The role of scientific and market knowledge in the inventive process: evidence from a survey of industrial inventors[1]

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Abstract

This paper studies the role of scientific and market knowledge in the inventive process by asking whether these two types of knowledge complement each other for the inventor's performance. The empirical analysis makes use of an original survey of industrial inventors carried out in three European regions in 2012 that aimed at exploring the inventive process of inventors working inside firms. The econometric analysis employs the so-called productivity approach, in which the inventors' knowledge sourcing strategies are used as explanatory factors for inventors' performance, measured in terms of both quantity and quality of inventions. To the best of the author's knowledge, this is one of the first attempts to apply this approach at the inventor's level. The results suggest that complementarity exists, since the joint use of scientific and market knowledge is positively and significantly related to the inventor's performance, across different estimations. Furthermore, variation exists across mobile and non-mobile inventors, especially as far as the quality of inventions in concerned. Tracing a positive link between the use of external knowledge and the inventive process at individual level is not only relevant for research, but also for policy, considering that knowledge exchange across a wide range of organisations is at the core of the innovation policy agendas in most countries.

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1 Introduction

It is nowadays well established that knowledge that is internal to the firms, though essential, is not sufficient for the creation of innovation and thus, in order to successfully produce innovation and stay competitive on the market, firms tap into knowledge that rests outside their boundaries (see e.g. Allen and Cohen, 1969; Allen, 1977; Arora and Gambardella, 1990; Cassiman and Veugelers, 2006; Chesbrough, 2003; Frenz and Ietto-Gillies, 2009; Tijssen, 2002). External-to-the-firm knowledge is supplied by a wide range of actors with different characteristics - hence providing different types of knowledge. It is possible to distinguish scientific knowledge, supplied by scientific actors, such as universities and research centres, and technical knowledge, supplied by market actors - and for this reason referred to as market knowledge - such as other competitor firms, suppliers and customers (see e.g. Von Hippel, 1988). Scientific knowledge is usually disconnected from the market and its purpose is to foster technological progress (Fleming and Sorenson, 2004), while market knowledge is more applicative because it aims at addressing specific users' problems and is, by definition, market-oriented (Cohen et al., 2002). As a consequence, scientific knowledge is seen as fundamental for the idea-generation phase of the innovation process, whereas market knowledge is essential for the technical realisation of a given innovation (see e.g. Aghion et al., 2005; Frenz and Ietto-Gillies, 2009; Hagedoorn, 1993; Tijssen, 2002; Utterback, 1971).

The empirical evidence on the relation between firms' knowledge sourcing strategies and the creation of innovation is vast, though not fully conclusive yet (see e.g. Arora and Gambardella, 1990, 1994; Cassiman and Veugelers, 2006, 2007; Frenz and Ietto-Gillies, 2009). Both complementarity and substitutability between internal and external knowledge, as well as between different types of external knowledge (e.g. scientific and market knowledge), have been found. This is suggestive of the need to get a closer look at the role of knowledge by exploiting a finer unit of analysis, such as the individuals inside firms. More recently, the empirical literature has indeed looked at the role of knowledge for the individual who is responsible of the innovative process, i.e. the inventor. By exploiting information provided by patents and by surveys of inventors, a number of papers uncovered some of the factors that influence the inventor's patenting activity, including individual characteristics (e.g. education, age, mobility) and knowledge flows (see e.g. Giuri et al., 2007; Hoisl, 2007; Mariani and Romanelli, 2007; Schneider, 2009). However, the relevance of different sources of knowledge and how these combine has been rarely addressed at the micro level of the individual inventor.

This paper focuses on the individuals that are primarily responsible for the inventive activity inside the firm, i.e. patent inventors, based on the consideration that innovation is not simply the product of firms and organisations, but also requires individual creativity. Morevoer, patents are commonly recognised as creative output (Huber, 1998) and therefore they represent the right innovative outcome to look at. The aim of this paper is to show that scientific and market knowledge sources are complementary for the patenting performance of inventors, by testing the hypothesis that the joint use of scientific and market knowledge has a higher impact on the inventor's performance than the separate use of each of the two knowledge sources. In addition, the role of both individual and employer's factors will be studied.

The novelty of the present study lies, in the first place, in the focus on the individual innovator as unit of analysis, instead of the firm, which is the typical unit of analysis for these types of studies. In addition, the paper exploits an original data source that combines a survey of industrial inventors carried out in three European regions with patent data from the European Patent Office (EPO). Whereas previous literature has mainly relied on proxies for the knowledge linkages of inventors to knowledge sources, the survey data here presented is likely to provide a better indicator since inventors were explicitly asked questions on the use of different knowledge sources in the inventive process.

In the empirical analysis, a number of measures of inventors' performance (i.e. quantity and quality of patents) will be estimated as a function of scientific and market knowledge sourcing strategies, controlling for individual-level characteristics as well as patent- and firm- level determinants. This is also known as the productivity (or direct) approach (Cassiman and Veugelers, 2006), which has been widely used in the management literature to analyse the relevance of knowledge flows for firms and, to the best of the author's knowledge, it is one of the first attempts to apply it at the inventor's level. Ordinary least squares with robust standard errors will be used. Along with the baseline regressions, the breakdown by inventor's job mobility will be shown and a further robustness check carried out.

The remainder of the paper is organised as follows: section 2 provides a review of the literature that leads to the hypothesis of the paper; sections 3 and 4 present the method and the data used for the empirical analysis; the empirical results are presented and commented in sections 5 and 6 and these include the baseline regressions as well as a robustness check. The last section will conclude the paper by summing up and discussing the empirical findings.

2 Theoretical framework and hypothesis

2.1 The role of scientific knowledge and market knowledge for firms

External knowledge acquisition is necessary for innovation activities carried out by firms, especially in the current context of market globalisation and rapid technological change. Both the early literature on technological change (see e.g. Allen and Cohen, 1969; Allen, 1977) and the more recent studies on the knowledge sourcing strategies of firms (see e.g. Arora and Gambardella, 1990, 1994; Cassiman and Veugelers, 2006, 2007; Frenz and Ietto-Gillies, 2009) assert that firms cannot rely only on their internal resources and have to tap into knowledge outside their boundaries in order to successfully produce innovation.

The long-standing debate on the nature of technological change - whether it is mainly market-pull or technology-push - has evolved around the distinction between market knowledge and scientific knowledge. The seminal works of e.g. Griliches (1987); Jaffe (1989); Adams (1990), have uncovered the role of external knowledge from academia - often referred to as scientific knowledge - for innovation activities of firms and economic development. For instance, Jaffe (1989) shows that there is a significant effect of university research on firms' patenting activity. Since then, the literature on firm-university links has grown and complemented those seminal studies (see e.g. Mansfield, 1995; Mansfield and Lee, 1996; Cohen et al., 2002), demonstrating that firms exploit scientific knowledge in order to produce innovations and stay competitive on the market. On the other hand, firms seek and exploit technical knowledge from external agents that are close to the market in order to reduce the uncertainty associated with innovation (Hagedoorn, 1993), that is, to find new ideas, or address technical issues that arise during the innovation process. These close-to-the-market actors are clients and customers, direct competitors, or suppliers (see e.g. Von Hippel, 1988). The literature usually refers to the knowledge provided by these actors as market knowledge in order to stress its source - as opposed to scientific knowledge that comes from scientific actors[2].

The theoretical literature has underlined how different typologies of knowledge originating from different sources are useful at different stages of the research process. In his seminal work on the process of technological innovation, Utterback (1971) distinguishes three overlapping stages through which an innovation is realised. The first is the idea-generation phase, which results in the origination of a technical proposal or design concept; the second is the problem-solving phase, resulting in an invention or an original technical solution; the third stage consists of the implementation and market introduction, culminating in the diffusion of the innovation[3]. Specifically referring to external knowledge, Utterback states that "*The greater the degree of communication between the firm and its environment at each stage of the process of innovation (...), the more effective the firm will be in generating, developing and implementing new technology*" (Utterback, 1971, pag. 85), thus suggesting that external knowledge is beneficial to the whole innovation process, from the idea-generation phase, to the implementation and commercialisation of an innovation. In addition, a recent theoretical contribution that investigates the advantages and disadvantages of academic and private research, demonstrates that academia is most useful in the early stages of the research process, while the private sector tends to do better in the later stages (Aghion et al., 2005). The reasons lie behind the different systems of incentives within academia and within firms. Academia, because of its commitment to leaving creative controls in the hands of scientists, can be indispensable for early stage research aimed at fostering new research lines; on the other hand, the private sector's focus on higher payoff activities makes it more useful for later-stage research, aimed at producing profitable innovations and introducing them to the market. Therefore, the theoretical literature first suggests that external knowledge is fundamental to the innovation process, and, second, that different sources of knowledge must be accounted for, because potentially having different effects on the different stages of the innovation process.

Besides, the empirical literature shows that firms adopt and use knowledge from different sources, often combining internal and external knowledge acquisition strategies (see e.g. Arora and Gambardella, 1990, 1994; Cockburn and Henderson, 1998). In this respect, the seminal work of Cohen and Levinthal (1990) on the concept of absorptive capacity - defined as the capacity of a firm to recognize, assimilate and exploit external knowledge - particularly stresses the co-existence

[2]It would also be appropriate to call it technical knowledge for its main problem-solving nature; since the present study stresses the channels through which knowledge reaches inventors, knowledge coming from market channels will be called market knowledge.

[3]The latter is not strictly considered as part of the process of innovation since it partly occurs outside the firm, hence the literature generally considers the first two (overlapping) phases as the main ones (Weck and Blomqvist, 2008).

of different types of knowledge inputs and their contribution to the firm's innovative activities. Among others, Cassiman and Veugelers (2006) show that internal R&D and external knowledge acquisition are complementary innovation activities, while the same authors finds evidence of substitution effect between embodied and disembodied technology acquisition strategies (Cassiman and Veugelers, 2007). Criscuolo et al. (2005) and Crespi et al. (2008) make use of firm-level data and estimate a knowledge production function to study the contribution of different knowledge flows to firm-level productivity. Whereas Criscuolo et al. (2005) show that globally engaged firms innovate more thanks to the intra-firm worldwide pool of information as well as from suppliers, customers and universities, Crespi et al. (2008) stresses the importance of clients, among the knowledge flows. Even if evidence is mixed, it seems quite clear that external knowledge contributes to the innovation process and that different typologies of knowledge flowing from a wide range of different actors matter.

2.2 The role of scientific knowledge and market knowledge for inventors

Whereas the existing evidence on the the role of external knowledge for innovation mainly takes the firm and its innovative activities (e.g. commercial activities, inventions, sales of innovative products) as the unit of analysis, recently the attention has also moved down to a finer level of analysis, such as the individual inventor inside the firm (see e.g. Giuri et al., 2007; Hoisl, 2007; Mariani and Romanelli, 2007; Pasquini et al., 2012; Schneider, 2009; Weck and Blomqvist, 2008). The interest in the inventor as the main unit of analysis is justified by the fact that innovation is not simply the product of firms and organisations. It ultimately requires individual creativity and patents are, indeed, commonly recognised as creative output (Huber, 1998). As a matter of fact, the empirical evidence about university inventors is vast, partly because of a large amount of information publicly available. Instead, evidence on industrial inventors is rather limited and not conclusive yet.

The empirical literature confirms that patent productivity among private inventors is skewed, similarly to that of academic inventors - i.e. few inventors produce a high number of innovations whereas the vast majority display a low invention rate - but, because of the lack of information at individual level, it is hard to identify the reasons behind this behaviour (Mariani and Romanelli, 2007; Menon, 2011). Furthermore, it has been shown that both inventor's factors and characteristics of the employers affect the inventor's performance (Giuri et al., 2007). As mentioned above, more recently there have been attempts to address the role of knowledge flows for inventors. Previous studies showed that scientific sources of knowledge are often the least important for inventors (and more generally, for firms) and market sources of knowledge are instead the most important ones (Eurostat, 2007; Giuri et al., 2007). This is not surprising, since the distance between purely scientific knowledge and technical knowledge stemming from market channels is quite large. Notwithstanding, only recently the interdependence of the two for the inventive process has been inquired in the literature. On the one hand, it has been shown that scientific and market sources of knowledge display a subadditive relationship for the monetary value of the inventions (Schneider, 2009). On the other hand, it has been uncovered a positive and significant contribution of external-to-the-firm knowledge to the probability that a patent is commercialised (Pasquini et al., 2012). Moreover, a qualitative case study on the inter-organisational relationships developed by inventors within a company, found that patent competitiveness benefits more from buyer-seller relationships than from R&D consortia (Weck and Blomqvist, 2008).

The evidence on the role of knowledge for industrial inventors and their performance is, therefore, still scarce and not yet conclusive. In addition, the existing studies, though accounting for the inventors' use of knowledge, exploits patents as the ultimate outcome measure, instead of the inventor. The present study intends to fill these gaps by focusing on the relationship between the industrial inventor's knowledge sourcing strategy and her patenting activity. In order to shed new light on the role of different knowledge sourcing strategies for inventors' performance, the research question that will be addressed in this paper is whether scientific and market knowledge are complement or substitute for the inventors' patenting activity. In other words, we will ask whether inventors who combine the use of both scientific and market sources of knowledge display higher (lower) productivity and produce higher (lower) quality inventions than inventors who use only one or none of them.

As previous studies suggest, scientific and market knowledge produce different effects on the inventive process, due to their very different nature. Scientific knowledge is usually disconnected from the market and its purpose is to foster technological progress (Fleming and Sorenson, 2004), whereas market knowledge is more applicative, aims at addressing specific users' problems and is, by definition, market-oriented (Cohen et al., 2002). These differences are evocative of very different impacts on the inventors' innovation activity, suggesting that inventors who merely use scientific knowledge might find radical ideas but create innovations that are far from the market or hard to commercialise, while inventors who prefer market knowledge might not focus on breakthrough innovation but instead create close-to-the-market and more profitable innovations. In reality, inventors often combine these sources of knowledge, which suggests that there could be a complementarity relationship between the two and this might have consequences on the inventors' performance. Hence, the following hypothesis will be tested:

Hp: The joint use of scientific knowledge and market knowledge has a higher impact on the inventors' performance than the separate use of each of the two knowledge sources

In line with the open innovation paradigm (Chesbrough, 2003), we expect that inventors drawing upon a higher number of knowledge sources - therefore having an "open" search strategy - display a better performance than inventors who do not. Hence, it will be argued that knowledge produced in and sourced from science-related channels (university and public research centres) display a complementarity relationship with knowledge from market-related actors (suppliers, customers, competitors, consultants) for the inventors' performance in terms of patent productivity and quality. The argument is that, by combining these two types of knowledge, inventors could exploit different characteristics of the latter that fulfil different needs throughout the inventive process: in other words, inventors would be merging the technological and innovative potential that derives from scientific knowledge with the market potential that derives from market knowledge.

In order to test the hypothesis, the inventors' knowledge sourcing strategies will be measured and used as explanatory variables for the inventors' productivity, by exploiting the so-called productivity approach (Cassiman and Veugelers, 2006). In the next section the data sources are first described, followed by the empirical strategy and the construction of the variables employed in the analysis, along with their descriptive statistics.

3 Data and method

3.1 The PickMe Survey of inventors and the EPO data

The data source consists of a survey of industrial inventors matched to patent data from the European Patent Office (EPO). The survey of private inventors is part of a European Union Seventh Framework Program funded project (PICK-ME) and was carried out between 2011 and 2012 in three European regions, namely, Catalonia (Spain), East and West Midlands (United Kingdom) and Piedmont (Italy). The aim of the survey is to explore the inventive process of industrial inventors in order to provide new insights about the demand of knowledge expressed by the actors directly involved in the innovative process. In addition, the survey aims at obtaining individual-level information that are not usually available in patent documents, such as their age, gender, education and occupation.

The questionnaire was sent to industrial inventors who filed one or more patent applications between 2000 and 2006 and whose residential address is in one of these regions. Information on the inventors' names and home address was extracted from the Patstat-Kites EPO dataset[4]. The selection of regions was based on a number of factors and for a matter of comparability. On the one hand, the aim was to choose non-core regions, particularly non-capital regions that, because of the presence of national research institutions and/or other core research organisations, display peculiar characteristics in terms of knowledge linkages. On the other hand, regions with a similar industrial structure were chosen and this applies particularly to the case of Piedmont and the Midlands, being both regions characterised by the presence of a core industry - in both cases the automotive - and having experienced similar de-industrialisation patterns in the last 30 years or so.

The survey includes a question on the use of different sources of knowledge, split into internal sources (colleagues inside the firm and other business unites/departments) and external sources, i.e. customers, competitors, suppliers, consultancy, universities and public research centres. The question asks to the inventor to rank the relevance of each source from 0 (not used) to 4 (very important). The sample of respondents includes 225 inventors from Catalonia (response rate 14%), 117 inventors from the Midlands (response rate 13%) and 533 inventors from Piedmont (response rate 45%). These have been matched to the Patstat-Kites database via the inventor's identifier. It has been possible to retrieve all patent information for each inventor, including the number of patent applications, the status of the application - whether the patent has been granted or not -, patent technological classes (reclassified into 7 macro-classes), number of forward citations of each patent, assignee of the patents (i.e. the owner).

[4] The EPO Patstat (PATent STATistical) database is a patent statistics raw database, held by the EPO and developed in cooperation with the World Intellectual Property Organisation (WIPO), the OECD and Eurostat. A clean version of the raw data is provided by Kites-Bocconi (http://db.kites.unibocconi.it/).

3.2 Empirical strategy

The estimation strategy follows the so-called productivity (or direct) approach (Cassiman and Veugelers, 2006), in which measures of inventors' productivity and quality are estimated as a function of the inventors' knowledge sourcing strategies, as well as a number of control variables to account for individual characteristics, patent features and firm factors. The knowledge sourcing strategies will be constructed as exclusive dummies that indicate whether the inventors use only scientific knowledge or only market knowledge, or both, or none of them. The model will be estimated with ordinary least squared regressions with robust standard errors.

In order to test the hypothesis of complementarity between scientific and market knowledge we estimate a model in which the dependent variables (Y_i) - fully explained in the next section - *lNpat* (log of number of patent applications per inventor), *Meanfcc* (average quality of inventions per inventor) and *Maxfcc* (quality of the best inventions per inventor), are regressed on the inventors' knowledge strategies plus the vector of control variables (X_i):

$$Y_i = \alpha + \beta_1 scionly_i + \beta_2 mktonly_i + \beta_3 scimkt_i + \gamma X_i + \epsilon_i \tag{1}$$

Where (1) *scionly* is a dummy variable taking value 1 for inventors who use only scientific knowledge, (2) *mktonly* is a dummy variable taking value 1 for inventors who use only market knowledge and (3) *scimkt* is a dummy variable taking value 1 for inventors who use both scientific and market knowledge. The strategy (4) *noscimkt*, taking value 1 for inventors who do not use any external source of knowledge, is excluded from the regression to avoid collinearity and hence is the baseline case. The hypothesis will be confirmed if the estimated coefficient on the joint use of scientific knowledge and market knowledge is positive (and significant) and larger than the coefficients of the use of scientific or market knowledge only.

The econometric analysis will be performed on the full sample as well as on the subsamples of mobile and non-mobile inventors. In addition, a robustness check for the quality measure will be carried out, in which a weighted measure of quality will be used.

4 Measures

4.1 Dependent variables

4.1.1 Inventor productivity

The variables of interests for the analysis are quantity and quality of inventions at inventor's level. In the patent literature, patent count is usually used as a measure of inventor's productivity (see e.g. Hoisl, 2007; Mariani and Romanelli, 2007). Patents suffer from one main limitation in this respect, that is, they do not capture the non-patented inventions. Therefore, by accounting only for inventions that successfully reached the market, one neglects the relevance of other inventions, whose patent applications are still under evaluation by the EPO or have been rejected, but that still represent the outcome of innovative activity. Since the EPO dataset keeps track of all the patent applications, it is possible to mitigate that bias by taking into account both granted patent and patent applications, hence capturing those inventions that had the potential to be patented and therefore applied for a patent but - at present - have not been granted a patent (yet). Therefore, we include in the patent count measure (*Npat*, used in log in the regression) both patent applications and granted patents between 2000 and 2006.

Due to the short time span, only a truncated measure of inventor's productivity can be observed. As a consequence, we would be treating inventors who started patenting before 2000 the same as inventors who start later or after 2000, hence not taking into account the past patenting activity (if any). This bias, known as truncation bias, can be mitigated by controlling for the age of inventors and for the year in which each inventor enters the sample. In particular, the aim of the latter control is to compare inventors with those that are part of the same cohort, namely those who "start" patenting in the same year.

4.1.2 Quality of inventions

The second variable of interest is the quality of each inventor's patents and will be measured with the forward citations received by each patent. Each patent has to cite the prior art on which it builds on, and the forward citations count is the number of times the patent is cited by other patents after it has been granted[5]. Previous empirical evidence shows that forward citations are highly correlated with the value of inventions (see e.g. Hall et al., 2001, 2005; Harhoff et al., 1999; Lanjouw and Schankerman, 2004; Trajtenberg, 1990). Therefore, the more forward citations a patent receives, the higher is the quality of the patent. This relationship relies on the assumption that a highly cited patent represents an important invention that will constitute relevant prior art for future patents. Although forward citations represent an imperfect measure, they are still considered a valuable proxy for the quality of a patent because they mirror the technological value of the patent (Nagaoka et al., 2010).

Based on the forward citations received by each inventor's patents, two measures of quality are created. Following inter alia Hoisl (2007) and Mariani and Romanelli (2007), in order to measure the patent quality at inventor's level, we use the average number of forward citations across each inventor's patent during 2000-2006 and the highest number of forward citations among each inventor's patents in the same period. The former (*Meanfcc*) measures the average quality of inventors[6], whereas the second (*Maxfcc*) accounts for the "best" invention among those produced by each inventor and thus measures the highest technological success of the inventor during the time span under consideration.

Table 1 summarises the descriptive statistics of the dependent variables in the whole sample as well as split by region of residence. The variables are *Npat* (number of patent applications)[7], *Meanfcc* (average number of forward citations) and *Maxfcc* (highest number of forward citations).

[5] Forward citations differ from backward citations, which are the past patents cited in patent applications.

[6] Patent citations take time and only a small number of citations occur for younger patents. In order to deal with this problem, usually only the number of forward citations received within 5 years (or so) from the publication is taken into account, based on the evidence that more than 50% of citations received occur within this period (Nagaoka et al., 2010). However, because of the peculiarity of the data, applying this correction would lead to a very small sample of observations.

[7] This variable will be use in log in the regression. It is here reported in absolute value in order to give a real measure of how many patents each inventor produces.

TABLE 1 ABOUT HERE

In the whole sample of 875 inventors, the average number of patent applications per inventor is 1.82. In line with previous evidence (Giuri et al., 2007; Menon, 2011), the variable is higly skewed, since the maximum number of patent applications is 27. The histogram in figure 1 shows the distribution of this variable: 67% of inventors applied for a patent only once between 2000 and 2006, while only 6% of the sample did it more than five times. Though it could be concluded that the majority of inventors in the sample are occasional inventors, because patenting only once, one has to account for the short time span, hence such conclusion cannot be proved. The average number of patent applications in Catalonia and the Midlands is the same (1.57) and below the average, while in Piedmont it is above the average (1.98).

Looking at the quality measures, the average number of forward citations across each inventor's patents is 2.21 and, similarly to the absolute number of patent applications, this variable is highly skewed. Looking at the inventions with the highest number of citations, 3.21 is the average, meaning that on average, the best invention has been cited 3.21 times by other patents. However, one can see that this figure rises up to 114, hence showing that there is a high variation across inventors.

FIGURE 1 ABOUT HERE

4.2 Explanatory variables

4.2.1 Knowledge sources

In order to build the knowledge variables we use one question of the survey that asks to the inventors to rank the importance of a number of sources of knowledge, from 0 (not applicable because not used) to 4 (very important). The question specifically states "*Please indicate whether interactions with any of the following actors have been important to get relevant information and knowledge for the work related to your patenting activity during the period 2000-2006*". The actors listed are both internal and external-to-the-firm. However, the focus of this paper is on the role of external organisations, which are (as listed in the question): suppliers, clients and customers, competitors and consultancy/private R&D laboratories; universities and public research centres (see Table 2).

TABLE 2 ABOUT HERE

Firstly, from the respondents' answers, we build a measure of the use of each knowledge source, hence six dummies indicating that the inventor used each given source if she answered 1 to 4, and not used it if she answered 0. In order to create the scientific and market knowledge measures, universities and public research centres are aggregated under the category "scientific knowledge" and all the others under the category "market knowledge". Therefore, the dummy variable that indicates whether the inventor used scientific knowledge (*SCIKnow*) has value 1 if she used either knowledge from universities or from public research centres (or both), while the variable indicating the use of market knowledge (*MKTKnow*) assumes value 1 if the inventor used at least one (or more) of the market sources. Table 3 shows the descriptive statistics of each knowledge source, as well as their aggregation into scientific and market sources. The share of inventors who used at least one scientific source is 62% and the correlation between the use of universities and that of public research centres is quite high, 0.62, supporting their aggregation. Almost every inventor used at least one of the market sources (91%), although it ranges from 54% of inventors exploiting knowledge from consultants to 71% of inventors using knowledge from clients and customers. As for the correlation among them, it is worth noticing that the figures are all above 0.30, with the highest for the correlation between knowledge from suppliers and knowledge from customers (0.43). Finally, the correlation between scientific knowledge and market knowledge is 0.2 and it is significant at the 5% level, suggesting that there is a positive link between the two.

TABLE 3 ABOUT HERE

4.2.2 Inventors' knowledge sourcing strategies

In order to apply the methodology of the productivity approach, the inventors' knowledge sourcing strategies have to be derived from the above mentioned knowledge dummies for scientific and market sources. Hence, we create the following mutually exclusive dummies:

1. *scionly*: taking value 1 for inventors who use only scientific knowledge (*SCIKnow*=1 and *MKTKnow*=0);
2. *mktonly*: taking value 1 for inventors who use only market knowledge (*SCIKnow*=0 and *MKTKnow*=1);
3. *scimkt*: taking value 1 for inventors who use both scientific and market knowledge (*SCIKnow*=1 and *MKTKnow*=1);
4. *noscimkt*: taking value 1 for inventors who use none of them (*SCIKnow*=0 and *MKTKnow*=0).

By using this approach we intend to compare the performance of inventors who used both scientific and market knowledge, with that of inventors who used only scientific or market knowledge or none of them. Table 4 shows the frequencies of the exclusive dummies and the values of the dependent variables for each sub-group of inventors.

The most widespread strategy is that of both using scientific and market knowledge sources (59% of inventors), followed by the use of market sources only (31,25%). Very few inventors used only scientific sources and none of the knowledge sources (3,06% and 6,65% respectively). The breakdown of the dependent variables by knowledge sourcing strategy shows that inventors using both scientific and market knowledge have the highest performance in terms of number of patent applications (*Npat*) (1,98), and best invention (*Maxfcc*) (3,51). Inventors who only use market sources have the highest number of average citations across patents (2,42), therefore the highest average quality of inventions (*Meanfcc*). The groups of inventors using only scientific knowledge and none of the sources have the lowest performance. These figures, although only descriptive, seems to tell that inventors who combine the two sources of knowledge benefit more than inventors who do not combine them, therefore suggesting the existence of a complementarity relationship between scientific and market knowledge. The correlation table shows that there is a positive - although weak - correlation between the joint use of scientific and market knowledge and the performance measures. Inventors' quality is also positively correlated with the use of market knowledge only.

TABLE 4 ABOUT HERE

4.3 Control variables

Control variables have been created at inventor level. These are: individual characteristics, which could be derived from the survey, patent features, which have been extracted from the patent data, and employer information provided by the inventors in the survey responses. As for individual characteristics, we control for inventor's gender, age and age squared, assuming that age might display a non linear (e.g. quadratic) relationship with inventor's performance, and the education level, by using 4 dummies for the highest education level attained by the inventors. From the survey it was possible to extract information on inventors' mobility between jobs and job position inside the firm (e.g. R&D department, sales, marketing, etc.). We also control for whether the inventor retired during the period under analysis. Finally, dummies for the region where inventors live are introduced. At patent level, we control for whether the inventor has ever realised patents with other inventors and for the share of foreign-owned patents, calculated as the share of patents whose owner is not located in the country where the inventor lives. Both variables serve as proxies for the inventors "openness" toward external knowledge (Hoisl, 2007).

In order to mitigate the truncation bias arising from using a short time span, we control for the year in which each inventor enters the sample. To do so we use the year indicated in the priority date of the first patent application (for each inventor) in the time frame 2000-2006. The priority date is the date of filing of an earlier (or the first) application for which priority is claimed. The aim of this control is to compare inventors that are part of the same cohort, namely those who start patenting in the same year. Finally, in order to account for variation across technological classes, we control for seven patent technological macro classes, following the reclassification of the International Patent Classification system developed by the french Observatoire des Sciences et des Techniques (OST). These are Electrical Engineering and Electronics (ost1), Instruments (ost2), Chemicals and Materials (ost3), Pharmaceuticals and Biotechnology (ost4), Industrial Processes (ost5), Mechanical Engineering, Machines and Transport (ost6), and Civil Engineering and Consumer goods (ost7)[8].

As for employer's features, we control for the international exposure of the most recent employer listed by the inventor, with a dummy that equals one if the firm is a multinational company [9]. This variable should account for the firm's "openness", assuming that more internationalised firms also tend to co-operate with external actors and hence widen the pool of knowledge that the

[8]These are non-exclusive dummies, because each patent can be classified under more than one class.
[9]This variable has been created by checking companies' webpages and/or companies accounts.

inventor can tap into. We also include firm fixed effects to control for the fact that some of the firms employ more than one inventor of the sample. A set of dummies has been hence created - one dummy variable for each firm - including both those that employ just one inventor and those that employ more than one inventor. By controlling for this, we aim at isolating unobservable drivers of inventors' performance that are explained by employer characteristics.

The average age of inventors in the sample[10] is 44 years old, 40% of them have a Bachelor Degree, while 18% also hold a PhD. Quite a large share of inventors (68%) changed job at least once during the period 2000-2006 and around 44% of the whole sample work in an R&D job position inside the firm. As for their patenting behaviour, most of them (70%) have co-invented at least one of their patents; on average, 16% of an inventor's patents is owned by an organisation located abroad with respect to the inventor's country of residence. Furthermore, the majority of inventors apply for patents classified in the technological classes of mechanical engineering (37%) and electrical engineering (28%), while pharmaceutical has the lowest frequency of patents applied for (11%). Finally, almost half of the inventors are employed by a multinational firm and roughly half of the inventors work in a firm where at least another inventor of the sample is employed too. The cross tabulation of the variables *mne* and *co-employment* shows that 38% of the inventors that are co-workers are employed by a multinational company.

TABLE 5 ABOUT HERE

5 Results

5.1 Inventors' performance: quantity of patents

Columns (1) to (4) in table 6 shows the results of the OLS regression of inventors' productivity measured as the number of patent applications between 2000 and 2006 (in log). The joint use of scientific and market knowledge (*scimkt*) is always positive and significant as well as constant across different estimations, while the sole use of scientific (*scionly*) or market (*mktonly*) knowledge is never significant. This indicates that inventors who jointly use knowledge from market sources and from university or research centres have a higher patent productivity than those who do not use any of them (the baseline is *noscimkt*) as well as than those who use only market or scientific knowledge. This suggests that, as hypothesised, inventors performing better are those who combine into their inventions the technological and scientific potential of knowledge sourced from university and research centres with the market potential of knowledge coming from market actors.

Along with the inventors' knowledge sourcing strategies, the inventors' personal characteristics are first introduced (column (1)), followed by dummies for the region of residence, job characteristics and year dummies (column (2)), then patent features are added (column (3)) and finally firm factors - dummy for MNEs and firm dummies - are controlled for (column (4)). The coefficient of age has the expected positive sign and is significant at 10% level, showing that older inventors have more patents, but this disappears once the year dummies to control for when

[10]The figures in table 5 are based on a sample of 710 observations, corresponding to the sample used in the regressions analysis. Descriptive statistics for the full sample are provided in table 12 in Appendix A.

inventors started patenting are introduced. Inventors with a PhD degree patent less (coefficient negative and significant at 5% level in column (1)) than inventors who just hold a high school diploma (baseline), which could be explained by the fact that the latter group enters the job market right after secondary education (or most likely after the university degree), hence start patenting earlier, but this relationship disappears once more factors are controlled for. Out of the other controls, only the dummy for co-inventors has some explanatory power and shows - as expected - that inventors who cooperate with other inventors (which are in fact the vast majority - 70% of the sample) are also more productive. The R squared in column (4) rises up to 0.7 once the firm dummies are introduced in the regression. These serve as controls for firm unobservable factors that it is not otherwise possible to control for, and show that employers' characteristics might play a role in individual decisions. Hence, it can be argued that inventors' productivity can be related to some extent to firm decisions aside individuals' ones. However, it should be noted that the joint use of scientific and market knowledge - although less significant than in the other estimations - still represents a driving factor of productivity, with a coefficient for *scimkt* of 0.198, corresponding to an increase in the number of patents per inventor by 21.8%[11]. In conclusion, it can be said that the joint use of scientific knowledge and market knowledge systematically shows a positive relationship with inventors' productivity, and that it is also quite stable when controlling for individual characteristics, patent features and firm factors.

TABLE 6 ABOUT HERE

5.2 Inventors' performance: average quality and top invention

Table 7 displays the OLS regression results for the inventor's quality, expressed in terms of number of average citations across the inventor's patents - *Meanfcc* - (columns (1) to (4)) and the highest number of citations obtained by one of the inventor's patents - *Maxfcc* - (column (5) to (8)). It can be noticed that the coefficient for the joint use of scientific and market knowledge (*scimkt*) is positive and significant until we do not control for employers' factors. In fact, the introduction of a control for MNEs and the firm dummies soaks up part of the explanatory power (apart for the coefficient for *co-inventor* that is still positively and significantly correlated to the highest number of citations received). Therefore, once controlling for firm factors, the hypothesis of complementarity between scientific and market sources seems to have no support. In addition, the coefficient for *scimkt* is very similar to that for *mktonly*, indicating that the joint use of different knowledge sources is not systematically better than the separate use of market knowledge for the quality of inventions. This is suggestive of the fact that the interaction of inventors with only market actors (i.e. other firms mainly) can have a positive impact on the quality of the inventions, whereas this was not the case for the quantity of patents applied for.

As for individual inventors' characteristics, it is worth noticing the existence of an inverted-U shape relationship between the age of the inventors and the quality of inventions - in columns (1) and (5) the coefficient for *age* is positive and significant and that for age squared (*agesq*) is negative and significant, both at 5% level) - though it loses significance once other factors are controlled for. As the inventors grow older, they tend to produce inventions of higher quality,

[11] Being this a log-linear model and *scimkt* a dummy variable, the estimated effect is calculated as exp(0.198)-1.

but after a threshold the relationship becomes negative, meaning that after a certain age (around 45 years old for both average quality and best invention), the quality of inventions decreases. The fact that the inventor works in an R&D department, rather than in other departments (e.g. marketing or sales) seems to be indicative of higher quality inventions - the coefficient for *R&Djob* is positive and significant in model (2), (3), (6) and (7) - which could be due to the fact that better inventors tend to be employed in R&D departments. Finally, similarly to the case of inventors' productivity, the dummy variable for co-inventors has a positive and significant coefficient in almost every model, but it is particularly important for the quality of the best invention. This could be explained by the fact that, working in teams of inventors rather than working alone, increases the chances to develop a technological hit as well as the quality of the latter. The variables of interest lose any significance in models (4) and (8) once firm factors are accounted for, which will bring to the argument that - similarly to the case of inventors' productivity - there might be some firms' unobservable factors that drive inventors' performance, as well as their decision to use any external source of knowledge. To sum up, there is a positive relationship between the joint use of different sources of knowledge and inventor's quality but this is less clear than it was for inventors' productivity. This is partly because the use of knowledge from market channels is almost qually relevant for the quality of inventions, and it is particularly true when employers' factors are accounted for.

TABLE 7 ABOUT HERE

5.3 Inventors' mobility and the use of scientific and market knowledge

The literature on inventors' performance has underlined that one of the influencing factors of inventors' productivity and quality is their job mobility pattern. Trajtenberg (2005) is one of the first who studied the link between mobility and productivity and shows that the former has a positive impact on innovative output. In particular, mobile inventors have more valuable patents, that is, more cited patents. Hoisl (2007) studies a sample of German inventors and shows that those who change job are more productive than those who do not, although increases in productivity decrease the probability of observing a move. Since 67.4% of inventors in our sample changed job at least once during the years 2000-06, it is interesting to look for any heterogeneity of the results across the two groups of mobile and non-mobile inventors. In order do so, the sample of inventors will be split into mobile and non-mobile inventors, by exploiting the dummy *jobmobility*, that has been constructed from the information provided by the survey respondents. Mobile inventors are those who moved from one job to another job between 2000 and 2006. Non-mobile inventors are those who did not change job in 2000-2006 (but may have done so earlier or later). The decision to observe mobility in this time frame is due to the fact that the key variables of interests - both dependent and independent - are observed during that time period.

Table 8 shows the OLS results obtained by regressing the measure of inventors' productivity (*lNpat*) against the knowledge sourcing strategies, the individual characteristics and patent factors, for the subsample of mobile inventors (67% of the sample) in the left panel and for non-mobile inventors (33% of the sample) in the right panel. Table 9 displays the same regressions results but on the measures of quality, both average forward citations (*Meanfcc*) and highest number of citations (*Maxfcc*). In both tables only the coefficients for the three knowledge sourcing strategies are reported[12].

Whereas there is not a striking difference between mobile and non-mobile inventors in terms of their number of patent applications (the coefficients for *scimkt* are very similar, though slightly higher for non-mobile inventors), the same cannot be said for the quality of their inventions, which instead displays some variation across the two sub-samples. In particular, there is no significance of the coefficients for the knowledge sourcing strategies in the sub-sample of non-mobile inventors. If one considers job mobility as a proxy for openness, this result can be interpreted as that non-mobile inventors are less open to external knowledge and when they use it, this does not impact the quality of their inventions because they lack the ability and competences to exploit it.

On the other hand, the joint use of scientific and market knowledge is positively and significantly related to both average quality of inventions and quality of the best inventions for mobile inventors. This can be explained by the fact that mobile inventors have developed connections with other (external) organisations due to their job experience and have, hence, the ability to exploit external knowledge, which, in turns improves the quality of their inventions.

TABLE 8 AND 9 ABOUT HERE

6 Robustness check for the quality of inventors

The empirical results discussed so far suggest that inventors' quality display more variation than quantity with respect to the use of external-to-the-firm sources of knowledge. It is thus worth to further check whether the results hold, by carrying out a robustness check. As mentioned before, the employment of the number of forward citations received by a patent, though a widely used proxy for inventors and inventions' quality, raises a number of concerns with respect to its reliability. Among other things, different technological classes might display quite large differences in terms of number of inventions and number of forward citations received by patents (see e.g. Hall et al., 2001). As shown in figure 2, there is quite a high variation in the total number of forward citations per technological class, ranging from around 4000 citations received by patents classified into civil engineering to more than 9000 citations received by patents into mechanical engineering. The mean value (number of total citations weighted for the number of patents) varies much less than the absolute, with the most cited - on average - patents into chemicals (3) and the lowest into civil engineering (1.6). By looking at figure 3 it is possible to notice that there is even more variation across both regions and technological classes.

It is hard to say whether such differences just depend on different citations practices, hence are somehow artifactual, or reflect a "real" phenomenon. In particular, these can be due to the fact some technological areas are more innovative and characterised by innovation breakthroughs -

[12]In tables 8 and 9 firm dummies are never introduced due to the small number of observations, especially in the sub-sample of non-mobile inventors.

hence by a higher rate of patenting and more citations - whereas some others are less innovative and mainly produce incremental innovation - hence less patenting activity and lower citations (Hall et al., 2001). When such differences exist, the use of the simple mean number of citations across each inventor's patent might not capture this heterogeneity. Therefore, as a robustness check for the estimation of inventor's quality, we will employ a different dependent variable with the dual aim of correcting for this potential bias and check whether the main results hold. This measure is a weighted average of forward citations at inventor level in which the number of citations received by each patent is firstly weighted for the average number of citations received by all patents in the same technological class (i.e.: for each patent, its "weighted quality" is calculated). This first step is done by region of residence of the inventor, so that each patent is compared to the average number of forward citations received by patents in the same class within the same region[13]. This is done to account for variation across both regions and technological classes and follows the rationale proposed by Hall et al. (2001), according to which, in order to remove all sources of variation in citation intensities, it is necessary to re-scale citation counts by dividing them for the average citation count of a group of patents to which the patent of interest belongs[14].

Secondly, the "weighted quality" of each patent is used to create the measure of inventor quality, by calculating the mean across each inventor's patents, similarly to what has been done for the variable *Meanfcc*[15]. Table 10 displays the mean values of the newly created variable *Meanfcc_ weighted*: the figures show that there is still some variation across regions, but less so across technological classes (within region), which is what the new measure was thought for[16].

FIGURE 2 AND 3 ABOUT HERE

TABLE 10 ABOUT HERE

The econometric analysis follows the same model employed in section 5 of the paper: the measure of inventor's quality is estimated as a function of the three knowledge sourcing strategies plus the usual vector of control variables. The OLS results in table 11 shows that the findings are generally consistent with the main estimation in table 7, hence confirming the positive relationship between the joint use of scientific and market knowledge and the performance of industrial inventors. Similarly to the previous estimates with *Meanfcc* and *Maxfcc* as dependent variables, it should be noticed that the sole use of market knowledge is also significantly related to inventors' quality. The coefficient for *mktonly* is indeed higher or very similar to that for *scimkt*. Therefore, it is arguable that the development of market channels is per se an influencing factor of the quality of the inventors' patents, and thus, it is not possible to fully confirm that the joint use of market and scientific knowledge has systematically a higher impact on quality than the separate use of either

[13]The total count and average of forward citations per technological class are calculated from the full patent sample in each region - hence not only on the sub-sample of respondents' patents.

[14]Hall et al. (2001) use the patent year as reference group for each patent, hence they weight the citation counts by the average citation count of patents granted in the same year.

[15]When a patent is classified into more than one technological class, its number of citations is weighted for the mean value of the average quality of each class.

[16]Note that the data in table 10 cannot be compared with those displayed in the histograms because the first are at inventor level whereas the diagrams display data at patent level.

scientific or market knowledge. Furthermore, the introduction of controls at firm level makes the variables of interest not significant, which has to be interpreted as the potential existence of unobservable factors at firm level that should be controlled for. Overall, by using a better measure of inventors' quality it is possible to confirm the main findings, and hence to conclude that inventors' performance is influenced by the use of external knowledge, although it is not possible to conclude that the joint use of scientific and market knowledge has a better effect than the use of each of the sources separately.

TABLE 11 ABOUT HERE

7 Discussion and conclusion

This paper has investigated the role of scientific and market knowledge in the inventive process inside firms by asking whether industrial patent inventors who exploit both types of knowledge at the same time display higher performance than those who use them separately. By applying an empirical framework only rarely employed at individual level, we estimate a model where the inventor's performance depends upon her knowledge sourcing strategies (using only scientific knowledge, using only market knowledge, using both of them) as well as a number of other individual, patent and firm level factors. The data comes from an original survey of private inventors who reside in three European regions, matched to patent data from the European Patent Office. The findings show that there is a positive and significant relation between both quantity - number of patent applications - and quality - average forward citations and highest forward citations received - of inventors' patenting activity and the joint use of scientific and market knowledge. The sole use of knowledge from market sources is also significantly related to the quality of inventors in some of the estimations. Furthermore, mobile inventors seem to benefit more than non-mobile ones from external knowledge, most likely because of their greater openness towards external-to-the-firm organisations. The robustness check carried out in the last section further shows that, when accounting for the uneven distribution of forward citations across different patent technological classes, the findings are consistent with the previous estimates. Finally, it is worth noticing that scientific knowledge seems to be never effective if used alone - the coefficient for the corresponding knowledge sourcing strategy never turns significant - and that some drivers of inventors' performance at firm-level may have remained unobserved, since the coefficients of interest lose significance once employer's factors are controlled for.

Before underlying the potential implications of this study, it is worth noticing that a number of limitations emerged. In first place, by administering the survey questionnaire to patent inventors only, non-patenting inventors have been automatically excluded from the sample, therefore nothing is known about the knowledge sourcing strategies of the latter group. This bias is partly overcome by taking into account both granted and not-yet granted patents. Moreover, the cross-sectional nature of the data does not allow to properly control for time-invariant factors. Finally, although forward citations are widely acknowledged as being among the best proxies for patent quality, it is also well-known that these have some limitations and might only provide a partial picture. The creation of a weighted count of forward citations represented an attempt to improve this measure of quality.

Yet, the findings of this study offer some contributions to the literature. First, the focus of this paper is on the individual who is primarily responsible for the inventive activity behind patents, this being justified by the fact that innovation is not simply the product of firms and organisations, but it ultimately requires individual creativity. Whereas previous evidence has extensively focused on the role of organisational-level factors and/or intrinsic patent features in explaining the outcomes of innovative activities (see e.g. Hall et al., 2005; Harhoff et al., 1999; Pasquini et al., 2012; Suzuki, 2011), in this paper individual decisions are taken into account as fundamental drivers of individual outcomes. Existing evidence suggests that inventors should rely on different sources of knowledge to increase the chances of patent commercialisations (Pasquini et al., 2012), though it seems that the opposite is true for the value of patented inventions (Schneider, 2009). This study adds that quantity as well as quality of inventors' patents benefit from the recombination of different sources of external knowledge. In addition, in order to analyse the role of inventors' knowledge sourcing strategies, the empirical analysis makes use of an original data source: the PickMe survey of industrial inventors in fact provides brand new insights about the demand of knowledge expressed by the actors directly involved in the innovative process and also provides a number of information at individual level, including biographical information, that are not available from patent applications.

This study also offers some implications for innovation policies. In particular, the evidence of a complementarity relationship between different sources of knowledge for the inventive process inside firms suggests that knowledge exchange across a wide range of organisations - both academic and non-academic - is beneficial and should be adequately supported.

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Tables

		Npat			*Meanfcc*			*Maxfcc*		
	Obs.	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**
CATALONIA	225	1.57	1	15	2.04	0	25	2.81	0	39
MIDLANDS	117	1.57	1	8	2.06	0	17	3.02	0	35
PIEMONTE	533	1.98	1	27	2.32	0	45.33	3.42	0	114
FULL SAMPLE	875	1.82	1	27	2.21	0	45.33	3.21	0	114

Table 1: Descriptive statistics of the dependent variables

Sources of knowledge	**Types of knowledge**
Suppliers of equipment/materials Clients and customers Competitors Consultants and private R&D laboratories	MARKET KNOWLEDGE
Universities Public research institutes	SCIENTIFIC KNOWLEDGE

Table 2: Sources of knowledge

Variable	**Obs.**	**Mean**	**1**	1a	1b	**2**	2a	2b	2c	2d
1 Scientific Know.	765	0.62	1							
1a University Know.	764	0.61	0.97	1						
1b Public research centres Know.	744	0.40	0.65	0.62	1					
2 Market Know.	783	0.91	0.20	0.21	0.23	1				
2a Clients Know.	761	0.71	0.16	0.15	0.22	0.52	1			
2b Competitors Know.	748	0.68	0.29	0.30	0.37	0.48	0.40	1		
2c Suppliers Know.	757	0.70	0.22	0.22	0.27	0.51	0.43	0.32	1	
2d Consultants Know.	745	0.54	0.46	0.46	0.48	0.36	0.31	0.33	0.31	1

Table 3: Descriptive statistics of the knowledge sources

			Correlations			**Means**		
Strategy	Freq.	Percent	*Npat*	*Meanfcc*	*Maxfcc*	*Npat*	*Meanfcc*	*Maxfcc*
1 scionly	23	3.06	-0.02	-0.02	-0.03	1.57	1.92	2.30
2 mktonly	235	31.25	-0.05	0.03	0.00	1.70	2.42	3.31
3 scimkt	444	59.04	0.09	0.01	0.04	1.98	2.30	3.51
4 noscimkt	50	6.65	-0.07	-0.05	-0.06	1.34	1.56	1.92

Table 4: Descriptive statistics of the independent variables. Note: the total number of inventors sums up to 752, which is less than the total of 875; this is due to missing answers.

Variable	Description	Obs.	Mean	St.Dev.	Min	Max
Female	Dummy equal to 1 for female inventors	710	0.1014	0.3020	0	1
Age	Age of the inventor in 2006	710	44.4	10.2125	22	79
Agesq	Age squared	710	2075.51	971.3473	484	6241
HiSc	Secondary school degree	710	0.2225	0.4162	0	1
BSc	Bachelor degree	710	0.4014	0.4905	0	1
MSc	Master degree	710	0.1845	0.3881	0	1
PhD	Doctoral studies	710	0.1802	0.3846	0	1
Jobmobility	Dummy 1/0 for inventors who changed job at least once in 2000-06	710	0.6831	0.4656	0	1
R&Djob	Dummy 1/0 for inventors whose job position is in the R&D department of the firm	710	0.4436	0.4971	0	1
Retired	Dummy 1/0 for inventors who retired in 2000-06	710	0.0760	0.26521	0	1
Piedmont	Dummy 1/0 for inventors from Piedmont	710	0.5957	0.4911	0	1
Catalonia	Dummy 1/0 for inventors from Catalonia	710	0.2464	0.4312	0	1
Midlands	Dummy 1/0 for inventors from the Midlands	710	0.1577	0.3647	0	1
ost1	Electrical Engineering; Electronics	710	0.2802	0.4494	0	1
ost2	Instruments	710	0.1746	0.3794	0	1
ost3	Chemicals; Materials	710	0.1746	0.3799	0	1
ost4	Pharmaceuticals; Biotechnology	710	0.1183	0.3232	0	1
ost5	Industrial Processes	710	0.1915	0.3937	0	1
ost6	Mechanical Engineering; Machines; Transport	710	0.3704	0.4832	0	1
ost7	Civil Engineering; Consumer goods	710	0.1225	0.3281	0	1
Co-inventor	Dummy 1/0 for whether the inventor has ever co-invented a patent	710	0.7056	0.4561	0	1
Share-foreign-patents	Share of the inventors' patents that are owned by firms not located in the country where the inventor lives	710	0.1608	0.3637	0	1
Mne	Dummy 1/0 for whether the firm (the last reported by the inventor in the survey) is a multinational company	710	0.5169	0.5000	0	1
Co-employment	Dummy 1/0 for inventors that work in the same firm	710	0.4985	0.5003	0	1

Table 5: Descriptive statistics of the control variables

VARIABLES	(1) lNpat	(2) lNpat	(3) lNpat	(4) lNpat
scionly	-0.0287	-0.0397	-0.0274	-0.0234
	(0.125)	(0.147)	(0.133)	(0.210)
mktonly	0.0983	0.0583	0.0147	0.0943
	(0.0649)	(0.0657)	(0.0634)	(0.134)
scimkt	0.211***	0.181***	0.147**	0.198*
	(0.0620)	(0.0628)	(0.0600)	(0.118)
female	-0.00399	-0.00271	-0.0348	0.110
	(0.0588)	(0.0590)	(0.0646)	(0.139)
age	0.0239*	0.00958	0.0104	0.0288
	(0.0136)	(0.0146)	(0.0139)	(0.0345)
agesq	-0.000224	-7.17e-05	-7.95e-05	-0.000301
	(0.000142)	(0.000160)	(0.000148)	(0.000377)
BSc	-0.0342	0.0340	0.0356	-0.00719
	(0.0603)	(0.0641)	(0.0568)	(0.127)
MSc	-0.107	-0.0459	-0.0342	-0.0319
	(0.0681)	(0.0728)	(0.0665)	(0.152)
PhD	-0.147**	-0.0380	-0.0296	0.188
	(0.0723)	(0.0766)	(0.0770)	(0.266)
jobmobility		0.00843	-0.0150	-0.0704
		(0.0461)	(0.0427)	(0.0937)
R&Djob		0.0451	0.0218	-0.0318
		(0.0482)	(0.0450)	(0.103)
retired		-0.0334	-0.0288	0.147
		(0.0990)	(0.0858)	(0.478)
coinventor			0.109**	0.258**
			(0.0463)	(0.104)
share_foreign_pat			0.00804	0.00103
			(0.0479)	(0.174)
mne				0.0217
				(0.424)
Constant	-0.332	0.0835	-0.480	-1.040
	(0.323)	(0.358)	(0.357)	(1.106)
Region dummies	-	Yes	Yes	Yes
Year dummies	-	Yes	Yes	Yes
Patent techn. classes	-	-	Yes	Yes
Firm dummies	-	-	-	Yes
F-test (*scionly, mktonly, scimkt*)	F(3,731)=5.02 Pr>F=0.0019	F(3,689)=4.10 Pr>F=0.0068	F(3,680)=4.08 Pr>F=0.0069	F(3,298)=1.27 Pr>F=0.2851
Observations	741	710	710	710
R-squared	0.027	0.111	0.278	0.699

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: OLS regression. Dependent variable: log of number of patent applications

VARIABLES	**(1)** *Meanfcc*	**(2)** *Meanfcc*	**(3)** *Meanfcc*	**(4)** *Meanfcc*	**(5)** *Maxfcc*	**(6)** *Maxfcc*	**(7)** *Maxfcc*	**(8)** *Maxfcc*
scionly	0.335	0.614	0.708	1.137	0.386	0.811	1.087	1.283
	(0.784)	(0.875)	(0.914)	(2.515)	(0.878)	(1.011)	(1.099)	(3.142)
mktonly	0.754**	0.650*	0.495	0.536	1.279**	1.010**	0.675	0.746
	(0.380)	(0.358)	(0.364)	(1.003)	(0.509)	(0.486)	(0.505)	(1.749)
scimkt	0.678*	0.721**	0.608*	0.534	1.522***	1.492***	1.265**	1.295
	(0.360)	(0.351)	(0.365)	(0.946)	(0.534)	(0.534)	(0.567)	(1.488)
female	0.206	0.211	0.307	1.081	-0.0383	-0.0841	0.0182	1.362
	(0.485)	(0.495)	(0.482)	(1.160)	(0.677)	(0.669)	(0.647)	(1.631)
age	0.176**	0.0766	0.0597	0.207	0.245**	0.105	0.0692	0.413
	(0.0785)	(0.0714)	(0.0703)	(0.212)	(0.114)	(0.106)	(0.0974)	(0.352)
agesq	-0.00195**	-0.00107	-0.000842	-0.00267	-0.00264**	-0.00139	-0.000977	-0.00487
	(0.000827)	(0.000772)	(0.000752)	(0.00226)	(0.00120)	(0.00114)	(0.00106)	(0.00371)
BSc	-0.380	-0.293	-0.324	-0.557	-0.373	-0.205	-0.203	-0.309
	(0.351)	(0.346)	(0.347)	(0.812)	(0.509)	(0.484)	(0.479)	(1.321)
MSc	-0.389	-0.471	-0.418	-0.686	-0.176	-0.209	-0.0822	0.402
	(0.515)	(0.510)	(0.537)	(1.423)	(0.968)	(0.954)	(1.035)	(3.081)
PhD	-0.321	-0.249	-0.183	-1.460	-0.387	-0.0579	0.240	-0.0196
	(0.446)	(0.454)	(0.539)	(1.413)	(0.670)	(0.678)	(0.892)	(2.744)
jobmobility		-0.0525	-0.0759	0.233		-0.184	-0.285	-0.122
		(0.299)	(0.309)	(0.592)		(0.538)	(0.572)	(1.022)
R&Djob		0.518*	0.515*	0.252		0.893**	0.838*	0.244
		(0.289)	(0.294)	(0.633)		(0.425)	(0.445)	(0.858)
retired		-0.117	-0.224	2.214		-0.0390	-0.161	1.955
		(0.464)	(0.469)	(2.710)		(0.811)	(0.824)	(5.030)
coinventor			0.546**	0.995			1.152***	2.600*
			(0.259)	(0.791)			(0.397)	(1.343)
share_foreign_pat			0.184	-0.612			-0.0292	-0.821
			(0.329)	(0.996)			(0.421)	(1.480)
mne				-3.513				-4.486
				(3.058)				(4.851)
Constant	-1.852	2.617	2.335	-0.869	-3.173	3.367	1.801	-3.947
	(1.833)	(1.696)	(1.798)	(7.041)	(2.648)	(2.592)	(2.618)	(10.91)
Region dummies	-	Yes	Yes	Yes	-	Yes	Yes	Yes
Year dummies	-	Yes	Yes	Yes	-	Yes	Yes	Yes
Patent techn. classes	-	-	Yes	Yes	-	-	Yes	Yes
Firm dummies	-	-	-	Yes	-	-	-	Yes
F-test (*scionly, mktonly, scimkt*)	F(3,731)=1.57 Pr>F=0.1962	F(3,689)=1.54 Pr>F=0.2030	F(3,680)=0.97 Pr>F=0.4048	F(3,298)=0.14 Pr>F=0.9384	F(3,731)=3.37 Pr>F=0.0182	F(3,689)=2.75 Pr>F=0.0420	F(3,680)=1.68 Pr>F=0.1699	F(3,298)= Pr>F=0.8491
Observations	741	710	710	710	741	710	710	710
R-squared	0.009	0.137	0.154	0.564	0.007	0.116	0.150	0.444

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: OLS regression. Dependent variables: Meanfcc (col. (1)-(4)), Maxfcc (col. (5)-(8))

	Mobile inventors		Non-mobile inventors	
VARIABLES	*lNpat*	*lNpat*	*lNpat*	*lNpat*
scionly	0.0428	-0.0187	-0.132	-0.188
	(0.181)	(0.177)	(0.0888)	(0.125)
mktonly	0.0675	-0.0161	0.154	0.0747
	(0.0919)	(0.0887)	(0.0951)	(0.0937)
scimkt	0.202**	0.146*	0.257***	0.168*
	(0.0914)	(0.0865)	(0.0912)	(0.0876)
Constant	-0.252	-0.300	-0.274	-0.483
	(0.445)	(0.509)	(0.522)	(0.519)
Region dummies	-	Yes	-	Yes
Year dummies	-	Yes	-	Yes
Patent techn. classes	-	Yes	-	Yes
Firm dummies	-	-	-	-
F-test (*scionly,*	F(3,475)=2.58	F(3,456)=3.45	F(3,216)=11.62	F(3,196)=3.41
mktonly, scimkt)	Pr>F=0.0532	Pr>F=0.0165	Pr>F=0.0000	Pr>F=0.0185
Observations	485	485	226	225
R-squared	0.038	0.280	0.044	0.351

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: OLS regression. Dependent variable:log(Npat), breakdown by inventor's mobility

	Mobile inventors		**Non-mobile inventors**		**Mobile inventors**		**Non-mobile inventors**	
VARIABLES	*Meanfcc*	*Meanfcc*	*Meanfcc*	*Meanfcc*	*Maxfcc*	*Maxfcc*	*Maxfcc*	*Maxfcc*
scionly	0.0159	-0.0125	2.700	3.523	0.365	0.283	2.111	3.326
	(0.607)	(0.680)	(2.821)	(3.147)	(0.897)	(0.962)	(2.986)	(3.733)
mktonly	1.077**	0.547	0.826	0.764	1.606**	0.757	1.292	1.096
	(0.485)	(0.466)	(0.629)	(0.614)	(0.660)	(0.629)	(0.871)	(1.056)
scimkt	1.236***	0.844*	0.499	0.653	2.055***	1.464**	1.514	1.697
	(0.461)	(0.487)	(0.603)	(0.637)	(0.668)	(0.679)	(1.121)	(1.219)
Constant	-2.554	2.287	-0.727	0.942	-3.780	2.059	-3.790	-0.142
	(2.415)	(2.589)	(3.433)	(3.113)	(3.247)	(3.585)	(6.176)	(5.271)
Region dummies	-	Yes	-	Yes	-	Yes	-	Yes
Year dummies	-	Yes	-	Yes	-	Yes	-	Yes
Patent techn. classes	-	Yes	-	Yes	-	Yes	-	Yes
Firm dummies	-	-	-	-	-	-	-	-
F-test (*scionly*,	F(3,475)=4.02	F(3,456)=1.49	F(3,216)=0.79	F(3,196)=0.85	F(3,475)=4.32	F(3,456)=2.01	F(3,216)=1.12	F(3,196)=0.94
mktonly, *scimkt*)	Pr>F=0.0077	Pr>F=0.2163	Pr>F=0.5018	Pr>F=0.4659	Pr>F=0.0051	Pr>F=0.1113	Pr>F=0.3416	Pr>F=0.4210
Observations	485	485	226	225	485	485	226	225
R-squared	0.028	0.188	0.022	0.180	0.031	0.229	0.016	0.165

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: OLS regression. Dependent variables: Meanfcc and Maxfcc, breakdown by inventor's mobility

	CATALONIA	MIDLANDS	PIEDMONT
electrical eng	1.25	1.15	0.95
instruments	1.09	0.51	1.27
chemicals	0.88	0.41	0.83
pharmaceuticals	0.88	0.23	0.97
industrial eng	0.95	1.20	1.10
mechanical eng	1.22	0.74	1.31
civil eng	1.20	0.89	0.73

Table 10: Mean values of Meanfcc_weighted, breakdown by technological class and region

VARIABLES	(1) *Meanfcc_w*	(2) *Meanfcc_w*	(3) *Meanfcc_w*	(4) *Meanfcc_w*	(5) *Meanfcc_w*
scionly	0.290	0.284	0.423	0.444	0.692
	(0.418)	(0.434)	(0.482)	(0.483)	(1.315)
mktonly	0.410**	0.357**	0.319*	0.306*	0.367
	(0.176)	(0.177)	(0.167)	(0.166)	(0.454)
scimkt	0.359**	0.335**	0.340**	0.338**	0.367
	(0.165)	(0.168)	(0.161)	(0.160)	(0.412)
Constant	0.714***	-0.709	1.059	0.833	-1.415
	(0.138)	(0.893)	(0.808)	(0.829)	(3.803)
Region dummies	-	Yes	Yes	Yes	Yes
Year dummies	-	-	Yes	Yes	Yes
Patent techn. clas.	-	-	Yes	Yes	Yes
Firm dummies	-	-	-	-	Yes
F-test (*scionly, mktonly, scimkt*)	F(3,741)=2.06 Pr>F=0.1045	F(3,728)=1.63 Pr>F=0.1805	F(3,686)=1.67 Pr>F=0.1726	F(3,684)=1.62 Pr>F=0.1824	F(3,304)=0.30 Pr>F=0.8239
Observations	745	738	707	707	707
R-squared	0.003	0.010	0.140	0.144	0.549

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: OLS regression. Dependent variable: Meanfcc_weighted

Figures

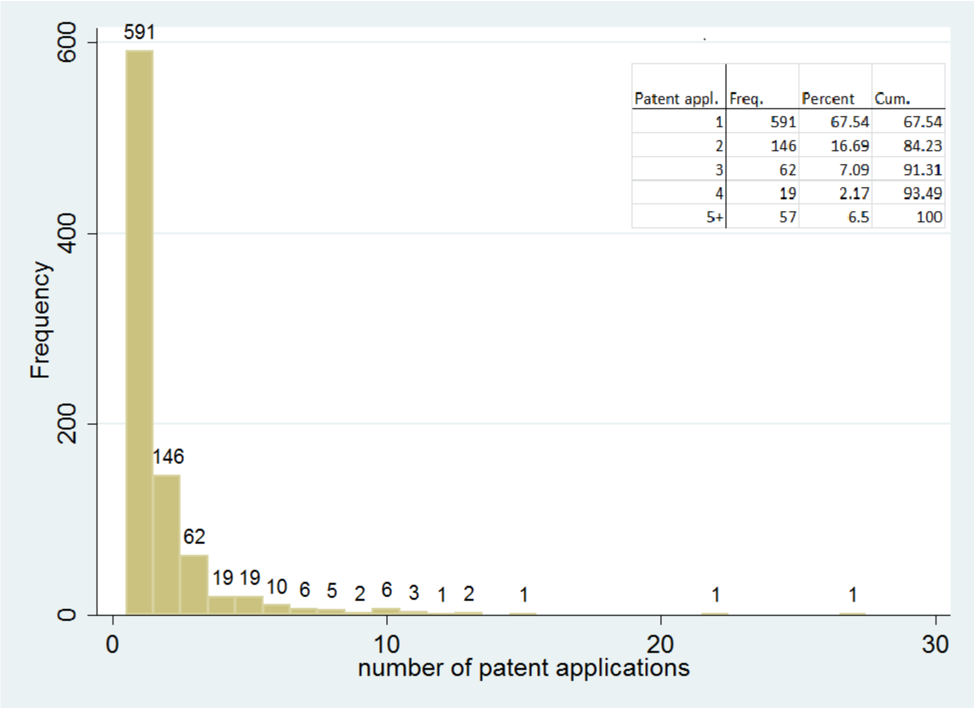

Figure 1: Distribution of patent applications per inventors

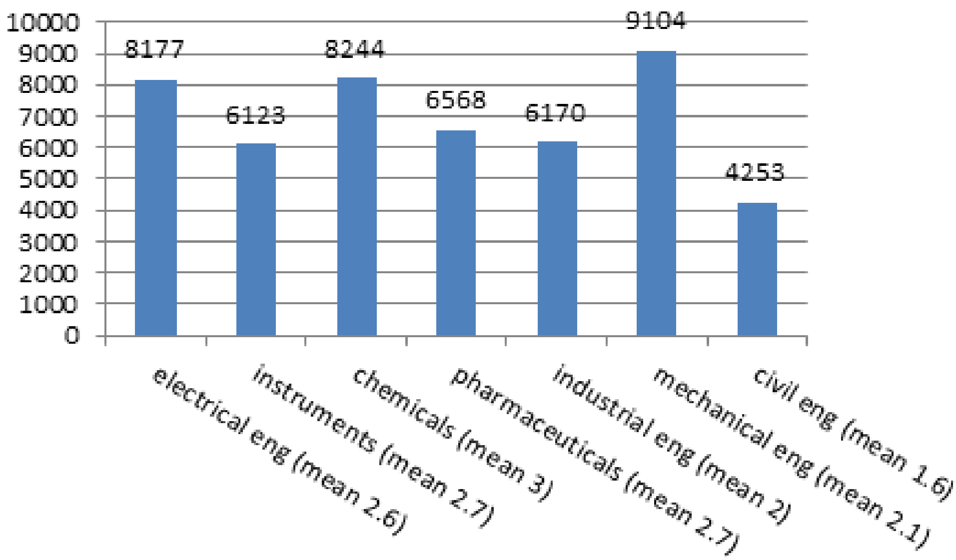

Figure 2: Forward citations received by all patents, breakdown by technological class (classification into 7 classes)

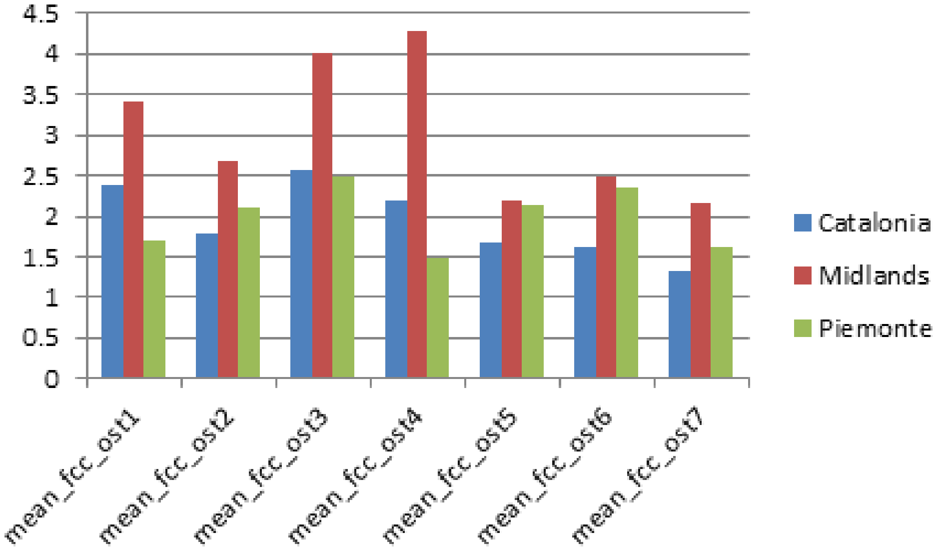

Figure 3: Average forward citations of all patents, breakdown by technological class and region

Appendix A

Variable	Obs.	Mean	St.Dev.	Min	Max
Female	881	0.1044268	0.3059871	0	1
Age	870	44.71954	10.39018	22	79
Agesq	870	2107.669	990.8317	484	6241
HiSc	881	0.2315551	0.4220658	0	1
BSc	881	0.3904654	0.4881318	0	1
MSc	881	0.1702611	0.3760755	0	1
PhD	881	0.1634506	0.3699863	0	1
Jobmobility	807	0.6741016	0.4690002	0	1
R&D	832	0.4290865	0.4952434	0	1
Retired	831	0.0746089	0.2629175	0	1
Piedmont	881	0.6118048	0.4876162	0	1
Catalonia	881	0.2553916	0.4363288	0	1
Midlands	881	0.1328036	0.3395551	0	1
ost1	875	0.272	0.4452444	0	1
ost2	875	0.1782857	0.382972	0	1
ost3	875	0.1748571	0.3800621	0	1
ost4	875	0.1154286	0.3197212	0	1
ost5	875	0.192	0.3940983	0	1
ost6	875	0.3782857	0.4852368	0	1
ost7	875	0.1291429	0.3355498	0	1
Co-inventor	875	0.7085714	0.4546804	0	1
Share-foreign-patents	875	0.1652	0.3677253	0	1
Mne	881	0.4892168	0.5001677	0	1
Co-employment	881	0.4687855	0.4993082	0	1

Table 12: Descriptive statistics of the control variables, full sample