Paper to be presented at the

DRUID Society Conference 2014, CBS, Copenhagen, June 16-18

Determinants of technological diversification in small serial innovators

Carlo Corradini
University of Birmingham
Business School
c.corradini@bham.ac.uk

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

Giuliana Battisti
University of Warwick
Business School
Giuliana.Battisti@wbs.ac.uk

Abstract

This paper 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.

Jelcodes:L19,O31

Determinants of technological diversification in small serial innovators

Abstract

This paper 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.

Keywords: Technological diversification; Serial innovators; Technological opportunity; Technological coherence; Persistent innovation; Fractional response model.

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 consequence 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 paper, 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 (Hicks and Hegde, 2005; Corradini et al., 2012). This calls for a more detailed study of technological diversification and its determinants across small companies.

This paper 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 paper is the following. In section 2 we provide an overview of the specific literature and define the research hypotheses of the paper. After a section on the patent dataset used for the analysis, we present descriptive statistics and stylised facts about technological diversification among serial innovators. Section 5 delineates the model and the variables used. The discussion of the findings is offered in section 6. Finally, section 7 provides some concluding remarks.

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).

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[1]. 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,

[1] This argument does not deny the importance of knowledge external to the firm on the innovation activity. However, as Nesta and Saviotti (2005) point out, such flows can be seen as channelled toward the construction of firms' core knowledge base.

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.

3. Data

The dataset used in this paper is based on all patents published in the period 1990-2006 by 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 dataset contains information on 811 companies, where 472 are large companies and 339 are small ones[2].

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[3], reported in Table A.1.

Drawbacks of using patent data are well known (For a discussion of strengths and weaknesses of patent data see Pavitt, 1988, Patel and Pavitt, 1997; Griliches, 1990). Patents are 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 paper, 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 its richness of detail that we use patent data. This choice is in line with most studies of technological competencies and diversification (Jaffe, 1986; Patel and Pavitt, 1997; Garcia-Vega, 2006; Quintana-Garcia and Benavides-Velasco, 2008).

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

4. Technological diversification and small serial innovators: a brief overview

To illustrate the degree of technological diversification within innovative companies, we first analyse the percentage of diversified innovators per number of technological classes where they patented in the period of time considered, which is reported in Figure 1[4]. The distribution of firms per technological class is highly right-skewed[5], with less than 5% of companies having innovated in more than 4 technological classes. The majority of these companies are small innovators in terms of patenting activity. As Figure 2 illustrates, innovative firms that operated in four or less technological classes only account for less than a half of the total number of patents[6]. 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.

[Figures 1 and 2 about here]

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 1 shows the percentage of diversified and specialised serial innovators alongside the number of patents by size class. 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 size class.

The presence of specialised companies is higher among small companies, accounting for almost 10% of the total. These firms hold almost 9% of all patents in this size class, with diversified companies accounting for the large majority of patents (91%).

[Table 1 about here]

Differences across size classes increase when we observe the distribution of companies per number of sectors where they have patented between 1990 and 2006. In Figure 3 we report the relative (%) distribution of innovative firms based upon the technological classes relative to their patents and also by size of the company. Results show that 50% of small companies versus only 13% of large companies patented in less than 4 sectors. We find a small number of companies much more

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

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

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

diversified than the average among small as well as large companies. They generate a highly positively skewed distribution in both size classes.

[Figure 3 about here]

5. Model specification

To test out hypotheses on the degree of technological diversification of serial innovators we use a series of variables, namely: opportunity conditions (OPPORTR), 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.

5.1. Dependent variable

To measure *technological diversification* (TECHDIV) we make use of an index which is based on a measure of technological proximity originally proposed by Jaffe (1986). Such index 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:

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

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, companies with less than two patents per year had to be omitted from the analysis.

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 $OPPORTR^2$, 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).

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:

$$S_{ij} = \frac{\sum_{k=1}^{30} C_{ik} C_{jk}}{\sum_{k=1}^{30} \sqrt{C_{ik}^2} \sum_{k=1}^{30} \sqrt{C_{jk}^2}} \qquad (2)$$

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[7]. 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 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^*.

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[8]. This is calculated using the declining balance formula usually proposed in the literature, with the depreciation rate set at 15% (Cockburn and Griliches, 1988, Hall et al., 2005). It is defined as follows:

$$KSTOCK_{it} = P_{it} + (1-\delta)KSTOCK_{it-1} \tag{3}$$

where P_{it} represent the number of patents of company *i* in year *t* and δ is the depreciation rate. 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, while our regressions start from 1993, allowing for a lag of at least 8 years between the first year for which we have patent

[7] For a discussion on the knowledge-relatedness matrix and company's core technological class, see Breschi et al. (2003).
[8] 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.

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.

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 need to take 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)[9]. 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.

6. Results

6.1. Summary statistics

In Table 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.

Initial evidence of the relationship between technological diversification and coherence in the knowledge-base is found in Table 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

[9] For a classification of the sectors according to these groups see Appendix, Table A.1.

correlation between COHERENCE and ORIGIN_CO, which is positive, and the one between COHERENCE and KSTOCK, which is negative.

[Tables 2 and 3 about here]

Finally, Figure 4 shows the technological diversification of serial innovators across four sectoral classes resembling those proposed by Pavitt (1984)[10]. 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 about here]

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)[11]. To account for heteroskedasticity and serial correlation in the standard errors within the panel dataset[12], we specify a generalised estimating equation (GEE) model (Liang and Zeger, 1986) with a binomial distribution and robust standard errors[13]. The estimates for the model are reported in Table 4[14].

[10] See Appendix, Table A.1.

[11] Coefficients are also robust to random effects maximum likelihood estimation.

[12] Considering that our panel is unbalanced, we cannot follow the specification of the fractional response model for panel data proposed by Papke and Wooldridge (2008), which is designed to account for unobserved heterogeneity. Instead, we use a pooled QMLE approach.

[13] We adopt a logit link function, although there isn't any particular reason to prefer the logit function as opposed to the probit function. In fact, our estimates are also robust to this second specification.

[14] Estimates are reported as odds-ratios. Standard coefficients are available on request.

To study the relationship between technological opportunities and diversification, as outlined in our first hypothesis, 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 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.

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 diversification, ceteris paribus. We also see that the variables for both the linear and the quadratic term OPPORTR and $OPPORTR^2$ 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 5, which presents the difference in the predicted probabilities across firm size for different values of opportunity conditions[15]. 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.

[Table 4 and figure 5 about here]

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.
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, 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

[15] All other variables are inserted in the model with their mean value.

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, explored in Model (4) using SCIBAS as base group, the only dummy statistically significant is the one related to companies operating in supplier dominated industries. 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.

7. Conclusions

In this paper, 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 paper 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.

References

Breschi, S., Lissoni, F., Malerba, F., 2003. Knowledge-relatedness in firm technological diversification. Research Policy 32, 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.

Cantwell, J., Fai, F., 1999. Firms as the source of innovation and growth: the evolution of technological competence. Journal of evolutionary economics 9, 331-366.

Chiu, Y., Lai, H., Liaw, Y., Lee, T., 2010. Technological scope: diversified or specialized. Scientometrics 82, 37-58.

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

Corradini, C., Battisti, G., Demirel, P., 2012. 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

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

Fai, F., Von Tunzelmann, N., 2001. Industry-specific competencies and converging technological systems: evidence from patents. Structural change and economic dynamics 12, 141-170.

Garcia-Vega, M., 2006. Does Technological Diversification Promote Innovation? An Empirical Analysis for European Firms. Research Policy 35, 230-246.

Granstrand, O., 1998. Towards a Theory of the Technology-Based Firm. Research Policy 17, 465-489.

Granstrand, O., Sjölander, S., 1990. Managing innovation in multi-technology corporations. Research Policy 19, 35-60.

Granstrand, O., Patel, P., Pavitt, K., 1997. Multi-technology corporations: why they have 'distributed' rather than 'distinctive core' competencies'. California Management Review 39, 8-25.

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

Hall, B., H., 2005. A Note on the Bias in Herfindahl-Type Measures Based on Count Data. Revue d'Economie Industrielle. Programme National Persee 110, 149-156.

Hall, B., H., Jaffe, A., Trajtenber, M., 2005. Market Value and Patent Citations. The RAND Journal of Economics 36, 16-38.

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

Jaffe, A., 1986. Technological opportunity and spillovers of R&D: evidence from firm's patents, profits and market value. American Economic Review 76, 986-1001.

Katila, R., Ahuja, G., 2002. Something old, something new: a longitudinal study of search behavior and new product introduction. Academy of Management Journal 45, 1183-1194.

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

Leten, B., Belderbos, R., Van Looy, B., 2007. Technological Diversification, Coherence, and Performance of Firms. Journal of Product Innovation Management 24, 567–579.

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

Malerba, F., Orsenigo, L., 1993. Technological regimes and firm behavior', Industrial and Corporate Change 2, 45-71.

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, 801-826.

March, J., 1991. Exploration and exploitation in organizational learning. Organization Science 2, 71-87.

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

Nelson, R., 1959. The simple economics of basic scientific research. Journal of Political Economy 67, 297-306.

Nelson, R. R., Winter, S., 1982. An Evolutionary Theory of Economic Change. Belknap Press: Cambridge, MA.

Nesta, L., Saviotti, P. P., 2005. Coherence of the knowledge base and the firm's innovative performance: evidence from the U.S. pharmaceutical industry. The Journal of Industrial Economics 53, 123–142.

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 11, 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 145, 121-133.

Park, G., Park, Y., 2006. On the measurement of patent stock as knowledge indicators. Technological Forecasting & Social Change 73, 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 26, 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: Chandler, A. ,D., Hageström, P., Slölvell, Ö. (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, 343-373.

Pavitt, K., 1988. Uses and abuses of patent statistics, in: van Raan, A. (Ed.), Handbook of Quantitative Studies of Science and Technology. North Holland, Amsterdam.

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

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

Piscitello, L., 2004. Corporate diversification, coherence and economic performance. Industrial and Corporate Change. 13, 757-787.

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

Schmoch, U., 2008. Concept of a Technology Classification for Country Comparisons. Final Report to the World Intellectual Property Organisation (WIPO). Available at: http://www.wipo.int/edocs/mdocs/classifications/en/ipc_ce_41/ipc_ce_41_5-annex1.pdf

Suzuki, J., Kodama, F., 2004. Technological Diversity of Persistent Innovators in Japan: Two Case studies of Large Japanese Firms. Research Policy 33, 531-549.

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

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

Wang, Q., von Tunzelmann, N., 2000. Complexity and the functions of the firm: breadth and depth. Research Policy 29, 805-818.

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

Tables and figures

Table 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

Table 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 3: Correlation matrix

	TECHDIV	OPPORTR	COHERENCE	ORIGIN_CO	KSTOCK	IMPIN
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

Table 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

Figure 1: Distribution of diversified innovators per number of technological classes where they patented

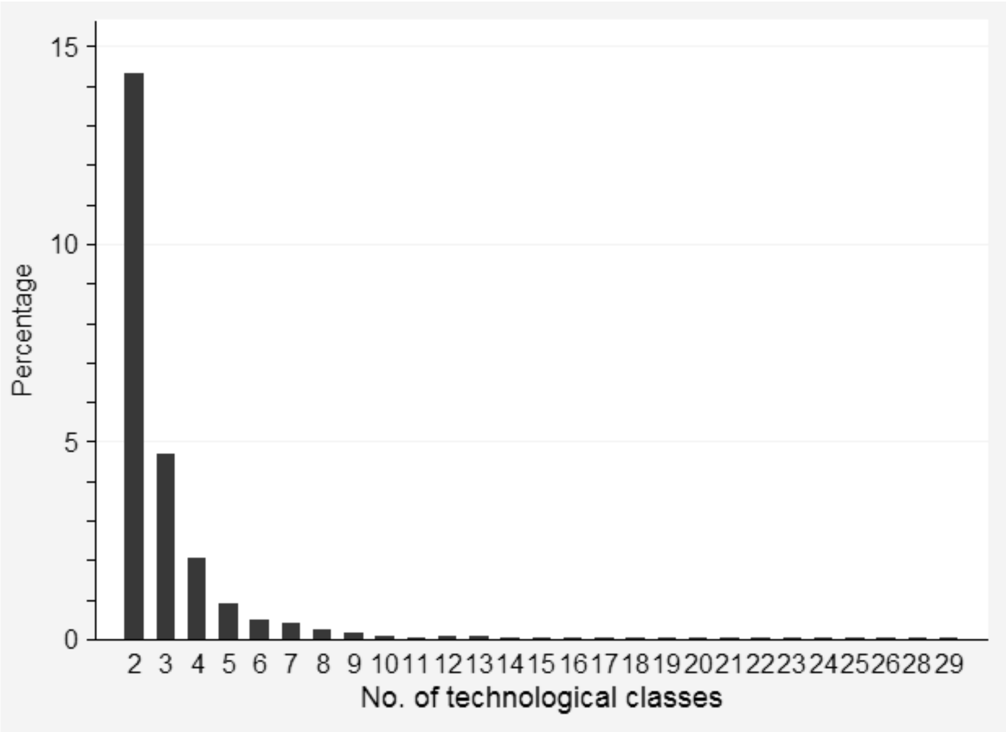


Figure 2: Distribution of total patents of diversified innovators per number of technological classes where they patented

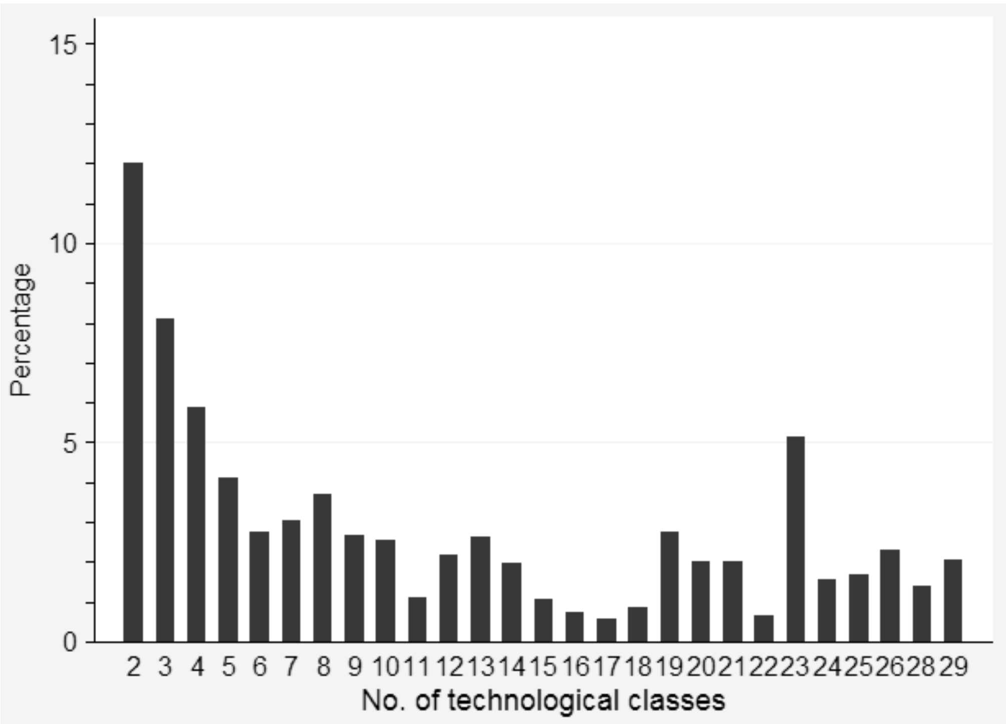


Figure 3: Distribution of small and large serial innovators across active technological classes

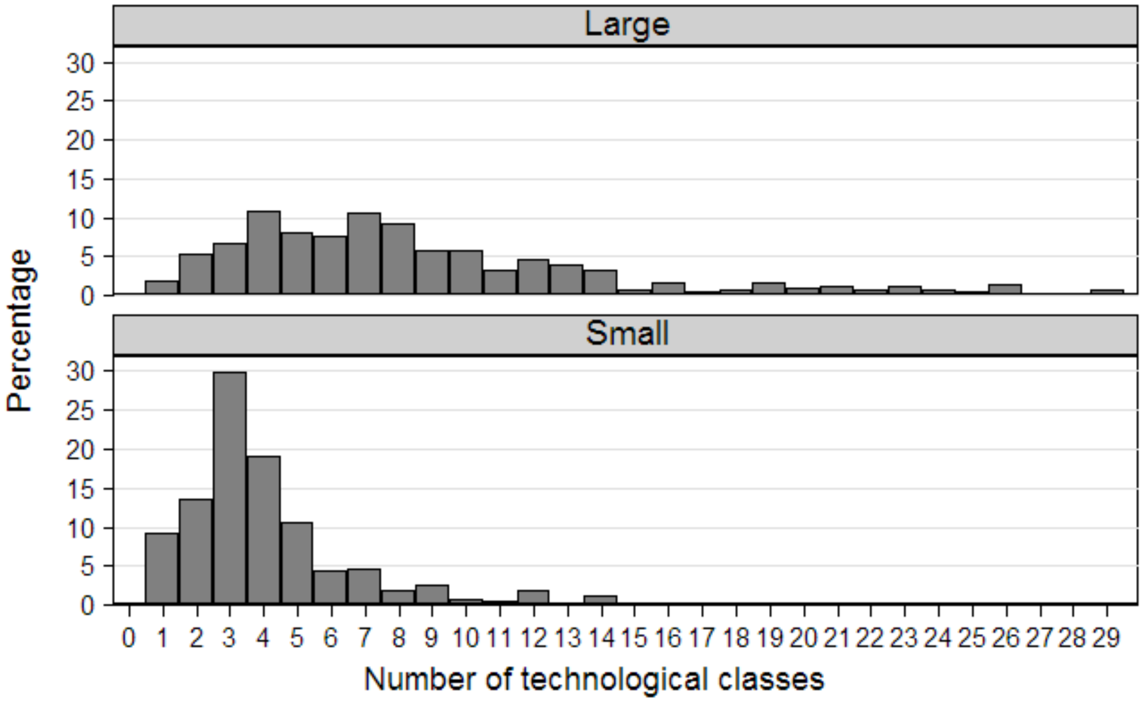


Figure 4: Distribution of technological diversification for small and large serial innovators across sectoral classes reflecting Pavitt's taxonomy

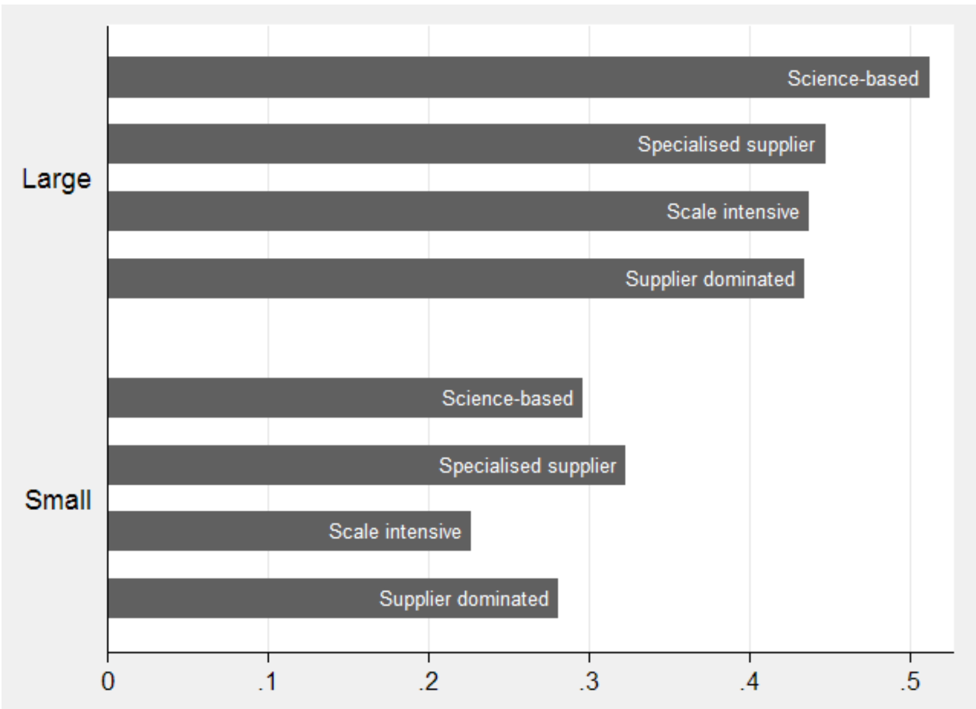
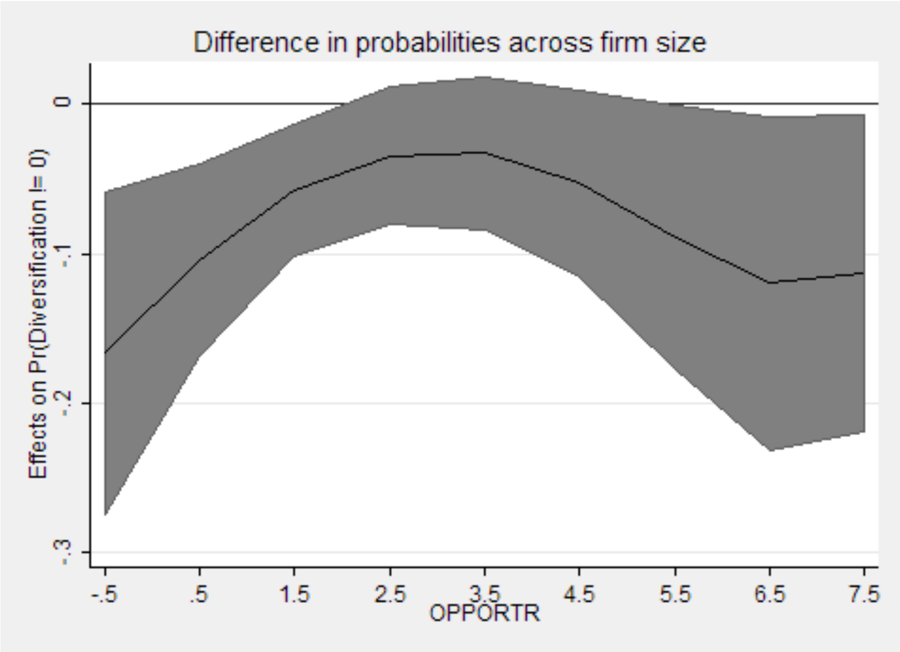


Figure 5: Predicted probabilities across firm size for different values of opportunity conditions



Appendix

Table A.1: Technology classification based on IPC

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

SB = Science based; SS = Specialised supplier; SI = Scale intensive; SD= Supplier dominated