Serial and Persistent Innovation in UK small companies

Carlo Corradini

Thesis submitted to the University of Nottingham
for the degree of Doctor of Philosophy

December 2013

STATEMENT OF ORIGINALITY

This thesis is submitted to the University of Nottingham in accordance with the requirements for the degree of Doctor of Philosophy. This thesis represents my own original work done while I was registered as a student of this University. All material presented has not been previously submitted for a degree or diploma at this University or any other institution.

However, parts of this thesis have already been published in the form of working papers, or they have been submitted to journals for publication. In particular, Chapters 3 and 4 are available as *SSRN papers* (See Corradini et al., 2012a; 2012b). Chapter 3 is in the "review and resubmit" stage for *Industrial and Corporate Change*. Finally, Chapter 3 has been presented at the DRUID Summer Conference 2012 and the 14th International Schumpeter Society Conference.

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Carlo Corradini

Nottingham University Business School

To my greatest passion

Abstract

In this thesis, we endeavour to explore the characteristics and the role of exceptionally innovative small and medium sized enterprises (SMEs) within the UK system of innovation. The focus is placed on 'serial' and ‘persistent’ innovators, defined as independent companies with an unusually high frequency of innovation over time. The aim of the thesis is to identify such companies and analyse those factors, both internal and external to the enterprise, which influence such a sustained stream of innovation within SMEs.

Persistence in innovation is an important element within the discussion on the properties of the patterns of innovative activities and industry dynamics. In this thesis, we propose three main empirical studies which look at rather unexplored areas in the literature on persistent innovation, focusing on the presence and the specific characteristics of small persistent and serial innovators and the role of cumulated knowledge capabilities in explaining the presence and the extent of such phenomenon. In particular, we follow a multidimensional approach, investigating the related and yet different phenomena of persistent and serial innovation through different perspectives built upon empirical evidence from patent data as well as innovation surveys.

Our intended contribution to the literature is centred around the presence of persistent and serial innovation across small companies, the role played by elements internal and external to the enterprise in sustaining their innovation activity and, finally, the extent and the determinants of technological diversification across small serial innovators. Additionally, we explore differences and similarities across firm size.

The first study explores the effect that specific patterns of innovative activity and firm-specific technology characteristics exert on the rate of innovation of

serial innovators. Then, it offers a comparative perspective observing the differences between small and large serial innovators. In particular, we test the hypothesis that the specific qualities of cumulativeness, described in terms of dynamic economies of scale and dynamic increasing returns, play a central role in defining the differences across firm size. Analysing patent counts and citation-weighted patent counts with a negative binomial GEE model, this study provides evidence that serial small innovators benefit from technological regimes characterized by patterns of creative accumulation and from combinative capabilities based on accumulated internal knowledge competencies as sources of both technological learning and creation.

The second study investigates the presence and the determinants of technological diversification across small serial innovators. After presenting stylised facts on the relationship between serial innovators and technological diversification, we focus on the elements that may bring small innovative firms to engage in the costly process of technological diversification, analysing the trade-off that is likely to take place between the need to explore new technological opportunities and the significant element of path dependency delineated by the specific core technological competencies that usually characterise small innovative companies. Using a fractional response model for panel data estimated within a GEE framework, we find that increasing technological opportunities present an inverted U relationship with diversification, while technological trajectories defined by coherence in both technological search and core competencies support specialization.

The third study addresses the question of whether there is persistence in innovative activities across UK companies. In particular, we analyse the presence of persistent innovation through a panel dataset obtained from three successive rounds of the UK Innovation Survey, covering the period of time between the year 2002 and the year 2008. Explicitly accounting for unobserved firm heterogeneity, we provide evidence of persistence in innovation for both large and small companies. Moreover, our findings confirm that important interaction effects exist between the effect exerted by the presence of persistent innovation, in the form of dynamic increasing returns within the process of knowledge accumulation, and technological intensity inherent to firms' innovation activity, at least among small companies.

Acknowledgements

As always - almost - in research and in life, there is no endeavour realised in aloneness, nor a solitary Atlas carrying the burden. This thesis is no exception. First and foremost, I would like to express my gratitude to my supervisors, Giuliana Battisti and Pelin Demirel, for their guide, support and advice. Throughout our meetings, they have been able to keep me focused on the right track and never lose the motivation for conducting research, while also providing essential support during times of confusion. Most importantly, their open and kind mentoring has contributed significantly to much more than just this thesis, making my experience as a PhD student at Nottingham a rewarding and inspirational experience.

A special mention goes to G. M. Peter Swann, who has been my supervisor during the first one and a half years of my PhD studies. His wise suggestions and insights have often been the silver lining during the difficult set up of the research framework, and his quiet approach to discussion has been an invaluable example. Their contributions to this thesis have been vast, and essential.

I would also like to thank Monica Giulietti, Pia Weiss and conference participants at DRUID Summer Conference 2012 and the 14th International Schumpeter Society Conference for their feedbacks and suggestions, as well as Andrea Tomlinson and the rest of the staff at Nottingham Business School for their help and support with all the every-day problems that always interfere with the research activity. Similarly, I would like to convey thanks to the Secure Data Service staff, with their wonderful support in having access and using the dataset from the Community Innovation Survey, and Gianluca Tarasconi for his insightful notes on the use of PATSTAT. In a different way, special thanks go to Maurice Ravel, Fryderyk Chopin, György Ligeti, Art Tatum, Oscar Peterson and all other composers and artists, whose music has inspired and accompanied me throughout this whole endeavour.

As money matters, I would also like to acknowledge the financial contribution received from Nottingham Business School and the ESRC, whose scholarships have funded and ultimately made possible this work.

Finally, I wish to thank my family for their discreet - but always felt - unconditional support. My deepest and warmest gratitude goes to my best half, Roberta. Her constant encouragement and patience, through interminable discussions and difficult moments, are the real backbone of this work. I also wish to express my gratitude to her for the caring and yet fiery help that has somehow eased the pain of going through endless, tortuous lines of SQL coding. For these reasons, this work is dedicated to her.

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CHAPTER 1

Introduction

"I can't understand why people are frightened of new ideas. I'm frightened of the old ones"

- John Cage

1.1 Research background

Since the remark of Schumpeter on competition for innovation being "much more effective than the other [price competition] as a bombardment is in comparison to forcing a door" (1942, p. 84), innovation activity has been increasingly regarded as one of the most important elements of firms' competitive advantage and, ultimately, an essential factor explaining firms' long term growth and survival (Baumol, 2002; Cefis and Marsili, 2006).
At the same time, a common view on inventions as well as innovations suggests that these are more often the result of casual discoveries or the 'work of a genius' rather than the fruit of an organised, sustained and collectively dedicated effort. While in the literature on innovation and technological change this view has been substantially reduced, invention and innovation are still intrinsically associated with elements such as uncertainty and risk. Accordingly, the outcome of innovation activity has been likened to a random process, whose returns are so positively skewed that the chances of success have been described to be similar to those of a lottery (Scherer and Harhoff, 2000; Scherer et al., 2000). Thus, it is not surprising that companies that try to stay at the top of their industries invest significantly in innovation activities[1]

[1] According to NESTA (2009a) Innovation Index, innovation investment – defined as the investment in knowledge or intangible assets - of UK companies in 2007 accounted for around 14 per cent of private sector gross value added.

and yet many of them, including some of the leading companies (Bower and Christensen, 1995), may fail to keep a sustained stream of innovations over time (Geroski et al., 1997; Cefis and Orsenigo, 2001).

Understanding the main determinants that allow companies to be innovative over time has proved particularly complex. Building on the so-called first Schumpeterian hypothesis[2], which states that a more concentrated market structure fosters innovative activity, economists have tried to find empirical evidence of the effects of the intensity of market concentration but results from both theoretical and empirical analysis have been mixed (van Cayseele, 1998).

A different strand of research, also based on Schumpeter's work, has put at the centre of the analysis the nature of technology, emphasising the essential role of learning and technological trajectories (Nelson and Winter, 1982; Dosi, 1982). These, in turn, take place within an environment defined by technological regimes, described in terms of specific combinations of opportunity conditions, appropriability, cumulativeness and properties of the knowledge base (Malerba and Orsenigo, 1990; 1993), ultimately modelling the way concentration and innovation evolve. Technological regimes influence industrial competition affecting the way firms enter and exit the market and defining the intra-firm processes of knowledge accumulation. In this way, they shape the patterns of innovative activity in terms of concentration, stability in the hierarchy of innovators and, therefore, persistence in innovation (Malerba et al., 1997; Breschi et al., 2000).

Two main patterns of innovative activity have been identified. Regimes characterised by low levels of cumulativeness in the knowledge base, favouring firm entry and bringing turbulence in the rank of innovative companies, have been labelled 'entrepreneurial' regimes. Conversely, 'routinised' regimes are characterised by high levels of cumulativeness in the innovative activity, thus fostering stability and concentration. According to these models, the central element that may explain the presence of stable market structure and an increasing likelihood of persistence in innovation is the quality of cumulativeness in knowledge capabilities and learning processes of firms. In other words, persistence is explained as originating from state

[2] See Tirole (1988).

dependence and non-reversible dynamic processes (David, 2001), where success in previous innovations leads to further innovation, following dynamic increasing returns or dynamic economies of scale in innovation. Similarly, persistent innovation may be supported by the presence of sunk costs in innovation activities, which generate barriers in entry and exit with respect to R&D investment and strategies (Sutton, 1991).

Several empirical contributions have provided support for this framework, but with respect to persistent innovation the literature has focused mainly on its presence and characteristics. Until recently, scholars have devoted little attention to the exploration of the different mechanisms that may lead to persistent innovation and whether there are differences in the way these operate across heterogeneous firms. In particular, the high barriers to entry and survival generated by accumulated competencies of incumbent firms operating in scale-intensive and concentrated oligopolies that define 'routinised' regimes have led to overlooking the potential role and the characteristics of small firms successfully operating within the very same technological environment, differently from the usual assumption that describes small innovative companies as the main actors of the 'entrepreneurial' regime.

In fact, in the literature as well as at the policy level, much attention has been dedicated to the study of new technology-based small firms (NTBFs) in the form of start-up or spin-off companies and gazelles, among others. However, few studies have been trying to analyse what happens to these companies after the first stages, usually assuming a standard perspective which predicts that successful small companies grow into larger firms, or they are bought up by established companies once they have introduced a successful new technology (Hicks and Hegde, 2005). These outcomes certainly account for the majority of small independent companies that do not fail, so that the lack of attention towards the presence of persistent innovation within small companies is hardly surprising, considering also that the contribution offered by the vast majority of small and medium companies to innovation is rather limited (NESTA, 2009b; Hughes and Mina, 2012). This perspective is reinforced by the analysis of patterns of creative accumulation, which have usually been described by the presence of large scale economies, associated with a lower likelihood of survival for small companies (Acs and Audretsch 1987; Audretsch 1995).

However, the increasing division of labour in innovation calls for a closer and more detailed analysis. In modern advanced economies, just like the Chandlerian firm built around the idea of mass production has been replaced by business strategies based on flexibility, customization and product differentiation, the locus of innovation is increasingly fragmented and grand research labs are no longer the sole source of technological change. In this new environment, innovation is envisioned and created in a complex and multidimensional network of very different agents, companies and institutions embedded in a social context, linked by formal or informal connections which dynamically evolve along business and technological trajectories. Proceeding along the vertical disintegration of economic activity (Stigler, 1951), knowledge based industries have been accompanied by an increasing number of specialised companies operating in very specific industry sub-disciplines. Biotechnology companies are a notable example of this fragmentation, but a much larger set of science and engineering-based sectors are going through an organizational change defined by interactive networks and new forms of division of innovative labour (Arora, 1997; Chesbrough, 2003).

Companies need to master a growing set of technological competencies as a consequence of the increasing pace and the complexity of advanced innovative activity. Hence, they rely on intra-firm cooperation in order to access the complementary knowledge they do not possess (Hagedoorn, 2002). This suggests that a new paradigm of open practices in technology transactions may be taking place, leading to an integrated process of innovation which is increasingly common across innovative companies. Consistently, Arora and Gambardella (1990) provide evidence of the complementarity between strategic relationships, research agreements and acquisitions developed by large pharmaceutical and chemical companies and universities, or more likely, new biotechnology firms. They conclude that the innovation activity has shifted from large firms to "a 'network' of inter-organizational relations" (Arora and Gambardella, 1990). As Tether (2002) summarises, companies enter into collaborations with different players mainly because they do not internally possess all the skills and knowledge required for new product development, or in the attempt to reduce the risks associated with innovation. Accordingly, R&D cooperation is more common in companies pursuing high level innovations (Tether, 2002).

In this sense, the emerging division of labour in the production of knowledge and technology allows companies to benefit from two main productivity benefits, that is, specialization with respect to comparative advantages and increasing returns from new knowledge creation (Arora et al., 2001; Arora and Gambardella, 2010). The consequences are significant for both large companies and small firms. The former are able to pursue a more active management of their intellectual property and technology licensing, which ensure greater flexibility at the strategy level, while the latter can narrow their activity to the development of a specific set of technologies, thanks to lower economies of scale and entry barriers. Accordingly, Arora et al. (2001) stress that "markets for technology may be critical for the very existence of high-tech start-ups".

At a broader level, the presence of modern innovation networks and modular innovation systems (Freeman 1991; Langlois and Robertson 1992) allows to relax the assumption of scale-intensive capabilities as a requirement to successfully operate in routinised regimes pursuing persistent innovation activities. Thus, taking into account the growing importance of integrated innovation networks and open innovation strategies, the analysis of persistent innovation among small companies or, more broadly, the presence of small and medium enterprises which may be able to successfully engage in a sustained stream of innovations over time becomes of central interest in order to integrate and complement the study of modern industry dynamics and the patterns of innovative activities.

In a context where there is an increasingly important role for small innovative companies, and considering the substantial modifications that have been taking place in the organization of innovative activity in advanced economies, we argue it is necessary to provide further evidence on the relationship between persistent innovation and small companies. This may offer critical insights on the contribution of small serial innovators to the economy, while also providing the opportunity to understand more clearly the mechanisms that might lead to the presence of persistent innovation. Accordingly, this thesis aims to contribute to the literature offering novel empirical evidence on the presence and the characteristics of small persistent and serial innovators, with a special attention to the analysis of those elements internal and external to these enterprises that contribute to sustain their innovation activity.

In the quest for understanding the characteristics of those companies that are able to develop a sustained stream of innovation over time, another question arises of whether such companies engage in technological diversification or whether the accumulated competencies during their innovative activity might push them more towards a strategy of technological specialisation. The literature points out a clear and strong relationship between persistent innovation and technological diversification (Breschi et al., 2003), with the presence of both phenomena being necessary for the long-term growth and survival of technology-based firms (Granstrand, 1998), especially within dynamic and technologically complex environments (Susuki and Kodama, 2004).

Given the amount of resources required to engage in technological diversification, it is not surprising that the economic literature has once again focused on large companies assuming perhaps that small firms might be relegated to strategies of specialisation as a consequence of limited R&D resources and economies of scope in innovation (Cohen and Klepper, 1996). However, the presence of small serial innovators calls for a new set of questions regarding technological diversification. In particular, is the relationship between diversification and persistence still relevant for such companies? If so, what is the role of diversification in their innovation strategy and how do they solve the tension that is generated between the costly process of diversification and the limited resources they possess as well as the quality of cumulativeness typical of innovation persistence?

The underlying perspective through which the empirical analysis is conducted in this thesis is mainly grounded in evolutionary economics theory. The reason for this is manifold. First, the evolutionary principles of path dependency and cumulativeness play a fundamental role in the mechanisms that shape persistence at the firm level. As such, they are at the centre of this thesis. In particular, in both Chapters 3 and 5 we argue that their specific qualities might represent the main difference across large and serial innovators, while Chapter 4 relies on the concept of knowledge coherence to define trajectories of technological diversification. Equally relevant is the focus on firm dynamics and heterogeneity that defines the way through which evolutionary economics literature describes innovation and the process of technological change. A final motivation for this approach is that many of the previous theoretical and empirical studies on both persistent innovation and technological diversification rely on the core elements that characterise research in evolutionary economics. Following the same perspective not only provides a fundamental guidance for this study, but it also offers opportunities for confronting and complementing our findings with previous literature.

The analysis offered in this thesis is mainly conducted at the technological level, thus offering only a partial description of small serial innovators and their characteristics. Among other limitations, there are two main caveats that we believe it is important to mention.

First, as the analysis we propose is based at the technological level, it does not take into consideration the financial aspects of innovation, and the relationship between R&D and capital investment[3], for the most part because of limitations in the data available. In particular, we do not investigate the role of investments as a determinant of patenting activity which has been the focus of an important stream of literature (See the seminal work by Schmookler (1966), the survey by Stoneman (1983, Chapter 2) and, more recently, the debate which has emerged from the endogenous growth theory (Lach and Schankerman (1989)). While this aspect certainly provides an interesting subject for further research, we think its omission from this work does not constitute a substantial flaw to the analysis presented. In particular, financial constrains do not seem to be a crucial issue considering that the set of companies observed throughout this thesis have a successful record of innovations which span for at least more than 5 years and, in

[3] See Hall (2002).

the majority of the cases, for more than 10 years. At the same time, this position is also supported by recent findings on the access to finance for innovative SMEs companies, suggesting a positive relationship between the access to funding and innovation activity among high-tech small companies, at least in the UK (Mina et al., 2011).

Second, the business environment where firms operate is also observed only at the technological level. However, we acknowledge the importance of formal and informal institutions in defining national and sectoral innovation systems (Lundvall, 1992; Nelson, 1993; Malerba, 2002) and the possible limitations that such omission may cause. We try to reduce this issue by focusing only on one single country, that is, the UK. It follows that all findings and possible implications from our analysis should be applied only to this specific country. In this sense, studies looking at different nations are welcome as they might constitute the basis for cross country comparisons.

1.2 Motivation and contribution

Small and medium enterprises, along with their innovative activities, are extremely heterogeneous. As such, they have received much attention in the specific literature from rather different approaches, leading to contrasting conclusions in terms of the nature and the impact of their innovation activity. This thesis aims to offer a new perspective on small innovative companies, contributing to previous research with the exploration of a topic that, surprisingly, has been much overlooked. In particular, we aim to study the presence and the characteristics of small companies which are able to present a sustained level of innovative activity over time.

Our intended contribution to the literature is centred around three main areas that have not been explored in previous research. These are related respectively to the presence of persistent innovation across small companies, the role played by elements internal and external to the enterprise in sustaining their innovation activity and, finally, the extent and the determinants of technological diversification across small serial innovators. In particular, we ask:

- What are the main characteristics of small companies defined by an unusually sustained stream of innovation over time, and what part do elements specific to the technology internally developed and the qualities of the technological environment where they operate play in fostering their innovation activity? How do these differ with respect to large serial innovators?

- Do small serial innovators engage in processes of technological diversification, and what are the main determinants that might bring them to engage in a broader spectrum of technological fields, shifting away from strategies of technological specialisation?

- Is there persistence in innovation across small companies in the UK, and what role does persistent innovation play in their process of innovation with respect to other elements of firms' innovation activity, such as R&D intensity?

In this thesis, we address these questions from two different – and yet related - perspectives. First, we make use of a novel dataset based on patent data covering the years from 1990 to 2006 to explore the determinants of the rate of innovative activity and technological diversification of serial innovators. Then, we use data from the Community Innovation Survey for the UK to study the presence of persistent innovation among small firms, and whether there are differences with their large counterparts.

Throughout the thesis, the contribution takes place on three different levels. First, we provide evidence on the presence, the characteristics and some general stylised facts regarding persistent and serial innovators in the UK, with a special attention to their technological activity. Second, we try to provide novel evidence on the effect exerted by the different sources behind persistent innovation, as proposed by theoretical literature. Third, we investigate the possible differences across small and large firms with respect to the sources of persistent and serial innovation in order to understand whether these can be explained as a homogeneous phenomenon.

With respect to these levels of analysis, our findings provide novel empirical evidence that innovation persistence takes place also within small companies and it exerts an important effect among them in sustaining dynamic learning effects, thus underpinning further innovation. Accordingly, we show that a central element in the inventive process of small serial innovators is the presence of 'combinative capabilities' that generate internal spillovers and economies of scope. Our research indicates that this process of knowledge accumulation around core technological competencies is also central in explaining the dichotomy between strategies of technological specialisation as opposed to technological diversification. Considering differences across firm size, the thesis offers novel findings showing that sustained innovative activity over time is not a specific quality of large companies but extends to a significant number of highly innovative small companies. While they share many characteristics, though, they are inherently different in their processes of knowledge accumulation and technological learning.

We believe such contribution may be quite relevant from an academic as well as a policy perspective. The analysis of small companies characterised by elements of persistent innovation may allow to integrate the framework of the Schumpeterian patterns of technological change with the recent process of division of innovative labour and the rising of integrated innovation networks. In this sense, this study may offer a new perspective on the mechanisms that generate persistent or serial innovation.

Differently from previous research, we study an unusual type of small companies, whose contribution is not limited within the entrepreneurial boundaries; rather, it lies in a sustained stream of innovation that spans over a long period of time. Thus, these companies may increase the innovative output of the economy as well as providing stability to their economic system. More generally, the thesis offers a new perspective on the role that small firms might play in fostering innovation within the economy.

1.3 Structure of the thesis

This thesis endeavours to provide a multi-dimensional approach to the concepts of persistent and serial innovation with a special attention dedicated to small innovative companies. To this end, it follows a common approach offering three separated studies looking at different - and yet related - topics using two main distinct longitudinal datasets based respectively on the UK innovation survey and patent data extracted from the PATSTAT database.

Chapter 2 offers a short overview of the main elements of the thesis describing the subtle qualities inherent to the concept of innovation, the working definition and its measurement. Then, we discuss the relevant difference between persistent and serial innovation, arguing that the latter might be a more appropriate approach for the study of small innovative companies. The Chapter ends with the introduction of the main data used in the analysis, that is, patent and innovation survey data, and the relevant methodology. We discuss their relative advantages as well as shortcomings with respect to the analysis proposed and we introduce the estimating techniques used in the thesis, including a brief consideration on the interpretation of interaction variables in non-linear models.

Chapter 3 presents an empirical analysis of the determinants of innovation among serial innovators using patent data. In this Chapter, we document the main characteristics of a novel dataset comprising information on 811 companies defined by a sustained record of innovation activity between 1990 and 2006. The dataset accounts for 66000 patent applications in the period of time considered. First, we present some stylised facts related to their regional dimension and their distribution across industrial sectors. Then, we analyse patent counts and citation-weighted patent counts by means of a negative binomial GEE model. That allows us to test the effect of variables related to technological regimes and to technology-specific characteristics (usually related to the presence of markets for technology) upon the rate of innovation of serial innovators. Our findings confirm that small serial innovators benefit from the presence of technological characteristics typical of a routinised regime, such as high opportunity conditions and cumulativeness, while also relying on high-quality technologies with a broad technological base. We also test for the presence of differences in the way elements typical of a technological regime impact on large and small firms. Our analysis shows that small firms benefit less from higher levels of opportunity conditions, probably as a consequence of the increased turbulence in the industry but also because of their greater focus towards internal capabilities. In fact, the distinctive qualities of cumulativeness, in the form of dynamic economies of scale and dynamic increasing returns, seem to constitute the main difference between small and large serial innovators, with small companies relying on cumulative processes characterised by internal combinative capabilities and search depth.

Chapter 4 proceeds exploiting the novel dataset introduced in the previous Chapter in order to explore the horizontal dimension of serial innovators, that is, their technological diversity. We start providing descriptive statistics on the degree of diversification among serial innovators as opposed to occasional innovators, to further analyse differences across large and small serial innovators. This allows us to show that while a significant difference exists among these two groups, small serial innovators are indeed diversified, thus rejecting the simplistic idea of them as one-technology companies. Hence, we make use of a fractional response model for panel data estimated within a GEE framework to study the determinants behind the trade-off that is likely to take place between the need to explore new technological opportunities and the significant element of path dependency delineated by the specific core technological competencies, which is characteristic of serial innovators. Small serial innovators seem to expand the degree of their technological activity when opportunity conditions increase, but this relationship becomes negative once the technological environment where they operate becomes widely turbulent. An opposite effect is found for coherence in the knowledge base. In line with the literature, coherence in the core competencies and technological search bring companies towards a specific trajectory characterised by strong path dependency. We also observe that a similar effect is generated by high impact technology developed by companies, which his likely to encourage further exploration along the same technological trajectory. Similar effects are found for large serial innovators, but the inverse U relationship between technological diversification and opportunity conditions appears to be more acute for small companies.

Chapter 5 concludes the empirical contribution of the thesis. Using data for over 4000 companies from a longitudinal dataset based on the Community Innovation Survey for the UK from the year 2002 to year 2008, this study serves as an introduction to the presence of persistent innovation among small firms. Following a recent econometric approach to account for both unobserved heterogeneity and the initial conditions bias in dynamic panel estimation, we observe a positive effect on the probability of introducing product innovations new to the market as a consequence of having already innovated in the previous time period. This effect is observed for both large and small companies. Furthermore, we explore the relationship between the level of technological intensity within firms' innovation activity, expressed in terms of firms' total R&D expenditure with respect to sector average R&D expenditure, and dynamic increasing returns in the form of economies of learning and accumulated capabilities from previous innovation. Our findings show that while in large companies both elements play a significant role there is no evidence of a significant interaction effect. Conversely, we find evidence of an interaction effect between previous innovation activity and technological intensity within small companies. In particular, this interaction effect indicates that accumulated knowledge capabilities inherent to higher levels of technological complexity may be able to offset the diminishing returns that characterise such innovation. In other words, the presence of accumulated innovation capabilities is particularly important for small persistent innovators that sustain high levels of R&D activity, as they provide a fruitful base on which develop further innovative efforts.

A brief summary of the findings of this thesis and its contribution to the literature are offered in Chapter 6. Along with a synoptic overview, we discuss some policy implications and a series of possible directions for future work. The Chapter ends with some concluding thoughts.

CHAPTER 2

Data and methodology

"On two occasions I have been asked, [...] 'If you put into the machine wrong figures, will the right answers come out?' I am not able rightly to apprehend the kind of confusion of ideas that could provoke such a question."

- Charles Babbage

2.1 Introduction

Following a multi-dimensional approach, this thesis endeavours to analyse persistent and serial innovation using the two types of data most adopted in the study of this particular phenomenon. In particular, the first and the second empirical Chapters (Chapter 3 and 4) utilise patent data, while the third Chapter (Chapter 5) is based on innovation surveys data. In the following sections, we introduce the definitions for the concepts of innovation and the different concepts of persistent and serial innovation, along with the general characteristics, strengths and weaknesses of innovation surveys and patents. Finally, we describe the specific datasets used in the thesis and we discuss some methodological considerations.

2.2 Persistent and serial innovation: an empirical definition

The central concept that motivates and shapes the analysis of this thesis is the subject of firms' persistent innovation. Considering the complex nature of this topic, the study of persistence in innovation raises several questions concerning the definition of persistence and the measurement of technological activity and, more broadly, innovation. Thus, these two main concepts need to be refined in order to conform them to our empirical and theoretical perspective.

First, it is fundamental to have a working definition of what constitutes an innovation. In the literature, there is no specific consensus about the definition of innovation. In fact, scholars have stressed out the importance of not treating it as a strictly defined and homogeneous term (Kline and Rosenberg, 1986). A systems perspective that recognises the multidimensional and dynamic nature of the innovation process can be considered a more appropriate and useful approach, as well as one based on the classification of different types of innovation (Fagerberg, 2005).

In this thesis, we take as a reference the definition proposed in the Oslo manual[4], where innovation is defined as "the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations" (OECD/Eurostat, 2005; p.46). This broad definition of innovation comprises a wide range of possible innovations, and yet it serves as a clear and well-defined starting point.

In our empirical analysis, however, it is important to acknowledge that different measures of innovation actually represent different aspects of this broad and complex concept. We must, therefore, explicitly address the issues and the limits inherent to the measurement of innovation, such as the measurement and the definition of novelty[5], and approach this concept relying on the specific nature of the data employed throughout the different chapters of the theses, that is, patent data and innovation surveys data.

Some important differences exist between the insights on innovation activity offered by patent data and those provided by innovation surveys. In particular, while the innovation activity covered by innovation surveys like the Community Innovation Survey (CIS) covers all sectors of the economy, patents are usually applied for a more specific subset (Arundel and Kabla, 1998). For example, services are for the most part excluded (Guellec and Pottelsberghe de la Potterie, 2007). Also, patents refer to the development of

[4] In turn, this definition is drawn from Schumpeter (1942).
[5] For a broad introduction, see Smith (2005).

novel inventions but they do not offer information on whether this invention was later used. Conversely, data gathered from the CIS offer insights on innovations that have been successfully exploited by companies[6].

Most importantly, our working definition of innovation should allow us to differentiate companies based on the basic set of strategies for technological change proposed by Nelson and Winter (1982). These are: *innovation, imitation and no change*. Throughout this work, in fact, our main interest lies in the first element as opposed to 'imitation' or 'no change'.

In the case of patent data, the application for a patent constitutes the minimum requirement for identifying innovative companies, with the inventive step of the patent ensuring a satisfactory adherence to our definition of innovation[7].

Innovation surveys provide a different perspective, offering information on innovation which, we argue, follow closely the definition of innovation as 'the successful exploitation of new ideas'[8]. In particular, the element of novelty is more articulated within innovation surveys, which offer information on innovation new to the market or new solely to the firm. With respect to this point, previous studies based on innovation surveys have usually adopted the broader definition of innovation, encompassing both innovation and imitation, as they have centred their analysis on products or processes new to the firm. Conversely, we identify innovations by focusing on the presence of 'a new good or service introduced to the market before the competitors' (see, for example, CIS6 questionnaire, question 9.a.). Thus, we delimit our interest solely towards product innovation through the adoption of a measure of innovation activity which has been used in previous empirical studies as a proxy for radical or 'higher level' innovation (Tether, 2002; Laursen and Salter, 2006), that is, the introduction of product innovations new to the world[9]. In other words, differently from previous work on persistence in innovation based on innovation surveys, we do not combine innovation and

[6] These points are further discussed in Section 2.3.2.

[7] For more details on the use of patents as measures of innovation, see Section 2.3.2.

[8] This is the definition of innovation commonly proposed by the UK Department for Innovation, Universities and Skills (2008).

[9] We do not explore process innovation to maintain a coherent analysis whose results can be compared with our findings based on patent data. Moreover, the nature of the elements behind product and process innovations can be quite different. As such, these require a specific and distinct analysis. The focus on product innovation is also in line with previous literature on innovation persistence based on innovation surveys.

imitation[10], focusing on firms that concurrently innovate but at the same time they are the first to innovate. Proceeding in this way, our measure of innovation activity based on innovation survey is closer to represent the same level of novelty inherent to patents. In this sense, it is possible to say that our measures – and more broadly our definition – of innovation provide the basis for the study of innovative leadership (Dujuet and Monjon, 2004).

With respect to the concept of innovation persistence, a first approach would be to consider it as something "continuing to occur over time" (Latham and Bas, 2005). In the specific literature, the traditional approach has been to define innovation persistence as the occurrence of a specific event representing innovation in subsequent units of time. In other words, companies show persistent innovation when they innovate in time t, having previously introduced an innovation in time t-1. This is the approach we follow in Chapter 5, where we make use of innovation survey data in the form of the Community Innovation Survey for the UK. In this case, companies are considered as persistent innovators if they introduced a product new to the world market in two successive rounds of the innovation surveys[11].

However, in the studies based on patent data (i.e. Chapters 3 and 4), we pursue a different perspective based on the idea that many innovations require many years to be fully developed[12]. Accordingly, even if the stream of patents is not continuous throughout the years, this does not imply that companies are not constantly engaged in the innovation process. For example, some years may be characterised by no patent activity, while in the following years, several patents might be applied for or published. This argument is particularly relevant for small companies that do not possess the same R&D resources of large enterprises. Hence, we argue that it may be possible to consider as persistent innovators all companies characterised by a sustained stream of innovation over time, even when the quality of continuity across units of time

[10] See Clausen and Pohjola (2013) for an exception.

[11] The dataset based on the Community Innovation Survey for the UK we use in Chapter 5 has a time frame of three years per round of questionnaire, and it comprises three separate waves of the survey, covering the years from 2002 to 2008.

[12] This issue is not present with the UK Innovation Survey, as each time period encompasses three years of firms' activity.

is removed. This approach is derived from the one presented by Hicks and Hegde (2005) in their study on small serial innovators in the US, where companies were defined as such if they had 15 or more USPTO patents issued in the period between 1996 and 2000. Thus, considering the approach we adopt, based on the frequency of innovations in a given time frame, we avoid the term persistent innovation in Chapters 3 and 4, using instead the label of 'serial innovators' introduced by Hicks and Hegde (2005). Yet, notwithstanding the definition employed, we argue that the theory and most of the empirical findings advanced in relation of innovation persistence can be still used to guide our own analysis.

To be considered serial innovators, companies had to present the following characteristics: being independent throughout the whole period considered, having at least five years of technological patenting activity, calculated as the difference between the first and the last patent published by the company in the period of time considered, possess at least 10 patented inventions and have an overall ratio of patents to years at least equal to 1.

Companies need to be independent to ensure that they are not financially dependent on a parent company, or that they can benefit from knowledge transfer and other types of direct support. In other words, they need to be able to survive only with their own manufacturing or licensing activities and, potentially, the financial capital these help them to gather.

The reason behind the five years threshold in classifying serial innovators lies in the attempt to separate those start-ups which enter the market with a bulk of innovations, but do not carry on their innovative activity thereafter, from those with a sustained record of innovative activity over time. Moreover, this constraint allows to exclude from the analysis new entrants which are not able to survive in highly innovative environments from those with a sustained record of innovative activity over time. Although survival rates vary significantly across sectors (Audretsch, 1991), more than half of new firms do not reach the 'five years' threshold (Mata and Portugal, 1994).

A similar rationale has been followed to choose 10 patents as minimum for the technological activity. Ten patents are a significant number for a small company. According to Acs and Audretsch (1990), in fact, the majority of small firms do not reach this level of innovations, thus we argue it can be considered a reasonably strong signal of consistent innovative activity.

Finally, the overall ratio of patents to years is meant to ensure that an increase in the time of technological activity is followed by a proportionate innovative output. Overall, a short period of innovation requires a higher ratio, as with five years this is equal to a minimum of 2 patents per year on average, while a longer period allows for a less intensive innovative output spread over the years. After ten years of activity, every year more has to be balanced by an additional patent. According to this definition, for example, a company which would have 9 patents in the year t and 1 more in the year t+4 would be included in the analysis, while one with 10 patents in the year t and 2 more in the year t+12 would be excluded. Similarly, a company with only 5 patents in the year t and 5 more in the year t+4 or even in the year t+9 would be considered a persistent innovator, while one with the same amount of patents would not be part of the analysis if the last one were applied for in the year t+3.

Given our attention to the role of small companies throughout the thesis, a final clarification regarding what constitutes small companies is required. Following a common practice, we distinguish between small and medium enterprises (SMEs) and large companies using the definition presented in the European Commission Recommendation (96/280/EC) of 3 April 1996, where SMEs are defined by the upper threshold of 250 employees[13]. However, we usually refer to the first group simply as ‘small’ companies.

2.3 Measures of innovation: characteristics, strengths and weaknesses

The traditional measures in the study of innovation and technological change are R&D statistics, patents and innovation surveys. In this thesis, we make use only of patents and innovation survey data, without exploring R&D statistics.

[13] All results are robust to a threshold of 500 employees for identifying small companies, as usually adopted in studies based on US data.

The reason for this choice is twofold. As Geroski et al. (1997) point out, the use of R&D spending is likely to identify a large number of companies as serial/persistent innovators while, in fact, measuring routine activities. Considering that many research projects last more than one year, then, such measure is likely to be an inaccurate proxy of persistent innovation. Also, many innovative small firms do not have a formal R&D department, hence this statistics is difficult to obtain and in many cases it is likely to be misleading.

As a consequence, the thesis explores and analyses the characteristics of persistent and serial innovation looking at output measures of innovation, as those provided by innovation surveys and patent data, which is also the perspective usually taken by the literature when discussing central elements of this research, such as dynamic economies of scale in innovation and the importance of learning effects in the innovation process (Peters, 2009).

In the following sections we provide a brief introduction to patents and innovation surveys, highlighting their strengths and weaknesses as measures of innovation. Then we describe their use in the specific context of the study of persistent and serial innovation.

2.3.1 Patents

Patents have been used as indicators of technological change for a long time, and their use in innovation studies is widespread in the literature since they have been made available on computerised data[14].

A patent is a legal document granted by a government body which confers upon its owner a territorial right to prevent third parties from making, using, selling or offering for sale the product or process which it is associated with[15]. From an economic perspective, the argument behind the introduction of the patent system lies in the creation of an incentive for investments in innovation. Without the patent, imitators could free ride on the investment incurred by the original inventor, thus offering the good at a lower price. As a consequence, this situation may discourage inventors from engaging in innovative activities

[14] For a short history of the use of patent data in economic studies, see Griliches (1990).

[15] For a more detailed description of the rights conferred by patents, see the Article 28 of the TRIPs, available at: http://www.wto.org/english/docs_e/legal_e/27-trips_04c_e.htm

in the first place. However, conferring a temporary monopoly to its owner, a patent generates a potential deadweight loss in the society as the product or process covered is sold above its marginal cost. Thus, the presence of patents creates a tension between static and dynamic efficiency (Guellec and van Pottelsberghe de la Potterie, 2007). While the temporary monopoly is a static inefficiency, the incentive to innovate is dynamically efficient.

Another two-sided effect of patents is related to the diffusion of innovations. To be granted, patents require applicants to present a precise description of the invention, whose secrets are made public. Yet, the use of this knowledge is restricted and protected by the very presence of the patent for a period of time which can usually last more than 15 years[16].

In the literature, strengths and weaknesses of patents as measures of innovative activity have been discussed in detail (Pavitt, 1988; Griliches, 1990). As summarised by Archibugi and Pianta (1996), the main advantages of patent statistics can be summarised as follows:

- Patents are a tangible outcome of the inventive process. More importantly, given the cost incurred to obtain a patent, they clearly indicate those inventions which are considered to have a potential for a commercial impact. In this sense, patents are likely to provide an appropriate indicator for inventions carrying a significant technological change. This is ensured by the inventive step requirement[17] which is necessary for the patent being granted. As argued by Geroski et al. (1997), this characteristic is particularly important in the study of persistent innovation, as it removes from the analysis minor technical improvements and changes that usually take place on a routine basis.

- Patent documents include information on the technology classes to which the invention belongs, along with data on prior art relevant to the patent, allowing to study not only the rate of inventive activity, but also its direction (Archibugi and Pianta, 1996). At the same time, they also

[16] In the UK, patents must be renewed every year after the third year from the filing date, and they can be renewed up to 20 years.

[17] This requirement is verified by the Patent Office where the patent application is filed.

provide general information on applicants and assignees, such as the country of origin.

- Given both the legal and the public nature of patents, they are consistently processed, classified and organised providing a unique and reliable source of information on the innovative activity in the economy which is available for very long time series.

Considering these characteristics, it is not surprising that patent statistics have been used extensively in the study of persistent and serial innovation as well as in the literature on technological diversification. However, patents also present some well-known limitations. These include the followings:

- Patents are a measure of invention more than innovation, with some products or processes covered by a patent that may never reach the commercialization stage.

- Patents are awarded to novel inventions, but the quality and the value of single patents might be particularly skewed, with a large majority of patents holding little economic value.

- Not all inventions are patented, as companies might rely on different methods of intellectual property protection. Accordingly, there is a wide variance in their use across industrial sectors[18], in line with their value as means of appropriating the returns from innovation investments (Levin et al., 1987).

- Not all inventions can be patented. Major exclusions comprise scientific discoveries (e.g. mathematical discoveries) and pure business methods, but there are also notable exclusions in areas related to

[18] Using survey data from 604 Europe's largest industrial firms, Arundel and Kabla (1998) show that patent propensity rates for product innovations average 35.9%, but there are significant variations across sectors, ranging from 8.1% in textiles to 79.2% in pharmaceuticals. A wide variance is also found by Mansfield (1986) using US data.

genetic materials, software and specific business methods, at least in Europe.

- Patent applications may not always be motivated by the desire to protect valuable inventions, while instead serving a strategic role. Using a survey of R&D executives, for example, Levin et al. (1987) indicate that many companies use patents to gain access to certain foreign markets or as a measure of R&D performance. Also, patents may be used in negotiations, managing patent pools or cross licenses (Shapiro, 2001), or to prevent infringement suits. Yet, they can even be the prey of the so-called patent trolls[19].

In the studies presented in this thesis, the relevance of these shortcomings is attenuated. Given the attention dedicated to small companies, we argue that the rationale indicating patents as a measure of innovation input is only partially appropriate. In fact, small companies are likely to apply for a patent for all those inventions which have a relevant and direct role in their innovation activity, particularly if they operate in high-tech industries[20]. Thus, as in several previous studies discussed in Chapter 3 and 4, we consider them a good measure of innovation output. Moreover, following the argument presented in Chapter 3 on the relationship between markets for technology and the presence of small serial innovators, it is also possible to argue that for many of these companies patented technologies may actually constitute the final product of their innovation activity, thus causing the distinction between invention and innovation almost to collapse.

With respect to the value of the single patents, a similar rationale may hold. Once again, it is possible to argue that small companies may be more likely to cover the costs of a patent application only for those inventions that have higher probabilities of being valuable for their business[21]. For the same reason, patent applications aimed at playing a strategic role are less likely to be filed

[19] See Reitzig et al. (2007) for more information.
[20] In line with this argument, data from the 1993 European Community Innovation Survey indicate that patents are particularly important for small R&D intensive firms (Arundel, 2001).
[21] Accordingly, patent propensity rates for both product and process innovations increase with firm size (Arundel & Kabla, 1998).

by small companies. In line with these arguments, Hicks and Hegde (2005) have shown that the average impact value of the patents of small serial innovators is higher than the value of large companies. More generally, the literature suggests several methods to account for this variance in patents' value. A strand of literature suggests counting forward citations associated with a patent, as they appear to be significantly correlated with the technological importance and the economic value of inventions (Trajtenberg 1990; Haroff et al., 1999, Hall et al. 2001). This is the approach we make use of when relevant to the study. Other possible methods include the use of patent renewal data or the study of the size of patent families[22].

Overall, patents remain a powerful and important indicator of innovative activity and their use is widespread in the literature. Given their intrinsic degree of novelty and the detailed information at the technological level available for long periods of time, they constitute an ideal measure for the study of serial innovation. Finally, patent data have been used extensively in analysing persistent innovation, as well as in the study of technological regimes and markets for technologies. As such, the use of patent data might offer the opportunity to provide some comparative insights with respect to previous analyses. For these reason, they can be considered the ideal basis for the present work. However, it is important to keep in mind their limitations when analysing the results presented in the following chapters.

2.3.2 Innovation surveys

Along with R&D expenditure and patent statistics, innovation surveys constitute one of the most important sources to study and monitor innovation activity and performance. Pioneered in the 1950s[23], their use in innovation studies has become increasingly widespread in the last decades following the introduction of regularly conducted and standardised surveys in many countries around the world. Following the framework proposed by Archibugi and Pianta (1996), innovation surveys can be divided into two main groups.

[22] See, for example, Pakes and Schankerman (1984) and Lanjouw et al. (1998).

[23] For a short introduction to the history of innovation surveys, see Mairesse and Mohnen (2010).

The first encompasses those that focus on the collection of information at the level of the individual innovations[24]. This design follows the so-called ‘object’ approach (Archibugi and Pianta, 1996). The second group is defined at the level of the individual company, regardless of whether the firm is engaged in innovative activity or not. This has been labelled the ‘subject’ approach. Considering its wide diffusion across many countries, it is on this second approach that we focus in this section.

In Europe, innovation surveys based on firms’ data are conducted at the national level and they are usually referred to as Community Innovation Surveys (CISs)[25]. In the UK, the CIS is a postal survey with a stratified random sampling design and a target population defined by all enterprises with at least 10 employees operating in sections C-K of the Standard Industrial Classification (SIC) 2003, thus covering both manufacturing and service industries.

Initially conducted every 4 years, since 2007 the CIS is carried out every 2 years following the recommendations included in the Oslo Manual[26] (OECD/Eurostat, 2005), from which it derives its most relevant definitions such as what constitutes a product or process innovation, what are the different degrees of novelty of innovations, along with other questions regarding the sources, obstacles and methods of intellectual protection for the innovation activity[27].

The main advantages offered by innovation surveys are the followings:

- Innovation surveys allow to take into account a broader definition of innovation than the one pictured by patents or R&D statistics. In fact, they contain information on the introduction of product and process innovation, as well as several forms of organizational innovation. Also, referring to the introduction of innovations in the market, they take into

[24] One notable example is the SPRU innovation database. See also Acs and Audretsch (1990).

[25] The UK version of the CIS is a survey conducted by the Office for National Statistics (ONS) on behalf of the Department for Business, Innovation and Skills (BIS).

[26] The Oslo Manual, firstly published in 1992, is the result of a joint collaboration between the OECD and Eurostat.

[27] In Chapter 5, we refer to three waves of the CIS covering respectively the years between 2002 and 2004 (CIS 4), 2004 and 2006 (CIS 5), and finally 2006 to 2008 (CIS 6).

account the commercialization step implicit in the concept of innovation.

- Including information on the degree of novelty of the innovation, that is, whether the innovation is new to the market or new to the firm, innovation surveys allow to distinguish between innovators and imitators or, as in several studies has been proposed, between radical and incremental innovation (See for example Tether, 2002; Laursen and Salter, 2006). At the same time, investigating both internal and external sources of innovation, this approach permits to study service industries in addition to traditional manufacturing industries.

- The CIS and other surveys based on the Oslo Manual integrate information on the introduction of product and process innovation with strategic aspects of the innovation activity such as organizational changes and different types of collaboration and sources of innovation. Also, they provide economic data regarding production, employment and companies' industrial sectors, among others.

- Innovation surveys cover both innovating and non-innovating companies, allowing to study potential incentives or barriers to innovation and other differences among the two groups (Archibugi and Pianta, 1996).

- The increasing standardisation and normalisation in the approach and structure of innovation surveys across different countries, in particular in Europe, provides opportunities for international comparison, at least to some extent.

While surveys following the 'object' approach share many of the issues indicated for patent statistics, common issues regarding innovation surveys at the firm level can be summarised as follows:

- Innovation surveys are conducted as simple cross-sections and, despite efforts to make them harmonised across countries and time, they still present differences between the various waves. In particular, up to the fourth round of the CIS, only a relatively small number of firms was retained across each wave of the survey and this number greatly reduced as one increased the periods of time under observation, allowing to exploit only partially the potential panel structure of the data in terms of both companies and questions included.

- The subjective approach of innovation surveys involves the presence of a degree of interpretation with respect to the definition of the key concepts and the questions asked. For example, even if general guidelines are provided within the questionnaire, the importance of different sources of innovation, or the very distinction between what constitutes a product or process new to the market or new to the firm all depend to a great extent on the personal judgement of the respondents. Also, such distinction would require a very good knowledge of firms' own market (Mairesse and Mohnen, 2010). A similar problem may arise for those questions where estimates are requested, as in the case of R&D expenditures.

- Although innovation surveys offer information on the degree of novelty of the innovations introduced, they do not offer data regarding the technological characteristics and the technological impact of the innovation. This implies that even with data on the industrial sector where firms operate it is not possible to study the technological diversification that many innovative firms decide to pursue (Granstrand et al., 1997; Patel and Pavitt, 1997).

- As all other surveys, significance and representativeness are dependent upon the response rate obtained[28] (Archibugi and Pianta, 1996).

[28] This issue is quite limited in the case of the CIS, as most rounds of this survey reach a response rate of almost 50%. For more details, see Section 2.4.2.

Innovation surveys like the CIS might not offer the subtleties and the details at the technological level presented by patents, yet their wide coverage and comprehensive approach towards innovation make them a valuable source of information for the exploration of innovative activities at a broader level. In fact, this perspective is particularly adequate for the study of persistent innovation, and it is not surprising that an increasing number of studies are adopting innovation surveys to explore this phenomenon. Of course, it is important to acknowledge their limitations, using and interpreting the insights they provide with adequate care.

2.4 The datasets for the empirical chapters

In this thesis, we make of use two distinct longitudinal datasets to perform our empirical analysis. In particular, we use a dataset based on the PATSTAT database for the analysis proposed in Chapters 3 and 4, while the dataset used in Chapter 5 is mainly based on data from the UK Innovation Survey. Their characteristics and the steps involved in their construction are outlined in the following sections[29].

2.4.1 The dataset based on patent data

The data used to investigate serial innovators in Chapter 3 and Chapter 4 come from two main sources, namely the PATSTAT database (Version: September 2009) and the FAME database. Both are extensively used for academic as well as business research. PATSTAT is the EPO Worldwide Patent Statistical Database, which contains data on over 80 different national patent offices, notably the EPO, the USPTO, the JPTO and the WIPO. The database, in particular, includes information on invention's applicants and assignees, their country and address, dates of application and publication as well as citations.

[29] Details of characteristics specific to each empirical analysis and the description of how relevant variables were generated through these data, along with the appropriate descriptive statistics, are presented in the respective Chapters where they are employed.

FAME is a database provided by Bureau Van Dijk, with detailed information on more than 7 million companies from UK and Ireland, covering more than 2 million active companies as well as 4 million ones now inactive. With respect to the present analysis, essential information included comprehends company financials, merger and acquisition deals, corporate structure and subsidiaries.

To obtain a dataset with companies presenting such characteristics we proceeded as follows. Initially, all the applicants which reported being based in the UK were identified. Of these, those with at least a patent application between the years 1990 and 2006 were selected. It is important to note that the unit of analysis is not the grant of a patent, but the publication date of an application for a grant, an approach commonly taken in the literature (Cefis and Orsenigo, 2001; Helmers and Rogers, 2009; Thoma et al., 2009). As the time between the application and the actual grant may take a number of years, this allows to study with more precision the inventive activity of a small firm. Also, the publication date marks the moment in which the patent application is disclosed to the public, hence forming potential prior art for other applications. Yet, not all applications are granted a patent. As Helmers and Rogers (2009) point out, though, especially for small companies the application is still a valuable indicator of innovative activity, as in the case the grant is finally rejected we can still consider the invention as new to the firm or new to the market. In the remainder of the thesis, then, the term patent has to be associated with the published application instead of its grant.

After this initial stage, single inventors or University applications were excluded. Name cleaning was applied, including trimming, standardization of recurrent keywords (e.g.: and = &, Ltd = limited...) and punctuation marks. A set of roughly 51 thousand companies was obtained. The data were manually checked to identify misspelled names or different names referring to the same entity. Only differences which were clearly unintentional were considered, using data on the addresses when possible. More complex algorithms such as the Levenshtein Distance algorithm or the LCS (Longest Common Subsequence) were not adopted, considering that the difference in the misspelled names was usually limited to a single letter and many companies' names also differ just in one letter. The dataset resulting was thus reduced to around 30 thousand companies.

Patent families were used as a proxy of firms' inventions, with patent family defined as "a set of patents taken in various countries to protect a single invention" (OECD, 2001). The main reason for this is to avoid double counting, as for the same invention different documents might be published from different patent offices around the world (Martinez, 2011). Such families were identified through the INPADOC patent family data in PATSTAT. Following our definition, at the end of this process a total of 1410 serial innovators were identified.

In order to complete the dataset with information on economic and business variables such as size, ownership and SIC code, all records had to be integrated with information from the FAME database.

Data merging is an important issue as it is easy to produce inaccurate integration which leads to biased results. In recent literature different experimental approaches have been proposed to perform automatic matching techniques to deal with large databases, which can be split between two main groups: perfect matching and approximate matching (Thoma and Torrisi, 2007; Thoma et al., 2009). While the precision of such techniques is increasing, they are in their infancy and there is still a lack of accuracy and possible recurrence of both false positives and false negatives. Considering the limited number of companies this study is interested in, even limited margins of errors may result in a further reduction of data available or a loss of precision. For this reason, we decided to proceed through manual matching, performed with a double check on the names and, where possible, on the address.

In particular, companies' names from PATSTAT were matched with the data in the FAME database to collect information on size, SIC sector, address and postcode, and independence. For those which resulted subsidiaries, data on the holding company were also collected, along with the year of acquisition when available. For a small number of records (around 5%) the use of secondary data was necessary. Information on size and merger and acquisition deals was gathered mainly from the companies' websites and the London Stock Exchange (LSE). Finally, the dates of the first year of activity were collected from

Companies House website, which contains the official UK register of companies.

2.4.2 The dataset based on the UK Innovation Survey

In Chapter 5, we investigate whether there is persistence among large and small companies using a balanced panel dataset obtained merging three successive rounds of the UK Innovation Survey. The first round covers years 2002 to 2004 (CIS 4), the second is related to years 2004 to 2006 (CIS 5) and the last round covers years 2006 to 2008 (CIS 6).

Our analysis is aimed at exploring the presence of persistent innovation in firms' innovative without trying to explore the degree of persistency in terms of intensity or technological impact of innovation[30]. In this sense, we do not explore innovation activities at the technological level, which prevents us from addressing the research questions presented in Chapter 3 and 4. This choice is dictated mainly by the nature of the data available, which are for the most part qualitative or categorical in nature. Similarly, we do not explore in detail the role of different degrees and types of financial activity on innovation due to the limited information available in the CIS on this area.

With respect to significance and representativeness, we note that each round of the UK version of the CIS offers information on over 25000 companies, with a response rate which almost reaches 50%. Unfortunately, the survey was not designed for a potential use in a panel structure and as a result only a small proportion of just over 4000 companies is present in all the three waves we take into consideration in Chapter 5.

With respect to the panel dataset we employ, two further observations are in order. First, the panel available to us is rather short (T = 3), including at most three observations per firm over time that reduce to two when introducing the lagged dependent variable as one of the regressors[31]. Second, a more important

[30] This approach is also similar to some patent-based studies which explore persistent innovation on a descriptive level. See, for example, Malerba & Orsenigo (1996) and Breschi et al. (2003).

[31] This problem is common among studies of persistent innovation based on the CIS. See, for example, Raymond et al. (2010) and Clausen et al. (2011).

caveat must be underlined. As the CIS is conducted every two years but it covers firms' activities for the preceding three years, there is a one-year overlap between each pair of consecutive waves of the questionnaire. This may generate a bias towards persistence in the case that companies which innovated only in the last year of one CIS wave and in the first year of the consecutive wave, that is, they introduced a new product or process only in the overlapping year, did not take into consideration this double counting. Yet, while it is important to be aware of such issue, previous literature has argued that this effect may be limited (Raymond et al., 2010). To further corroborate this point, we briefly discuss the results from a robustness analysis conducted using CIS data for Spain (See Chapter 5), where the issue of the overlapping year is not present. Aware of the differences that may take place at the national level, we believe these findings support the view of a rather limited bias.

2.5 Econometric specifications

This thesis is centred around the concepts of persistent and serial innovation. Thus, our interest lies in the analysis of the innovative behaviour of companies across time. This requires the use of longitudinal datasets as well as appropriate econometric techniques that allow to take into account the specific issues related to the longitudinal and/or multilevel nature of the data being employed.

In this section, we briefly introduce the main characteristics of the estimation techniques applied in the empirical section of the thesis in order to describe their strengths in relation to the issues presented by the analysis conducted in the following Chapters. More details are offered in the Chapters where these techniques are used. We conclude this section with a primer on the analysis of interaction effects across non-linear models, as these constitute one of the main elements in the empirical framework of this thesis. Again, details specific to each econometric model are discussed in the related Chapter.

2.5.1 Longitudinal and multilevel data

As previously underlined, the study of persistent and serial innovation requires observations to be followed across time. Consistently, traditional regression methods offer biased results due to the violation of the assumption about independent observations. Panel data methods and, more generally, multilevel models have been usually adopted to address this issue.

Panel data certainly present some limitations in terms of data collection and may possibly cover only a short time span for each unit of interest. But set against that is an important series of other benefits they can offer. For example, Baltagi (2005) indicates that panel data may allow to control for individual heterogeneity capturing all unobserved, time-constant factors that exert an effect on the variable of interest. Also, they offer more information and variability, reducing collinearity among variables. Crucially for the study of persistent innovation, panel data enable us to study dynamics across time and test more complex behavioural models than cross-section and time-series data[32].

2.5.2 Generalised estimating equations and dynamic probit models

In this thesis, longitudinal and multilevel data are exploited using three different estimation approaches. In particular, the study of serial innovators proposed in Chapters 3 and 4 rely on generalised estimating equations (GEEs), first introduced by Liang and Zeger (1986), while the analysis of persistent innovation offered in Chapter 5 is based on a dynamic probit estimator proposed by Wooldridge (2005).

In Chapter 3, we model the count of patents and citations for small and large serial innovators between the years 1990 to 2006. As the data present significant overdispersion, Poisson models may present biased coefficients. At the same time, we do not adopt traditional count panel models such as conditional fixed-effects or random-effects negative binomial models that are designed to handle overdispersion. With respect to the first, Allison and

[32] For a detailed discussion of strengths and weaknesses of panel data, see Baltagi (2005).

Waterman (2002) have recently shown that this is not a true fixed-effects model and estimates hold only when a specific set of assumptions are met. Conversely, the use of random-effects model was discarded following a significant Hausman test. Multinomial models have also been excluded as they suffer from the same limitation of Poisson models with respect to overdispersion (Hilbe, 2011). Instead, we make use of GEE models. Similarly, in Chapter 4 we model the degree of technological diversification of serial innovators using GEEs, in order to take into account the open bounded interval between 0 and 1 of our dependent variable. Following Papke and Wooldridge (1996), GEEs allow us to run a quasi-maximum likelihood estimation (QMLE), explicitly accounting for heteroskedasticity and serial correlation in the standard errors within the panel dataset.

GEE models can be seen as an extension of generalized linear models (GLMs), in that they allow to take into consideration the correlated nature of the data within clusters or different levels. Just like GLMs, GEEs encompass several families of functional forms such as binomial, Gaussian, Poisson and negative binomial. A central difference between GEEs and more traditional conditional or subject-specific methods is that GEE estimate population-averaged models, also called marginal models, as they describe changes in the population mean for a given change in the covariates of interest. In other words, GEEs model the average response of the units of observation presenting the same predictors across all levels of analysis, so that regression coefficients of GEE models describe the average population response curve (Hilbe, 2011). Also differently from GLM models, which are based on maximum likelihood for independent observations, GEEs rely on quasi-likelihood theory with no assumption on the distribution of the response observations. At the same time, one of the main strengths of GEEs results from a consistent and unbiased estimation despite possible misspecification of the correlation structure[33]. Yet, more efficient estimates of parameters' standard errors can be obtained when the specified

[33] For this reason, the intra-cluster correlation matrix is usually referred to as working correlation matrix.

correlation structure resemble the true dependence structure[34] (Rabe-Hesketh and Skrondal, 2012).

In Chapter 5, we follow a different approach addressing the question of whether there is persistence across UK companies through a non-linear dynamic random effects panel data model. The crucial issue in this type of models is constituted by the presence of the lagged dependent variable among the set of explanatory variables and the related treatment of the initial conditions. This problem occurs in the case that for some - or indeed all - observations the stochastic process may start before these enter the observation period. While several appropriate solutions have been suggested for linear models, the initial conditions problem is more complex in the case of non-linear models (Wooldridge, 2005). In particular, the assumption that the initial values are independent from exogenous variables and the unobserved heterogeneity in the model is likely to lead to biased estimates.

Two main approaches have been offered by the literature. The first, suggested by Heckman (1981), is based on considering the initial conditions as endogenous variables whose conditional distribution can be estimated through a reduced-form equation based on the exogenous variables and unobserved individual-effects.

While this method offers much flexibility, its computational burden has led researchers to increasingly adopt a simpler alternative suggested by Wooldridge (2005) which resemble standard random-effects models. The intuition of this approach lies in modelling the distribution of heterogeneity conditional on the initial conditions. However, this method requires a balanced panel dataset and stands on the assumption of strict exogeneity of the covariates[35]. Nonetheless, given its easier implementation and a performance very similar to the Heckman solution (Akay, 2009; Arulampalam and Stewart,

[34] Differently from GLM models, there is no Akaike's information criterion available for model selection in GEEs. Therefore, we make use of the quasi-likelihood information criterion (QIC) proposed by Pan (2001) to select the working correlation structure for GEE analysis in Chapters 3 and 4. See also Hardin and Hilbe (2003).

[35] See Wooldridge (2005) for more details.

2009), this method has been increasingly adopted in the empirical literature[36]. For similar reasons, this is the approach followed in Chapter 5.

2.5.3 Interaction variables in non-linear models

Each empirical Chapter offered in this thesis presents a non-linear model containing interaction variables. Thus, given the non-linearity in the model function, traditional interpretation of the marginal effects for such interactions is no longer valid. In particular, the marginal effect of a unit change in both interacted variables is no longer equal to the marginal effect of the interaction term alone. The relative sign might be different, and the statistical significance cannot be obtained from standard z-statistics (Ai and Norton, 2003; Norton et al., 2004).

In general terms, the interaction effect is calculated as the cross partial derivative of E(y) with respect to two independent variables x_1 and x_2. This represents an approximation of the change in the derivative of E(y) with respect to x_1 for a unit change in x_2 (Buis, 2010). In linear models, the interaction effect of two given variables x_1 and x_2 is simply the coefficient of the term x_1x_2. In other words, the common interpretation of the interaction effect in linear models is assumed to be the first derivative of the multiplicative term of x_1 and x_2. The same approach cannot be extended to non-linear models, where the interaction effect, that is, the cross-partial derivative of the expected value of y with respect to x_1 and x_2, is usually different from the first derivative of E(y) with respect to the multiplicative term x_1x_2.

An alternative approach for the interpretation of interaction effects in non-linear models can be found in presenting the effects in terms of multiplicative effects, such as odds-ratios or incidence-rate ratios (Buis, 2010). We follow this approach in Chapters 3 and 4, where we use respectively incidence-rate ratios and odds-ratios, so that the effect of the variables of interest can be interpreted directly. Similarly, the interaction effects and their statistical significance can also be observed directly, although the effect should be read

[36] In particular, this approach has been used extensively in previous studies on innovation persistence. See Chapter 5 for more details.

in multiplicative terms[37]. With respect to the analysis presented in Chapter 5, where we estimate a probit model where no multiplicative effects are available, we resort to the use of adjusted probabilities, offering a graphical representation of the interaction effect (See Figure 5.2).

[37] More details on the interpretation of incidence-rate ratios and odds-ratios are offered in Chapters 3 and 4.

CHAPTER 3

Serial Innovators in the UK: does size matter?

"Life must be lived forward, but it can only be understood backward."

- Søren Kierkegaard

Abstract

This study explores the characteristics and determinants of innovation for 811 UK-based, highly innovative companies that patented over 66000 inventions from 1990 to 2006. These firms, we refer to as 'serial' innovators, are independent companies with a persistent and unusually high frequency of innovations over time. The aim of the study is to shed light on the presence and importance of a significant number of small firms amongst these serial innovators and analyse how the determinants of inventive activity differ for small and large serial innovators. Contrary to the common expectation in the innovative persistence literature, we find that small serial innovators indeed benefit from operating within patterns of creative accumulation. However, differently from large companies that benefit more from the volume of their previous innovation efforts to generate further innovations, small serial innovators build on cumulative processes characterised by internal combinative capabilities and search depth.

3.1 Introduction

The literature on technological change assumes persistence in innovation to take place within a technological environment characterized by Schumpeterian patterns of creative accumulation, where innovation advantages due to knowledge accumulation and technological learning generate concentration-increasing growth (Schumpeter, 1942; Nelson and Winter, 1982). Such patterns are characterised by high barriers to innovative entry, stability in the ranks of innovators and routinised processes that sustain the innovative activity of a small number of large established firms competing in highly concentrated oligopolies (Winter, 1984; Malerba and Orsenigo, 1996, 1999).

In this picture, small firms have a smaller presence and a lower likelihood of survival (Acs and Audretsch, 1987; Audretsch, 1995). Thus, while the relationship between firm size and innovation persistence is acknowledged to be non-linear, with many large firms showing no sign of persistence and some small firms being persistent innovators (Cefis and Orsenigo, 2001; Geroski et al., 1997; Malerba et al., 1997), the emphasis in the literature has traditionally been on large firms. Conversely, the presence and specific characteristics of persistently innovating small firms have been much overlooked.

In this Chapter, we examine the innovative activities and characteristics of all persistent innovators in the UK between 1990-2006 with a special emphasis on small persistent innovators. By doing so, we do not only highlight the presence and importance of small persistent innovators in routinised innovation regimes, but also compare their innovative characteristics and activities with those of their large counterparts.

Using patent data from the EPO PATSTAT database for the period between 1990 and 2006, we identify those companies characterized by a sustained record of inventive activity over time, defined as serial innovators[38], and explore the effects that specific patterns of innovative activity and firm-specific technology characteristics exert on their rate of innovation. In particular, we offer a comparative perspective observing the differences between small and large serial innovators in order to shed light on the

[38] We use this term, as opposed to persistent innovators, as our definition resembles the one introduced by Hicks and Hegde (2005).

moderating effects of firm size through which innovation persistence manifests itself.

In line with the literature on persistence, we find that small serial innovators, like their large counterparts, benefit from an environment replete with innovative opportunities. They also rely on their accumulated competencies to sustain inventive activities. However, it is in the role played by cumulativeness and its specific qualities that we identify the main difference with respect to large serial innovators: while the presence of dynamic economies of scale due to accumulated R&D resources is at the core of the innovation activity for large companies, small serial innovators benefit more from dynamic increasing returns defined by spill-overs from previous innovative activity and internal combinative capabilities (Kogut and Zander, 1992).

3.2 Literature Review and hypotheses

The literature suggests that a number of factors characterize persistent innovation[39]. We concentrate in particular on technological regimes and the firm's technology characteristics as detailed below. In Section 3.2.1, we focus on the role of different characteristics of technological regimes as important determinants of innovative activity while in Section 3.2.2 we consider the firm-specific technology characteristics that drive innovative activities. Each section includes the relevant hypotheses.

3.2.1 The characteristics of technological regimes

Several empirical studies demonstrate that persistence in innovative activity may be explained through qualities of the relevant technological regime (Malerba and Orsenigo, 1996; Breschi et al., 2000), which can be seen as the knowledge environment shaping the firm-specific routines and boundaries;

[39] The present analysis does not explicitly addresses the role of investment in patenting activity discussed in the "demand pull" "technology push" debate (Schmookler, 1966; Kleinknecht and Verspagen, 1990). Instead, in line with the evolutionary economics perspective and the findings by Lach and Schankerman (1989), we focus on the relationship between the specific qualities of technological change and firms' innovation rate.

thus defining firms' technological trajectory (Nelson and Winter, 1982; Dosi, 1982). This Chapter examines the impact of different dimensions of a technological regime upon the innovative behaviour of small and large serial innovators. In what follows, we briefly review the literature on some important dimensions of technological regimes, namely opportunity conditions, cumulativeness of innovation, appropriability conditions and properties of the knowledge base.

Opportunity conditions describe the increase in the innovative activity for a given amount of money or resources spent in search (Malerba and Orsenigo, 1993). By generating a rich innovative environment, opportunity conditions widen the scope of firms' technological frontier. At the same time, they may ease the effect of size-related disadvantages allowing for small innovators to exist alongside large ones (Audretsch, 1995).

Cumulativeness describes the degree by which innovations in a specific period of time depend on previous innovations. As Malerba and Orsenigo (1993) point out, cumulativeness takes place on different levels. It is linked to the firm-specific learning processes and the features of the technologies developed, while also depending on the R&D organization within the firm and the characteristics of the firm itself. In particular, two main elements have been proposed to explain the presence of persistence in innovation. The first element is constituted by *'dynamic economies of scale'* where the accumulation of knowledge resulting from the volume of previous innovation exerts a positive effect on the successive round of innovations. In other words, "*the more innovations a firm produces, the more likely it is to continue to innovate*" (Geroski et al., 1997: 33). This hypothesis can also be seen as related to the concept of sunk costs (Sutton, 1991), through which high costs in R&D investments generate high barriers to entry and exit in innovation, thus supporting persistent innovation.

The second element is related to the notion of *'dynamic increasing returns'*, which describe the incremental nature of the process of knowledge creation and technological learning (Rosenberg, 1982). In this perspective, new innovations derive from the capacity to absorb and dynamically use the set of competencies defined by the firm's technological trajectory (Nelson and

Winter, 1982; Cohen and Levinthal, 1989). In this sense, innovative capabilities may benefit from processes of 'learning by doing' and 'learning to learn', across different degrees of formal and informal know-how (Teece et al., 1997).

Appropriability conditions expresses the possibility for the firm to protect its inventions and, more generally, to extract financial returns from its innovative activity. High levels of appropriability are associated with a deepening pattern of innovative activity since financial returns to innovation create resources and incentives for future innovations. Companies use a wide range of formal and informal protection methods for their innovations. Moreover, their use in different industries can vary significantly (Levin et al., 1987; Arundel and Kabla, 1998). Patent data used in this Chapter present a limitation in this respect, and we need to make an assumption on the level of appropriability in our dataset. Given the high cost of patenting, we argue that companies which present a sustained level of patenting activity are likely to consider patents an efficient and viable method of protection, in line with the findings in Arundel (2001). Therefore, we assume a high level of appropriability fixed for all companies in this study.

Properties of the knowledge base refers to the multidimensional complexity of the technological knowledge on which the firm's innovative efforts are built. While the theory identifies various characteristics such as specificity, tacitness and complexity (Winter, 1987), previous research has usually measured this variable using the simpler dichotomy between applied and science-based technology[40] (Breschi et al., 2000). In particular, science-based technology is associated with a non-cumulative and universal knowledge base, while applied technology is sector specific and requires accumulated capabilities to be fully exploited (Winter, 1984).

These four dimensions of technology regimes are important elements that shape the innovative activities of firms. Within the analytical framework of Schumpeterian patterns of technological change, persistence is an inherent quality of routinised processes of creative accumulation described by a 'deepening pattern' characterised by high opportunity and strict appropriability

[40] See Table 3.6 for the classification used in this Chapter.

conditions, more cumulativeness and a knowledge base which is cumulative at the industry level and, therefore, more applied in nature (Winter, 1984; Malerba and Orsenigo, 1990, 1993). Even though it is more common to find large serial innovators prosper in such regimes, as shown in this Chapter, there is a significant number of small serial innovators that also exist in these regimes. Besides overlooking the presence of small serial innovators in routinised regimes, the literature does not engage in a debate on whether and how these firms are different from their large counterparts. In this Chapter, we aim to explore this question in more detail.

Our expectation is that small serial innovators behave similarly to large serial innovators in most ways with the exception of how knowledge accumulation processes take place, as outlined in *Hypotheses 1* and *2* below. The starting point of our rationale is that small firms inevitably have smaller amounts of R&D resources. They cannot shape their innovation activity around the highly routinised and R&D intensive structures that generate dynamic economies of scale in innovation, whose costs need to be spread across a great level of output (Cohen and Klepper, 1996), as is frequently the case for large companies. Conversely, acting as specialised suppliers of technological inputs, the competitive advantage in innovation of small serial innovators is likely to lie more in dynamic increasing returns defined by incremental search and 'combinative' capabilities rather than scale advantages (Kogut and Zander, 1992). Their innovation is intrinsically connected to 'learning by doing' and 'learning to learn' effects and they benefit from developing technology that presents characteristics of pervasiveness along the technological trajectory close to firm's core competencies, engaging in processes of search depth (Katila and Ahuja, 2002). Therefore, we hypothesise the following:

Hypothesis 1. For both small and large serial innovators, the rate of innovation is enhanced in the presence of high opportunity conditions, high levels of cumulativeness and a knowledge base close to applied technology.

Hypothesis 2. Large and small serial innovators differ in the nature of their cumulative processes. While the volume of previous innovation is more relevant for large firms, small companies build incrementally on their prior innovations to generate further innovations.

3.2.2 The role of firm-specific technology characteristics

As discussed in Section 3.2.1, technological regimes are essential in defining the technological trajectory followed by companies. However, firms' innovative behaviour is also shaped by the characteristics inherent to firm-specific technologies. In this section, we explore some important dimensions of firm-specific technology that can take place differently in small and large serial innovators and consequently affect their innovative behaviour. They are the impact, the generality and the originality of innovation.

The impact of innovation represents the value of a given piece of knowledge or technology. It is clear that innovations with higher impact also have a higher commercial value (Hicks and Hegde, 2005). Moreover, the competencies necessary for the development of such patents, as well as the knowledge acquired in that process, are likely to exert a positive effect on following inventive efforts, supporting persistence dynamics.

We argue that innovations with higher impact are more crucial to the existence of small serial innovators than they are for large serial innovators. This point is explained by Hicks and Hegde (2005) who suggest that the presence of small serial innovators in routinised regimes may be found in the recent theory on "markets for technology" defined by the division of labour in the production of knowledge and "trade in technology disembodied from physical goods" in modern innovation networks with modular systems (Arora et al., 2001; Arora and Gambardella, 2010; Freeman, 1991; Langlois and Robertson, 1992). To be effective partners in trade in technology, small companies need to develop high impact technologies, while large firms take part in the trade mostly based on their large scale R&D activities.

Generality of innovation describes technology that is generic and can be used for the development of a wide variety of products, resembling the concept of 'general purpose technology' (GPT) introduced by Bresnahan and Trajtenberg (1995). They describe GPTs as 'enabling technologies', characterized by high levels of dynamism and pervasiveness which generate processes of 'innovational complementarity'. Such complementarities can be important in facilitating a greater tradability across innovation networks or markets for technologies. Hence, similar to the case of impact of innovations, we argue that higher generality of innovations carries a bigger importance for small serial innovators by facilitating their participation in modular innovation systems and offsetting the need for large scale in R&D. Innovations characterised by higher levels of generality open up opportunities for further innovations supporting persistent innovation.

Originality of innovation indicates the degree to which a given innovation is original or radical, as "technology that has less immediate precedents in its technology class is likely to be more radical innovation and should be more marketable" (Hicks & Hegde, 2005: 708). Granstrand et al. (1997) indicate that while technological competencies depend on past innovative activity, persistently innovative companies need to diversify their technological capabilities in order to incorporate new opportunities and manage their complex production systems. In this sense, firms whose innovations derive from a broad range of technology classes demonstrate to possess strong absorptive capacities and innovation synthesis, and are more likely to benefit from new technological possibilities (Trajtenberg et al., 1997; Cohen and Levinthal, 1990). As in the cases of impact and generality, we believe originality is another characteristic that is especially important for the innovating behaviour of small serial innovators by enabling them to engage in a sustained stream of innovative activities without the need to possess the scale-intensive capabilities usually assumed in the traditional models of persistent innovation.

Hypothesis 3. Patents defined by high technological impact, generality and originality exert a more significant positive effect on the innovation rate of small serial innovators compared to large serial innovators.

3.3 Data

In this Chapter, we define as serial innovators those companies that are independent throughout the observation period, with at least five years of technological patenting activity (calculated as the difference between the first and the last patent published by the company in the period of time considered) and that possess at least 10 patented inventions with an overall ratio of patents to years at least equal to 1[41]. Small serial innovators are then defined as having less than 250 employees throughout the period of time considered while large serial innovators have at least 250 employees[42].

The use of patent data is widespread in the literature as patents are officially recorded and easily accessible, provide a large quantity of detailed data at the firm level and are available for long time series. Moreover, the inventive step required to obtain a patent ensures an objective degree of novelty. Drawbacks are also well known[43]. In particular, patents are criticised for the wide variance in their value, yet recent studies indicate that the use of patents weighted by citation, also utilised in the Chapter, may solve this issue (Trajtenberg, 1990; Hall et al., 2005).

To build our dataset, we proceeded as follows. All applicants based in the UK with at least one patent application between the years 1990 and 2006 were selected. Then, single inventors or University applications were excluded. The data were manually checked to identify misspelled names or different names referring to the same entity. At this stage, a set of roughly 30 thousand companies was obtained. Patent families were used as a proxy for firms' inventions[44], with patent family being defined as “a set of patents taken in various countries to protect a single invention” (OECD, 2001). This allowed us

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[41] The traditional approach to the study of persistent innovation focuses on the presence on innovation in subsequent periods of time. In this Chapter we follow the approach of Hicks and Hegde (2005), imposing a minimum threshold of innovative activity within a larger window of time, which allows us to focus on the overall stream of inventions rather than their sequentiality over time.

[42] This definition follows the European Commission Recommendation (96/280/EC) of 3 April 1996, where SMEs are defined by the upper of 250 employees. According to this threshold, only three small companies turned into large companies in the period considered, and they are included in the latter group.

[43] For a discussion of strengths and weaknesses of patent data see Pavitt (1988) and Griliches (1990).

[44] See Martinez (2011) for a detailed discussion on patent families.

to uniquely identify single inventions, regardless of the number of applications made in different patent offices to protect the same new technology[45].

In order to complete the dataset with information on economic and business variables such as size, ownership and SIC code, all records were integrated with information from the FAME database and Companies House website, which contains the official UK register of companies. Then, all patents belonging to subsidiaries which were part of a group throughout the period of time considered were grouped together with the main holding company in order to enable consistent counting of patents.

3.4 Small serial innovators: some stylised facts

Table 3.1 reports descriptive statistics for the firms in our dataset by size group. As expected, the differences between large and small-sized companies are sensible, with the first group accounting for the large majority of patents in the dataset, with the mean equal to 126 patents for large firms and 20 for small second quartile underlines, half of the large companies have less than 38 patents. Instead, small companies show a median value of 16 inventions over the sixteen years analysed. Looking at the 10 companies with more than 100 patent families, we see that 50% operate in R&D, while the others are in chemical and telecommunication sectors.

Considering the difference between the first application and the last in this time-period, there are not many differences between large and small companies with a mean of respectively 12 and 10 years, which are almost equal to the second quartile in the distribution. While it is clear that major differences may appear if we consider longer periods of time, it is interesting to note that the majority of these companies are not short-lived, with half of the small companies being active for at least 9 years in the period of time considered. If

[45] Note that, unlike studies that use patent data from a single patent office (e.g: USPTO), identification of patent families is crucial to this study in order to avoid multiple counting based on different patents issued for the same invention in different countries since PATSTAT combines patent applications from various patent offices.

Table 3.1: Serial innovators: total number of patents (PAT), years of innovative activity (Year Diff.), average number of patents per year of innovative activity (Ratio)

		MEAN	SD	Q25	Q50	Q75	MAX	MIN	Patents	Firms
LARGE	PAT	125.8	335.7	20	37.5	90	4832	10	59410	472
	Year Diff.	11.5	3.6	8	12	15	16	5		
	Ratio	10	23.1	2.15	3.64	7.41	304.7	1		
SMALL	PAT	20.5	17.2	12	16	21	181	10	6948	339
	Year Diff.	9.6	3.4	7	9	12	16	5		
	Ratio	2.3	1.7	1.38	1.83	2.5	17.22	1		
TOTAL	PAT	81.8	261.5	15	23	49	4832	10	66358	811
	Year Diff.	10.7	3.7	8	10	14	16	5		
	Ratio	6.8	18.1	1.63	2.5	4.7	304.7	1		

we look at the date of incorporation, many are much more long lived, with the average number of years of innovative activity being equal to 20. ones. Nonetheless, it is important to note that the majority of the large firms do not present a higher level of patents than small or medium-sized firms. As the

The distribution across industrial sectors of small sized companies reported in Table 3.2. Research & Development is the most represented sector, accounting for roughly a third of the total number of companies (28%). The manufacturing sectors constitute the other main group in the data, with the predominance of metal products and machinery (10% and 6%) followed by plastic products, precision instruments and chemical products (6%, 6% and 4% respectively).

Table 3.2: Small Serial innovators by industrial classification (Two-digit SIC code)

Sector	SIC Code	Patents	% Firms	% Patents
Extraction of Crude Petroleum and Natural Gas	11	55	0.88%	0.79%
Manufacture of Wearing Apparel	18	11	0.29%	0.16%
Manufacture of Pulp, Paperand Paper Products	21	64	1.18%	0.92%
Manufacture of Chemicals and Chemical Products	24	265	4.42%	3.81%
Manufacture of Rubber and Plastic Products	25	367	6.19%	5.28%
Manufacture of Other Non-metallic Mineral Products	26	37	0.59%	0.53%
Manufacture of Basic Metals	27	20	0.59%	0.29%
Manufacture of Fabricated Metal Products, Except Machinery	28	696	10.32%	10.02%
Manufacture of Other Machinery and Equipment	29	326	6.19%	4.69%
Manufacture of Office Machinery and Computers	30	39	0.88%	0.56%
Manufacture of Electrical Machinery and Other Apparatus	31	165	2.65%	2.37%
Manufacture of Radio, Television and Communication Equipment	32	118	2.36%	1.70%
Manufacture of Medical, Precision and Optical Instruments	33	413	5.90%	5.94%
Manufacture of Other Transport Equipment	35	28	0.59%	0.40%
Manufacture of Furniture; Manufacturing Not Elsewhere Classified	36	463	7.67%	6.66%
Wholesale Trade and Commission Trade	51	133	2.36%	1.91%
Retail Trade, Except of Motor Vehicles and Motorcycles	52	10	0.29%	0.14%
Post and Telecommunications	64	95	1.47%	1.37%
Computer and Related Activities	72	108	2.06%	1.55%
R&D	73	2576	28.32%	37.08%
Other Business Activities	74	652	9.73%	9.38%
Health and Social Work	85	29	0.59%	0.42%
Recreational, Cultural and Sporting Activities	92	68	0.88%	0.98%
Other Service Activities	93	98	1.47%	1.41%
Miscellaneous		112	2.06%	1.61%
TOTAL		6948	100%	100%

3.4.1 The regional distribution

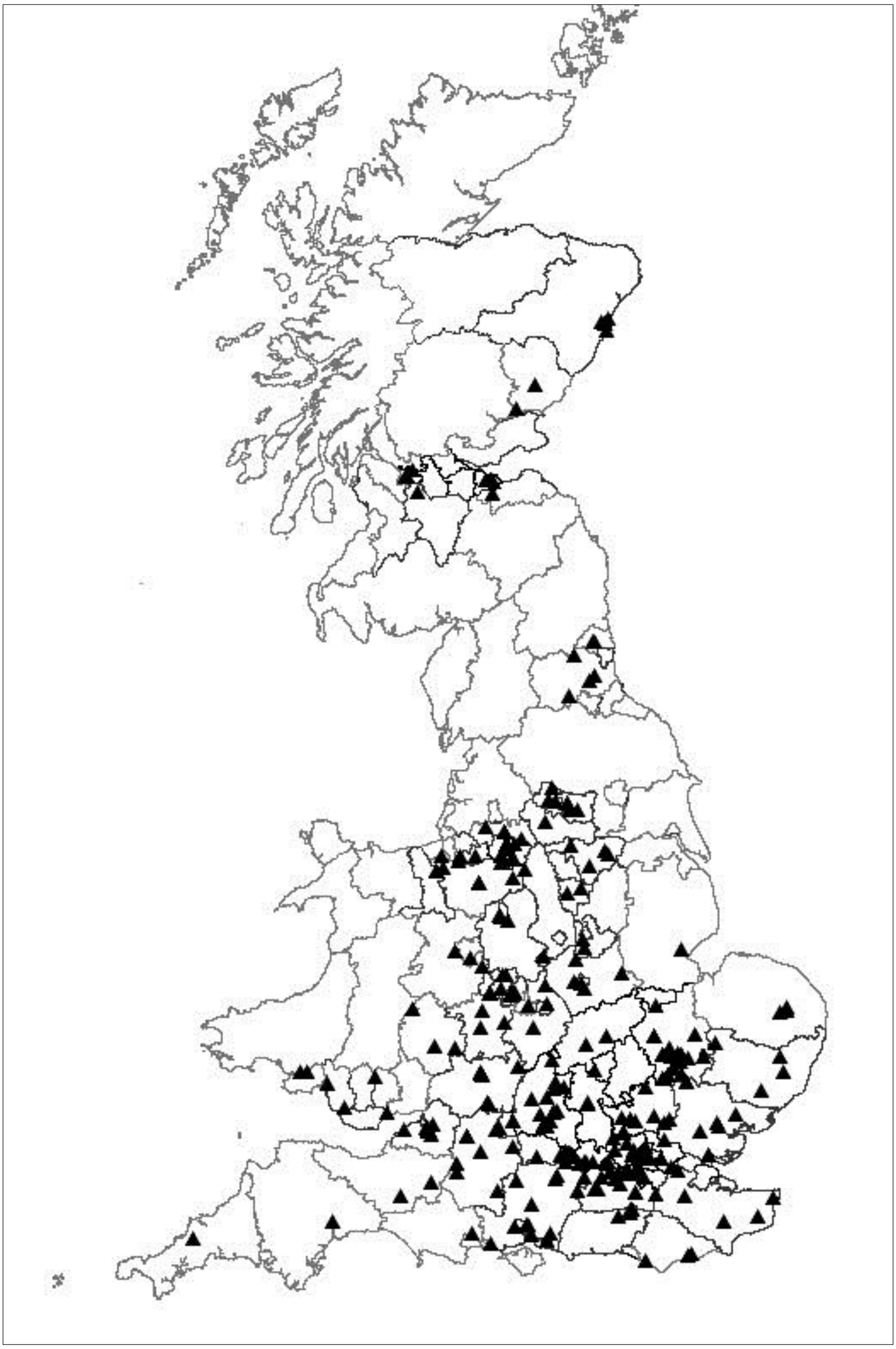
In the literature, the importance of firm location and the presence of clusters on the innovative activity of firms has been analysed since Marshall (Marshall, 1890; Baptista, 1998), with various studies underlying the presence of a positive relationship (Baptista and Swann, 1998; Lychagin et al., 2011). In particular, industrial clustering might exert a stronger effect on firm performance for companies with a high level of technological competence, such as small serial innovators. In line with this argument, Libaers and Meyer (2011) make use of patent data on small firms with highly distinct levels of inventive prowess to study their capabilities in leveraging cluster-based resources more effectively in order to enhance firm performance. Their findings suggest that the level of industrial clustering has a positive linear relationship with the level of firm internationalization for small serial innovators, while non-serial innovators present diminishing returns in international performance at elevated levels of industrial clustering.

While a specific cluster analysis is beyond the scope of this Chapter, looking at the regional distribution of small serial innovators can provide some initial insight on this topic, allowing us to make some general considerations. The distribution of small serial innovators at the regional level is reported in Figure 3.1. Clearly, the majority of companies in the sample are located mainly in England, with a higher density around the city of London, in south central England and East Anglia. In particular, we can see from Figure 3.1 that the distribution of companies loosely resembles the major clusters in the UK industry, especially the so called 'M4 corridor' and the 'Golden triangle', located in the area around the cities of London, Cambridge and Oxford. In fact, the number of companies located only in these three cities account for almost a quarter of the total, with respectively 45, 33 and 16 firms.

Other important clusters are present around Birmingham and in the area between Manchester and Stroke-on-Trent. Interestingly, only a small number of companies are located outside major metropolitan areas.

When we look at the industry sector, we observe that more than a third (35%) of R&D companies is in London, Cambridge or Oxford, while other relevant clusters are near Reading and Guildford (9%) and Manchester (4%). Manufacture of fabricated metal products appears to be clustered in the Midlands, with 12% of the companies in Birmingham for a total of 28% in the whole region. There is also a link with the chemical cluster in Cheshire and Merseyside, with around 25% of companies in this sector located around such area. Also, almost all the companies in the computer sector are distributed along the 'M4 corridor'. For less represented sectors, we observe that of five paper related companies four are equally distributed in Birmingham and the London area, while the two companies focused on petroleum and natural gas extraction, both in the city of Aberdeen.

Figure 3.4: Spatial distribution of small serial innovators



While further analysis is required, the data seem to suggest that there is indeed a relationship between spatial distribution and industry sector, and that the clusters of small serial innovators resemble those more general one of the British industry as a whole. Although to a descriptive level, hence, the regional distribution of small serial innovators in the UK seems to reflect the findings proposed by Libaers and Meyer (2011) on the importance of industrial clustering in improving their performance, thanks to their ability to access and leverage cluster-based resources.

3.5 Econometric specifications

We model the inventive performance of small serial innovators as a function of two broad categories of explanatory variables reflecting the characteristics of technological regimes and the quality of the firm-specific inventive activity as discussed in Sections 3.2.1 and 3.2.2. Among the former we include **opportunity conditions** (OPPORTR), two distinct variables to reflect **cumulativeness**, that is, knowledge stock (KSTOCK) and increasing returns (SELFCITE) as well as one variable for properties of the knowledge base (KNOWTR). We measure firm-specific technology characteristics including **impact** (IMPIN), **generality** (GENIN) and **originality** (ORIGIN) of innovation.

Furthermore, in order to investigate the different effects exerted by technological regimes on small and large serial innovators, we focus on the technological regime variables and test interaction effects based on firm size. In what follows all dependent and independent variables are described in detail.

3.5.1 Dependent Variable

In order to measure the rate of innovation of serial innovators, we use the number of patents applied for by firm *i* with publication date in year *t* ($PATENTS_{it}$). However, patents present a significant variance in their individual technological and economic value. To account for this issue, a recent strand of literature has focused on the use of citation-based indices, providing evidence that patent citations are significantly correlated with the technological importance of inventions (Trajtenberg, 1990; Trajtenberg et al., 1997, Hall et al., 2001). Accordingly, we use a second dependent variable which is the citation-weighted patent count $CITATIONS_{it}$[46].

3.5.2 Independent Variables

The first group of independent variables refers to the concept of technological regime as discussed in Section 2.1 and describe the nature of the technological environment that bounds firms' knowledge base.

Given the complexity and the multifaceted nature, ***opportunity conditions*** (OPPORTR) have been formalized and measured in different ways in the applied literature. We follow the approach of Patel and Pavitt (1998) based on the increase in the patenting activity within a sector, and build an index of *opportunity conditions* (OPPORTR) by taking into account the year-over-year percentage increase in the number of patents for each IPC sector where the firm patented:

$$OPPORTR_{it} = \frac{1}{P_{it}} \sum_{p_{it}=1}^{P_{it}} \frac{a_{p,t} - a_{p,t-1}}{a_{p,t-1}} \tag{3.1}$$

where P is the number of patents of the company *i* in year *t*, while $a_{p,t}$ and $a_{p,t-1}$ represent the total number of patents in the same IPC technological class of the patent *p* in time *t* and *t-1* respectively. As discussed earlier, we expect OPPORTR to have a positive impact for the innovation rates of both small and large serial innovators as environments with abundant technological

[46] The weighting scheme adopted to obtain $CITATIONS_{it}$ follows the approach presented by Trajtenberg (1990), who indicates as a simple possibility to weight each patent *i* by the total number of citations received in the following years. See also Section 5.3 for our approach to the issue of truncation in citations.

opportunities increase the likelihood and possibility of innovating for both types of companies.

Cumulativeness summarizes the idea that inventions in time t depend on existing knowledge capabilities and the previous level of innovation. To capture these aspects we use two distinct variables, *knowledge stock* (KSTOCK) and *increasing returns* (SELFCITE).

The first one is a proxy measure for dynamic economies of scale in the form of the past history of R&D capacity (see Bloom and Van Reenen, 2002; Hall et al., 2005) whereby increases in the volume of innovation up to a given time period lead to further increases in the innovation produced in subsequent periods. In this sense, innovation persistence may simply derive from sustained R&D efforts. In line with the existing literature we measure *knowledge stock* (KSTOCK) as the firm's patent stock:

$$KSTOCK_{it} = P_{it} + (1-\delta)KSTOCK_{it-1} \tag{3.2}$$

where P represents the number of patents of the company *i* at the beginning of year *t* and δ is the depreciation rate, which is assumed to be 15%[47] (Cockburn and Griliches, 1988, Hall et al., 2005). Following Hall et al. (2005), we account for the effect of the missing initial condition by collecting information on the number of patents for all companies in the study from 1985, while our regressions use data starting from 1995, allowing for a lag of at least 10 years between the first year for which we have patent data and the first year analysed. To control for potential endogeneity, we allow KSTOCK to enter the estimating equation with a lag after being log transformed.

The second variable may be considered a direct measure of dynamic increasing returns resulting from accumulated knowledge competencies and internal knowledge spillovers (Hall et al., 2005). *Increasing returns* (SELFCITE)

[47] A depreciation of 15% represents the standard rate adopted in the literature. A detailed discussion is offered by Griliches and Mairesse (1981), who found little variation in production functions when using higher or lower values for δ. We also tried different values for δ, such as 5% and 20%. In line with the findings of Griliches and Mairesse (1981), our estimates are also robust to the different specifications tested.

measures the average percentage of self-citations made by the ith firm in year t. For every patent p, we count the number of citations made to other patents with the same assignee Nsamep, divided by the total number of citations Np :

$$SELFCITE_{it} = \frac{1}{P_{it}} \sum_{p_{it}=1}^{P_{it}} \frac{Nsame_{p_{it}}}{N_{p_{it}}} \tag{3.3}$$

Between KSTOCK and SELFCITE variables, we expect that two different aspects of cumulativeness are captured: SELFCITE is likely to reflect the ability of the firm to build on the firm's own incremental knowledge and to use combinative capabilities to generate new knowledge; while KSTOCK is likely to capture the effects of formal R&D efforts over the history of a firm's innovation history.

In line with our first hypothesis we expect the rate of innovation of serial innovators to be significantly affected by high opportunity conditions, high levels of cumulativeness and a knowledge base close to applied technology. Our second hypothesis would suggest that the nature of the cumulative processes differs across serial innovators with KSTOCK being more relevant for the innovations of large firms and SELFCITE being more relevant for small firms.

Properties of the knowledge base (KNOWTR) refers to the nature of the technology and the knowledge embedded in the firm's innovative activities. Following Breschi et al., (2000), our measure is obtained by the relative number of patent citations made to science-based or applied sectors[48], with the number of patent citations on academic patents included in the first group, where positive values indicate a close relationship with science-based sectors. The index is:

[48] See Breschi et al. (2000). See also Table 3.6 for a classification of science-based or applied sectors.

$$KNOWTR_{it} = \frac{c_{b,it} + u_{it}}{C_{it} + u_{it}} - \frac{c_{a,it}}{C_{it} + u_{it}} \tag{3.4}$$

where c_b is the number of citations from science-based sectors and c_a that of applied sectors. The u represents citations made to university patents, while C is simply $c_b + c_a$. As we have seen, companies may use different knowledge competencies in their innovative activity, therefore it is difficult to predict the sign for this variable.

The second group of variables refer to characteristics of the technology developed internally to the firm. To control for potential endogeneity, these variables are lagged one period.

As discussed in Section 3.2.1, **the *impact of innovation*** (IMPIN) is an important element of the innovation activity of small companies without the downstream capabilities to manufacture their products and operate as intermediate suppliers in a market for technology (Hicks and Hegde, 2005). In order to pick up such dimension we need a measure which takes into account the substantial differences in citation rates across different technologies and over time. For these reasons, we make use of the citation index proposed by Hicks and Hegde (2005), defined as the ratio of the citation count over the citation count of all patents in the same year and technological class. We define such measure as *impact of the innovation* (IMPIN). More formally we have:

$$IMPIN_{it} = \frac{1}{P_{it}} \sum_{p_{it}=1}^{P_{it}} \frac{N_{fp_{it},k}}{N_{ft,k}} \tag{3.5}$$

where $N_{fp_{it},k}$ represent the number of forward citations for the patent p of company i in the technology class k, while $N_{ft,k}$ is the total number of forward citations for any patent published in year t in the same class k. Considering the importance of high-impact patents in terms of both knowledge competencies and as financial signals[49], we expect IMPIN to display a positive impact for the innovation rates of both small and large serial innovator but especially so in the case of small firms as a facilitator in trade in technologies.

Generality of innovation (GENIN) is related to the idea that innovative companies benefit from the development of pervasive technologies which may generate successive innovations in different sectors. To calculate this variable, we follow the approach proposed by Trajtenberg et al. (1997). Including the bias correction presented in Hall (2005), the generality index is here defined for each patent as:

$$\hat{G}_p = GENERALITY_p = \frac{N_{fp}}{N_{fp}-1}\left(1-\sum_{k=1}^{K}\left(\frac{N_{fp,k}}{N_{fp}}\right)^2\right) \qquad (3.6a)$$

where K is the number of different IPC technological classes where the patent was cited, $N_{fp,k}$ is the number of forward citations for the *k* sector and N_{fp} the total number of citations received. The index is the inverse of the Herfindahl index, with values closer to 1 for patents with citations from a large spread across different technological classes and values close to 0 for patents cited in a small number of technological classes. Hence, the index for the generality of invention is simply defined for each company *i* in year *t* as:

$$GENIN_{it} = \frac{1}{P_{it}}\sum_{p_{it}=1}^{P_{it}}\hat{G}_{p_{it}} \qquad (3.6b)$$

We again expect to see a positive impact of generality (GENIN) upon the innovation rates of serial innovators and this impact is likely to be more pronounced in the case of small firms as more general innovations boost the

[49] High impact technologies hold more commercial potential, and they are more attractive to buyers (Hicks & Hegde, 2005). Similarly, companies holding such patents have a higher market value (Hall et al., 2005).

potential of participating in trade in technologies for these companies and consequently also boost the opportunities for future innovations.

Originality of innovation (ORIGIN) is related to the argument that more original innovations build upon technological advances from a broad set of sectors (Hicks and Hegde, 2005). Following Trajtenberg et al. (1997), the index is calculated as the generality index, except that citations received are replaced by citations made by the company. Including the bias correction introduced above, we have:

$$\hat{O}_p = ORIGINALITY_p = \frac{N_{bp}}{N_{bp}-1}\left(1-\sum_{k=1}^{K}\left(\frac{N_{bp,k}}{N_{bp}}\right)^2\right) \qquad (3.7a)$$

where K is the number of different IPC technological classes where the patent made citations, $N_{bp,k}$ is the number of backward citations made to the *k* sector and N_{bp} the total number of citations made. Our originality index is:

$$ORIGIN_{it} = \frac{1}{P_{it}}\sum_{p_{it}=1}^{P_{it}}\hat{O}_{p_{it}} \qquad (3.7b)$$

As in the case of GENIN, originality (ORIGIN) is a factor that increases the value of a given innovation. Therefore, we expect to see this variable to impose a positive impact upon the innovation rates of serial innovators. As previously discussed, we argue this impact will be especially significant and important for small firms as specialist suppliers of technologies.

To study the role of firm size, we do not only use the full sample of serial innovators making use of a firm size dummy variable; but also we run regressions individually on the samples of small and large serial innovators. We believe it is important to focus on small serial innovators in order to shed more light on this commonly overlooked group of firms. To further investigate the role of firm size in the sample that includes small and large firms, we make use of a dichotomous variable SMALL equal to one if the company has less than 250 employees and zero if it is a large company. Then, we introduce interactions between SMALL and the variables OPPORTR, KSTOCK, SELFCITE, KNOWTR,IMPIN, GENIN and ORIGIN in order to tease out the differences in how these variables affect small and large companies. We also include as control variables four sectoral[50] dummies representing the so-called Pavitt taxonomy (Pavitt, 1984), where firms are classified[51] into science-based (SCI_BAS), scale-intensive (SCAL_INT), supplier-dominated (SUPPL_DOM) and specialised suppliers (SPEC_SUPL), as well as time dummies.

Table 3.3 reports the descriptive statistics for all variables used in the regressions. We observe that large serial innovators have a higher average

Table 3.3: Descriptive statistics for small and large serial innovators

Small Serial Innovators							
	Mean	St.Dev	Median	Max	Min	VIF	Tolerance
Patents	3.30	3.19	2	44	1		
Citations	9.35	14.25	5	288	2		
Opportr	2.65	1.64	2.45	7.62	-0.82	1.09	0.92
Kstock	9.94	10.71	7.28	104.47	1	1.08	0.92
Selfcite	0.35	0.59	0	4	0	1.13	0.89
Knowtr	-0.21	0.80	-0.50	1	-1	1.05	0.95
Impin	1.13	1.74	0.56	16.96	0	1.02	0.98
Genin	0.39	0.33	0.40	1	0	1.17	0.86
Origin	0.37	0.30	0.38	1	0	1.17	0.86
Large Serial Innovators							
	Mean	St.Dev	Median	Max	Min	VIF	Tolerance
Patents	14.11	30.03	5	356.00	1		
Citations	32.93	85.45	9	1171.00	2		
Opportr	2.53	1.46	2.41	7.62	-0.85	1.06	0.94
Kstock	71.34	158.86	21.66	1749.12	1	1.07	0.93
Selfcite	0.26	0.50	0	9	0	1.04	0.96
Knowtr	-0.36	0.69	-0.67	1	-1	1.06	0.95
Impin	1.26	1.49	0.97	21.15	0	1.02	0.98
Genin	0.36	0.26	0.34	1	0	1.15	0.87
Origin	0.34	0.22	0.34	1	0	1.16	0.86

50 Sectoral dummies are based on the main technological class of firms' patent portfolio, as these reflect more accurately the nature of the knowledge base of companies than SIC codes. Also, their distribution is more balanced across large and small firms.

51 Science-based firms constitute the base group across all model specifications. Individual technological classes forming each group are reported in Table 4.5.

Table 3.4: Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Patents	1.00								
Citations	0.87	1.00							
Opportr	0.22	0.21	1.00						
Kstock	0.87	0.76	0.16	1.00					
Selfcite	0.12	0.15	0.21	0.11	1.00				
Knowtr	0.04	0.05	-0.05	0.06	-0.07	1.00			
Impin	0.11	0.15	0.15	0.09	0.15	-0.05	1.00		
Genin	-0.01	0.01	0.00	0.00	0.04	0.11	0.05	1.00	
Origin	0.01	0.02	0.00	0.01	0.05	0.10	0.09	0.36	1.00

value for patents, citations and knowledge stock but also much dispersion around the mean. Interestingly, small serial innovators present a more sustained level of self-citations, as well as generality and originality within their technological output. Finally, correlations figures from Table 3.4 as well as VIF and Tolerance values reported in Table 3.3 suggest that multicollinearity is not a significant concern in this study.

3.5.3 The negative binomial count model and truncation

Given the stochastic nature of the inventive process, the flow of patenting activity of a company is usually dotted with years where a new discovery or invention does not take place. Hence, given the discrete and non-negative nature of both our dependent variables PATENTS and CITATIONS, traditional linear estimators such as ordinary least squares are limited, yielding inconsistent, inefficient and biased estimates (Cameron and Trivedi, 1998). In this case, count models provide a more appropriate means of analysis.

The common starting point for count data is the Poisson model. However, one of the main assumptions of the Poisson model is that the conditional mean equal the conditional variance. To test the mean-variance assumption we run Z-tests and the Lagrange Multiplier test for over-dispersion, with both tests rejecting the hypothesis of no over-dispersion at the .01 level[52] (Hilbe, 2011).

[52] We report the p value for the LM test in Table 3.5.

Many possible extensions have been proposed to account for this issue (See Hausman et al., 1984; Cameron and Trivedi, 1998). Among these, negative binomial models are the most common, and constitute the standard approach in the studies based on patent counts. To fit such model, we make use of generalized estimating equations (GEEs), first proposed by Liang and Zeger (1986), with a negative binomial distribution[53].

Another common problem when using citation data is that of truncation. To address this issue, we follow the fixed-effects approach discussed by Hall et al. (2001), which is built around the assumption that all systematic variations across different cohorts of patents are artefactual and therefore should be removed. To do so, the variable CITATIONS reflecting patent citation count is divided by the average citation count of all patents belonging to the same group of the reference patent, and then scaled up by 100.

3.6 Results

In Table 3.5 we report the results of the negative binomial model. For both measures of innovativeness (PATENTS and CITATIONS) we report the results for small only (column 1 and 2), large only (column 3 and 4) and the total number (column 5 and 6) of serial innovators in the sample. As good practice when analysing interaction variables in nonlinear models and for ease of interpretation, all the coefficients are expressed in terms of incidence rate ratios (IRRs). IRRs can be read as the percentage increase/decrease in the dependent variable following a unit change in the independent variable, ceteris paribus. The percentage increase/decrease in the dependent variable is determined by whether the IRR coefficient is below or above 1. For example, an IRR of 1.270 on the OPPORTR variable in Column (1) of Table 3.5 indicates that the patenting rates increase by 27% for every one unit of increase in the OPPORTR variable while the IRR of 0.857 on the KNOWTR variable

[53] We estimated the negative binomial heterogeneity parameter α using the STATA command nbreg, following Hilbe (2011).

suggests that patenting rates decrease by an average of 14.3% (1-0.857) for every 1 unit increase in KNOWTR.

The interaction effects and their statistical significance can also be observed directly, although the effect should be read in multiplicative terms. In column (5) of Table 3.5, for example, the effect of OPPORTR for small firms is expected to decrease by (0.94-1=-0.06) 6% with respect to large companies.

In this section, we first analyse the results specifically related to small serial innovators to gain insights into the determinants of innovating for these firms. We, then, broaden up our investigations to directly compare and contrast the determinants of innovations amongst small and large serial innovators.

In particular, columns (1) and (2) of Table 3.5 show the GEE estimates of the model for only small serial innovators. For this group of firms we find that the set of variables related to our first hypothesis, (OPPORTR, KSTOCK, SELFCITE and KNOWTR) exert an overall positive effect on the rate of innovation. This is consisted across both dependent variables.

Table 3.5: GEE Negative binomial regression estimates for serial innovators

	(1)	(2)	(3)	(4)	(5)	(6)
	PAT.	CIT.	PAT.	CIT.	PAT.	CIT.
Sample	Small Firms only		Large firms Only		Small and Large firms	
			Technological regimes variables			
Opportr	1.270***	1.483***	1.330***	1.443***	1.346***	1.477***
	(0.022)	(0.064)	(0.019)	(0.039)	(0.018)	(0.041)
Kstock	1.783***	1.848***	2.022***	1.963***	2.020***	1.957***
	(0.070)	(0.176)	(0.032)	(0.058)	(0.031)	(0.064)
Selfcite	1.190***	1.917***	0.910*	1.314**	0.900*	1.217*
	(0.059)	(0.263)	(0.039)	(0.104)	(0.041)	(0.115)
Knowtr	0.857***	0.668***	0.864***	0.797**	0.827***	0.738***
	(0.038)	(0.075)	(0.030)	(0.052)	(0.028)	(0.053)
			Firm specific technology related variables			
Impin	1.059***	1.204***	1.012	1.157***	1.012	1.140***
	(0.015)	(0.044)	(0.014)	(0.028)	(0.014)	(0.031)
Genin	1.056	0.761	0.980	1.134	0.969	1.200
	(0.096)	(0.164)	(0.074)	(0.155)	(0.071)	(0.181)
Origin	1.051	1.571+	1.094	1.267	1.104	1.267
	(0.115)	(0.412)	(0.106)	(0.221)	(0.104)	(0.242)

Size and interaction variables						
Small					1.042	0.743
					(0.138)	(0.174)
Opportr_Sm					0.945**	0.979
					(0.0173)	(0.0365)
Kstock_Sm					0.863***	0.947
					(0.0374)	(0.0752)
Selfcite_Sm					1.290***	1.557**
					(0.0857)	(0.213)
Knowtr_Sm					1.102+	1.017
					(0.0546)	(0.102)
Impin_Sm					1.046*	1.061
					(0.0214)	(0.0419)
Genin_Sm					1.066	0.634*
					(0.131)	(0.147)
Origin					0.967	1.317
					(0.148)	(0.379)
Scal_int	0.697***	0.586**	0.827**	0.759**	0.799***	0.705***
	(0.062)	(0.120)	(0.048)	(0.080)	(0.038)	(0.067)
Suppl_dom	0.784+	0.721	0.806*	0.726+	0.793**	0.723*
	(0.116)	(0.238)	(0.074)	(0.118)	(0.062)	(0.108)
Spec_sup	0.795*	0.568**	0.919	0.837+	0.877**	0.751**
	(0.073)	(0.119)	(0.053)	(0.089)	(0.043)	(0.073)
N	1152	1152	2359	2359	3511	3511
Lagrange Multiplier Test					p value =	0

All columns report IRRs.
All regressions include year dummies. S.E. in parentheses
+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001

Opportunity conditions present a positive relationship with the rate of innovation, with a one unit increase in its value resulting in an increase in the rate of PATENTS by a factor of 1.27 and a factor of 1.48 for CITATIONS. As we would expect, an economic environment replete with new technological discoveries (captured by the OPPORTR variable) provides fertile ground for the innovation activity of small serial innovators. There are several ways through which this effect might occur. Increasing technological opportunities offer new perspectives and avenues of research, fostering the exploration activity that is necessary in the creation of new ideas. They also generate incentives for further investment in research.

Both indicators of cumulativeness (KSTOCK and SELFCITE) are positively related to PATENTS and CITATIONS confirming the importance of cumulativeness for small serial innovators. In particular, the importance of previous innovations (as expressed by SELFCITE) indicates that economies of specialization may be particularly important for small serial innovators, allowing them to develop specific competitive advantages. At the same time, they may enhance synergies across projects as well as between the different departments within the company. In others words, it is possible that these companies may benefit from an innovation premium when their research activity is built upon their own distinctive competencies (Nesta and Saviotti, 2005).

Finally, the IRRs less than 1 (i.e. 0857 and 0.668) for KNOWTR in columns (1) and (2) suggest that small serial innovators benefit from having linkages with applied sectors, as opposed to basic sectors. One possible explanation for this finding is that small companies may find it more difficult to develop a product based on complex technologies which require large R&D laboratories. It is also possible that the companies in our dataset specialize as intermediate technology developers, therefore, operating more with applied knowledge than basic science. Overall, the results provide support towards *Hypothesis 1* that the rate of innovation of small serial innovators is enhanced in the presence of deepening patterns of technological activity.

The second group of variables classified under Firm Specific Technology variables reveals that only high-quality patents, proxied by a higher IMPIN index, increase the patenting rates of small serial innovators. In this sense, promising and valuable technologies are more likely to generate further ideas and innovations which can be licensed or become the basis for further development. Conversely, we find no evidence that generality (GENIN) and originality (ORIGIN) indices have a significant impact when considering PATENTS. In the case of CITATIONS, though, we observe a positive effect of ORIGIN.

To test our second and third hypotheses related to different effects across firm size, we start looking briefly into a sample of large serial innovators in columns (3) and (4). The results are very similar to those identified for small serial innovators, as we find that the innovative activities of large firms are enhanced in deepening patterns of technological regimes characterised by high technology conditions and increased levels of cumulativeness. As in the case of small firms, we find that applied technology bases are more supportive of innovation for large serial innovators. Differently from small serial innovators, the variable SELFCITE is lower and negative in column (3) (i.e. IRR smaller than 1) for large companies, confirming our *Hypothesis 2* that the scale of previous innovations captured by KSTOCK is more relevant in the case of large serial innovators. Finally, results in relation to technology specific variables are similar to those in the case of small firms. We find that only the impact of innovation (IMPIN) has a positive effect on innovation rates of large firms but this effect is not significant in the case of column (3) where the dependent variable is PATENTS. This finding provides preliminary evidence towards *Hypothesis 3* that the impact of innovations is more crucial for small serial innovators.

To capture the significance of the differences between firm size, we extend our analysis to a sample that includes large as well as small serial innovators in columns (5) and (6) of Table 3.5. In particular, we include a size dummy (SIZE) and size interaction variables in the models in order to better understand how firm size moderates the effects of both the Technological Regime variables and Firm Specific Technology variables.

We note that the coefficient of the SMALL dummy variable is insignificant in both columns, revealing that there are no significant differences in the patenting rates of small and large serial innovators once we account for technological regime specific and firm specific variables. This is an interesting insight that highlights the similarities between the innovation rates of small and large serial innovators.

Looking at the interaction variables in columns (5) and (6), we can observe the different effects exerted by technological regimes and firm-specific technology characteristics upon firms of different size. Opportunity conditions have an effect that is around 6% higher for large companies, suggesting that small serial innovators may be less responsive than large serial innovators to external opportunities, supporting the idea that their innovation activity may be characterized by incremental search based on the exploitation of internal capabilities and competencies.

The estimates related to cumulativeness KSTOCK_SM and SELFCITE_SM reveal the most important differences between small and large firms. In line with *Hypothesis 2*, the positive effect on PATENTS derived from having a larger patent stock is reduced for small companies by around 15%. As we expected, we observe the opposite effect for SELFCITE_SM, which is 1.3 times higher for models based on PATENTS and 1.5 times higher with respect to CITATIONS. In this sense, the sign of SELFCITE_SM may indicate that small serial innovators which follow a specific technological trajectory increase their chances of developing higher-quality innovations. Again, this supports the view of a positive return from strategies of technological specialization.

Finally, small companies seem to be slightly more related to basic science technologies compared to large companies even though the coefficient of KNOWTR_SM is only significant at 10% significance level in column (5) and not significant at all in column (6). We note that this finding may be related to collaborations of small serial innovators with universities.

With respect to our third hypothesis, the interaction for technology specific variables reveals that high impact patents of small firms (captured by IMPIN_SM) are likely to increase their innovation rates as measured by PATENTS, while a higher generality in the case of small company patents (GENIN_SM) is likely to reduce innovation rates when considering CITATIONS. The unexpected negative effect in the case of GENIN_SM variable may be explained by the need to focus efforts down to a well-defined narrow trajectory for small firms that have limited R&D resources in order to produce high quality innovations. In the case of ORIGIN_SM, no significant difference is found with respect to either patents or citations of small serial innovators. Therefore, *Hypothesis 3* is only partially confirmed as only the impact of innovations appears to offer a positive influence upon innovation rates of small serial innovators.

With respect to the different sectoral dummies, our results reflect the different propensity to patenting across the four groups. As expected, science-based companies – the base group in all model specifications – are more likely to patent than all other companies, ceteris paribus. Differences across the other three groups are less clear, although specialised suppliers seem to have a higher likelihood of patenting than supplier-dominated and scale-intensive companies[54].

3.7 Conclusions

This Chapter has shown that sustained innovative activity over time is not a specific quality of large companies but extends to a significant number of highly innovative small companies. We examine persistence in innovation at the firm level in the UK using patent data from the PATSTAT database during the period 1990 – 2006 with a special emphasis on highlighting the impact of technological regimes and firm specific technological characteristics upon the rate of innovation of small and large serial innovators. Our findings provide evidence to support our first two hypotheses that opportunity conditions and cumulativeness are central elements in persistent innovation. This Chapter also confirms that small serial innovators benefit more from high-quality patents with a broad technological base (Hicks and Hegde, 2005).

Cumulativeness plays a central role in serial innovation, and its specific qualities constitute the main difference between small and large serial innovators. In large firms, it is the continuous stream and the volume in the past history of innovations that sustains the rate of innovation, while the role of dynamic increasing returns is less relevant. Conversely, small companies need to rely more on past innovations and internal knowledge capabilities as sources of technological learning. Perhaps, it may be this very process of knowledge integration that supports small serial innovators across turbulent technological environments, generating internal spillovers and economies of scope. In other words, serial innovation in small companies can be seen as being characterized

[54] To further investigate differences across these categories, we run our model separately for each group, but we found our results to be robust to this exercise.

by ‘combinative’ capabilities (Kogut and Zander, 1992) and processes of search depth (Katila and Ahuja, 2002).

The study has certain limitations. First, although patents constitute an important means of appropriability for small R&D companies (Arundel, 2001), they allow to study only a specific kind of serial innovators. Patents are more widespread in certain industries and technologies (Arundel and Kabla, 1998), thus our results must be considered cautiously outside those sectors where patents are usually applied for. In particular, we were not able to test the role of appropriability, and we deem this an interesting area for future research. Second, while this study has focused on the technological level of serial innovation, we believe that the role of finance and capital investments, especially with respect to the differences between manufacturing and services industries, and the presence of innovation networking are likely to be decisive elements in the activity of small serial innovators. We were unable to test these hypotheses and we deem it an interesting venue for future research.

In summary, our results confirm what found in previous studies, that is, serial innovators account for the majority of the innovations in the UK (Geroski et al., 1997). Yet, we have challenged the idea that persistent innovation is a peculiar quality of large companies. Small serial innovators may be few in number, but their contribution in terms of innovative output is significant. Even if they may not target growth in economic terms, they represent a stable source of innovation in the economy.

Appendix

Table 3.6: IPC technological classes

IPC Code	IPC Code Name	Applied Science	Basic Science
1	Electrical engineering	Electrical engineering	
2	Audiovisual technology		Audiovisual technology
3	Telecommunications		Telecommunications
4	Information technology	Information technology	
5	Semiconductors		Semiconductors
6	Optics		Optics
7	Technologies for Control/Measures/Analysis	Technologies for Control/Measures/Analysis	
8	Medical engineering	Medical engineering	
9	Nuclear technology		Nuclear technology
10	Organic chemistry		Organic chemistry
11	Macromolecular chemistry		Macromolecular chemistry
12	Basic chemistry		Basic chemistry
13	Surface technology	Surface technology	
14	Materials; Metallurgy	Materials; Metallurgy	
15	Biotechnologies		Biotechnologies
16	Pharmaceuticals; Cosmetics		Pharmaceuticals; Cosmetics
17	Agricultural and food products	Agricultural and food products	
18	Mechanical engineering (excl. Transport)	Mechanical engineering (excl. Transport)	
19	Handling; Printing	Handling; Printing	
20	Agricultural and food apparatuses	Agricultural and food apparatuses	
21	Materials processing	Materials processing	
22	Environmental technologies		Environmental technologies
23	Machine tools	Machine tools	
24	Engines; Pumps; Turbines	Engines; Pumps; Turbines	
25	Thermal processes		Thermal processes
26	Mechanical elements	Mechanical elements	
27	Transport technology	Transport technology	
28	Space technology; Weapons		Space technology; Weapons
29	Consumer goods	Consumer goods	
30	Civil engineering	Civil engineering	

CHAPTER 4

Determinants of technological diversification in small serial innovators

"People are very open-minded about new things - as long as they're exactly like the old ones"

- Charles Kettering

Abstract

This Chapter analyses the determinants of technological diversification for small innovative companies. Using patent data from the PATSTAT database for the period between 1990 and 2006, we explore technological diversification through a panel data set comprising 811 UK based serial innovators characterized by a sustained record of innovations over time, accounting for more than 66000 patents. In particular, we analyse the trade-off that is likely to take place between the need to explore new technological opportunities and the significant element of path dependency delineated by the specific core technological competencies that usually characterise small innovative companies. We find that increasing technological opportunities present an inverted U type relationship with diversification, while technological trajectories defined by coherence in both technological search and core competencies support specialization.

4.1 Introduction

In the last decades, the level of competencies and the range of technological capabilities required to develop new products and technologies have expanded significantly as a result of the increasing pace of innovative activity and the multidimensional nature of emerging technological paradigms (Pavitt et al., 1989; Patel and Pavitt, 1997). As a consequence, the growing complexity of technology development in both cognitive and relational dimensions has resulted in an increasing technological diversification within innovative companies (Fai and von Tunzelmann, 2001). In particular, technological diversification plays a central role in increasing firms' absorptive capacity, enabling them to explore and exploit new opportunities, and it generates economies of scope and speed in technology (Granstrand et al., 1997; Granstrand, 1998). Accordingly, several studies indicate that technological diversification is common across large innovative firms, leading to the conceptualisation of the multi-technology corporation (Granstrand and Sjölander, 1990). In this Chapter, we take a different perspective asking whether technological diversification may also be relevant for a specific set of small firms characterised by a sustained level of innovation over time. Hence, we try to explore the main elements that may bring these small companies to engage in technological diversification.

Recent research has pointed out that technological diversification is a common characteristic of the technological activity of persistent innovators (Breschi et al., 2003). In particular, Breschi et al. (2003) find that technologically diversified companies represent a minor part of the total population of patenting companies. Yet, they account for the large majority of patent applications. They also point out that diversification is a pervasive element in firms characterized by persistent innovation, defined by the presence of a sustained level of innovative activity over time. In this sense, persistence and technological diversification can be seen as closely related phenomena as they are both essential for technology-based firms in order to survive and grow in dynamic environments (Susuki and Kodama, 2004).

However, the literature on diversification tends to concentrate on corporations and large firms. Small companies are often excluded from strategies of technological diversification on the grounds that they lack the resources to sustain and manage the high costs of integration, coordination and the scale of R&D capabilities that diversification requires (Wang and von Tunzelmann, 2000). For similar reasons small firms are usually not associated with persistent innovation either (Malerba et al., 1997). While this might be true for some small or medium enterprises, it might not apply to small serial innovators, defined as those companies with an unusually high level of innovative activity over time[55] (Hicks and Hegde, 2005). This calls for a more detailed study of technological diversification and its determinants across small companies.

This Chapter contributes to the literature by addressing the following questions. We ask to what extent small serial innovators are technologically diversified and how technological opportunities and technological coherence, defined by the presence of common or complementary characteristics within firms' technological capabilities (Teece et al., 1994; Breschi et al., 2004), shape technological diversification within small serial innovators. Using a longitudinal study of 811 UK based companies, accounting for over 66000 patents in the period between the year 1990 and the year 2006, we explore the reasons that lead small firms to engage in the costly process of technological diversification. In particular, we focus on the trade-off that is likely to take place between the need to explore new technological opportunities and the significant element of path dependency delineated by the specific core technological competencies often observed in small innovative companies.

The structure of the Chapter is the following. In Section 4.2 we provide an overview of the specific literature and define the research hypotheses of the Chapter. After a Section on the patent dataset used for the analysis (Section 4.3), we present descriptive statistics and stylised facts about technological diversification among serial innovators (Section 4.4). Section 4.5 delineates the model and the variables used. The discussion of the findings is offered in section 4.6. Finally, section 4.7 provides some concluding remarks.

[55] See also Chapter 3.

4.2 Literature review and hypotheses

The literature on technological change has emphasised the role of cumulativeness and technological trajectories as central determinants of firms' innovative activities (Nelson and Winter, 1982), especially for those companies characterized by elements of persistent innovation (Malerba et al., 1997). As Granstrand et al. (1997) and Pavitt et al. (1989) have indicated, another important dimension that is linked to these elements is represented by technological diversification. According to Granstrand (1998), companies can be characterized by two types of diversification, business and resource diversification. Business diversification refers to products and services developed or, more generally, to the output market of firms. Resource diversification is related to the input side of firm activities, with technology diversification being a special case. The interaction between these elements is fundamental as it defines the evolution of the firm (Granstrand, 1998).

To a first approximation, companies can follow two different strategies when they organize their innovation activities: they could either specialize or – to different degrees - diversify. The literature indicates the presence of innovative advantages for those companies that choose to broaden their technological competencies by embarking on strategies of technological diversification. (See for example Garcia Vega, 2006; Quintana-Garcia and Benavides-Velasco, 2008). There are two main reasons for this.

First, technological diversification may enhance the organization and management of the complex technical interdependence that connects processes of change and improvement across products and processes, as well as along the supply chain (Granstrand et al., 1997; Patel and Pavitt, 1997). Accordingly, Piscitello (2004) indicates that exploring and exploiting inherited managerial competencies and the relationships between the different elements of a company is a potential determinant of firm innovativeness. Granstrand (1998) presents a theoretical model of the technology-based firm that highlights the importance of diversification in fostering cross-fertilization between different technologies and generating economies of scale and scope, speed and space. In this sense, technological diversification supports economies of scope in research and internal technology spillovers, allowing companies to cope with multi-technology and, more generally, complex innovations.

Second, diversification allows innovative companies to explore and eventually exploit new technological opportunities (Patel and Pavitt, 1997). Firms need an extensive knowledge-base if they want to recognize new avenues of research and be actually capable to assimilate new external information. In other words, technology diversification plays an important function in the development and sustainability of a strong absorptive capacity especially in increasingly dynamic and complex markets (Cohen and Levinthal, 1990; Quintana-Garcia and Benavides-Velasco, 2008). At the same time, diversification enables innovative firms to avoid lock-in effects in a specific technology (Susuki and Kodama, 2004). In this context, the ability to recognise and absorb these new opportunities is a fundamental capability in the long-term survival of corporations (Fai and von Tunzelmann, 2001). A third possible reason is suggested by Garcia Vega (2006), and is related to risk reduction in research activity. Given the intrinsically risky nature of the innovation activity, investment in different technologies can lower the volatility associated with research projects thus increasing the overall return from innovation.

Conversely, companies with limited R&D resources, perhaps operating in very specific markets, can focus their innovative efforts on a small and specific number of technologies. In this way, they may benefit from specialization in research, generating economies of scale in learning and increasing the returns on their cumulative technological capabilities (Breschi et al., 2003; Garcia Vega, 2006). According to the resource-based theory of the firm, competencies are a major determinant of firm performance, but equally important is their specific combination (Penrose, 1959). In this sense, Teece et al. (1994) argue that companies which are coherent in their technological competencies and complementary assets benefit from economies of scope that foster their activity. Accordingly, Nesta and Saviotti (2005) find a positive relationship between coherence and innovation, underlying the fundamental contribution of a coherent knowledge base in addition to diversification. While diversification is important in the discovery process (Quintana-Garcia and Benavides-Velasco, 2008), innovative firms benefit from a strong coherence in their internal competencies to gain their competitive advantage. Consistently, Leten et al. (2007) indicate the presence of a positive effect of diversification on the innovation rate, but they go further suggesting the presence of decreasing returns, that is, after a specific threshold the benefit of wide technological competencies brings lower marginal benefits due to high levels of coordination and insufficient levels of scale. They also find evidence that coherence in the strategies of diversification is positively related to innovation, perhaps because it allows reducing the costs of integration and coordination across different technological activities and enhances processes of cross-fertilization. Similar findings are proposed by Miller (2006) and Chiu et al. (2010).

4.2.1 Hypotheses

Hicks and Hegde (2005) indicate that small serial innovators are mainly specialized suppliers of intermediate goods. In this sense, we would expect them to follow strategies of technological specialisation. Yet, technological competencies are more dispersed than production activities (Granstrand et al., 1997). Small serial innovators still need to be able to explore, monitor and exploit new technological opportunities or simply maintain the levels of absorptive capacity required to sustain an intensive record of innovative activities over time. Diversification might be necessary for them to operate within formal and informal networks of systemic technology interdependence, providing the necessary base to develop tiers with the other actors of the innovation system. However, in the presence of a more turbulent environment, such as one characterised by the presence of radical innovations as in the Schumpeterian processes of creative destruction, the faster pace of innovation may lead small serial innovators back to a strategy of specialization developed around firm's core technological capabilities. In such environment, small serial innovators may move towards specialisation and focus on the technologies where they have a competitive advantage. The more radical the evolution of the technology environment, the more limited the time and the resources available. That reduces the opportunities for engaging in strategies of exploration of current technological capabilities to new avenues of research.

Instead, we argue, they are more likely to focus on the exploitation of internal, distinctive competencies along the firm specific technological trajectory, thus relying on their combinative capabilities (Kogut and Zander, 1992) as engines for future innovations. These arguments constitute our first research hypothesis:

Hypothesis 1. Increasing opportunity conditions present an inverted U relationship with respect to the technological diversification and exploration across different technology classes of small serial innovators.

At the same time, there are other factors that constitute a barrier to diversification. In particular, Breschi et al. (2003) argue that technological-relatedness, defined by proximity, commonality and complementarity in knowledge and learning, is an important element in defining the patterns of technological diversification. In this sense, technological competencies are strongly path-dependent, generating a stable technology profile around the core knowledge-base that strongly constrains the direction of technological search (Dosi, 1982; Patel and Pavitt, 1997). Within small firms, hence, while the presence of strong coherent technological capabilities forms a necessary base to develop competitive advantages in innovation, it is also likely to reduce the technology areas companies may be able or willing to explore and subsequently exploit during their research activity.

Hypothesis 2. Coherence in the knowledge-base and in technological search is negatively related to the degree of technological diversification in small serial innovators.

4.3 Data

The Chapter is based on all patents in the period 1990-2006 for all UK serial innovators, defined as UK based independent companies with at least 10 patent applications, distributed in a period of at least 5 years, and with an overall ratio of patents to years of technological activity equal or greater than one. The resulting dataset comprises information on 811 companies, where 472 are large companies and 339 are small ones[56].

Patent data were obtained from the PATSTAT database and include assignee name, patent publication date, technological field assigned by patent examiners, as well as backward and forward citations for each application. Economic data such as size, ownership, SIC code and merger and acquisitions were obtained using Companies House website, which provides information for all registered UK companies, as well as secondary sources such as companies' website. Finally, data on the patent technological field, which follow the International Patent Classification (IPC), have been reclassified into 30 different macro classes[57], reported in the Appendix (See Table 4.5).

Patent data are used extensively in the innovation literature for they have a wide coverage of innovative activity in almost all technological sectors, while ensuring the presence of a significant inventive step. Moreover, they are available for long periods of time and provide detailed and fine information on the inventive activity of companies. Drawbacks are also well known (For a discussion of strengths and weaknesses of patent data see Pavitt, 1988, Patel and Pavitt, 1997; Griliches, 1990). Patents represent more a measure of invention than innovation, and as such they should be considered indicative of the input side of the innovative process, that is, they measure the innovative effort of companies (Trajtenberg, 1990). Patents are also criticised for the wide variance in their value, although recent studies indicate that the use of patents weighted by citation may solve this issue (Trajtenberg, 1990; Hall et al., 2005). These issues are less problematic in the context of this Chapter, as we are mostly interested in the information patents provide on the different technology classes where companies innovate, as well as the flow of knowledge used in this process, delineated by backward and forward citations included in each document. It is for this richness of detail that patent data are increasingly used in the study of technological competencies and diversification (Jaffe, 1986; Patel and Pavitt, 1997; Garcia-Vega, 2006; Quintana-Garcia and Benavides-Velasco, 2008).

[56] Small companies are defined by the upper threshold of 250 employees.
[57] In our analysis, we make use of a patent classification designed following Schmoch (2008).

4.4 Technological diversification and small serial innovators: a brief overview

To illustrate the degree of technological diversification within innovative companies, we first analyse the whole population of UK based companies which had at least one patent publication between years 1990 and 2006. We find that the majority of innovators patent only in one technology class. Figure 4.1 shows the percentage of diversified innovators per number of technological classes where they patented in the period of time considered[58]. Even considering only diversified innovators, the distribution of firms per technological class is highly right-skewed[59], with less than 5% of companies having innovated in more than 4 technological classes.

At the same time, the majority of these companies are small innovators in terms of patenting activity. As Figure 4.2 illustrates, companies that operated in four or less technological classes only account for less than a half of the total number of patents[60]. In other words, the 5% most technologically diversified companies account for more than half of the total number of patents in the period of time considered.

The observation presented in Breschi et al. (2003) that the vast majority of persistent innovators are also diversified innovators is also confirmed by our data. Table 4.1 shows the percentage of diversified serial innovators by size class and the number of patents they hold. The majority of large firms are diversified, with only 2% of cases of specialisation, which account for less than 1% of the total number of patents for this class.

The presence of specialised companies is higher when observing small companies, reaching almost 10% of the total. These firms hold almost 9% of all patents in this class, with diversified companies still accounting for the large majority of patents (91%). Differences across size classes increase when we observe the distribution of companies per number of sectors where they have patented between 1990 and 2006.

[58] Specialised innovators, that is, companies that patented only in one technological class, are not reported. They account for about the 75% of the total number of companies.

[59] This finding is consistent with the study by Breschi et al. (2003), which is based on the population of firms from six different countries.

[60] Specialised innovators that patented only in one technological class are not reported and account for about the 20% of the total number of patents.

Figure 4.1: Distribution of diversified innovators per number of technological classes where they patented

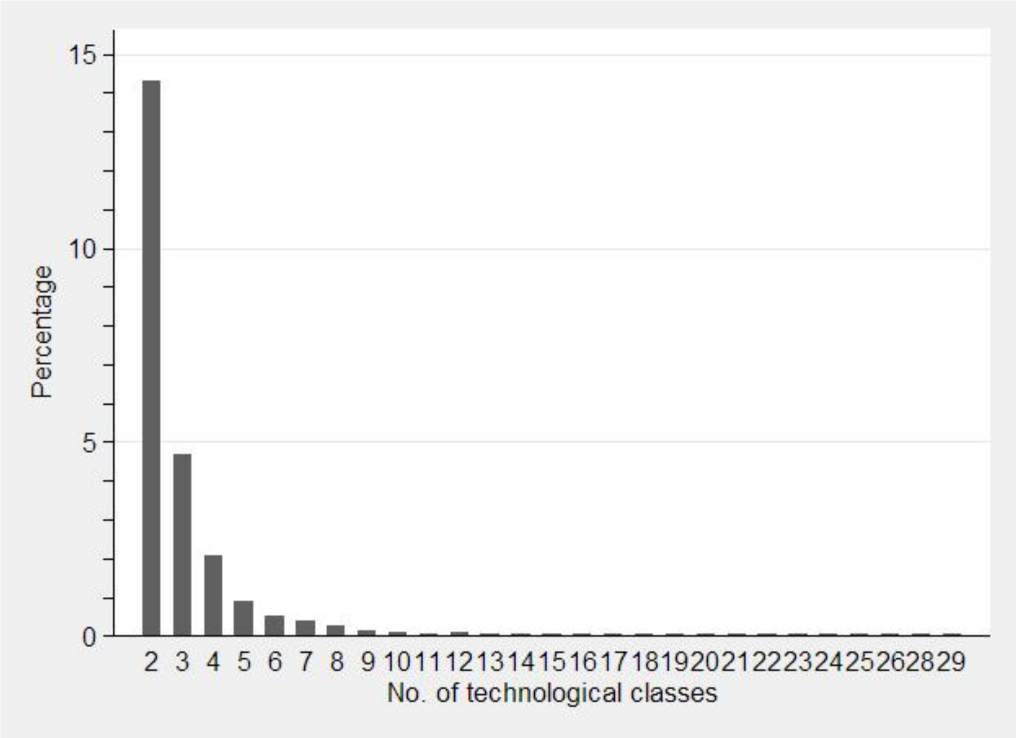


Figure 4.2: Distribution of total patents of diversified innovators per number of technological classes where they patented

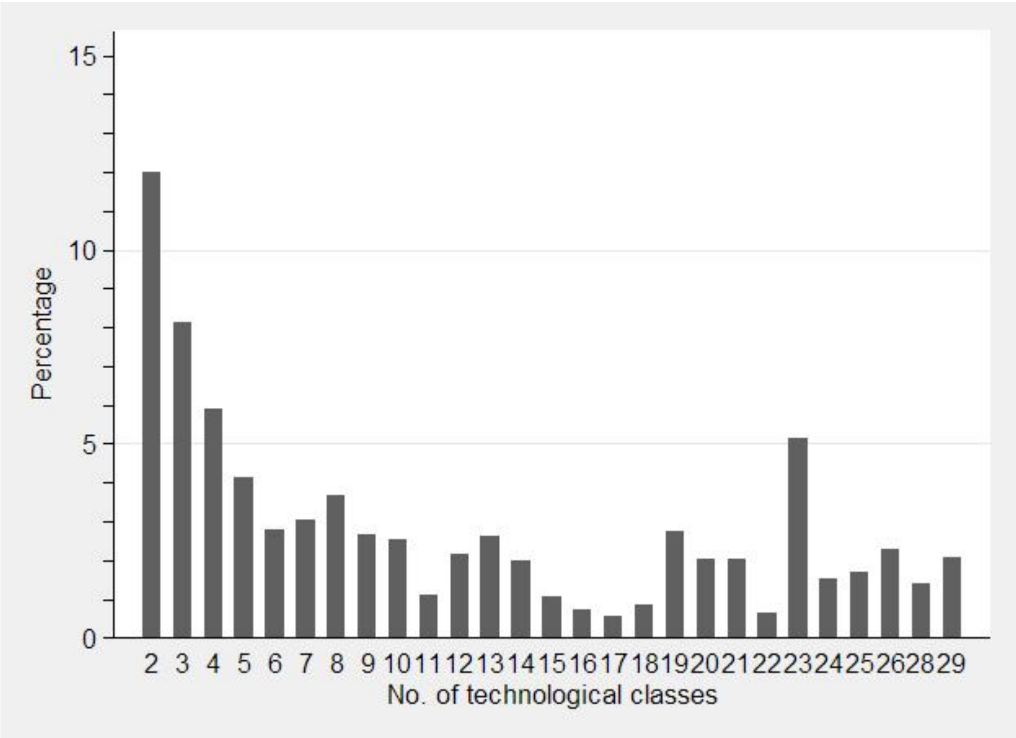
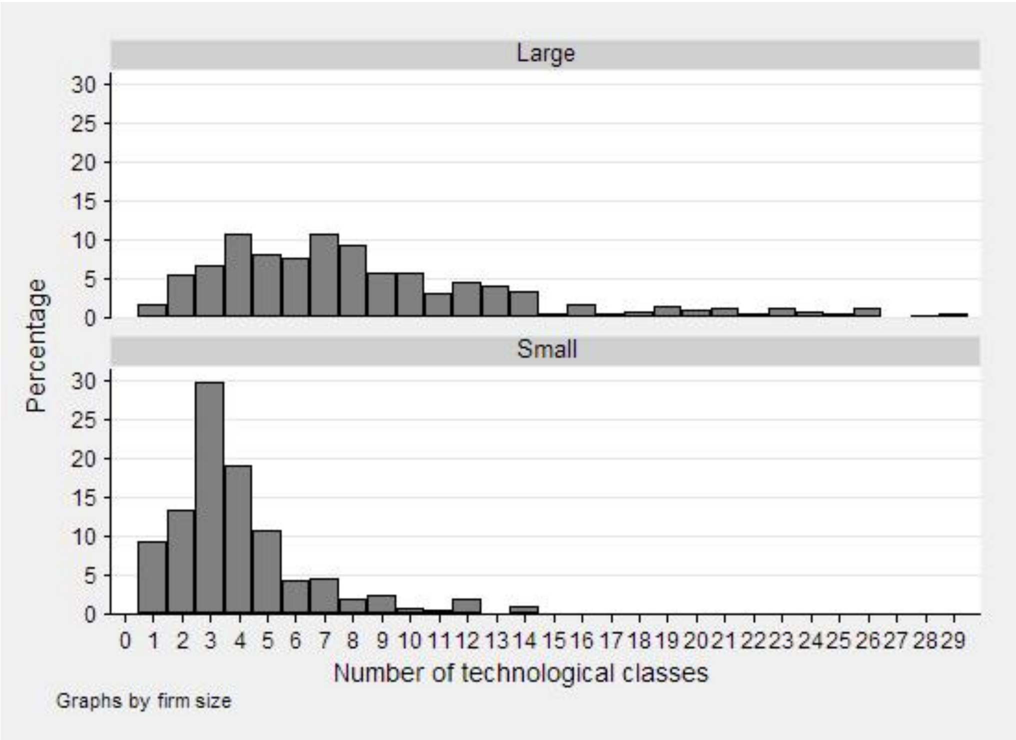


Figure 4.3 indicates that 50% of small companies operated in less than 4 sectors, while this threshold includes only 13% of large companies. At the same time, we observe the presence of a small number of companies much more diversified than the average in small as well as large companies, generating a highly positively skewed distribution in both size classes.

Table 4.1: Share of firms and patents: diversified and specialized, percentage values

	Companies			Patents		
	% Specialised	% Diversified	Total	% Specialised	% Diversified	Total
Large	2.75	97.25	100	0.004	0.996	100
Small	9.73	90.27	100	0.086	0.914	100

Figure 4.5: Distribution of small and large serial innovators across active technological classes



4.5 Model specification

In this Chapter, we model the technological diversification of serial innovators using a series of variables derived from our discussion in Section 5.2. In particular, the main explanatory variables include **opportunity conditions** (OPPORTR), which is modelled with a non-linear effect obtained adding its square $OPPORTR^2$, **coherence** in the core knowledge capabilities (COHERENCE) and **coherence in the backward citations** (ORIGIN_CO). Additionally, we also control for firms' **patent stock** (KSTOCK) and the **impact of innovation** (IMPIN). Finally, we include a set of dummy variables to control for companies' main technological class.

4.5.1 Dependent variable

To measure *technological diversification* (TECHDIV) we make use of an index which is based on a measure of technological proximity that has already been used in several empirical studies to estimate the effect of diversification on R&D intensity and innovation activity (Garcia-Vega, 2006; Leten et al., 2007; Garcia et al., 2008). It is calculated as the inverse of the Herfindahl index, confronting patents for each IPC technological class against the total number of patent of a given company for each year. We correct the index using the bias correction (i.e. N_{it} / N_{it} - 1) indicated by Hall (2005) to account for observations with few patents per year, the index is formally defined as follows:

$$TECHDIV_{it} = \frac{N_{it}}{N_{it}-1}\left(1-\sum_{k=1}^{K}\left(\frac{N_{it,k}}{N_{it}}\right)^2\right) \tag{4.1}$$

where N_{it} is the total number of patents for the *i*th company in year *t*, while *k* represents the IPC category where the firm patented and K is the total number of technological classes where the company was active. It follows that due to the nature of the formula of TECHDIV, observations where companies presented less than two patents per year had to be omitted from the analysis.

4.5.2 Independent variables

We test our first hypothesis about the relationship between opportunity conditions and technological diversification via *Opportunity conditions (OPPORTR)*, a variable measuring the increase in the innovative activity for a given amount of money or resources spent in search (Malerba and Orsenigo, 1993). In industrial sectors characterised by a fast pace of innovation, firms may try to diversify their technology portfolio in the attempt to keep up with new opportunities through processes of exploration and exploitation (Granstrand et al., 1997), as well as consolidation of their absorptive capacity. Accordingly, we expect a positive effect of OPPORTR on firms' technological diversification. However, in markets characterized by higher levels of opportunity conditions, the higher turbulence in innovation and the specialized nature of the technology may direct companies toward a specialization strategy. To account for this effect, we add the squared term $\mathrm{OPPORTR}^2$, which is expected to present a negative sign.
The index is calculated for each firm as the average value defined by the year-over-year percentage increase in the number of patents for each IPC sector where the firm patented, following the approach of Patel and Pavitt (1998) already discussed in Chapter 3.

The second hypothesis is about the coherence in the knowledge base that we test by the means of two proxies, namely core technological-coherence and level of coherence in the complementary knowledge and technologies used to develop new technologies. The first measure underpins from the literature on technological diversification indicating that firms’ technological competencies and the direction of technological search are constrained by accumulated core capabilities (Patel and Pavitt, 1997). Accordingly, technological diversification is not random, but follows a coherent pattern of technological activities (Teece et al., 1994; Breschi et al., 2003). Hence, we may expect high coherence in past innovative activities to limit the scope of technological diversification.

Following form this hypothesis, we define *core technological-coherence (COHERENCE)* as a measure of how diversified the company is within its technological trajectory. It is based on the concept of knowledge-relatedness suggested by Breschi et al. (2003), and indicates how similar new patents are with respect to firm core competencies developed through time. We proceed calculating the knowledge-relatedness matrix whose elements are given by the cosine index $S_{ij,}$ that measure the similarity between two technological classes *i* and *j* with respect to their relationship with all other IPC classes (For a detailed description, see Breschi et al., 2003). Formally, we have:

$$S_{ij} = \frac{\sum_{k=1}^{30} C_{ik} C_{jk}}{\sqrt{\sum_{k=1}^{30} C_{ik}^2} \sqrt{\sum_{k=1}^{30} C_{jk}^2}} \tag{4.2}$$

where $S_{i,j}$ represents the number of patents that have been classified in both sectors *i* and *j* using information on all UK patents between 1990 and 2006. This process generates a 30X30 square matrix M that can be used to measure knowledge-relatedness between patents in time *t* and firms' core technological class. For each company, the core technological class is defined as the one having the highest share of patents with respect to the total number of patents at the UK level in that class[61]. Hence, for every year *t* in which firms are technologically active, we use the matrix M to calculate an index D_{it} measuring the technological distance between the IPC sector of the patents for that given year and the core technological class of the company. Finally, the index $\mathrm{COHERENCE}_{it*}$ for the *i*th company in year $t*$ is calculated as the average value of all indices D_{it} up to time t^*.

[61] For a discussion on the knowledge-relatedness matrix and company's core technological class, see Breschi et al. (2003).

Similarly, another constraint on technological diversification is represented by the breadth of firms' technological search. Companies which are able to acquire information and absorb knowledge from technologies distant from their core competencies are more likely to develop innovations in a broader spectrum of technological classes. In other words, higher levels of coherence between backwards citations and the core technological class of companies are likely to reduce technological diversification in the innovation activity of small serial innovators (Nelson & Winter, 1982; Quintana-Garcia and Benavides-Velasco, 2008).

Consequently, *Origin Coherence* (ORIGIN_CO) indicates the level of coherence in the complementary knowledge and technologies that are used to develop new technologies. As for the previous variable COHERENCE, we make use of the cosine index S_{ij} proposed by Breschi et al. (2003) to study knowledge relatedness to calculate the technological distance between the IPC class of the patents cited for a given year and firms' core technological class. As before, the index ORIGIN_CO is the average of all values in the years before the present time *t*.

Our first control variable is *Knowledge stock (KSTOCK)*, which represents the accumulated stock of knowledge capabilities for the firms in the dataset, measured as the stock of patents accumulated by the company in previous periods of time[62]. This is calculated using the declining balance formula usually proposed in the literature, with the depreciation rate set at 15%[63] (Cockburn and Griliches, 1988, Hall et al., 2005). It is defined as follows:

$$KSTOCK_{it} = P_{it} + (1-\delta)KSTOCK_{it-1} \tag{4.3}$$

where P_{it} represent the number of patents of company *i* in year *t* and δ is the depreciation rate. As in the previous Chapter, we account for the effect of the missing initial condition collecting information on the number of patents for all

[62] Following Hall et al. (2005), we account for the effect of the missing initial condition collecting information on the number of patents for all companies in the study from 1985.

[63] As in Chapter 3, we calculated KSTOCK using different depreciation rates, that is, 5% and 20%. Our findings are robust to these different specifications.

companies in the study from 1985, while our regressions start from 1993, allowing for a lag of at least 8 years between the first year for which we have patent data and the first year analysed (See also Hall et al., 2005). To control for potential endogeneity we allow KSTOCK to enter the estimating equation with a lag after being log transformed.

It is well known that the variance in the value of patents can be quite widespread. To account for the different quality of the patents developed by companies, we introduce a variable representing the *impact of innovation (IMPIN)*, that is, a measure of the technological novelty added to the flow of new knowledge generated in a specific year and sector. Given the amount of resources necessary to develop high-quality patents, the technological diversification of small companies is likely to reduce after the development of such innovations. Also, patents with high impact provide incentives to continue in the same stream of research for future research.

To generate this variable, we again follow the procedure illustrated in Chapter 3 taking into account the substantial differences in citation rates across different technologies and over time. For this reason, we make use of the citation index proposed by Hicks and Hegde (2005), defined as the ratio of the citation count over the citation count of all patents in the same year and technological class. To account for potential endogeneity, the estimate for IMPIN is also lagged one period.

To control for differences at the industry level, we classify the companies in our sample according to four categories reflecting those proposed in Pavitt's taxonomy (Pavitt, 1984)[64]. They are the following. SCALINT is a dummy being equal to one for companies whose sector is characterized by scale-intensive activity. Similarly, SUPDOM refers to the category of supplier-dominated firms, SPESUP to the category of specialized suppliers and SCIBAS to science-based companies.

[64] For a classification of the sectors according to these groups see Appendix, Table 4.5.

4.6 Results

4.6.1 Summary statistics

In Table 4.2, we report the descriptive statistics for the main variables with respect to small serial innovators. Looking at the mean and median value of the index TECHDIV, we see that these companies are in fact technologically specialised, with the distribution of technological diversification slightly negatively skewed. Over the long period, though, small serial innovators seem to be active in a coherent and strongly related set of technological classes. With respect to this, we observe positively skewed distributions for both COHERENCE and ORIGIN_CO.

Table 4.2: Descriptive statistics

	MEAN	SD	Q50	MAX	MIN
TECHDIV	0.453	0.415	0.50	1	0
OPPORTR	2.441	1.592	2.24	7.62	-0.82
COHERENCE	0.885	0.131	0.92	1	0.29
ORIGIN_CO	0.669	0.180	0.67	1	0.12
KSTOCK	2.258	0.655	2.24	4.67	0.69
IMPIN	1.525	1.880	0.99	16.96	0

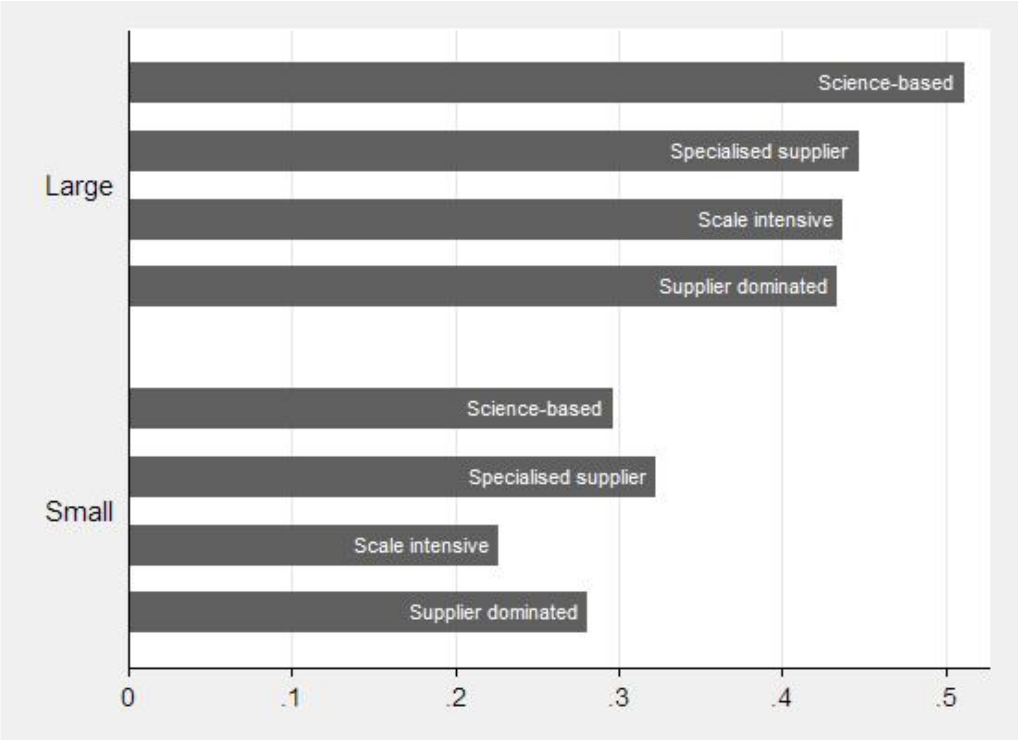
Table 4.3: Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)
TECHDIV	1					
OPPORTR	-0.066	1				
COHERENCE	-0.333	0.096	1			
ORIGIN_CO	-0.361	0.068	0.463	1		
KSTOCK	0.067	-0.080	-0.374	-0.085	1	
IMPIN	-0.049	-0.046	-0.084	-0.114	0.032	1

Initial evidence of the relationship between technological diversification and coherence in the knowledge-base is found in Table 4.3, which reports the correlation matrix for the main variables. As expected, this relationship appears to be negative. Also interesting and moderately strong are the correlation between COHERENCE and ORIGIN_CO, which is positive, and the one between COHERENCE and KSTOCK, which is negative.

Finally, Figure 4.4 shows the technological diversification of serial innovators across four sectoral classes resembling those proposed by Pavitt (1984). The Figure shows that the higher propensity of large firms to diversify with respect to small ones. More interestingly, it shows that there are important differences in the distribution across sectors: large firms in science-based sectors present the highest level of technological diversification, followed by those in scale-intensive industries. The level for supplier dominated is quite lower. Small serial innovators diversify more when they are specialised suppliers, while those in science-based sectors seem to be more focused. As we would expect, in this group the least diversified companies are those operating in scale-intensive sectors.

Figure 4.5: Distribution of technological diversification for small and large serial innovators across sectoral classes reflecting Pavitt's taxonomy



4.6.2 Econometric analysis

In our analysis, the dependent variable y is represented by a measure of technological diversification whose values fall within the open bounded interval I = (0, 1). Such data does not follow a normal distribution. Moreover, its bounded nature (between 0 and 1) may lead to predicted values from a standard OLS regression that could lie outside the unit interval. As Papke and Wooldridge point out (1996), the alternative to model the log-odds ratio as a linear function is also inappropriate as it cannot handle those cases where the dependent variable equals the interval boundaries zero and one. At the same time, adjusting extreme values when these account for a large percentage in the data is also difficult to justify. To account for these issues, we make use of the fractional response model suggested by Papke and Wooldridge (1996), applying quasi-maximum likelihood estimation (QMLE) to obtain robust estimators of the conditional mean parameters (Papke and Wooldridge, 1996; Wooldridge, 2002). To account for heteroskedasticity and serial correlation in the standard errors within the panel dataset, we specify a generalised estimating equation (GEE) model (Liang and Zeger, 1986) with a binomial distribution and robust standard errors. The estimates for the model are reported as odds-ratios in Table 4.4. Odds ratios represent a measure of association between a covariate and an outcome, where the odds that an outcome will occur given a specific value for the covariate are compared to the odds of the outcome taking place in the absence of that exposure. As for incidence rate ratios presented in Chapter 3, odds ratios allow for a more straightforward interpretation of the effect of the covariates in non-linear models, especially in the presence of interaction variables[65].

To study the relationship between technological opportunities and diversification, as outlined in *Hypothesis 1*, we start our analysis adding only a linear variable for the role of opportunity conditions, along with the other two main variables of interest, that is, COHERENCE and ORIGIN_CO. However, the effect of opportunity conditions is found to be not significant when it is considered only as a linear predictor. In model (2), reported in the second

[65] For a broader discussion, see Chapter 3 and Section 2.5.3.

column of table 4, we add the quadratic term $OPPORTR^2$ to account for non-linearity in the relationship between technological diversification and opportunity conditions, as proposed in the research hypotheses. In this case, both linear and quadratic terms for opportunity conditions are statistically significant at the .001 level, indicating that Model (2) fits the data better. These results are robust to all different model specifications in Table 4.4.

With respect to our first hypothesis, hence, our findings seem to suggest the presence of an inverted-U relationship with technological diversification. As we expected, companies patenting in sectors characterized by an increasing level of innovation tend to move in a larger number of technological sectors. In line with previous research on technological diversification, it is possible to argue that companies operating in increasingly dynamic industries may expand their technological domain in response to new and promising avenues of research within the technological environment.

However, the negative sign for $OPPORTR^2$ indicates that when opportunities increase even further, companies are more likely to focus on a more specific set of technologies. This inverted-U relationship seems to suggest a relevant role of the risk involved in innovation in shaping technological diversification among small serial innovators, for as turbulence in sectoral activity increases these companies tend to follow strategies of specialization. At the same time, if we observe higher technological opportunities as related to a faster pace of technological advance, our findings suggest that the novelty and the complexity of the innovations developed in such context require the development of specific – and resource intensive - technological competencies that may prevent small companies from diversifying.

These observations are also supported by the differences in the relationship between technological opportunities and diversification across firm size. These can be seen in Model (5), the last column of Table 4, where all serial innovators are considered, with large companies constituting the base group. Given that we are observing odds-ratios in Table 4, it is immediate to see that small companies are likely to present lower levels of technological

Table 4.4: GEE estimates of technological diversification for serial innovators

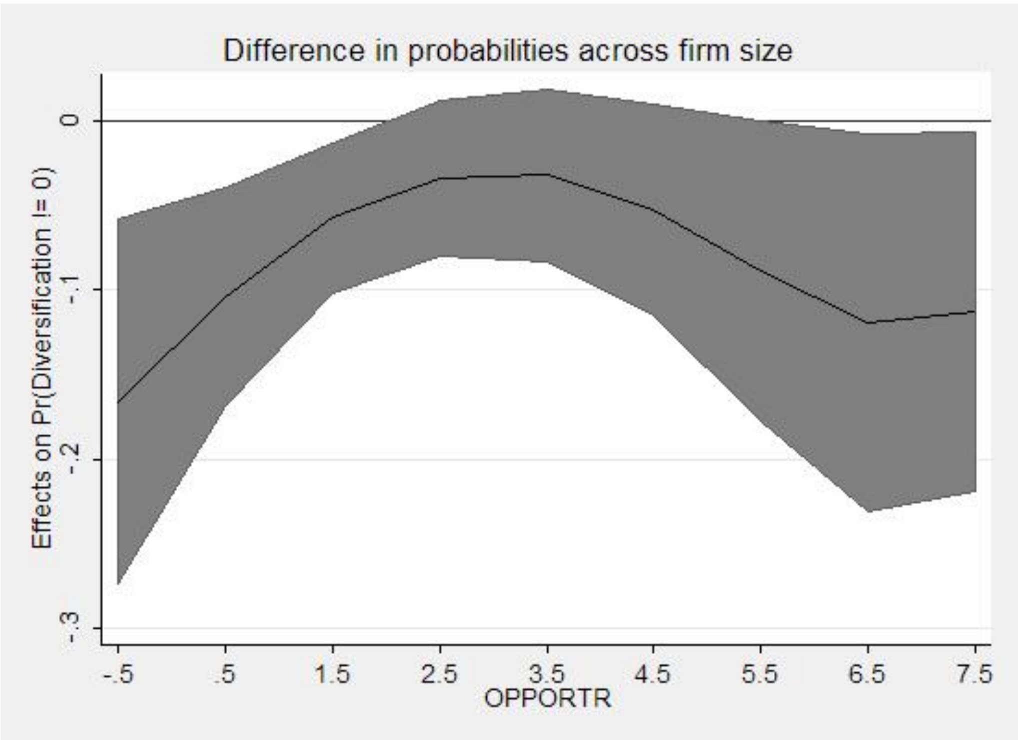
	SMALL FIRMS				ALL FIRMS
	(1)	(2)	(3)	(4)	(5)
OPPORTR	0.948	1.834***	1.855***	1.928***	1.351***
	(0.039)	(0.206)	(0.229)	(0.249)	(0.106)
OPPORTR^2		0.891***	0.888***	0.885***	0.932***
		(0.016)	(0.0177)	(0.0181)	(0.0120)
COHERENCE	0.346*	0.377*	0.146**	0.136**	0.135***
	(0.171)	(0.183)	(0.0885)	(0.0835)	(0.0325)
ORIGIN_CO	0.067***	0.058***	0.0529***	0.0553***	0.0772***
	(0.023)	(0.021)	(0.0230)	(0.0253)	(0.0219)
KSTOCK			1.010	1.014	0.952
			(0.0821)	(0.0831)	(0.0317)
IMPIN			0.927**	0.926**	0.945***
			(0.0260)	(0.0265)	(0.0143)
SMALL					0.553**
					(0.107)
SMALL_OPPORTR					1.342*
					(0.185)
SMALL_OPPORTR^2					0.954*
					(0.0219)
SPESUP				1.386	0.905
				(0.292)	(0.0872)
SCALINT				0.829	0.798*
				(0.169)	(0.0775)
SUPDOM				1.801*	1.003
				(0.537)	(0.133)
N	1275	1275	1007	1007	3656
χ^2	(16)	(17)	(19)	(22)	(25)
	102***	121***	128**	138***	486***

All regressions include year dummies
S.E. in parentheses
+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001

diversification, ceteris paribus. We also see that the variables for both the linear and the quadratic term OPPORTR and OPPORTR2 suggest a similar inverted U curve for large as well as for small serial innovators. More interestingly, though, the odds-ratios for the second group indicate that this inverted U relationship is more pronounced for small serial innovators. This is shown in Figure 4.5, which presents the difference in the predicted probabilities across firm size for different values of opportunity conditions. This finding supports the idea that small companies may be more likely to engage in a broader set of technological directions as opportunities for innovation increase from lower values, but they may have to rely on strategies of specialization once the technological environment becomes more turbulent.

Considering our second hypothesis that coherence in the knowledge-base and in technological search is negatively related to the degree of technological diversification, we can see that both COHERENCE and ORIGIN_CO exert a negative effect on diversification, with estimates statistically significant at the .01 level across the different regressions reported in Table 4.4.

Figure 4.5: Predicted probabilities across firm size for different values of opportunity conditions



This result confirms the relevance of technological trajectories in defining the direction of technological search within firms' innovative activity (Dosi, 1982). In fact, odds-ratios for COHERENCE are quite below 1, in line with the findings of previous empirical studies that point out the path-dependent and stable nature of technological competence within innovative companies (Granstrand et al., 1997; Patel and Pavitt, 1997; Cantwell and Fai, 1999). Given the limited amount of R&D resources available to small firms, it is not surprising that a highly coherent knowledge base presents such a strong negative relationship with technological diversification.

Coherence in backward citations is likewise negatively related with TECHDIV. Estimates for ORIGIN_CO present a negative sign and odds-ratios below 1, which are statistically significant across all regressions. It is clear that the role played by core competencies and the cumulative nature of technological learning influence not just the outcome of the innovation process; they also influence how firms search for new products. Coherence in backwards citations may also be linked to the importance of external sources of knowledge. Companies that tend to look for new ideas and inspiration in technological fields which are akin to their technological trajectory are more likely to develop specialized competencies. In this sense, it is possible to find a resemblance with the ideas of exploration and exploitation (March, 1991). As Katila and Ahuja (2002) point out, exploration is important when companies need to find new avenues of research and it is key in the search for completely new solutions. Yet, exploitation can also lead to new knowledge creation, supporting the creation of new combinations through the recombination of acquired competencies. This process might be particularly important for companies operating with rapidly changing technologies, where the sources of innovation are scarce and likely to be quite specific.

Model (3), reported in the third column of Table 4.4, includes also the other control variables for the knowledge stock, proxied by the stock of patents, and the impact of the patents. With respect to the quality of patents, an increase in the variable IMPIN seems to bring small companies towards technological specialization. It is possible that companies with a promising and valuable technology may decide to focus their resources in the same technology area in order to maximise complementarities across their competencies and their research effort. In this sense, another possible reason for this finding is that companies working on high-value patents may need to dedicate a larger amount of resources to their development, in terms of both time and research capabilities. This, in turn, provides further incentives to follow strategies of specialization. Albeit positive, the coefficient we found for KSTOCK is not statistically significant.

With respect to differences across industrial sectors, the lack of significant differences for many of the dummies reported in columns (4) and (5) of Table 4.4 deserves careful consideration[66]. While we might expect more variation in the degree of technological diversification across the sectoral breakdown, we need to consider the peculiar nature of the companies considered, which are characterised by definition by high levels of innovation over time. As pointed out by previous literature, there is a strong correlation between persistent innovation and technological diversification (Breschi et al., 2003), so that once we account for the two main determinants of technological diversification, that is, opportunity conditions and cumulativeness in the knowledge base, sectoral differences as those usually observed in innovation rates may be less strong when looking at the degree of technological diversification.

With respect to small serial innovators, explored in column (4) using SCIBAS as base group, the only dummy statistically significant is the one related to companies operating in supplier dominated industries (SUPDOM). While companies in such sectors are usually found to have low levels of internal innovative activity (Pavitt, 1984), we need to consider that we are looking at the most innovative members of this sector. As such, it is possible that these companies may operate as problem solvers for their suppliers. Benefiting from a lower sectoral technological intensity, these companies may develop a broader technological base – ceteris paribus - in order to offer solutions to problems across the board. In column (5), where also large serial innovators are considered, we find a negative coefficient for scale intensive firms (SCALINT), which seems to indicate that the economies of scale that

[66] Single sector dummies present similar results.

characterise the activity of such firms may increase the likelihood of a more specialised innovation activity, ceteris paribus.

4.7 Conclusions

In this Chapter, we have explored the degree of technological diversification of serial innovators focusing on the role exerted by technological trajectories, expressed in terms of coherence in the knowledge base and breadth of technological exploration. Our results show that technological diversification is not a quality unique to large companies. Although to a lesser extent, the small companies observed in this study are indeed diversified.

Using patent data from the PATSTAT database, we have explored patterns of technological diversification across all UK-based companies with at least one patent application for the period between 1990 and 2006. Hence, we have analysed potential determinants of diversification for a panel data set comprising information on 811 large and small UK-based companies characterised by sustained record of innovation activities over time, defined serial innovators. We find that increasing technological opportunities present an inverted U relationship with technological diversification, and that such relationship is more pronounced for small companies. As hypothesised, the need to explore and exploit new opportunities pushes companies to develop capabilities in an increasing range of technological domains. However, when the pace of technological advance becomes even faster, these are more likely to pursue strategies of technological specialization, suggesting a negative relationship between innovation turbulence and technological diversification.

Conversely, a negative effect is exerted by coherence in the knowledge-base. The spectrum of technological diversification as well as the future direction of the technological trajectory for small serial innovators is heavily dependent and constrained by accumulated competencies gathered around firms' core capabilities. Likewise, when technological search is bounded around these core capabilities, diversification is likely to reduce. Similar dynamics are activated by research projects that bring to life high-impact innovations, which may ask for deeper specialization in research, in the form of cumulative technological capabilities, thus creating incentives to further operate along the same technological trajectory.

These findings are in line with previous studies indicating that technological diversification may have a stronger effect on exploratory rather than exploitative innovation capabilities (Quintana-Garcia and Benavides-Velasco, 2008), and while diversification is important in the discovery process, innovative firms benefit from a strong coherence in their internal competencies to gain their competitive advantage (Nesta and Saviotti, 2005).

Analysing the innovative activity of serial innovators, characterized by a sustained record of innovations over time, this Chapter shows that these companies tend to follow strategies of technological specialization based on the cumulativeness in their core competencies and capabilities. However, a broader diversification is pursued in the presence of increasing opportunity conditions, until these become pervasive. Our results support the notion that firms are coherent in their processes of exploration and exploitation of knowledge, but they also point to the need of more research regarding the specific dynamics that shape internal combinative capabilities, in the form of dynamic economies of scale in innovation and dynamic capabilities among serial innovators, and the role that is played by the specific pattern of the relevant technological regime.

Appendix

Table 4.5: Technology classification based on IPC

1	Electrical engineering	SS
2	Audiovisual technology	SB
3	Telecommunications	SB
4	Information technology	SB
5	Semiconductors	SB
6	Optics	SB
7	Technologies for Control/Measures/Analysis	SB
8	Medical engineering	SB
9	Nuclear technology	SI
10	Organic chemistry	SB
11	Macromolecular chemistry	SB
12	Basic chemistry	SB
13	Surface technology	SI
14	Materials; Metallurgy	SI
15	Biotechnologies	SB
16	Pharmaceuticals; Cosmetics	SB
17	Agricultural and food products	SD
18	Mechanical engineering (excl. Transport)	SS
19	Handling; Printing	SI
20	Agricultural and food apparatuses	SS
21	Materials processing	SI
22	Environmental technologies	SS
23	Machine tools	SS
24	Engines; Pumps; Turbines	SI
25	Thermal processes	SB
26	Mechanical elements	SS
27	Transport technology	SS
28	Space technology; Weapons	SI
29	Consumer goods	SD
30	Civil engineering	SI

CHAPTER 5

Persistent innovation in small and large companies: evidence from the UK Innovation Survey

"Sure I am of this, that you have only to endure to conquer."

- Winston Churchill

Abstract

In this Chapter, we examine whether there is persistent innovation among small and large companies and the role this phenomenon plays as a source of innovation with respect to different levels of R&D intensity. In particular, we use a panel dataset obtained from three successive rounds of the UK Community Innovation Survey to study whether there is persistence in innovation controlling for unobserved firm heterogeneity. We also explicitly account for possible interaction effects between different aspects of innovation persistence, in the form of dynamic increasing returns within the process of knowledge accumulation, and the level of technological complexity. Our findings provide evidence of persistence in product innovations new to the market for both small and large companies, and confirm the presence of an important relationship between dynamic increasing returns in innovation and R&D intensity, at least among small companies.

5.1 Introduction

In the literature on the patterns of innovative activity, the idea that companies may have a higher probability of innovating if they already innovated before represents an important element in explaining industry dynamics and firm-specific technical change (Cefis, 2003). This phenomenon, usually associated with Schumpeterian patterns of creative accumulation (Schupeter, 1942; Malerba et al., 1997), is referred to as persistent innovation.

Previous empirical research has addressed the question whether there is persistence in innovative activities (Geroski et al., 1997; Peters, 2009; Raymond et al., 2010). However, very few studies have tried to investigate the presence of such phenomenon within small companies[67]. Most surprisingly, no prior investigation has tried to study the relationship that it is likely to take place between the effect of persistent innovation, in the form of dynamic increasing returns in innovation defined by learning by doing and learning to learn processes in the accumulation of knowledge, and the level of R&D intensity in companies' innovation activity.

In the literature, the presence of persistence of innovation has been explained in terms of the cumulative nature of knowledge as well as sustained R&D efforts and the sunk costs of research and development (R&D) associated with the technological complexity within firms' research activity (Nelson and Winter, 1982; Cohen and Klepper, 1996; Sutton, 1991). As both elements generate relevant barriers to entry to new innovators, the resulting dynamics have been suggested to lead to a concentration of innovative activity and a higher stability in the rank of innovators, eventually supporting a stable oligopoly of few large companies operating within patterns of 'creative accumulation' (Schumpeter, 1942; Malerba et al., 1997). Accordingly, empirical studies at the industry level have indicated persistence of innovation to be industry or technology specific, with a significant heterogeneity across sectors, while small firms have been usually associated with patterns of 'creative destruction' (Malerba and Orsenigo, 1999; Cefis and Orsenigo, 2001).

[67] See Chapter 3.

Studies at the firm level have placed the attention upon technologic and organizational learning in the process of knowledge creation within the firm. As successful innovation activity offers the foundation upon which future technological competencies develop, the presence of persistent innovation has been regarded as providing evidence of the cumulative nature of technological capabilities at the centre of the patterns of technological change (Cefis, 2003; Peters, 2009; Clausen and Pohjola, 2013). In this perspective, A positive outcome from this process of knowledge accumulation would thus imply an "underlying ability of firms/economies to absorb and then productively use knowledge" (Geroski et al., 1997: 45). In this strand of research, however, persistence has been investigated as a homogeneous phenomenon, with little attention towards firm size or the relationship between persistence and the level of R&D intensity within firms' innovation activity. Yet, this relationship constitutes an important element in the analysis of persistent innovation, as we may expect dynamic increasing returns resulting from accumulated knowledge to exert a different effect on innovation for higher levels of technological complexity and R&D intensity. In particular, we argue this interaction might be especially relevant among small companies, as they usually have more constrains in terms of R&D capabilities.

In this Chapter, we endeavour to test two hypotheses. First, we provide novel empirical evidence of the presence of persistence in innovation among small innovative companies using data at the firm level, explicitly accounting for unobserved firm heterogeneity, so that innovation output in a given period of time may act as innovation input in subsequent periods. In other words, we investigate the presence of true state dependence in persistent innovation, that is, the presence of a direct causal relationship between the introduction of a product innovation in one period and the probability of innovating in the following, as opposed to spurious state dependence, where this effect cannot be separated from other unobserved characteristics correlated over time which may increase the likelihood of innovating for some companies (Peters, 2009). The second hypothesis expands the first point to investigate interactions among dynamic increasing returns in the accumulation of knowledge generated by persistent innovation and the technological complexity within firms' innovation activity, as reflected by R&D intensity.

To test our hypotheses, we use the evidence on innovation persistence contained in the UK Community Innovation Survey (CIS). In particular, we resort to a balanced panel dataset of around 4000 UK companies present in the three waves of the UK CIS covering the period 2002 - 2008. We then use a dynamic random effects probit model initially proposed by Wooldridge (2005), which has been extensively used in the recent studies on persistent innovation (Peters, 2009; Raymond et al., 2010; Clausen et al., 2011). This approach explicitly accounts for structural differences among companies while controlling for unobserved firm heterogeneity, allowing us to investigate the hypothesis of true state dependence.The remainder of the Chapter is organised as follows. Section 5.2 summarises the main theoretical contributions of the literature on the persistence of innovation and specifies the research questions for this Chapter. The data employed are described in section 5.3, along with some preliminary descriptive statistics. In section 5.4 we present the methodology and the estimating model, followed by the discussion of the results in section 5.5. Section 5.6 concludes with some final remarks.

5.2 Literature review

In the literature, several explanations have been proposed to describe why persistence of innovation may occur within companies. A first perspective underlines the central role of organizational features at the firm level and, in particular, the traditional relationship between firms' R&D expenditure and their innovations[68]. First, as companies are able to support the sunk costs inherent to R&D activity, continuity in R&D expenditure may generate a stable stream of innovation over time (Geroski et al., 1997; Duguet and Monjon, 2004). In other words, innovation persistence may simply derive from sustained R&D efforts. A strategy consideration has also been proposed in relation to sunk costs in R&D, as these cannot be easily recouped if such activity is interrupted. These may include, for example, the set-up of

[68] See Mairesse and Mohnen (2005) for an empirical investigation using CIS data.

laboratories for research as well as specialized personnel. Hence, while these costs constitute a barrier to entry in innovation, they contemporaneously provide incentives not to interrupt R&D activity even in presence of occasional failures (Sutton, 1991).

A second perspective has placed at the centre of the analysis the specific qualities of technological capabilities and knowledge dynamics (Nelson and Winter, 1982; Malerba et al., 1997). According to this strand of research, persistent innovation may derive from the presence of dynamic increasing returns in innovation, defined by the presence of dynamic learning economies, such as learning by doing and learning to learn effects in innovation (Rosenberg, 1976; Klevorick et al., 1995). This hypothesis refers to a common concept in evolutionary economics theory indicating learning and knowledge capabilities as the central determinants of the innovation activity within companies. These, in turn, present a cumulative nature and follow a path dependent trajectory (Nelson and Winter, 1982; Dosi, 1988). In other words, cumulativeness depicts the idea that history matters in innovation and what constituted innovation output in a given period of time becomes an input in following innovation activities. Similarly, Teece et al. (1997) indicate that firms need to possess dynamic capabilities in order to successfully innovate in turbulent and competitive markets. Dynamic capabilities emphasize the nature of the learning process and define how companies learn, or the 'patterned' activity through which they build new competencies over prior accumulated knowledge (Winter, 2003).

Empirical evidence for this perspective has been offered by previous literature testing the hypothesis of true state dependence in innovation new to the market or new to the firm (Peters, 2009; Raymond et al., 2010). Clausen and Pohjola (2013) have also provided additional findings looking separately at both types of innovation.

However, these elements offer contrasting predictions when we take into consideration the role of firm size. The presence of consistent sunk costs in R&D and the resulting barriers to entry in innovation seem to favour persistence across large companies, as R&D efforts vary proportionally with firm size, and these costs can be spread across a greater level of output (Cohen and Klepper, 1996). For opposite reasons, they do not support the hypothesis that there may be persistence across small companies. Conversely, we might expect the cumulative nature of learning to exert a positive effect potentially on both small and large companies. Yet, economic theory has paid little attention to the presence of persistent innovation in small companies as the elements of R&D capabilities and technological cumulativeness have usually been modelled as connected and interdependent aspects of same process in the evolution of industry dynamics. Persistence in innovation is often identified as an intrinsic characteristic of a technological environment where companies seem to benefit from accumulated competencies in terms of both R&D intensity and technological learning that allow them to develop innovations building on their previous accumulated capabilities. Thus, both elements contribute to shape industries characterised by 'routinised regimes' defined by low turbulence in innovation, a cumulative nature of innovative competencies and high stability in the rank of innovators[69] (Winter, 1984; Malerba et al., 1997).

Several scholars have provided empirical evidence for this framework. According to this strand of research, major differences are present across different technologies and industries (Malerba and Orsenigo, 1996). Moreover, such heterogeneity seems to be invariant across countries (Cefis and Orsenigo, 2001). Thus, companies are persistent in their state, that is, companies which start as occasional innovators are unlikely to become persistent innovators and vice-versa.

With respect to firm size, however, the evidence is less clear. Descriptive analyses point towards a positive relationship with respect to persistence, but such relationship is complex and certainly not linear, with cases of large companies presenting occasional innovation patterns and small firms innovating persistently (Geroski et al., 1997; Cefis and Orsenigo, 2001). Duguet and Monjon (2004) explore with more attention the role of firm size suggesting that persistence may be caused by different elements depending on the size of companies. In line with the linear model of innovation, they provide

[69] Strategic incentives to sustained innovative activity have also been discussed with respect to the role exerted by market structure. See, for example, Gilbert and& Newberry (1982) and Reinganum (1983).

evidence that while the role of formal R&D activity is the major determinant of persistence for large companies, small companies mostly benefit from dynamic increasing returns in innovation, in the form of learning by doing and learning to learn effects, generated by previous innovative activity. However, they do not account for unobserved firm heterogeneity.

5.2.1 Hypotheses

In this Chapter, we put forward a possible interpretation for these findings that is centred on the distinction between the effects exerted by the two main determinants of persistent innovation, namely (i) dynamic increasing returns in the process of knowledge accumulation and (ii) R&D intensity related to the technological complexity within firms' innovation activity.

Dynamic increasing returns generated by processes of learning by doing and learning to learn have usually been investigated through the hypothesis of true state dependence in innovation, which expresses the idea that the introduction of a product innovation in one period of time increases the likelihood of further innovation in the following period, controlling for unobserved characteristics correlated over time which may sustain innovation activity across some companies. As we have discussed, previous research has addressed this question, yet treating innovation and imitation as a homogeneous group (See Peters, 2009; Raymond et al., 2010; Clausen and Pohjola, 2013)[70]. Also, it has not focused on persistence among small companies. Our first hypothesis extends this approach looking for true state dependence in product innovation new to the world across both small and large companies.

Hypothesis 1. Previous innovative activity has a positive effect on the likelihood of introducing product innovations new to the market among both small and large companies.

[70] Clausen and Pohjola (2013) represent an exception, as they investigate separately persistence in innovation new to the market or new to the firm.

At the same time, we would also expect persistent innovation to take place where investment in formal R&D capabilities and the associated sunk costs in R&D play an important role, as it is usually the case in the presence of R&D intensive technologies. Accordingly, Raymond et al. (2010) use a dynamic type 2 Tobit model offering evidence of persistence in high-technology industries, while no evidence was found in low-technology sectors. To explain this finding, they suggest that operating near the technological frontier might generate competitive pressure for companies to engage in sustained innovation activity over time. Following a different approach based on the strategy level, Clausen et al. (2011) provide empirical evidence that differences in innovation strategies may play an important role as sources of innovation persistence, with R&D intensive companies presenting the highest probabilities of innovation.

In line with the literature presented in the previous Section, dynamic increasing returns in the process of knowledge accumulation should be stronger in the presence of R&D intensive technologies. However, for companies that attain persistence in innovation relying mostly on their formal R&D capacity, as it is often the case for large firms, we might expect no interaction effect taking place for increasing levels of R&D intensity. As Duguet and Monjon (2004) point out, the different generations of innovation over time are not necessarily connected directly in the so-called linear model of innovation, as the only linkage between them is constituted by the continuity in R&D expenditure. Instead, dynamic increasing returns in the process of knowledge accumulation, defined by learning by doing and learning to learn effect, may be central for small innovators operating with R&D intensive technologies, due to their limited R&D resources (Cohen and Klepper, 1996). As long as small firms are able to exploit their internal knowledge capabilities, these effects might offset the diminishing returns associated with high R&D intensity. Hence, we state the following hypotheses:

Hypothesis 2. Increasing R&D intensity has a positive effect on the probability of introducing product innovations new to the market among large companies.

Hypothesis 3. Dynamic increasing returns associated with previous innovative activity offset the diminishing returns associated with high R&D intensity among small companies.

5.3 Data

In this study, we make use of a panel data set based on three successive rounds of the UK Community Innovation Survey (henceforth CIS)[71] covering the period between the year 2002 up to year 2008[72]. The CIS is a postal survey with a target population defined by all UK enterprises with at least 10 employees operating in sections C-K of the Standard Industrial Classification (SIC) 2003. As such, it covers both manufacturing and service industries.

The CIS survey contains information on a number of company and market characteristics and whether the company has introduced any product innovation in for each wave of the survey. For the innovative companies it reports the sources of information acquisition, R&D expenditure for innovation activities as well as the degree of novelty of the final product. In particular, it contains information on whether the innovator introduced '*a new good or service to the market before ... [the] competitors'* (see CIS6 questionnaire, question 9.a.). However, the survey also presents a set of well-known drawbacks which are related to the way the questionnaire is designed, that limit our analysis. In particular, many indicators are qualitative in nature and are available only for innovative companies. Also, the CIS offers a limited coverage of companies' finances and investments[73].

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[71] The UKIS is part of the Community Innovation Survey (CIS) and follows the guidelines for innovation surveys indicated in the Oslo Manual (OECD, 2005).

[72] Similarly to patent data, the use of innovation surveys presents a series of specific limitations. For a broad overview, see Chapter 2. In particular, with respect to the issue of an overlapping year between consecutive waves of the UK Innovation Survey, we follow Raymond et al. (2010) who suggest the bias to be quite limited, and proceed with the panel presented aware of this potential limitation. Additionally, we have conducted a robustness analysis of our findings using CIS data for Spain, where there is no overlapping year across the different waves of the survey. Using the same methodology, we find similar results suggesting that this bias may indeed be limited.

[73] For a broader discussion about strengths and weaknesses of the CIS, see Sections 2.3.2 and 2.4.2.

With respect to sample size, all three surveys considered follow a stratified random sampling procedure and have a response rate of approximately 50%[74]. Each survey provides information on over 25000 companies. However, not all companies surveyed in a given year are present in successive rounds of the survey, reducing significantly the size of the panel available. In particular, the three rounds considered in this Chapter offer a balanced panel[75] comprising information for over 4000 firms[76]. Within this sample, we use the threshold of 250 employees to distinguish between large and small companies[77]. Thus, about 25% (1012) of the companies within the dataset are large, while about 75% (2012) are small companies (<250 employees). With respect to industrial sector, 34% of large companies are in manufacturing, while the percentage goes up to 44% for small companies. Table 5.1 reports the sectoral classification of the companies present in the panel, along with the percentage of large and small companies present in each section.

Table 5.1. Distribution of firms across sectors (%)

SIC code	Large	Small
Production		
10-14	<1%	<1%
15-22	9.06	10.53
23-29	7.84	14.4
30-33	4.05	4.53
34-35	3.53	1.79
36-37	1.86	3.02
40-41	<1%	<1%
45	5.68	8.64
Services		
50-51	10.66	9.87
52	9.09	6.76
55	6.52	5.04
60-64	6.9	10.3
65-67	2.63	3.43
70-74	30.57	20.05

[74] For more information, see http://www.bis.gov.uk/policies/science/science-innovation-analysis/cis

[75] The balanced panel is required by the estimating technique adopted in this study. See Wooldridge (2005).

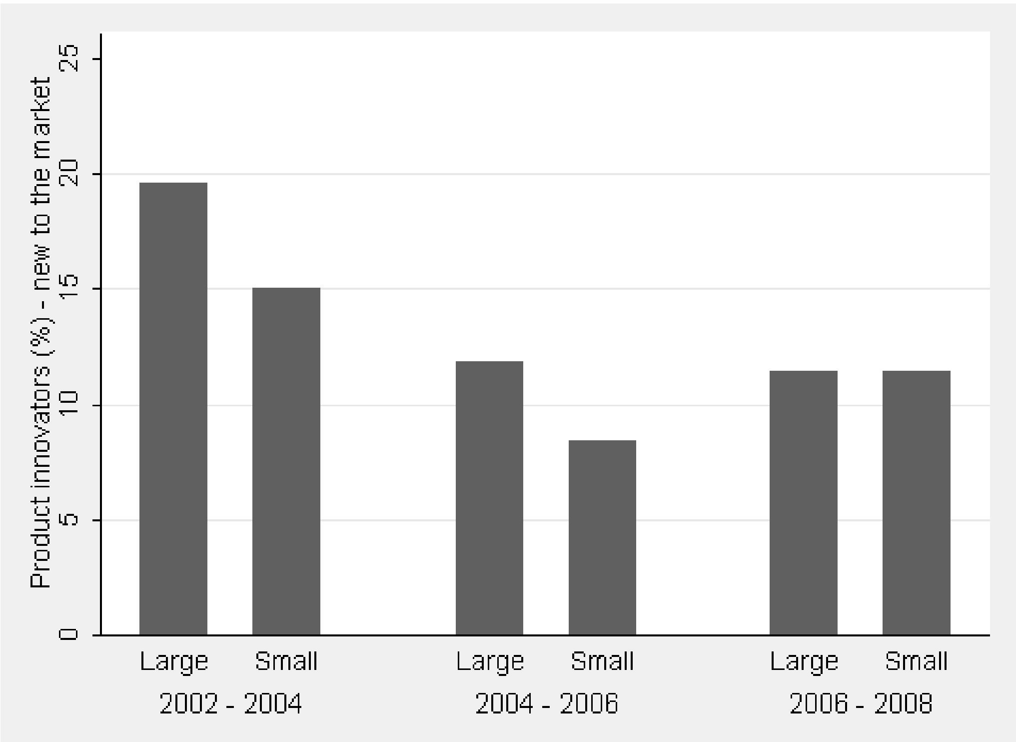
[76] See Office for National Statistics, 2011.

[77] As indicated in Chapter 2, the definition of SMEs follows the European Commission Recommendation (96/280/EC) of 3 April 1996, where SMEs are defined by the upper threshold of 250 employees.

5.3.1 Descriptive statistics

In Figure 5.1, we report the percentage of companies which introduced a product innovation new to the market in the three CIS surveys considered across firm size. Overall, we observe that almost 20% of large companies introduced goods or services new to the business and the market between 2002 and 2004, while the proportion goes down to 15% for small companies. Such percentage lowers slightly in the following period between 2004 and 2006, where around 13% of large companies and 8% of small companies respectively innovated according to this definition. In the last round of the CIS comprised between the years 2006 to 2008, there are not substantial differences across firm size with respect to product innovations new to the business, with both groups having around 12% of innovative companies.

Figure 5.1: Percentage of companies introducing products new to the market by firm size



An introductory overview on persistence in innovation can be offered by transition probability matrices, which show the transition frequency from a given state to another or, more specifically to this analysis, the percentage change in the innovative status of companies. In Table 5.2 we can observe two transition probability matrices which refer to the percentage change occurring between the first two rounds of the CIS, and the change in the last two rounds, for both manufacturing and services sectors. In each matrix, the first row is calculated on large companies, while the second on small and medium companies. Similarly, for each section, the first percentage represents the number of companies not introducing product innovations new to the market in the first wave considered (reported on the left side) nor in the second (reported on the top side). Hence, the second percentage represents the number of companies not innovating in the first wave of the CIS but innovating in the second. Similarly, the second row of each section reports the percentage of companies innovating in the first wave but not in the second, while the last value is the percentage of those companies innovating in both periods of time. It follows that on the diagonal of each cell it is reported the number and percentage of companies which did not change innovative state. For example, 92.63% of large manufacturing companies which did not innovate in the first wave did not change their status to innovative companies in the following period. Similarly, the 52.73% in the same size group innovated in the second time period, having already innovated in the first. As observed by Cefis and Orsenigo (2001), companies are indeed persistent in their state. Non-innovating companies, in particular, are unlikely to become innovators in the following period of time. Interestingly, the percentage of companies that did not innovate in the first period and innovated in the second is much smaller than the percentage of those which stopped innovating in the second period, suggesting that the majority of innovators are indeed occasional. With respect to firm size, finally, we notice a similar pattern emerging from the transitional probabilities matrix, with percentage values quite close except for a slightly higher presence of persistent innovators within large companies. Similarities are also present across manufacturing and services industries, although persistence in innovation seems to be stronger among the first group.

Table 5.2: Transition probabilities for persistence of innovation

Manufacturing industries								
	Period 1 (2002 - 2004 / 2004 - 2006)				Period 2 (2004 - 2006 / 2006 - 2008)			
Large			Wave 2				Wave 3	
			No	Yes			No	Yes
	Wave 1	No	92.63	7.37	Wave 2	No	91.67	8.33
		Yes	47.27	52.73		Yes	44.59	55.41
Small			Wave 2				Wave 3	
			No	Yes			No	Yes
	Wave 1	No	94.02	5.98	Wave 2	No	89.44	10.56
		Yes	62.14	37.86		Yes	48.39	51.61

Services industries								
	Period 1 (2002 - 2004 / 2004 - 2006)				Period 2 (2004 - 2006 / 2006 - 2008)			
Large			Wave 2				Wave 3	
			No	Yes			No	Yes
	Wave 1	No	97.02	2.98	Wave 2	No	94.55	5.45
		Yes	65.48	34.52		Yes	62.5	37.5
Small			Wave 2				Wave 3	
			No	Yes			No	Yes
	Wave 1	No	97.29	2.71	Wave 2	No	93.72	6.28
		Yes	72.87	27.18		Yes	58.24	41.76

5.4 Model specifications

As described earlier, this Chapter aims to analyse the presence and the dynamics of persistent innovation. To this end, we make use of a specific question contained in the CIS panel on the introduction of product innovation, defined following the guidelines offered in the Oslo manual (OECD and Eurostat, 2005). In particular, companies were asked whether they introduced products new to the firm or new to the market. This provides a series of dichotomy variables that offer a natural approach to the study of innovation persistence. Previous research on persistent innovation has usually adopted the broader definition referring to the introduction of products new to the market or new to the firm. However, these two different types of product innovation are likely to present different dynamics because of their dissimilar nature (See Clausen and Pohjola, 2013). As Geroski et al. (1997) point out, taking into account all minor technical improvements and innovations is likely to generate an upward bias in the level of persistence[78]. In this Chapter, we aim to reduce this effect by focusing only on the introduction of products new to the market, thus adopting a measure of innovation activity which has been used in previous empirical studies as a proxy for radical or 'higher level' innovation (Tether, 2002; Laursen and Salter, 2006). Hence, the dependent variable is defined as a dichotomous variable taking value 1 if companies introduced product innovations that were new to the market, and 0 otherwise. Considering the binary nature of the dependent variable, we proceed adopting a probit regression model.

Persistent innovation is usually defined in the literature as the increase in the probability of innovating in a given period of time having already innovated in the previous period (Cefis and Orsenigo, 2001; Peters, 2009). To account for the importance of previous innovation in the hypothesis of persistent innovation, we follow a common approach in the literature introducing a lagged dependent variable as regressor through a dynamic model. This leads to the standard dynamic probit model expressed as:

$$\Pr[y_{it}= 1 \mid y_{it-1}, x_{it}, c_i, \epsilon_{it}] = \Phi(\gamma y_{it-1} + x_{it}\beta + c_i + \epsilon_{it}) \qquad (5.1)$$

In this model, the probability to innovate in time *t* is dependent upon having innovated in previous time *t-1* plus a vector x of exogenous regressors in time *t* representing specific technological regimes and firm characteristics. The model includes a random intercept c_i to account for the presence of unobserved firm specific characteristics. Yet, for estimate γ to represent the effect of true state dependence, we must also account for the presence of spurious state dependence addressing what in the literature is referred to as the initial conditions problem (Heckman, 1981). This problem can arise because of omitted individual heterogeneity across companies[79]. Several models,

[78] See also Section 2.2.
[79] For a general introduction to the initial conditions problem, see Section 2.5.2.

collectively referred to as dynamic type 2 Tobit models, have been proposed to account for these problems.

Following recent literature on persistent innovation, we use the conditional maximum likelihood estimator suggested by Wooldridge (2005), where the distribution of the unobserved effects is conditional on the initial value and a set of strictly exogenous variables. Estimation of the model (1) would require making a strong assumption of independence with respect to the relationship between the initial observation y_{i0} and c_i. In particular, if the initial conditions are correlated with c_i, the estimator will be inconsistent, providing biased results on the extent of state dependence. The approach suggested by Wooldridge (2005) is to specify the density of (y_{i0} , … ,y_{iT}) conditional on (y_{i0}, x_i). Hence, we specify the unobserved firm heterogeneity as a function of the initial values of the innovation dummy and a set of time-averaged covariates X_i as follows:

$$c_i = \alpha_0 + \alpha_1 y_{i0} + \alpha_2 X_i + a_i \qquad (5.2)$$

Substituting equation (2) in equation (1) yields the probability of being an innovating company *i* in time *t* as follows:

$$\Pr[y_{it}= 1 \mid y_{i0} , \dots ,y_{iT,} x_{it}, X_{i,} a_i] = \Phi(\gamma y_{it-1} + x_{it}\beta + \alpha_0 + \alpha_1 y_{i0} + \alpha_2 X_i + a_i) \qquad (5.3)$$

Integrating out a_i from equation (3) results in a likelihood function which can be analysed within the standard random effects probit model.

5.4.1 Independent variables

In order to test our main hypothesis regarding the presence of true state dependence in innovation among small companies, we allow the lagged dependent variable to enter the model as an explanatory variable. In other words, we study the effect that previous innovation output may exert as innovation input in the following round of innovation activity.

To isolate the effect of dynamic increasing returns and address our second and third hypotheses of a possible interaction effect between the effect of persistent innovation and the level of R&D intensity within firms' innovation activity, we make use of an interaction term between the total amount of R&D expenditure, given by the sum of internal and external R&D expenditure at firm level, as a share of the average sector R&D expenditure (TOTAL_R&D) and the variable indicating the presence of persistent innovation within the innovation activity (lagged PRODMAR). Controlling for the role exerted by formal R&D activity, a positive effect for the lagged dependent variable (PRODMAR) would then provide evidence of dynamic increasing returns in innovation, which represent the positive effect generated by learning in technology and knowledge. This approach also allows us to test the extent to which the relationship between increasing levels of R&D intensity and dynamic increasing returns within the process of knowledge accumulation from previous innovations affect the likelihood of introducing radical product innovations. In particular, to account for the presence of diminishing returns in R&D investment we also include a variable calculated as the squared total R&D expenditure. Thus, we enter the variable TOTAL_R&D and its quadratic term with a one period lag.

As the estimator we use assumes exogeneity of all covariates, we first model the likelihood of introducing product innovations new to the market using only the lagged dependent variable (See Peters, 2009). Then, we proceed inserting an additional set of control variables.

The first control variable is aimed at capturing the role of opportunity conditions in the sector where firms operate. Thus, *opportunity conditions* (OPPOR) describes the pace of the innovation advance in the technological environment where firms operate. To calculate this covariate, we follow an approach similar to Patel and Pavitt (1998), and define opportunity conditions using the proportion of innovative companies which introduced product innovations new to the market on the overall number of companies for every sector obtained from the 5 digit SIC (2003) classification.

Besides the usual time and industry dummies, the decision to innovate is also explained by covariates representing the availability of finance and other market structure characteristics. In particular, the *availability of finance* (FINANCE) measures one common barrier to innovation, providing a window on the relationship between innovation activities and financial constrains that we were not able to observe in the previous Chapters. However, the nature of such information as offered by the CIS limits its role within our model. As such, FINANCE is not a measure of credit worthiness nor it represents the nature of the financial instruments used by companies, often explored by previous studies (Aghion et al., 2004; Magri, 2009). Instead, this variable provides a subjective measure of how the availability of finance constrained innovation activity in the period of time considered. Then, we capture the importance of *operating in international markets* using another dummy variable, INTER.

Recent papers have also underlined the role of synergies across different dimensions of innovative activities, such as interactions between technological and organizational innovations (Battisti and Stoneman, 2010). To capture this

Table 5.3: Descriptive statistics

Variables	All observations			
	Obs.	Mean	Std. Dev.	VIF
Small firms				
PRODMAR	9048	0.12	0.32	1.22
PRODMAR_t-1	6006	0.12	0.32	1.22
TOTAL_R&D_t-1	6006	0.26	2.20	1.01
OPPOR	9048	0.13	0.09	1.22
ORGCHANGE_t-1	6006	0.31	0.46	1.09
FINANCE	8551	0.48	0.50	1.07
INTER	9048	0.33	0.47	1.21
Large firms				
PRODMAR	3114	0.14	0.35	1.36
PRODMAR_t-1	2102	0.15	0.36	1.40
TOTAL_R&D_t-1	2102	3.12	20.47	1.02
OPPOR	3114	0.11	0.08	1.37
ORGCHANGE_t-1	2102	0.49	0.50	1.07
FINANCE	2897	0.53	0.50	1.11
INTER	3114	0.39	0.49	1.33

effect, we also introduce a variable reflecting the presence of managerial, marketing and organizational changes within companies, named ORGCHANGE. To account for potential endogeneity, the covariate for ORGCHANGE is lagged one period. Table 5.3 reports the descriptive statistics[80] for the main variables used in the estimations presented in the next section.

5.5 Results

The estimates for our model are reported in Table 5.4 for small companies and Table 5.5 for large companies[81][82]. The first column for each size class reports the results for the simple model, where only the effect of past innovation activities is included. In columns 2 and 3 we report two versions of the extended model, where we account for the role of R&D expenditure, to show the consistency of our results to alternative specifications. Finally, in column 4 we report the full model with also ORGCHANGE as regressor.

To test the hypothesis of true state dependence, we start with a simplified specification of the model where we include only the lagged dependent variable that measures true state dependence, or the impact of having innovated in the previous period, accounting for firm heterogeneity. This approach allows to start addressing our first hypothesis avoiding endogeneity issues that might arise with some of the independent variables (See Peters, 2009).

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[80] Statistics on maximum and minim for each variable cannot be disclosed for confidentiality reasons, as requested by the agreement on the use of the UK Innovation Survey supplied by the Secure Data Service at the UK Data Archive.

[81] Coefficients for the constant term and relative standard errors in each model cannot be disclosed for confidentiality reasons, as requested by the agreement on the use of the UK Innovation Survey supplied by the Secure Data Service at the UK Data Archive. Estimates for the individual heterogeneity part of the model are reported in the Appendix (See Tables 5.6 and 5.7).

[82] Sectoral dummies are not reported as for the most part they are not statistically significant. Similarly, the test of the joint significance of services as opposed to manufacturing sectors is not significant. This is likely to be a consequence of PRODMAR and TOTAL_R&D accounting for much part of sectoral variance.

With respect to *Hypothesis 1*, we find that past innovation has a positive effect on the likelihood of introducing higher level product innovations new to the market, even after accounting for individual unobserved heterogeneity[83]. The

Table 5.4: Dynamic probit estimates for small firms

Small firms				
	(1) Coeff	(2) Coeff	(3) Coeff	(4) Coeff
PRODMAR_t-1	0.487***	0.568***	0.465**	0.434***
	(0.133)	(0.131)	(0.146)	(0.145)
TOTAL_R&D_t-1		0.569***	0.414***	0.357***
		(0.109)	(0.114)	(0.111)
TOTAL_R&D_t-1^2		-0.055***	-0.039**	-0.033**
		(0.016)	(0.015)	(0.015)
PRODMAR_t-1*TOTAL_R&D_t-1		-0.502***	-0.374***	-0.316***
		(0.111)	(0.116)	(0.113)
PRODMAR_t-1*TOTAL_R&D_t-1^2		0.054***	0.039**	0.035**
		(0.016)	(0.015)	(0.014)
OPPOR			6.259***	6.323***
			(2.229)	(2.235)
ORGCHANGE_t-1				0.237***
				(0.080)
FINANCE			0.226**	0.245***
			(0.090)	(0.090)
INTER			0.269*	0.271*
			(0.141)	(0.141)
Const	-	-	-	-
Rho	0.263	0.233	0.248	0.234
LR Test	0.001	0.004	0.005	0.007
WALD chi2	420.4***	448.5***	404.2***	411.5***
Log Likelihood	-1562.5	-1537.8	-1285.6	-1268.03
Obs	6006	6006	5100	5100

Regressions include industry and time dummy variables.

* p<0.10 ** p<0.05 *** p<0.01

[83] All estimations are based on Gauss–Hermite quadrature approximations with twelve quadrature points. The results are robust to different numbers of integration points, as confirmed by the STATA command `quadchk`.

Table 5.5: Dynamic probit estimates for large firms

	Large firms			
	(1)	(2)	(3)	(4)
	Coeff	Coeff	Coeff	Coeff
PRODMAR_t-1	0.942***	0.872***	0.732***	0.721***
	(0.204)	(0.208)	(0.242)	(0.243)
TOTAL_R&D_t-1		0.027***	0.030***	0.030***
		(0.008)	(0.010)	(0.010)
TOTAL_R&D_t-1^2		-0.000***	-0.000***	-0.000**
		(0.001)	(0.000)	(0.000)
PRODMAR_t-1*TOTAL_R&D_t-1		-0.013	-0.008	-0.007
		(0.015)	(0.020)	(0.018)
PRODMAR_t-1*TOTAL_R&D_t-1^2		0.001	0.000	0.000
		(0.000)	(0.000)	(0.000)
OPPOR			4.392	4.326
			(3.563)	(3.552)
ORGCHANGE_t-1				0.079
				(0.142)
FINANCE			0.501***	0.500***
			(0.162)	(0.162)
INTER			0.565**	0.555**
			(0.271)	(0.270)
Const	-	-	-	-
Rho	0.093	0.091	0.214	0.206
LR Test	0.279	0.228	0.101	0.111
WALD chi2	253.1***	249.8***	181.0***	182.5***
Log Likelihood	-563.7	-548.4	-435.7	-435.05
Obs	2102	2102	1716	1716

Regressions include industry and time dummy variables.

* p<0.10 ** p<0.05 *** p<0.01

lagged variable (PRODMAR) in all specifications referring to both small and large firms is positive and statistically significant at the .01 level, indicating the presence of persistency within both classes of companies. As found in previous studies, unobserved firm heterogeneity, here labelled Rho[84], plays a significant role in explaining innovation, accounting for about one fifth of the unexplained

[84] Rho represents the proportion of the total variance explained by the panel-level variance, and it is obtained as follows: $\rho = \sigma_v^2 / 1 + \sigma_v^2$.

variation in the dependent variable across the models, although it is statistically significant only in the model based on small companies.

However, in this model we do not explicitly account for the role exerted by R&D intensity, as expressed by TOTAL_R&D. We therefore extend the model to account for the role of R&D intensity, also including an interaction term between the lagged dependent variable and the variables representing R&D intensity. Considering column (2), we observe a positive effect with respect to TOTAL_R&D for both small and large companies. The quadratic term capturing decreasing returns in R&D is also significant for both groups across all model specifications, although the effect of the quadratic term seems to be negligible among large companies.

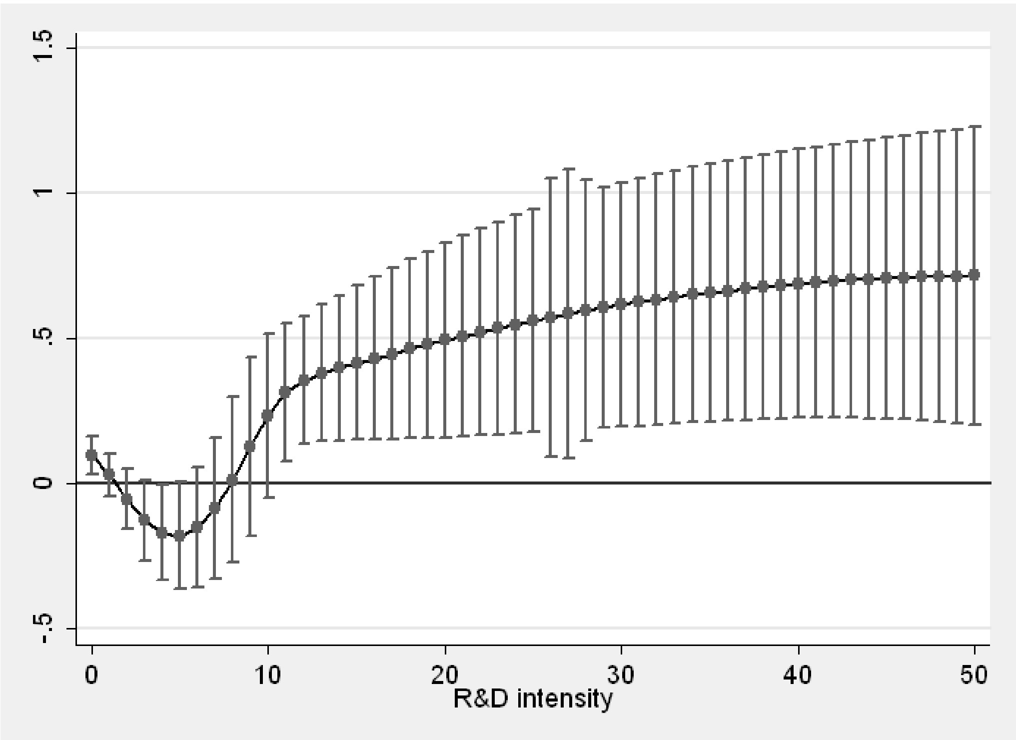
In order to test our second and third hypotheses, we look at the interaction between the lagged dependent variable representing dynamic increasing returns and the quadratic term for TOTAL_R&D. Our results do not provide evidence for an interaction effect between dynamic increasing returns and increasing levels of technological complexity among large companies. Thus, our findings seem to be in line with our second hypothesis that persistent innovation may derive from sustained formal R&D efforts, proxied by the effect of R&D intensity, and the inherent sunk costs in R&D.

Conversely, in line with our third hypothesis, the estimates for small companies suggest that an important interaction effect takes place among previous innovation activity and R&D intensity, offsetting the diminishing returns with respect to the development of increasingly complex technology.

This positive and statistically significant interaction indicates that while companies present a lower likelihood of innovating in the presence of higher levels of technological complexity, the effect of accumulated knowledge capabilities inherent to such technologies may be able to offset these diminishing returns. In this sense, dynamic increasing returns from innovation, as proxied by previous innovation, seem to enhance companies' 'combinative' capabilities (Kogut and Zander, 1992). Hence, intensive R&D activity can be fully exploited through cumulative competencies acquired in previous innovation activity.

This relationship is represented by Figure 5.2, which reports the difference in predicted probabilities, at different levels of R&D intensity, for small companies which present persistent innovation as opposed to those that did not innovate in *t-1*, holding other covariates at their mean values. While probabilities are still higher for companies that innovated in the previous period, we observe a lower likelihood in correspondence of low levels of R&D intensity, suggesting that these companies might be actually focus on incremental innovations after the introduction of a higher level innovation. In line with *Hypothesis 3*, the positive effect of dynamic increasing returns only starts at higher levels of R&D intensity, which corresponds to the 5% highest R&D investing companies. In this case, we can observe that the likelihood of innovating becomes increasingly higher. Including the other covariates has no effect on the main finding on true state dependence in innovation, as for both small and large companies' innovations in the previous period of time still present a positive and significant effect on the respective dependent variable. Similarly, the sign and the statistical significance for the coefficients related to

Figure 5.6: Difference in predicted probabilities for small companies with respect to PRODMAR_t-1



total R&D expenditure are not affected, nor is their interaction with PRODMAR_t-1.

With respect to control variables, the presence of increasing opportunity conditions (OPPOR) is also a significant determinant of innovation, as suggested in previous literature (Scherer, 1980; Malerba and Orsenigo, 1993), providing evidence for the hypothesis that competition near the technological frontier may create pressure to engage in further innovation (Aghion et al., 2005; Raymond et al., 2010). This finding holds for all model specifications.

The coefficient of ORGCHANGE_t-1 suggests that organizational innovations are an important element within innovative companies, in line with the findings on synergies across different types of innovation found by Battisti and Stoneman (2010), at least for small companies. This suggests that the more flexible structure of small companies may be important for them to deliver a sustained innovation output over time.

Of the additional variables, the variable representing companies operating in international markets is positive and statistically significant in both models. Similarly, FINANCE is also significant for both large and small companies. While a positive coefficient for FINANCE might surprise, we must remember that the question in CIS indicates whether availability of finance constrains the innovative activity of the company. In this sense, this variable is likely to capture a problem which is particularly relevant for the most innovative companies.

5.6 Conclusions

In this Chapter, we have explored the phenomenon of persistent innovation within UK innovative companies using a panel dataset comprising three successive rounds of the UK Community Innovation Survey, covering the years between 2002 and 2008. The contribution of this study to the literature on innovation is twofold. First, we have presented evidence based on novel data on persistent innovation in the UK using innovation surveys as opposed to patent data, with a special attention dedicated to small companies. Thus, using the dynamic probit model proposed by Wooldridge (2005), we have provided evidence of persistent product innovation in large as well as companies, even after accounting for unobserved firm heterogeneity. Secondly, we have offered novel findings on the relationship between the effect exerted by the presence of persistent innovation, in the form of dynamic increasing returns in the process of knowledge accumulation, and the level of R&D intensity within firms' innovation activity.

Overall, our results confirm the insights offered in previous studies on persistent innovation. Companies are persistent in their innovative state, that is, companies which innovate tend to pursue innovative activities in following periods of time, while non-innovative companies are likely not to start engaging in innovation. Differently from previous research, we have also offered novel evidence that this phenomenon is also important within small companies. More interestingly, allowing for an interaction between R&D intensity, expressed in terms of firm total R&D expenditure over sector average R&D expenditure, and the dynamic increasing returns generated by previous innovation, this Chapter offers evidence of a linear relationship with the introduction of innovation among large companies for increasing levels of technological complexity, supporting the theory of sunk costs in innovation for this group.

With respect to small companies, our results indicate that the diminishing returns associated with high technological complexity are offset by the presence of dynamic increasing returns in the process of knowledge accumulation, suggesting that these may be indeed much stronger in the presence of highly complex technologies. Thus, our results underline the crucial element represented by the ability to exploit internal knowledge capabilities among small persistent innovators.

At the same time, our analysis confirms the role of opportunity conditions as one of the most important factors in explaining differences in the innovation activity, as underlined by Scherer (1980). Finally, potential evidence of the positive effect of the introduction of organizational and managerial innovations for persistent innovation is found, although further analysis is needed to assess the robustness of this finding with respect to the assumption of strict exogeneity assumed in the model used.

The present Chapter is based on what is becoming the standard approach in the study of persistent innovation. However, more empirical efforts should be devoted to extend the discussion to serial innovators, defined as those companies with an unusually high level of innovation over time, where the role of cumulativeness is not defined through a relationship of sequentially between successive time periods. Another interesting extension to the analysis proposed might involve exploring further the role of organizational innovation in persistent innovation, explicitly accounting for synergies and complementarities among technological and organizational innovations, as those explored by Battisti and Stoneman (2010) and Hall et al. (2011).

Acknowledgements

This work was based on data from the UK Innovation Survey produced by the Office for National Statistics (ONS) and supplied by the Secure Data Service at the UK Data Archive. The data are Crown Copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of the data in this work does not imply the endorsement of ONS or the Secure Data Service at the UK Data Archive in relation to the interpretation or analysis of the data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.

Appendix

Table 5.6: Dynamic probit estimates for small firms with individual heterogeneity

Small firms				
	(1) Coeff	(2) Coeff	(3) Coeff	(4) Coeff
Structural equation				
PRODMAR_t-1	0.487***	0.568***	0.465**	0.434***
	(0.133)	(0.131)	(0.146)	(0.145)
TOTAL_R&D_t-1		0.569***	0.414***	0.357***
		(0.109)	(0.114)	(0.111)
TOTAL_R&D_t-1^2		-0.055***	-0.039**	-0.033**
		(0.016)	(0.015)	(0.015)
PRODMAR_t-1*TOTAL_R&D_t-1		-0.502***	-0.374***	-0.316***
		(0.111)	(0.116)	(0.113)
PRODMAR_t-1*TOTAL_R&D_t-1^2		0.038**	0.054***	0.039**
		(0.016)	(0.015)	(0.014)
OPPOR			6.259***	6.323***
			(2.229)	(2.235)
ORGCHANGE_t-1				0.237***
				(0.080)
FINANCE			0.226**	0.245***
			(0.090)	(0.090)
INTER			0.269*	0.271*
			(0.141)	(0.141)
Individual Heterogeneity				
PRODMAR_0	0.845***	0.715***	0.780***	0.709***
	(0.152)	(0.145)	(0.160)	(0.154)
TOTAL_R&D_0		0.014	0.012	0.010
		(0.012)	(0.013)	(0.014)
M_OPPOR			2.677	2.430
			(1.952)	(1.930)
ORGCHANGE_0				0.221**
				(0.087)
M_FINANCE			0.299**	0.184
			(0.136)	(0.136)
M_INTER			0.269*	0.254
			(0.141)	(0.166)
Const	-	-	-	-
Rho	0.263	0.257	0.271	0.234
LR Test	0.001	0.001	0.002	0.007
WALD chi2	420.4***	430.7***	384.8***	411.5***
Log Likelihood	-1562.5	-1468.2	-1251.9	-1268.03
Obs	6006	6006	5100	5100

Regressions include industry and time dummy variables.
* p<0.10 ** p<0.05 *** p<0.01

Table 5.7: Dynamic probit estimates for large firms with individual heterogeneity

	Large firms			
	(1)	(2)	(3)	(4)
	Coeff	Coeff	Coeff	Coeff
Structural equation				
PRODMAR_t-1	0.942***	0.872***	0.732***	0.721***
	(0.204)	(0.208)	(0.242)	(0.243)
TOTAL_R&D_t-1		0.027***	0.030***	0.030***
		(0.008)	(0.010)	(0.010)
TOTAL_R&D_t-1^2		-0.000***	-0.000***	-0.000**
		(0.001)	(0.000)	(0.000)
PRODMAR_t-1*TOTAL_R&D_t-1		-0.013	-0.008	-0.007
		(0.015)	(0.020)	(0.018)
PRODMAR_t-1*TOTAL_R&D_t-1^2		0.012	0.001	0.000
		(0.000)	(0.000)	(0.000)
OPPOR			4.392	4.326
			(3.563)	(3.552)
ORGCHANGE_t-1				0.079
				(0.142)
FINANCE			0.501***	0.500***
			(0.162)	(0.162)
INTER			0.565**	0.555**
			(0.271)	(0.270)
Individual Heterogeneity				
PRODMAR_0	0.547**	0.529**	0.799***	0.802***
	(0.248)	(0.237)	(0.300)	(0.300)
TOTAL_R&D_0		0.001	0.003	0.002
		(0.004)	(0.005)	(0.005)
M_OPPOR			-0.097	-0.160
			(4.343)	(4.312)
ORGCHANGE_0				-0.076
				(0.148)
M_FINANCE			0.179	0.146
			(0.244)	(0.244)
M_INTER			-0.245	-0.252
			(0.317)	(0.315)
Const	-	-	-	-
Rho	0.093	0.091	0.214	0.206
LR Test	0.279	0.228	0.101	0.111
WALD chi2	253.1***	249.8***	181.0***	182.5***
Log Likelihood	-563.7	-548.4	-435.7	-435.05
Obs	2102	2102	1716	1716

Regressions include industry and time dummy variables.

* p<0.10 ** p<0.05 *** p<0.01

CHAPTER 6

Conclusions

"The beautiful thing about learning is nobody can take it away from you."

- B. B. King

6.1 Overview

In this thesis, we have tried to provide a contribution to the research on persistence in innovation and technological change. In particular, the thesis has sought to explore the presence and the fundamental characteristics of persistence and serial innovation within small innovative companies in the UK while providing comparisons with large companies.

The presence of persistent innovation or, more broadly, the presence of companies which may be able to successfully engage in a sustained stream of innovations over time is of central interest in the study of industry dynamics and the patterns of innovative activities. What is particularly interesting is the comprehension of the forces that shape the asymmetries in the innovation competencies of companies and, in particular, the potential contribution played by cumulative processes in the form of dynamic economies of scale, resulting from the volume of innovation along past history of R&D capacity, and dynamic increasing returns in research in the form of learning by doing and learning to learn effects in innovation. Not surprisingly, hence, scholars have discussed this topic since the insights by Schumpeter on creative destruction and creative accumulation (Schumpeter, 1934; 1942), with important theoretical contributions from neoclassical as well as evolutionary economics perspectives. However, since the seminal paper by Geroski et al. (1997), the

most fruitful strand of research that has investigated this phenomenon is rooted in a significant number of contributions following an empirical approach.
This work proceeds along this direction, exploring an area that has received surprisingly little attention in the literature, that is, the presence of persistent and serial innovation across small companies. The theory based on Schumpeterian patterns of technological change has always offered little space for processes of knowledge accumulation within small companies, and while the recent emphasis of the literature of entrepreneurship has usually highlighted the role of new technology based companies or innovative start-ups in promoting and fostering innovation within the economy, little evidence has been provided on what happens in later stages, and whether their activity might present signs of persistent or serial innovation.
Thus, the main contribution of the thesis lies in the empirical investigation of small companies characterised by a sustained record of innovations over time.
In this final chapter, we provide a comprehensive overview of the main contributions of the thesis to the specific literature, trying to underline the rationale behind the research questions being asked and the relevance of the findings. Hence, we start by briefly summarising and discussing the main elements of each empirical chapter. Some possible guidelines for future research and policy considerations are also discussed. A short section concludes with some final considerations.

6.2 Contribution and main findings

This thesis aims to add a series of relevant and new insights from an academic as well as a policy perspective. The contribution specific to the literature is centred on the exploration of the presence and the main characteristics of small and medium enterprises in the UK, defined by a sustained and unusually high record of innovations over time.
Throughout this research, we have followed a multidimensional approach, investigating two similar yet different phenomena, that is, persistent and serial innovation, as well as using data from patent data and innovation surveys. We have discussed how the distinction between persistent and serial innovation

might be particularly relevant for the study of small innovative companies, arguing that innovation activity may be continuous and indeed quite persistent even when this is not shown in firms' innovation output, as measured by patents. In this sense, the approach followed, where determinants of persistence are studied within companies with a sustained record of innovation over time, is an effective alternative.

At the same time, both phenomena are captured only partially by a specific type of data. Hence, we have put forward the argument that there are indeed different types of persistent innovation occurring at different levels, which are related to the degree of novelty of the innovation pursued.

On the empirical level, this thesis provides new evidence on the presence of small companies that escape the simple association between persistence and large companies, thus offering an additional dimension to the concept of routinized regimes. We have also offered further insights on the mechanisms that sustain innovation activity over time through the process of cumulativeness in knowledge. In this respect, the role of combinative capabilities and dynamic increasing returns seem to be at the core of the innovation activity within serial and persistent innovators, especially for small companies. The main findings of the thesis are discussed further in the following section.

6.2.1 Main findings

After a synoptic introduction to the research context and the main questions investigated in Chapter 1, the thesis provides a discussion on the most relevant terms and concepts discussed throughout this empirical investigation in Chapter 2, as well as outlining its multidimensional approach based on both patent and innovation survey data. In particular, we first delineated how the concepts of innovation and persistence are approached in the thesis. Hence, we introduced the concept of serial innovation as opposed to persistent innovation, the former being based upon a stream of innovations – with perhaps some gaps - over time while the latter calls for the quality of sequentiality over time. In the second part of the Chapter, we have described the type of data employed in the empirical analysis, trying to show the implications that these involve with respect to the perspective adopted in the research, their specific strengths and weaknesses, and how they allow to look at different sides of persistent and serial innovation.

The empirical section of the thesis start with Chapter 3 and Chapter 4, where we exploit a novel dataset based on patent information for a panel of 811 UK companies with a sustained innovative activity between year 1990 and year 2006. In particular, we make use of this dataset to investigate the differences among small and large serial innovators at the vertical and horizontal dimension.

In Chapter 3, we have looked at the influence of variables related to the concept of technological regime on the rate of innovation of serial innovators and firm-specific technology variables that may characterize the activity of companies operating within innovation networks or even markets for technology[85].

Three very interesting stylized facts emerge from a descriptive analysis of small serial innovators. First, these companies are not short lived, with an average technological life[86] of about 20 years. Second, their distribution across industrial sectors shows that they might be divided into two main groups, one operating with formal R&D and accounting for almost a third of all companies, and another related to machinery and precision instruments and other mature industries. Third, at least to a descriptive level, the regional distribution of small serial innovators resembles the structure of British industrial clusters as a whole.

Then, we proceeded fitting a negative binomial model to account for overdispersion in the number of patents and citation-weighted patents. We observed that the rate of innovation of small companies present a positive relationship with a technological environment shaped by qualities characteristic of a routinized regime, that is, high opportunity conditions, appropriability and a cumulative nature of technological competencies. The

[85] See Hicks & Hegde (2005).

[86] In our dataset, the technological life of a company is defined by the first and the last patent application.

effect of the technology specific variables is less clear. While innovation with a high technological impact is also an important determinant of the future stream of innovations, patents with a broad technological base seem to be significant only when explicitly accounting for patent value using their forward citations.

After having observed that small serial innovators benefit from characteristics typical of a 'routinised' regime, we proceeded testing whether there are differences on the way these elements might act among small and large companies. Our analysis indicates that small companies are more sensitive to opportunity conditions, perhaps as a consequence of their limited R&D capabilities in terms of resources and external connections available, as also suggested by the findings presented in the following Chapters. More interestingly, we found an opposite effect between large and small companies when observing the variables related to the hypotheses of dynamic increasing returns and dynamic economies of scale in innovation. While both effects are positive among the two groups, an increase in the number of patents accumulated over time has a stronger effect on the rate of innovation for large companies, while the use of previous discoveries, in the form of self-citations, in firm's innovative activity is more relevant for small serial innovators. These findings seem to support the idea that serial innovation may follow different paths among large and small companies, with the former relying more on the magnitude of their R&D capabilities and research investment and the latter exploiting the competencies and the knowledge acquired during their own previous innovation activity. In other words, as also suggested by our results from Chapter 5, small serial innovators are particularly likely to benefit from a cumulative processes characterised by internal 'combinative capabilities' (Kogut and Zander, 1992) and and search depth (Katila and Ahuja, 2002).

Chapter 4 follows, shifting the attention towards the horizontal dimension of serial innovation, that is, the degree of technological diversification. Using the same dataset of the previous Chapter, we first took a descriptive approach to see whether small serial innovators are diversified with respect to the whole population of patenting companies in the period of time considered, and the difference from large innovators. As expected, these companies are less diversified than their large counterparts, but they show a degree of technological diversification significantly higher than all other companies. To study the determinants of technological diversification, we looked at the contrasting effect towards diversification that is likely to take place in a technological environment characterised by increasing opportunity conditions as opposed to the effect exerted by firms' technological trajectories in the form of accumulated knowledge coherence in core competencies and technological search.

Using a fractional logit model, we confirm the presence of both these forces, but the relationship among them appears to be not linear, at least for opportunity conditions. In fact, we find an inverted U relationship between opportunity conditions and technological diversification. Just like their large counterparts, small serial innovators try to broaden their technological domain when there are sufficient opportunities to do so, in order to explore and eventually exploit new technological opportunities. As the literature suggests, this allows companies to benefit from cross-fertilization between different technologies, thus generating economies of scale and scope, speed and space. In this sense, technological diversification supports economies of scope in research and internal technology spillovers, allowing companies to cope with multi-technology and, more generally, complex innovations. However, when technological opportunities become pervasive, thus increasing innovation turbulence, companies might focus on a more limited number of technological products, in order to avoid the uncertainties in the market or simply to focus on the sectors where they have core competitive advantages. In other words, they may try to reduce the risks and the cost inherent to innovation when it is not clear the direction of technology development in the industry, leading to volatile markets. Similarly, companies may decide to stick with technologies where they have more experience, thus exploiting their internal capabilities and adopting processes of search depth to contrast the uncertainty in the technological environment.

Another strong effect towards specialisation is played by previous accumulated competencies. In line with the literature, we find that there is a powerful element of path dependency defined by the coherent core of knowledge accumulated over time by the firm. Evolutionary economics literature suggests that the cumulative process behind innovation activity is defined by elements of path dependency and coherence in the knowledge base. Our results clearly support this view. This is not surprising, as a strong coherence in firms' internal competencies is an important source of competitive advantage, providing the base for economies of scope that ultimately foster their innovative activity (Teece et al., 1994). A similar effect is generated by the variety in the processes of technological search. In other words, companies whose technology relies on innovations that are close to their domain of technological specialisation do not benefit from a learning premium where having a stronger competence in one field helps companies to look in and move around new directions, away from previous research. Put simply, the closer firms look around themselves, the least they move.

As in the previous Chapter, we have also provided some insights into possible differences across firm size. As expected, large serial innovators are more likely to engage in technological diversification, holding the other variables fixed. More importantly, though, there is an important difference in the way opportunity conditions affect small and large serial innovators. Our results point to a more peaked distribution for small companies, suggesting that these are more likely to engage in technological diversification when opportunities start to increase, yet at the same time they shift towards strategies of specialization more rapidly when such opportunities become pervasive and the technological environment is more turbulent. This may suggests that small companies might be more flexible in their innovative activities, while also being more sensible to increases in the risk inherent to this very innovation activity.

The last empirical contribution is offered by Chapter 5, where we use a longitudinal dataset composed of three rounds of the Community Innovation Survey for the UK to study the presence of persistent innovation among small and large companies. In line with previous literature, we find evidence suggesting that having introduced new products in the past increases the likelihood of innovating in subsequent periods of time, thus confirming the hypothesis of true state dependence in innovation.

We also investigate the different effect exerted by the level of R&D intensity within firms' innovation activity, as proxied by total R&D expenditure at the firm level over sector average R&D expenditure, with respect to the "persistence effect" generated by previous innovation, which is used as a proxy for dynamic increasing return in knowledge accumulation. Interestingly, while we observe a linear positive effect for both forces among large companies, the interaction between R&D intensity and the dynamic increasing returns generated by previous innovation in small persistent innovators seems to indicate that for increasing levels of technological complexity, the role of technological learning from accumulated knowledge capabilities becomes a central element in their innovative processes. In fact, our findings seem to indicate that it is the very presence of this element that allows small persistent innovators to be able offset the diminishing returns associated with high technological complexity.

In this sense, dynamic increasing returns from innovation, as proxied by previous innovation, seem to enhance companies' 'combinative' capabilities (Kogut and Zander, 1992). Hence, our results suggest that intensive R&D activity can be fully exploited through cumulative competencies acquired in previous innovation activity which allow for a reconfiguration of existing knowledge into new technological opportunities for the firm.

6.3 Suggestions for future research

One of the main arguments of this thesis is that the topic of small serial and persistent innovations may represent an interesting and relevant field of research in light of the emerging division of labour in the production of knowledge and technology that characterises modern advanced economies (Arora et al., 2001; Chesbrough, 2003). In this sense, while we have tried to provide new insights on important aspects of these peculiar companies, and certainly further analysis of the role of cumulativeness in innovation or technological diversification among small firms and the relationship between serial innovation and small firms' performance as well as market share are certainly necessary, many additional elements remain unexplored that we believe may constitute interesting subjects for future research. This section briefly presents three of such topics and concludes with a methodological consideration. As we mentioned in Chapter 1, we do not focus on the role of finance in this thesis. While specific information on the importance of finance for small persistent and serial innovators would offer interesting elements for the analysis of these peculiar companies, one specific mechanism is particularly relevant to this research. This is related to the process through which previous innovations provide the financial resources for further innovation activity (Lach and Schankerman, 1989). This element, associated with the hypothesis that “success breeds success” (Nelson and Winter, 1982) represents an important piece of evidence for the study of persistence, and becomes particularly interesting in the context of small companies, in consideration of their limited R&D resources (Cohen and Klepper, 1996). More generally, the role of capital investments constitutes an interesting venue of future research especially in the comparison of the manufacturing versus services innovation modes.

The second topic we identify that needs further research is related to the importance of innovation networks, inter-firm linkages and the market for technologies. While we have tried to investigate some of the characteristics inherent to small companies operating in innovation networks in Chapter 3, we have not offered clear and direct evidence of these elements on the innovation activity of serial and persistent innovators. Similarly, our simple exercise on the regional distribution of serial innovators described in Chapter 3 pointed to an interesting resemblance of such distribution with the map of industrial clusters in the UK economy as a whole. This suggests that clusters may be important for these companies. Yet, our data do not allow us to offer any insight on this point, nor on the type of interactions or collaborations that may take place across different firms or with university research. While innovation surveys and patents constitute a valid source of information to address these topics, case studies may also open a window on the complex network of relations that it is likely to take place around these companies.

The last line of research we present refers to the role of national systems of innovation and, more generally, to cross-country analysis. Throughout the thesis, we have tried to provide a coherent perspective on small serial and persistent innovators addressing this phenomenon only within the UK context. This approach has allowed us to avoid the issues related to country specificities, such as different industrial or academic systems. At the same time, it prevents us from suggesting considerations that may have a general validity across different contexts. Thus, we believe that further analyses conducted across different countries, and explicitly taking into account the differences that may characterise them, would provide important pieces of evidence on the topic of this thesis. In this respect, the type of data we have adopted offer a useful starting point, as both patent data and innovation surveys are available for a large number of advanced economies.

To conclude, we underline the importance held by the analysis of interaction variables to investigate differences across size among serial innovators. It may be easy to lose sight of small serial and persistent innovators in empirical investigations, as these are associated with large companies in studies based on innovation activity and with small companies in studies based on firm size. Comparative analysis, as offered by interaction variables, may represent a powerful tool of research to approach these issues. Thus, we believe their role should be even more central for future work on this topic.

6.4 Policy considerations

In both academic and policy literature, small innovative companies have often received great attention for their potential to fully exploit knowledge spillovers, sustaining innovation and economic growth, as well as job creation (OECD, 1997; Audretsch, 2002). Such expectations haven't always been met, with many new technology-based firms failing to act as generators of new employment. In many cases, these companies do not even want nor need to grow in terms of total employment (Autio, 1994). At the same time, however, small innovative firms have shown a remarkably low failure rate (Autio, 1994), with similar survival rates with respect to large firms in mature and high-tech product markets (Agarwal and Audretsch, 2001). Yet, the possibility of small firms to survive in such industries does not tell much about their role as sources of innovation. In fact, Huergo and Jaumandreu (2004) present empirical evidence showing that entrant firms present the highest probability of innovation, while the opposite holds for the oldest firms.

More generally, there is an intense debate about whether the level and the quality of innovation generated within small companies is limited (Hoffman et al., 1998; Tether, 1998). Hughes and Mina (2012), for example, pointing out the limited contribution in terms of total expenditure offered by small and medium independent enterprises to the UK business sector R&D, ask what may be the future role for these companies in R&D. This thesis offers a partial answer to such question.

Treated as a homogeneous group, the contribution of small independent companies in the UK might appear limited, yet there is a significant variance in the level and impact of their innovative activity. The findings advanced in this thesis offer a specific and yet important set of contributions at the policy level. In the studies presented, we have confirmed what already found in previous research, which pointed out that persistent and serial innovators account for the majority of the innovations in the UK (Geroski et al., 1997; Cefis and Orsenigo, 2001). Most importantly, though, our results show that small serial innovators play a significant part among them, even in terms of patents. They may account for a small section of the population of UK companies, but they provide an unusually high record of innovations, largely characterised by high technological impact. Even if they do not aim to grow in economic terms, they represent a stable source of innovation in the economy. Thus, the presence of small serial innovators and their rich technological activity calls for a more articulated and specific policy strategy towards small firms that might take into account the heterogeneity that characterise their innovation activity.

Our findings underline the importance of explicitly acknowledging the differences that exist between different types of small innovative firms. In this sense, we emphasise that the role and dynamics of small serial and persistent innovators may be quite different from other innovation intensive small companies, such as high-tech start-up and spin-off companies or new technology-based firms, which have received much attention from policy makers and scholars alike.

While small serial innovators seem to share the same limited contribution to job creation of other small innovative companies, their peculiar contribution to the innovation activity of the economy lies in their unique ability to exploit combinative capabilities along the technological trajectory close to firm's core competencies in order to foster successive rounds of innovation. In other words, their innovation output is not limited to the first entrepreneurial stage. Instead, they generate a sustained stream of innovations over time, thus providing stability to the innovation system. In this sense, policies aimed at encouraging the creation of new high technology firms might pay more attention not just to the fostering effect that innovation systems exert on these companies, but also to the specific mechanisms through which these support and shape their internal combinative capabilities.

A specific set of policy formulations is outside the scope of this thesis. We have not carried out a welfare analysis nor have we explored the presence of possible market failures associated with the presence or the innovation activity of small serial and persistent innovators. However, even if it is not possible to advance clear policy indications, our results offer novel and informative insights that we deem to be of interest to innovation policy makers, offering new perspectives along which articulate novel policy thinking. In particular, our findings suggest that policy makers should not limit their perspective on small innovative firms as engines of job creation. Nor should they limit their innovative contribution to the first entrepreneurial stages. Rather, it is important to recognise the role of the peculiar small firms observed throughout this thesis in fostering innovation, especially in the long term, and broaden the way the contribution of small companies to innovation is intended, framed and supported at the policy level.

6.5 Final considerations

The presence of positive returns in innovation from previous innovation activity and knowledge accumulation occupies a very important place in the theories on industry dynamics and patterns of technological change. In this thesis, we have tried to provide evidence on these mechanisms among small innovative companies. These companies may be few in number, but their contribution in terms of innovative output is significant. As such, they represent a stable source of innovation within the economy.

In particular, we have tried to explore the mechanisms behind persistent and serial innovation, explicitly investigating the different ways through which these take place and how they affect innovation activities within small and large companies. Our findings provide a relevant contribution to the literature on persistent innovation and industry dynamics, offering empirical evidence on the presence of small companies characterised by a sustained stream of innovation over time. In particular, the small companies we have focused on share many of the qualities associated with large persistent innovators, such as the capability to respond and react to high levels of technological opportunity conditions and cumulativeness.

However, they also present important differences. Investigating the two most common mechanisms through which cumulativeness emerges, we have shown that large companies benefit more from the presence of dynamic economies of scale, while small serial innovators rely more on past innovations and internal knowledge capabilities as sources of technological learning. In other words, serial innovation in small companies can be seen as being characterized by 'combinative' capabilities and processes of search depth. Accordingly, these companies tend to follow strategies of technological specialization based on the cumulativeness in their core competencies and capabilities. However, a broader diversification is pursued in the presence of increasing opportunity conditions, until these become pervasive.

References

Acs, Z. J., Audretsch, D. B. (1987). ‘Innovation, Market Structure, and Firm Size’. *The Review of Economics and Statistics,* Vol. 69, No. 4, pp. 567-574.

Acs, Z. J., Audretsch, D. B. (1988). ‘Innovation in Large and Small Firms: An Empirical Analysis’. *American Economic Review,* Vol. 78, No.4, pp. 678-90.

Acs, Z., Audretsch, D., B. (1990). *Innovation and Small Firms*. Cambridge: MIT Press.

Agarwal, R. (1998). ‘Small Firm Survival and Technological Activity’. *Small Business Economics*, Vol. 11, No. 3, pp. 215-224.

Agarwal, R., Audretsch, D., B. (2001). ‘Does Entry Size Matter? The Impact of the Life Cycle and Technology on Firm Survival’. *The Journal of Industrial Economics*, Vol. 49, No. 1, pp. 21-43.

Aghion, P., Bond, S. , Klemm, A., Marinescu, I. (2004). ‘Technology and financial structure: Are innovative firms different?’, *Journal of the European Economic Association*, Vol. 2, pp. 277-288.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., Howitt, P. (2005). ‘Competition and Innovation: An Inverted-U Relationship’. *The Quarterly Journal of Economics.* Vol. 120, No. 2, pp. 701-728.

Ai, C., Norton, E. (2003). ‘Interaction terms in logit and probit models’, *Economics Letters*, Vol. 80, pp. 123–129.

Akay, A. (2009). ‘The Wooldridge Method for the Initial Values Problem Is Simple: What About Performance?’, *IZA Discussion Paper*, No. 3943.

Allison, P. D., Waterman, R. P. (2002). ‘Fixed-effects negative binomial regression models’, *Sociological Methodology*, Vol. 32, pp. 247--265.

Archibugi, D., Pianta, M. (1996). ‘Measuring technological change through patents and innovation surveys’, *Technovation*. Vol. 16, pp. 451–468.

Arora, A., Fosfuri, A., Gambardella, A. (2001). ‘Markets for Technology and Their Implications for Corporate Strategy’. *Industrial and Corporate Change*, Vol. 10, No. 2, pp. 419-451.

Arora, A., Gambardella, A. (1990). ‘Complementarity and external linkages: the strategies of the large firms in biotechnology’, *Journal of Industrial Economics*, Vol. 38, pp. 361–379.

Arora, A., Gambardella, A. (1994). ‘The changing technology of technological change: general and abstract knowledge and the division of innovative labour’. *Research Policy*, Vol. 23, pp. 523–532.

Arora, A., Gambardella, A. (2010). The markets for technology. In B. H. Hall & N. Rosenberg (Eds.): *Handbook of the economics of innovation*. North Holland.

Arulampalam, W., Stewart, M. B. (2009). ‘Simplified Implementation of the Heckman Estimator of the Dynamic Probit Model and a Comparison with Alternative Estimators’, Oxford Bulletin of Economics and Statistics, Vol. 71, No. 5, pp. 659–681.

Arundel, A. (2001). ‘The relative effectiveness of patents and secrecy for appropriation’. *Research Policy*, Vol. 30, No. 4, pp. 611-624.

Arundel, A., Kabla, I. (1998). ‘What percentage of innovations are patented? empirical estimates for European firms’. *Research Policy*, Vol. 27, No. 2, pp. 127-141.

Audretsch, D. (1991). 'New firm survival and the technological regime', *The Review of Economics and Statistics*, Vol. 73, No. 3, pp. 441-450.

Audretsch, D. B. (1995). Innovation, growth and survival. *International Journal of Industrial Organization*, Vol. 13, pp. 441-457.

Audretsch, D. B. (2002). The Dynamic Role of Small Firms: Evidence from the US. *Small Business Economics*, Vol. 18, pp. 13-40.

Autio, E. (1994). ‘New, technology-based firms as agents of R&D and innovation: an empirical study’, *Technovation*, Vol. 14, No. 4, pp. 259-273.

Baltagi, B. H. (2005). *Econometric Analysis of Panel Data*. Third Edition. John Wiley & Sons.

Baptista, R. (1998). 'Clusters, innovation and growth: A survey of the literature', in Swann, G. M. P., Prevezer, M., Stout, D. (Eds.): *The Dynamics of Industrial Clustering: International Comparisons in Computing and Biotechnology*. Oxford University Press: New York.

Baptista, R., Swann, G. M. P. (1998). ‘Do firms in clusters innovate more?’. *Research Policy*, Vol. 27 No. 5, pp. 525-540.

Battisti, G., Stoneman, P. (2010). ‘How Innovative are UK Firms? Evidence from the Fourth UK Community Innovation Survey on synergies between technological and organizational innovations’. *British Journal of Management*, Vol. 21, pp. 187-206.

Baumol, W. J. (2002). *Free Market Innovation Machine: Analyzing the Growth Miracle of Capitalism*. Princeton University Press.

Bower, J. L., Christensen, C.M. (1995). ‘Disruptive Technologies: Catching the Wave’, *Harvard Business Review*, Vol. 73, pp. 43–53.

Breschi, S., Lissoni, F., and Malerba, F. (2003). ‘Knowledge-relatedness in firm technological diversification’. *Research Policy*, Vol. 32, pp. 69-87.

Breschi, S., Lissoni, F., Malerba, F., 2004. The empirical assessment of firms’ technological “coherence”, in: Cantwell, J., Gambardella, A., Granstrand, O. (Eds): *The economics and management of technological diversification*, Chap. 3. Routledge.

Breschi, S., Malerba, F., Orsenigo, L. (2000). ‘Technological regimes and Schumpeterian patterns of innovation’. *The Economic Journal*, Vol. 110, No. 4, pp. 388-410.

Bresnahan, T. F., Trajtenberg, M. (1995). ‘General purpose technologies ‘Engines of growth’?’. *Journal of Econometrics*, Vol. 6, No. 1, pp. 83-108.

Buis, M. (2010). ‘Stata tip 87: Interpretation of interactions in non-linear models’, *The Stata Journal*, Vol. 10, pp. 305-308.

Cameron, A. C., Trivedi, P. K. (1986). ‘Econometric Models Based on Count Data: Comparisons and Applications of Some Estimators and Tests’. *Journal of Applied Econometrics*, Vol. 1, pp. 29–54.

Cameron, A. C., Trivedi, P. K. (1998). *Regression analysis of count data*. Cambridge University Press.

Cantwell, J., Fai, F. (1999). ‘Firms as the source of innovation and growth: the evolution of technological competence’. *Journal of evolutionary economics*, Vol. 9, pp. 331-366.

Cefis, E. (2003). ‘Is there persistence in innovative activities?’. *International Journal of Industrial Organization*, Vol. 21, No. 4, pp. 489-515.

Cefis, E., Marsili, O. (2006). 'Survivor: The role of innovation in firms’ survival', *Research Policy*, Vol. 35, No. 5, pp. 626-641.

Cefis, E., Orsenigo, L. (2001). The persistence of innovative activities, a cross-countries and cross-sectors comparative analysis. *Research Policy*, Vol. 30, No. 7, pp. 1139–1158.

Chesbrough, H. (2003). *Open Innovation*. Harvard University Press: Cambridge, MA.

Chiu, Y., Lai, H., Liaw, Y., Lee, T. (2010). ‘Technological scope: diversified or specialized’. *Scientometrics*, Vol. 82, pp. 37-58.

Clausen, T., Pohjola, M. (2013). ‘Persistence of product innovation: comparing breakthrough and incremental product innovation’, *Technology Analysis & Strategic Management*, Vol. 25, No. 4, pp. 369–385.

Clausen, T., Pohjola, M., Sapprasert, K., Verspagen, B. (2011). ‘Innovation strategies as a source of persistent innovation’. *Industrial and corporate change*, doi: 10.1093/icc/dtr051.

Cockburn, I., Griliches, Z. (1988). ‘Industry effects and appropriability measures in the stock markets valuation of R&D and patents’. *American Economic Review*, Vol. 78, No. 2, pp. 419-423.

Cohen, W. M., Klepper, S. (1996). ‘A reprise of size and R&D’. *The Economic Journal*, Vol. 106, pp. 925-951.

Cohen, W. M., Levinthal, D. A. (1989). ‘Innovation and Learning: The Two Faces of R & D’. *The Economic Journal*, Vol. 99, pp. 569-596.

Cohen, W. M., Levinthal, D. A. (1990). ‘Absorptive Capacity: A New Perspective on Learning and Innovation’. *Administrative Science Quarterly*, Vol. 35, No. 1, pp. 128-152.

Colombelli, A., von Tunzelmann., N. (2011). Persistence of innovation and path dependence. In C. Antonelli (Ed.): *Handbook on the Economic Complexity of Technological Change*. Cheltenham: Edward Elgar, 105-119.

Corradini, C., Battisti, G., Demirel, P., 2012a. ‘Small serial innovators in the UK: does size matter?’, *Nottingham University Business School Research Paper*. No. 2012-10. Available at SSRN: http://ssrn.com/abstract=2148312

Corradini, C., Battisti, G., Demirel, P., 2012b. ‘Determinants of Technological Diversification in Small Serial Innovators’, *Nottingham University Business School Research Paper*. No. 2012-09.
Available at SSRN: http://ssrn.com/abstract=2147877

DIUS (Department for Innovation, Universities and Skills) (2008).*Innovation Nation*. London: HMSO.

Dosi, G. (1982). ‘Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change’. *Research Policy*, Vol. 11, No. 3, pp. 147-162.

Dosi, G., (1988). ‘Sources, procedures, and microeconomic effects of innovation’. *Journal of Economic Literature*, Vol. 26, pp. 1120-1171.

Duguet, E. ,Monjon, S. (2004). ‘Is Innovation Persistent at the Firm Level? An Econometric Examination Comparing the Propensity Score and Regression Methods’. *Cahiers de la Maison des Sciences Economiques*, Université Panthéon-Sorbonne, Paris.

EPO (1994). ‘Utilisation of Patent Protection in Europe. *Eposcript*, Vol. 3. European Patent Office, Munich.

Fagerberg, J. (2005). ‘Innovation: A Guide to the Literature’, in Fagerberg, J., Mowery, D. C., Nelson, R. R (Eds): *Oxford Handbook of Innovation*. Oxford: Oxford University Press.

Fai, F., Von Tunzelmann, N. (2001). ‘Industry-specific competencies and converging technological systems: evidence from patents’. *Structural change and economic dynamics*, Vol. 12, pp. 141-170.

Freeman, C. (1991). Networks of innovators: A synthesis of research issues. *Research Policy*, Vol. 20, No. 5, pp. 499-514.

Frenz, M, Prevezer, M. (2010). ‘The impact of technological regimes on patterns of sustained andsporadic innovation activities in UK industries’. *Working Papers* 33, Queen Mary, University of London, School of Business and Management, Centre for Globalisation Research.

Gambardella, A., Giuri, P., Luzzi, A. (2007). ‘The market for patents in Europe’. *Research Policy*, Vol. 36, No. 8, pp. 1163-1183.

Garcia Vega, M. (2006). ‘Does technological diversification promote innovation?: An empirical analysis for European firms’. *Research Policy*, Vol. 35, No. 2, pp. 230-246.

Geroski, P. A., Van Reenen, J., Walters, C. F. (1997). ‘How Persistently Do Firms Innovate?’. *Research Policy*, Vol. 26, No. 1, pp. 33–48.

Gilbert, R., Newberry, D. (1982). 'Pre-emptive patenting and the persistence of monopoly'. *American Economic Review*, Vol. 72, No. 3, pp. 514-526.

Granstrand, O., (1998). 'Towards a theory of the technology-based firm'. *Research Policy*, Vol. 27, No. 5, pp. 467–491.

Granstrand, O., Patel, P. and Pavitt K., (1997). 'Multi-technology corporations: Why they have "distributed" rather than "distinctive core" competencies'. *California Management Review,* Vol. 3, No. 4, pp. 8-25.

Granstrand, O., Sjölander, S. (1990). 'Managing innovation in multi-technology corporations'. *Research Policy,* Vol. 19, pp. 35-60.

Griliches, Z. (1981). 'Market value, R&D, and patents'. *Economics Letters,* Vol. 7, No. 2, pp. 183–187.

Griliches, Z., Mairesse, J. (1981). 'Productivity and R&d at the firm level', NBER Working Paper No. 826.

Griliches, Z. (1990). 'Patent Statistics as Economic Indicators: A Survey'. *Journal of Economic Literature,* Vol. 28, No. 4, pp. 1661-1707.

Guellec, D., van Pottelsberghe de la Potterie, B. (2007). *The Economics of the European Patent System*. Oxford University Press.

Hall, B. H. (2002). 'The Financing of Research and Development', *Oxford Review of Economic Policy,* Vol. 18, pp. 35-51.

Hall, B. H. (2005). 'A Note on the Bias in Herfindahl-Type Measures Based on Count Data'. *Revue d'Économie Industrielle,* Programme National Persée, Vol. 110, No. 1, pp. 149-156.

Hall, B. H., Jaffe, A., Trajtenber, M. (2001). ‘The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools’. *NBER Working Paper 8498*.

Hall, B. H., Jaffe, A., Trajtenber, M. (2005). ‘Market Value and Patent Citations’. *The RAND Journal of Economics,* Vol. 36, No. 1, pp. 16-38.

Hall, B. H., Lotti, F., Mairesse, J. (2011). ‘Evidence on the Impact of R&D and ICT Investment on Innovation and Productivity in Italian Firms’. Available online at: http://elsa.berkeley.edu/~bhhall/papers/HallLottiMairese11_ICT.pdf

Hardin, J. W., Hilbe, J. M. (2003). *Generalized Estimating Equations*. Chapman and Hall/CRC.

Harhoff, D., Narin, F, Scherer, F. M., Vopel, K. (1999). ‘Citation Frequency and the Value of Patented Inventions’. *The Review of Economics and Statistics*, Vol. 81, pp. 511-515.

Hausman, J., Hall, B. H., Griliches, Z. (1984). ‘Econometric Models for Count Data with an application to the Patents-R&D Relationship’. *Econometrica*, Vol. 52, No. 4, pp. 909-938.

Heckman, J., J. (1981). ‘The incidental parameters problem and the problem of initial conditions in estimating a discrete time–discrete data stochastic process’, in Manski, C., F., McFadden, D. (Eds): *Structural Analysis of Discrete Data with Econometric Applications*. MIT Press: Cambridge, MA; pp. 179–195.

Hedeker, D., Gibbons, R., D. (2006). *Longitudinal Data Analysis*. Wiley-Blackwell.

Helmers, C., Rogers, M. (2009). 'Patents, entrepreneurship and performance'. *Global COE Hi-Stat Discussion Paper Series gd09-095*, Institute of Economic Research, Hitotsubashi University.

Hicks, D., Hegde, D. (2005). ‘Highly innovative small firms in the markets for technology’. *Research Policy*, Vol. 34, No. 5, pp. 703-716.

Hilbe, J., M. (2011). *Negative binomial regression*. Second edition. Cambridge University Press.

Hoffman, K., Parejo, M., Bessant, J., Perren, L. (1998). ‘Small firms, R&D, technology and innovation in the UK: a literature review’. *Technovation*, Vol. 10, No. 1, pp. 39-55.

Huergo, E., Jaumandreu, J. (2004). ‘How Does Probability of Innovation Change with Firm Age?’. *Small Business Economics*, Vol. 22, pp. 193-207.

Hughes, A., Mina, A. (2012). *The UK R&D Landscape*. CIHE-UK~IRC Task Force Report.

Jaffe, A. B., Romer, P. M., Trajtenberg, M. (2002). *Patents, citations, and innovations: a window on the knowledge economy*. MIT Press.

Katila, R., Ahuja, G. (2002). ‘Something old, something new: a longitudinal study of search behavior and new product introduction’. *Academy of Management Journal*, Vol. 45, No. 6, pp. 1183-1194.

Kleinknecht, A., Verspagen, B. (1990). ‘Demand and innovation: Schmookler re-examined’. *Research Policy*, Vol. 19, No. 4, pp. 387-394.

Klevorick, A. K., Levin, R. C., Nelson, R. R., Winter, S. G. (1995). ‘On the sources and significance of interindustry differences in technological opportunities’. *Research Policy*, Vol. 24, No. 2, pp. 185-205.

Kline, S. J., Rosenberg, N. (1986). ‘An overview of innovation’, in Landau, R., Rosenberg, N. (Eds.): *The Positive Sum Game*. National Academy Press, Washington, DC.

Kogut, B., Zander, U. (1992). ‘Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology’. *Organization Science*, Vol. 3, No. 3, pp. 393-397.

Lach, S., Schankerman M. (1989), ‘Dynamics of R&D and Investment in the Scientific Sector’. *Journal of Political Economy*, Vol. 97, pp. 880-904

Langlois, R. N., Robertson, P. L. (1992). ‘Networks and innovation in a modular system: lessons from the microcomputer and stereo component industries’. *Research Policy*, Vol. 21, No. 4, pp. 297- 313.

Lanjouw, J. O., Pakes, A., Putnam, J. (1998). ‘How to Count Patents and Value Intellectual Property: The Uses of Patent Renewal and Application Data’. Journal of Industrial Economics, Vol. 46, No. 4, pp. 405–32.

Latham, W., Bas, C. (2005). ‘Introduction', in Bas, C., Latham, W. (Eds.): *The Economics of Persistent Innovation: An Evolutionary View*. Springer: New York.

Laursen, K. Salter, A. (2006). ‘Open for innovation: the role of openness in explaining innovation performance among UK manufacturing firms’. *Strategic Management Journal*, Vol. 27, pp. 131-150.

Leten, B., Belderbos, R., Van Looy, B. (2007). ‘Technological Diversification, Coherence, and Performance of Firms’. *Journal of Product Innovation Management*, Vol. 24, pp. 567–579.

Levin, R. C., Klevorick, A. K., Nelson, R. R., Winter, S. G. (1987). 'Appropriating the Returns from Industrial Research and Development' *Brookings Papers on Economic Activity*, Vol. 18, No. 3, pp. 783-832.

Liang, K., Zeger, S. (1986). 'Longitudinal Data Analysis Using Generalized Linear Models'. *Biometrika*, Vol. 73, No. 1, pp. 13-22.

Libaers, D., Meyer, M. (2011). 'Highly innovative small technology firms, industrial clusters and firm internationalization', *Research Policy*, Vol. 40, pp. 1426-1437.

Long, J. (1997). *Modeling Frequency and Count Data*. Oxford: Oxford University Press.

Lychagin, S.,Pinkse, J., Slade, M., Van Reenen, J. (2011). 'Spillovers in Space: Does Geography Matter?'. *CEP Discussion Paper*, No. 991. Available online at: http://cep.lse.ac.uk/pubs/download/dp0991.pdf

Magri, S. (2009). 'The financing of small innovative firms: The Italian case', *Economics of Innovation and New Technology*, Vol. 18, pp. 181-204.

Mairesse, J., Mohnen, P. (2005). 'The Importance of R&D for innovation: a reassessment using French survey data', Journal of Technology Transfer, Vol. 30, No. 1/2, pp. 183–197.

Mairesse, J., Mohnen, P. (2010). Using innovation surveys for econometric analysis. In B. H., Hall, Rosenberg, N (Eds): *Handbook of the economics of innovation*. Elsevier.

Malerba, F., Orsenigo, L. (1990). Technological Regimes and Patterns of Innovation: A Theoretical and Empirical Investigation of the Italian Case. In A. Heertje & M. Perlman (Eds.): *Evolving Technologies and Market Structure*. Cambridge: Cambridge University Press.

Malerba, F., Orsenigo, L. (1993). ‘Technological regimes and firm behaviour’. *Industrial and Corporate Change*, Vol. 2, No. 1, pp. 45-71.

Malerba, F., Orsenigo, L. (1996). ‘Schumpeterian patterns of innovation are technology-specific’. *Research Policy,* Vol. 25, No. 3, pp. 451-478.

Malerba, F., Orsenigo, L. (1999). ‘Technological Entry, Exit and Survival: An Empirical Analysis of Patent Data’. *Research Policy*, Vol. 28, pp. 643–660.

Malerba, F., Orsenigo, L., Peretto, P. (1997). ‘Persistence of innovative activities, sectoral patterns of innovation and international technological specialization’. *International Journal of Industrial Organization*, Vol. 15, No. 6, pp. 801-826.

Mansfield, E. (1986). ‘Patents and innovation: an empirical study’. *Management Science*, Vol. 32, pp. 173–181.

March, J., 1991. ‘Exploration and exploitation in organizational learning’. *Organization Science*, Vol. 2, pp. 71-87.

Marshall, A. (1890). 'Principles of Economics', 8th Edition, Book IV, available at http://oll.libertyfund.org/index.php?option=com_staticxt&staticfile=show.php%3Ftitle=1676&Itemid=28

Martinez, C. (2011). ‘Patent families: When do different definitions really matter?’. *Scientometrics*, Vol. 86, No. 1, pp. 39-63.

Mata, J., Portugal, P. (1994). 'Life Duration of New Firms', *The Journal of Industrial Economics*, Vol. 42, No. 3, pp. 227-245.

Miller, D. J., 2006. ‘Technological diversity, related diversification, and firm performance’. *Strategic Management Journal*. Vol. 27, pp. 601–619.

Mina, A., Lahr, H., Hughes, A. (2011). 'The Demand and Supply of External Finance for Innovative Firms', FINNOV DP 3.5.

Nelson, R., (1959). ‘The simple economics of basic scientific research’. *Journal of Political Economy*, Vol. 67, No. 3, pp. 297-306.

Nelson, R. R., Winter, S. (1982). *An Evolutionary Theory of Economic Change*. Belknap Press.

Nesta, L., Saviotti, P. P. (2005). ‘Coherence of the knowledge base and the firm's innovative performance: evidence from the US pharmaceutical industry’. *The Journal of Industrial Economics*, Vol. 53, pp. 123–142.

NESTA (2009a). The Innovation Index. Measuring the UK’s investment in innovation and its effects, Index Report 2009. Available at: http://www.nesta.org.uk/library/documents/innovation-index.pdf

NESTA (2009b). The vital 6 per cent. Available at: http://www.nesta.org.uk/events/assets/features/the_vital_6_per_cent

Norton, E., Wang, H., Ai, C. (2004). ‘Computing interaction effects and standard errors in logit and probit models’, *The Stata Journal*, Vol. 4, pp. 154–167.

OECD (1997). Small Business, Job Creation and Growth: Facts, Obstacles and Best Practices. OECD.

OECD, 2001. 'Science, technology and industry scoreboard: towards a knowledge-based economy', OECD Publishing, 2001.

OECD/Eurostat Statistical Office of the European Communities, Luxembourg (2005). ‘Oslo Manual: Guidelines for Collecting and Interpreting Innovation Data’, 3rd Edition, The Measurement of Scientific and Technological Activities, OECD Publishing.

Office for National Statistics, *UK Innovation Survey, 1996-2008: Secure Data Service Access* [computer file]. Colchester, Essex: UK Data Archive [distributor], July 2011. SN: 6699.

Pakes, A., Schankerman, M. (1984). The Rate of Obsolescence of Patents, Research Gestation Lags, and the Private Rate of Return to Research Resources. In Z. Griliches (Ed.): *R&D, Patents, and Productivity*, NBER Conference Report, 73–88.

Pan, W. (2001). ‘Akaike's information criterion in generalized estimating equations’, *Biometrics*, Vol. 57, pp. 120-125.

Papke, L. E., Wooldridge, J. M. (1996). ‘Econometric methods for fractional response variables with an application to 401(k) plan participation rates’. *Journal of Applied Econometrics*, Vol. 11, pp. 619–632.

Papke, L. E., Wooldridge, J. M. (2008). ‘Panel data methods for fractional response variables with an application to test pass rates’. *Journal of Econometrics*, Vol. 145, pp. 121-133.

Park, G., Park, Y. (2006). On the measurement of patent stock as knowledge indicators. *Technological Forecasting & Social Change*, Vol. 73, pp. 793–812.

Patel, P., Pavitt, K. (1997). ‘The Technological Competencies of the World’s Largest Firms: Complex and Path-dependent, but Not Much Variety’. *Research Policy*, Vol. 26, pp. 141-156.

Patel, P., Pavitt, K. (1998). The Wide (and Increasing) Spread of Technological Competencies in the World's Largest Firms: A Challenge to Conventional Wisdom. In A. D. Chandler & P. Hageström & Ö. Slölvell (Eds.): *The Dynamic Firm. The Role of Technology, Strategy, Organization, and Regions*. Oxford: Oxford University Press.

Pavitt, K. (1984). 'Sectoral patterns of technical change: towards a taxonomy and a Theory'. *Research Policy*, Vol. 13, No. 6, pp. 343-373.

Pavitt, K., (1988). Uses and abuses of patent statistics. In A. van Raan (Ed.): H*andbook of Quantitative Studies of Science and Technology*. North Holland.

Pavitt., K., Patel, P. (1994). 'The continuing, widespread (and neglected) importance of improvements in mechanical technologies'. *Research Policy*, Vol. 23, No. 5, pp. 533-545.

Pavitt, K., Robson, M., Townsend, J. (1989). 'Technological accumulation, diversification and organization in UK companies 1945–1983'. *Management Science*, Vol. 35, pp. 81-99.

Penrose, E., 1959. *The Theory of the Growth of the Firm*. Oxford University Press.Oxford.

Peters, B. (2009). 'Persistence of innovation: stylized facts and panel data evidence'. *Journal of Technology Transfer*, Vol. 34, No. 2, pp. 226 – 243.

Piscitello, L., (2004). 'Corporate diversification, coherence and economic performance'. *Industrial and Corporate Change*. Vol. 13, No. 757-787.

Quintana-Garcia, C., Benavides-Velasco, C. (2008). 'Innovative competence, exploration and exploitation: The influence of technological diversification'. *Research Policy*, Vol. 37, pp. 492-507.

Rabe-Hesketh, S., Skrondal, A. (2012). *Multilevel and Longitudinal Modeling Using Stata*. Third Edition. Stata Press.

Raymond, W., Mohnen, P., Palm, F., van der Loeff, S., S. (2010). 'Persistence of Innovation in Dutch Manufacturing: Is It Spurious?', *The review of economics and statistics*, Vol. 92, No. 3, pp. 495-504.

Reinganum, J. F. (1983). 'Uncertain Innovation and the Persistence of Monopoly'. *The American Economic Review*, Vol. 73, No. 4, pp. 741-748.

Reitzig, M., Henkel, J., Heath. C. H. (2007). 'On sharks, trolls, and their patent prey – Unrealistic damage awards and firms' strategies of 'being infringed'', *Research Policy*, Vol. 36, pp. 134-154.

Rosenberg, N. (1976). *Perspectives on Technology*. Cambridge University Press, Cambridge.

Rosenberg, N. (1982). *Inside the Black Box*. Cambridge: Cambridge University Press.

Scherer, F. M. (1980). *Industrial Market Structure and Economic Performance*. Rand McNally College Publishing Company.

Scherer, F. M., Harhoff, D. (2000). 'Technology policy for a world of skew-distributed outcomes', *Research Policy*, Vol. 29, pp. 559-566.

Scherer, F. M., Harhoff, D., Kukies, J. (2000). 'Uncertainty and the size distribution of rewards from innovation', *Journal of Evolutionary Economics*, Vol. 10, No. 1-2, pp. 175-200.

Schmoch, U. (2008). Concept of a Technology Classification for Country Comparisons. Final Report to the World Intellectual Property Organisation (WIPO).

http://www.wipo.int/edocs/mdocs/classifications/en/ipc_ce_41/ipc_ce_41_5-annex1.pdf

Schumpeter, J. A. (1934/1982). *The theory of economic development*. Transaction Publishers.

Schumpeter, J. A. (1942/2008). *Capitalism, socialism and democracy*. New York: Harper Perennial.

Shapiro, C. (2001). Navigating the Patent Thicket: Cross Licenses, Patent Pools, and Standard Setting. In Jaffe, A., Lerner, J., Stern, S. (Eds.): *Innovation Policy and the Economy*, Volume 1. MIT Press.

Smith, K. (2005). Measuring innovation. In Fagerberg, J., Mowery, D. C., Nelson, R. R (Eds): *Oxford Handbook of Innovation*. Oxford: Oxford University Press.

Schmookler, J. (1966), *Investment and Economic Growth*, Harvard Univ. Press.

Stigler, G. J. (1951). ‘The division of labour is limited by the extent of the market’, *Journal of Political Econom*y, Vol. 59, pp. 185–193.
Stoneman P. (1983). *The Economic Analysis of Technological Change*. Oxford University Press, Chap. 2.

Sutton, J. (1991). *Sunk costs and market structure*. MIT Press.

Suzuki, J., Kodama, F. (2004). ‘Technological Diversity of Persistent Innovators in Japan: Two Case studies of Large Japanese Firms’. *Research Policy*, Vol. 33, pp. 531-549.

Teece, J., Pisano G., Shuen, A. (1997). ‘Dynamic Capabilities and Strategic Management’. *Strategic Management Journal*, Vol. 18, No. 7, pp. 509-533.

Teece, D. J., Rumelt, R., Dosi, G., Winter, S. (1994). ‘Understanding Corporate Coherence: Theory and Evidence’. *Journal of Economic Behavior and Organisation*, Vol. 22, pp. 1-30.

Tether, B. S. (1998). ‘Small and large firms: sources of unequal innovations?’. *Research Policy*, Vol. 27, pp. 725-745.

Tether, B. S. (2002). ‘Who co-operates for innovation, and why. An empirical analysis’. *Research Policy,* Vol. 31, pp. 947-967.

Thoma, G., Torrisi, S. (2007). 'Creating Powerful Indicators for Innovation Studies with Approximate Matching Algorithms. A test based on PATSTAT and Amadeus databases', *KITeS Working Papers 211*, KITeS, Centre for Knowledge, Internationalization and Technology Studies, Universita' Bocconi, Milano, Italy, revised Dec 2007.

Thoma, G., Torrisi, S., Gambardella, A., Guellec, D., Hall, B.H., Harhoff, D. (2009). 'Methods and software for the harmonization and combination of datasets: A test based on IP-related data and accounting databases with a large panel of companies at the worldwide level', Draft Version 2009, Available at: http://www.esf-ape-inv.eu/doc/upload/TTGGHH_200920091117120005.pdf

Tirole, J. (1988). *The Theory of Industrial Organization*. MIT Press, Cambridge, MA.

Trajtenberg, M. (1990). ‘A Penny for Your Quotes: Patent Citations and the Value of Innovations’. *The Rand Journal of Economics*, Vol. 21, pp. 172-187.

Trajtenberg, M., Henderson, R., Jaffe, A. (1997). ‘University versus Corporate Patents: A Window on the Basicness of Invention’. *Economics of Innovation and New Technology*, Vol. 5, pp. 19-50.

Van Cayseele, P. J. G. (1998). ‘Market structure and innovation: A survey of the last twenty years’, *The Economist*, Vol. 146, No. 3, pp. 391–417.

Von Hippel, E. (1988). *The sources of innovation*. Oxford University Press. http://web.mit.edu/evhippel/www/sources.htm

Wang, Q., von Tunzelmann, N. (2000). ‘Complexity and the functions of the firm: breadth and depth’. *Research Policy*, Vol. 29, pp. 805-818.

Winter, S. (1984). ‘Technological competition in alternative technological regimes’. *Journal of Economic Behaviour and Organization*, Vol. 5, pp. 287-320.

Winter, S. G. (1987). Knowledge and competence as strategic assets. In D. J. Teece (Ed.): *The competitive challenge: Strategies for industrial innovation and renewal* (pp. 159-184), Cambridge, Massachusetts: Ballinger Publishing Company.

Winter, S. G. (2003). ‘Understanding Dynamic Capabilities’. *Strategic Management Journal*, Vol. 24, No. 10, pp. 991-995.

Wooldridge, J. M., 2002. *Econometric Analysis of Cross Section and Panel Data*. MIT Press.

Wooldridge, J. (2005). ‘Simple solutions to the initial conditions problem in dynamic nonlinear panel data models with unobserved heterogeneity’. *Journal of Applied Econometrics*, Vol. 20, No. 1, pp. 39–54.