Paper to be presented at the DRUID 2012

on

June 19 to June 21

at

CBS, Copenhagen, Denmark,

Small Serial Innovators in the UK: does size matter?

Carlo Corradini
University of Nottingham
Nottingham University Business School
lixcc28@nottingham.ac.uk

Giuliana Battisti
University of Nottingham
Nottingham University Business School
Giuliana.Battisti@nottingham.ac.uk

Pelin Demirel
University of Nottingham
Nottingham University Business School
Pelin.Demirel@nottingham.ac.uk

Abstract

This study explores the characteristics and determinants of innovation of exceptionally innovative small and medium sized UK enterprises. The focus is placed on 'serial' innovators, defined as independent companies with a persistent, unusually high frequency of innovations over time. The aim of the study is to identify such companies and analyse those factors, both internal and external to the enterprise, which may influence their inventive activity. In particular, we draw upon the concept of technological regime and other firm-specific technology characteristics to study the determinants of the rate of innovation in small serial innovators. We also provide comparisons to whether differences exist with respect to large serial innovators, traditionally associated with persistent innovation. Our empirical evidence is based upon a longitudinal dataset of 811 UK-based highly innovative companies that have patented over 66000 innovations from 1990 to 2006. Our findings indicate that small serial innovators benefit from developing high-quality technologies with a broad technological base. To do so, they rely on cumulative processes characterised by internal combinative capabilities and search depth. The very qualities of cumulativeness seem to be the main difference between small and large serial innovators.

Jelcodes:O30,-

Small Serial Innovators in the UK: does size matter?

Abstract

This study explores the characteristics and determinants of innovation of exceptionally innovative small and medium sized UK enterprises. The focus is placed on 'serial' innovators, defined as independent companies with a persistent, unusually high frequency of innovations over time. The aim of the study is to identify such companies and analyse those factors, both internal and external to the enterprise, which may influence their inventive activity. In particular, we draw upon the concept of technological regime and other firm-specific technology characteristics to study the determinants of the rate of innovation in small serial innovators. We also provide comparisons to whether differences exist with respect to large serial innovators, traditionally associated with persistent innovation. Our empirical evidence is based upon a longitudinal dataset of 811 UK-based highly innovative companies that have patented over 66000 innovations from 1990 to 2006. Our findings indicate that small serial innovators benefit from developing high-quality technologies with a broad technological base. To do so, they rely on cumulative processes characterised by internal combinative capabilities and search depth. The very qualities of cumulativeness seem to be the main difference between small and large serial innovators.

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. Such patterns are defined by high barriers to entry and routinised processes that sustain the innovative activity of a small number of large established firms competing in highly concentrated oligopolies (Schumpeter 1942; Nelson and Winter 1982; Malerba and Orsenigo 1996). Consequently, the innovative persistence literature has often overlooked the presence and the specific characteristics of small firms with persistent patterns of innovation, providing scant and contrasting evidence that point to a positive - albeit not simple - relationship between persistence and firm size (Geroski et al. 1997; Cefis and Orsenigo 2001). Moreover, these studies do not offer any insight on the specific qualities of small persistent innovators. Most importantly, they do not analyse the mechanisms that may generate such phenomenon, thus explaining the very presence of these companies.

In this paper, we aim to fill in an important gap by exploring the characteristics of small persistent innovators in the UK and the factors which affect their innovative activity within the analytical framework of Schumpeterian patterns of technological change. Differently from previous research, we do not focus on the presence or the possible determinants of persistence in the innovation activity. Instead, 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 innovative activity over time, defined as serial innovators[1], and explore the effect that specific patterns of innovative activity and firm-specific technology characteristics exert on their rate of innovation. Hence, we offer a comparative perspective observing the differences between small and large serial innovators in order to shed light on the moderating effects of firm size among persistent innovators.

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

At the same time, our results suggest that small companies which persistently engage in innovative activities may also need to develop innovations characterized by higher quality and a broad technological base (Hicks and Hegde 2005). Such technology could reinforce a positive feedback effect in firms' inventive activity. Moreover, it would allow small serial innovators to operate in modular innovation systems (Langlois and Robertson 1992) or as specialist technology suppliers in markets for technology (Hicks and Hegde 2005).

2. Literature Review and hypotheses

In the economic literature, persistence in innovation is seen as a result of market forces braided with processes of accumulation of technological capabilities and it is rooted in the Schumpeterian theories of 'creative destruction' and 'creative accumulation' (Schumpeter 1934, 1942). Following an evolutionary perspective, the literature on technological change has developed Schumpeter's insights into two models, respectively referred to

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

as Schumpeter Mark I and Mark II (Nelson and Winter 1982). The first model is characterized by a 'widening pattern', where ease of technological entry and low concentration in innovative activities result in a turbulent environment in which incumbent firms are constantly challenged by new entrants and the likelihood of survival is low (Audretsch 1995). In this context, new opportunities are often seized by small, newly established firms, thus preventing the mechanisms that lead to innovation persistence. The second model is described as a ‘deepening pattern’, where innovation advantages due to knowledge accumulation and technological learning generate concentration-increasing growth. Eventually, greater stability in the ranks of innovators and low entry lead to the presence of a restricted number of established, usually large, firms (Winter 1984; Malerba and Orsenigo 1996, 1999). According to this paradigm, persistence is an inherent quality of the process of innovative activity rooted in the routinised patterns of creative accumulation described by the Schumpeter Mark II model (Malerba and Orsenigo 1997).

Small companies have been excluded from the analysis of patterns of creative accumulation as these are usually linked with the presence of large scale economies, which are associated with a lower likelihood of survival for small companies (Acs and Audretsch 1987; Audretsch 1995). However, the extent of technological opportunities available in high-tech industries may allow small firms to follow strategies of niche marketing, thus reducing scale disadvantages. This hypothesis is put forward by Agarwal and Audretsch (2001), who find that the survival rate of small and large companies is almost the same in mature and high-tech product markets. However, the possibility of small firms to survive in such industries does not constitute evidence of their ability to engage in persistent innovation. In fact, Huergo and Jaumandreu (2004) find empirical evidence showing that entrant firms present the highest probability of innovation, while the opposite holds for the oldest firms. Yet, they also find that some peculiar sets of firms are able to survive for more than 20 years through a sustained record of innovative activities. While operating in a niche market may be a viable strategy for some firms, it is possible that a sustained innovative activity may prove to be an essential element in contrasting the obsolescence of incumbent knowledge typical of high-tech environments (Agarwal 1998) and, ultimately, for the very survival of small companies (Cefis and Marsili 2006).

In this regard, the assumption of scale-intensive capabilities to innovate in routinised regimes can also be relaxed in the presence of modern innovation networks and modular systems (Freeman 1991; Langlois and Robertson 1992). In particular, Hicks and Hegde (2005) suggest that one possible explanation for the presence of small serial innovators may be found in the recent theory on markets for technology (Arora et al. 2001), defined by “trade in technology disembodied from physical goods” (Arora and Gambardella 2010). According to this theory, the division of labour in the production of knowledge allows for a greater technological specialization, as well as lower economies of scale and entry barriers (Arora et al. 2001). Hence, Hicks and Hegde (2005) argue that small serial innovators may benefit from the division of labour in innovation acting as specialized suppliers of technological inputs. To do so, they argue these companies may need to develop high quality patents focused on generic technology and with a broad base. In this context, the relevance of scale economies in research is substituted by a very specific set of knowledge capabilities, and small firm survival depends more on the persistent development of a viable technology than upon the production of a viable product. Within this framework, the determinants of persistent innovation do not preclude small companies from presenting a sustained record of innovative activities, at least at the theoretical level.

Economic theory suggests three different elements that may explain persistence in innovation, which emphasize the role of knowledge accumulation and technological learning. The first element is related to the notion of cumulativeness, which describes the incremental nature of the process of knowledge creation and technical change (Rosenberg 1982). In this perspective, new innovations derive from the previous stock of competencies defined by the firm technological trajectory (Nelson and Winter 1982). Hence, innovative capabilities may benefit from dynamic increasing returns, defined by processes of learning by doing and learning to learn, across different degrees of formal and informal know-how (Cohen and Levinthal 1989; Teece et al. 1997). Another element may be constituted by dynamic economies of scale. In this case, commercial success is seen both as an incentive and a necessary condition for the firm to re-invest in further innovation projects, thus leading to increased market power, broader technological opportunities and persistence in innovation (Nelson and Winter 1982). The third hypothesis is related to the concept of sunk costs (Sutton 1991), through which high costs in R&D investments can be seen as constituting barriers to entry and exit in innovation, thus supporting and perpetuating the mechanisms seen before. Naturally, other elements are necessary for persistence to take place. In particular, technological opportunities and market demand are essential to support positive feedbacks in the innovation activity of companies, although these elements have rarely been tested empirically (Geroski et al. 1997).

Empirical evidence on the relationship between size and persistence is limited and partially contrasting. Studies based on patent data find that only a small number of companies are able to innovate constantly over time and persistence tends to increase with firm size. Malerba et al. (1997) find that persistent innovation exerts a significant effect on concentration and stability, confirming the linkages with Schumpeterian patterns of creative accumulation. Consistently, small firms present higher probabilities to stop innovating earlier than large ones. Yet, the relationship between persistence and firm size is not linear, with many large firms which do not show elements of persistence and small firms that are persistent innovators, and significant differences across countries (Cefis and Orsenigo 2001). In particular, Geroski et al. (1997) point out that persistence in innovation is likely to depend more on the level of previous innovative activity rather than firm size. Yet, these studies do not explore further the specific characteristics of small persistent innovators and offer little insights on the different effects that the determinants of persistent innovation may exert with respect to large companies.

Studies based on survey data offer different findings, suggesting that innovation is persistence to a large extent. Duguet and Monjon (2004) argue that determinants of persistence depend on the size of the firm. They find evidence that in small firms a central role is played by dynamic increasing returns, while for large companies the determinants of persistence are mostly internal R&D capabilities, market power and technological opportunities. Peters (2009) also highlights the importance of dynamic innovative capabilities, but she finds that firm size matters only in manufacturing industries.

2.1. The characteristics of technological regimes

Several empirical studies have demonstrated that the patterns of innovative activity may be explained through the qualities of the relevant technological regime (Malerba and Orsenigo 1996, 1999; Breschi et al. 2000), which influences the innovative activity of both large and small companies, as well as firm entry and survival (Acs and Audretsch 1988; Audretsch 1995). A technological regime can be seen as the knowledge environment which shapes and constrains the firm-specific routines and boundaries, and define its technological trajectory (Nelson and Winter 1982; Dosi 1982). Four main characteristics can be utilized to describe a specific technological regime, namely opportunity conditions, appropriability conditions, cumulativeness and properties of the knowledge base (Malerba and Orsenigo 1990, 1993).

Opportunity conditions describes the increase in the innovative activity for a given amount of money or resources spent in search (Malerba and Orsenigo 1993). An important element of such concept is the level of technological opportunities, which can be described as the set of possibilities available to companies in their technological activity. Generating this rich innovative environment, opportunity conditions ease the effect of size-related disadvantages (Audretsch 1995). Thus, we expect a positive effect for both large and small serial innovators.

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 this sense, the competencies acquired in the past direct and sustain a stream of new innovations along the firm-specific technological paradigm (Dosi 1982). For this reason, higher degrees of cumulativeness are likely to be positively associated with persistence in innovation.

Appropriability conditions expresses the possibility for the firm to protect its inventions and, more generally, to gain the profit from its innovative activity. Therefore, high levels of appropriability are associated with a deepening pattern of innovative activity. 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 presents 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 on. While the theory has identified various characteristics such as specificity, tacitness and complexity (Winter 1987), empirical analysis has usually measured this variable using the simpler dichotomy between tacit and codified knowledge. As Breschi et al. (2000) suggest, these two categories can be also related to different types of science. In fact, they use survey data to define properties of the knowledge base measuring the relative importance and the linkages with basic science (e.g.: physics, chemistry) or applied science (e.g.: engineering).

2.2. The role of firm-specific technology characteristics

Technological regimes describe the knowledge environment where firms' innovative activity takes place. While this is an essential element in defining the technological trajectory followed by companies, it does not describe the specific characteristics of the technology they develop. Accordingly to the theory of markets for technology, Hicks & Hegde (2005) indicate that small companies may need to develop technologies characterised by high quality, with a broad technological base and wide applicability to effectively operate as technology suppliers. More generally, given the relevance of innovation networks and modularity for small companies (Freeman

1991; Langlois and Robertson 1992), patents presenting such qualities are likely to be important elements in the technological activity of all small serial innovators.

The impact of innovation is a close concept to patent value, but we argue it represents something more. While the value of a patent is usually calculated with respect to the average number of citations for all the patents within an industry, the impact is calculated with respect to the total number of citations. It is a measure of the technological novelty added to the flow of new knowledge generated in a specific year and sector. A patent with a high impact does not necessarily generate an increase in the number of patents within a company. On the other hand, it is clear that patents with a higher impact also have a higher commercial value (Hicks and Hegde 2005). Moreover, the competencies necessary to 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.

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) first 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'. In other words, the general scope of these technologies opens a stream of technological opportunities that scatter around the GPT fostering the R&D productivity of related sectors. More generally, persistence may be sustained by the stream of innovations that may spin off from highly pervasive technologies and generalised knowledge (Arora and Gambardella 1994).

Originality of innovation indicates the level of complementary knowledge and technologies that are used to develop a new technology. Granstrand et al. (1997) indicate that while technological competencies depend on past innovative activity, persistent innovative companies need to diversify their technological capabilities in order to incorporate new opportunities and manage their complex production system. In this sense, firms whose innovations derive from a broad range of technological 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). Hence, this accumulation of external knowledge may increase the rate of invention of companies and reinforce processes of persistence in innovation.

2.3. Hypotheses

We conceptualize the presence and the industrial dynamics of small serial innovators as being defined by processes of creative accumulation. In this sense, their innovative activity is supported by technological regimes characterised by high opportunity conditions and high cumulativeness. The main difference we expect them to present with respect to large serial innovators is defined by the specific qualities of the cumulative process. The starting point of our rationale is that small firms inevitably have a limited amount of R&D resources. Hence, they cannot rely on highly routinised and formal research structures which describe the linear model of innovation usually associated with large companies. Conversely, we argue that their innovation activity is characterised by dynamic increasing returns, defined by incremental search and 'combinative' capabilities (Kogut and Zander 1992). In this sense, small serial innovators 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). Similarly, technology that is tradeable within modular systems or markets for technology is likely to support the division of innovative labour, enabling small

companies 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.
Thus, considering the qualities of technological regimes and the firm-specific technology characteristics identified, we propose to test three hypotheses in this paper.

Hypothesis 1. The rate of innovation of small serial innovators is enhanced in the presence of high opportunity conditions and high levels of cumulativeness.

Hypothesis 2. Small serial innovators benefit from high-quality patents, with a broad technological base and generic nature.

Hypothesis 3. Large and small serial innovators differ in the nature of their cumulative processes. While the level of formal R&D is more relevant for the first group, small companies need to rely more on internal competencies and incremental search.

3. Data

In this paper, we label as serial innovators those companies that are independent throughout the observation period, with at least five years of technological patenting activity, defined 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.
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[2]. 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 analysed in the paper, may solve this issue (Trajtenberg 1990; Hall et al. 2005). More generally, patent data have further advantages over other measures of innovative activity, such as R&D spending, in the study of persistent innovation[3]. Hence, they have been used extensively in analysing persistent innovation, as well as technological regimes and markets for technologies.
To build our dataset, we proceeded as follows. All applicants based in the UK with at least a 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[4], with patent family being defined as "a set of patents taken in various countries to protect a single invention" (OECD 2001). Following our definition, at the end of this process a total of 1410 serial innovators were identified. Then, all records were integrated with information from the FAME database and Companies House website, which contains the official UK register of companies. For 296 companies it has not been possible to collect information on size, ownership and sector**,** and they have been removed from the analysis. Excluding also those companies which were not independent or were acquired in the period of time

[2] For a discussion of strengths and weaknesses of patent data see Griliches (1990).
[3] See Geroski et al. (1997).
[4] See Martinez (2011) for a detailed discussion on patent families.

considered, the final dataset contained information on 811 companies: 419 large, 53 medium and 339 small companies.

4. Small serial innovators: some stylised facts

Table 1 reports descriptive statistics for the firms in our dataset by size group. As expected, the differences between large and medium or small-sized companies are sensible, with the first group accounting for the large majority of patents in the dataset, with the mean equal to 138 patents for large firms and 22 for small 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 second quartile underlines, half of the large companies have less than 41 patents, with the ten highest patenting companies holding almost one third of the patents considered. Small and medium-sized companies show on average of about 22 inventions over the sixteen years analysed, but with a large variance in the data, with 90% of them set under 38 applications. In fact, the median is 16, while the third quartile is 23. 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. 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. If we look at the date of incorporation, many are much more long lived: the average number of years is equal to 20 for small companies and 37 for medium ones (The median is once again lower, with values of 14 and 23 respectively).

Considering the distribution across industrial sectors of small and medium companies reported in Table 2, we find that Research & Development is the most represented sector, accounting for a quarter of the total number of companies (26%). Interestingly, the majority of these firms are small, with only six cases of medium-sized companies. The manufacturing sectors constitute the other main group in the data, with the predominance of metal products and machinery (11% and 7%) followed by chemical and plastic products (4% and 6% respectively).

Table 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	137.90	354.43	21	41	96	4832	10	57778	419
	Year Diff.	11.54	3.66	8	12	15	16	5		
	Ratio	10.37	22.90	2.22	3.85	8.38	302	1		
SMALL	PAT	21.89	19.55	13	16	23	181	10	8580	392
	Year Diff.	9.89	3.53	7	9	13	16	5		
	Ratio	2.33	1.93	1.35	1.81	2.50	21.2	1		
TOTAL	PAT	81.82	261.49	15	23	49	4832	10	66358	811
	Year Diff.	10.74	3.69	8	10	14	16	5		
	Ratio	6.48	16.99	1.6	2.43	4.67	302	1		

Table 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	0.77%	0.64%
Manufacture of Wearing Apparel	18	11	0.26%	0.13%
Manufacture of Pulp, Paperand Paper Products	21	81	1.28%	0.94%
Manufacture of Chemicals and Chemical Products	24	342	4.34%	3.99%
Manufacture of Rubber and Plastic Products	25	470	6.63%	5.48%
Manufacture of Other Non-metallic Mineral Products	26	37	0.51%	0.43%
Manufacture of Basic Metals	27	20	0.51%	0.23%
Manufacture of Fabricated Metal Products, Except Machinery	28	832	10.71%	9.70%
Manufacture of Machinery and Equipment Not Elsewhere Classified	29	403	6.63%	4.70%
Manufacture of Office Machinery and Computers	30	69	1.02%	0.80%
Manufacture of Electrical Machinery and Other Apparatus	31	227	3.32%	2.65%
Manufacture of Radio, Television and Communication Equipment	32	360	3.57%	4.20%
Manufacture of Medical, Precision and Optical Instruments	33	481	5.87%	5.61%
Manufacture of Motor Vehicles, Trailers and Semi-Trailers	34	23	0.51%	0.27%
Manufacture of Other Transport Equipment	35	49	0.77%	0.57%
Manufacture of Furniture; Manufacturing Not Elsewhere Classified	36	610	7.65%	7.11%
Wholesale Trade and Commission Trade	51	154	2.30%	1.79%
Retail Trade, Except of Motor Vehicles and Motorcycles	52	10	0.26%	0.12%
Water Transport	61	29	0.26%	0.34%
Post and Telecommunications	64	95	1.28%	1.11%
Computer and Related Activities	72	265	2.04%	3.09%
R&D	73	2793	25.77%	32.55%
Other Business Activities	74	777	8.93%	9.06%
Education	80	47	0.26%	0.55%
Health and Social Work	85	29	0.51%	0.34%
Recreational, Cultural and Sporting Activities	92	68	0.77%	0.79%
Other Service Activities	93	131	1.53%	1.53%
Miscellaneous		112	1.79%	1.31%
TOTAL		8580	100%	100%

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. Among the former we include opportunity conditions (OPPORTR), knowledge stock (KSTOCK), cumulativeness (CUMULTR) and properties of the knowledge base (KNOWTR). We measure firm-specific technology characteristics via impact (IMPIN), generality (GENIN) and originality (ORIGIN) of innovation. In particular, we aim to specify and test a model of the type:

$$PATENTS_{it} = f\,(OPPORTR_{it},\ \log(KSTOCK_{it-1}),\ CUMULTR_{it},\ KNOWTR_{it},\ IMPIN_{it-1},\ GENIN_{it-1},\ ORIGIN_{it-1}) \quad (5.1)$$

Furthermore, in order to investigate the different effects exerted by technological regimes on small and large serial innovators, we test the following model with interaction effects based on firm size:

$$PATENTS_{it} = f\,(OPPORTR_{it},\ \log(KSTOCK_{it-1}),\ CUMULTR_{it},\ KNOWTR_{it},\ SMALL,\ OPPORTS\_SM_{it},\ \log(KSTOCK\_SM_{it-1}),\ CUMULTR\_SM_{it},\ KNOWTR\_SM_{it}) \quad (5.2)$$

The rationale for both the model and the variables specification is reported below.

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, while the number of patents is a direct and intuitive way to study the inventive activity of a company, one of the shortcomings of such measure lies in the absence of a control factor for the significant variance in the economic value of individual patents. 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 two measures of the rate of innovation of serial innovators. The first is the number of patents per year $PATENTS_{it}$ the second is the citation-weighted patent count $CITATIONS_{it}$[5].

5.2. Independent Variable

5.2.1. Technological Regime Variables

The first group of independent variables refers to the concept of technological regime, which describes the nature of the technological environment bounded by 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:

$$OPPORTR_{it} = \frac{1}{P_{it}} \sum_{p_{it}=1}^{P_{it}} \frac{a_{p,t} - a_{p,t-1}}{a_{p,t-1}} \qquad (5.3)$$

[5] 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.

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. Consistently with the theory on Schumpeterian patterns of technological change we expect OPPORTR to present a positive sign upon the patenting rates of firms.

Cumulativeness summarizes the idea that inventions in time t depends on existing knowledge capabilities and previous innovation. To capture these two aspects we use two distinct variables, *knowledge stock* and *cumulativeness*. . The first one is a proxy measure for dynamic economies of scale whereby increases in the volume of innovation in a given time period lead to further increases in the innovation produced in subsequent periods while the second may be considered a direct measure of accumulated knowledge competencies and dynamic increasing returns (Hall et al. 2005). In line with the existing literature we measure *Knowledge stock (KSTOCK)* as the firm patent stock[6]:

$$KSTOCK_{it} = P_{it} + (1-\delta)KSTOCK_{it-1} \tag{5.4}$$

where P_{it} represents the number of patents at the beginning of year *t* and δ is the depreciation rate, which is assumed to be 15% (Cockburn and Griliches 1988, Hall et al. 2005)[7]. To control for potential endogeneity we allow KSTOCK to enter the estimating equation with a lag after being log transformed. Given the relationship between cumulativeness and persistence, we expect a positive sign for both variables.

Cumulativeness (CUMULTR) measures the average percentage of self-citations made by the *i*th firm in year *t*. For every patent *p* we count the number of citations made to other patents with the same assignee $Nsame_p$, divided by the total number of citations N_p[8]:

$$CUMULTR_{it} = \frac{1}{P_{it}} \sum_{p_{it}=1}^{P_{it}} \frac{Nsame_{p_{it}}}{N_{p_{it}}} \tag{5.5}$$

Properties of the knowledge base (KNOWTR) refers to the nature of the technology and the knowledge in the 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[9], 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:

6 In the following analysis, we use the log of KSTOCK.
7 As a further test we have also set δ = 20% and δ = 25%, but estimates do not change significantly.
8 Note that this is the index proposed by Trajtenberg et al. (1997) to measure appropriability.
9 See Appendix, Table A.1.

$$KNOWTR_{it} = \frac{c_{b,it} + u_{it}}{C_{it} + u_{it}} - \frac{c_{a,it}}{C_{it} + u_{it}} \tag{5.6}$$

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.

5.2.2. Firm Specific Technology Variables

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.

It has been argued that firms need high quality inventions in order to succeed as persistent innovators, especially 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:

$$IMPIN_{it} = \frac{1}{P_{it}} \sum_{p_{it}=1}^{P_{it}} \frac{N_{fp_{it},k}}{N_{ft,k}} \tag{5.7}$$

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 as financial signals, we expect a positive sign for IMPIN.

Generality of innovation (GENIN) is related to the idea that innovative companies benefit from the development of pervasive technologies which may generate or even require successive innovations in different sectors. While we would expect a positive sign for GENIN, we also need to consider that not all companies may be able to or even interested in exploring the new possibilities opened by generic innovations. 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:

$$\hat{G}_p = GENERALITY_p = \frac{N_{fp}}{N_{fp} - 1} \left(1 - \sum_{k=1}^{K} \left(\frac{N_{fp,k}}{N_{fp}} \right)^2 \right) \tag{5.8a}$$

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 hence 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:

$$GENIN_{it} = \frac{1}{P_{it}} \sum_{p_{it}=1}^{P_{it}} \hat{G}_{p_{it}} \qquad (5.8b)$$

Originality of innovation (ORIGIN) is related to the argument that small technology suppliers may develop more original inventions, thus referencing and building upon technological advances from a broad set of sectors (Hicks and Hegde 2005). It is also a proxy for firms' technological diversification, as it indicates the spectrum of technological competencies that companies are able to explore and exploit. As we have seen, an increase in the technological diversification is expected to affect positively the number of patents, especially for the technology-based firms (Garcia Vega 2006). Accordingly, we expect ORIGIN to present a positive sign. 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:

$$\hat{O}_p = ORIGINALITY_p = \frac{N_{bp}}{N_{bp}-1}\left(1-\sum_{k=1}^{K}\left(\frac{N_{bp,k}}{N_{bp}}\right)^2\right) \qquad (5.9a)$$

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. Again, our originality index is:

$$ORIGIN_{it} = \frac{1}{P_{it}} \sum_{p_{it}=1}^{P_{it}} \hat{O}_{p_{it}} \qquad (5.9b)$$

By construction, both GENIN and ORIGIN are not defined, hence excluded from the analysis, when the number of citations received or made is less than 2.

To study the role of firm size, we make use of a series of dummy variables. SMALL is a variable being equal to one if the company is medium-sized or small-sized, that is, has a number of employees lower than 500, zero if it is a large company. More interestingly, interactions between SMALL and the variables already introduced enable to test whether their effect is the same for small and large companies. According to the model proposed in this paper, we expect differences with respect to large firms in the variables related to opportunity conditions and cumulativeness. In particular, we expect the interaction variable related to dynamic economies of scale

KSTOCK_SM to present a negative sign, while the variable related to dynamic increasing returns CUMULTR_SM to be positive.

5.3. Descriptive statistics

Tables 3 and 4 report descriptive statistics and the correlation matrix for the variables introduced.

5.4. 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

Table 3: Descriptive statistics

	Small Serial Innovators				
	Mean	St.Dev	Median	Max	Min
Patents	3.33	3.42	2.00	57.00	1.00
Citations	10.54	16.80	5.00	288.00	2.00
Opportr	2.46	1.60	2.27	7.62	-0.82
Kstock	1.74	0.95	1.75	4.52	-0.97
Cumultr	0.35	0.62	0.00	7.33	0.00
Knowtr	-0.26	0.80	-0.60	1.00	-1.00
Impin	1.17	1.89	0.58	21.15	0.00
Genin	0.38	0.32	0.36	1.00	0.00
Origin	0.37	0.29	0.36	1.00	0.00

Table 4: Correlation matrix

	Patents	Citations	Opportr	Kstock	Cumultr	Knowtr	Impin	Genin	Origin
Patents	1								
Citations	0.6587	1							
Opportr	0.3868	0.2174	1						
Kstock	0.2913	0.2204	0.0541	1					
Cumultr	0.2388	0.2726	0.2287	0.1909	1				
Knowtr	-0.0274	-0.0056	-0.012	0.0011	-0.0683	1			
Impin	0.1952	0.2242	0.106	0.1477	0.1418	-0.0113	1		
Genin	0.0199	0.0212	-0.0199	-0.0176	0.023	0.1197	0.024	1	
Origin	0.021	0.0632	-0.0053	-0.007	0.0555	0.0867	0.0925	0.3734	1

All values significant at the .05 level

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[10] (Hilbe 2011). 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[11].

A 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 patent citation count is divided by the average citation count of all patents belonging to the same group of the reference patent.

6. Results

Table 5 shows the GEE estimates of the relationship between the rate of innovation of small serial innovators and the variables representing technological regimes and firm-specific technologies. All regressions include year dummies. In the following discussion, we focus on regressions (3) and (4) where the dependent variable is respectively PATENTS and CITATIONS. The coefficients are expressed in terms of IRRs as they are easier to interpret, especially when analysing interaction variables in nonlinear models. IRRs can be read as the factor increase – or decrease – in the dependent variable following an increase – or decrease - of one unit in the independent variable, ceteris paribus[12].

Opportunity conditions present a positive relationship with the rate of innovation. As we would expect, an economic environment replete with new technological discoveries provides fertile ground for the innovation activity of small serial innovators. They also generate incentives to further investment in research. Similarly, they may imply increasing spill-over effects from public research institutes or collaboration with other companies. These elements, perhaps coupled with the presence of cumulativeness, seem to offset the negative effect of technological turbulence. This relationship is robust to both models with the number of patents and the citation-weighted number of patents as dependent variables.

The log of the patent stock (KSTOCK) is also positively related to both PATENTS and CITATIONS. This finding suggests that cumulativeness is indeed an important element in small serial innovators, at least when measured in terms of accumulated resources and innovation output. While our data seem to point towards a positive relationship between dynamic economies of scale and the rate of innovation of serial innovators, there are different mechanisms through which this effect may be taking place. For example, companies may as well benefit from having innovated in the past as a consequence of more experience of the innovative process, including the patenting process, or simply for better access to financial resources.

[10] We report the p value for the LM test in table 5.

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

[12] An incidence rate ratio is simply the ratio of two ratios, which are defined by the occurrence of an event in a given time period.

Table 5: GEE Negative binomial regression estimates for small serial innovators

	(1) PATENTS	(2) CITATIONS	(3) PATENTS	(4) CITATIONS
	Technological regimes variables			
Opportr	0.284***	0.471***	1.328***	1.601***
	(0.0155)	(0.0369)	(0.0207)	(0.0592)
Kstock	0.575***	0.605***	1.777***	1.830***
	(0.0325)	(0.0767)	(0.0578)	(0.140)
Cumultr	0.157***	0.647***	1.169***	1.909***
	(0.0402)	(0.110)	(0.0470)	(0.210)
Knowtr	-0.067+	-0.252**	0.934+	0.776**
	(0.0358)	(0.0873)	(0.0335)	(0.0678)
	Firm specific technology related variables			
Impin	0.052***	0.189***	1.053***	1.199***
	(0.0115)	(0.0283)	(0.0122)	(0.0339)
Genin	0.055	-0.225	1.057	0.798
	(0.0809)	(0.187)	(0.0856)	(0.149)
Origin	0.058	0.438*	1.060	1.549*
	(0.0966)	(0.2226)	(0.1024)	(0.345)
_cons	-0.881***	3.546***		
	(0.139)	(0.309)		
N	1560	1560	1560	1560
Lagrange Multiplier Test			p value =	.000

All regressions include year dummies

S.E. in parentheses

+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001

We find the same relationship for CUMULTR. Previous innovations may be important for small innovators as they define the technological trajectory the company will follow. In this sense, the coefficient of CUMULTR might indicate the centrality of the path-dependent nature of internal capabilities in enhancing innovation in these companies. Without the extensive budget for R&D found in large companies, the competencies acquired internally become the primary source of invention for the next generation of technologies. This process may generate synergies across projects as well as between the different departments within the company. Also, the importance of previous innovations suggests that economies of specialization may be particularly important for small serial innovators, allowing them to develop specific competitive advantages. 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). As we noted earlier, the importance of cumulativeness may also defend small serial innovators from turbulent environments and obsolescence of incumbent knowledge, without preventing them from exploring new opportunities.

Finally, the negative sign for KNOWTR indicate that serial innovators benefit from having linkages with applied sectors, as opposed to basic sectors. One possible explanation for this is that the companies in our dataset specialize as intermediate technology developers, therefore operating more with applied knowledge than basic science.

Considering the second group of variables, our estimates confirm the role played by high-quality patents with a broad technological base. The positive sign of IMPIN suggests that promising and valuable technologies are more likely to generate further ideas and innovations which can be licensed or become the basis for further development. They also act as a signal on financial markets, enabling small companies to have access to external funding or venture capital. More generally, the estimates of IMPIN support the theory that "success breeds success", at least at the technological level.

The hypothesis of a positive effect generated by broad technological competencies is confirmed by the estimate of ORIGIN, at least when the dependent variable is the citation-weighted patent count. A possible interpretation for this result is that serial innovators may benefit from developing radical innovations, as any other firm, which are likely to conduct to a series of related patents based on a specific breakthrough. Another explanation is that serial innovators may benefit from knowledge complementarities.

6.1. Technological regimes and firm size

To explore the different effect exerted by technological regimes across firm size we introduce the dummy variable SMALL and its interactions with the independent variables representing technological regimes. As before, we focus on columns (3) and (4) of Table 6, which report the IRRs for the model based on PATENTS and CITATIONS respectively.

Overall, we see that the signs of the estimates for the base group, constituted by large companies, are substantially the same we observed in the previous section. Higher opportunity conditions and cumulativeness favour innovation for large serial innovators, which is consistent with the Schumpeterian pattern of creative accumulation. Again, we find a negative sign for KNOWTR, which could be explained by the incremental nature of innovation within such regime. While basic science may provide the initial elements for the development of a new technology, several intermediate passages are still needed to produce innovations.

Differences across firm size are given by the interaction variables at the bottom of columns (3) and (4). In particular, more than the innovation rate differential between small and large companies, we are interested in the different effect exerted by technological regimes and firm-specific technology characteristics[13]. Technological regimes seem to affect differently small and large serial innovators, with the IRRs being statistically significant for each variable considered.

Opportunity conditions, while still being positive for both groups, have a greater positive effect for large companies. There are at least two reasons why this can happen. In presence of high appropriability, high

[13] The coefficient for SMALL is positive. Yet, when we run the models after centering all explanatory variables, its IRR reduces to almost zero and it is no longer statistically significant in model (4), while it is equal to .82 in model (3) at the .001 level.

Table 6: GEE Negative binomial regression estimates for differences across firm size

	(1) PATENTS	(2) CITATIONS	(3) PATENTS	(4) CITATIONS
	Technological regimes variables			
Opportr	0.545***	0.764***	1.726***	2.147***
	(0.0106)	(0.0270)	(0.0184)	(0.058)
Kstock	0.662***	0.654***	1.938***	1.923***
	(0.0121)	(0.0300)	(0.0234)	(0.0577)
Cumultr	0.091*	0.763***	1.095*	2.146***
	(0.0416)	(0.115)	(0.0456)	(0.2462)
Knowtr	-0.317***	-0.521***	0.728***	0.594***
	(0.0267)	(0.0701)	(0.0194)	(0.0416)
	Size and interaction variables			
Small	0.395***	0.750***	1.484***	2.117***
	(0.0690)	(0.137)	(0.1025)	(0.2916)
Opportr_Sm	-0.0998***	-0.155***	0.904***	0.856***
	(0.0151)	(0.0375)	(0.0137)	(0.0321)
Kstock_Sm	-0.218***	-0.237***	0.803***	0.788***
	(0.0277)	(0.0619)	(0.0222)	(0.0488)
Cumultr_Sm	0.273***	0.507***	1.313***	1.661***
	(0.0556)	(0.151)	(0.0731)	(0.251)
Knowtr_Sm	0.134**	0.411***	1.143**	1.509***
	(0.0403)	(0.101)	(0.0461)	(0.152)
_cons	-1.073***	3.212***		
	(0.0669)	(0.155)		
N	9828	9828	9828	9828
Lagrange Multiplier Test			p value =	.000

All regressions include year dummies

S.E. in parentheses

+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001

opportunity conditions may cause an increase in the differences among the rates of innovation of incumbent companies. This process eventually generates higher concentration and therefore persistence (Malerba and Orsenigo 1990). Also, large companies have greater technological diversification than small firms. This, in turn, allows them to be able to benefit from a broader range of technological advances that can spur innovation horizontally across the different firm divisions. In other words, if we consider the centrality of cumulativeness in small serial innovators we have observed in the previous section, it is possible that such companies may be less responsive to external opportunities, as they lack the resources and the time needed to engage in radical search and exploration.

This idea is confirmed by the estimates related to cumulativeness, KSTOCK_SM and CUMUL_SM. The positive effect derived from having a larger patent stock is reduced for small companies. As we expected, we observe the opposite effect for CUMULTR_SM. Relying on previous inventions also improve the number and the quality of the technology developed, as measured by the two dependent variables. In this sense, the sign of CUMULTR_SM may indicate that small serial innovators which follow a specific technological trajectory increase their chances to develop higher-quality innovations. This may also indicate the presence of a positive return from strategies of technological specialization. In line with the estimates found for OPPORTR_SM, small serial innovators seem to be characterized by incremental search based on the exploitation of internal capabilities and competencies (Malerba and Orsenigo 1993). These findings seem to be in line with the argument proposed by Duguet and Mojon (2004), who find that persistence in innovation for companies with large R&D budgets comes from persistence in formal research. This is the effect that KSTOCK may be capturing. On the other hand, dynamic increasing returns are more important for the innovative activity of small persistent innovators, which are likely to rely on more informal research capabilities.

Finally, small companies seem to be more related to basic science technologies. While collaboration with universities may be part of this effect, it is likely that the positive sign for KNOWTR_SM refer to the importance of technological inputs from research intensive sectors and science-based firms (Pavitt 1984). As discussed before, this effect may be less strong in large companies due to the number of intermediate technologies needed to develop innovations from basic inventions.

7. Conclusions

This paper has shown that sustained innovative activity over time is not a specific quality of large companies. Examining persistence in innovation at the firm level in the UK using patent data from the PATSTAT database during the period 1990 – 2006, we proposed estimates of the relationship between variables related to technological regimes and firm specific technological characteristics and the rate of innovation of small and large serial innovators. Our findings provide evidence to support the hypothesis that opportunity conditions, cumulativeness and the quality of innovations are central elements in persistent innovation.

This paper confirms that small serial innovators benefit from high-quality patents with a broad technological base (Hicks and Hegde 2005). While these elements are essential to a sustained innovative activity, the technological environment is also paramount. As for large companies, technological regimes characterized by patterns of creative accumulation provide small serial innovators with new opportunities and incentives to further innovate along their technological trajectory.

Cumulativeness plays a central role in serial innovation, and its specific qualities constitute the main difference between small and large serial innovators. If we consider the patent stock as a proxy for research investment, our results confirm the findings of Duguet and Monjon (2004). In large firms, it is the continuous stream 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 by ‘combinative’ capabilities (Kogut and Zander 1992) and processes of search depth (Katila and Ahuja 2002).

The study has certain limitations. 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 innovator. 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. Also, we were not able to test the role of appropriability, and we deem this an interesting area 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 (Cefis 2003). 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 do not aim to growth in economic terms, they represent a stable source of innovation in the economy.

References

Acs, Z. J., Audretsch, D. B. (1987). Innovation, Market Structure, and Firm Size. *The Review of Economics and Statistics*, 69(4), 567-574.

Acs, Z. J., Audretsch, D. B. (1988). Innovation in Large and Small Firms: An Empirical Analysis. *American Economic Review*, 78(4), 678-90.

Agarwal, R. (1998). Small Firm Survival and Technological Activity. *Small Business Economics*, 11(3), 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*, 49(1), 21-43.

Arora, A., Fosfuri, A., Gambardella, A. (2001). Markets for Technology and Their Implications for Corporate Strategy. *Industrial and Corporate Change*, 10(2), 419-451.

Arora, A., Gambardella, A. (1994). The changing technology of technological change: general and abstract knowledge and the division of innovative labour. *Research Policy,* 23, 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.

Arundel, A. (2001). The relative effectiveness of patents and secrecy for appropriation. *Research Policy*, 30(4), 611-624.

Arundel, A., Kabla, I. (1998). What percentage of innovations are patented? empirical estimates for European firms. *Research Policy,* 27(2), 127-141.

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

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

Breschi, S., Malerba, F., Orsenigo, L. (2000). Technological regimes and Schumpeterian patterns of innovation. *The Economic Journal*, 110(4), 388-410.

Bresnahan, T. F., Trajtenberg, M. (1995). General purpose technologies ‘Engines of growth’?. *Journal of Econometrics,* 6(1), 83-108.

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

Cefis, E. (2003). Is there persistence in innovative activities?. *International Journal of Industrial Organization*, 21(4), 489-515.

Cefis, E., Marsili, O. (2006). Survivor: The role of innovation in firms’ survival. *Research Policy*, 3(5), 626-641.

Cefis, E., Orsenigo, L. (2001). The persistence of innovative activities, a cross-countries and cross-sectors comparative analysis. *Research Policy*, 30(7), 1139–1158.

Cockburn, I., Griliches, Z. (1988). Industry effects and appropriability measures in the stock markets valuation of R&D and patents. *American Economic Review,* 78(2), 419-423.

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

Cohen, W. M., Levinthal, D. A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, 35(1), 128-152.

Dosi, G. (1982). Technological paradigms and technological trajectories : A suggested interpretation of the determinants and directions of technical change. *Research Policy*, 11(3), 147-162.

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.

Freeman, C. (1991). Networks of innovators: A synthesis of research issues. *Research Policy*, 20(5), 499-514.

Garcia Vega, M. (2006). Does technological diversification promote innovation?: An empirical analysis for European firms. *Research Policy*, 35(2), 230-246.

Geroski, P. A., Van Reenen, J., Walters, C. F. (1997). How Persistently Do Firms Innovate?. *Research Policy*, 26(1), 33–48.

Granstrand, O., (1998). Towards a theory of the technology-based firm. *Research Policy*, 27(5), 467–491.

Granstrand, O., Patel, P. and Pavitt K., (1997). Multitechnology corporations: Why they have “distributed” rather than “distinctive core” competencies. *California Management Review*, 3(4), 8-25.

Griliches, Z. (1990). Patent Statistics as Economic Indicators: A Survey. *Journal of Economic Literature*, 28(4), 1661-1707.

Hall, B. H. (2005). A Note on the Bias in Herfindahl-Type Measures Based on Count Data. *Revue d'Économie Industrielle*, Programme National Persée, 110(1), 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*, 36(1), 16-38.

Hausman, J., Hall, B. H., Griliches, Z. (1984). Econometric Models for Count Data with an application to the Patents-R&D Relationship. *Econometrica*, 52(4), 909-938.

Hicks, D., Hegde, D. (2005). Highly innovative small firms in the markets for technology. *Research Policy*, 34(5), 703-716.

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

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

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*, 45(6), 1183-1194.

Kogut, B, Zander, U. (1992). Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. *Organization Science*, 3(3), 393-397.

Langlois, R. N., Robertson, P. L. (1992). Networks and innovation in a modular system: lessons from the microcomputer and stereo component industries. *Research Policy*, 21(4), 297- 313.

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*, 18(3), 783-832.

Liang, K., Zeger, S. (1986). Longitudinal Data Analysis Using Generalized Linear Models. *Biometrika*, 73(1), 13-22.

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*, 2(1), 45-71.

Malerba, F., Orsenigo, L. (1996). Schumpeterian patterns of innovation are technology-specific. *Research Policy*, 25(3), 451-478.

Malerba, F., Orsenigo, L. (1999). Technological Entry, Exit and Survival: An Empirical Analysis of Patent Data. *Research Policy*, 28, 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*, 15(6), 801-826.

Martinez, C. (2011). Patent families: When do different definitions really matter?. *Scientometrics*, 86(1), 39-63.

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*, 53, 123–142.

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

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*, 13(6), 343-373.

Pavitt., K., Patel, P. (1994). The continuing, widespread (and neglected) importance of improvements in mechanical technologies. *Research Policy*, 23(5), 533-545.

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

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.

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

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

Teece, J., Pisano G., Shuen, A. (1997). Dynamic Capabilities and Strategic Management. *Strategic Management Journal*, 18(7), 509-533.

Trajtenberg, M. (1990). A Penny for Your Quotes: Patent Citations and the Value of Innovations. *The Rand Journal of Economics*, 21, 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*, 5, 19-50.

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

Winter, S. (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: Ballinger Publishing Company.

APPENDIX

Table A.1. : 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	