of all, this finding is consistent with the literature in evolutionary economics and some empirical works. Nelson and Winter [2009] claim that the Schumpeterian dynamics differ depending on the nature of the innovation, namely, a new product or a new process innovation. For product innovation, the profitability of the firm depends strongly on the uncertain reactions of potential customers. As for process innovation which does not change the nature of the product, the market constraints are far more relaxed and the firms are less concern for consumer reaction. In addition, Leiponen [2000] discovers the positive impact of process innovation and negative impact of product innovation on profit. The major reason of difference resides in the life-cycle effects and market cannibalization effects. As discussed in section 2.3, based on the product life cycle theory, the initial introduction stage is associated with the high costs in launching a new product, such as research and development cost, consumer testing and the marketing. The size of the market for new products is small and sales are low to start off with, which leads to the negative profits for the initial stage of the product life cycle. Although the amount and duration of the negative profits differ from one market to another. Some manufacturers could start earning a profit quite quickly, while for companies in other sectors it could take years (Miller and Friesen [1984]). In consideration of short lag period in the model, the negative effect of product innovation on firm performance is likely to be temporary. Our research is confined to the short panel period which fails to capture the long-lasting positive effects of product innovation. The estimates do not preclude the possibility of better firm performance in the long run attributed to the current product innovation. Additionally, the new product is accompanied by cannibalization effect if a firm produces multiple products. In other words, new products may simply drive out old products or compete with firms existing products hence hurt the total sales. The net effect of product innovation on firms' total sales is determined by the relative size of these two effects.

It is comforting to notice that the estimates of other determinants are quite consistent across innovation types. The negative sign of tangible investment intensity reflects the tendency for overinvestment and the poor productivity of the heavy investment, a similar result as Leiponen [2000] for Finnish manufacturing firms. Market share exhibits expected significant and positive effect on firm performance for both product and process innovator.

Table 3.3: FIML estimates of the model with latent product innovation propensity to explain firm performance: unbalanced yearly panel data from Luxembourg over the period 2003-2012

Regressor	Coef.	(Std. Err.)
Product Innovation$_{t-1}$		
Turnover in log$_{t-2}$	-0.934^{***}	(0.20)
Log R&D intensity$_{t-2}$	0.004	(0.05)
Non-R&D performer$_{t-2}$	-0.303^{**}	(0.13)
Subsidy$_{t-2}$	0.162	(0.17)
Cooperation$_{t-2}$	0.349^{**}	(0.15)
Medium-sized$_{t-1}$	0.146	(0.29)
Large$_{t-1}$	0.965^{**}	(0.43)
Headquarter$_{t-1}$	-0.417^{*}	(0.25)
Firm dummies	YES	YES
Year dummies	YES	YES
Turnover in log$_t$		
Product Innovation$_{t-1}$	-0.079^{***}	(0.03)
Log of tangible investment intensity$_{t-1}$	-0.003	(0.00)
Non-investor in tangible goods$_{t-1}$	-0.013	(0.02)
Log of market share$_{t-1}$	0.048^{***}	(0.01)
Concentration ratio$_t$	0.251	(0.18)
Log of market share$_{t-1}$ $\times$ concentration ratio$_t$	0.038	(0.04)
Person employed in log$_t$	1.039^{***}	(0.03)
Wage in log$_t$	0.679^{***}	(0.05)
Education$_t$	0.009	(0.02)
Market competition$_t$		
Low	-0.009	(0.02)
Medium	-0.002	(0.02)
High	-0.014	(0.02)
Firm dummies	YES	YES
Year dummies	YES	YES
σ_2	0.212^{***}	(0.02)
ρ_{12}	0.511^{***}	(0.11)
Observations	2086	
Log-likelihood	153.60	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4: FIML estimates of the model with latent process innovation propensity to explain firm performance: unbalanced yearly panel data from Luxembourg over the period 2003-2012.

Regressor	Coef.	(Std. Err.)
Process Innovation$_{t-1}$		
Turnover in log$_{t-2}$	0.606***	(0.17)
Log R&D intensity$_{t-2}$	0.093**	(0.04)
Non-R&D performer$_{t-2}$	0.168*	(0.10)
Subsidy$_{t-2}$	0.119	(0.12)
Cooperation$_{t-2}$	0.117	(0.12)
Medium-sized$_{t-1}$	−0.559***	(0.20)
Large$_{t-1}$	−0.752**	(0.33)
Headquarter$_{t-1}$	−0.035	(0.14)
Log of tangible investment intensity$_{t-2}$	−0.001	(0.02)
Non-investor in tangible goods$_{t-2}$	0.151	(0.09)
Firm dummies	YES	YES
Year dummies	YES	YES
Turnover in log$_t$		
Process Innovation$_{t-1}$	0.154***	(0.05)
Log of tangible investment intensity$_{t-1}$	−0.003	(0.00)
Non-investor in tangible goods$_{t-1}$	−0.018	(0.02)
Log of market share$_{-1}$	0.048***	(0.01)
Concentration ratio$_t$	0.246	(0.18)
Log of market share$_{t-1}$ $\times$ concentration ratio$_t$	0.039	(0.04)
Person employed, in log$_t$	1.038***	(0.03)
Wage in log$_t$	0.686***	(0.05)
Education$_t$	0.002	(0.02)
Market competition$_t$		
Low	−0.013	(0.02)
Medium	−0.002	(0.02)
High	−0.012	(0.02)
Firm dummies	YES	YES
Year dummies	YES	YES
σ_2	0.249***	(0.03)
ρ_{12}	−0.680***	(0.11)
Observations	2085	
Log-likelihood	107.00	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The coefficient of market share indicates that 10% increase in market share will lead to 0.48% increase in turnover for product innovator and process innovator. In addition, a positive and significant effect of employment and wage on firm performance is observed with similar magnitude across innovation types. The full set of time dummies captures the influence of general macroeconomic demand shocks, inflation and economic growth. The negative and significant coefficients of year dummies since 2008 (particularly for the year 2009) capture the adverse effects of the financial crisis on firm performance. [15]

Based on Roodman [2009], cmp represents the covariance matrix of residuals in "sigma-rho" form, that is, with a standard deviation (σ) parameter for each error and a correlation coefficient (ρ) for each pair. The correlations between the idiosyncratic effects in the innovation and firm performance equation after accounting for common determinants and individual effects are significant and positive for product innovator, and significant and negative for process innovator. This negative correlation can be explained by a missing term such as firm age. Young firms may tend to implement process innovation more rigorously. Meanwhile, young firms may start with low sales by virtue of the absence of experience and established reputation. To illustrate. Coad et al. [2013] find evidence that firms improve with age. Coad et al. [2013] argue that aging firms have steadily increasing levels of productivity, higher profits, larger size, lower debt ratios and higher equity ratios.

3.5.3 The model with both latent product and process innovation propensity to explain firm performance

Alternatively, product and process innovation can be jointly determined and incorporated simultaneously into the firm performance equation. In other words, we apply bivariate probit estimation at the first step to capture the fact that the decisions of product and process innovations are correlated. The revised model can be written as follows:

$$Prod^*_{it-1} = \beta_{31} lnturn_{it-2} + \beta'_{32} X_{3it-1} + \tau_{3t} + \alpha_{3i} + \varepsilon_{3it-1}. \tag{3.5.1a}$$

$$Proc^*_{it-1} = \beta_{41} lnturn_{it-2} + \beta'_{42} X_{4it-1} + \tau_{4t} + \alpha_{4i} + \varepsilon_{4it-1}. \tag{3.5.1b}$$

$$Prod_{it-1} = 1\left[Innov^*_{it-1} > 0\right]. \tag{3.5.1c}$$

$$Proc_{it-1} = 1\left[Innov^*_{it-1} > 0\right]. \tag{3.5.1d}$$

$$lnturn_{it} = \beta_{51} Prod^*_{it-1} + \beta_{52} Proc^*_{it-1} + \beta'_{53} X_{5it} + \tau_{5t} + \alpha_{5i} + \varepsilon_{5it}. \tag{3.5.1e}$$

[15] Although the coefficients of year dummies are not reported, for example, the coefficient of year dummy 2009 for the firm performance equation with latent product innovation propensity is equal to -0.07, which captures the lagged effect of the financial crisis. All year dummies from 2009 on are negative and significant.

$(\varepsilon_{3it-1}, \varepsilon_{4it-1}, \varepsilon_{5it}) \sim i.i.d.N(0, \Sigma)$ where Σ is a positive-definite symmetric matrix.

$$\Sigma = \begin{bmatrix} 1 & & \\ \rho_{34} & 1 & \\ \rho_{35}\sigma_5 & \rho_{45}\sigma_5 & \sigma_5^2 \end{bmatrix} \tag{3.5.2}$$

Equation 3.5.1a-3.5.1d define a bivariate probit model which takes into account the case that product and process innovation can be jointly determined. Equation 3.5.1e relates the firm performance to the endogenous dummy variables, namely, product and process innovation aside from other potential determinants. We can rewrite equations 3.5.1a-3.5.1e by including individual firm dummies to capture the unobserved heterogeneity.

$$Prod_{it-1}^{*} = \beta_{31} lnturn_{it-2} + \beta_{32}' X_{3it-1} + \tau_{3t} + \sum_{i=2}^{N} \mu_{3i} d_i + \varepsilon_{3it-1}. \tag{3.5.3a}$$

$$Proc_{it-1}^{*} = \beta_{41} lnturn_{it-2} + \beta_{42}' X_{4it-1} + \tau_{4t} + \sum_{i=2}^{N} \mu_{4i} d_i + \varepsilon_{4it-1}. \tag{3.5.3b}$$

$$Prod_{it-1} = 1\left[Innov_{it-1}^{*} > 0\right]. \tag{3.5.3c}$$

$$Proc_{it-1} = 1\left[Innov_{it-1}^{*} > 0\right]. \tag{3.5.3d}$$

$$lnturn_{it} = \beta_{51} Prod_{it-1}^{*} + \beta_{52} Proc_{it-1}^{*} + \beta_{53}' X_{5it} + \tau_{5t} + \sum_{i=2}^{N} \mu_{5i} d_i + \varepsilon_{5it}. \tag{3.5.3e}$$

The reduced form of a system of equations 3.5.3a-3.5.3e can be written as:

$$\begin{aligned} lnturn_{it} = {} & (\beta_{31}\beta_{51} + \beta_{41}\beta_{52}) lnturn_{it-2} + \beta_{51}\beta_{32}' X_{3it-1} + \beta_{52}\beta_{42}' X_{4it-1} + \beta_{53}' X_{5it} \\ & + \beta_{51}\tau_{3t} + \beta_{52}\tau_{4t} + \tau_{5t} + \beta_{51}\sum_{i=2}^{N} \mu_{3i} d_i + \beta_{52}\sum_{i=2}^{N} \mu_{4i} d_i + \sum_{i=2}^{N} \mu_{5i} d_i \\ & + \underbrace{\beta_{51}\varepsilon_{3it-1} + \beta_{52}\varepsilon_{4it-1} + \varepsilon_{5it}}_{\zeta_{5it}}. \end{aligned} \tag{3.5.4}$$

ζ_{5it} is the linear combination of the trivariate normal distribution $(\varepsilon_{3it-1}, \varepsilon_{4it-1}, \varepsilon_{5it})$, thus follows the normal distribution: [16]

$$\zeta_{5it} \sim N(0, {\sigma_{\zeta_{5it}}}^2) \tag{3.5.5}$$

where ${\sigma_{\zeta_{5it}}}^2 = \beta_{51}^2 + \beta_{52}^2 + \sigma_5^2 + 2\beta_{51}\beta_{52}\rho_{34} + 2\beta_{51}\rho_{35}\sigma_5 + 2\beta_{52}\rho_{45}\sigma_5$

[16] We can write $\zeta_{5it} = A\varepsilon$, where A is an 1×3 vector, and ε is a 3×1 multivariate normal random vector and $\varepsilon \sim N(\mu, \Sigma)$, then $\zeta_{5it} \sim N(A\mu, A\Sigma A^T)$

The individual likelihood function encompasses both innovators and non-innovators. It is effectively the probability density function of the compound error term ζ_{5it} of reduced-form equation coupled with the contribution from the first bivariate probit model, which can be written as:

$$
\begin{aligned}
L_i = \prod_{t=0_i+1}^{T_i} & \Phi_2((2Prod_{it-1}-1)(\beta_{31}lnturn_{it-2}+\beta_{32}'X_{3it-1}+\tau_{3t}+\sum_{i=2}^{N}\mu_{3i}d_i), \\
& (2Proc_{it-1}-1)(\beta_{41}lnturn_{it-2}+\beta_{42}'X_{4it-1}+\tau_{4t}+\sum_{i=2}^{N}\mu_{4i}d_i), \\
& (2Prod_{it-1}-1)(2Proc_{it-1}-1)\rho_{34}))\frac{1}{\sqrt{2\pi\sigma_{\zeta_{5it}}{}^2}}exp^{-\frac{\zeta_{5it}^2}{2\sigma_{\zeta_{5it}}{}^2}}
\end{aligned}
\tag{3.5.6}
$$

where Φ_2 denotes the cumulative distribution function of the bivariate normal distribution.

$$
\begin{aligned}
\zeta_{5it} =& lnturn_{it}-(\beta_{31}\beta_{51}+\beta_{41}\beta_{52})lnturn_{it-2}-\beta_{51}\beta_{32}'X_{3it-1}-\beta_{52}\beta_{42}'X_{4it-1}-\beta_{53}'X_{5it} \\
& -\beta_{51}\tau_{3t}-\beta_{52}\tau_{4t}-\tau_{5t}-\beta_{51}\sum_{i=2}^{N}\mu_{3i}d_i-\beta_{52}\sum_{i=2}^{N}\mu_{4i}d_i-\sum_{i=2}^{N}\mu_{5i}d_i
\end{aligned}
\tag{3.5.7}
$$

$$
\sigma_{\zeta_{5it}}{}^2 = \beta_{51}^2+\beta_{52}^2+\sigma_5^2+2\beta_{51}\beta_{52}\rho_{34}+2\beta_{51}\rho_{35}\sigma_5+2\beta_{52}\rho_{45}\sigma_5 \tag{3.5.8}
$$

In order to speed up the convergence, the Geweke-Hajivassiliou-Keane algorithm simulation is triggered for higher-dimensional cumulative multivariate normal distributions. The number of draws per observation is changed in the simulation sequence to 20. The default is twice the square root of the number of observations for which the simulation is needed (Cappellari et al. [2003]). According to Roodman [2009], raising simulation accuracy by increasing the number of draws is necessary for convergence, however slows down the execution. On the other hand, when the number of observations is high, convergence can be achieved with few draws per observation (Cappellari et al. [2003]).

Table 3.5 presents the estimation results for the model with both latent product and process innovation propensity to explain firm performance. It is remarkable to notice that the estimates are consistent and robust across model specifications. Table 3.5 displays an intensified two-way relationship between innovation and firm performance and conforming estimates for other determinants. Looking at the firm performance equation, product and process innovation jointly exert an accentuated impact on firm performance. The estimation of other explanatory variables of firm performance shows strikingly similar results compared to the Table 3.3 and Table 3.4. As for product and process innovation equation, the impact of past firm performance has been attenuated. R&D intensity, subsidy and cooperation variables become more significant with increased magnitude for both

Table 3.5: FIML estimates of the model with both latent product and process innovation propensity to explain firm performance: unbalanced yearly panel data from Luxembourg over the period 2003-2012.

Regressor	Coef.	(Std. Err.)
Product Innovation$_{t-1}$		
Turnover in log$_{t-2}$	-0.628^{***}	(0.22)
Log R&D intensity$_{t-2}$	0.116^{**}	(0.06)
Non-R&D performer$_{t-2}$	-0.261	(0.16)
Subsidy$_{t-2}$	0.343^{*}	(0.21)
Cooperation$_{t-2}$	0.595^{***}	(0.17)
Medium-sized$_{t-1}$	-0.792^{**}	(0.39)
Large$_{t-1}$	0.148	(0.58)
Headquarter$_{t-1}$	-0.889^{***}	(0.30)
Firm dummies	YES	YES
Year dummies	YES	YES
Process Innovation$_{t-1}$		
Turnover in log$_{t-2}$	0.302	(0.20)
Log R&D intensity$_{t-2}$	0.113^{***}	(0.04)
Non-R&D performer$_{t-2}$	0.030	(0.11)
Subsidy$_{t-2}$	0.208	(0.14)
Cooperation$_{t-2}$	0.273^{*}	(0.15)
Medium-sized$_{t-1}$	-0.729^{***}	(0.21)
Large$_{t-1}$	-0.631^{*}	(0.38)
Headquarter$_{t-1}$	-0.321^{*}	(0.19)
Log of tangible investment intensity $_{t-2}$	-0.001	(0.02)
Non-investor in tangible goods$_{t-2}$	0.127	(0.08)
Firm dummies	YES	YES
Year dummies	YES	YES
Turnover in log$_t$		
Product Innovation$_{t-1}$	-0.079^{**}	(0.04)
Process Innovation$_{t-1}$	0.189^{**}	(0.07)
Log of tangible investment intensity$_{t-1}$	-0.003	(0.00)
Non-investor in tangible goods$_{t-1}$	-0.016	(0.02)
Log of market share$_{t-1}$	0.046^{***}	(0.01)
Concentration ratio$_t$	0.239	(0.18)
Log of market share$_{t-1}$ $\times$ concentration ratio$_t$	0.037	(0.04)
Person employed in log$_t$	1.037^{***}	(0.03)
Wage in log$_t$	0.687^{***}	(0.05)
Education$_t$	0.005	(0.02)
Market competition$_t$		
Low	-0.011	(0.02)
Medium	-0.001	(0.02)
High	-0.015	(0.02)
Firm dummies	YES	YES
Year dummies	YES	YES
σ_3	0.254^{***}	(0.04)
ρ_{12}	0.632^{***}	(0.06)
ρ_{13}	-0.066	(0.16)
ρ_{23}	-0.588^{***}	(0.15)
Observations	2086	
Log-likelihood	-260.91	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

product and process innovation. The dummy variable of non-R&D performer becomes insignificant for both product and process innovation. Moreover, the variable headquarter becomes more statistically significant with enlarged magnitude for both product and process innovation.

3.6 Robustness checks

Various robustness checks are implemented to assess the sensitivity of the findings. Table 3.6 and Table3.7 present estimates with realized observed innovation indicator in lieu of latent variable in the firm performance equation. In this context, the absence of innovative strategies exerts homogeneous impact on firm performance regardless the distance between underlying latent variable and threshold zero. By the same token, no distinction is made between innovative firms with underlying latent variable well above the threshold zero and marginally above the threshold. By and large, estimates with realized product innovation indicator exhibit consistent features with previous findings. An intensified negative two-way relationship is observed for product innovation. Subsidy variable becomes significant with the increased magnitude, while medium-sized class exerts significant negative impact on the probability of delivering product innovation. As for process innovation, the impact of process innovation on firm performance is no longer significant with altered sign. The coefficient of non-R&D performer becomes insignificant, while subsidy and cooperation variables become significant with the increased magnitude. In consideration of cost reduction and improved efficiency in production, prevalent systemic transformation and less market uncertainty associated with process innovation, it is unlikely that process innovation exerts negative effect on firm performance. Accordingly, the inclusion of latent innovation propensity to explain firm performance in the baseline model is a more justified approach. Table 3.8 shows estimates with both realized product and process innovation in the firm performance equation. This difference in model specifications leads to some variation in estimates. Process innovation exerts negative impact on firm performance, although not significant in the bivariate case.

Table 3.9 and Table 3.10 reveal the distinct pattern between radical product innovation and incremental product innovation. Radical innovation is defined as the introduction of a new or significantly improved good or service which is new to the market. Incremental innovation is defined as the introduction of a new or significantly improved good or service which is new to the firm. Consistent with literature (Dewar and Dutton [1986], Ettlie et al. [1984], Green et al. [1995]), radical innovation and incremental innovation are differently determined and associated with different capabilities and skills. It appears that superior past firm performance discourages the emergence of radical innovation, and the introduction of radical innovation decreases log of turnover in the subsequent period. An opposite pattern is identified for the incremental innovation, although the coefficients of two-way relationship between incremental innovation and firm performance are insignificant. Table

3.9 and Table 3.10 show striking features and reveal the differentiated role of innovation strategies in firm performance. The reason of this phenomenon can be traced back to the argument that radical innovation involves huge uncertainties, long-term devotion and potential higher level of rewards at the later stage (Leifer et al. [2001], Chandy and Tellis [1998]). Radical innovation does not often reap immediate payoff. The new products are associated with limited demand and huge marketing and promotion costs are indispensable to create consumer needs in order to achieve new product success. By contrast, incremental innovation typically encompasses six months to two years. Incremental innovation often involves less uncertainties and implies immediate reward. Therefore, it is reasonable to observe a positive (although insignificant) two-way relationship between incremental innovation and firm performance. Moreover, Table 3.9 shows that medium-sized and large firms tend to delivery more radical innovation than small firms on account of better financing channels and resource bases. The estimates of other determinants in the firm performance equation are quite consistent across innovation types.

The nonlinear fixed-effects model has two main disadvantages. The practical difficulty stems from computing MLE with possibly thousands of fixed-effects dummies. However, computing the MLE of our model with 496 firm dummies is actually feasible. Another methodological obstacle relates to the incidental parameters problem. In the presence of fixed effects, MLE estimators are asymptotically unbiased and consistent for the binary probit model only if $N \to \infty$ and $T \to \infty$. Thus, the ML estimator in the fixed effects model performs poorly when T is small (Neyman and Scott [1948], Lancaster [2000], Greene et al. [2002]). Nonetheless, Greene [2004] admits that incidental parameters problem is essentially small T problem, while the bias of the estimator diminishes with increasing group size. Greene [2004] compares the simulation results between three alternatives: the fixed effects estimator, the random effects estimator, and ignoring the heterogeneity with the pooed estimator. Greene [2004] suggests that for T larger than 8, the estimation results still favor the fixed effects estimator compared with random effects and pooled estimators leaving out heterogeneity for the probit model. Although the MLE in the presence of fixed effects shows finite sample bias when T is small, in our case when $T = 10$, probit model with the fixed effects is still preferred model. As Greene [2004] has advised, whether one should use this estimator really depends on time horizon and the model in question.

Tackling the incidental parameters problem, I will compare other alternatives such as linear probability model in place of probit model to assess the sensitivity of our findings. [17] Linear probability model has certain advantages over the probit as it allows us to include fixed effects dummies. The fixed effects model eliminates firm heterogeneity by demeaning the variables using the within transformation, which consequently circumvents the incidental parameters problem. Probit estimates can be inconsistent unless the error terms are truly normally distributed. Nonetheless, linear probability model suffers from the unbound-

[17] We exclude the estimation on the untransformed biennial data in consideration of the incidental problem of fixed effects probit analysis in case of short time periods, i.e. $T = 5$.

edness problem (Studenmund and Cassidy [1987]). Table 3.11 and Table3.12 use linear probability model in place of probit model for product and process innovation. In Table 3.13 both product and process innovation enter firm performance equation simultaneously. Our estimates resemble the findings with the realized innovation indicators in terms of insignificant negative impact of process innovation on firm performance.

In addition, the variable cooperation may potentially pick up the spurious persistence effect of innovation. Table 3.14 and 3.15 provide an assessment of estimates excluding the variable cooperation$_{t-2}$ in the innovation equation for respective innovation types. In effect, cooperation and innovation strategy are not highly correlated. [18] Only 29.43% of innovative firms cooperate. Occasionally, some non-innovative firms have cooperated for their ongoing or planed innovation activities or abandoned innovation projects during the reference period. Within and between standard deviation of cooperation also show similar magnitude. Compared to Table 3.3 and Table 3.4 , it is comforting to notice that the estimates of determinants are quite consistent before and after excluding the cooperation variable. Accordingly, the significant positive effect of cooperation cannot be attributed to spurious persistence effect of innovation. [19] Cooperation is in a weak relationship with other explanatory variables the omission of which will lead to a worse fit.

[18] The correlation between cooperation variable and TPP innovator (technological product and process innovator) equals to 0.39.

[19] In effect, the direct inclusion of lagged innovation variable in the innovation equation leads to unsatisfactory estimates. For example, the coefficient of $Prod_{t-2}$ is not significant. The estimates are not reported here.

Table 3.6: FIML estimates of the model with realized product innovation: unbalanced yearly panel data from Luxembourg over the period 2003-2012.

Regressor	Coef.	(Std. Err.)
Product Innovation$_{t-1}$		
Turnover in log$_{t-2}$	-1.454^{***}	(0.26)
Log R&D intensity$_{t-2}$	0.033	(0.06)
Non-R&D performer$_{t-2}$	-0.368^{**}	(0.15)
Subsidy$_{t-2}$	0.351^{*}	(0.19)
Cooperation$_{t-2}$	0.475^{***}	(0.16)
Medium-sized$_{t-1}$	-0.700^{**}	(0.32)
Large$_{t-1}$	0.464	(0.52)
Headquarter$_{t-1}$	-0.668^{**}	(0.28)
Firm dummies	YES	YES
Year dummies	YES	YES
Turnover in log$_t$		
Product Innovation$_{t-1}$	-0.105^{***}	(0.03)
Log of tangible investment intensity$_{t-1}$	0.002	(0.00)
Non-investor in tangible goods$_{t-1}$	0.005	(0.01)
Log of market share$_{t-1}$	0.077^{***}	(0.01)
Concentration ratio$_t$	0.021	(0.15)
Log of market share$_{t-1}$ $\times$ concentration ratio$_t$	0.006	(0.03)
Person employed in log$_t$	1.011^{***}	(0.03)
Wage in log$_t$	0.649^{***}	(0.05)
Education$_t$	0.028	(0.02)
Market competition$_t$		
Low	0.004	(0.01)
Medium	-0.008	(0.02)
High	0.002	(0.02)
Firm dummies	YES	YES
Year dummies	YES	YES
σ_2	0.208^{***}	(0.00)
ρ_{12}	0.545^{***}	(0.10)
Observations	2600	
Log-likelihood	24.92	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: FIML estimates of the model with realized process innovation: unbalanced yearly panel data from Luxembourg over the period 2003-2012.

Regressor	Coef.	(Std. Err.)
Process Innovation$_{t-1}$		
Turnover in log$_{t-2}$	0.350*	(0.20)
Log R&D intensity$_{t-2}$	0.114**	(0.06)
Non-R&D performer$_{t-2}$	0.132	(0.17)
Subsidy$_{t-2}$	0.379*	(0.20)
Cooperation$_{t-2}$	0.685***	(0.17)
Medium-sized$_{t-1}$	−0.056	(0.34)
Large$_{t-1}$	0.086	(0.60)
Headquarter$_{t-1}$	−0.146	(0.28)
Log of tangible investment intensity$_{t-2}$	0.057	(0.05)
Non-investor in tangible goods$_{t-2}$	−0.132	(0.20)
Firm dummies	YES	YES
Year dummies	YES	YES
Turnover in log$_{t}$		
Process Innovation$_{t-1}$	−0.026	(0.02)
Log of tangible investment intensity$_{t-1}$	0.000	(0.00)
Non-investor in tangible goods$_{t-1}$	0.004	(0.02)
Log of market share$_{t-1}$	0.079***	(0.01)
Concentration ratio$_{t}$	−0.026	(0.15)
Log of market share$_{t-1}$ × concentration ratio$_{t}$	−0.004	(0.03)
Person employed in log$_{t}$	1.012***	(0.03)
Wage in log$_{t}$	0.647***	(0.05)
Education$_{t}$	0.022	(0.02)
Market competition$_{t}$		
Low	0.005	(0.01)
Medium	−0.008	(0.02)
High	0.004	(0.02)
Firm dummies	YES	YES
Year dummies	YES	YES
σ_2	0.205***	(0.00)
ρ_{12}	0.026	(0.08)
Observations	2599	
Log-likelihood	−33.43	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.8: FIML estimates of the model with both realized product and process innovation to explain firm performance: unbalanced yearly panel data from Luxembourg over the period 2003-2012.

Regressor	Coef.	(Std. Err.)
Product Innovation$_{t-1}$		
Turnover in log$_{t-2}$	-1.431^{***}	(0.24)
Log R&D intensity$_{t-2}$	0.038	(0.05)
Non-R&D performer$_{t-2}$	-0.359^{**}	(0.15)
Subsidy$_{t-2}$	0.327^{*}	(0.19)
Cooperation$_{t-2}$	0.477^{***}	(0.16)
Medium-sized$_{t-1}$	-0.813^{**}	(0.33)
Large$_{t-1}$	0.370	(0.52)
Headquarter$_{t-1}$	-0.785^{***}	(0.28)
Firm dummies	YES	YES
Year dummies	YES	YES
Process Innovation$_{t-1}$		
Turnover in log$_{t-2}$	0.373^{*}	(0.20)
Log R&D intensity$_{t-2}$	0.098^{*}	(0.05)
Non-R&D performer$_{t-2}$	-0.024	(0.17)
Subsidy$_{t-2}$	0.367^{*}	(0.20)
Cooperation$_{t-2}$	0.693^{***}	(0.17)
Medium-sized$_{t-1}$	-0.001	(0.35)
Large$_{t-1}$	-0.036	(0.58)
Headquarter $_{t-1}$	-0.132	(0.28)
Log of tangible investment intensity$_{t-2}$	0.057	(0.05)
Non-investor in tangible goods$_{t-2}$	-0.155	(0.20)
Firm dummies	YES	YES
Year dummies	YES	YES
Turnover in log$_t$		
Product Innovation$_{t-1}$	-0.104^{***}	(0.03)
Process Innovation$_{t-1}$	-0.019	(0.02)
Log of tangible investment intensity$_{t-1}$	0.002	(0.00)
Non-investor in tangible goods$_{t-1}$	0.004	(0.01)
Log of market share$_{t-1}$	0.078^{***}	(0.01)
Concentration ratio$_t$	0.000	(0.15)
Log of market share$_{t-1}$ × concentration ratio$_t$	0.000	(0.03)
Person employed in log$_t$	1.012^{***}	(0.03)
Wage in log$_t$	0.654^{***}	(0.05)
Education$_t$	0.029	(0.02)
Market competition$_t$		
Low	0.005	(0.01)
Medium	-0.008	(0.02)
High	0.002	(0.02)
Firm dummies	YES	YES
Year dummies	YES	YES
σ_3	0.208^{***}	(0.00)
ρ_{12}	0.620^{***}	(0.06)
ρ_{13}	0.555^{***}	(0.09)
ρ_{23}	0.082	(0.07)
Observations	2600	
Log-likelihood	-398.21	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9: FIML estimates of the model with latent radical product innovation: unbalanced yearly panel data from Luxembourg over the period 2003-2012.

Regressor	Coef.	(Std. Err.)
Radical Product Innovation$_{t-1}$		
Turnover in log$_{t-2}$	-0.487^{***}	(0.16)
Log R&D intensity$_{t-2}$	-0.030	(0.03)
Non-R&D performer$_{t-2}$	-0.146	(0.09)
Subsidy$_{t-2}$	-0.024	(0.09)
Cooperation$_{t-2}$	0.164	(0.10)
Medium-sized$_{t-1}$	0.331^{**}	(0.14)
Large$_{t-1}$	0.651^{**}	(0.30)
Headquarter$_{t-1}$	0.014	(0.12)
Firm dummies	YES	YES
Year dummies	YES	YES
Turnover in log$_t$		
Radical Product Innovation$_{t-1}$	-0.195^{***}	(0.07)
Log of tangible investment intensity$_{t-1}$	-0.003	(0.00)
Non-investor in tangible goods$_{t-1}$	-0.016	(0.02)
Log of market share$_{t-1}$	0.047^{***}	(0.01)
Concentration ratio$_t$	0.230	(0.18)
Log of market share$_{t-1}$ $\times$ concentration ratio$_t$	0.036	(0.04)
Person employed in log$_t$	1.043^{***}	(0.03)
Wage in log$_t$	0.685^{***}	(0.05)
Education$_t$	0.004	(0.02)
Market competition$_t$		
Low	-0.010	(0.02)
Medium	-0.001	(0.02)
High	-0.012	(0.02)
Firm dummies	YES	YES
Year dummies	YES	YES
σ_2	0.273^{***}	(0.05)
ρ_{12}	0.740^{***}	(0.12)
Observations	2086	
Log-likelihood	181.25	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.10: FIML estimates of the model with latent incremental product innovation: unbalanced yearly panel data from Luxembourg over the period 2003-2012.

Regressor	Coef.	(Std. Err.)
Incremental Product Innovation$_{t-1}$		
Turnover in log$_{t-2}$	0.193	(0.24)
Log R&D intensity$_{t-2}$	0.024	(0.03)
Non-R&D performer$_{t-2}$	0.047	(0.06)
Subsidy$_{t-2}$	0.023	(0.07)
Cooperation$_{t-2}$	−0.025	(0.04)
Medium-sized$_{t-1}$	−0.250	(0.36)
Large$_{t-1}$	−0.359	(0.52)
Headquarter$_{t-1}$	−0.017	(0.07)
Firm dummies	YES	YES
Year dummies	YES	YES
Turnover in log$_t$		
Incremental Product Innovation$_{t-1}$	0.482	(0.64)
Log of tangible investment intensity$_{t-1}$	−0.003	(0.00)
Non-investor in tangible goods$_{t-1}$	−0.020	(0.02)
Log of market share$_{t-1}$	0.048***	(0.01)
Concentration ratio$_t$	0.226	(0.18)
Log of market share$_{t-1}$ × concentration ratio$_t$	0.034	(0.04)
Person employed in log$_t$	1.057***	(0.03)
Wage in log$_t$	0.689***	(0.05)
Education$_t$	0.007	(0.02)
Market competition$_t$		
Low	−0.014	(0.02)
Medium	−0.003	(0.02)
High	−0.016	(0.02)
Firm dummies	YES	YES
Year dummies	YES	YES
σ_2	0.495***	(0.59)
ρ_{12}	−0.930***	(0.17)
Observations	2086	
Log-likelihood	128.52	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.11: FIML estimates with linear probability model with product innovation.

Regressor	Coef.	(Std. Err.)
Product Innovation$_{t-1}$		
Turnover in log$_{t-2}$	-0.085^{***}	(0.02)
Log R&D intensity$_{t-2}$	0.022^{**}	(0.01)
Non-R&D performer$_{t-2}$	-0.052^{**}	(0.02)
Subsidy$_{t-2}$	0.020	(0.03)
Cooperation$_{t-2}$	0.043^{*}	(0.02)
Medium-sized$_{t-1}$	-0.095^{**}	(0.04)
Large$_{t-1}$	0.059	(0.08)
Headquarter$_{t-1}$	-0.100^{***}	(0.04)
Firm dummies	YES	YES
Year dummies	YES	YES
Turnover in log$_t$		
Product Innovation$_{t-1}$	-0.065^{**}	(0.03)
Log of tangible investment intensity$_{t-1}$	0.000	(0.00)
Non-investor in tangible goods$_{t-1}$	0.006	(0.02)
Log of market share$_{t-1}$	0.077^{***}	(0.01)
Concentration ratio$_t$	−0.006	(0.15)
Log of market share$_{t-1}$ × concentration ratio$_t$	−0.001	(0.03)
Person employed in log$_t$	1.013^{***}	(0.03)
Wage in log$_t$	0.638^{***}	(0.05)
Education$_t$	0.027	(0.02)
Market competition$_t$		
Low	0.004	(0.01)
Medium	−0.010	(0.02)
High	0.001	(0.02)
Firm dummies	YES	YES
Year dummies	YES	YES
σ_2	0.207^{***}	(0.00)
ρ_{12}	0.156^{***}	(0.06)
Observations	2600	
Log-likelihood	172.54	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.12: FIML estimates with linear probability model with process innovation.

Regressor	Coef.	(Std. Err.)
Process Innovation$_{t-1}$		
Turnover in log$_{t-2}$	0.043	(0.03)
Log R&D intensity$_{t-2}$	0.025***	(0.01)
Non-R&D performer$_{t-2}$	0.015	(0.03)
Subsidy$_{t-2}$	0.030	(0.03)
Cooperation$_{t-2}$	0.095***	(0.03)
Medium-sized$_{t-1}$	−0.037	(0.05)
Large$_{t-1}$	0.004	(0.09)
Headquarter$_{t-1}$	−0.019	(0.04)
Log of tangible investment intensity$_{t-2}$	0.007	(0.01)
Non-investor in tangible goods$_{t-2}$	−0.011	(0.03)
Firm dummies	YES	YES
Year dummies	YES	YES
Turnover in log$_t$		
Process Innovation$_{t-1}$	−0.047	(0.03)
Log of tangible investment intensity$_{t-1}$	0.000	(0.00)
Non-investor in tangible goods$_{t-1}$	0.004	(0.02)
Log of market share$_{t-1}$	0.079***	(0.01)
Concentration ratio$_t$	−0.026	(0.15)
Log of market share$_{t-1}$ × concentration ratio$_t$	−0.005	(0.03)
Person employed in log$_t$	1.013***	(0.03)
Wage in log$_t$	0.650***	(0.05)
Education$_t$	0.022	(0.02)
Market competition$_t$		
Low	0.005	(0.01)
Medium	−0.007	(0.02)
High	0.004	(0.02)
Firm dummies	YES	YES
Year dummies	YES	YES
σ_2	0.206***	(0.00)
ρ_{12}	0.055	(0.06)
Observations	2600	
Log-likelihood	62.33	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.13: FIML estimates with linear probability model with both product and process innovations .

Regressor	Coef.	(Std. Err.)
Product Innovation$_{t-1}$		
Turnover in log$_{t-2}$	-0.086^{***}	(0.02)
Log R&D intensity$_{t-2}$	0.022^{**}	(0.01)
Non-R&D performer$_{t-2}$	-0.053^{**}	(0.02)
Subsidy$_{t-2}$	0.020	(0.03)
Cooperation$_{t-2}$	0.042^{*}	(0.02)
Medium-sized$_{t-1}$	-0.094^{**}	(0.04)
Large$_{t-1}$	0.061	(0.08)
Headquarter$_{t-1}$	-0.100^{***}	(0.04)
Firm dummies	YES	YES
Year dummies	YES	YES
Process Innovation$_{t-1}$		
Turnover in log$_{t-2}$	0.042	(0.03)
Log R&D intensity$_{t-2}$	0.025^{***}	(0.01)
Non-R&D performer$_{t-2}$	0.015	(0.03)
Subsidy$_{t-2}$	0.030	(0.03)
Cooperation$_{t-2}$	0.096^{***}	(0.03)
Medium-sized$_{t-1}$	-0.035	(0.05)
Large$_{t-1}$	0.006	(0.09)
Headquarter$_{t-1}$	-0.019	(0.04)
Log of tangible investment intensity$_{t-2}$	0.009	(0.01)
Non-investor in tangible goods$_{t-2}$	-0.013	(0.03)
Firm dummies	YES	YES
Year dummies	YES	YES
Turnover in log$_t$		
Product Innovation$_{t-1}$	-0.061^{*}	(0.03)
Process Innovation$_{t-1}$	-0.041	(0.03)
Log of tangible investment intensity$_{t-1}$	0.001	(0.00)
Non-investor in tangible goods$_{t-1}$	0.005	(0.02)
Log of market share$_{t-1}$	0.078^{***}	(0.01)
Concentration ratio$_t$	-0.016	(0.15)
Log of market share$_{t-1}$ $\times$ concentration ratio$_t$	-0.004	(0.03)
Person employed in log$_t$	1.016^{***}	(0.03)
Wage in log$_t$	0.645^{***}	(0.05)
Education$_t$	0.026	(0.02)
Market competition$_t$		
Low	0.005	(0.01)
Medium	-0.008	(0.02)
High	0.002	(0.02)
Firm dummies	YES	YES
Year dummies	YES	YES
σ_3	0.207^{***}	(0.00)
ρ_{12}	0.214^{***}	(0.02)
ρ_{13}	0.163^{**}	(0.06)
ρ_{23}	0.066	(0.06)
Observations	2600	
Log-likelihood	-141.81	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.14: FIML estimates model with latent product innovation, excluding cooperation variable.

Regressor	Coef.	(Std. Err.)
Product Innovation$_{t-1}$		
Turnover in log$_{t-2}$	-0.848^{***}	(0.18)
Log R&D intensity$_{t-2}$	-0.001	(0.05)
Non-R&D performer$_{t-2}$	-0.366^{***}	(0.13)
Subsidy$_{t-2}$	0.229	(0.17)
Medium-sized$_{t-1}$	0.179	(0.28)
Large$_{t-1}$	0.985^{**}	(0.43)
Headquarter$_{t-1}$	-0.419^{*}	(0.24)
Firm dummies	YES	YES
Year dummies	YES	YES
Turnover in log$_t$		
Product Innovation$_{t-1}$	-0.078^{***}	(0.03)
Log of tangible investment intensity$_{t-1}$	-0.003	(0.00)
Non-investor in tangible goods$_{t-1}$	-0.013	(0.02)
Log of market share$_{t-1}$	0.048^{***}	(0.01)
Concentration ratio$_t$	0.266	(0.18)
Log of market share$_{t-1}$ × concentration ratio$_t$	0.041	(0.04)
Person employed in log$_t$	1.050^{***}	(0.03)
Wage in log$_t$	0.685^{***}	(0.05)
Education$_t$	0.008	(0.02)
Market competition$_t$		
Low	-0.010	(0.02)
Medium	-0.004	(0.02)
High	-0.014	(0.02)
Firm dummies	YES	YES
Year dummies	YES	YES
σ_2	0.210^{***}	(0.01)
ρ_{12}	0.497^{***}	(0.10)
Observations	2086	
Log-likelihood	149.73	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.15: FIML estimates model with latent process innovation, excluding cooperation variable.

Regressor	Coef.	(Std. Err.)
Process Innovation$_{t-1}$		
Turnover in log$_{t-2}$	0.441***	(0.17)
Log R&D intensity$_{t-2}$	0.068**	(0.03)
Non-R&D performer$_{t-2}$	0.120	(0.07)
Subsidy$_{t-2}$	0.081	(0.09)
Medium-sized$_{t-1}$	−0.435**	(0.18)
Large$_{t-1}$	−0.596**	(0.29)
Headquarter$_{t-1}$	−0.022	(0.10)
Log of tangible investment intensity$_{t-2}$	−0.004	(0.02)
Non-investor in tangible goods$_{t-2}$	0.125*	(0.08)
Firm dummies	YES	YES
Year dummies	YES	YES
Turnover in log$_t$		
Process Innovation$_{t-1}$	0.225**	(0.09)
Log of tangible investment intensity$_{t-1}$	−0.003	(0.00)
Non-investor in tangible goods$_{t-1}$	−0.018	(0.02)
Log of market share$_{t-1}$	0.048***	(0.01)
Concentration ratio$_t$	0.243	(0.18)
Log of market share$_{t-1}$ × concentration ratio$_t$	0.039	(0.04)
Person employed in log$_t$	1.043***	(0.03)
Wage in log$_t$	0.689***	(0.05)
Education$_t$	0.002	(0.02)
Market competition$_t$		
Low	−0.012	(0.02)
Medium	0.000	(0.02)
High	−0.013	(0.02)
Firm dummies	YES	YES
Year dummies	YES	YES
σ_2	0.300***	(0.07)
ρ_{12}	−0.793***	(0.11)
Observations	2085	
Log-likelihood	106.78	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.7 Conclusion

This chapter aims at capturing the two-way relationship between innovation and firm performance. In particular, different mechanisms of product and process innovation are distinguished with their distinct impacts on firm performance. To shed light on this issue, an unbalanced longitudinal dataset is applied over the period 2003-2012 which stems from merging five waves of the innovation survey with annual structural business surveys of Luxembourg. A simultaneous structural model is established with the fully recursive form which involves underlying continuous unobservable variables. The lagged latent innovation variable is dependent on the past firm performance, which further determines the current firm performance. A system of equations with mixed structure is estimated by full information maximum likelihood methods. Full information maximum likelihood methods suggest the estimation of nonlinear simultaneous equations for all equations and all the unknown parameters, rather than estimating a single structural equation at a time. In particular, I use cmp package proposed by Roodman [2009] which fits a large family of multi-equation, multi-level and mixed-process estimators.

By and large, I discover that superior firm performance facilitates the emergence of process innovations, and process innovation contributes to firm performance by gaining successful and sustainable competitive advantage, which forms a virtuous circle. However, an opposite pattern is identified for the product innovation on the ground of cannibalization effect and inherent market risks associated with new products. For future extension, longer panel data might be indispensable to explore the presence of possible positive two-way relationship between product innovation and firm performance.

Our results are consistent with the empirical findings of Leiponen [2000]. Leiponen [2000] reveals that product innovation tends to have adverse effects on firm performance measured by the profit margin, whereas process innovation has strong and stable positive effects on firm performance. By the same token, Leiponen [2000] attributes this phenomenon to the initial stage of the product life cycle. In addition, Cainelli et al. [2006] confirms that process innovation has a positive impact on the economic performance, and better-performing firms are more likely to devote more resources to innovation in services. Moreover, Isogawa et al. [2012] demonstrates that the introduction of new products exerts significant negative impacts on sales of existing products, which provides evidence for the negative relationship between product innovation and firm performance.

Our result appears to have relevant managerial implications. Product cannibalization occurs when a company decides to introduce new products which replace an existing product. Managers may need to take into account the market position of existing products and introduce product innovation in light of the products life cycle phase. It is crucial to identify the optimal time to introduce new products which may otherwise lead to the potential retirement of firms existing products. Advantageous combination of marketing strategies is substantial and conductive to improve the overall firm performance for the subsequent remaining periods of existing product.

Managers should also take into account the potential positive feedback between innovation and firm performance. For example, the adoption of process innovation contributes to firm performance, which in turn produces more process innovation. Positive feedback suggests long-term implications and sustaining impacts in future. Additionally, managers need to be mindful of the differentiated significant impacts of innovation strategies on firm performance. For risk-averse firms which aim at immediate payoff to innovation output, process innovation might be a more appropriate strategy than product innovation (particularly radical product innovation) on ground of evident virtuous circle between process innovation and firm performance. The two-way relationship between product innovation and firm performance is more inconclusive considering our short panel. Product innovation is associated with cannibalization effect and uncertain market reactions, which leads to initial negative impacts on firm performance. Some findings related to the control variables are also worthy of comment. R&D inputs, subsidy and cooperation are all conducive to the adoption of innovation strategies.

Several limitations inherent in this research relate to the application of Luxembourgish database. The research is confined to the short panel period. In consideration of short lag period incorporated in the model, the negative effect of product innovation on firm performance is likely to be temporary. The negative impact of product innovation on firm performance should be interpreted as strong association with the introduction stage of new products and cannibalization effect. This does not preclude the possibility of better firm performance in the long run attributed to the current product innovation. Nevertheless, the long-lasting positive effects of product innovation cannot be captured by virtue of the disparity of duration of initial introduction stage across firms. [20]

In addition, larger sample size would allow us to compare two-way relationship between innovation and firm performance for manufacturing and service firms. Barras [1986] and Barras [1990] point out that the dynamics of the adoption of product and process innovation differ for service than manufacturing sectors. Service firms might tend to adopt different innovation strategies, focus on different dimensions of innovation in terms of novelty, and benefit from innovation to a different degree than manufacturing firms. For example, Gallouj [2002] points out that service sectors place more emphasis on process innovation than product innovation. In particular, the importance of process innovation is acknowledged in terms of improvements in the quality of the service delivered, and completely new set of services offered. Prajogo [2006] demonstrates that service firms

[20] Corresponding to the conclusion of my first chapter, product innovation positively contributes to employment while exerts (temporary) negative effect on firm performance. This is not contradictory as many studies have shown curvilinear relationship between firm performance and firm size. Beyond some optimal point, overemployment can harm firm performance due to bureaucratic insularity, incentive limits, transaction cost and communication distortion (Canback [2002]).

benefit less from innovation compared to manufacturing firms. Furthermore, Gallouj and Weinstein [1997] point out that product and process innovations are often closely intertwined for services sector. As the service sector forms a large component of the Grand Duchys economy, this may partly explain the presence of positive impact associated with process innovation on firm performance, rather than product innovation in our findings.

Chapter 4

Persistence of differentiated types of innovation activities: new evidence from Luxembourgish panel data

4.1 Introduction

This chapter investigates the state dependent characteristics at the firm level. The persistence of innovation is identified as the phenomenon that firms that have innovated during a given period innovate in the subsequent period. A true state dependence implies a causal relationship between innovation in one period and decision to innovate in the subsequent period. While spurious state dependence can be caused by unobserved individual effects that are left out and correlated over time.

The assessment of characteristics and determinants of innovation persistence has implications on firm performance and competitiveness at the firm level. Le Bas et al. [2011] argue that firm's competitive advantages are built upon the capability to sustain the continuous undertaking of innovative activities. Meanwhile, Cefis [1999] suggests that systematic innovators can earn profits above the average and sustain incentives to innovate in the subsequent period. Similarly, innovation persistence is strongly linked to the persistence of above-average profits at the firm level (Geroski et al. [1997], Le Bas et al. [2011], Ganter and Hecker [2013]). Therefore, an empirical investigation on innovation persistence can shed important light on the issue of asymmetries in firm performance and competitive advantages.

Secondly, the investigation of innovation persistence at the firm level has far-reaching policy implications. In case of true state dependence of innovation persistence, innovation policy not only affects current innovation but also all future innovation activities. Therefore, it is crucial to spur the undertaking of the initial innovation activity. To illustrate, if innovation exhibits true state dependence regardless of public financial support from local or regional authorities, government intervention on firms' innovative activity might be modified in terms of funding allocation. In order to foster innovation efficiently, the government might give non-innovators a financial preference to encourage them to embark on an innovation journey, on the grounds that innovative firms are more likely to innovate in subsequent period in the light of true state dependence. In addition, if the observed innovation persistence is the consequence of other underlying firm characteristics, policy makers should aim to stimulate those underlying characteristics which drive innovation (Karlsson et al. [2015]).

In order to clarify the definition of firm persistence in innovation, we could consider the scenario with two time periods and two possible decisions in each time period: innovate or not innovate, which engenders four possible cases. A single-shot innovator refers to firms that innovate during only one period. Sporadic innovators implement innovations occasionally in a discontinuous manner. In other words, it encompasses two cases: innovators at time t stop innovation at time $t+1$ and non-innovators at time t start innovation at time $t+1$. Given the limited resources for investing in technological activities, non-innovators are less likely to convert to innovators, relative to the case of innovators winking out innovations (Le Bas and Latham [2006]).

Economic theory has provided three potential explanations of innovation persistence over time. The first factor is knowledge, learning and dynamic increasing return (Cohen and Levinthal [1989], Geroski et al. [1997], Peters [2009], Antonelli et al. [2012]). Other than a unidirectional causation of linear model, the positive feedback enables knowledge to serve simultaneously as an input and output of generation of new knowledge (David [1992]). Nelson [1959] emphasizes the cumulative, non-exhaustible nature of knowledge and the irreversible transformations produced. In other words, knowledge is essential in the innovation process as it represents not only important input, but also the output of the innovation process. In addition, Stiglitz [1987] points out that previous learning experience strengthens the ability to learn. Arrow [1971] also emphasizes the effect of learning by doing. Cohen and Levinthal [1989] propose that R&D investment brings about both effects of innovation and learning. Development in learning builds up accumulative stock of absorptive capacity which facilitates the innovation in the subsequent period (Cohen and Levinthal [1990]). Innovation process is characterized by dynamic increasing returns. The larger the cumulative size of the innovation activities carried out, the more knowledge, learning capacity generated from such interactions. The absorptive capacity furthermore permits a more efficient accumulation of external knowledge and learning, thus fosters innovation in subsequent periods. Therefore, the cumulative nature of knowledge and dynamic increasing return gives rise to innovation persistence (Winter and Nelson [1982], Malerba and Orsenigo [1996]). In other words, state dependence in innovation indicates that the development of innovation constitutes an important source of subsequent innovation in terms of learning effect and knowledge stocks.

The second factor contributing to the persistence of innovation can be identified as sunk costs relevant to R&D expenditures (Sutton [1991], Mañez et al. [2009], Mañez et al. [2009], Antonelli et al. [2012]). The development of R&D may involve creating an R&D department, purchasing specific physical assets and hiring or training R&D staff, which constitute significant sunk costs that are usually unrecoverable. Stiglitz et al. [1987] [p. 889] argue that: “most expenditures on R&D are, by their nature, sunk costs. The resources spend on a scientist to do research cannot be recovered. Once this time is spent, it is spent.” Innovation often involves creating embedded routines by repeating the same types of innovations, which implies high switching costs upon exit. Moreover, the opportunity cost to give up the ongoing R&D projects is large in the context of dynamic increasing returns. Investment in R&D creates specific knowledge and hands-on experience relevant to innovation operations, which are largely lost upon exit (Martin [1993]). In consequence, sunk costs and irreversibility in R&D lead to barriers to entry and exit in innovative activities (Sutton [1991] , Antonelli et al. [2012]).

The third explanation refers to “success breeds success” phenomenon and alleviated financial constraints. Successful innovations positively affect the conditions for subsequent innovation through elevated market power (Phillips [1971]). On the other hand, Mansfield [1968] emphasizes that successful innovation broadens the technological opportunities which facilitate the delivery of subsequent innovation. Moreover, innovation projects are usually characterized by longer term devotion, large financial investment and high risk. Due to capital market imperfection, the flow of internal finance is the principle determinant of innovation expenditures (Arrow [1962], Himmelberg and Petersen [1994]). High-tech firms rely heavily on internal financing due to the difficulty in obtaining external financing (Himmelberg and Petersen [1994]). Successful innovations alleviate the financial constraints by providing prosperous innovators with greater internal funding to support further innovations. Moreover, external funding may be more available as prosperous innovators attract more investments from banks, venture capitalists and business angels for ongoing innovative activities, which facilitate the delivery of subsequent innovation.

Nonetheless, the standard approach of industrial organization accentuates the incentive mechanism of innovation, which elucidates various reasons that prevent innovative firms from remaining innovative. For example, if a firm in a formerly competitive market has innovated and has monopoly power, such firm has a lower incentive for innovating again (Arrow [1962], Tirole [1988]). In addition, if a firm produces multiple products, an incumbent innovator may fear the cannibalization effect where new products may simply drive out old products or compete with firms existing products from previous innovations (Schumpeter [1942]). Moreover, from the perspective of consumer demand, perhaps all demand is satisfied due to prior innovations and there is no need for further innovation (Peters [2009]). It may also turn out that adverse demand is associated with particular product innovation (Schmookler [1966], Peters [2009]).

The rest of the chapter is organized as follows. Section 4.2 presents a short overview of the prior empirical studies on innovation persistence, and subsequently discusses the mechanism of differentiated persistence patterns across innovation types. Section 4.3 provides the data description and detailed discussion of variables selection. In section 4.4 the descriptive statistics are summarized and the analysis of innovation persistence is displayed based on transition probability matrixes. Section 4.5 presents the econometric analysis for the innovation persistence using both Wooldridge [2005] and Albarrán et al. [2015] approaches and contrast the results obtained. Section 4.6 provides the robustness check and section 4.7 concludes.

4.2 Theoretical background and prior literature

4.2.1 Prior empirical studies on innovation persistence

There is a substantial body of literature which focuses on the analysis of innovation persistence using patent data (Geroski et al. [1997], Malerba and Orsenigo [1996], Cefis [2003], Latham and Le Bas [2006]). For example, Geroski et al. [1997] show that only a few innovative firms are persistently innovative, using a patent sample of 3304 US firms in the period 1969-1988 and a patent sample of 1624 UK firms from 1945 to 1982. In contrast, Cefis [2003] confirms the hypothesis of true state dependence among major innovations using patent applications of 577 UK manufacturing firms. By and large, empirical analysis based on patent data as innovation indicator often finds weak evidence of innovation persistence relative to empirical findings based on innovation survey data. Patent data may underestimate the persistence of innovation on the grounds that patent data measures the persistence of innovation leadership rather than innovation persistence (Duguet and Monjon [2004]). Moreover, Arundel and Kabla [1998] argue that firms tend to patent more product innovations than process innovations. In consequence, the patent data is biased in favor of product innovations (Duguet and Monjon [2004]).

Another strand of empirical studies focuses on innovation survey and provides insights on the existence and significance of innovation persistence (Peters [2009], Raymond et al. [2010b], Clausen et al. [2011], Antonelli et al. [2012]). Based on a German innovation panel data for the period 1994-2002, Peters [2009] discovers a strong innovation persistence at the firm level using the Wooldridge [2005] approach in the context of dynamic random effects discrete choice model. Raymond et al. [2010b] confirm the hypothesis of true state dependence in the high-tech industries using four waves of Community Innovation Survey of Dutch manufacturing firms over the period 1994-2002. A dynamic type 2 Tobit model is estimated by maximum likelihood method after accounting for individual effects and initial conditions problem. Using corresponding innovation survey, a stream of empirical studies stresses the disparate impacts of differentiated types of innovation on innovation persistence. To illustrate, based on a sample of 451 Italian manufacturing firms during the years 1998-2006, Antonelli et al. [2012] provide new insights on the role of R&D investments in innovation persistence and analyze differentiated patterns of persistence across product and process innovation. The highest level of persistence is found for R&D-based innovation activities, particularly for product innovation. In addition, Clausen and Pohjola [2013] analyze the innovation persistence by distinguishing between incremental and radical innovation and confirm the distinct persistence patterns across types of innovations. Clausen and Pohjola [2013] demonstrate more prominent innovation persistence associated with radical innovation than incremental innovation.

In this study, I evaluate the degree of innovation persistence at the firm level and explore whether persistence patterns vary across types of innovations. Moreover, most prior studies are based on the Wooldridge [2005] method, which neglects the fact that the Wooldridge [2005] method is derived for the balanced panel. This work is the first attempt to empirically analyze the true state dependence and the role of sunk costs in forming the innovation persistence by means of Albarrán et al. [2015] method, which takes into account the individual effects, initial conditions problem and unbalanced structure of panels jointly. In order to correctly assess the true persistence in innovation, it is necessary to account for the initial conditions and individual effects (Peters [2009], Raymond et al. [2010b]). The spurious state dependence may otherwise emerge due to innovation-prone unobserved effects that are correlated across time (Hsiao [2014]). This empirical analysis is based on a longitudinal Community Innovation Survey (CIS) at the firm level. Panel data enables us to control for unobserved firm heterogeneity through individual effects. Moreover, sample selection is controlled for as not all firms implement innovation.

The justification for the Albarrán et al. [2015] approach comes from the prominence to account for the unbalanced structure of panels. The initial conditions problem in dynamic models with balanced panel data is intensified for the unbalanced panel, as the unbalancedness affects the first period observations in the data set. Unless the process is in the steady state or the initial observations come from the same exogenous distribution for all individuals and initial periods, applying the Wooldridge [2005] method to unbalanced panels can lead to inconsistent coefficient estimates by ignoring the unbalancedness. The simulation results of Albarrán et al. [2015] actually demonstrate that, the bias of Wooldridge [2005] method using balanced sub-panel is substantial for the long panel (e.g. $T = 15$). Therefore, the unbalancedness cannot be overlooked for consistent estimation of dynamic models. The dynamic nonlinear random effects model proposed by Albarrán et al.

[2015] takes into account the individual effects, initial conditions problem and unbalanced structure of panels jointly. The Albarrán et al. [2015] methodology has the advantage of allowing different distributions of individual effects across sub-panels.

In addition, this study provides a differentiated analysis on persistence of different types of innovation indicators, as innovation is a highly differentiated phenomenon associated with diverse firm strategies (Pianta and Crespi [2008], Antonelli et al. [2012]). In view of sunk-cost hypothesis we expect to find evidence of state dependence in particular for R&D based innovation activities. Finally, I explore whether persistence patterns vary across diverse types of product innovation, namely, radical and incremental product innovation. The analysis presented in this chapter resembles Clausen and Pohjola [2013] in terms of clear distinction between radical product innovation and incremental product innovation, where radical innovations (defined as new-to-market product innovation) open up new markets and fundamentally transform a firm's value chain. The determinants of persistence of radical and incremental product innovation can be distinctively constituted. In the light of positive feedback among knowledge, learning effect, dynamic capabilities and capacity to deliver radical innovations, the introduction of new market products may be characterized by major persistence even after accounting for sunk costs relevant to R&D.

4.2.2 Innovation persistence across differentiated innovation types

The role of product and process innovation

Innovation is a highly differentiated phenomenon associated with disparate strategies. In particular, Utterback and Abernathy [1975] reveal that innovation strategies vary systematically with differences in the development state achieved in the production process, firm's environment and strategy for competition and growth. Hence, innovation persistence may depend upon the diverse types of innovation strategy adopted. Product innovation takes place when the enterprise introduces new or significantly improved goods and new or significantly improved services. New products are perceived as the important element for long-term firm growth by gaining successful and sustainable competitive advantage. Product innovations are usually associated with firms in-house R&D (Winter and Nelson [1982]), thus more relevant to sunk-cost hypothesis which stimulates the continuous undertaking of innovation activities. Moreover, product innovation shows a high degree of persistence since the introduction of new product is embedded in firm's regular and predictable routine related to product portfolio management (Antonelli et al. [2012], Gruber [1992]). A large body of empirical studies validates the state dependence for both product and process innovation (Antonelli et al. [2012], Clausen et al. [2011], Tavassoli and Karlsson [2015]). Moreover, Antonelli et al. [2012], Clausen et al. [2011] and Tavassoli and

Karlsson [2015] discover a higher level of persistence associated with product innovation relative to process innovation.

In contrast, process innovations aim to reduce unit costs of production and improve quality of products. Process innovations often come from the R&D done by suppliers which reinforce the different impact (Winter and Nelson [1982]). Process innovation often leads the firm to invest in physical capital such as machinery, equipment and structures which are already embodied in the new technology. Moreover, process innovators tend to use different information sources and innovation channels (Arundel et al. [2007]). Arundel et al. [2007] also argue that non-R&D innovators, compared to R&D performers, are more likely to focus on process innovation and to source ideas from production engineers and design staff. Therefore, the sunk-cost hypothesis is less relevant for process innovation. For example, Ganter and Hecker [2013] identify the true state dependence for product innovation, but not for process innovation.

Another strand of literature uses technological product and process innovation (TPP) indicator which encompasses both product and process innovation without distinguishing between them (Raymond et al. [2010b], Duguet and Monjon [2004]). TPP innovation indicator enables us to account for the complementarity effect between product and process innovation. Previously, a firm is considered to innovate persistently if it produces an innovation in the same field (either product or process) in the two periods of time. The adoption of TPP innovation measure relaxes the definition of innovation persistence and include the technological natality cases (Malerba and Orsenigo [1999]). In other words, a firm is now considered to innovate persistently even it produces innovations in the different fields in the two periods of time. As product and process innovation are highly correlated, the use of TPP innovation indicator takes into account possible effects of complementarity between two types of innovation outcome. Both Raymond et al. [2010b] and Duguet and Monjon [2004] confirm true state dependence of innovation persistence by adopting TPP indicator. This chapter aims to analyze the true state dependence using product, process innovation and TPP indicator jointly.

The role of radical and incremental innovation

This chapter also contributes to the literature by proposing a differentiated analysis of innovation persistence where incremental and radical innovation are explicitly distinguished within the category of product innovation. Radical innovation is defined as the introduction of a new or significantly improved good or service which is new to the market, whereas incremental innovation is defined as the introduction of a new or significantly improved good or service which is new to the firm (Olson et al. [1995], Garcia and Calantone [2002]).[1]

Radical innovation is fundamentally different from incremental innovation (Dewar and Dutton [1986], Ettlie et al. [1984], Green et al. [1995]). The difference in nature between two innovation types suggests divergent roles for absorptive capacity, knowledge and learning effect, which implies an inherent difference in persistence pattern (Ritala and Hurmelinna-Laukkanen [2013]). Radical innovation involves huge uncertainties, discontinuities and potential higher level of rewards (Leifer et al. [2001], Chandy and Tellis [1998]). [2] In addition, radical innovation is associated with more intangible assets (Nonaka [1994], Teece [2007]) and different management strategies (McDermott and O'Connor [2002]). Furthermore, McDermott and O'Connor [2002] demonstrate that radical innovation contains a different set of knowledge and capabilities than incremental innovation. According to Leifer [2000], radical innovation differs substantially from incremental innovation in the following aspects: project time line, trajectory, idea generation and opportunity recognition, process, business case, the role of key players, organizational structures, resources and competencies, operating unit involvement.

To the best of my knowledge, Clausen and Pohjola [2013] is the only study which analyzes the innovation persistence by distinguishing between incremental and radical innovation. Using a panel database from the Norwegian Community Innovation Survey (CIS), Clausen and Pohjola [2013] find that lagged radical innovation has a significant and positive influence on firms' ability to develop current radical innovation. In contrast, an analogous pattern cannot be identified for incremental innovation. Their findings demonstrate that homogeneous treatment between diverse types of product innovations can give a misleading view of innovation persistence. Nonetheless, relatively little attention has been paid to explain the different mechanisms of innovation persistence between incremental and radical innovation. It calls for a thorough examination to identify the source of disparity in the persistence pattern.

In the first place, radical innovation is different from incremental innovation in terms of project life cycle. Radical innovation often implies longer term devotion and larger financial investment relative to incremental innovations (McDermott and O'Connor [2002],

[1] To measure the degree of newness of the product, the shares of new products sales are not applied to this case in order to avoid sale factors. Rather, radical innovator is the dummy variable which takes the value 1 if the enterprise introduces new or significantly improved goods or service which is new to the market. Incremental innovator is the dummy variable which takes the value 1 if the enterprise introduces new or significantly improved goods or service which is new to the firm only. In addition, radical innovations require long-term (typically ten years or longer) development time and large financial investment. It is crucial to develop variations and extensions of radical innovation products in order to optimize the risk and investment. The modifications, variations and improvements upon the radical innovation products or vertical follow-up innovation are still radical as long as the products are new to the market before any competitor. This situation usually ends quickly as the fast second company appears, extends and improves upon the radical innovation products launched by previous firm.

[2] Those uncertainties include organizational uncertainty, resource uncertainties, technological uncertainties and market uncertainties.

Morone [1993]). [3] A radical innovation life cycle usually spans ten years and more. In contrast, incremental innovation typically encompasses six months to two years. The longevity of radical innovation projects implies a potentially high level of innovation persistence.

Secondly, knowledge, learning effect and dynamic increasing returns might exert a greater influence on fostering innovation persistence for radical innovation than incremental innovation. As aforementioned, incremental innovation and radical innovation often imply different knowledge sets. To a large degree, incremental innovation is associated with internal knowledge whereas radical innovation often relates to external knowledge (Forés and Camisón [2016]). Chiang and Hung [2010] demonstrate that accessing knowledge from a broad range of external channels can enhance the innovating firm's radical innovation performance. Similarly, Subramaniam and Youndt [2005] argue that broader horizons with respect to knowledge sources are related to radical innovation. In addition, Dewar and Dutton [1986] point out that diverse types of knowledge and complex organization lead to high potential of radical innovation adoption. Thus, radical innovation is strongly related to large knowledge base and access and exposure to diverse knowledge domains. In addition, radical innovation by definition incorporates a large degree of novel knowledge (Dewar and Dutton [1986]). As Schoenmakers and Duysters [2010] manifest, firms that are quick in understanding the possibilities of emergent technologies and combining it with mature and well understood knowledge, are more capable of delivering radical inventions.

Furthermore, the significance of creativity, developing dynamic capabilities are more recognized for radical innovations. Leifer et al. [2001] emphasize that radical innovation differs from incremental innovation in terms of resources and competencies. Leifer et al. [2001] stress the importance of creativity and skill in resource and competency acquisition to the success of radical innovation. In addition, Zhou and Wu [2010] suggest that in order to sustain explorative or radical innovation in products, firms should combine their technological capabilities with the development of dynamic capabilities which enable them to reallocate resources, to break down existing operational routines and absorb new knowledge to address discontinuities in the fast-changing environment. Moreover, Peters [2009] argue that firm's technological capabilities are primarily determined by human capital, i.e., by the knowledge, skills and creativity of their employees. Similarly, Madjar et al. [2011] argue that radical innovation is more associated with resources for creativity, willingness to take risks and career commitment. In contrast, incremental innovation is associated with organizational identification, presence of creative coworkers and conformity.

Knowledge serves simultaneously as an input and output of generation of new knowledge (David [1992]). As aforementioned, radical innovations require a higher level of assembly of diverse knowledge, and often imply fundamental changes that represent revolutions

[3] Leifer [2000] points out that radical innovation life cycle is characterized by several traits, such as involving long term, highly uncertain and unpredictable, sporadic, nonlinear, stochastic and context dependent.

in technology and clear departures from existing practice (Duchesneau et al. [1979], Ettlie et al. [1984]). Therefore, prior successful radical innovation generates more novel knowledge and learning effect, brings about more profound transformation of a firms internal capabilities. Consequently, a self-reinforcing mechanism of dynamic increasing return emerges for radical innovation. Prior radical innovation facilitates a more efficient accumulation of external knowledge in the subsequent period (Peters [2009], Cohen and Levinthal [1989]), a deepening learning process, and an enhanced transformation of dynamic capabilities. New knowledge, elevated learning effect in conjunction with intensified dynamic capabilities furthermore contribute to the successful delivery of radical innovation in future, which forms a virtuous circle. Therefore, the mechanism of positive feedback and increasing return among the accumulation of knowledge, learning, dynamic capabilities induces a higher level of state dependence for radical innovation.

4.3 Data

4.3.1 Data description

The empirical analysis is based on a longitudinal dataset derived from the biennial Luxembourgish Community Innovation Survey (CIS), which consists of five questionnaire waves 2002-2004, 2004-2006, 2006-2008, 2008-2010, 2010-2012. [4] The survey methodology and innovation definition are consistent with the Oslo Manual which produces internationally comparable data. The CIS questionnaires collect information on different aspects of innovation activities regarding different types of innovations introduced by firms during the reference period (i.e., process innovation, product innovations, new-to-market innovations, new-to-firm innovations), along with other firm-level characteristics such as intramural and extramural R&D expenditures, subsidy, innovation cooperation, the percentage of employees with higher education, the degree of market competition. The rich structure of data allows us to explore the role of R&D activities in explaining innovation persistence and differentiated patterns of persistence across diverse typologies of innovation outputs.

In order to avoid shell corporations, the dataset is cleaned by eliminating firms with less than 10 employees and negative turnover, on the grounds that Luxembourg earns the reputation as the European top tax haven where certain taxes are levied at a low rate. Furthermore, in order to carry out the analysis of Albarrán et al. [2015] method, we consider enterprises that take part in at least three consecutive innovation surveys. [5]

[4] In this chapter, the original biennial Luxembourgish CIS data is applied rather than the merged CIS and SBS data. Dissimilar to Chapter 2 and Chapter 3, we do not face the same issue of merging two datasets with different periodicities. In other words, we do not have the same issue of overlapping years as in the previous imputed annual data.

[5] It is worth noting that preserving firms with at least three consecutive periods will not alter the unbalanced structure of the panel. This can be clearly demonstrated by the panel pattern, which involves 111.. , 111.1 ,

In addition, the following sectors are not part of the study on account of sparse observations: mining & quarrying, construction, real estate, accounting, consultancy, other technicals, rental leasing, travel, health, and service NEC. In the following, two panel datasets are distinguished: an unbalanced panel comprising all firms and a balanced subsample comprising firms which are observed in all five waves. The latter is needed for estimation purposes with the Wooldridge [2005] approach. In contrast, the dynamic nonlinear random effects model proposed by Albarrán et al. [2015] deals with unbalanced panel which exploits all the observations.

4.3.2 Selection of variables

In order to examine differentiated types of innovation persistence, the dependent variables are distinguished between product, process and TPP innovators. The distinction between product and process innovation has long been recognized as crucial different strategies of firms in response to different challenges (Utterback and Abernathy [1975]).

Product innovator is the dummy variable which takes the value 1 if the enterprise introduces new or significantly improved goods (excluding the simple resale of new goods purchased from other enterprises and changes of a solely aesthetic nature), and new or significantly improved services during the period under review. A product innovation can be either new to the enterprise or new to the sector or market. It could be originally developed by the enterprise or by other enterprises. Product innovation can be further distinguished between radical product innovation (defined as product innovations that are new and previously unknown to the market the firms operate in) and incremental innovation (defined as product innovations that are only new to the firm).

Process innovation refers to the dummy variable which takes the value 1 if the enterprise introduces new or significantly improved methods of manufacturing or producing goods or services, new or significantly improved logistics, delivery or distribution methods for inputs, goods or services, or new or significantly improved supporting activities for processes, such as maintenance systems or operations for purchasing, accounting, or computing.

Technological product and process innovation (TPP) is a dummy variable which takes the value 1 if firms implement either product or process innovation. TPP innovation indicator enables us to account for the complementarity effect between product and process innovation. Previously, a firm is considered to innovate persistently if it produces an innovation in the same field (either product or process) in the two periods of time. The adoption of TPP innovation measure relaxes the definition of innovation persistence and

.111. , ..111 , 1.111 , 1111. , .1111 , 11111. The pattern indicates the participation pattern where 1 indicating one observation for a specific year, a dot indicating no observation. The dynamic model usually needs at least two consecutive observations over time to identify the parameters of the lagged dependent variables. One more consecutive period is required for the random effect with the Albarrán et al. [2015] method.

include the technological natality cases (Malerba and Orsenigo [1999]). In other words, a firm is now considered to innovate persistently even it produces innovations in the different fields in the two periods of time. As product and process innovation are highly correlated, the use of TPP innovation indicator takes into account possible effects of complementarity between two types of innovation outcome.

Given our interest in analyzing innovation persistence, the dynamic specification calls for the lagged endogenous variable in order to capture the effect of true state dependence. In addition, theoretical and empirical studies have identified a spectrum of innovation determinants. In this chapter, innovation persistence is further explained by the following variables: firm size, group, subsidy, innovation cooperation, education, market share, concentration ratio, market competition, time dummies and firm-specific individual effects.

Large firms tend to innovate more by virtue of favorable R&D research environment, better financing channels and job attraction of high-skilled specialists. In addition, larger market power provides them with a higher capacity to reap the returns from innovation. In contrast, small firms suffer from the lack of financial resources and face the obstacles in accessing external financial resources (Schumpeter [2013]). Positive impacts of firm size on subsequent innovations are thus to be expected. In this chapter, firm size is measured by the logarithm value of employment in the CIS survey. Two periods lagged firm size is included in the estimation in order to avoid endogeneity issue.

Le Bas and Latham [2006] emphasize the importance of inter-firm linkage as a determinant of innovation persistence. The inter-firm linkage in the form of horizontal or vertical linkage deepens the learning process and facilitates the technology transfer. The inter-firm linkage can embody in various forms: learning by interacting, innovation cooperation, or establishment of technological districts. In this chapter, two variables are used to capture the inter-firm linkage. Group is a dummy variable which takes value 1 if the enterprise is part of an enterprise group. Innovation cooperation is the dummy variable which takes the value 1 if the enterprise cooperates for any of innovation activities with other enterprises or institutions. Innovation cooperation focuses on active participation with other enterprises or non-commercial institutions on innovation activities.

Moreover, technological capabilities of firms highly rely on human capital, in particular, the skills, learning capability and creativity of individual employees. Therefore, education is used in order to capture the individual capability to learn, adapt and innovate. Education is a dummy variable which takes value 1 if the firm has more than 25% highly educated employees (including post-secondary college diplomas and university graduates diplomas), and value 0 if the firm has less than 25% highly educated employees. [6]

[6] The survey contains a variable empud, a categorical variable which indicates the estimated percentage of employees that have a university degree. More specifically, it ranges from 0-6, which indicates 0% , 1% to 4% , 5% to 9%, 10% to 24%, 25% to 49%, 50% to 74%, 75% to 100%. As the median value of this variable is 3, a

The literature in industrial organization relates market structure to incentives to innovate. For example, a firm that has innovated and gained monopoly power may impair incentive to remain innovative (Arrow [1962], Tirole [1988]). Moreover, Winter and Nelson [1982]) emphasize the co-evolution of market structure and innovation. Firms evolve along with the industry conditions over time which nourish firms in reverse. Thus it points to a jointly dependent evolving path between firm behavior and market structure. Three variables are defined to measure the market structure in this chapter: firm's market share, 3 concentration ratio and self-report measure of market competition. Market share is defined as the proportion of the firms turnover to total turnover in the domestic 2-digit sector. 3 Concentration ratio is the measure of the percentage of market share in an industry held by the three largest firms within that industry. Both market share and concentration ratio are calculated with respect to Luxembourg market, which is irrelevant to many exporting firms. For this reason, additional self-report measure of market competition is included. Market competition is a categorical variable which measures how fast products and services are rapidly old-fashioned or outdated. It is defined on a 0-3 scale where 0 indicating not relevant, 1 indicating low market competition and 3 indicating high market competition. The correlation matrix (Table 4.A.2) shows low correlation within those measures.

In order to assess the determinants of firm-level innovation persistence, two R&D indicators are further included to capture the effect of sunk costs (Antonelli et al. [2012]). Average R&D intensity is measured by total R&D expenditures per employee. Intramural R&D share is measured by the share of intramural R&D expenditures over total R&D expenditures. Intramural R&D expenditures are spent within firms performing the R&D, which suggest the large set-up for laboratories and substantial resources such as labour costs of R&D personnel. It involves creation of new routines and dedication to the implementation of routines relevant to product portfolio strategies. In other words, it may involve long-term dedication and more substantial transformation.

Moreover, subsidy is a dummy variable which takes the value 1 if the enterprise receives any public financial support for innovation activities from local or regional authorities, the European Union or the central government including central government agencies or ministries. In order to avoid endogeneity, two periods lagged subsidy is included in the estimation.

4.4 Descriptive statistics

A preliminary descriptive comparison of two samples is provided in Table 4.1. A similar level of the overall mean is found for the balanced and unbalanced sample except for firm size. The balanced panel exhibits an upward bias in terms of firm size, on the grounds that

dummy variable is generated to indicate the firm with the level of highly educated employees above the median value 25%, or below the median value 25%.

large firms are inclined to survive 2008 financial crisis and present in all questionnaire waves. The unbalanced panel consists of 306 firms, which can be further classified as 224 product innovators, 228 process innovators and 256 TPP innovators. The sample is characterized by high proportion of SMEs. 50% of the firms size lies below 93.5 and 75% of the firms size lies below 239.25, which is lower than the mean value of the sample. For most variables, the variation across firms (between variation) is much higher compared to variation within a firm over time. For example, little within variation shows up for market share and concentration ratio. By and large, the unbalanced panel is representative of the population and contains more observations.

The balanced sub-panel is comprised of 135 firms, among which are 113 product innovators, 115 process innovators and 123 TPP innovators. The balanced panel is characterized by higher ratio of innovators regardless of innovation types, higher ratio of subsidy and innovation cooperation. In addition, the firm size distribution is skewed in the balanced sample, 50% of the firms size lies below 139 and 75% of the firms size lies below 343. [7]

As aforementioned, the balanced panel is prone to survivorship bias. The global financial crisis that unfolded in 2008 causes subsequent economic recession. Small firms are certainly not immune to large contractions in the general demand for goods and services, and more affected during tight credit periods than large firms. Consequently, the balanced panel is constituted by higher share of large enterprises which survive the 2008 financial crisis. [8]

Table 4.1: Summary statistics for the unbalanced and balanced sample over the period 2002-2012

	Unbalanced						Balanced					
Variable Dependent variables	Mean	Std. Dev.	Between	Within	Min	Max	Mean	Std. Dev.	Between	Within	Min	Max
TPP	0.60	0.49	0.36	0.34	0	1	0.65	0.48	0.33	0.34	0	1
Product innovation	0.48	0.50	0.37	0.34	0	1	0.52	0.50	0.35	0.36	0	1
Process innovation	0.42	0.49	0.33	0.37	0	1	0.46	0.50	0.32	0.38	0	1
Radical innovation	0.34	0.47	0.33	0.34	0	1	0.37	0.48	0.32	0.36	0	1
Incremental innovation	0.38	0.48	0.33	0.36	0	1	0.41	0.49	0.31	0.38	0	1
Explanatory variables												
Employment	266.24	562.57	512.23	116.06	10	6491	387.37	722.18	708.04	152.35	11	6491
Education	0.44	0.50	0.43	0.26	0	1	0.41	0.49	0.41	0.28	0	1
Part of a group	0.64	0.48	0.42	0.24	0	1	0.67	0.47	0.39	0.26	0	1
Subsidy	0.22	0.42	0.30	0.27	0	1	0.28	0.45	0.34	0.30	0	1
Cooperation	0.23	0.42	0.28	0.31	0	1	0.29	0.45	0.30	0.34	0	1
Average R&D intensity	4.40	11.63	6.65	9.45	0	168.54	4.83	13.01	7.07	10.93	0	168.54
Intramural R&D share	0.21	0.34	0.27	0.21	0	1	0.26	0.37	0.29	0.24	0	1
Market competition												
None	0.27	0.44	0.28	0.34	0	1	0.28	0.45	0.28	0.35	0	1
Low	0.31	0.46	0.22	0.41	0	1	0.30	0.46	0.22	0.41	0	1
Medium	0.28	0.45	0.24	0.38	0	1	0.28	0.45	0.24	0.38	0	1
High	0.15	0.36	0.18	0.31	0	1	0.14	0.34	0.15	0.31	0	1
Market share	0.01	0.06	0.05	0.02	0.00	0.89	0.02	0.08	0.07	0.03	0.00	0.89
Concentration ratio	0.51	0.23	0.19	0.12	0.20	0.95	0.54	0.22	0.18	0.12	0.20	0.95
N = 1262							N = 675					

[7] The distributions of employment for both unbalanced and balanced panel are right-skewed. The skewness for the unbalanced panel is 5.2 whereas the skewness for the balanced panel is 4.0.

[8] The balanced panel is biased towards large firms. Therefore, estimates are based on the unbalanced panel. In addition, 32.59% of balanced sample are large firms in comparison to 24.09 % share of large firms in the unbalanced panel.

Table 4.2: Transition Probabilities: persistence of TPP

	TPP status in t+2					
	Unbalanced			Balanced		
	TPP status in t	Non-Inno	Inno	Innovation status in t	Non-Inno	Inno
2002-2004 — 2004-2006	Non-Inno	0.59	0.41	Non-Inno	0.61	0.39
	Inno	0.20	0.80	Inno	0.17	0.83
2004-2006 — 2006-2008	Non-Inno	0.69	0.31	Non-Inno	0.66	0.34
	Inno	0.24	0.76	Inno	0.21	0.79
2006-2008 — 2008-2010	Non-Inno	0.73	0.27	Non-Inno	0.66	0.34
	Inno	0.21	0.79	Inno	0.16	0.84
2008-2010 — 2010-2012	Non-Inno	0.68	0.32	Non-Inno	0.69	0.31
	Inno	0.33	0.67	Inno	0.36	0.64

Table 4.3: Transition Probabilities: persistence of product innovation

	Product innovation in t+2					
	Unbalanced			Balanced		
	Product innovation in t	Non-Inno	Inno	Product innovation in t	Non-Inno	Inno
2002-2004 — 2004-2006	Non-Inno	0.65	0.35	Non-Inno	0.63	0.37
	Inno	0.18	0.82	Inno	0.15	0.85
2004-2006 — 2006-2008	Non-Inno	0.77	0.23	Non-Inno	0.76	0.24
	Inno	0.39	0.61	Inno	0.37	0.63
2006-2008 — 2008-2010	Non-Inno	0.75	0.25	Non-Inno	0.69	0.31
	Inno	0.26	0.74	Inno	0.22	0.78
2008-2010 — 2010-2012	Non-Inno	0.78	0.22	Non-Inno	0.74	0.26
	Inno	0.40	0.60	Inno	0.41	0.59

Table 4.4: Transition Probabilities: persistence of process innovation

	Process innovation in t+2					
	Unbalanced			Balanced		
	Process innovation in t	Non-Inno	Inno	Process innovation in t	Non-Inno	Inno
2002-2004 — 2004-2006	Non-Inno	0.71	0.29	Non-Inno	0.71	0.29
	Inno	0.39	0.61	Inno	0.36	0.64
2004-2006 — 2006-2008	Non-Inno	0.63	0.37	Non-Inno	0.62	0.38
	Inno	0.39	0.61	Inno	0.34	0.66
2006-2008 — 2008-2010	Non-Inno	0.75	0.25	Non-Inno	0.68	0.32
	Inno	0.47	0.53	Inno	0.39	0.61
2008-2010 — 2010-2012	Non-Inno	0.76	0.24	Non-Inno	0.75	0.25
	Inno	0.45	0.55	Inno	0.44	0.56

Table 4.2 - 4.4 report transition probability from period t to period t+2 for both unbalanced and balanced panels over the period 2002- 2012 . Table 4.2 shows that for the unbalanced panel, 80% of initial TPP innovator and 59% of initial non-innovator in the 2002-2004 wave remain their status in the subsequent 2004-2006 wave. The corresponding figures are 83% and 61% in the balanced panel. For the unbalanced panel, the unconditional probability of being innovative in period 2004-2006 is about 39 percentage points higher for innovators than for non-innovators in 2002-2004. The general pattern is that TPP innovation status are fairly persistent over time, which may emerge from true or spurious state dependence. It turns out that there are no disparate patterns of persistence among unbalanced panel and balanced panel. Although the balanced panel exhibits slightly higher persistence for innovators to remain innovative before crisis.

Moreover, Table 4.2 - 4.3 show that in a time of economic crisis, there is higher probability for TPP and product innovators to stop innovation engagement, and lower probability for TPP and product innovators to remain innovative compared to pre-crisis period. Table 4.3 - 4.4 show that in the unbalanced panel, there is lower probability for non-innovator to become innovative than for product and process innovators to stop innovation engagement. This phenomenon can be explained by limited resources for investing in technological activities for non-innovators. By and large, product innovation exhibits relatively higher innovation persistence than process innovation, which can be explained by higher R&D investments associated with product innovation and the sunk-cost hypothesis. In order to identify the true state dependence, a model of innovative behavior is developed in a dynamic panel data framework which accounts for unobserved individual effects that are correlated with the initial conditions.

4.5 Econometric modeling and estimation results

4.5.1 Dynamic random effects model (Wooldridge [2005])

Before proceeding with the analysis of Albarrán et al. [2015] method, I apply a dynamic random effects discrete choice model in the framework of Wooldridge [2005]. Let y_{it}^* denotes a latent variable underlying firm's (i=1, ..., N) propensity to innovate at period t (t=0,..., T) , given past observed innovation occurrence $y_{i,t-1}$, and the set of additional explanatory variables X_{it}. c_i indicates individual effects and u_{it} denotes idiosyncratic errors. Moreover, $u_{it} \mid (X_i, y_{i,t-1}, y_{i,t-2}, ..., y_{i0}, c_i) \sim i.i.d.N(0,1)$.
The baseline specification for a dynamic discrete response model with the latent variable can be written as:

$$y_{it}^* = \rho y_{i,t-1} + X_{it}\gamma + c_i + u_{it}. \tag{4.5.1}$$

$$y_{it} = 1\left[y_{it}^* > 0\right]. \tag{4.5.2}$$

The estimation of the above model is premised based on two important assumptions. (1) Only one lag of y_{it} appears in the conditional distribution density of outcome (or structural density) conditional on the individual effects and history of past realizations. (2) The set of additional explanatory variables X_{it} is assumed to be strictly exogenous.
In place of obtaining the joint distribution of all outcomes $(y_{i0}, y_{i1}, ..., y_{iT} \mid c_i, X_i)$ and specifying the conditional distribution of initial condition and individual effects, Wooldridge [2005] proposes to use the distribution of individual effects conditional on initial values. In order to solve the 'initial conditions' problem, individual effects can be expressed as a linear function of exogenous explanatory variables and initial conditions. More specifically,

$$c_i = \alpha_0 + \alpha_1 y_{i0} + X_i \alpha_2 + \alpha_i, \tag{4.5.3}$$

where $X_i = (X_{i1}, ..., X_{iT})$ and $\alpha_i \mid (y_{i0}, X_i) \sim N(0, \sigma_\alpha^2)$.
Similarly, we assume the individual effects to be correlated with the time average of covariates X_{it} rather than the entire history (Peters [2009] and Raymond et al. [2010b]) based on the following relationship:

$$c_i = \alpha_0 + \alpha_1 y_{i0} + \overline{X_i} \alpha_2 + \alpha_i, \tag{4.5.4}$$

where $\overline{X_i} = T^{-1} \sum_{t=1}^{T} X_{it}$. Plugging c_i from expression 4.5.4 to equation 4.5.1 we obtain that:

$$y_{it}^* = \rho y_{i,t-1} + X_{it}\gamma + \alpha_0 + \alpha_1 y_{i0} + \overline{X_i}\alpha_2 + \alpha_i + u_{it}, \tag{4.5.5}$$

where $u_{it} \mid (X_i, y_{i,t-1}, y_{i,t-2}, ..., y_{i0}, \alpha_i) \sim N(0,1)$.

Therefore, the density of $(y_{i1}, y_{i2} ..., y_{iT})$ given $(y_{i0} = y_0, X_i = X, \alpha_i = \alpha)$ for each individual i can be written as:

$$\prod_{t=1}^{T} \left\{ \Phi(X_t\gamma + \rho y_{t-1} + \alpha_0 + \alpha_1 y_0 + \overline{X}\alpha_2 + \alpha)^{y_t} \times \left[1 - \Phi(X_t\gamma + \rho y_{t-1} + \alpha_0 + \alpha_1 y_0 + \overline{X}\alpha_2 + \alpha)\right]^{1-y_t} \right\}$$

We integrate out the equation against the normal density of α_i, which gives rise to the density of outcomes conditional on the initial values and exogenous explanatory variables. This likelihood function can be estimated by the standard software with the random effects probit model, apart from that we have the new set of explanatory variables at time t: $Z_{it} = (1, X_{it}, y_{i,t-1}, y_{i0}, \overline{X_i})$.
In this framework, it is essential to have substantial time-variance of covariates X_{it} for the estimation, as X_{it} will be highly correlated with respective time-average values otherwise. In this respect, the inclusion of both X_{it} and time-average values can lead to multicollinearity problems. Hardly any within variations show up for market share and concentration ratio. Although the variables firm size, education, group, subsidy, cooperation, market competition vary across firm and time periods, the correlation matrix shows that a high correlation is present between those variables and respective mean value.[9] Therefore, these

[9] See the appendix Table 4.A.2 for the correlation matrix between explanatory variables and their time-averaged values. Although the cooperation variable and self-report market competition show certain within variation, the

explanatory variables are treated as time-constant firm-specific variables and are included in structural equation only. [10]

The Wooldridge [2005] estimator is derived for the balanced panel. Nonetheless, it has been applied to the unbalanced panel for various reasons (for example, see Esteve-Pérez and Rodríguez [2009] and Martinez-Ros and Labeaga [2009]). First of all, selecting a balanced panel from the sample discards useful information, which leads to efficiency losses and attrition problems. Secondly, the balanced sample may not contain enough number of common periods across individuals, which render consistent estimation infeasible. The balanced panel is prone to survivorship bias; on the other hand, the unbalanced panel is more representative of the population and contains more observations. I perform the analysis with the Wooldridge [2005] approach using both panels and contrast the results obtained to assess the persistence effects. Table 4.5 displays the estimates of partial effects at average value of individual heterogeneity (PEA) using unbalanced panel, while Table 4.6 shows the estimates of PEA using balanced panel. The partial effects at average value of individual heterogeneity assume that the individual heterogeneity takes its average value, which can be consistently estimated by:

$$\widehat{E[c_i]} = \hat{\alpha}_0 + \hat{\alpha}_1 \overline{y_0} + \overline{X}\hat{\alpha}_2, \tag{4.5.6}$$

where $\overline{y_0} = \sum_{i=1}^{N} y_{i0}$, $\overline{X} = \sum_{i=1}^{N} \overline{X_i}$.

The partial effect of lagged dependent variable at average value of individual heterogeneity is calculated as follows:

$$\widehat{PEA} = \Phi\left[\hat{\rho} + X^e\hat{\gamma} + \hat{\alpha}_0 + \hat{\alpha}_1\overline{y_0} + \overline{X}\hat{\alpha}_2\right] - \Phi\left[X^e\hat{\gamma} + \hat{\alpha}_0 + \hat{\alpha}_1\overline{y_0} + \overline{X}\hat{\alpha}_2\right], \tag{4.5.7}$$

where X^e indicates sample means averaged across individuals and time. Alternatively, we can calculate the average partial effect (APE), which measures the change of the expected probability of y=1 at time t, either due to an infinitesimal increase for a continuous variable or a change from 0 to 1 for a binary explanatory variable. The difference is that expectation is averaging over the distribution of the individual heterogeneity. The APE of the binary lagged dependent variable is given in equation (4.5.8), where the subscript a denotes

inclusion of respective time-averages value does not lead to good estimation. In particular, the means of market competition are insignificant and coefficients of cooperation and respective means have opposite signs, which suggest the presence of multicollinearity.

[10] Additional explanatory variables hardly vary across time partly as a result of short sample period. The drawback lies in the fact that the effects of time-constant exogenous covariates in structural equation cannot be clearly separated from the heterogeneity equation. This will likely exert influence on the measurement of innovation persistence in the long run. If exogenous forces do not vary substantially, eventually innovation will tend to fluctuate around its constant long-run mean in spite of the presence of lagged values of the endogenous variable. Nonetheless, the identification of state dependence parameter alone is our true concern. Moreover, the addition of time-constant exogenous covariates enhances the explanatory power of the model.

original parameter estimates multiplied by $(1+\hat{\sigma_\alpha}^2)^{-0.5}$:

$$\widehat{APE} = \frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{t=1}^{T}\Phi\left[\hat{\rho}_a + X^e\hat{\gamma}_a + \hat{\alpha_{0a}} + \hat{\alpha_{1a}}y_{i0} + \overline{X_i}\hat{\alpha_{2a}}\right] - \frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{t=1}^{T}\Phi\left[X^e\hat{\gamma}_a + \hat{\alpha_{0a}} + \hat{\alpha_{1a}}y_{i0} + \overline{X_i}\hat{\alpha_{2a}}\right], \quad (4.5.8)$$

where X^e indicates sample means averaged across individuals and time. The estimates of APE and PEA will be contrasted in the subsequent section using various approaches.

Table 4.5: Partial effects at average value of individual heterogeneity- Dynamic RE model Wooldridge [2005] with the unbalanced panel.

Regressor	(1)	(2)	(3)
TPP_{t-2}	0.153***		
	(0.05)		
Product innovation$_{t-2}$		0.171***	
		(0.05)	
Process innovation$_{t-2}$			0.102**
			(0.05)
TPP_0	0.190***		
	(0.05)		
Product innovation$_0$		0.181***	
		(0.05)	
Process innovation$_0$			0.130***
			(0.05)
Employment in log$_{t-2}$	0.087***	0.110***	0.077***
	(0.02)	(0.02)	(0.02)
Education$_t$	−0.007	−0.020	−0.052
	(0.05)	(0.06)	(0.05)
Group$_t$	−0.008	−0.003	0.068
	(0.04)	(0.05)	(0.04)
Subsidy$_{t-2}$	0.130**	0.101*	0.071
	(0.06)	(0.06)	(0.05)
Market share$_{t-2}$	−0.145	0.340	−0.305
	(0.43)	(0.49)	(0.34)
Concentration ratio$_t$	0.059	0.020	0.032
	(0.15)	(0.16)	(0.15)
Cooperation$_{t-2}$	0.126**	0.118**	0.055
	(0.05)	(0.05)	(0.04)
Market competition			
Low	0.156***	0.113**	0.106**
	(0.05)	(0.05)	(0.05)
Medium	0.110**	0.047	0.127**
	(0.05)	(0.06)	(0.05)
High	0.216***	0.207***	0.080
	(0.07)	(0.07)	(0.06)
Sector dummies	YES	YES	YES
Time dummies	YES	YES	YES
$\hat{\sigma_\alpha}$	0.001	0.000	0.040
	(0.02)	(0.01)	(0.39)
Log likelihood	−472.51	−462.62	−537.32
Observations	929	921	941

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.6: Partial effects at average value of individual heterogeneity- Dynamic RE model Wooldridge [2005] with balanced panel.

Regressor	(1)	(2)	(3)
TPP_{t-2}	0.105		
	(0.07)		
Product innovation_{t-2}		0.127^{*}	
		(0.07)	
Process innovation_{t-2}			0.050
			(0.06)
TPP_0	0.140^{*}		
	(0.07)		
Product innovation_0		0.139^{**}	
		(0.07)	
Process innovation_0			0.139^{**}
			(0.06)
Employment in $\log_{t-2}$	0.145^{***}	0.117^{***}	0.120^{***}
	(0.04)	(0.04)	(0.03)
Education_t	−0.101	−0.111	-0.135^{**}
	(0.08)	(0.08)	(0.07)
Group_t	0.079	0.072	0.176^{***}
	(0.06)	(0.07)	(0.06)
Subsidy_{t-2}	0.072	0.061	0.029
	(0.07)	(0.07)	(0.07)
Market share_{t-2}	−0.133	0.693	−0.459
	(0.51)	(0.59)	(0.37)
Concentration ratio_t	0.109	0.018	0.073
	(0.23)	(0.24)	(0.22)
Cooperation_{t-2}	0.189^{***}	0.182^{***}	0.060
	(0.07)	(0.07)	(0.06)
Market competition			
Low	0.255^{***}	0.136^{*}	0.169^{**}
	(0.07)	(0.07)	(0.07)
Medium	0.212^{***}	0.141^{*}	0.127^{*}
	(0.07)	(0.08)	(0.07)
High	0.241^{***}	0.161^{*}	0.085
	(0.09)	(0.09)	(0.09)
Sector dummies	YES	YES	YES
Time dummies	YES	YES	YES
$\hat{\sigma}_\alpha$	0.001	0.001	0.000
	(0.01)	(0.11)	(0.07)
Log likelihood	−238.07	−254.61	−285.64
Observations	492	516	535

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Innovation groups are distinguished among technological product and process innovators (TPP), product innovators, and process innovators. Table 4.5 manifests that, after accounting for individual effects and tackling the initial condition problem, true persistent effects emerge for all innovation groups. Conditional on unobserved firm characteristics and holding all other explanatory variables at their means, the predicted probability of implementing TPP at t is 0.153 greater for a past TPP innovator than a non-innovator at t-2. Similarly, the predicted probability of implementing product innovation at t is 0.171 greater for a past product innovator than a non-innovator at t-2, whereas implementing process innovation at t is 0.102 PP higher for a past process innovator than non-innovator. In addition, lagged firm size, lagged subsidy, cooperation, self-report market competition affect positively and significantly the probability to implement TPP and product innovation. $\hat{\sigma_\alpha}$ indicates the estimates of standard deviation of random term of individual effects conditional on the initial values and explanatory variables. The small magnitude of $\hat{\sigma_\alpha}$ indicates that there is not much firm heterogeneity after accounting for the initial values and explanatory variables. [11] The estimates are based on the Gauss-Hermite quadrature approximation with default 12 quadrature points. The stability of estimates is guaranteed by using the STATA command quadchk.

Moreover, the estimates of initial condition remain significant at the 5% level for all innovation groups, which implies the high correlation between the unobserved heterogeneity and the initial condition. It corroborates the importance to account for the heterogeneity of the initial conditions. In addition, it is interesting to note that the estimates of initial condition are larger than the persistence parameters of innovation regardless of innovation type. This phenomenon has shed some light on the state dependence mechanism of innovation. To a large extent, unobserved heterogeneity endogenously selects firm to pertain to certain innovation groups in the initial period, then true state dependence helps firms to secure the innovative status.

Table 4.6 shows the estimates of PEA using balanced panel. Given the similarities of the mean values between the unbalanced and balanced sample (see Table 4.1), the discrepancy in estimation results might arise from the fact that the unbalanced sample has twice the size of the balanced sample. The persistence parameter for product innovation is still positive and significant at the 10% level with reduced magnitude, whereas the estimates of lagged TPP and process innovation are no longer significant. The initial conditions of all types of innovation are proved to be highly correlated with the individual effects. In addition, lagged firm size and self-report market competition affect positively and significantly the

[11] The LR test indicates that we fail to reject the null hypothesis of no heterogeneity. The limited sample size and short sample periods might give rise to the absence of variation of unobserved individual heterogeneity after accounting for the initial values and explanatory variables. The assumption of random effects model should still hold. Another possibility is to use fixed-effects dynamic model and construct the log-likelihood function that treats the unobserved effects as parameters to be estimated. This approach suffers from an incidental parameters problem with fixed T and leads to inconsistent estimates. In appendix, Table 4.B.1 provides estimates with the dynamic pooled probit model without individual heterogeneity. The state dependence parameters have been falsely augmented compared with the baseline model which accounts for individual heterogeneity.

probability to implement TPP, product and process innovation. While being part of a group affects positively and significantly the probability to implement process innovation.

4.5.2 Dynamic nonlinear random effects models with unbalanced panels (Albarrán et al. [2015])

This section dedicates to explain our preferred Albarrán et al. [2015] model. The estimator proposed by Albarrán et al. [2015] will be discussed in various scenarios, then the estimation results are presented when assuming unbalancedness correlated with the individual effects with constant variance of individual effects across sub-panels.

One limitation of the Wooldridge [2005] method is that it addresses the balanced panel and cannot directly apply to unbalanced panel data. Unbalancedness affects initial values, thereby augments the initial condition problem and calls for additional treatment. Albarrán et al. [2015] argue that unless two conditions are satisfied, the estimates obtained by ignoring the unbalancedness are inconsistent. These conditions are:

- The process stays in a steady state from the initial period. Alternatively, the initial values come from the same exogenous distribution for all individuals and initial periods.

- The sample selection process is independent of the shocks to the initial values.

When the above-mentioned condition is violated, the estimates with unbalanced panel lead to inconsistent results. This holds true even in the case of independence between the sample selection process and individual effects. In this case, unbalancedness still directly affects the first observation period. In general, the density of individual effects conditional on the initial conditions will be different for each sub-panel, rendering an account of unbalancedness crucial. Moreover, taking the balanced sub-panel is no single panacea. Selecting a balanced panel from the unbalanced sample can produce efficiency losses. Albarrán et al. [2015] have shown that conditional distribution of individual effects must satisfy certain conditions to derive consistent MLE for balanced sub-panel. The problem arises when the unbalancedness is correlated with the individual effects, then choosing a subset with equal periods implies an endogenous selection of the sample which leads to inconsistent estimates of average marginal effects. Now and again, estimates using balanced sub-sample and unbalanced sample by ignoring the unbalanced structure give rise to bias in the same direction. Therefore, in order to correctly deal with the issue of unbalancedness, we adopt the Albarrán et al. [2015]) approach based on a dynamic non-linear model with correlated random effects to assess the true persistence effects.

Albarrán et al. [2015] define the set of selection indicator $S_i = (s_{i1}, s_{i2}, ..., s_{iT})$ as follows:

$$s_{it} = \begin{cases} 1 & \text{if } y_{it} \text{ and } X_{it} \text{ are observed} \\ 0 & \text{otherwise} \end{cases} \tag{4.5.9}$$

Albarrán et al. [2015] only take into account the cases when y_{it} and X_{it} are jointly observed. Balanced panel can be characterized by $s_{it} = 1$ for all firms and time periods. Furthermore, for analyzing the dynamics in firms innovation behaviour with the Albarrán et al. [2015] methods, only those firms which have answered at least three consecutive time periods can be taken into account. [12] t_i is defined as the first period where individual i is observed.

$$t_i = \left\{ t : s_{it} = 1 \quad \text{and} \quad s_{ij} = 0 \quad \forall j < t \right\} \tag{4.5.10}$$

T_i denotes total number of periods observed for individual i, i. e.,

$$T_i = \sum_{t=1}^{T} s_{it} \tag{4.5.11}$$

Albarrán et al. [2015] assume that conditional distribution function of outcomes $F(y_{it} \mid y_{it-1}, X_i, c_i, S_i) = F(y_{it} \mid y_{it-1}, X_i, c_i)$. In other words, sample selection process S_i is strictly exogenous to the idiosyncratic shocks u_{it}. Albarrán et al. [2015] distinguish several scenarios and examine separately the possibilities of applying Heckman [1978] and Wooldridge [2005] solutions to tackle the initial conditions problem: assuming independence between the unbalancedness and the individual effects, a general case when allowing for correlation between the unbalancedness and the individual effects, the third case when allowing for correlation between the unbalancedness and the individual effects in the presence of constant variance of individual effects across sub-panels.

Not all solutions can be easily applied in the context of Luxembourgish data. In the first scenario, when the unbalancedness is independent of the individual effects, the assumption can be written as:

$$h(c_i \mid X_i, S_i) = h(c_i \mid X_i), \tag{4.5.12}$$

where $h(c_i \mid X_i, S_i)$ is correctly specified conditional density. Albarrán et al. [2015] demonstrate that the Heckman [1978] approach leads to an individual likelihood function that can be maximized by implementing the command gllamm (see Arulampalam and Stewart [2009]). Notwithstanding the facility, this approach necessitates the substantial time variation of exogenous covariates, along with substantial variation at the level of sub-panels. In the case of correlation between the unbalancedness and the individual effects, this is likely when the unbalancedness is related to missing explanatory variables (e.g. age of the

[12] As all firms in the sample are observed at least three consecutive waves, it is not an issue where the lagged variables coincide with the initial conditions. Three consecutive observations are required, since two consecutive periods are needed for the random effect and one additional period for the initial condition and dynamic analysis.

firm), the effect of which is picked up by the individual effects and leads to correlation between individual effects and unbalancedness. Albarrán et al. [2015] propose the application of minimum distance estimation in this case. MD estimation involves estimating the coefficients for each sub-panel in the first stage, then minimizing the weighted difference between the coefficients from the first stage. Nevertheless, the MD estimator necessitates the substantial variation of exogenous covariates at the level of sub-panels. It is undesirable to apply to the Luxembourgish panel as most exogenous covariates are time-constant. Additionally, MD estimation involves dropping a great number of observations as the estimation is implemented at the level of sub-panel. [13] Combined with the Wooldridge [2005] method to solve the initial conditions problem, Albarrán et al. [2015] also propose the application of gsem and gllamm commands to estimate the general likelihood function. However, the implementation of this technique is computationally cumbersome and extremely time-consuming, eventually rendering this solution infeasible. Therefore, we focus on the third scenario, when assuming constant variance of individual effects across sub-panels and allowing for correlation between the unbalancedness and the individual effects.

4.5.3 Assuming unbalancedness correlated with the individual effects with constant variance of individual effects across sub-panels

The scenario when allowing for correlation between the unbalancedness and the individual effects is more relevant in the context of Luxembourgish data over the period 2002-2012. As aforementioned, this is likely the case when the unbalancedness is related to missing explanatory variables such as the age of the firm, the effect of which is picked up by the individual effects and leads to correlation between individual effects and unbalancedness. Moreover, the individual effects which encompass absorptive capacity are highly likely to correlate with the right-side unbalancedness. As higher absorptive capacity is associated with higher chance to survive 2008 financial crisis.

For each individual i, we can write the conditional probability to observe the joint outcomes as:

$$Pr(s_{i1}y_{i1},...,s_{iT}y_{iT} \mid X_i,S_i) = \prod_{t=t_i+1}^{t_i+T_i-1} Pr(y_{it} \mid y_{it-1},X_i,S_i)Pr(y_{it_i} \mid X_i,S_i). \tag{4.5.13}$$

[13] Before proceeding to the scenario when assuming unbalancedness correlated with the individual effects with constant variance of individual effects across sub-panels, I have experimented with minimum distance estimation. The MD estimator requires dropping too many observations. For certain sub-panel, the observation could drop to around 35 observations which produce rather unreasonable estimation results. As Albarrán et al. [2015] point out, although computationally feasible, the practical problem arises due to potential lack of variability in a specific sub-panel.

[14] If one decides to consider the distribution conditional on the initial period observation, $c_i \mid X_i, S_i$ only depends on t_i rather than the rest of S_i, equation 4.5.13 can be further written as :

$$Pr(s_{i1}y_{i1},...,s_{iT}y_{iT} \mid X_i,S_i) = \left[\int_{c_i} \prod_{t=t_i+1}^{t_i+T_i-1} Pr(y_{it} \mid y_{it-1},X_i,S_i,c_i)h(c_i \mid y_{it_i},X_i,S_i)dc_i\right] \cdot Pr(y_{it_i} \mid X_i,S_i), \quad (4.5.14)$$

where $h(c_i \mid X_i, S_i)$ indicates the conditional density of the individual effects.
Similar to the Wooldridge [2005] method to tackle the initial conditions problem, Albarrán et al. [2015] impose parametric assumptions on the conditional distribution of the individual effects:

$$c_i \mid y_{it_i}, X_i, S_i \sim N(\pi_{0S_i} + \pi_{1S_i} y_{it_i} + \overline{X_{S_i}}\pi_{2S_i}, \sigma_c^2). \quad (4.5.15)$$

This expression is differentiated from equation 4.5.4 by intercepts and slopes which are specific to each sub-panel. Conditional on initial values, the variance of the conditional distribution of individual effects is constant across sub-panels. In other words, the heterogeneity equation consists of intercepts for each sub-panel, initial values for each sub-panel, and vector of means of exogenous explanatory variables for each sub-panel [15]. In consideration of time-invariant nature, we include exogenous covariates rather than respective means specific to each sub-panel. As aforementioned, the coefficients of time-invariant exogenous explanatory variables indicate the combined effects from structural equation and heterogeneity equation. As for the Luxembourgish panel, it consists of five waves of innovation survey which can be further decomposed to 6 sub-panels.

In addition, as Albarrán et al. [2015] impose the assumption that the variance of the distribution of individual effects conditional on initial values is constant across sub-panels, the implementation of ML becomes easier since it can be obtained using standard software (STATA code xtprobit) for the simple random-effects probit model.

Before proceeding with the analysis of innovation persistence with the Albarrán et al. [2015] approach, Table 4.7 presents the definition and summary statistics by sub-panel. A distinct pattern can be identified in terms of firm size and innovation behavior at the level of sub-panel. In particular, Table 4.7 provides us with interesting hints for the relevance of sub-panel 2, 5, 6 for estimates at later stages. Sub-panel 2 is characterized by SMEs with an average number of employees below 50. In contrast, sub-panel 6 is the balanced panel which makes up a predominant part of sample and biased towards large firms. Sub-panel 5 resembles sub-panel 6 in terms of firm size and survivorship during the 2008

[14] For example, for the panel pattern .111., with initial period $t_i = 2$ and total number of periods observed $T_i = 3$, the duration from non-initial period sums from $t_i + 1 = 3$ to $t_i + T_i - 1 = 4$.

[15] The vector of means of exogenous explanatory variables for each sub-panel can be obtained by interacting the vector of means of exogenous explanatory variables with dummies variables which indicate sub-panel respectively.

Table 4.7: Summary statistics for sub-panels over the period 2002-2012.

Sub-panel	1	2	3	4	5	6	Total
Pattern †	111.. or 111.1	.111.	..111 or 1.111	1111.	.1111	11111	Total
Frequency	7.29	4.04	16.16	5.71	13.31	53.49	100.00
TPP	0.49	0.39	0.51	0.64	0.59	0.65	0.60
TPP_0	0.50	0.41	0.59	0.61	0.60	0.70	0.63
Product innovator	0.38	0.31	0.38	0.58	0.47	0.52	0.48
Product $innovator_0$	0.43	0.35	0.47	0.56	0.55	0.53	0.51
Process innovator	0.38	0.25	0.37	0.33	0.40	0.46	0.42
Process $innovator_0$	0.35	0.18	0.50	0.39	0.36	0.49	0.44
Radical innovation	0.29	0.22	0.24	0.43	0.33	0.37	0.34
Incremental innovation	0.25	0.22	0.31	0.50	0.37	0.41	0.38
Employment	130.77	29.04	142.34	106.69	144.57	387.37	266.24
Education	0.48	0.39	0.51	0.47	0.45	0.41	0.44
Part of a group	0.55	0.35	0.63	0.65	0.67	0.67	0.64
Subsidy	0.07	0.10	0.11	0.19	0.24	0.28	0.22
Cooperation	0.12	0.16	0.17	0.31	0.16	0.29	0.23
Average R&D intensity	3.86	2.25	3.08	4.80	5.05	4.83	4.40
Intramural R&D share	0.15	0.11	0.10	0.31	0.16	0.26	0.21
Market competition							
None	0.23	0.29	0.25	0.17	0.30	0.28	0.27
Low	0.32	0.24	0.34	0.36	0.27	0.30	0.31
Medium	0.29	0.22	0.27	0.24	0.29	0.28	0.28
High	0.16	0.25	0.13	0.24	0.14	0.14	0.15
Market share	0.00	0.00	0.00	0.00	0.01	0.02	0.01
Concentration ratio	0.43	0.51	0.42	0.55	0.51	0.54	0.51
Observations	1262						

† Pattern demonstrates the participation pattern, where 1 indicating one observation for a specific year, a dot indicating no observation.

financial crisis. Ranging from manufacturing sector to information and communication, sub-panel 2 captures the phenomenon of burgeoning SMEs in Luxembourg in various industry. Nonetheless, they quickly die out during the economic winter and leave the panel after the economic crisis. Based on a firm-level survey collected by the Banque Centrale du Luxembourg (BCL) in mid-2008 and mid-2009, three out of four firms reported that they were negatively affected by the crisis, those firms, in particularly in manufacturing industry, have experienced demand shrink, financing difficulties and hardship of paying for their products and services (Lünnemann et al. [2011]). Interestingly, sub-panel 3, 5, 6 which survive the post-crisis period, exhibit the consistent features and are characterized by large firm size.

Table 4.8 displays the estimates of PEA using the unbalanced data with the Albarrán et al. [2015] method for TPP, product and process innovators. As aforementioned, the estimates are derived by Maximum Likelihood estimator via implementing STATA code xtprobit. After accounting for individual effects, initial condition problem and the unbalancedness, past product and process innovation still exhibit a true persistent effect. The highest level of persistence is found for product innovation which might be associated with important R&D sunk costs. TPP innovation also shows positive and significant persistence effect, which captures possible complementary effects of product and process innovation. The estimates of partial effects at average value of individual heterogeneity indicate that, conditional on unobserved firm characteristics and holding all other explanatory variables at their means, the predicted probability of implementing TPP at t is 0.145 greater for a past TPP innovator than a non-innovator at t- 2. The predicted probability of implementing product innovation at t is 0.159 greater for a past product innovator than a non-innovator at t-2. The predicted probability of implementing process innovation at t is 0.102 greater for a past process innovator than a non-innovator at t-2.

Consistent with Antonelli et al. [2012], Le Bas and Poussing [2014] and Karlsson et al. [2015], product innovator exhibits a relatively higher persistence level than process innovators. The reason resides in the relevance of sunk costs associated with product innovations, which represents an essential motive for entering and adhering to a specific regime of R&D activity. Moreover, Winter and Nelson [1982] argue that product innovation usually comes from a firm's own R&D, whereas significant process innovations often come from the R&D done by suppliers and are embodied in their products, which reinforce the different impact. Process innovators tend to use different information sources and innovation channels. Arundel et al. [2007] argue that non-R&D innovators, compared to R&D performers, are more likely to focus on process innovation and to source ideas from production engineers and design staff. The higher prevalence of process innovation among non-R&D performers suggests that there are more options for developing process innovations without performing R&D. Moreover, lagged firm size and self-report market competition significantly contribute to all innovation indicators. Such result confirms the idea that large firms tend to innovate more in view of favorable R&D research environment and better financing channels. In addition, competitive pressure fosters incentives to innovate. Lagged subsidy and lagged cooperation contribute to implementation of TPP and product innovation. Phillips [1971] emphasizes that successful innovation enhances the probability of subsequent innovation by increased market share. Nonetheless, the insignificant coefficients of market share take a dim view of this argument. For unobserved heterogeneity equation, the estimates of initial condition remain significant for several sub-panels for TPP, product and process innovation, in particular, sub-panel 2, 5, 6. This indicates the presence of high correlation between the unobserved heterogeneity and the initial condition in these sub-panels.

The disadvantage of using partial effects at average is that PEA is assessed at the mean value of the individual effect which only represents a small fraction of firms. Table 4.1 shows that most variables in the Luxembourgish panel have skewed distribution, wherein the average value is driven upward by the few large firms. Alternatively, we can calculate the average partial effect (APE) where the expectation is averaging over the distribution of the individual heterogeneity. Table 4.8 contrasts the partial effect averaging over the distribution of the unobserved heterogeneity with PEA using different methods. It is not surprising that in some cases, state dependence effects using APE are slightly reduced in comparison to PEA. [16]

Table 4.8 reveals that, the estimates with the Wooldridge [2005] method based on unbalanced panel bears a resemblance to Albarrán et al. [2015] method in terms of APE and PEA. The similarity can be traced back to various reasons. First, we have a relatively short panel period. The simulation results of Albarrán et al. [2015] demonstrate that, the bias of Wooldridge [2005] method using balanced sub-panel seems increasing with the number of time periods in the case of double unbalancedness. In addition, when T equals to 4 or 6, the estimates of average marginal effects of lagged dependent variables by means of Albarrán et al. [2015] estimator are analogous to Wooldridge [2005] estimator with balanced sub-panel. The divergence of two estimators becomes conspicuous when the time periods increase.

Secondly, although the estimator that ignores the unbalancedness and the estimator derived from taking balanced sub-panel are inconsistent, as they prevent the individual effects from varying at the level of sub-panels. It imposes on the panel the assumption of independence between the distribution of the individual effects and unbalancedness. However as for Luxembourgish panel, there is not much heterogeneity varying at the level of sub-panels after accounting for individual effects that are correlated with the initial conditions. In other words, initial values and exogenous explanatory variables alone already explain the main part of individual effects, wherein little sub-panel specific heterogeneity is left out. This reflects on the small magnitude of $\hat{\sigma_\alpha}$, the standard deviation of individual effects conditional on the initial values and covariates. In other words, the innovative behaviors of firms are relatively homogeneous after accounting for individual effects that are correlated with the initial conditions. In addition, balanced sample constitutes only 56% of unbalanced sample, which explains the differences of estimates between balanced and unbalanced sample. For larger dataset with longer time periods, the disparity between two estimators will be more distinct.

By and large, the similarity between two estimates does not impair the essentiality of using Albarrán et al. [2015] method. From a theoretical perspective, applying Wooldridge [2005] method directly to unbalanced panel is incorrect. In addition, selecting a balanced panel discards a potentially high proportion of the sample and leads to unsatisfactory results. The similar results are driven by various reasons, in particular, few time periods.

[16] APE are calculated averaging individual effects and evaluated at the value of time-averages of explanatory variables. As we treat all explanatory variables as time-constant, the explanatory variables rather than the mean values of explanatory variables are included in the structural equation. The time dummies and sector dummies are included in the heterogeneity equation. Moreover, the heterogeneity equation encompasses initial conditions for each subpanel and intercepts for each subpanel. Instead of adding means of explanatory variables for each individual averaging across time, we include the level of explanatory variables directly as they are treated as time-constant.

In order to identify the sources of innovation persistence at the firm level, Table 4.9 presents the estimates including two additional indicators of sunk costs in the baseline model specification. Consistent with Antonelli et al. [2012], average R&D intensity is measured by the total R&D expenditures per employee, intramural R&D share indicates the share of intramural R&D expenditures over total expenditures. Intramural R&D expenditures are spent within firms performing the R&D, which suggests the large set-up for laboratories and substantial spending such as costs of R&D personnel. It implies creating new routines and dedicating to the embedded routines relevant to product portfolio strategies. In other words, it may involve long-term dedication and more profound transformation. The average R&D intensity and intramural R&D share exhibit time-varying feature, therefore, time average of these covariates are included in the individual heterogeneity equation at the level of sub-panels. In order to avoid a potential violation of the strict exogeneity assumption, these indicators are included in a stepwise procedure. In addition, endogeneity is not a major concern on the grounds that the innovative behaviors of firms are relatively homogeneous after accounting for individual effects that are correlated with the initial conditions at this stage.

Table 4.8: The partial effects at average value of individual heterogeneity - Dynamic RE model (Albarrán et al. [2015]) with correlation between the unbalancedness and the individual effects with constant variance of the individual effects across sub-panels.

	(1)	**(2)**	**(3)**
Structural equation			
TPP_{t-2}	0.145^{***}		
	(0.05)		
Product innovation$_{t-2}$		0.159^{***}	
		(0.05)	
Process Innovation$_{t-2}$			0.102^{**}
			(0.04)
Employment in log$_{t-2}$	0.087^{***}	0.110^{***}	0.086^{***}
	(0.02)	(0.03)	(0.02)
Education$_t$	−0.006	−0.029	−0.057
	(0.05)	(0.06)	(0.05)
Group$_t$	−0.011	−0.001	0.069
	(0.04)	(0.05)	(0.04)
Subsidy$_{t-2}$	0.122^{**}	0.102^{*}	0.058
	(0.06)	(0.06)	(0.05)
Market share$_{t-2}$	−0.088	0.336	−0.338
	(0.44)	(0.48)	(0.34)
Concentration ratio$_t$	0.064	0.017	0.039
	(0.16)	(0.17)	(0.15)
Cooperation$_{t-2}$	0.130^{**}	0.121^{**}	0.059
	(0.05)	(0.05)	(0.05)
Market competition			
Low	0.163^{***}	0.121^{**}	0.125^{**}
	(0.05)	(0.05)	(0.05)
Medium	0.115^{**}	0.055	0.144^{***}
	(0.05)	(0.06)	(0.05)
High	0.216^{***}	0.210^{***}	0.091

	(0.07)	(0.07)	(0.06)
Individual heterogeneity			
TPP_{0S1}	0.044		
	(0.15)		
TPP_{0S2}	0.483**		
	(0.20)		
TPP_{0S3}	0.118		
	(0.10)		
TPP_{0S4}	0.203		
	(0.17)		
TPP_{0S5}	0.361***		
	(0.12)		
TPP_{0S6}	0.175***		
	(0.06)		
Product innovation$_{0S1}$		0.204	
		(0.18)	
Product innovation$_{0S2}$		0.453**	
		(0.22)	
Product innovation$_{0S3}$		0.270**	
		(0.11)	
Product innovation$_{0S4}$		0.078	
		(0.17)	
Product innovation$_{0S5}$		0.268**	
		(0.12)	
Product innovation$_{0S6}$		0.132**	
		(0.06)	
Process innovation$_{0S1}$			0.152
			(0.16)
Process innovation$_{0S2}$			0.585**
			(0.23)
Process innovation$_{0S3}$			−0.007
			(0.10)
Process innovation$_{0S4}$			0.058
			(0.16)
Process innovation$_{0S5}$			0.213*
			(0.11)
Process innovation$_{0S6}$			0.136**
			(0.06)
constant$_1$	−0.745***	−1.028***	−0.739***
	(0.19)	(0.21)	(0.18)
constant$_2$	−0.947***	−1.023***	−0.742***
	(0.22)	(0.23)	(0.19)
constant$_3$	−0.698***	−1.011***	−0.651***
	(0.18)	(0.20)	(0.17)
constant$_4$	−0.738***	−0.804***	−0.810***
	(0.21)	(0.22)	(0.19)
constant$_5$	−0.743***	−0.891***	−0.690***
	(0.19)	(0.20)	(0.17)
constant$_6$	−0.719***	−0.890***	−0.716***
	(0.18)	(0.19)	(0.17)
Sector dummies	YES	YES	YES
Time dummies	YES	YES	YES

$\hat{\sigma_\alpha}$	0.002	0.001	0.004
	(0.02)	(0.01)	(0.04)
Log likelihood	−467.23	−458.39	−531.65
Observations	929	921	941

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.8: Contrast of state dependence using PEA and APE

		$\widehat{PEA}$	$\widehat{APE}$
Unbalanced Wooldridge [2005]	TPP	0.15	0.12
	Product Innovation	0.17	0.13
	Process Innovation	0.10	0.09
Balanced Wooldridge [2005]	TPP	0.11	0.08
	Product Innovation	0.13	0.09
	Process Innovation	0.05	0.04
Unbalanced Albarrán et al. [2015]	TPP	0.15	0.12
	Product Innovation	0.16	0.12
	Process Innovation	0.10	0.09

All estimates are based on the baseline specification as in Table 4.5, 4.6 and 4.8.
PEA refers to partial effects at the average value of individual heterogeneity, as defined in equation 4.5.7.
APE refers to the average partial effect where the expectation is averaging over the distribution of the individual heterogeneity, as defined in equation 4.5.8.

Table 4.9 shows that, after accounting for average R&D intensity and intramural R&D share, the persistence effects in product innovation disappear whereas the persistence effects remain for TPP and process innovation with reduced magnitude. Consistent with Antonelli et al. [2012], this estimation result confirms the idea that product innovation is mainly associated with the presence of sunk costs which motivates the continuous undertaking of innovation activities. In contrast, the state dependence in process innovation cannot be explained entirely by the sunk-cost hypothesis. It can also be driven by dynamic increasing return to innovation, and cumulative effects of learning. Geroski et al. [1993] emphasize that the process of innovation transforms a firm's internal capabilities, building up its core competencies in various ways that make it more flexible and adaptable, more capable in dealing with market pressures than non-innovating firms. In this view, innovation is itself often the consequence of a more fundamental transformation that occurs within an innovating firm.

After accounting for time average of covariates related to sunk costs at the level of sub-panels, average R&D intensity and intramural R&D share still exert significant positive influence on generating innovation over time. Surprisingly, a high proportion of educated employees seems to discourage subsequent innovation, which might stem from negative correlation between firm size class and proportion of educated employees. Consistent with my previous findings, lagged firm size and self-report market competition affect positively and significantly the probability to implement all types of innovation.

In addition, Utterback and Abernathy [1975] and Antonelli et al. [2012] point out, it appears to be relevant to distinguish between repeated process innovations aimed at continuously enhancing the efficiency of production processes, and process innovations immediately ensuing the introduction of new products which induces subsequential changes in the production processes. Laforet [2008] also emphasizes the underpinning effect of process innovation for successful product launches. It appears that the first scenario is more relevant in the context of Luxembourgish data. In effect, as process innovation is usually associated with purchasing technologies introduced by others, robustness tests are implemented to assess the sensitivity of the findings by controlling for investment in physical capital intensity and external R&D intensity in the Appendix Table 17. Investment in physical capital intensity is defined as gross investment in tangible goods per person employed, while external R&D intensity is defined as extramural R&D expenditure per person employed. In order to obtain information with regard to investment, CIS data has to be merged with annual Structural Business Statistics (SBS) of Luxembourg. Structural Business Statistics is an annual database which provides us with a rich range of information on firms activities and performances such as turnover, employment level, gross investment in tangible goods and wages. [17] In addition, the true state dependence of process innovation is analyzed by means of Albarrán et al. [2015] method. Both investment in physical capital intensity and external R&D intensity are treated as time-varying variables. Based on the merged dataset of Community Innovation Survey and Structural Business Statistics over the period 2004 to 2012, Table 17 reveals that persistence characterizes the introduction of process innovation even after accounting for investment in physical capital intensity and external R&D intensity. Nonetheless, persistence of process innovation disappears after accounting for R&D sunk-cost relevant variables such as average R&D intensity and intramural R&D share additionally.

To further illustrate the source of innovation persistence, Table 4.10 completes the picture by reporting the estimation results of radical and incremental innovation with the Albarrán et al. [2015] method aside from accounting for sunk costs.[18] In other words, Table 4.10 contrasts with Table 4.9 by decomposing product innovation to radical innovation and incremental innovation. As aforementioned, radical innovator is defined as a firm which introduces product innovations that are new to the market, incremental innovator is defined as a firm which introduces product innovations that are only new to the firm. Interesting features emerge: even after accounting for sunk costs, the unbalancedness

[17] Accordingly, the observations decrease on the grounds that merging leads to loss of observations from CIS innovation data. Moreover, CIS is a questionnaire collected biennially over the period 2002-2012 and SBS is an annual database over the period 2003-2013, therefore, merging two datasets with different periodicities leads to a biennial panel which discards the information contained in SBS for 2003, 2005, 2007, 2009, 2011 and 2013.

[18] We have to exclude the initial values for radical innovators in the sub-sample 2, as only 1% of them are radical innovators.

and individual effects that are correlated with the initial conditions, true state dependence is found for radical innovators. In contrast, an analogous pattern cannot be identified for the incremental product innovation indicator. This result appears to have relevant implications which shed light on the generic differences between innovation groups. Table 4.10 reveals that the state dependence for incremental innovation mainly comes from the sunk costs relevant to R&D. As for radical innovation, the joint significance of sunk cost variables as well as the past realization of radical product innovation suggests that the state dependence is not exclusively related to sunk costs associated with R&D activities, which can be further attributed to other factors such as dynamic increasing return to innovation, and cumulative effects of learning. Radical innovation is perceived as the most important element for long-term firm growth by gaining successful and sustainable competitive advantage. Radical innovations often imply more profound transformation of a firm's internal capabilities, more embedded routines relevant to product portfolio strategies. Radical innovation prevails incremental innovation in terms of novelty and potential market impact. Radical innovation are often associated with a fundamentally different set of novel knowledge and creativity, higher degree of dynamic increasing return (see Damanpour and Wischnevsky [2006], and Garcia and Calantone [2002]). Moreover, radical product innovations become a stable component of firms routines and market strategies, which generate continuous undertaking of innovation activities ((Antonelli et al. [2012])). In line with my findings, Clausen and Pohjola [2013] also find that lagged new-to-market product innovation has a significant and positive influence on firms ability to develop current breakthrough innovation, while this is not the case for new-to-firm product innovation. Their findings show that the dynamics of innovation persistence differ across types of (product) innovations.

Table 4.9: The partial effects at average value of individual heterogeneity - Dynamic RE model (Albarrán et al. [2015]) accounting for sunk costs related to R&D activities, with correlation between the unbalancedness and the individual effects with constant variance of the individual effects across sub-panels.

	(1)	(2)	(3)
Structural equation			
TPP_{t-2}	0.095^{*}		
	(0.05)		
Product innovation$_{t-2}$		0.066	
		(0.05)	
Process Innovation$_{t-2}$			0.089^{**}
			(0.04)
Employment in log$_{t-2}$	0.058^{**}	0.086^{***}	0.062^{***}
	(0.02)	(0.03)	(0.02)
Education$_t$	-0.099^{*}	-0.142^{**}	-0.126^{**}
	(0.06)	(0.06)	(0.05)
Group$_t$	-0.016	-0.023	0.067
	(0.05)	(0.05)	(0.05)
Subsidy$_{t-2}$	0.025	0.023	0.000
	(0.06)	(0.06)	(0.05)
Market share$_{t-2}$	0.129	0.660	-0.231

	(0.46)	(0.55)	(0.35)
Concentration ratio$_t$	−0.010	−0.037	0.003
	(0.16)	(0.18)	(0.16)
Cooperation$_{t-2}$	0.080	0.093*	0.032
	(0.05)	(0.06)	(0.05)
Intramural R&D share	0.418***	0.394***	0.148*
	(0.10)	(0.10)	(0.08)
Average R&D intensity	0.017***	0.011***	0.004**
	(0.00)	(0.00)	(0.00)
Market competition			
Low	0.127**	0.102*	0.104**
	(0.05)	(0.06)	(0.05)
Medium	0.093*	0.044	0.124**
	(0.05)	(0.06)	(0.05)
High	0.186***	0.192***	0.070
	(0.07)	(0.07)	(0.06)
Individual heterogeneity			
TPP$_{0S1}$	−0.041		
	(0.17)		
TPP$_{0S2}$	0.585**		
	(0.24)		
TPP$_{0S3}$	0.036		
	(0.11)		
TPP$_{0S4}$	0.264		
	(0.18)		
TPP$_{0S5}$	0.250*		
	(0.14)		
TPP$_{0S6}$	0.109*		
	(0.07)		
Product innovation$_{0S1}$		0.055	
		(0.22)	
Product innovation$_{0S2}$		0.606*	
		(0.31)	
Product innovation$_{0S3}$		0.259*	
		(0.13)	
Product innovation$_{0S4}$		0.077	
		(0.21)	
Product innovation$_{0S5}$		0.337**	
		(0.14)	
Product innovation$_{0S6}$		0.062	
		(0.07)	
Process innovation$_{0S1}$			0.111
			(0.17)
Process innovation$_{0S2}$			0.418
			(0.26)
Process innovation$_{0S3}$			−0.004
			(0.10)
Process innovation$_{0S4}$			0.060
			(0.16)
Process innovation$_{0S5}$			0.274**
			(0.12)
Process innovation$_{0S6}$			0.092
			(0.06)

Average R&D intensity$_{MS1}$	0.021	0.046	0.035
	(0.03)	(0.04)	(0.02)
Average R&D intensity$_{MS2}$	0.055	0.075**	0.050
	(0.03)	(0.04)	(0.03)
Average R&D intensity$_{MS3}$	−0.004	0.002	0.003
	(0.01)	(0.01)	(0.01)
Average R&D intensity$_{MS4}$	−0.006	0.013	0.005
	(0.02)	(0.02)	(0.02)
Average R&D intensity$_{MS5}$	0.018	0.049***	−0.002
	(0.02)	(0.02)	(0.01)
Average R&D intensity$_{MS6}$	0.010	0.014**	0.003
	(0.01)	(0.01)	(0.00)
Intramural R&D share$_{MS1}$	−0.012	0.116	−0.116
	(0.51)	(0.57)	(0.48)
Intramural R&D share$_{MS2}$	0.516	1.173	0.568
	(0.69)	(0.83)	(0.52)
Intramural R&D share$_{MS3}$	0.871**	0.263	0.326
	(0.41)	(0.30)	(0.24)
Intramural R&D share$_{MS4}$	−0.318	−0.180	0.108
	(0.30)	(0.33)	(0.26)
Intramural R&D share$_{MS5}$	0.937*	0.210	0.773***
	(0.54)	(0.38)	(0.29)
Intramural R&D share$_{MS6}$	0.031	0.124	0.215
	(0.17)	(0.18)	(0.15)
constant$_{S1}$	−0.633***	−1.021***	−0.723***
	(0.20)	(0.24)	(0.20)
constant$_{S2}$	−1.040***	−1.345***	−0.779***
	(0.28)	(0.35)	(0.22)
constant$_{S3}$	−0.545***	−0.936***	−0.576***
	(0.18)	(0.22)	(0.18)
constant$_{S4}$	−0.526**	−0.654***	−0.694***
	(0.23)	(0.25)	(0.23)
constant$_{S5}$	−0.629***	−0.993***	−0.668***
	(0.20)	(0.23)	(0.19)
constant$_{S6}$	−0.531***	−0.757***	−0.580***
	(0.18)	(0.20)	(0.18)
Sector dummies	YES	YES	YES
Time dummies	YES	YES	YES
$\hat{\sigma_\alpha}$	0.002	0.001	0.001
	(0.02)	(0.02)	(0.01)
Log likelihood	−407.74	−402.41	−505.96
Observations	929	921	941

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.10: The partial effects at average value of individual heterogeneity - Dynamic RE model (Albarrán et al. [2015]) for radical and incremental innovation after accounting for sunk costs related to R&D activities, with correlation between the unbalancedness and the individual effects with constant variance of the individual effects across sub-panels.

	(1)	**(2)**
Structural equation		

Radical innovation$_{t-2}$	0.117***	
	(0.04)	
Incremental innovation$_{t-2}$		0.043
		(0.04)
Employment in log$_{t-2}$	0.035*	0.057**
	(0.02)	(0.02)
Education$_t$	−0.090*	−0.040
	(0.05)	(0.05)
Group$_t$	0.001	0.027
	(0.05)	(0.05)
Subsidy$_{t-2}$	−0.001	−0.047
	(0.05)	(0.05)
Market share$_{t-2}$	0.392	0.448
	(0.37)	(0.34)
Concentration ratio$_t$	−0.280**	−0.037
	(0.12)	(0.16)
Cooperation$_{t-2}$	0.074*	0.051
	(0.04)	(0.05)
Average R&D intensity	0.005***	0.005*
	(0.00)	(0.00)
Intramural R&D share	0.198***	0.217***
	(0.08)	(0.08)
Market competition		
Low	0.069	0.062
	(0.05)	(0.05)
Medium	0.050	0.009
	(0.05)	(0.05)
High	0.048	0.166**
	(0.06)	(0.07)
Individual heterogeneity		
Radical innovation$_{0S1}$	−0.033	
	(0.17)	
Radical innovation$_{0S3}$	0.196*	
	(0.12)	
Radical innovation$_{0S4}$	−0.011	
	(0.16)	
Radical innovation$_{0S5}$	0.222*	
	(0.12)	
Radical innovation$_{0S6}$	0.101*	
	(0.06)	
Incremental innovation$_{0S1}$		−0.521*
		(0.30)
Incremental innovation$_{0S2}$		0.211
		(0.23)
Incremental innovation$_{0S3}$		0.257**
		(0.12)
Incremental innovation$_{0S4}$		0.115
		(0.16)
Incremental innovation$_{0S5}$		0.328***
		(0.13)
Incremental innovation$_{0S6}$		0.076
		(0.06)

Average R&D intensity$_{MS1}$	0.017	0.096***
	(0.02)	(0.03)
Average R&D intensity$_{MS2}$		0.023
		(0.02)
Average R&D intensity$_{MS3}$	−0.003	−0.003
	(0.01)	(0.01)
Average R&D intensity$_{MS4}$	0.011	0.006
	(0.02)	(0.02)
Average R&D intensity$_{MS5}$	0.022*	0.022
	(0.01)	(0.02)
Average R&D intensity$_{MS6}$	−0.005	0.010*
	(0.00)	(0.00)
Intramural R&D share$_{MS1}$	0.142	−0.201
	(0.44)	(0.52)
Intramural R&D share$_{MS2}$		0.353
		(0.49)
Intramural R&D share$_{MS3}$	0.373	0.322
	(0.23)	(0.24)
Intramural R&D share$_{MS4}$	0.116	−0.073
	(0.25)	(0.26)
Intramural R&D share$_{MS5}$	0.091	0.687**
	(0.27)	(0.31)
Intramural R&D share$_{MS6}$	0.239*	0.180
	(0.13)	(0.15)
constant$_{S1}$	−0.371**	−0.940***
	(0.16)	(0.22)
constant$_{S2}$		−0.797***
		(0.22)
constant$_{S3}$	−0.379***	−0.759***
	(0.12)	(0.19)
constant$_{S4}$	−0.199	−0.490**
	(0.16)	(0.22)
constant$_{S5}$	−0.239**	−0.889***
	(0.12)	(0.21)
constant$_{S6}$	−0.245**	−0.627***
	(0.10)	(0.18)
Sector dummies	YES	YES
Time dummies	YES	YES
$\hat{\sigma_\alpha}$	0.001	0.002
	(0.01)	(0.01)
Log likelihood	−421.65	−440.95
Observations	910	929

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In addition, observed firm characteristics such as firm size, cooperation are also found to be crucial factors in encouraging innovation. Surprisingly, high proportion of educated employees seems to discourage subsequent radical innovation. Interestingly, this result resonates with Subramaniam and Youndt [2005] which discover that human capital by itself is negatively associated with the radical innovative capability. Subramaniam and

Youndt [2005] imply that individual expertise on its own is not conductive to radical innovation. Rather, cooperation and diffusion of knowledge are more important than individual expertise within the organization. Subramaniam and Youndt [2005] suggest that human capital plays a vital role in fostering radical innovation capabilities when it is strongly tied to social capital. The negative correlation between firm size class and proportion of educated employees indicates that, it might be the phenomenon that small firms attract more highly educated employees in Luxembourg. After accounting for time average of covariates related to sunk costs at the level of sub-panels, average R&D intensity and intramural R&D share still exert significant positive influence on generating product innovation over time. A negative and significant effect of concentration ratio on innovation is observed for radical innovation. High concentration ratio suggests an oligopoly or monopoly market. In line with the theory of industrial organization, the lack of competition impairs the incentive to innovate.

Table 4.9: Contrast of state dependence using PEA and APE

		$\widehat{PEA}$	$\widehat{APE}$
Unbalanced Albarrán et al. [2015] [a]	TPP	0.10	0.08
	Product	0.07	0.05
	Process	0.09	0.08
Unbalanced Albarrán et al. [2015] [b]	Radical	0.12	0.10
	Incremental	0.04	0.03

PEA refers to partial effects at the average value of individual heterogeneity, as defined in equation 4.5.7.
APE refers to the average partial effect where the expectation is averaging over the distribution of the individual heterogeneity, as defined in equation 4.5.8.
[a] Both PEA and APE are based on the estimates in Table 4.9, which accounts for sunk costs related to R&D activities, with correlation between the unbalancedness and the individual effects with constant variance of the individual effects across sub-panels.
[b] Both PEA and APE are based on the estimates in Table 4.10, which differentiates radical and incremental innovation after accounting for sunk costs related to R&D activities, with correlation between the unbalancedness and the individual effects with constant variance of the individual effects across sub-panels.

Table 4.9 contrasts the partial effect averaging over the distribution of the unobserved heterogeneity with PEA based on the estimates in Table 4.9 and 4.10. It is not surprising that state dependence effects using APE are slightly reduced in comparison to PEA. PEA measures the partial effect of an individual with mean heterogeneity, which usually only represents a small fraction of firms. Given the fact that most variables in the Luxembourgish panel have skewed distributions, wherein the average values are driven upward by the few large firms, APE might provide a more accurate picture of state dependence effects. [19]

[19] In calculating APE for Table 4.9, average R&D intensity and intramural R&D share are treated as time-varying variables. In the structural equation, time-constant explanatory variables are included respectively, while as for time-varying variables, the mean values of average R&D intensity and intramural R&D share enter the structural equation. In addition to the initial conditions for each subpanel and intercepts for each subpanel, the heterogeneity equation encompasses the mean values of average R&D intensity and intramural R&D share averaging across time for each individual for each subpanel.

4.6 Robustness check

Robustness tests are implemented in this section to assess the sensitivity of the findings. The results derived in the previous sections focus on the persistence of innovation output. The binary variable of innovation captures attempt to innovate at the extensive margin. Peters [2009] points out that the "success breeds success" hypothesis is outcome-oriented. Crépon et al. [1998] suggest that to a certain degree, input persistence should be translated into output persistence. Nonetheless, it is likely that the effect of innovation effort on the introduction of new products or processes operates with a certain time lag. In consideration of our short biennial panel, the adoption of innovation output measure appears to be a more favorable approach. Moreover, this chapter aims to capture the critical role of knowledge, learning effect and dynamic increasing return in generating innovation persistence. Peters [2009] argue that evolutionary theory is likewise more outcome-oriented by emphasizing the accumulative nature of innovation and the importance of knowledge and learning effect in fostering innovation process. This dimension will be lost in the input-measure approach since the process of learning involves successful implementation of innovation in place of mere resource allocations.

Table 4.10 and Table 4.11 present an alternative view by examining innovation persistence at the intensive margin. Table 4.10 examines the persistence of innovation input measured by total R&D expenditures and Table 4.11 examines the persistence of innovation output measured by the share of sales of new products in total sales. [20] Both tables report the OLS estimation results of the lagged-dependent variable model leaving out unobserved individual effects (Angrist and Pischke [2008]). Table 4.10 shows that lagged R&D expenditures exert a significant and positive influence on firms' current R&D expenditures, which confirms the persistence of innovation input. As Crépon et al. [1998] suggest, input persistence can be translated into output persistence to a certain degree. The coefficient of lagged-dependent variable indicates that 10% increase in past R&D expenditures will lead to 8.62% increase in the current R&D expenditures. Moreover, being part of a group affects positively and significantly the current R&D expenditures. Table 4.11 investigates the persistence of the share of sales of new products in total sales. The coefficient of lagged-dependent variable indicates that 10% increase in the past share of sales of new products in total sales will lead to 1.63% increase in the current share of sales of new products in total sales. Column (2) and column (3) further look into the persistence of the share of sales of products new to the market and the share in total sales of products new to the firm. The share of sales of products new to the market exhibits higher persistence, whereas the share in total sales of products new to the firm shows no significant persistence effect. The results derived here are largely consistent with previous findings on radical

[20] Total R&D expenditures include intramural R&D expenditure, extramural R&D expenditure, acquisition of machinery expenditure and external knowledge expenditure.

and incremental innovation using dichotomous measures. Both Table 4.10 and Table 4.11 validate innovation persistence at the intensive margin.

The baseline model specification can be further extended by accommodating difference in persistence behavior associated with technology categories. This can be achieved by including the interaction term between lagged innovation and technology classes in the structural equation, and allowing for different industry category intercepts. For example, Raymond et al. [2010b] find true persistence in the probability of innovating in the high-tech category of industries and spurious persistence in the low-tech category. Acemoglu et al. [2006] point out that firms tend to have higher propensity to innovate in high-tech industry which is closer to the technology frontier (see Blundell et al. [1999], Aghion et al. [2005], and Acemoglu et al. [2006]). Following this logic, a pronounced persistent effect is expected for high tech companies.

The three-digit industries can be regrouped into six categories according to the Eurostat classification: primary sector, low-technology, high-technology, less knowledge-intensive services (LKIS), knowledge-intensive services (KIS) and utilities. Our sample is composed of 26.94% of low-technology sector, 15.13% of high-technology, 16.24% of LKIS, 35.74% of KIS and 5.94% of utilities.

Table 4.12 presents the estimates of both coefficients and marginal effects using unbalanced panel with the Albarrán et al. [2015] method with the interaction term between lagged innovation and technology classes in the structural equation. [21] After accounting for individual effects, initial condition problem and potential differences in persistence effects, the marginal effects of lagged TPP, product and process innovation are still positive and significant, with even more pronounced magnitude.

Moreover, insignificant coefficients of most interaction terms indicate the absence of potential difference in persistence in innovation behavior associated with technology categories. In other words, the persistence effects induced by lagged innovation in achieving new TPP, product and process innovations do not seem to depend on technology industries, which is consistent with Duguet and Monjon [2002]. Admittedly, it is observed that being a past product innovator is estimated to have lower probability to implement current product innovation for firms in knowledge-intensive services than it is for low-tech industry.

Moreover, we do observe significant and positive industry category intercepts for high-tech industry. The separate industry category intercepts, rather than interaction term partly explain the strong persistence in innovation for high tech industry. In addition, the coefficients of lagged employment indicate that lagged firm size positively and significantly contributes to the probability to implement TPP, product and process innovation. Self-

[21] STATAs margins command does not provide marginal effects for interactions terms. The interaction terms can only be changed through the marginal effects of the component terms. Therefore, Table4.12 presents the estimates of both coefficients and PEA.

report market competition affects positively and significantly the probability to implement all types of innovation, while lagged cooperation affects positively and significantly the probability to implement TPP and product innovation.

For unobserved heterogeneity equation, the estimates of initial condition remain significant for several sub-panels for TPP, product and process innovation, in particular, sub-panel 2, 5, 6. This indicates the presence of high correlation between the unobserved heterogeneity and the initial condition in these sub-panels. [22] Moreover, we leave out the discussion of estimation with the interaction term between initial conditions and technology groups on account of sparse data in the sample, which leads to unsatisfactory estimation results.

By and large, the previous conclusion is confirmed that true persistence is discovered regardless of the innovation type. Moreover, rather than differentiating persistence effects associated with technology categories, to a large extent, unobserved heterogeneity endogenously selects firm to pertain to certain innovation groups in the initial period, then true state dependence helps firms to secure the innovative status.

Table 4.10: Persistence of innovation input - Dynamic OLS model without firm heterogeneity.

Regressor	Dependent variable:R&D expenditure$_t$	
	Coef.	(Std. Err.)
R&D expenditure$_{t-2}$	0.862***	(0.11)
Employment in log$_{t-2}$	0.098	(0.18)
Education$_t$	−0.129	(0.49)
Group$_t$	0.616*	(0.34)
Subsidy$_{t-2}$	−0.091	(0.48)
Market share$_{t-2}$	4.818	(3.82)
Concentration ratio$_t$	−0.594	(0.85)
Cooperation$_{t-2}$	−0.038	(0.33)
Market competition		
Low	−0.667	(0.44)
Medium	−0.481	(0.44)
High	−0.508	(0.55)
Sector dummies	YES	YES
Time dummies	YES	YES
Observations	941	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[22] It is confirmed by presence of empty or singleton cells in the cross-tabulation table of industry groups and initial values per sub-panel. For example, out of 205 observations of LKIS, there are only 3 observations which implement product innovation in the initial period in the sub-panel 1, and no firms implement product innovation in the initial period in the sub-panel 4, essentially rendering the estimation difficult.

Table 4.11: Persistence of the share in sales of new products - Dynamic OLS model without firm heterogeneity.

Regressor	Dependent variable: % sales of new products$_t$		
	(1)	(2)	(3)
% sales of new products$_{t-2}$	0.163***		
	(0.04)		
% sales of products new to the market$_{t-2}$		0.199***	
		(0.04)	
% sales of products new to the firm$_{t-2}$			0.050
			(0.05)
Employment in log$_{t-2}$	1.091*	0.705**	0.375
	(0.56)	(0.33)	(0.41)
Education$_t$	−0.496	−0.347	−0.005
	(1.98)	(1.50)	(1.17)
Group$_t$	0.375	−0.500	0.958
	(1.27)	(0.96)	(0.79)
Subsidy$_{t-2}$	0.706	0.223	0.912
	(1.55)	(0.92)	(1.10)
Market share$_{t-2}$	4.932	3.263	1.408
	(6.67)	(4.79)	(5.45)
Concentration ratio$_t$	−8.465*	−4.836	−3.826
	(4.91)	(4.20)	(2.47)
Cooperation$_{t-2}$	−0.221	0.286	−0.399
	(1.42)	(0.91)	(0.92)
Market competition			
Low	1.381	0.853	0.559
	(1.24)	(0.85)	(0.82)
Medium	2.820*	1.842**	1.246
	(1.46)	(0.91)	(1.02)
High	3.631*	1.095	2.587**
	(2.01)	(1.37)	(1.32)
Sector dummies	YES	YES	YES
Time dummies	YES	YES	YES
Observations	941	941	941

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.12: Dynamic RE model (Albarrán et al. [2015]) with interaction terms between lagged innovation and technology classes, with correlation between the unbalancedness and the individual effects with constant variance of the individual effects across sub-panels.

	Coefficients			PEA		
	(1)	(2)	(3)	(4)	(5)	(6)
Structural equation						
TPP_{t-2}	0.631***			0.199***		
	(0.20)			(0.05)		
Product innovation_{t-2}		0.932***			0.230***	
		(0.23)			(0.06)	
Process innovation_{t-2}			0.295			0.104*
			(0.23)			(0.06)
Employment in $\log_{t-2}$	0.237***	0.215***	0.273***	0.090***	0.085***	0.105***
	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)
Education_t	0.030	−0.061	−0.064	0.011	−0.024	−0.025
	(0.13)	(0.13)	(0.13)	(0.05)	(0.05)	(0.05)
Group_t	0.027	0.071	0.172	0.010	0.028	0.066
	(0.11)	(0.11)	(0.11)	(0.04)	(0.04)	(0.04)
Subsidy_{t-2}	0.191	0.103	0.124	0.073	0.041	0.048
	(0.14)	(0.13)	(0.13)	(0.05)	(0.05)	(0.05)
Market share_{t-2}	−0.196	1.138	−0.647	−0.075	0.452	−0.250
	(1.06)	(1.15)	(0.87)	(0.40)	(0.46)	(0.34)
Concentration ratio_t	0.077	0.283	0.097	0.029	0.113	0.037
	(0.34)	(0.35)	(0.34)	(0.13)	(0.14)	(0.13)
Cooperation_{t-2}	0.353***	0.333***	0.107	0.134***	0.132***	0.041
	(0.13)	(0.13)	(0.12)	(0.05)	(0.05)	(0.05)
Market competition						
Low	0.426***	0.345***	0.308**	0.162***	0.137***	0.119**
	(0.13)	(0.13)	(0.13)	(0.05)	(0.05)	(0.05)
Medium	0.313**	0.220	0.325**	0.119**	0.087	0.125**
	(0.13)	(0.14)	(0.13)	(0.05)	(0.05)	(0.05)
High	0.573***	0.537***	0.212	0.218***	0.214***	0.082
	(0.17)	(0.17)	(0.16)	(0.06)	(0.07)	(0.06)
$\text{TPP}_{t-2}\times$ High-tech	−0.165					
	(0.35)					
$\text{TPP}_{t-2}\times$ LKIS	0.121					
	(0.29)					
$\text{TPP}_{t-2}\times$ KIS	−0.253					
	(0.25)					
$\text{TPP}_{t-2}\times$ Utilities	−0.289					
	(0.41)					
Product $\text{innovation}_{t-2}\times$ High-tech		−0.325				
		(0.31)				
Product $\text{innovation}_{t-2}\times$ LKIS		−0.407				
		(0.31)				
Product $\text{innovation}_{t-2}\times$ KIS		−0.546**				
		(0.25)				
Product $\text{innovation}_{t-2}\times$ Utilities		−0.662				
		(0.48)				
Process $\text{innovation}_{t-2}\times$ High-tech			−0.049			
			(0.30)			
Process $\text{innovation}_{t-2}\times$ LKIS			0.094			
			(0.31)			
Process $\text{innovation}_{t-2}\times$ KIS			0.004			
			(0.24)			
Process $\text{innovation}_{t-2}\times$ Utilities			−0.573			
			(0.46)			
High-tech	0.551*	0.669***	0.254	0.162***	0.200***	0.092
	(0.30)	(0.24)	(0.22)	(0.06)	(0.06)	(0.06)
LKIS	−0.165	0.099	−0.219	−0.035	−0.040	−0.068
	(0.22)	(0.22)	(0.21)	(0.06)	(0.06)	(0.06)
KIS	0.250	0.639***	−0.129	0.036	0.144*	−0.049
	(0.25)	(0.24)	(0.23)	(0.08)	(0.08)	(0.08)
Utilities	0.294	−0.041	0.132	0.044	−0.135	−0.046
	(0.30)	(0.31)	(0.28)	(0.09)	(0.09)	(0.10)
Individual heterogeneity						
TPP_{0S1}	0.023			0.009		
	(0.38)			(0.14)		
TPP_{0S2}	1.017**			0.388**		
	(0.49)			(0.19)		
TPP_{0S3}	0.175			0.067		

	(0.25)			(0.10)		
TPP_{0S4}	0.551			0.210		
	(0.40)			(0.15)		
TPP_{0S5}	0.726**			0.276**		
	(0.28)			(0.11)		
TPP_{0S6}	0.383**			0.146**		
	(0.15)			(0.06)		
Product innovation$_{0S1}$		0.444			0.176	
		(0.42)			(0.17)	
Product innovation$_{0S2}$		1.025*			0.407*	
		(0.55)			(0.22)	
Product innovation$_{0S3}$		0.615**			0.244**	
		(0.30)			(0.12)	
Product innovation$_{0S4}$		0.219			0.087	
		(0.39)			(0.15)	
Product innovation$_{0S5}$		0.488			0.194	
		(0.30)			(0.12)	
Product innovation$_{0S6}$		0.274*			0.109*	
		(0.16)			(0.07)	
Process innovation$_{0S1}$			0.297			0.114
			(0.42)			(0.16)
Process innovation$_{0S2}$			1.521**			0.586**
			(0.64)			(0.25)
Process innovation$_{0S3}$			−0.036			−0.014
			(0.27)			(0.10)
Process innovation$_{0S4}$			0.226			0.087
			(0.42)			(0.16)
Process innovation$_{0S5}$			0.518*			0.200*
			(0.29)			(0.11)
Process innovation$_{0S6}$			0.379**			0.146**
			(0.16)			(0.06)
constant$_1$	−1.813***	−2.306***	−2.042***	−0.691***	−0.917***	−0.787***
	(0.43)	(0.46)	(0.43)	(0.17)	(0.18)	(0.16)
constant$_2$	−2.185***	−2.381***	−2.141***	−0.832***	−0.946***	−0.825***
	(0.48)	(0.51)	(0.45)	(0.18)	(0.20)	(0.17)
constant$_3$	−1.755***	−2.463***	−1.891***	−0.669***	−0.979***	−0.729***
	(0.41)	(0.44)	(0.41)	(0.16)	(0.18)	(0.16)
constant$_4$	−1.973***	−1.966***	−2.375***	−0.752***	−0.781***	−0.915***
	(0.47)	(0.47)	(0.45)	(0.18)	(0.19)	(0.17)
constant$_5$	−1.861***	−2.124***	−2.019***	−0.709***	−0.844***	−0.778***
	(0.42)	(0.44)	(0.40)	(0.16)	(0.17)	(0.15)
constant$_6$	−1.912***	−2.115***	−2.191***	−0.729***	−0.841***	−0.845***
	(0.37)	(0.38)	(0.38)	(0.14)	(0.15)	(0.15)
Time dummies	YES	YES	YES	YES	YES	YES
$\hat{\sigma_\alpha}$	0.000	0.050	0.252			
	(0.15)	(0.92)	(0.20)			
Log likelihood	−488.41	−485.44	−545.57			
Observations	941	941	941	941	941	941

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.7 Conclusion

4.7.1 Discussion

Using five questionnaire waves of Luxembourgish Community Innovation Surveys (CIS) for the years 2002-2012, I explore innovation persistence by means of dynamic nonlinear random effects models based on the estimator proposed by Albarrán et al. [2015]. The econometric results show that past innovation activity is a crucial determinant for all types of innovation, hence confirm the hypothesis of true state dependence. Moreover, the highest level of persistence is found for product innovation, particular for radical product innovation.

The analysis presented in this chapter thereby contributes to the validation of innovation persistence on several fronts: in the first place, I have used a brand new approach to study innovation persistence at the firm level. The application of the Albarrán et al. [2015] method correctly accounts for unobserved individual effects that are correlated with the initial conditions as well as the unbalanced structure of panel, which has been largely ignored in the earlier research.

Secondly, the analysis presented in this chapter is one of the first to distinguish between radical and incremental product innovation. Given the fundamental differences between innovation types, an universalistic theory which explains the innovation persistence homogeneously might be inappropriate (Downs Jr and Mohr [1976], Damanpour [1987], Kimberly and Evanisko [1981], Moch and Morse [1977]). Nonetheless, the disparate patterns of innovation persistence, particularly for radical and incremental innovation are rarely investigated in the literature. This study aims to fill the gap in the literature by evaluating differentiated persistence patterns across diverse types of innovation. The critical role of knowledge, learning effect and dynamic increasing return is recognized in creating innovation persistence in this study.

In order to test the role of dynamic increasing return in the innovation persistence, I examine the degree of persistence after accounting for R&D sunk costs apart from unobserved individual effects that are correlated with the initial conditions as well as the unbalanced structure of panel. If the dynamic increasing returns play an important role in fostering innovation persistence, past innovation should remain significant (Duguet and Monjon [2004]). The results highlight differentiated patterns of persistence among product and process innovation. The state dependence of product innovation (particularly, incremental product innovation) is mainly associated with sunk costs related to R&D. In contrast, the state dependence of process innovations cannot be explained entirely by the sunk-cost hypothesis, which suggests that it can be further attributed to dynamic increasing returns and learning effect. To further look into the product innovation category, a significant state dependence is observed for the radical product innovation. In contrast, an analogous pattern cannot be identified for the incremental product innovation indicator after accounting for the sunk costs related to R&D. This result appears to have relevant implications, which reveals the potential different size of cumulative stock of knowledge and dynamic increasing return induced by radical and incremental innovation. As radical innovations often imply more profound transformation of a firm's internal capabilities, it suggests the role of other factors such as dynamic increasing returns and learning effect in fostering state dependence for radical innovations.

4.7.2 Implications and limitations

The findings also provide important managerial and policy implications. The development of innovation generates a strategic commitment to the pursuit of subsequent innovations. Therefore, managers should be cautious to adopt the right innovation in the right way at the right time. Innovations in general are more likely to be adopted by large firms. The highest level of persistence is found for product innovation, in particular, for radical innovation. For managers, firm's decision to develop radical innovation has long-term implications and sustaining impacts on future innovation performance. Admitting the different persistence pattern among process innovation, radical product innovation and incremental product innovation, managers need to recognize the significant lasting impacts of innovation strategies adopted and pay particular attention to choose the type of innovation to perform, especially for those firms with the first innovation attempt.

Some findings related to the control variables are also worthy of comment. If managers intend to encourage innovation persistence, for instance for product innovations, they should be aware of the vital role of subsidy, cooperation and sunk costs in fostering subsequent product innovations. As for process innovation, managers need to be mindful about investing in all elements of expanding knowledge diversity and deepening knowledge depth, strengthening the learning effect, and building up dynamic capability to foster a cumulative self-reinforcing circle which helps firms to sustain innovative status.

Moreover, consistent with Subramaniam and Youndt [2005], surprisingly, high proportion of educated employees seems to discourage subsequent radical innovation. As Subramaniam and Youndt [2005] state, individual expertise on its own is not conductive to radical innovation. Subramaniam and Youndt [2005] suggest that human capital plays a vital role in fostering radical innovation capabilities when it is strongly tied to social capital. A corporate structure poor in social capital will concentrate on individual skill and knowledge in a competitive top-down fashion, which underplays the importance of knowledge diffusion through meaningful social interactions. In order to transform human capital to structural organizational capital, it is crucial to combine human capital and social capital (Styhre [2008]). Knowledge should not be conceived as solely individual property, but a social accomplishment which enables firms to facilitate innovative activities.

The OECD Review of Innovation Policy report (2015) points out that, Luxembourg as a small open economy, still faces challenges for lack of well-articulated strategy for directing innovation policy and limited business R&D investments. Policy makers should provide stronger incentives for accumulating innovation capabilities and extending innovation efforts in business sector. In the context of innovation persistence, innovation policy not only affects current innovation but all future innovation activities. Therefore, it is crucial to spur the undertaking of the initial innovation activity. Policy makers should implement support instruments and funding schemes to stimulate the initial innovation attempt, to identify and remove barriers to innovation for initial innovators. As the state dependence is not exclusively related to sunk costs associated with R&D activities, policy makers should dedicate to stimulate underlying fostering factors such as knowledge and learning which contribute to innovation persistence. Moreover, as radical innovations imply more profound transformation of a firm's internal capabilities and show a distinctive pattern in terms of persistence, policy makers should explore means to promote radical innovation as a source of innovation persistence and a vehicle for gaining economic growth and sustainable competitive advantage. Moreover, if innovation exhibits true state dependence regardless of public financial support from local or regional authorities, government intervention on firms' innovative activity might be modified in terms of funding allocation. In order to foster innovation efficiently, the government might give non-innovators a financial preference to encourage them to embark on an innovation journey, on the grounds that innovative firms are more likely to innovate in subsequent period in the light of true state dependence. Moreover, there is some evidence in support of innovation persistence at the intensive margin. In addition to encouraging non-innovative firms to convert to innovative firms, policy makers should implement support instruments to intensify the R&D investment effort and increase the share of sales of new products, particularly the share of sales of products new to the market.

The study also has some limitations which are relevant to the CIS database. The disadvantage of using CIS questionnaire resides in the fact that whether a firm has introduced an innovation is relevant to a 3-year period. This may result in a high artificial persistence due to double counting for the overlapping years. For example, if actual innovation takes place in the year 2006, innovation activities in CIS 2004-2006 and 2006-2008 wave are reported as positively implemented even in the absence of innovation for the year 2004, 2005, 2007, 2008. Innovation persistence thus in this case is false as only one innovation takes place between two consecutive waves. Nonetheless, this limitation is present in all studies based on CIS survey. [23] There is not much we can improve on this front due to inherent design flaw. Yearly data such as innovation expenditure contained in the biennial CIS is scarce and insufficient for estimation. In addition, the transition probability matrixes and estimation based on the nonconsecutive waves (such as CIS 2004-2006 and 2008-2010 wave) show

[23] Raymond et al. [2010b] has pointed out the same problem of overlapping year based on an unbalanced panel of Dutch manufacturing firm with four waves of the Community Innovation Survey over the period 1994-2002.

unsatisfactory results, wherein innovation persistence hardly emerges [24]. However, as no evidence of persistence is found for incremental innovation after accounting for sunk costs related to R&D activities, it may be concluded that the effect of the overlapping year is not substantial and not sufficient to explain the entire persistence discovered.

For future extension, longer panel would enrich the current study substantially, as the divergence of application of Wooldridge [2005] and Albarrán et al. [2015] estimators becomes conspicuous when the time periods increase. Accordingly, most explanatory variables hardly vary across time as a result of a relatively short panel period and have to be treated as time-constant. Future studies may advance this line of research by showing innovation persistence across industries and firm sizes with more dataset, as dynamic increasing returns might play a more different role in innovation persistence for the small firms.

[24] This phenomenon is reasonable as innovation persistence subsides in view of long span of two nonconsecutive waves.

Appendix

4.A Sectoral composition of the sub-panel and cross-correlation table

Table 4.A.1 shows low proportion (3.26%) of high-tech industry in the sub-panel 1 and sub-panel 3(1.47%). High-tech industry constitutes relatively high share in the sub-panel 2 (17.65%), sub panel 5 (14.29%) and sub panel 6 (17.78%). Sub-panel 4 consists only of low-tech, high-tech (44.44%) and knowledge-intensive services. In addition, the industrial compositions of the unbalanced sample are 26.94% of low-tech, 15.13% of high-tech, 16.24% of less knowledge-intensive services (LKIS), 35.74 % of knowledge intensive services (KIS) and 5.94% of utilities.

Table 4.A.1: Sectoral composition of the sub-panel.

Sub-panel 1	**sector**	**Percent**
	Low-tech	18.48
	High-tech	3.26
	LKIS	22.83
	KIS	55.43
Sub-panel 2	Low-tech	23.53
	High-tech	17.65
	LKIS	23.53
	KIS	29.41
	Utilities	5.88
Sub-panel 3	Low-tech	14.71
	High-tech	1.47
	LKIS	23.53
	KIS	52.94
	Utilities	7.35
Sub-panel 4	Low-tech	22.22
	High-tech	44.44
	KIS	33.33
Sub-panel 5	Low-tech	21.43
	High-tech	14.29
	LKIS	26.19
	KIS	30.95
	Utilities	7.14
Sub-panel 6	Low-tech	33.93
	High-tech	17.78
	LKIS	11.85
	KIS	29.78
	Utilities	6.67

Table 4.A.2: Cross-correlation table

Variables	l2em	l2em_m	Educ	Educ_m	Gp	Gp_m	l2sub	l2sub_m	l2ms	l2ms_m	con	con_m	l2co	l2co_m	in	in_m	R&D int	R&D int_m	MC2	MC2_m	MC3	MC3_m	MC4	MC4_m
Employment in $\log_{t-2}$	1.00																							
Employment in $\log_{t-2}$_m	0.99	1.00																						
Education	0.08	0.05	1.00																					
Education_m	0.06	0.06	0.85	1.00																				
Group	0.29	0.32	0.24	0.28	1.00																			
Group_m	0.36	0.36	0.27	0.32	0.87	1.00																		
Subsidy_{t-2}	0.25	0.25	-0.05	-0.04	0.17	0.17	1.00																	
Subsidy_{t-2}_m	0.32	0.31	-0.04	-0.05	0.18	0.21	0.79	1.00																
Market share_{t-2}	0.29	0.29	-0.00	-0.02	0.12	0.13	0.13	0.16	1.00															
Market share_{t-2}_m	0.30	0.31	-0.02	-0.02	0.12	0.14	0.13	0.17	0.94	1.00														
Concentration ratio	-0.14	-0.13	-0.41	-0.49	-0.09	-0.09	0.12	0.15	0.13	0.13	1.00													
Concentration ratio_m	-0.17	-0.16	-0.50	-0.58	-0.09	-0.11	0.14	0.18	0.15	0.16	0.84	1.00												
Cooperation_{t-2}	0.27	0.26	0.12	0.12	0.19	0.23	0.39	0.38	0.14	0.13	-0.02	0.00	1.00											
Cooperation_{t-2}_m	0.36	0.36	0.14	0.16	0.27	0.31	0.43	0.54	0.17	0.18	0.00	0.00	0.71	1.00										
Intramural R&D share	0.22	0.22	0.06	0.08	0.18	0.19	0.36	0.45	0.07	0.06	0.10	0.11	0.33	0.43	1.00									
Intramural R&D share _m	0.28	0.28	0.08	0.10	0.21	0.24	0.45	0.57	0.07	0.08	0.11	0.14	0.39	0.54	0.79	1.00								
Average R&D intensity	0.10	0.12	0.07	0.09	0.10	0.11	0.16	0.22	0.01	0.02	-0.00	-0.03	0.10	0.20	0.18	0.24	1.00							
Average R&D intensity_m	0.20	0.20	0.13	0.15	0.16	0.18	0.30	0.38	0.03	0.03	-0.04	-0.04	0.24	0.34	0.32	0.41	0.58	1.00						
Market competition																								
Low	0.03	0.00	-0.01	-0.01	0.04	0.06	-0.01	0.01	-0.06	-0.05	0.04	-0.00	0.03	-0.01	0.05	0.01	-0.03	-0.01	1.00					
Low _m	0.00	0.00	-0.03	-0.03	0.12	0.13	0.02	0.03	-0.10	-0.10	-0.00	-0.00	-0.01	-0.03	0.01	0.01	-0.02	-0.03	0.47	1.00				
Medium	0.07	0.04	0.12	0.10	0.10	0.10	0.09	0.09	0.06	0.02	-0.04	-0.04	0.08	0.08	0.06	0.11	0.06	0.11	-0.41	-0.14	1.00			
Medium_m	0.08	0.08	0.17	0.19	0.16	0.18	0.14	0.17	0.03	0.03	-0.07	-0.08	0.12	0.16	0.16	0.20	0.12	0.20	-0.13	-0.27	0.53	1.00		
High	0.01	0.02	0.00	0.03	0.04	0.04	0.03	0.05	0.01	0.00	-0.04	-0.06	-0.02	0.03	0.04	0.07	0.05	0.05	-0.28	-0.06	-0.26	-0.11	1.00	
High_m	0.05	0.04	0.05	0.06	0.08	0.09	0.08	0.09	0.01	0.01	-0.09	-0.11	0.05	0.07	0.11	0.14	0.05	0.09	-0.06	-0.12	-0.12	-0.23	0.50	1.00

4.B Additional estimation results

Table 4.B.1: Dynamic pooled probit with clustered standard errors

Regressor	(1)	(2)	(3)
TPP_{t-2}	0.233^{***}		
	(0.05)		
$\text{Product innovation}_{t-2}$		0.249^{***}	
		(0.05)	
$\text{Process innovation}_{t-2}$			0.155^{***}
			(0.04)
$\text{Employment in log}_{t-2}$	0.089^{***}	0.112^{***}	0.079^{***}
	(0.02)	(0.02)	(0.02)
Education_t	-0.006	-0.009	-0.052
	(0.05)	(0.06)	(0.05)
Group_t	0.009	0.003	0.076^{*}
	(0.04)	(0.04)	(0.05)
Subsidy_{t-2}	0.140^{***}	0.109^{*}	0.078
	(0.05)	(0.06)	(0.05)
$\text{Market share}_{t-2}$	-0.006	0.286	-0.191
	(0.29)	(0.41)	(0.35)
$\text{Concentration ratio}_t$	0.061	0.024	0.023
	(0.13)	(0.16)	(0.15)
Cooperation_{t-2}	0.126^{**}	0.127^{**}	0.053
	(0.05)	(0.05)	(0.05)
Market competition			
Low	0.158^{***}	0.124^{***}	0.107^{**}
	(0.05)	(0.05)	(0.05)
Medium	0.115^{**}	0.066	0.126^{**}
	(0.05)	(0.05)	(0.05)
High	0.220^{***}	0.228^{***}	0.079
	(0.07)	(0.07)	(0.06)
Sector dummies	YES	YES	YES
Time dummies	YES	YES	YES
Log likelihood	-479.63		-541.69
Observations	929	921	941

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.B.2: The partial effects at average value of individual heterogeneity - Robustness check for the process innovation with the Dynamic RE model (Albarrán et al. [2015]) after accounting for investment in physical capital intensity and external R&D intensity. †

	(1)	(2)
Structural equation		
Process innovation$_{t-2}$	0.086*	0.072
	(0.05)	(0.05)
Employment in log$_{t-2}$	0.081***	0.058**
	(0.02)	(0.03)
Education$_t$	−0.083	−0.146**
	(0.05)	(0.06)
Group$_t$	0.065	0.055
	(0.05)	(0.05)
Subsidy$_{t-2}$	0.096*	0.000
	(0.05)	(0.06)
Market share$_{t-2}$	−0.357	−0.229
	(0.35)	(0.36)
Concentration ratio$_t$	0.000	−0.047
	(0.15)	(0.16)
Cooperation$_{t-2}$	0.036	0.013
	(0.05)	(0.05)
Intramural R&D share		0.141
		(0.09)
Average R&D intensity		0.005**
		(0.00)
External R&D intensity	−0.004	−0.010
	(0.01)	(0.01)
Investment in physical capital intensity	0.000	−0.001
	(0.00)	(0.00)
Market competition		
Low	0.080	0.067
	(0.05)	(0.05)
Medium	0.133**	0.095*
	(0.05)	(0.06)
High	0.069	0.042
	(0.07)	(0.07)
Individual heterogeneity		
Process innovation$_{0S1}$	0.061	−0.248
	(0.22)	(0.32)
Process innovation$_{0S2}$	0.751**	0.352
	(0.30)	(0.38)
Process innovation$_{0S3}$	0.043	0.055
	(0.11)	(0.11)
Process innovation$_{0S4}$	0.021	0.048
	(0.19)	(0.20)
Process innovation$_{0S5}$	0.077	0.221
	(0.14)	(0.17)
Process innovation$_{0S6}$	0.124**	0.079
	(0.06)	(0.06)
Average R&D intensity$_{0S1}$		0.156*
		(0.08)
Average R&D intensity$_{0S2}$		0.042
		(0.03)
Average R&D intensity$_{0S3}$		0.007
		(0.01)
Average R&D intensity$_{0S4}$		0.006
		(0.02)
Average R&D intensity$_{0S5}$		−0.019*
		(0.01)

Average R&D intensity$_{0S6}$		0.001
		(0.01)
Intramural R&D share$_{0S1}$		−0.215
		(0.83)
Intramural R&D share$_{0S2}$		0.632
		(0.52)
Intramural R&D share$_{0S3}$		0.422
		(0.31)
Intramural R&D share$_{0S4}$		0.369
		(0.32)
Intramural R&D share$_{0S5}$		1.064***
		(0.33)
Intramural R&D share$_{0S6}$		0.300*
		(0.15)
External R&D intensity$_{0S1}$	0.267	−0.701
	(0.31)	(0.63)
External R&D intensity$_{0S2}$	0.235	0.055
	(0.17)	(0.20)
External R&D intensity$_{0S3}$	−0.258	−0.492
	(0.32)	(0.40)
External R&D intensity$_{0S4}$	0.056	−0.077
	(0.17)	(0.19)
External R&D intensity$_{0S5}$	0.127	0.182*
	(0.08)	(0.10)
External R&D intensity$_{0S6}$	0.006	−0.002
	(0.01)	(0.01)
Investment in physical capital intensity$_{0S1}$	0.047	0.139
	(0.09)	(0.11)
Investment in physical capital intensity$_{0S2}$	0.036	0.037
	(0.04)	(0.05)
Investment in physical capital intensity$_{0S3}$	−0.004	−0.005
	(0.00)	(0.00)
Investment in physical capital intensity$_{0S4}$	−0.022	−0.031
	(0.02)	(0.02)
Investment in physical capital intensity$_{0S5}$	0.005**	0.010**
	(0.00)	(0.00)
Investment in physical capital intensity$_{0S6}$	0.001	0.001
	(0.00)	(0.00)
constant$_1$	−0.843***	−1.022***
	(0.25)	(0.31)
constant$_2$	−0.736***	−0.703***
	(0.22)	(0.25)
constant$_3$	−0.516***	−0.439**
	(0.18)	(0.19)
constant$_4$	−0.678***	−0.540**
	(0.20)	(0.24)
constant$_5$	−0.691***	−0.682***
	(0.18)	(0.20)
constant$_6$	−0.641***	−0.484***
	(0.17)	(0.18)
Sector dummies	YES	YES
Time dummies	YES	YES
$\hat{\sigma_\alpha}$	0.003	0.001
	(0.04)	(0.01)
Log likelihood	−453.96	−425.66
Observations	820	820

†This estimation results are based on the merged dataset of Community Innovation Survey and Structural Business Statistics over the period 2004 to 2012 .
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 5

Conclusion

5.1 Summary

This doctoral dissertation has comprehensively explored three vital topics central to innovations: the dynamic relationship between technological innovation and employment, the two-way relationship between technological innovation and firm performance, and innovation persistence of differentiated innovation types at the firm level. Chapter 2 investigates whether technological change creates or destroys jobs at the firm level. We develop a simple theoretical model with endogenized product and process innovation which allows a separate investigation of the employment effects of product and process innovation. Product innovation is found to exert a positive effect on employment where the semi-elasticity of the latter with respect to the percentage of turnover from new product lies between 0.2% and 0.5%. Unlike product innovation, process innovation does not exert a significant effect on the firm level of employment. Our empirical findings are consistent with the literature which emphasizes the positive impact of product innovation on employment along with inconclusive and equivocal evidence for process innovation. For instance, using data on Italian SMEs over the period 1995-2003, Hall et al. [2009] discover positive effects of new and old products and no evidence of displacement effect associated with process innovation. In line with our results, Hall et al. [2009] highlight the equal contribution of product innovation and sales of old products to employment growth.

The conclusion of Chapter 2 should be interpreted with caution. The positive impact associated with product innovation, if we take a closer look, implies that the increase of the share in total sales of products new to the firm or new to the market contributes positively and significantly to employment, holding everything else constant including the sales of old or unchanged products. In other words, the interpretation of positive impact of product innovation implicitly assumes the absence of cannibalization effect, as the sales of old or unchanged products have been controlled for. In other words, our model in essence measures solely the compensation effect through sales of new products rather than the net impact of product innovation.

If a firm produces multiple products, new products may simply drive out old products, which will reduce the magnitude of the compensation effect if both old and new products are substitutes. As a result, the net employment effect of product innovation depends upon the degree of substitutability between existing and new products. The simple model presented here does not separately measure this particular cannibalization effect induced by product innovation. Nonetheless, in the empirical model we control for the degree of substitutability between existing and new products by using market competition variables as regressors which measure how rapidly products are becoming old-fashioned or outdated. It is likely that the overall sales decrease within certain periods of time on account of the dominant role of cannibalization effect induced by the product innovation, which is consistent with the conclusion of Chapter 3.

Chapter 3 aims at capturing the two-way relationship between innovation and firm performance. In particular, different mechanisms of product and process innovation are distinguished with their distinct impacts on firm performance. To shed light on this issue, an unbalanced longitudinal dataset is applied over the period 2003-2012 which stems from merging five waves of the innovation survey with annual Structural Business Surveys of Luxembourg. A simultaneous structural model is established with the fully recursive form which involves underlying continuous unobservable variables. This system of equations with mixed structure is estimated by full information maximum likelihood methods.

By and large, I discover that superior firm performance facilitates the emergence of process innovations, and process innovation contributes to firm performance by gaining successful and sustainable competitive advantage which forms a virtuous circle. Nonetheless, an opposite pattern is identified for the product innovation in view of cannibalization effect and inherent market risks associated with new products.

The seemingly contradictory conclusions in Chapter 2 and Chapter 3 can plausibly coexist. As aforementioned, our model presented in Chapter 2 measures solely the compensation effect through sales of new products on employment rather than separately measuring the cannibalization effect induced by product innovation. The overall sales are determined by the dynamic interaction between existing and new products which depends upon the respective products life cycle and the degree of substitutability between existing and new products. It is highly likely that the cannibalization effect plays a predominant role one year after the introduction of new products, which is consistent with the conclusion of Chapter 3.

In Chapter 3, when the increase of the share of sales of new products in total sales exerts positive and significant contemporaneous impact on employment, holding the sales of old or unchanged products constant, it is possible that in reality, the overall sales decrease one year after the introduction of product innovation on account of the dominant cannibalization effect after controlling for the employment level. In light of inherent market risks associated with new products, it is also reasonable that an increase in turnover at t-2 decreases the predicted probability of product innovation at t-1 holding everything else constant including the firm size. Likewise, process innovation may not exert an immediate positive effect on the firm level of employment. Nonetheless, it is plausible that after accounting for the employment level, for a representative firm, the introduction of process innovation will increase future turnover, on account of cost reduction and improved efficiency in production, prevalent systemic transformation and less market uncertainty. Holding everything else constant including the firm size, an increase in turnover may increase the predicted probability of future process innovation on account of more available financial resources and low market risks associated with process innovation.

In addition, firms do not react instantaneously to sales reduction by laying off workers on the grounds of employment adjustment cost (Peters et al. [2014], Calvino and Virgillito [2017]), particularly when sales reduction is temporarily induced by the cannibalization effect. Therefore, even when the cannibalization effect plays a temporarily predominant role one year after the introduction of new products and overall sales decrease, the displacement effect of product innovation may not exert a surpassing and immediate impact on employment.

Using five questionnaire waves of Luxembourgish Community Innovation Surveys (CIS) for the years 2002-2012, Chapter 4 explores innovation persistence by means of dynamic nonlinear random effects models based on the estimator proposed by Albarrán et al. [2015]. The application of the Albarrán et al. [2015] method correctly accounts for unobserved individual effects that are correlated with the initial conditions as well as the unbalanced structure of panel, which has been largely ignored in the earlier research. Given the fundamental differences between innovation types, the analysis presented in this chapter is one of the first to distinguish between radical and incremental product innovation. The econometric results show that past innovation activity is a crucial determinant for all types of innovation, hence confirm the hypothesis of true state dependence. The highest level of persistence is found for product innovation, particular for radical product innovation. The results highlight differentiated patterns of persistence among product and process innovation. The state dependence of product innovation (particularly, incremental product innovation) is mainly associated with sunk costs related to R&D. By contrast, the state dependence of process innovations cannot be explained entirely by the sunk-cost hypothesis, which suggests that it can be further attributed to dynamic increasing returns and learning effect. To further look into the product innovation category, a significant state dependence is observed for the radical product innovation. By contrast, an analogous pattern cannot be identified for the incremental product innovation indicator after accounting for the sunk costs related to R&D. This result appears to have relevant implications, which reveals the potential different size of cumulative stock of knowledge and dynamic increasing return induced by radical and incremental innovation.

Chapter 4 corroborates the view conveyed by Chapter 3 that process innovation often signals a systemic transformation of firms' internal capabilities, which relates to dynamic increasing returns and learning effect (Geroski et al. [1993]). By contrast, the influence induced by product innovation is rather confined to the R&D department. Tornatzky et al. [1990] support the view that the impact of process innovation is systemic and the adoption of process innovation often implies a large aggregate of tools, machines, human resources and social systems and is, thus, more disruptive than product innovation. Furthermore, the above-mentioned self-reinforcing mechanism of dynamic increasing returns revealed in Chapter 3 might be strengthened in light of true innovation persistence discovered in Chapter 4. In other words, firms with superior past performance, which signals healthy cash flow, tend to implement more process innovation, which further contributes to firm performance by gaining successful and sustainable competitive advantage. The adoption of process innovation engenders a higher likelihood of delivering process innovation in the subsequent period, which further contributes to firm performance and forms a self-reinforcing virtuous circle. Accordingly, the innovation persistence and two-way relationship between process innovation and firm performance operate concurrently and interdependently, which further forms an intensified dynamic self-reinforcing mechanism. The relationship between product innovation and firm performance tends to be inconclusive and ambiguous, as product life cycle and the magnitude and duration of cannibalization effect can differ from one market to another. [1]

5.2 Economic, managerial and policy implications

Chapter 2 acknowledges the substantial positive impact of new-to-the-firm and new-to-the-market products on employment. Managers should take into account the differentiated role of innovation types in stimulating firm-level employment. Moreover, if firms aim

[1] It is worth noting that Chapter 4 measures the persistence of innovation which is identified as the phenomenon that firms that have innovated during a given period innovate again in the subsequent period. It should be distinguished from what has been captured by the dummy variable non-R&D performer in Chapter 3 in the innovation equation, which measures the probability to switch from non-R&D performer to either product or process innovator. This is different from our definition of true state dependence, which captures the causal phenomenon that the decision to innovate in one period enhances the probability of innovating in the subsequent period (Peters [2009]). Log transformation has been implemented for enterprises with positive R&D expenditures. The log R&D intensity is set to zero for enterprises with zero R&D expenditures. Accordingly, the inclusion of this dummy variable merely compensates for this correction. Moreover, this dummy variable measures the innovation input rather than innovation output. In Chapter 3, the negative and significant coefficient of non-R&D performer associated with product innovation in the baseline model estimates suggests that being non-R&D performer last period leads to a decrease in the predicted probability of being product innovator in current period, which indirectly corroborates the findings in Chapter 4.

at creating immediate employment growth, process innovation may not live up to the expectations as process innovation does not exert a significant contemporaneous effect on the firm level of employment. Moreover, our results highlight the crucial contribution of sales of old products to employment growth. Consequently, managers should aim at minimizing the effects of cannibalization, further secure the sales of old products and corresponding market share. Managers may need to take into account the market position of existing products and introduce product innovation in light of the products life cycle phase.

Chapter 3 also appears to have relevant managerial implications. The findings emphasize the self-reinforcing mechanism in determining the innovation-performance trajectory. Managers should take into account the potential positive feedback between innovation and firm performance when adopting certain innovation types. Positive feedback suggests long-term implications and sustaining impacts in the future. Firms with superior past performance, which signals healthy cash flow, tend to implement more process innovation, which further contributes to firm performance by gaining successful and sustainable competitive advantage and forms a virtuous circle.

Additionally, managers need to be mindful of the differentiated impacts of innovation strategies on firm performance. For risk-averse firms which aim at immediate payoff to innovation output, process innovation might be a more appropriate strategy than product innovation (particularly radical product innovation) given evident virtuous circle between process innovation and firm performance. The two-way relationship between product innovation and firm performance is more inconclusive considering our short panel. Moreover, some findings related to the control variables are also worthy of comment. R&D inputs, subsidy and cooperation are all conducive to the adoption of innovation strategies.

Product innovation is associated with the cannibalization effect and uncertain market reactions, which leads to initial negative impacts on firm performance. Mason and Milne [1994] argue that very few firms are immune to the effect of cannibalization as the majority of new products are minor modifications or line extensions of existing products. Cannibalization effects are prevalent in many sectors: computer hardware and software, banking services, airline service, pharmaceutical products, etc., (Mazumdar et al. [1996]). Managers may need to take into account the market position of existing products and introduce product innovation in light of the products life cycle phase. It is crucial to identify the optimal time to introduce new products which may otherwise lead to the potential retirement of firms' existing products. Traylor [1986] and Mazumdar et al. [1996] argue that the aim of strategic cannibalization is to replace firm's own existing product at the appropriate time, hence prevents the customers from switching from the existing products to competitor's product.

Managers should examine the similarity between existing and new products and between the respective markets. Similar new products are often introduced when the existing products reach the maturity phase (Mazumdar et al. [1996]). By and large, the optimal timing of launching new products depends on the assessment of sales growth pattern of both products, specific product attributes such as price, quality and performance, relative market potentials and cannibalization rates (Mazumdar et al. [1996], Moorthy and Png [1992]). Advantageous combination of marketing strategies is substantial and conductive to improve the overall firm performance for the subsequent remaining periods of the existing product.

In consideration of the short lag period (one period) in the model, it is highly likely that the negative relationship between product innovation and firm performance tends to be temporary. It is possible that the cannibalization effect only temporarily plays a dominant role one year after the introduction of new products. Mazumdar et al. [1996]) also argue that the new product manager tends to delay the launch of a new product on the grounds that the surplus generated from the new product cannot fully compensate for the loss of sales from the existing product during the initial years. Nonetheless, the long-term positive impact of new product on firm performance should be acknowledged. [Chandy and Tellis, 1998, pp.475] have stated, "Willingness to cannibalize is an attitudinal trait of the key decision makers of the firm, and resides in the culture or shared values and beliefs of the firm" (referring to Deshpande and Webster Jr [1989]) . Therefore, firms should not be daunted by the cannibalization effect and temporary sales decline. Firms can acquire elevated temporary market power through product innovations. In the long run, product innovation can be more advantageous, as revenues generated from successful products can be more substantial than cost reduction brought by process innovation (Pisano and Wheelwright [1995]).

Chapter 4 reveals the true innovation persistence regardless of the innovation type, which strengthens the above-mentioned self-reinforcing mechanism of dynamic increasing returns. Managers should be aware of the presence of a potential self-reinforcing mechanism and positive feedback between innovation and firm performance. Moreover, managers should be cautious to adopt the right innovation given the right opportunity, as firm's decision to develop certain innovation has long-term implications and sustaining impacts on future firm performance and innovation activities.

If managers intend to encourage innovation persistence, for instance for product innovations, they should be aware of the vital role of subsidy, cooperation and sunk costs in fostering subsequent product innovations. As for process innovation, managers need to be mindful about investing in all elements of expanding knowledge diversity, deepening knowledge depth, strengthening the learning effect and building up dynamic capability in order to foster a cumulative self-reinforcing circle which helps firms to sustain innovative status.

This doctoral dissertation also appears to have far-reaching economic policy implications. Luxembourg is an open small economy with the highest GDP in the OECD area and among the highest in the world. The OECD Review of Innovation Policy report (2015) points out that Luxembourg still faces challenges including reducing unemployment, strengthening productivity growth and diversifying the economy. The overall objective of Luxembourg innovation policy is to strengthen innovation as a driver of sustainable productivity, employment growth and competitiveness. Consistent with previous findings, our results highlight the substantial positive impact of product innovation on employment. The immediate economic implication calls for the support of product innovation. There is some evidence that the effect of radical innovation measured by the share of sales of products new to the market is more sizable than incremental innovation, measured by the share in total sales of products new to the firm. In this context, policy makers should aim to encourage companies to undertake innovation activities, particularly, radical innovations as a constant driver of national employment growth.

Secondly, this dissertation emphasizes the self-reinforcing mechanism in determining the innovation-performance trajectory. The adoption of process innovation contributes to firm performance, which in turn produces more process innovation. Policy makers need to be mindful about the presence of positive feedback which suggests long-term implications and sustaining impacts in future. Policy makers should implement support instruments and funding schemes to stimulate innovation and foster a virtuous circle between innovation and firm performance, particularly for process innovation.

The OECD Review of Innovation Policy report (2015) points out that, after the transformation towards a service economy, Luxembourg still faces challenges for lack of well-articulated strategy for directing innovation policy and limited business R&D investments. Policy makers should provide stronger incentives for accumulating innovation capabilities and extending innovation efforts in business sector. In case of true state dependence of innovation persistence, innovation policy not only affects current innovation but also all future innovation activities. Therefore, it is crucial to spur the undertaking of the initial innovation activity and remove barriers to innovation for initial innovators. As the state dependence is not exclusively related to sunk costs associated with R&D activities, policy makers should dedicate to stimulate underlying fostering factors such as knowledge and learning which contribute to innovation persistence. Moreover, as radical innovations imply more profound transformation of a firm's internal capabilities and show a distinctive pattern in terms of persistence, policy makers should explore means to promote radical innovation as a source of innovation persistence and a vehicle for gaining economic growth and sustainable competitive advantage. In addition, if innovation exhibits true state dependence regardless of public financial support from local or regional authorities, government intervention on firms' innovative activity might be modified in terms of funding allocation. In order to foster innovation efficiently, the government might give non-innovators a financial preference to encourage them to embark on an innovation journey, on the grounds that innovative firms are more likely to innovate in subsequent period in the light of true state dependence. Moreover, there is some evidence in support of innovation persistence at the intensive margin. In addition to encouraging non-innovative firms to convert to innovative firms, policy makers should implement support instruments to intensify the R&D investment effort and increase the share of sales of new products, particularly the share of sales of products new to the market. Furthermore, policy makers should be mindful of the strengthened self-reinforcing mechanism in the context of innovation persistence. Firms with superior past performance tend to implement more process innovation which further contributes to firm performance. The adoption of process innovation generates more process innovation, which contributes to firm performance and forms a self-reinforcing virtuous circle. Policy makers should dedicate to stimulate underlying fostering factors and spur the emergence of self-reinforcing mechanism. These policy recommendations may be used in an effort to help Luxembourg to achieve and maintain economic competitiveness and productivity growth in the long term.

5.3 Limitations and future research

Several limitations inherent in this research relate to the application of Luxembourgish CIS database. As Mairesse and Mohnen [2010] point out, most of CIS data are qualitative, subjective and censored. The accuracy of the answer hinges chiefly on the judgment and knowledge of the respondents.

The CIS questionnaire is designed in such a way that whether a firm has introduced an innovation is relevant to a 3- year period. Therefore, the information regarding the exact year of occurrence of innovation over each 3-year period is effectively absent in the questionnaire. This design flaw appears to be relevant to Chapter 3 and Chapter 4. For example, in Chapter 3, considering the 2004-2006 wave, it may well be the case that innovation in 2005 or 2006 is explained by firm performance in 2005 depending on the exact year of innovation occurrence, and turnover in 2007 is explained by innovation occurrence in 2005 or 2006 depending on the exact year of innovation occurrence. The disadvantage resides in the fact that we cannot distinguish between the contemporaneous and lagged effects case. As for Chapter 4, using the CIS questionnaire may result in a high artificial persistence due to double counting for the overlapping years. For example, if actual innovation takes place in the year 2006, innovation activities in CIS 2004-2006 and 2006-2008 wave are reported as positively implemented even in the absence of innovation for the year 2004, 2005, 2007, 2008. Innovation persistence thus in this case is false as only one innovation takes place between two consecutive waves. Nonetheless, this limitation is present in all studies based on the CIS survey. There is not much we can improve on this front due to an inherent design flaw. Yearly data such as innovation expenditure contained in the biennial CIS is scarce and insufficient for estimation. However, as no evidence of persistence is found for incremental innovation after accounting for sunk costs related to R&D activities, it can be concluded that the effect of the overlapping year is not substantial and not sufficient to explain the entire persistence discovered. Moreover, this research is confined by the short panel period, which may otherwise capture the long-lasting positive effects of product innovation. For future extension, longer panel data might be indispensable to explore the presence of possible positive two-way relationship between product innovation and firm performance.

For future extension, Chapter 2 may clearly identify the compensation effect and displacement effect induced by the product innovation. For example, Harrison et al. [2008] decompose the growth of employment into the growth of employment due to production of the old products and the growth of employment due to production of the new products. In addition, the assumption of a short-run fixed capital stock can be released in the theoretical model so that a capital stock regressor is included in the empirical model. Moreover, Evangelista and Vezzani [2011] have applied a novel three-step approach by first examining the impact of innovation on sales increase, then investigate to which degree the employment growth can be ascribed to sales increase induced by innovation. Incorporating this stepwise approach can better clarify the channels through which compensation mechanisms operate and enrich the current analysis.

Furthermore, the relationship between employment dynamics, firm performance and innovation persistence can be investigated during different phases of the business cycle. A similar approach has been adopted by Peters et al. [2014], for example, to study the link between employment and innovation using CIS data from 26 European countries. Linkage to business cycle will add interesting dimension to the current study.

This doctoral dissertation can be further extended to explore the impact of the degree of persistence of innovation strategies on employment and firm performance. For example, Triguero et al. [2014] have discovered a positive link between persistent process innovation activities and employment growth. By contrast, no significant impact has been found for persistence in product innovation on employment growth. Investigating the impact of the degree of persistence of differentiated innovation strategies on employment and firm performance can shed light on the closely-intertwined relationship among three essential topics central to innovation.

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Valorization

In accordance with Article 23 of the Regulation Governing de Attainment for Doctoral Degree in the Maastricht University, the following section discusses the valorization opportunities presented by this doctoral dissertation. Conforming to the corresponding guidelines, these opportunities are analyzed in terms of the social and economic relevance, the target groups who may potentially benefit from the scientific results, and the degree of innovativeness of the research method.

This doctoral dissertation provides an assessment of the role of differentiated innovation strategies in employment, firm performance and innovation persistence, which shows far-reaching social and economic implications. Innovation is widely regarded as the primary source of economic growth. Public policies to promote firm-level innovation are high on the agenda in most EU countries. It is important to understand whether technological change creates or destroys jobs. Nonetheless, firm-level evidence on the relationship between innovation and employment tends to be inconclusive and ambiguous. The results are illuminating about the relative roles of product and process innovation in employment, which are beneficial for policy makers in terms of effective design of innovation policy and labour market regulations. Moreover, the firm-level relationship between innovation and employment growth relates to people from all corners of society. Neo-Luddite' fears about technological unemployment can be alleviated as our results identify a positive relationship between product innovation and employment. In other words, technological change can create jobs rather than destroying jobs at the firm level.

The two-way relationship between innovation and firm performance is an important research topic with policies and social implications. The firm-level effects of differentiated innovation strategies on performance are likely to determine the incentives of managers to innovate along with the types of innovations introduced. The results provide an assessment of subsequent effects on firm performance and precautions of differentiated innovation strategies that managers should take into account.

The results also reveal the true innovation persistence regardless of the innovation type, which strengthens the self-reinforcing mechanism of a two-way relationship between innovation and firm performance. Firms with superior past performance, which signals healthy cash flow, tend to implement more process innovation, which further contributes to firm performance by gaining successful and sustainable competitive advantage. The adoption of process innovation engenders a higher likelihood of delivery of process innovation in the subsequent period, which further contributes to firm performance and forms a self-reinforcing virtuous circle. Therefore, managers should be cautious to adopt the right innovation given the right opportunity, as firm's decision to develop certain innovation has long-term implications and sustaining impacts on future firm performance and innovation activities.

The results of this doctoral dissertation imply the social and economic relevance which goes beyond pure scientific analysis. The findings derived from this doctoral dissertation can be equally useful for further academic research, for policy makers as well as firm's managers and employees. In particular, the results provide interesting insights for decision makers in terms of dynamic relationship among employment, firm performance and innovation persistence.

Regarding the novelty of research approach, this dissertation contributes to the prior literature on the topics of employment dynamics, firm performance and innovation persistence in manifold ways. Firstly, this dissertation builds the analysis upon longitudinal dataset of innovation survey. Moreover, this dissertation establishes a theoretical model with endogenized product and process innovation which allows a separate identification of the employment effects of product and process innovation. The employment effect of product innovation is furthermore distinguished between radical and incremental innovation. Given the generic differences between innovation types, which are differently determined and associated with different capabilities and skills, this doctoral dissertation contributes to previous empirical work by explicitly distinguishing different mechanisms of product and process innovation and reveals their distinct impacts on firm performance. In addition, this dissertation applies a brand new econometric approach to study innovation persistence at the firm level. In effect, this work is the first attempt to empirically analyze the true state dependence and the role of sunk costs in forming the innovation persistence within the context of the Albarrán et al. [2015] framework.

In terms of diffusion of the research, some results have been presented at various international conferences and workshops, which are excellent opportunities for disseminating research findings and receiving valuable comments. Results were presented, for instance, in the Maastricht Innovation Workshop in 2017; in the 6th Asia-Pacific Innovation Conference, China; in the 21st International Panel Data Conference, Budapest; in the IAAE 2nd Annual Conference , Thessaloniki; in the DRUID15 Conference on the Relevance of Innovation, Rome; in the Doctoral Workshop in Management, Luxembourg; and in the Economics Seminar in STATEC, Luxembourg. Some chapters are currently being reformulated for submission to journals in the field of innovation.

Biography

Ni Zhen was born on July 16th 1985 in China. She obtained her Bachelor's degree in Economics at the Zhejiang University, P.R. China. After graduating, she obtained a scholarship to study economics at the Autonomous University of Barcelona, Spain, where she attained Master's degree in Economic Analysis in 2010. Before starting her PhD, Ni has worked as a junior researcher at STATEC (National Institute of Statistics and Economic Studies of Luxembourg) in 2014. She was also the prize-winner of Best Master Thesis Prize in Economics awarded by Economist Club Luxembourg. Ni joined the Centre for Research in Economics and Management of University of Luxembourg in 2014. During her PhD fellowship she participated in several workshops and conferences to present her research in progress, including DRUID Conference 2015 in Rome, IAAE Conference 2015 in Thessaloniki, International Panel Data Conference 2015 in Budapest, Asia-Pacific Innovation Conference 2015 in China.