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The role of scientific and market knowledge in the inventive process: Evidence from a survey of industrial inventors*

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Abstract

This paper investigates the contribution of external-to-the-firm knowledge to the inventive process inside companies by exploiting a survey of industrial inventors combined with patent data. In the empirical analysis, inventors' knowledge sourcing strategies are employed as explanatory factors for their inventive performance. The results suggest that both the separate and joint use of external scientific and market knowledge are positively and significantly associated with inventors' quantity and quality of inventions. In addition, higher levels of education act as a moderating factor of the joint use of scientific and market knowledge. Tracing a positive link between external knowledge and individual inventive process is relevant for research as well as policy, considering that knowledge exchange across a wide range of organisations is at the core of the innovation policy agendas in most countries.

Keywords: market knowledge, scientific knowledge, patents, inventors
Jel codes: O31, O32

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1 Introduction

External knowledge acquisition is necessary for firms' innovation activities, especially in the current context of market globalisation and rapid technological change (Dahlander and Gann, 2010). Both the early literature on technological change (see e.g. Allen and Cohen, 1969; Allen, 1977), and more recent studies on firms' knowledge sourcing strategies (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 but have to tap into knowledge outside their boundaries in order to successfully produce innovation. On the same vein, it is suggested by Chesbrough (2003) that innovative firms shifted to an "open innovation" model, according to which they exploit a wide range of external actors and knowledge sources to help them reach and sustain innovation. The empirical innovation literature on the relation between firms' knowledge sourcing strategies and the creation of innovation is vast (see e.g. Arora and Gambardella, 1990, 1994; Cassiman and Veugelers, 2006, 2007; Frenz and Ietto-Gillies, 2009). Recently, scholars have started looking at the role of external knowledge for inventors as the individuals who are primarily responsible of the innovative process. By exploiting information available from patent documents and surveys of inventors, several studies uncover some of the factors that influence inventors' 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; Mohammadi and Franzoni, 2014). Nonetheless, the relevance of different sources of external 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, on the basis of the consideration that innovation is not simply the product of firms and organisations, but it also requires individual creativity. Besides, patents are commonly recognised as creative output (Huber, 1998), hence representing the ideal innovative outcome to look at.

Inventors' role inside firms has been historically that of coming up with new knowledge, thus focusing most of their effort on purely scientific and creative activities, often in isolation (Huber, 1998; Wuchty et al., 2007). However, the process of knowledge creation has dramatically changed in the last century: nowadays, research is increasingly done in teams across almost every field of science, therefore allowing for specialisation and hence, better performance (Wuchty et al., 2007). Recently, the inventor-patent literature has also pointed out to a more integrated role of inventors, whereby although they tend to specialise in a given activity, they are also responsible and often highly concerned with the decisions surrounding the R&D process (Weck and Blomqvist, 2008; Schneider, 2009; Pasquini et al., 2012; Mohammadi and Franzoni, 2014).

Inventors nowadays are engaged into establishing collaboration inside and outside the company, acting often as "inventors-managers" in the inventive process. In particular, they are engaged into both the scientific side and the market side of knowledge creation and commercialisation processes. Carrying out both these activities independently may create tensions in the inventive process (Pasquini et al., 2012; Fleming, 2002). However, the integration of them has been proven to be positively linked to patent success, as we will explore later in this work.

In line with recent trends, in this work we investigate the contribution of external-to-the-firm scientific and market knowledge to inventors' patenting performance. In particular, we argue that inventors who combine knowledge from scientific and industrial organisations exploit different characteristics of both types of knowledge that fulfill different needs of the R&D process throughout different stages of the inventive flow. In addition, we test two sub-hypotheses to investigate moderating effects of the relationship between knowledge complementarity and inventors' outcomes. To test our hypotheses, we exploit information from an original survey of industry inventors that investigates their use of knowledge from a wide set of external actors, including universities, research centers, suppliers, customers and competitor firms, which we combine with patent data collected from the European Patent Office.

Inventors' patenting performance may take various forms. We investigate whether the joint use of knowledge sourced from science-related channels (university and research centres) and from market-related actors (suppliers, customers, competitors) positively influences inventors' quantity and quality of patents produced. In fact, while the number of patents that inventors produce simply indicates the quantity of inventions, inventors also acquire visibility depending on the technological and economic relevance of their patents (Mariani and Romanelli, 2007). Therefore, it is fundamental to consider indicators of both quantity and value of patents, in order to fully grasp inventors' patenting performance.

In the empirical analysis, three measures of inventors' performance 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. The outcome measures are the amount of patents produced by inventors in 2000-06, the count of forward citations received by inventors' patents within 5 years from patents' priority date, and the count of claims included in each inventor's patents produced in 2000-06. Count data models are employed. Together with the baseline regressions, two robustness checks are performed to check the reliability of the results.

The novelty of the present study lies 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 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 knowledge sources in the inventive process.

The remainder of the paper is organised as follows: section 2 provides the theoretical framework and hypotheses development; in sections 3 and 4 we present the variables and methods used in the econometric analysis; the results from the baseline regressions, as well as from two robustness checks, are presented in section 5; the last section concludes the paper by summing up and discussing our findings.

2 Theoretical framework and hypotheses

2.1 The role of scientific and market knowledge for innovative activities

The long-standing debate on the nature of technological change, being it mainly market-pull or technology-push, has evolved around the distinction between scientific knowledge and market knowledge. The seminal works of e.g. Griliches (1987), Jaffe (1989), Adams (1990), have uncovered the role of external knowledge from academia for innovation activities of firms and economic development. Jaffe (1989) in particular, was among the first scholars to show that there is a significant effect of university research on firms' patenting activity. Since then, the literature on firm-university links has flourished (see e.g. Mansfield, 1995; Mansfield and Lee, 1996; Cohen et al., 2002), showing that firms extensively exploit scientific knowledge from academia in order to produce innovations and stay competitive on the market.[1]

However, firms also seek and exploit technical knowledge from external agents that are close to the market in order to find new ideas and address technical issues that arise during the innovation process. This helps businesses to reduce the uncertainties associated with the innovation process (Hagedoorn, 1993). The literature often refers to technical knowledge provided by close-to-the-market actors, such as customers, competitors and suppliers, as market or industrial knowledge, so to stress its source (see e.g. Von Hippel, 1988), as opposed to scientific knowledge that comes from research organisations.

Because of their intrinsic characteristics, scientific and market knowledge may affect the research process in different ways. Investigating theoretically the advantages and disadvantages of academic and private research, Aghion et al. (2005) posit that the former is most useful in the early stages of the research process, whereas industrial research is more valuable at later stages. The reasons lie behind the different systems of incentives within academia and within firms. Because of its commitment to leaving creative controls in the hands of scientists, academia can be indispensable for early stage research aimed at

[1] More recent empirical works on this topic include Arvanitis et al. (2008); Becker (2003); Fritsch and Franke (2004); Lööf and Broström (2008); Belderbos et al. (2004); Medda et al. (2006); D'Este et al. (2012); Scandura (2016).

fostering new research lines; instead, 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.

Besides theoretical predictions, the empirical literature extensively shows that firms use knowledge from different channels, often combining internal and external knowledge acquisition strategies (see e.g. Arora and Gambardella, 1990, 1994; Cockburn and Henderson, 1998; Laursen and Salter, 2006). 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 of different types of knowledge inputs and their contribution to firms' innovative activities. Cassiman and Veugelers (2006) show that internal R&D and external knowledge acquisition are complementary innovation activities, but they also find 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: while the former study shows that globally engaged firms innovate more thanks to the intra-firm worldwide pool of information as well as from suppliers, customers and universities, the latter particularly stresses the importance of clients, among knowledge flows.

However, negative effects from interacting with external agents have also been traced. For instance, by linking UK firms' search strategy to their innovative performance, Laursen and Salter (2006) show that searching "widely" and "deeply" takes a curvilinear relationship with performance: this implies that open search strategies have positive effects on performance up to a certain level after which the costs associated with them may offset the benefits, hence bearing a negative effect on innovative performance.

2.2 The role of scientific and market knowledge for inventors

Most empirical works on the the role of external knowledge for innovation take the firm and its innovative activities as the unit of analysis. Nonetheless, the attention has recently shifted to a finer level of analysis, such as the team of inventors and the individual inventor inside the firm (see e.g. Giuri et al., 2007; Hoisl, 2007; Mariani and Romanelli, 2007; Pasquini et al., 2012; Weck and Blomqvist, 2008; Schneider, 2009; Walsh et al., 2016). The interest in the inventor is grounded on the fact that innovation is not simply the product of firms and organisations. New ideas are inherent to individuals, and innovation ultimately requires individual creativity to happen (Ahuja et al., 2008). Besides, patents are commonly recognised as creative output (Huber, 1998). It derives that patent inventors are of particular interest to shed new lights on firm innovation.

In their study of the relationship between individuals' motives and innovative performances, Sauermann and Cohen (2010) highlight that the analyses of innovation can be improved upon by paying attention to the individuals who are engaged in innovative activities within firms, and particularly to their motivations. The reason for this is twofold. On the one hand, R&D employees are able to exercise high degree of autonomy due to the typical uncertainty of technical change (Sauermann and Stephan, 2010; Vallas and Kleinman, 2007) and they often have greater expertise (and experience) than management. On the other hand, inventive effort is hard to observe by managers, who have limited opportunity to use standard economic incentives based on observable outputs, this in turn reinforcing the degree of authority of the individual employee (Ouchi, 1979; Prendergast, 1999). As a consequence, it is reasonable to expect that firms' innovation highly depend on individuals' innovative effort, which remains very often an unexplored "black box".

As a matter of fact, the empirical evidence about academic inventors is vast, partly because of a large amount of information publicly available, while evidence on private inventors is rather limited. The literature confirms that patent productivity among private inventors is skewed, similarly to that of academic inventors: few inventors produce a high number of innovations whereas the vast majority display a low invention rate. However, because of lack of information at the 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 inventors' factors, including gender, age and education, and characteristics of the employers affect the inventor's performance (Giuri et al., 2007).

It also turns out that industrial inventors' motivations are similar to those of academic inventors, especially gaining prestige and reputation, caring for employer's performance and achieving personal satisfaction (Giuri et al., 2007). In fact, it is arguable that being both academic and industrial inventors creative individuals, they also have common characteristics, motivations and goals (Giuri et al., 2007). Analysing the motivations of a sample of over 1,700 U.S. PhD scientists and engineers, Sauermann and Cohen (2010) find that motivations regarding intellectual challenge, independence and money are positively related to the number of patent applications, whereas motives regarding job security and responsibility tend to have a negative relationship.

On the relationship between inventors' knowledge sources and their performance, several empirical works exist on academic inventors that suggest the existence of a strong link between past scientific activity and future patent production. This literature has extensively documented that inventions are often realised and patented after a prolific period of scholarly publications (Calderini et al., 2007), and that the most productive scientists are more likely to patent their inventions than their less-productive peers (Breschi et al., 2007; Stephan et al., 2007; Fabrizio and Di Minin, 2008). As pointed out by Mohammadi and Franzoni (2014), these findings suggest that commercial activities, particularly inventions, are a byproduct of a prolific research activity conducted for scientific purposes. This is in line with the argument that scientific research and, more generally, scientific knowledge is an important antecedent of inventive output, as it was also confirmed by studies at the firm-level (see e.g. Gittelman and Kogut, 2003; Fleming and Sorenson, 2004; Zucker et al., 2002).

However, previous studies also show that, if compared to technical knowledge from industrial channels, especially customers, scientific sources of knowledge are often the least important for inventors (Eurostat, 2007; Giuri et al., 2007; Weck and Blomqvist, 2008). This is not surprising, since the distance between purely scientific knowledge and market knowledge is quite large. Notwithstanding, scientific literature often scores higher than other sources of scientific knowledge, suggesting that the latter is not unimportant per se, but interacting with universities or public research laboratories may require high effort and investment in establishing relationships (Giuri et al., 2007). A recent study of US triadic patents reveals that heterogeneity of collaboration patterns in inventing, including university-industry collaboration, drive higher invention quality, but vertical collaboration is more critical to commercialization than is university-industry collaboration (Walsh et al., 2016).

Only recently the interdependence between various source of external knowledge for the inventive process has been investigated. 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). A qualitative case study on the inter-organisational relationships developed by inventors within a company shows that patent competitiveness benefits more from buyer-seller relationships than from R&D consortia (Weck and Blomqvist, 2008). More recently, Mohammadi and Franzoni (2014) show that inventions based on prior scientific knowledge receive more citations than those that are not, hence highlighting positive returns to this type of knowledge; prior technical knowledge also correlates positively to highly cited patents, but only up to a certain level, after which the relationship becomes negative.

2.3 Hypotheses development

To put it in Fleming and Sorenson (2004) words, "*Before considering how science alters the process of invention, one must first ask what inventors actually do*". Similarly, we should know what inventors do and how knowledge acquired through external interactions can be characterised, before arguing about how external knowledge may alter the inventive process inside companies.

Inventions have been described by a popular view in the history of technology as a process of recombination of technological components, where the latter refer to any fundamental bits of knowledge that may be used to develop inventions (Fleming and Sorenson, 2004). According to this view, inventions originate either from the combination of components in a novel manner, or from the reconfiguration of existing combinations (Schumpeter, 1939; Nelson and Winter, 1982; Henderson and Clark, 1990; Weitzman, 1996).

In particular, in the view of Fleming and Sorenson (2004), the search for new components occurs "locally", in cognitive areas that are close to the prior experience of the inventor. Notably, in the process of so-called local search, scientific knowledge (or scientific research) helps inventors in directing their efforts towards more effective combinations not fully exploited yet. Scientific knowledge can be described as basic science providing the theoretical understanding of technological components that is necessary to generate and test theories. For this reason, science may positively influence the search process by eliminating fruitless avenues and avoiding wasted efforts (Nelson, 1982), hence leading inventors to the proper combination of components (Fleming and Sorenson, 2004). In addition, since universities are repositories of scientific knowledge having a wide range of applications that potentially can produce better technology, it is highly likely that firms interacting with universities will advance their scientific understanding and generate radical invention (Goto, 2000; Maine and Garnsey, 2006; Perkmann et al., 2013; Walsh et al., 2016)

The purpose of scientific knowledge so conceived is to foster technological progress, but it is usually disconnected from the market (Fleming and Sorenson, 2004). On the contrary, market knowledge is more applicative, since its aim and usefulness lie in solving well-defined users' problems (Aghion et al., 2005; Lüthje et al., 2005). Although it is often referred to as technical knowledge, market knowledge is frequently acquired through repetitive collaborations with market actors, including suppliers, competitors and customers (Pasquini et al., 2012). For its characteristics, the exploitation of market knowledge is unlikely to lead to technological breakthrough (Cohen et al., 2002; Von Hippel, 2005), however it is the major source of innovative ideas (Pasquini et al., 2012) and it is often ranked the most important source of external knowledge by inventors (Eurostat, 2007;

Giuri et al., 2007; Weck and Blomqvist, 2008).

Given their different and, to some extent, opposite characteristics, scientific and market knowledge may yield different effects on the inventive process. Inventors who merely use scientific knowledge may have radical ideas but create innovations that are far from the market or hard to commercialise, whereas inventors who exploit market knowledge do not focus on breakthrough innovation but instead create close-to-the-market and more profitable innovations. In reality, inventors often combine several sources of knowledge (Weck and Blomqvist, 2008; Schneider, 2009; Pasquini et al., 2012; Mohammadi and Franzoni, 2014), which suggests that there could be a complementarity relationship between the two that have consequences on inventors' performance.

Therefore, we hypothesise that the joint use of scientific and market knowledge has positive effects on inventive activity. This is because for an invention to be successful, the interaction between "the application of science" and "technological diversity", the integration of "experimental and theoretical research", or, in other words, the combination of technological potential and marketability, are not only beneficial but in many cases fundamental (Vincenti, 1990; Fleming, 2002).

We argue that the joint use of knowledge sourced from science-related channels and from market-related actors positively relates to inventors' performance in terms of patent quantity and quality. Our argument is that inventors who combine scientific and market knowledge exploit characteristics of both kinds of knowledge that fulfill different needs of the inventive process: they would be merging the technological and innovative potential that derives from scientific knowledge with the market potential arising from market knowledge. Moreover, inventors are likely to benefit from scientific and market knowledge throughout different stages of the inventive process. Academic research is likely to be more useful in earlier stages of the process due to its commitment to leave creative controls in the hands of scientists. Instead, research carried out by market actors, aimed at producing profitable innovations, is likely to be more useful for later-stage research (Aghion et al., 2005). Hence, we put forward the following hypothesis:

Hp 1: The joint use of external scientific and market knowledge is positively associated *with industry inventors' performance.*

Furthermore, we test two additional sub-hypotheses, with the aim to study factors that moderate the effect of knowledge complementarities on inventors' outcomes. Since this study focuses on individual inventors working inside companies, we investigate whether the working environment and individual characteristics influence the above described relationship.

In the first place, we focus on the job position inside firms, testing whether working in a well-defined R&D department or division moderates the effect of knowledge recombination on inventors' performance. Although new ideas are inherent to individuals, the organisation of the R&D structure and processes inside companies certainly influences the activity of inventors (Ahuja et al., 2008). In addition, depending on the characteristics of the knowledge available to inventors, the effectiveness of learning for innovation in a R&D or non-R&D division can vary (Lee and Walsh, 2016). Lee and Walsh (2016) show that invention productivity is higher for non-R&D inventors if knowledge is highly "visible", whereas the productivity of R&D inventors increases as knowledge "generality" goes up. Inventors employed on specific R&D tasks might be subject to centrally defined R&D targets, thus enjoying lower levels of autonomy (Cardinal, 2001; Conti et al., 2013), which implies higher costs of sourcing external knowledge. In addition, inventors working in R&D divisions may access highly specialised knowledge available internally, hence being less in need of external knowledge recombination. For this reason, we contend that inventors working in R&D divisions and jointly sourcing knowledge from various external channels display a lower performance than inventors who do not work on specific R&D jobs. This is because of the (higher) costs related to accessing external knowledge as compared to using internal knowledge. Therefore, we postulate the following hypothesis:

Hp 2a: The joint use of external scientific and market knowledge is less beneficial for industry inventors' working in R&D-specific firms' divisions.

Secondly, we investigate the effect of education on the relationship between knowledge complementarities and inventors' performance. To do so, we test whether holding a PhD moderates the effect of knowledge recombination on patenting activity. On the one hand, having a PhD *per se* is expected to be positively related to inventors' performance, particularly to the value of a patent (see e.g. Gambardella et al., 2008). This is because inventors with better ability and scientific knowledge are expected to be more productive, but also because education represents a signal that inventors and employers use to find the right "match" between the research potential of the former and the characteristics of the latter (Giuri et al., 2007).

On the other hand, better educated inventors are endowed with a highly specialised knowledge set that allows them to need less external knowledge. As a consequence, the cost of sourcing various types of external knowledge jointly may be higher than the potential benefit accruing from that. Therefore, we postulate that having a PhD moderates the positive effect of external knowledge recombination on inventors' patenting activity. We put forward the following hypothesis:

Hp 2b: The joint use of external scientific and market knowledge is less beneficial for industry inventors who hold a PhD.

In order to test our hypotheses, we study the role of inventors' knowledge set for their patent production and quality. Although we consider quantity and quality of patents together, it is worth to underline that there is a trade-off between them, as pointed out by Conti et al. (2013) among others. In particular, while increasing the invention rate is typically based on the exploitation and refinement of clearly established research paths (see e.g. Sørensen and Stuart, 2000), raising the likelihood that new inventions result in breakthroughs is tightly linked to the exploration of so-called "outside-the-box" thinking (see e.g. Azoulay et al., 2011).

As a consequence, the quantity-quality trade-off translates onto resources allocation inside companies: on the one hand, allocating resources to inventors who are prolific thanks to the exploitation of well-established approaches will most likely increase the inventive rate of the company; on the other hand, such allocation is also likely to reduce the likelihood of new inventions being breakthrough, because the latter results from inventors who think "outside the box". For this reason, we expect that the relationship between inventors' performance and external knowledge may differ depending on whether we consider quantity or quality of patents.

In addition, a trade-off exists in terms of appropriability between knowledge from universities and research centres and knowledge from industry. Because of their differences, these two types of knowledge have different degrees of appropriability: scientific knowledge may be characterised by low level of appropriability due to its high degree of tacitness, while industrial knowledge may have higher appropriability because of its higher level of codification. The combination of the two can raise appropriability thanks to the combination of pieces of knowledge coming from different domains (Saviotti, 1998).

3 Data and variables

3.1 The Survey of inventors and the EPO data

The data consists of a survey of inventors combined with patent records of the European Patent Office (EPO) provided by the Bocconi University CRIOS Research Centre. The survey is part of a European Union Seventh Framework Program funded project, carried out between 2011 and 2012 in the following European regions: 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 age, gender, education and occupation. The selection of regions was based on comparability. On the one hand, the aim was to choose non-core regional innovation systems, particularly non-capital regions that, because of the presence of national research institutions and/or other core research organisations, would display peculiar characteristics in terms of knowledge linkages and often higher innovative performances. Indeed, according to the 2012 and 2009 European Commission Regional Innovation Scoreboards, none of the regions in our sample was part of the group showing the highest innovation performance (i.e. “high innovators” or “innovation leaders”) in the years pre-2006.[2] On the other hand, regions displaying similar innovation

[2] https://publications.europa.eu/s/d7pp
https://publications.europa.eu/s/d7pq

performances were to be chosen; in fact, as of 2006, the three regions were categorised in the same group in terms of innovation performance, namely "average to medium-high innovators" or "innovation followers" on the basis of several indicators. The latter include regional enabling factors (education level and public R&D expenditure), firm activities (business investments in R&D, knowledge linkages in entrepreneurship, intellectual assets), and outputs (product/process/organisational business innovation, innovative sales, R&D employment). Innovation followers are characterised by a balanced performance structure in terms of all indicators.[3]

The survey targeted the population of inventors resident in Catalonia, the Midlands and Piedmont, named on at least one EPO patent application between 2000 and 2006.[4] Information on inventors' names and residential address was extracted from the Patstat-CRIOS EPO dataset in early 2011 and is up to date to the end of 2011. 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 was provided by CRIOS-Bocconi.[5] After cleaning the address list[6], and excluding inventors working at universities and public research centers, the Pick-Me questionnaire was distributed during winter and spring 2012 to 1607 inventors in Catalonia, 882 inventors in the Midlands and 1293 inventors in Piedmont; it resulted in 873 valid responses, 223 of which are from Catalan inventors (14% response rate), 117 are from Midlands' inventors (13% response rate) and 533 are from Piedmontese inventors (41% response rate).

[3]Ibid.

[4]The reason for a relatively recent and short time frame is that if we sampled very "old" patents, it would have been difficult to track down the inventors and moreover, they may not remember enough about the invention process. On the contrary, very "recent" patents might not provide enough information about their value or use.

[5]See `http://ricercaweb.unibocconi.it/criospatstatdb/` for further information.

[6]The cleaning process follows various steps and differs across regions, although only to a small extent. Differences depend on how the survey has been distributed in each region. In Catalonia, the questionnaire has been sent in hard copy to 1607 inventors; the original raw number of inventors was 4186, the cleaning procedure consisted in excluding duplicate observations in terms of name and address. Inventors from Piedmont received the survey via email in electronic format. Email addresses of 1293 inventors have been retrieved out of 3690 inventors' records. Similarly to Catalonia, inventors from the Midlands received a hard copy of the questionnaire. The raw sample of 6458 inventors has been validated by verifying home addresses on public telephone and address directories so to avoid sending questionnaires to wrong addresses and/or sending duplicate copies. The clean sample includes 882 inventors with verified address.

Sample representativeness analysis was carried out at inventor level on patent variables, in each region. We compared patent count, forward citations received within 5 years from priority date, claim count, backward citations count, share of co-invented patents and share of foreign owned patents across the raw sample of inventors per region, the sub-sample of contacted inventors and the sub-sample of respondents. The results are reported in Tables 11, 12, 13 in Appendix A. In the case of the Midlands, the sub-sample of contacted inventors is not statistically different from the whole raw sample of inventors. Similarly, there are no significant differences between the sub-sample of respondents and the sub-sample of contacted inventors. In the case of Piedmont, the sub-sample of contacted inventors is significantly different from the raw sample of inventors, in terms of all variables, however differences are rather small in most cases; instead, no significant differences emerge from the comparison of contacted inventors with respondents, except for the share of foreign patents, which is higher among respondents. As far as Catalan inventors are concerned, due to lack of information it was only possible to compare the raw sample of inventors with the sub-sample of respondents. With the exception of patent and claim count, no significant differences emerge from the comparison. Overall and with only few exceptions, respondents represent quite well the samples of inventors contacted to fill in the survey or the entire sample of inventors in the regions.

The survey includes a question on the use of various sources of knowledge, split into internal sources (colleagues inside the firm and other business units/departments) and external sources, i.e. customers, competitors, suppliers, private research centres/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 survey data have been combined with the Patstat-Kites database via inventor's identifier.[7] It has been possible to retrieve all patent information for each inventor, including the number of patent applications, the status of each application (granted or not), patent technological classes (reclassified into 7 macro-classes), number of forward and backward citations per patent,

[7]Inventor's identifier (*codinv2*) uniquely identifies inventors in the survey data but not in the patent database, where more than one entry exists for multi-patent inventors. Data has been collapsed at inventor's level as in the survey data.

number of claims per patent and assignee of the patents (i.e. the owner). The final dataset is a cross-section of 873 inventors with information collected from the survey and from patent data.

3.2 Dependent variables

3.2.1 Quantity of inventions

In the patent literature, patent count is usually employed and widely accepted as a measure of inventor's production of patents (see e.g. Hoisl, 2007; Mariani and Romanelli, 2007). However, patent count suffers from the limitation that it does not capture non-patented inventions, thus not informing about different propensities to patent across individuals. By accounting only for inventions that successfully reach the market, this measure does not consider the relevance of other inventions, including those whose patent applications are still under evaluation by the EPO or have been rejected, and those whose inventors will never apply for a patent. In addition, very often patented inventions are not commercialised, hence their value remain partly unknown.[8] Nonetheless, non-patented and non-commercialised inventions do represent the outcome of innovative activity. Since the EPO keeps track of all patent applications, it is possible to partly mitigate this bias by taking into account both granted patent and patent applications, hence accounting for all the patenting activity of inventors. Therefore, we include in the patent count (*Npat*) both patent applications and granted patents between 2000 and 2006.[9]

Due to the limited time span, only a truncated measure of inventors' patent count can be observed, hence not considering the past patenting activity (if any). As a consequence, we

[8]The limitations to the use of patents are more generally related to the reasons for patenting. As a matter of fact, patents may be used by companies for various strategic motives: they are an instrument for delimiting the present and future technological space against competitors or for restricting competitors' technological opportunities; patents are also used as assets in collaborations, to generate licensing revenues or to get better access to the capital market; finally, they can also be used by companies' management as a performance indicator and even linked to reward schemes for employees (Blind et al., 2009). Besides, it must be noted that a company having a patentable innovation in hand has three options, where applying for a patent is only one: it can patent, maintain trade secrecy, or defensively publish. In particular, defensive publishing prevents anyone (including the publishing firm) from patenting, and hence guarantees the company the right to use its innovation (Johnson, 2014).

[9]As a robustness check we will also employ the mean number of patents invented during the years of activity in the time span under consideration.

would be treating inventors who started patenting before 2000 the same as inventors who start later or after 2000. This bias, known as truncation bias, can hardly be eliminated. However, as previously noted, a limited time span has been chosen in order to track more easily the inventors to be surveyed and ask them about a well-defined and limited inventive period. Although the truncation bias cannot be corrected, we include various control variables in the attempt to partly mitigate it. These are the age of inventors (and its square), a dummy indicating whether inventors retired during the time span under consideration and a set of year dummies indicating the year in which each inventor enters the sample.

3.2.2 Quality of inventions

The most used measures of patent quality are derived from the number of forward citations received by a patent (Trajtenberg, 1990; Harhoff et al., 1999; Hall et al., 2005). The idea behind the use of forward citations is that they represent the technological relevance of a patent in terms of potential development of related technologies, thus mirroring the technological and economic value of the patent (Nagaoka et al., 2010). Indeed, previous empirical evidence extensively 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): such relationship relies on the assumption that highly cited patents represent important inventions that will constitute relevant prior art for future patents.

However, forward citations may be noisy measures of knowledge flows for various reasons (Jaffe et al., 1998; Agrawal and Henderson, 2002; Roach and Cohen, 2013). In particular, their use is questionable because their purpose, unlike citations in academic publications, is not to identify the antecedent knowledge upon which a given invention or discovery is built, but rather to delimit the scope of the patented invention (Jaffe et al., 1993).[10] Despite their limitations, forward citations have been found to reflect meaningful aspects

[10] Other reasons include the fact that not all innovations are patented (Scherer, 1983; Griliches, 1990; Cohen et al., 2000), not all knowledge flows are cited or even citable (Griliches, 1990; Pavitt, 1991), what is cited is influenced not only by the inventor, but also by firms' citing strategies (Lampe, 2012), by patent attorneys, and by patent examiners (Alcacer and Gittelman, 2006; Alcacer et al., 2009).

of knowledge flows, particularly from public research (Roach and Cohen, 2013).

As for the construction of the variable, simply counting forward citations generates some inconsistency when dealing with recent patents. This is due to the time lag between priority, application and publication of both cited and citing patents. This would limit substantially the reliability of the indicator for patents filed in more recent years (Hall et al., 2005), for which we may underestimate the actual number of forward citations. In the attempt to mitigate this bias, we build a dependent variable that accounts for the amount of citations received (by patents filed between 2000 and 2006) within five years from priority date (*ForwCit*), following usual practice in the patent literature (see e.g. Mariani and Romanelli, 2007).[11]

Moreover, we rely on one more measure of patent quality, based on the count of claims in each patent application. Claims define the technology and subject matter that are protected by the patent, thus determining the breadth of the rights conferred by a patent (OECD, 2009). In addition, the structure of patent fees is generally based on the number of claims contained in the document, hence a large number of claims might also imply higher fees (Squicciarini et al., 2013). Therefore, the number of claims in a patent document mirrors, on the one hand, the technological breadth of a patent, and on the other hand, its expected market value: the higher the number of claims, the higher the expected value of the patent (Tong and Frame, 1994; Lanjouw and Schankerman, 2001, 2004).[12] Our claim-based indicator (*Claims*) is calculated by adding up the number of claims in each inventor's patent.[13]

TABLE 1 ABOUT HERE

FIGURE 1 ABOUT HERE

[11] As a robustness check we will also employ the mean number of forward citations received within five years from priority date.

[12] To some extent, this indicator is also subject to truncation, similarly to forward citations, given that claims are reviewed during the examination process, e.g. claims may be dropped or redefined by examiners. Hence, latest patent cohorts, where a relatively higher number of patents may still be under examination, may have higher mean values of the indicator. However, as our data includes patents filed up to 2006 with information updated to the end of 2011, and given the average time lag between priority, application and publication (typically 18 months between application and publication for the EPO) we could assume that the truncation problem may be small or negligible in our sample, even for patents filed in 2006.

[13] As a robustness check we will also employ the mean number of claims across patents invented during during the time span under consideration.

Table 1 summarises the descriptive statistics of the dependent variables in the whole sample as well as across region. The mean number of patent applications (both granted and not) per inventor in the whole sample is 1.82. In line with previous evidence (Giuri et al., 2007; Menon, 2011), the variable is highly skewed: the maximum number of patent applications per inventor is 27 and 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 (see Figure 1). The mean number of patent applications per inventor in Catalonia and the Midlands is 1.57, whereas it is above the average (1.98) in Piedmont. In all regions the distribution is skewed, with the vast majority of inventors (between 63 and 75% across regions) having produced only one invention.
As far as quality is concerned, inventors' patents have been cited on average 4.11 times within 5 years from priority date. Similarly to the patent count, this measure is left-skewed: in fact, around 40% of inventors received no forward citations at all. Among inventors who received at least one citation, the mean citation count is 7.3. The most highly cited inventors are found in Catalonia and Piedmont, whereas inventors in the Midlands cumulated on average only 2.5 forward citations. Finally, the mean count of claims per inventor is 28.3 in the full sample, ranging between 26 and 29 across region. 50% of inventors' patents have 16 claims or less, while only 4% of inventors have more than 100 claims in all their patents. This measure is particularly skewed among inventors from Piedmont, where its maximum is 568.

3.3 Explanatory variables

3.3.1 Knowledge sources

In order to build the main explanatory variables we exploit one question of the survey that asks inventors to rank the importance of eight sources of knowledge, from 0 (not applicable because not used) to 4 (very important). The question 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*". This question does not refer to one specific invention, but rather to the inventive activity during a well-defined time frame. The actors listed in the question include internal ones (colleagues and other business units inside the company) and external-to-the-firm people/organisations. The focus of this paper is on the role of external organisations, which are, as in the question: suppliers, clients and customers, competitors, consultancy/private R&D laboratories, universities and public research centres.

In order to construct knowledge strategies we perform factor analysis aimed at identifying underlying driving factors among knowledge sources. On the basis of the identified factors, we build knowledge variables that depend on the typology of knowledge involved in the interaction. The factor analysis reveals three major factors with eigenvalues above 1 that (jointly) explain 67% of the variation in the original eight knowledge sources. The factor loadings from the factor analysis are reported in Appendix B (Tables 14 and 15). The first factor includes colleagues and other business units inside the company, hence internal-to-the-firm sources of knowledge; the second factor explains variation for knowledge provided by suppliers, customers, competitors, thus external-to-the-firm "market" or"industrial" sources; finally, universities, public research centers and private R&D laboratories are pooled under the third factor, which indicates external-to-the-firm "scientific" sources of knowledge.[14] Market and scientific knowledge sources are the relevant measures for our analysis, whereas internal knowledge will be used in the regression analysis as a controlling factor for firm-level resources available to inventors.

Following the factor analysis, we build eight yes/no dummies indicating the use of each knowledge source from the respondents' answers. We use those dummies to create "scientific" and "market" knowledge variables as well as internal knowledge. For each of the eight dummies (colleagues, other business units, suppliers, customers, competitors, universities, public research centers, private R&D laboratories) we assign value 1 to indicate that inventors used a given source, if they answered 2 to 4, and we assign 0 (not used) if they ticked 0 or 1. We choose to apply this aggregation due to the fact that almost

[14]The distinction between internal and external knowledge sources and, in the latter case, between market (or industrial) and scientific sources, is empirically employed and verified in the innovation literature in various contexts. See for instance Arora and Gambardella (1990) and Cassiman and Veugelers (2006) for firms and Schneider (2009) and Mohammadi and Franzoni (2014) for patents and inventors. See also Walsh at al (2016) and Arora et al (2016) for recent developments on the role of outside sources, notably vertical relations with customers, suppliers and technology specialists.

all inventors declared having used some knowledge sources, hence there are relatively few zeros.[15]

Finally, we create three dummies indicating whether inventors used at least one internal source (*intern knowl*), at least one market source ($MKTKnow$) and at least one scientific source ($SCIKnow$). Scientific and market knowledge are our main knowledge variables of interest, which we use to work out inventors' knowledge sourcing strategies.

TABLE 2 ABOUT HERE

Table 2 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 source of market knowledge is 71% and those who used at least one scientific source are 50% of the sample. Knowledge from customers, competitors and suppliers are the most highly exploited (50%). The correlation between market sources of knowledge and $MKTKnow$ is always positive and significant, and above 0.5. Similarly, the correlation between scientific knowledge sources and $SCIKnow$ is strongly positive and significant. Finally, the correlation between scientific knowledge and market knowledge is 0.2 and it is significant at the 10% level, suggesting that there is a positive link between the two.

3.3.2 Inventors' knowledge sourcing strategies

After aggregating knowledge sources into scientific and market knowledge, we work out inventors' knowledge sourcing strategies as exclusive dummies, as follows:

1. *sci only*: taking value 1 for inventors using only scientific knowledge (*SCIKnow*=1 and *MKTKnow*=0);
2. *mkt only*: taking value 1 for inventors using only market knowledge (*SCIKnow*=0 and *MKTKnow*=1);
3. *sci&mkt*: taking value 1 for inventors using both scientific and market knowledge (*SCIKnow*=1 and *MKTKnow*=1);

[15] As a robustness check we work out those dummies assigning value 1 if respondents gave a rating higher than the average rating in the sample, and 0 otherwise.

4. *none*: taking value 1 for inventors using none of them (*SCIKnow*=0 and *MKT-Know*=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 3 shows the frequencies of the exclusive dummies and the values of the dependent variables for each sub-group of inventors.

TABLE 3 ABOUT HERE

The most widespread strategy is that of using both scientific and market knowledge sources (39% of inventors), followed by the use of only market sources (31%). Fewer inventors used only scientific sources and none of the knowledge sources (10% and 19% respectively). The breakdown of the dependent variables by knowledge sourcing strategy shows that inventors using only market knowledge and those using only scientific knowledge have the highest performance in terms of number of patent applications (*Npat*), having produced on average 1.94 patents between 2000 and 2006. The performance of inventors using both scientific and market knowledge is slightly lower (1.89 patents), yet very similar. Inventors who declared not having used any external-to-the-firm knowledge source display the lowest number of patents produced (1.5).

As for the forward citation count, the most cited inventors are those using both scientific and market knowledge (5 citations received), followed by those using only scientific and only market knowledge. Patents with the largest number of claims are found among inventors using both sources of knowledge (34 claims), followed by those using only scientific sources (31 claims). The correlations are positive and significant at 5% level between the joint use of scientific and market knowledge and forward citations as well as claims. There is a negative and significant correlation between the use of none of the knowledge sources and all of the dependent variables.

3.4 Control variables

All control variables are created at inventor level. We include in the regression analysis individual characteristics collected from the survey data, patent-related characteristics extracted from the patent data, and information on inventors' employers provided in the survey responses.

As for individual characteristics, we control for inventor's gender, age at time of survey and its square, assuming that age may display a quadratic relationship with inventor's performance, and education level, by using four dummies indicating the highest education level attained by the inventors (Secondary school degree, Bachelor degree, Master degree, Doctoral studies). Furthermore, from the survey it was possible to extract information on inventors' mobility between jobs, which we measure with a dummy equaling one if inventors changed job at least once in 2000-06. We also control for whether inventors retired during the period under analysis. In order to better isolate the relationship between the use of external knowledge and inventors' performance, we also control for the use of internal knowledge, either from colleagues inside the firm or from other business units. Internal knowledge is usually the first and most important source of knowledge exploited for innovation activities (Giuri et al., 2007), thus it is necessary to include it in our model to avoid omitting a relevant variable. This variable helps controlling for the internal resources available to inventors for their research activity. Internal knowledge together with individual skills (most likely those acquired via education) form inventors' ability to filter external knowledge, thus allowing them to recognise and exploit the most relevant bits of knowledge.[16] Finally, we introduce three dummies for inventors' region of residence and seven year dummies indicating when each inventor start patenting in the period 2000-2006.

As for patent-related characteristics, we control for the share of co-invented patents per inventor and for the share of foreign-owned patents, calculated as the share of patents whose assignee is not located in the inventors' country of residence. Both variables measure the inventors "openness" toward external knowledge (Hoisl, 2007). 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

[16]In other words, they allow inventors to reap the benefits of different types of knowledge characterised by different degrees of appropriability. More generally, the inclusion of control variables both at individual and firm level intend to capture heterogeneity of appropriability of scientific and market knowledge across inventors and firms.

by the French Observatoire des Sciences et des Techniques (OST). These are Electrical Engineering and Electronics (*ost*1), Instruments (*ost*2), Chemicals and Materials (*ost*3), Pharmaceuticals and Biotechnology (*ost*4), Industrial Processes (*ost*5), Mechanical Engineering, Machines and Transport (*ost*6), and Civil Engineering and Consumer goods (*ost*7).[17]

Together with individual actions, organisation-level factors influence individual outcomes inside companies. For this reason, we include a number of control variables to capture firms' characteristics that are related to the organisational design of R&D activities. Firstly, we control for the international exposure of the most recent employer in the time frame under study (2000-06), with a dummy that equals one if it is a multinational company.[18] This variable accounts for firms' "openness", assuming that more internationalised firms also tend to have more open search strategies, hence co-operating with external actors and widening the pool of knowledge where inventors can tap into.

We also include firm dummies to control for the fact that some firms employ more than one inventor in our sample. A set of 71 firm dummies has been hence created, including only those that employ more than one inventor. By controlling for this, we aim at isolating unobservable drivers of inventors' performance that are explained by employers' characteristics, including firms' attitude towards collaboration with external organisations. Finally, we control for inventors' job position inside the company with a dummy equaling one if they work in a well-defined R&D department. This variable, as well as firm dummies, are informative of the extent to which the organisational design of R&D processes inside companies influence the performance of inventors (Ahuja et al., 2008).

TABLE 4 ABOUT HERE

Descriptive statistics of the control variables are presented in Table 4.[19] 10% of inventors in our sample are women, however they are almost 15% in Catalonia and only 5% in the Midlands. The average age of inventors is 44 years old, 39% of them have a Bachelor Degree, while 17% of them hold a Master degree and 16% pursued doctoral studies.

[17]We assign each inventor to the most widespread technological class across all her patent applications. For 1% of the sample it is not possible to identify only one class, therefore we chose it randomly.

[18]This variable has been created by checking companies' webpages and/or companies accounts.

[19]See Tables 5 and 6 for the full correlation matrix.

Around 2/3 of inventors changed job at least once during the period 2000-2006 and 4% of the whole sample retired during the same period. As for their patenting behaviour, the vast majority of inventors declared having used at least one source of internal-to-the firm knowledge for their patenting activity. On average, 67% of inventors' patents comes out of collaboration with other inventors through co-patenting, and 16% of the patents is owned by an organisation located abroad with respect to the inventor's country of residence. Most of the inventors in the sample started patenting between year 2000 and 2002 within the time span under consideration. Furthermore, the majority of inventors apply for patents classified in the technological classes of mechanical engineering (27%) and electrical engineering (24%), whereas pharmaceutical has the lowest frequency of patents applied for (4%). Finally, almost half of the inventors are employed by a multinational firm and around 40% of inventors work in a well-defined R&D department inside the company.

TABLE 5 ABOUT HERE

TABLE 6 ABOUT HERE

4 Empirical strategy

The estimation strategy follows the so-called productivity (or direct) approach (Cassiman and Veugelers, 2006), in which three measures of inventors' performance are estimated as a function of inventors' knowledge sourcing strategies, as well as a number of control variables to account for individual characteristics, patent characteristics and firm-related factors.

The model takes the following specification:

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

Where the dependent variables (Y_i) are $Npat$, $ForwCit$, and $Claims$, the knowledge sourcing strategy *none* - taking value 1 for inventors who do not use any external source of knowledge - is excluded from the regression to avoid collinearity, and X_i is the vector of control variables.

The variable of interest to test our first and main hypothesis (*Hp 1*) is *sci&mkt*. To test hypotheses *2a* and *2b*, we introduce two interaction terms, respectively. Firstly, we add to Equation 1 the term *sci&mkt*R&Djob*, to check whether the job position inside companies has any moderating effect on the role of *sci&mkt* for inventors' performance. Secondly, we add the term *sci&mkt*PhD* to test the moderating effect of holding a PhD. Since all the outcomes of interest are measured with count data variables, the models will be estimated with count data regressions. In particular, due to over-dispersion of all the dependent variables (variances higher than means) we estimate negative binomial regressions (Cameron and Trivedi, 2005). We employ robust standard errors clustered at the firm-level.

Hp 1 is confirmed if the estimated coefficient of the joint use of scientific knowledge and market knowledge (*sci&mkt*) is positive and significant, indicating that the joint exploitation of different typologies of knowledge from external-to-the-organisation knowledge is positively linked to patenting performance inside firms. *Hp 2a* and *Hp 2b* will be confirmed if the coefficients of the interaction terms are negative and significant, indicating a moderating effect of the interacted variables on *sci&mkt*.[20]

5 Results

5.1 Baseline regressions

Table 7 shows the baseline regressions on the three dependent variables *Npat*, *ForwCit*, and *Claims*. For each of them we report two specifications: in the first one we include knowledge variables, individual and patent factors, whereas in the second one we add organisation level factors.

[20] The econometric analysis aims at identifying relationships between knowledge sourcing variables and inventors' performance. However, clear links of causality may be difficult to ascertain in some cases. For instance, reverse causality could arise as better inventors are likely to interact with external organisation because they are better known, rather than because they aim at becoming so. Moreover, some of the control variables may raise endogeneity concerns, particularly those related to both inventors' patenting performance and their knowledge sourcing strategies (e.g. job mobility, job position inside firms). Since it is very difficult to find plausible instruments to tackle these issues, the baseline results will be followed by two robustness checks, aiming at confirming the main findings.

The amount of patents produced by inventors is positively influenced by the use of market knowledge and the joint use of market and scientific knowledge in the first model. Once we control for organisational-level factor, the use of scientific knowledge turns to be a more important determinant (although less significant) than other knowledge sourcing strategies. The difference in the logs of expected patent counts is 0.319 unit higher for inventors using only scientific knowledge compared to others, while holding the other variables constant. This means that they are expected to have a rate 1.37 higher for $Npat$.[21] It is 1.34 for *mkt only* and 1.29 for *sci&mkt*.

A similar pattern is found in the $ForwCit$ estimates, where in the full model *sci only* has a higher coefficient than other knowledge sourcing strategies. The difference in the number of citations is expected to be 1.7 for inventors using only scientific knowledge and 1.5 for those jointly using the two of them.[22] In the last two estimates, $Claims$ appear to be positively influenced more by *sci&mkt* than by other knowledge strategies. The difference in claim count amounts to 1.3 in this case, 1.2 for *sci only* and 1.2 for *mkt only*.

Our first hypothesis (*Hp 1*) is confirmed since the data shows that the joint use of external knowledge positively and significantly influences inventors' performance. In addition, the other knowledge sourcing strategies are important, particularly in the case of *sci only* for quantity of patents and citations received. As noted in the literature section, scientific knowledge is a relevant determinant because it helps eliminating fruitless research routes, thus allowing inventors to focus on the most useful and promising ones (Fleming and Sorenson, 2004). Instead, knowledge from market actors is useful to solve well-defined users' problems, hence it is likely to speed up and improve the research process so to end up with more inventions, and of higher quality (Aghion et al., 2005; Lüthje et al.,

[21] The rate change is obtained computing the incidence rate ratios after the regressions.

[22] Due to the excess of zeros in $ForwCit$ (44% of the inventors with zero citations to their patents), we also estimate a zero-inflated negative binomial model, where the probability of forward citations depends from the covariate R&Djob, this being the most highly correlated with the probability of receiving citations at all. The results are reported in Appendix C, table 16 column 1. They show very similar results to the baseline regressions, but the Vuong test comparing negative binomial and zero-inflated negative binomial models does not support the latter over the former. In column 2 the results of a zero-inflated negative binomial model where more covariates are added to the logit part are reported: the Vuong test supports the use of the zero-inflated model, and the results are very similar to those achieved in the baseline regressions.

2005). The joint use of the two knowledge sources favours the combination of technological potential and marketability, thus benefiting the whole invention process (Vincenti, 1990; Fleming, 2002).

The significant coefficients of the control variables show that female inventors are less productive than males, inventors holding a PhD produce inventors with higher number of claims, and retired inventors have patents with lower claim count. Working in a specific R&D division and exploiting knowledge that is internal to the firm are positively related to the amount of forward citations received, hence to patent quality. Finally, the share of foreign-owned patents negatively correlates the patent count and working in a multinational company is negatively related to patent quantity and citations received, suggesting that links to foreign companies may be detrimental to inventors' performance.

TABLE 7 ABOUT HERE

Table 8 shows the results of the regressions carried out to test *Hp 2a* and *Hp 2b*, in Panel A and B respectively. The moderating effect of *R&D job* is not confirmed by the data since the coefficient of *sci&mkt*R&Djob* is always negative but never significant. Therefore, working in a well-defined R&D environment inside companies does not seem to affect in any way the positive influence of the joint use of external knowledge sources on inventors' patenting performance.

In Panel B, we find that *Hp 2b* is confirmed for the count of claims. The coefficient of the interaction term *sci&mkt*PhD* is negative and significant in column 5, indicating a moderating effect. In particular, the effect of *sci&mkt* for the group of inventors without a PhD is 0.5, corresponding to an increase in the number of claims by a rate of 1.66 (incidence rate ratio of 0.5), but this is diminished by a factor of 0.62 (incidence rate ratio of -0.47) in the group of inventors holding a PhD. In other words, inventors' patent quality as measured in terms of technological breadth and expected market value of their patents is positively influenced by external knowledge, but this effect is smaller for inventors holding a PhD compared to those not holding it. This finding in qualitatively confirmed in the model that includes organisation level factor (column 6).

The results of the analysis show the positive contribution of external-to-the-firm knowledge to inventors' performance: in particular, the joint use of scientific and market knowledge is positive and significant in every estimate carried out. Moreover, in line with existing empirical evidence, other factors emerge as drivers of invention production and their quality, including individual characteristics such as gender and education, internal knowledge and job position inside companies. However, one of these (i.e. education) acts as a moderating factor of the positive effect of external knowledge on inventive activity.

TABLE 8 ABOUT HERE

5.2 Robustness checks

In this section, we test the validity of our results through two robustness checks. In the first place, we check that the results are robust to a different codification of knowledge variables. In particular, we replicate the analysis after assigning values 0 and 1 using the mean rating as a threshold. Each individual knowledge variable has value 1 for inventors who gave a rating higher than the average rating in the sample, 0 otherwise. By doing so, we use a threshold that is directly related to the distribution of the variables in the sample, hence being less arbitrary. After creating the knowledge dummies and aggregating them under scientific and market knowledge, we construct the four knowledge sourcing strategies *sci only*, *mkt only*, *sci&mkt* and *none* as described in section 3.3.2.[23]

Table 9 shows the results of the robustness check based on the newly created knowledge sourcing strategies. We carry out negative binomial regressions because the dependent variables are count variables. Overall, the main results are fully confirmed by this check. As far as patent count is concerned, we note that all knowledge strategies are significant in both models and *sci&mkt* has a slightly larger coefficient than the two others. This mirrors a 1.3 difference in $Npat$ compared to inventors not using scientific and market knowledge jointly. Such figure is very similar to that obtained in the baseline estimates, thus confirming the main results. The results are qualitatively confirmed as far as the count of forward citations is concerned, since the coefficients of the knowledge strategies are positive but not significant (column 4). Finally, similarly to what obtained in the main

[23]Descriptive statistics of the newly created variables are reported in Appendix D, table 17.

results, the count of claims is positively and significantly influenced by *sci only*, *mkt only* and *sci&mkt*, and more so by the latter. A 0.309 coefficient implies a 1.3 difference in number of claims for inventors jointly using external sources of knowledge, which confirms the main results.

As for control variables, the negative relationship between $Npat$ and female is confirmed, as much as the positive influence of holding a PhD on the number of claims in each inventors' patents. Similarly, retired inventors show lower number of claims, as in the main estimates. In addition to this, we confirm the positive role of R&D job and of internal knowledge for the total number of forward citations received as well as the negative relationship between patent count and the share of foreign patents. Finally, *mne* has a negative and significant coefficient in all models.

TABLE 9 ABOUT HERE

The second robustness check carried out consists of changing dependent variables, in search of similar but alternative measures of patent quantity and quality at inventor level. In particular, we construct averages of patent count, citation count and claim count, with the aim of obtaining weighted measures that are more easily comparable across inventors. To achieve this, we compute $MeanNpat$ as $Npat$ divided for the number of years of activity between the first and last patent invented in 2000-2006, where the priority year is used to work out each inventor's patenting period. $MeanForwCit$ is obtained dividing $ForwCit$ for $Npat$ and $MeanClaims$ corresponds to $Claims/Npat$.[24]

Since these are continuous variable, the regressions have been estimated by means of ordinary least squares with robust standard errors, clustered at the level of the firm. The results of the second robustness check are reported in Table 10. The figures shows a positive and significant contribution of *mkt only* and *sci&mkt* on inventors' quantity of patents produced during their years of activity. This is in line with what underlined by our main findings. Similarly, the data show a positive and significant influence of *sci&mkt* on the average forward citation count. The second check also qualitatively confirms the

[24]Descriptive statistics of the newly created variables are reported in Appendix D, table 18. Inventors in our sample apply for a patent every other year (yearly mean=0.5), their patents have 15 claims on average and they receive 1.8 citations per patent. The correlation between claims and citations is 0.1.

positive link between knowledge sourcing strategies and the average claim count, because the coefficients are positive but not significant. In addition, Table 10 confirms the sign and significant of female, PhD and R&D job.

To sum up, the first robustness check fully confirms the main finding of this work, thus showing that these are not sensitive to data issues regarding the methods employed to aggregate knowledge variables. The second robustness check confirms the signs of the relationships previously underlined, but it also shows that the use of external knowledge is slightly less relevant for average measures of patent quantity and quality than it is for absolute measures.

TABLE 10 ABOUT HERE

6 Discussion and conclusion

This paper has investigated the role of scientific and market knowledge for the inventive process inside firms. We show that the joint use of the two knowledge sources is positively associated with industry inventors' performance. To do that, we exploit data from a survey of inventors combined with EPO patent data and we estimate a model where inventors' performance depends upon their knowledge sourcing strategies as well as a number of other individual, patent and firm level factors.

This work relies on a survey of patent inventors, thus limiting the possibility to know about the knowledge strategies of non-patenting inventors. This problem is partly overcome by counting both granted and not-yet granted patents, which allows to consider all the inventive activity of inventors. Another limitation is represented by potential endogeneity concerns, which cannot be ruled out even though we include in the regressions a comprehensive set of control variables. In particular, we cannot exclude that more productive and better inventors are likely to interact with external organisations because they are better known, rather than because they aim at becoming so. With this respect, it should be noted that our findings are confirmed by two robustness checks.

Nonetheless, this study provides interesting associations between individual inventors' patenting activities and their use of various sets of knowledge. For this reason, the results offer various contributions to the literature and elements of novelty. Firstly, we show that individuals are key agents in the innovative process inside firms and that externally sourced knowledge is as important for individuals as it is for companies. Moreover, their knowledge sourcing strategies are relevant for their inventive outcome even when accounting for individual characteristics, patent factors and organisational determinants. Previous empirical evidence in the innovation literature 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). More recently, it has also been shown that inventors should rely on various sources of knowledge to increase the chances of patent commercialisations (Pasquini et al., 2012), although the opposite is true for the value of patented inventions (Schneider, 2009). Our findings show a positive and significant relation between quantity and quality of inventors' patents and the joint use of scientific and market knowledge, confirming the importance of external-to-the firm knowledge for companies' innovation activities.

With respect to extant research, we add that quantity as well as quality of inventors' patents benefit from the combination of both types of external knowledge. In particular, we contend that inventors using knowledge from a wide set of external organisations exploit characteristics of different kinds of knowledge that fulfil different needs of the inventive process. In other words, they merge the technological and scientific potential deriving from scientific knowledge with the practical and technical support deriving from market knowledge. Besides, the independent use of scientific and market knowledge are also significant explanatory factor of inventors' performance, thus showing positive returns to both scientific and technical knowledge, in line with Mohammadi and Franzoni (2014). In addition, if we look at the relative value of scientific with respect to industrial knowledge sources, our data shows that the former are more important than the latter, notably for patent and citation count. This is in line with a study by Arora et al. (2016), which specifically considers outside sourced inventions rather than knowledge sources. Yet, they show that inventions sourced from universities and other technology specialists tend to be the most valuable for companies, whereas those from customers provide the highest net surplus because less costly. Finally, we also show that having a higher level of education moderates the positive effect of the joint use of external knowledge sources, most likely because better educated inventors are endowed with a highly specialised knowledge set that allows them to need less external knowledge.

Aside from what we have learned, our work offers methodological benefits. The empirical analysis in based on an original survey that provides brand new insights about the demand of knowledge expressed by the actors directly involved in the innovative process, along with information at individual level not available from patent applications. This type of data is not easy to collect since it requires the realisation of ad-hoc surveys. Although survey data present various challenges to confront with, notably the issue of self-reporting, they offer a unique opportunity to disentangle the determinants of innovative output inside firms. In addition, we apply an empirical framework that is only rarely employed at the individual level.

This study also offers implications for innovation policies. The evidence of a complementarity relationship between various and different sources of knowledge for the inventive process supports the well-known argument that knowledge exchange across a wide range of organisations is beneficial to firms' innovation performance and competitiveness. This is particularly true with respect to universities, given that they are often among the less used sources of external knowledge (although highly valuable), notably if compared to firms (Giuri et al., 2007). Since our study addresses individual innovativeness, it is arguable that knowledge sharing between firms' employees and universities or research centres, as well as other market actors, requires constant effort and investment in establishing relationships. Policies that create incentives for information and idea sharing with external agents, as well as across firms' departments, could be beneficial to improve the overall organisational innovative process.

In addition, our findings are also relevant for the European regional context. We have shown that "innovation followers" such as the Midlands, Catalonia e Piedmont host private inventors that take advantage of knowledge linkages arising from their network of interactions with the external innovation environment. As a consequence, firms' competitiveness could benefit from this because it increases their patent stock, the technological value of their patent portfolio, and the expected market value of their inventions. If this is the case, companies' knowledge sourcing strategies should put inventors at their core in order to improve their innovation performance and in turns, trigger success for regions that are catching up with respect to top performers. This line of reasoning is aligned with the policy objective of achieving in the European Union a smart, sustainable and inclusive economic growth, as promoted by the 10-year growth strategy "Europe 2020".[25] In particular, it should be noted that the EU has committed to strengthening links in the regional innovation chain by encouraging and supporting cooperation between the world of science (Universities and public research organisations) and the world of business.

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[25] http://ec.europa.eu/europe2020/index_en.htm

Tables

		Catalonia	Midlands	Piedmont	Full sample
	Obs.	223	117	533	873
Npat	Mean	1.5695	1.5726	1.9849	1.8235
	St Dev	1.5948	1.1545	2.3218	2.0383
	Min	1	1	1	1
	Max	15	8	27	27
ForwCit	Mean	4.4529	2.5726	4.3095	4.1134
	St Dev	12.2657	3.8131	10.1011	10.1418
	Min	0	0	0	0
	Max	114	17	106	114
Claims	Mean	26.0583	27.1025	29.4840	28.2898
	St Dev	35.8544	25.77	47.0160	42.0305
	Min	1	1	1	1
	Max	315	155	568	568

Table 1: Descriptive statistics of the dependent variables

Variable	Mean	St Dev	MKT	suppl.	custom.	compet.	SCIENT.	private labs	univ.	public labs
MARKET K.	0.7122	0.4530	1							
suppliers	0.4050	0.4912	0.5384*	1						
customers	0.4808	0.4999	0.6263*	0.3232*	1					
competitors	0.4206	0.4940	0.5575*	0.1837*	0.3684*	1				
SCIENTIFIC K.	0.5039	0.5003	0.1826*	0.1743*	0.1541*	0.2067*	1			
private R&D labs	0.2941	0.4559	0.2177*	0.1975*	0.1616*	0.2302*	0.6668*	1		
university	0.3855	0.4870	0.1163*	0.1595*	0.0924*	0.1613*	0.8015*	0.3706*	1	
public R&D labs	0.2013	0.4012	0.1307*	0.1756*	0.1594*	0.1859*	0.5191*	0.4035*	0.5593*	1

Table 2: Descriptive statistics of the knowledge sources (* correlations significant and 5% level). Obs = 704.

				Mean			Corr		
Variable	Freq	Mean	St Dev	Npat	ForwCit	Claims	Npat	ForwCit	Claims
sci only	78	0.1049	0.3067	1.9487	4.2564	31.5769	0.0191	0.0035	0.0253
mkt only	233	0.3135	0.4642	1.9442	4.1115	25.8583	0.0361	-0.0032	-0.0491
sci&mkt	290	0.3903	0.4881	1.8931	5.0379	33.9724	0.0216	0.0725*	0.1083*
none	142	0.1911	0.3934	1.5070	2.3802	20.9788	-0.0843*	-0.0889*	-0.0962*

Table 3: Descriptive statistics of knowledge sourcing strategies; mean and correlation table of dependent variables across knowledge sourcing strategies (* correlations significant at 5% level). Obs = 704.

Variable	Description	Mean	St Dev	Min	Max
female	Dummy 1/0 for female inventors	0.1054	0.3072	0	1
age	Age of the inventor	44.71	10.39	22	79
age sq	Age squared	2106.4	991	484	6241
HighSc	Dummy 1/0 for secondary school degree	0.2302	0.4212	0	1
BSc	Dummy 1/0 for bachelor degree	0.3906	0.4882	0	1
MSc	Dummy 1/0 for master degree	0.1718	0.3774	0	1
PhD	Dummy 1/0 for doctoral studies	0.1627	0.3693	0	1
job mob	Dummy 1/0 for inventors who changed job in 2000-06	0.6763	0.4682	0	1
retired	Dummy 1/0 for inventors who retired in 2000-06	0.0413	0.1990	0	1
intern knowl	Dummy 1/0 for inventors using internal knowledge	0.8802	0.3249	0	1
piedmont	Dummy 1/0 for inventors from Piedmont	0.6105	0.4879	0	1
catalonia	Dummy 1/0 for inventors from Catalonia	0.2554	0.4364	0	1
midlands	Dummy 1/0 for inventors from Midlands	0.1340	0.3409	0	1
y1	Dummy 1/0 for inventors starting patenting in 2000	0.1898	0.3924	0	1
y2	Dummy 1/0 for inventors starting patenting in 2001	0.1750	0.3802	0	1
y3	Dummy 1/0 for inventors starting patenting in 2002	0.1561	0.3632	0	1
y4	Dummy 1/0 for inventors starting patenting in 2003	0.1279	0.3342	0	1
y5	Dummy 1/0 for inventors starting patenting in 2004	0.1036	0.3050	0	1
y6	Dummy 1/0 for inventors starting patenting in 2005	0.0902	0.2866	0	1
y7	Dummy 1/0 for inventors starting patenting in 2006	0.1575	0.3645	0	1
share coinv	Share of co-invented patents	0.6788	0.4529	0	1
share foreign	Share of patents owned by foreign firms	0.1656	0.3681	0	1
electrical eng	Dummy 1/0 for ost1	0.2468	0.4314	0	1
instruments	Dummy 1/0 for ost2	0.1160	0.3204	0	1
chemicals	Dummy 1/0 forost 3	0.1424	0.3496	0	1
pharmaceut.	Dummy 1/0 for ost4	0.0471	0.2119	0	1
industrial eng	Dummy 1/0 for ost5	0.1114	0.3148	0	1
mechanical eng	Dummy 1/0 for ost6	0.2710	0.4447	0	1
civil eng	Dummy 1/0 for ost7	0.0654	0.2474	0	1
mne	Dummy 1/0 for whether the firm is multinational	0.4868	0.5001	0	1
R&D job	Dummy 1/0 for inventors working in R&D division	0.4327	0.4958	0	1

Table 4: Descriptive statistics of the control variables. Obs = 704.

	Npat	ForwCit	Claims	sci only	mkt only	sci&mkt	none	female	age2006	BSc	MSc	PhD	job mob	R&D job	retired	intern know
Npat	1															
ForwCit	0.6567*	1														
Claims	0.8356*	0.6435*	1													
sci only	0.0191	0.0035	0.0253	1												
mkt only	0.0361	-0.0032	-0.0491	-0.2315*	1											
sci&mkt	0.0216	0.0725*	0.1083*	-0.2740*	-0.5408*	1										
none	-0.0843*	-0.0889*	-0.0962*	-0.1665*	-0.3285*	-0.3889*	1									
female	0.0261	0.0819*	0.0584	0.0767*	-0.002	-0.0173	-0.0359	1								
age2006	0.0514	-0.0069	0.0119	-0.0376	0.0007	-0.0141	0.046	-0.1510*	1							
BSc	0.029	-0.0127	0.0278	-0.0303	0.0487	-0.0377	0.013	-0.053	-0.0119	1						
MSc	-0.0515	-0.0566	-0.0522	-0.0145	0.0101	-0.0006	0.0001	0.1008*	-0.1739*	-0.3647*	1					
PhD	-0.0197	0.0845*	0.0591	0.1444*	-0.1873*	0.1941*	-0.1324*	0.1116*	-0.032	-0.3529*	-0.2008*	1				
job mob	0.0052	0.0141	0.0094	0.0147	0.0177	0.0467	-0.0912*	-0.0274	0.0452	-0.0750*	-0.0886*	0.1391*	1			
R&D job	0.0657	0.0841*	0.0673	0.0085	-0.0798*	0.0048	0.0821*	0.1184*	-0.2548*	0.0871*	0.1114*	-0.0168	-0.0860*	1		
retired	-0.0117	-0.0375	-0.0353	0.0426	0.0376	-0.0384	-0.0298	-0.0509	0.3617*	0.0276	-0.0658	-0.0451	-0.3061*	-0.1814*	1	
intern knowl	0.0502	0.0671	0.0474	-0.0155	0.0972*	0.1050*	-0.2328*	-0.0154	-0.1297*	0.0525	-0.0207	0.0299	0.0448	0.0894*	-0.0642	1
share coinv	-0.0095	0.0689*	0.0247	0.0304	0.0188	-0.0042	-0.0406	0.054	-0.2714*	0.0542	0.0292	0.0458	-0.0191	0.2094*	-0.1167*	0.1919*
share foreign	-0.0728*	-0.0621	-0.0378	-0.0215	0.0184	0.0396	-0.0542	0.0078	0.0111	0.0694*	-0.0829*	0.0758*	0.0943*	-0.0940*	0.0337	0.0736*
catalonia	-0.0731*	0.0196	-0.0311	-0.0184	-0.0755*	0.2396*	-0.1938*	0.0727*	-0.1131*	-0.0975*	0.0048	0.3824*	0.0965*	-0.0489	-0.0523	0.0219
midlands	-0.0485	-0.0598	-0.0111	-0.0373	0.0556	-0.0449	0.0191	-0.0693*	0.3049*	0.0227	-0.0277	0.0999*	0.0398	-0.1633*	0.2143*	-0.1452*
ost1	-0.0552	-0.0361	0.0007	0.0705	-0.0566	-0.0387	0.0596	-0.0589	-0.2275*	0.0691*	0.1324*	-0.0719*	-0.0729*	0.1619*	-0.0486	0.0949*
ost2	-0.0552	-0.0355	-0.0439	-0.0333	-0.0194	0.0584	-0.0236	0.0155	0.0426	-0.0619	-0.0037	0.1037*	-0.0012	-0.0766*	0.0376	-0.0541
ost3	0.1251*	0.2214*	0.1447*	0.0686	-0.0996*	0.1366*	-0.1054*	0.1914*	-0.0025	-0.0499	-0.0118	0.2402*	0.0505	0.0368	-0.0322	-0.0016
ost4	-0.0102	-0.026	0.0362	0.1818*	-0.1034*	0.0152	-0.0386	0.1176*	0.0664	-0.1001*	-0.0009	0.2850*	0.0702*	-0.0337	-0.0176	0.0258
ost5	-0.0261	-0.0739*	-0.0413	-0.0920*	0.0619	-0.0141	0.0162	-0.0171	0.1697*	-0.0122	-0.0388	-0.0886*	-0.0095	-0.0569	0.0415	-0.0766*
ost6	0.019	-0.0354	-0.1015*	-0.1042*	0.1143*	-0.0797*	0.0454	-0.1163*	0.0277	0.0756*	-0.0717*	-0.2110*	-0.0174	-0.0348	0.0394	0.0242
ost7	-0.0009	-0.0234	0.0563	-0.0304	0.0766*	-0.0604	0.0082	-0.0585	0.0213	-0.0045	-0.0309	-0.1013*	0.0389	-0.0724*	-0.0281	-0.0619
y1	0.1800*	0.1289*	0.1657*	-0.0426	-0.009	0.0279	0.0092	-0.0208	0.2014*	-0.0221	-0.0624	-0.0041	0.0476	-0.0531	0.0399	-0.0182
y2	0.0483	0.0388	0.0185	-0.0768*	0.0476	0.0019	0.0014	-0.0367	-0.0035	0.0112	0.0113	-0.0679*	-0.014	0.0753*	0.0491	0.0925*
y3	0.0113	0.0295	0.0044	0.0583	-0.003	-0.0781*	0.055	0.0047	-0.0048	0.0071	-0.0309	-0.0378	-0.0532	0.0335	-0.0367	0.0205
y4	-0.0561	-0.0198	-0.0058	0.0135	0.0018	-0.0254	0.0189	0.0222	-0.0702*	-0.0218	0.1023*	0.0088	-0.0674	0.0361	0.0332	-0.1014*
y5	0.0053	-0.0198	-0.0075	0.0564	-0.0109	-0.0095	-0.0193	0.0225	-0.01	-0.0112	0.0049	0.0435	-0.0074	0.0136	0.0031	0.0447
y6	-0.0731*	-0.0671*	-0.0589	0.0455	-0.0609	0.0852*	-0.0694	-0.0198	-0.0645	-0.0294	0.0323	0.1158*	0.0473	-0.0648	-0.0247	-0.0045
y7	-0.1484*	-0.1182*	-0.1408*	-0.0275	0.0184	0.0101	-0.0128	0.0318	-0.0836*	0.0569	-0.0349	-0.0248	0.0454	-0.0472	-0.0717*	-0.0398

Table 5: Correlation matrix (* coefficients significant at 5% level). Obs = 704.

	share c	share f	mne	catalonia	midlands	ost1	ost2	ost3	ost4	ost5	ost7
share coinv	1										
share foreign	-0.1647*	1									
catalonia	0.0980*	0.1731*	1								
midlands	-0.1468*	0.0651	-0.2304*	1							
ost1	0.1526*	-0.0840*	-0.1101*	-0.1015*	1						
ost2	-0.0625	-0.0682*	0.035	0.0361	-0.2080*	1					
ost3	0.0281	0.0856*	0.1990*	-0.0063	-0.2340*	-0.1476*	1				
ost4	-0.0287	0.0774*	0.2059*	-0.0081	-0.1276*	-0.0805*	-0.0906*	1			
ost5	-0.0602	0.0659	-0.0019	0.0074	-0.2056*	-0.1297*	-0.1459*	-0.0796*	1		
ost6	-0.0068	-0.006	-0.1775*	0.0564	-0.3491*	-0.2202*	-0.2477*	-0.1351*	-0.2177*	1	
ost7	-0.1130*	-0.0265	0.0106	0.0362	-0.1491*	-0.0940*	-0.1058*	-0.0577	-0.0930*	-0.1578*	1
y1	-0.0801*	0.0134	-0.065	0.0531	-0.0165	0.0285	0.0235	-0.0232	0.0693*	-0.0662	0.0086
y2	0.0148	-0.0607	-0.0702*	0.0092	-0.0208	0.0164	0.0156	-0.0002	-0.0282	0.0261	-0.0177
y3	0.0219	-0.0471	-0.1026*	-0.0599	0.0275	-0.0589	-0.0418	-0.0371	0.0328	0.0621	-0.0351
y4	-0.0034	0.0088	-0.0147	0.0199	0.0532	0.0339	-0.0576	0.0025	-0.0527	0.0257	-0.0366
y5	0.017	0.0052	0.046	-0.0201	-0.0153	-0.0244	-0.0175	0.0429	0.001	0.0173	0.0141
y6	0.0307	0.0492	0.2020*	0.0249	-0.0374	0.0198	0.0619	0.0035	0.0223	-0.0432	-0.0019
y7	0.0123	0.0436	0.057	-0.0265	0.0075	-0.0131	0.0172	0.0201	-0.0494	-0.0214	0.0653

Table 6: Correlation matrix (cont.).

Hp 1	1	2	3	4	5	6
VARIABLES	Npat	Npat	ForwCit	ForwCit	Claims	Claims
sci only	0.252	0.319*	0.346	0.533**	0.269**	0.220*
	(0.169)	(0.177)	(0.214)	(0.233)	(0.130)	(0.121)
mkt only	0.255**	0.293**	0.302*	0.250	0.253**	0.246**
	(0.111)	(0.115)	(0.171)	(0.229)	(0.110)	(0.114)
sci&mkt	0.246**	0.255**	0.447***	0.421*	0.428***	0.270**
	(0.107)	(0.116)	(0.166)	(0.221)	(0.124)	(0.117)
female	-0.187*	-0.167	-0.107	-0.0385	-0.162	-0.116
	(0.109)	(0.113)	(0.201)	(0.199)	(0.120)	(0.117)
age	0.0048	0.0187	-0.0113	-0.0081	-0.0166	0.00451
	(0.0242)	(0.0238)	(0.0503)	(0.0633)	(0.0250)	(0.0250)
age sq	6.55e-06	-0.0001	0.0002	0.0001	0.0002	-0.0001
	(0.0002)	(0.0002)	(0.0005)	(0.0006)	(0.0002)	(0.0002)
BSc	0.0773	0.0716	0.0266	-0.0608	0.164	0.113
	(0.105)	(0.104)	(0.183)	(0.205)	(0.107)	(0.106)
MSc	-0.0498	-0.0419	-0.218	-0.357	-0.0164	-0.0104
	(0.111)	(0.110)	(0.235)	(0.241)	(0.122)	(0.113)
PhD	0.0299	0.0522	0.358	-0.224	0.302**	0.218
	(0.122)	(0.129)	(0.307)	(0.298)	(0.134)	(0.134)
job mob	-0.0151	-0.0395	-0.0820	0.0603	-0.0990	0.0360
	(0.0667)	(0.0730)	(0.143)	(0.146)	(0.0745)	(0.0786)
R&D job	0.0949	0.0486	0.357**	0.166	0.0995	0.0631
	(0.0702)	(0.0766)	(0.140)	(0.158)	(0.0815)	(0.0806)
retired	-0.141	-0.139	-0.239	-0.170	-0.303**	-0.101
	(0.149)	(0.136)	(0.251)	(0.261)	(0.122)	(0.124)
intern knowl	0.0532	0.0970	0.521	0.465	0.0280	0.0491
	(0.141)	(0.148)	(0.322)	(0.320)	(0.171)	(0.165)
share coinv	-0.0924	-0.112	0.0632	0.0960	0.0546	0.0340
	(0.0809)	(0.0862)	(0.173)	(0.154)	(0.0991)	(0.102)
share foreign	-0.233***	-0.159*	-0.261	0.0406	-0.129	-0.0109
	(0.0833)	(0.0933)	(0.192)	(0.197)	(0.104)	(0.102)
mne		-0.215*		-0.562**		-0.150
		(0.110)		(0.220)		(0.105)
Constant	-0.185	-0.485	-0.417	-0.470	2.517***	2.236***
	(0.616)	(0.585)	(1.283)	(1.527)	(0.614)	(0.604)
Observations	704	704	704	704	704	704
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Patent techn. classes	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummies	-	Yes	-	Yes	-	Yes
Loglikelihood	-1117	-1064	-1530	-1455	-2959	-2853
Lnalpha	-2.045***	-2.763***	0.876***	0.527***	-0.450***	-0.740***
	(0.301)	(0.553)	(0.0778)	(0.0755)	(0.0791)	(0.0812)

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

Table 7: Negative binomial regressions. Baseline results Hp 1.

Panel A: *Hp 2a*	1	2	3	4	5	6
VARIABLES	Npat	Npat	ForwCit	ForwCit	Claims	Claims
sci only	0.257	0.325*	0.350	0.541**	0.271**	0.221*
	(0.168)	(0.175)	(0.217)	(0.236)	(0.131)	(0.122)
mkt only	0.263**	0.304***	0.306*	0.257	0.258**	0.249**
	(0.112)	(0.117)	(0.170)	(0.222)	(0.111)	(0.116)
sci&mkt	0.294**	0.312**	0.503**	0.503**	0.483***	0.288**
	(0.132)	(0.143)	(0.222)	(0.238)	(0.150)	(0.146)
R&D job	0.132	0.0931	0.402**	0.237	0.143	0.0785
	(0.0928)	(0.102)	(0.198)	(0.236)	(0.104)	(0.113)
sci&mkt*R&Djob	-0.0897	-0.108	-0.111	-0.166	-0.112	-0.0370
	(0.132)	(0.143)	(0.271)	(0.314)	(0.165)	(0.167)
Constant	-0.195	-0.496	-0.430	-0.435	2.524***	2.244***
	(0.617)	(0.582)	(1.290)	(1.508)	(0.616)	(0.603)
Observations	704	704	704	704	704	704
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	-	Yes	-	Yes	-	Yes
Loglikelihood	-1117	-1064	-1530	-1455	-2960	-2854
Lnalpha	-2.046***	-2.771***	0.876***	0.526***	-0.451***	-0.740***
	(0.302)	(0.565)	(0.0786)	(0.0762)	(0.0795)	(0.0812)

Panel B: *Hp 2b*	1	2	3	4	5	6
VARIABLES	Npat	Npat	ForwCit	ForwCit	Claims	Claims
sci only	0.208	0.291	0.302	0.486**	0.188	0.182
	(0.168)	(0.185)	(0.210)	(0.234)	(0.121)	(0.123)
mkt only	0.258**	0.296***	0.298*	0.251	0.261**	0.251**
	(0.111)	(0.115)	(0.168)	(0.227)	(0.110)	(0.114)
sci&mkt	0.285***	0.285**	0.494***	0.495**	0.509***	0.318***
	(0.106)	(0.114)	(0.175)	(0.229)	(0.132)	(0.119)
PhD	0.187	0.156	0.520	0.00974	0.572***	0.376**
	(0.198)	(0.203)	(0.415)	(0.382)	(0.200)	(0.182)
sci&mkt*PhD	-0.271	-0.191	-0.309	-0.436	-0.470*	-0.281
	(0.235)	(0.224)	(0.447)	(0.360)	(0.246)	(0.222)
Constant	-0.174	-0.473	-0.347	-0.400	2.558***	2.236***
	(0.610)	(0.583)	(1.297)	(1.522)	(0.611)	(0.603)
Observations	704	704	704	704	704	704
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	-	Yes	-	Yes	-	Yes
Loglikelihood	-1116	-1063	-1530	-1455	-2956	-2853
Lnalpha	-2.052***	-2.773***	0.874***	0.523***	-0.460***	-0.744***
	(0.302)	(0.564)	(0.0774)	(0.0748)	(0.0767)	(0.0811)

Clustered standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Negative binomial regressions. Baseline results Hp 2a and Hp 2b.

	1	2	3	4	5	6
VARIABLES	Npat	Npat	ForwCit	ForwCit	Claims	Claims
sci only	0.258**	0.246**	0.307	0.338	0.265**	0.225**
	(0.111)	(0.121)	(0.207)	(0.217)	(0.112)	(0.105)
mkt only	0.193**	0.237***	0.0780	0.140	0.220**	0.225**
	(0.0757)	(0.0759)	(0.203)	(0.245)	(0.0919)	(0.0889)
sci&mkt	0.304***	0.277***	0.463**	0.328	0.417***	0.309***
	(0.0963)	(0.0983)	(0.185)	(0.210)	(0.115)	(0.116)
female	-0.179*	-0.165*	-0.110	-0.119	-0.191*	-0.169
	(0.0988)	(0.0994)	(0.198)	(0.194)	(0.114)	(0.108)
age	0.0176	0.0327	0.0067	0.0189	-0.0023	0.0107
	(0.0218)	(0.0216)	(0.0487)	(0.0585)	(0.0233)	(0.0224)
age sq	-0.0001	-0.0003	-4.72e-05	-0.0002	3.36e-05	-0.0002
	(0.0002)	(0.0002)	(0.0005)	(0.0006)	(0.0002)	(0.0002)
BSc	0.0883	0.0869	0.0424	-0.0666	0.193*	0.131
	(0.101)	(0.101)	(0.174)	(0.198)	(0.101)	(0.0995)
MSc	-0.0211	-0.0136	-0.185	-0.338	0.0343	0.00725
	(0.110)	(0.108)	(0.216)	(0.229)	(0.115)	(0.110)
PhD	0.0457	0.0636	0.404	-0.169	0.352***	0.208
	(0.115)	(0.122)	(0.292)	(0.302)	(0.133)	(0.130)
job mob	0.0165	-0.0131	-0.0288	0.114	-0.0540	0.0588
	(0.0640)	(0.0710)	(0.136)	(0.147)	(0.0730)	(0.0758)
R&D job	0.0755	0.0432	0.348***	0.188	0.0896	0.0751
	(0.0670)	(0.0738)	(0.133)	(0.154)	(0.0797)	(0.0795)
retired	-0.0575	-0.0737	-0.124	-0.0194	-0.242**	-0.0689
	(0.122)	(0.123)	(0.259)	(0.273)	(0.119)	(0.126)
intern knowl	0.0467	0.104	0.506*	0.449	0.0232	0.0240
	(0.133)	(0.141)	(0.305)	(0.298)	(0.160)	(0.155)
share coinv	-0.0820	-0.0927	0.0702	0.0675	0.0481	0.0441
	(0.0773)	(0.0868)	(0.160)	(0.153)	(0.0944)	(0.0975)
share foreign	-0.178**	-0.105	-0.204	0.0993	-0.0606	0.0467
	(0.0827)	(0.0927)	(0.184)	(0.188)	(0.104)	(0.0944)
mne		-0.223**		-0.573***		-0.163*
		(0.102)		(0.213)		(0.0979)
Constant	-0.498	-0.814	-0.806	-0.936	2.115***	2.096***
	(0.566)	(0.545)	(1.232)	(1.408)	(0.588)	(0.559)
Observations	704	704	704	704	704	704
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Patent techn. classes	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummies	-	Yes	-	Yes	-	Yes
Loglikelihood	-1182	-1130	-1603	-1530	-3141	-3030
Lnalpha	-2.114***	-2.774***	0.896***	0.579***	-0.445***	-0.729***
	(0.326)	(0.597)	(0.0741)	(0.0726)	(0.0785)	(0.0856)

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

Table 9: Negative binomial regressions. Robustness check No 1.

VARIABLES	1 MeanNpat	2 MeanNpat	3 MeanForwCit	4 MeanForwCit	5 MeanClaims	6 MeanClaims
sci only	0.0978	0.116	-0.233	0.105	0.881	0.312
	(0.0803)	(0.0867)	(0.483)	(0.353)	(1.351)	(1.558)
mkt only	0.0738*	0.0908**	0.0459	0.387	0.726	0.553
	(0.0404)	(0.0456)	(0.325)	(0.368)	(0.992)	(1.140)
sci&mkt	0.0848*	0.0846*	0.256	0.426*	2.072	1.043
	(0.0434)	(0.0490)	(0.237)	(0.250)	(1.313)	(1.198)
female	-0.109**	-0.0911	0.298	0.505	0.154	0.172
	(0.0520)	(0.0557)	(0.460)	(0.476)	(1.265)	(1.359)
age	0.0036	0.0076	0.0408	-0.0089	-0.162	-0.199
	(0.009)	(0.0103)	(0.0761)	(0.0881)	(0.247)	(0.266)
age sq	-0.0000	-0.0000	-0.0005	0.0001	0.0006	0.0007
	(0.0001)	(0.0001)	(0.001)	(0.001)	(0.0024)	(0.0026)
BSc	0.0033	-0.0036	-0.560*	-0.423	0.93	0.881
	(0.0451)	(0.0487)	(0.306)	(0.336)	(0.924)	(1.049)
MSc	-0.0097	-0.0283	-0.794***	-0.674**	-0.643	-0.112
	(0.0493)	(0.0527)	(0.304)	(0.303)	(1.027)	(1.310)
PhD	-0.00363	0.0159	0.251	-0.385	3.134*	2.737
	(0.0529)	(0.0685)	(0.658)	(0.447)	(1.777)	(2.098)
job mob	-0.0267	-0.0244	-0.122	0.230	0.203	1.336
	(0.0306)	(0.0369)	(0.278)	(0.256)	(0.996)	(0.935)
R&D job	0.0183	-0.00415	0.502**	0.0555	0.497	0.559
	(0.0317)	(0.0389)	(0.230)	(0.234)	(0.810)	(0.897)
retired	-0.0524	-0.0411	-0.0342	-0.0510	-1.337	-0.179
	(0.0661)	(0.0637)	(0.467)	(0.381)	(1.097)	(1.301)
intern knowl	0.00112	0.0211	0.615	0.177	0.199	-0.213
	(0.0686)	(0.0582)	(0.398)	(0.398)	(1.625)	(1.763)
share coinv	-0.0199	-0.0257	0.431	0.275	0.56	0.386
	(0.0367)	(0.0394)	(0.315)	(0.276)	(1.144)	(1.223)
share foreign	-0.0543	-0.0178	-0.215	0.0281	1.29	2.372
	(0.0411)	(0.0504)	(0.383)	(0.361)	(1.312)	(1.752)
mne		-0.0319		-0.323		0.162
		(0.0558)		(0.247)		(1.389)
Constant	0.590**	0.497*	-0.0142	0.459	13.54**	16.32**
	(0.280)	(0.260)	(1.796)	(2.218)	(6.341)	(6.831)
Observations	704	704	704	704	704	704
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Patent techn. classes	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummies	-	Yes	-	Yes	-	Yes
Adj. R-squared	0.3225	0.3528	0.0566	0.2358	0.0907	0.1982

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

Table 10: OLS regressions. Robustness check No. 2.

Figures

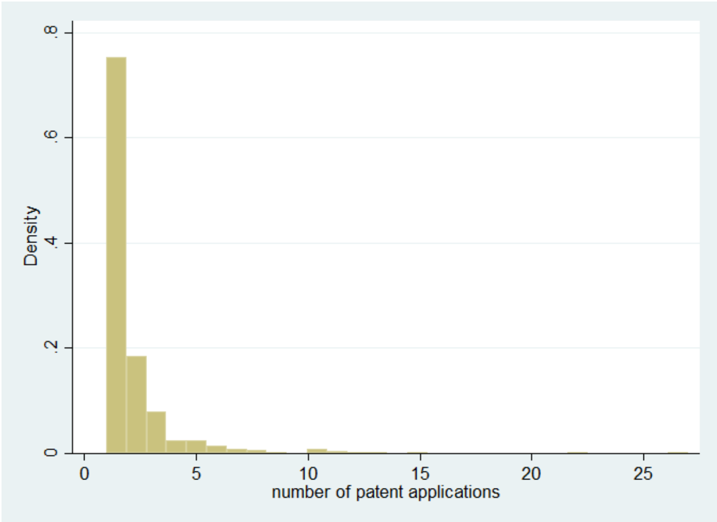

Figure 1: Distribution of patent applications

Appendices

Appendix A

	MIDLANDS			PIEDMONT		
	mean whole sample	mean contacted	diff in mean	mean whole sample	mean contacted	diff in mean
	N=6458	N=881		N=3690	N=1293	
Npat	1.393	1.4297	-0.0367	1.6818	1.9466	-0.2648***
tot_forw_cit	3.6946	2.5816	1.113	3.239	4.0572	-0.8182***
max_forw_cit	2.8323	2.1768	0.6555	2.371	2.8259	-0.4549***
count_claims	25.3434	25.0623	0.2811	25.0775	28.5228	-3.4453***
count_backw_cit	5.1466	6.0634	-0.9168	4.759	6.5073	-1.7483***
share_coinv_pat	0.5861	0.5068	0.0793	0.6622	0.686	-0.0238*
share_forei_pat	0.2567	0.2391	0.0176	0.1151	0.0702	0.0449***

Table 11: Sample representativeness: comparison of whole sample vs. contacted inventors.

	MIDLANDS			PIEDMONT		
	mean contacted	mean respondents	diff in mean	mean contacted	mean respondents	diff in mean
	N=881	N=117		N=1293	N=539	
Npat	1.4297	1.5726	-0.1429	1.9466	1.9849	-0.0383
tot_forw_cit	2.5816	2.5726	0.009	4.0572	4.3095	-0.2523
max_forw_cit	2.1768	1.923	0.2538	2.8259	2.7861	0.0398
count_claims	25.0623	27.0854	-2.0231	28.5228	29.4784	-0.9556
count_backw_cit	6.0634	6.7094	-0.646	6.5073	7.2195	-0.7122
share_coinv_pat	0.5068	0.5098	-0.003	0.686	0.6841	0.0019
share_forei_pat	0.2391	0.2264	0.0127	0.0702	0.1067	-0.0365***

Table 12: Sample representativeness: comparison of contacted inventors vs. respondents.

	CATALONIA			MIDLANDS			PIEDMONT		
	m. whole sample	m. respondents	diff	m. whole sample	m. respondents	diff	m. whole sample	m. respondents	diff
	N=4186	N=225		N=6458	N=117		N=3690	N=539	
Npat	1.3557	1.5695	-0.2138	1.393	1.5726	-0.1796*	1.6818	1.9849	-0.3031***
tot_forw_cit	3.3392	4.4529	-1.1137	3.6946	2.5726	1.122***	3.239	4.3095	-1.0705**
max_forw_cit	2.6426	2.991	-0.3484	2.8323	1.923	0.9093***	2.371	2.7861	-0.4151*
count_claims	20.8296	26.0583	-5.2286*	25.3113	27.0854	-1.7741	24.3345	29.4784	-5.1439**
count_backw_cit	3.2873	4.0269	-0.7396	5.1466	6.7094	-1.5628*	4.759	7.2195	-2.4605***
share_coinv_pat	0.7244	0.7544	-0.03	0.5861	0.5098	0.07629*	0.6622	0.6841	-0.0219
share_forei_pat	0.228	0.2742	-0.0462	0.2567	0.2264	0.0303	0.1151	0.1067	0.0084

Table 13: Sample representativeness: comparison of whole sample vs. respondents.

Appendix B

Factor	Variance	Difference	Proportion	Cumulative
Factor 1	1.95895	0.14896	0.2449	0.2449
Factor 2	1.80999	0.26028	0.2262	0.4711
Factor 3	1.54971	.	0.1937	0.6648

Table 14: Factor analysis/correlation. Method: principal-component factors. Retained factors = 3.

	Factor 1	Factor 2	Factor 3	Uniqueness
colleagues			0.8589	0.2473
business others			0.7801	0.3162
suppliers		0.6556		0.4688
customers		0.8166		0.3054
competitors		0.7005		0.4437
private R&D labs	0.6578			0.381
university	0.8331			0.2597
public R&D labs	0.8424			0.2592

Table 15: Rotated factor loadings (pattern matrix) and unique variances (blanks represent abs(loading)<.6).

Appendix C

	1	2
	ForwCit	ForwCit
sci only	0.376	0.398
	(0.257)	(0.259)
mkt only	0.419**	0.432**
	(0.190)	(0.191)
sci&mkt	0.453**	0.361*
	(0.189)	(0.193)
	Inflate	Inflate
sci&mkt		-0.634*
		(0.378)
MSc		0.985**
		(0.406)
PhD		0.249
		(0.462)
R&D job	-0.771	-0.577
	(0.476)	(0.369)
share coinv		-0.724*
		(0.411)
Constant	-0.274	-0.231
	(1.302)	(1.296)
Observations	704	704
Control variables	Yes	Yes
Loglikelihood	-1544	-1538
Vuong test	1.448	2.170

*** p<0.01, ** p<0.05, * p<0.1

Table 16: Zero-inflated negative binomial regressions. Dependent variable $ForwCit$.

Appendix D

Variable	Obs	Mean	St Dev	Min	Max
sci only	120	0.1615	0.3682	0	1
mkt only	138	0.1857	0.3891	0	1
sci&mkt	385	0.5181	0.5000	0	1
none	100	0.1345	0.3415	0	1

Table 17: Descriptive statistics of knowledge variables employed in Robustness check No. 1.

Variable	Obs	Mean	St Dev	Min	Max
MeanNpat	743	0.5472	0.5054	0.1428	5
MeanForwCit	743	1.8730	3.1895	0	26
MeanClaims	743	15.2070	9.8300	1	83

Table 18: Descriptive statistics of dependent variables employed in Robustness check No. 2.

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