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The Contribution of Academic Knowledge to the Value of Industrial Inventions: Micro level evidence from patent inventors

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Abstract

Although it is well known that the transfer of academic knowledge to industry often leads to economically valuable outcomes, little evidence exists on what specific characteristics of the process of university-industry knowledge transfer lead to the generation of more valuable inventions. Using an original survey of industrial inventors of European patents, resident in the Italian region of Piedmont, we analyze the determinants of the value of inventions that have benefited from the contribution of academic knowledge. We focus on a set of project, inventor and firm characteristics. We find that inventors with greater cognitive proximity to the university and with high patenting productivity are more likely to benefit from university knowledge. Concerning the determinants of invention value, we find that the transfer of theoretical academic knowledge, rather than solutions to more technical and specified problems, leads to more valuable inventions. The contribution of the university is stronger when it involves the theoretical advances in which it specializes. Knowledge transfer processes involving a direct collaboration between the inventor and the university (and particularly individual researchers) are positively associated with the relative value of inventions. To produce more valuable inventions, company inventors need to interact directly with university researchers to appropriate and transform codified and tacit academic knowledge.

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Abstract

Although it is well known that the transfer of academic knowledge to industry often leads to economically valuable outcomes, little evidence exists on what specific characteristics of the process of university-industry knowledge transfer lead to the generation of more valuable inventions. Using an original survey of industrial inventors of European patents, resident in the Italian region of Piedmont, we analyze the determinants of the value of inventions that have benefited from the contribution of academic knowledge. We focus on a set of project, inventor and firm characteristics. We find that inventors with greater cognitive proximity to the university and with high patenting productivity are more likely to benefit from university knowledge. Concerning the determinants of invention value, we find that the transfer of theoretical academic knowledge, rather than solutions to more technical and specified problems, leads to more valuable inventions. The contribution of the university is stronger when it involves the theoretical advances in which it specializes. Knowledge transfer processes involving a direct collaboration between the inventor and the university (and particularly individual researchers) are positively associated with the relative value of inventions. To produce more valuable inventions, company inventors need to interact directly with university researchers to appropriate and transform codified and tacit academic knowledge.

1. Introduction

Much evidence has been produced, particularly since the 1990s, proving that the transfer of academic knowledge to industry leads to economically valuable outcomes. Macroeconomic studies have estimated the elasticity of technological progress, measured in terms of variation in total factor productivity (TFP), to investment in public research (Guellec and van Pottlesberghe (2002) or the impact of academic research on TFP (Adams, 1990) finding positive and significant values. Other studies have investigated the impact of expenditure on academic research on the innovation performance of firms localized in the same region (in terms of their research expenditures, patents produced or new products announced), repeatedly finding evidence of a positive relationship between these variables (Jaffe, 1989; Acs et al, 1992; Autant-Bernard, 2001). Academic knowledge has been linked to firms' productivity growth and to the development of a large number of inventions that, in the absence of available research outcomes produced by universities, would have been developed only much later, if at all (Mansfield, 1991, 1998). Finally, the literature has tried to understand how and why academic knowledge contributes to innovation in firms, exploring the direct links between firms' innovation performance and their reliance upon scientific research (Fleming and Sorenson, 2004; Gittelman, 2005). However, many of these studies have used only indirect proxies to capture the use of academic knowledge on the part of firms, such as patent citations to the scientific literature, the employment of researchers previously affiliated to scientific institutions, the co-autorship of publications with academic scientists (Cockburn and Henderson, 1998; Zucker et al., 2002; Cassiman et al., 2008; Cassiman et al., 2012). Very little is known about the specific processes through which academic research increases the productivity of business innovation.

One important aspect of the contribution of academic knowledge to innovation in industry is the extent to which it contributes to the development of valuable inventions. Especially in the last twenty years much research has been done on the determinants of the value of patented inventions (reviews are included in Reitzig, 2003, Sapsalis and van Pottlesberghe de la Potterie, 2003, and Gambardella et al., 2005). However very little evidence, if at all, exists on the contribution of academic knowledge to such value. While some studies have explored the contribution of academic knowledge to the quality of patents measured in terms of forward citations accrued, the contribution of academic knowledge to the direct economic value of inventions is largely unexplored.

In this paper we investigate under which conditions the reliance upon academic knowledge in the invention process contributes to the development of more valuable inventions, thus contributing to both streams of literature. First, while most studies assume that the impact of academic knowledge on invention value occurs through the exploitation of basic research findings (the latter usually captured by indirect proxies such as patent citations to the scientific literature), we aim to test directly what type of academic knowledge is more valuable to inventors. Secondly, we study what organizational set ups of the university-firm interaction contribute to more valuable inventions. Thirdly, we exploit direct estimates of the economic value of inventions, as provided by the inventors who developed them, rather than proxies such as forward citations to patents. We also control for the knowledge, individual and firm characteristics that can affect the value of the invention.

We rely upon an original survey of industry inventors residing in the Italian region of Piedmont, one of the most advanced Italian regions with a scientific and technological performance just below the average of EU15 countries (Bodas Freitas, Geuna, Rossi; 2013). The PIEMINV survey (Cecchelli et al., 2012), described in greater detail in Section 4, included numerous questions on the inventors' interaction with academic research. Among other questions, inventors were asked to estimate the monetary values of their invention with the highest economic impact and of their invention that benefited the most from the contribution of academic knowledge. This information allows us to analyze the contribution of academic research avoiding the usual problems of quantification and limiting the intrinsic shortcomings of asking the value of a patent to an inventor, as we could calculate the value of the invention that mostly benefited from academic knowledge in relation to their most valuable invention.

Checking a variety of model specifications and controlling for selection bias and endogeneity, we find that it is the transfer of *theoretical* academic knowledge that has a significant positive impact on the value of the invention rather then the transfer of technological knowledge. Concerning the organization of knowledge transfer processes, those involving a private contract with an individual researcher, rather than a contract signed with the university, are correlated to more valuable inventions. We also find a positive age effect for inventors older than 29 years. Consistently with what we know about the process of knowledge transfer, inventors with greater cognitive proximity to the university (more educated, with experience of having worked at a university) and with greater patenting experience, have higher absorptive capacity and thus are more likely to benefit from academic knowledge.

The paper is structured as follows. In the next section, we briefly review the main results of the literature on the economic contribution of academic research, particularly focusing on its impact on innovation. In Section 3 we discuss the channels through which academic research is likely to influence the value of inventions, and the role of other individual and firm characteristics. In Section 4, we discuss the data, while in Section 5 we explain our empirical strategy. Finally, in Section 6 we present our empirical results and in Section 7 we draw some conclusions and implications for policy.

2. The contribution of academic knowledge to the value of inventions

There is by now a wealth of evidence suggesting that academic knowledge positively contributes to processes of innovation in industry. The nature and extent of these contributions have been explored from a number of different perspectives, using both macroeconomic data at the national or regional level, and firm-level data obtained from ad-hoc surveys or existing patent and publication databases. Here we briefly discuss the relevant literature at the firm level, which is the focus of our empirical analysis.

One of the earliest studies of the impact of academic knowledge on innovation was Mansfield's (1991) investigation of 76 major US companies. Based on extensive interviews, Mansfield showed that 11% of new products and 9% of new processes introduced by these firms over a ten-year period would not have been developed without academic research, or would only have been developed with substantial delays. In a later study (1998) he found that the importance of academic research for industrial innovation processes had increased over time and that the average time lag between the publication of research results and their commercial exploitation had shortened. Cockburn and Henderson (1998) found that only 24% of a sample of US pharmaceutical drugs developed between 1950 and 1980 had been generated without input from public research. Since then, much evidence has shown that firms' innovation performance – measured in terms of investment in R&D (Adams et al., 2003), innovation productivity (Cassiman et al., 2012) and sales (Belderbos et al., 2004) – increases when firms collaborate or otherwise interact with universities. In particular, firms' interactions with highly productive "star scientists", at least in the biotechnology field, leads them to develop more and more highly cited industry patents (Zucker et al., 2002). The channels of interactions conducive to firms' innovation performance are varied. Based on 62 case studies of firms in the medical devices industry, MacPherson (2002) found that innovative manufacturers interacted with the academic sector more strongly than their less innovative counterparts, and that formal and informal linkages played an equally important role. Consistently, a quantitative study by Grimpe and Hussinger (2013) on 2092 German firms, found that firms' innovation performance increased when they used both formal and informal channels of interaction with universities, as opposed to using only one of these. Beyond direct interactions with academic scientists, employment links can also provide important conduits for academic knowledge to increase industrial innovation: Ejsing et al. (2013), using panel employment data at firm level, found that newly hired former university researchers contributed more to innovative activity than newly hired recent graduates or joiners from other firms.

A substantial literature has attempted to assess the influence of scientific knowledge on the *quality* of industry patents, the latter usually measured in terms of the number of forward citations that the patent received over time: a patent is deemed more valuable the more other patents have cited it, indicating its contribution to the development of many other inventions (Lerner, 1994; Hall, Thoma and Torrisi, 2007). In several of these studies, the presence of links with scientific knowledge has been assessed in terms of whether a patent included backward citations to the scientific literature. Narin et al. (1997) found that citations of US patents to scientific papers grew rapidly during the 1980s and the 1990s, although patterns varied across technological fields (Callaert et al., 2006). In a study of over 16000 US patents granted in 1990, Fleming and Sorenson (2004) showed that patents were more frequently cited if they contained references to scientific papers. They also found that this effect was particularly strong for patents that combined a wider variety of sources of knowledge. The authors argued that when firms attempt to develop more complex new knowledge by recombining many sources, reliance upon scientific knowledge and methods can serve as a "map" that helps to structure the search process more systematically. Cassiman et al. (2008) analyzing 1186 European patents granted to 79 Flemish firms in 1995-2001, found that patents citing the scientific literature tended to generate forward citations in a broader range of technological fields, indicating that scientific knowledge helps develop inventions that enjoy greater applicability. However, they reported that citations to the scientific literature did not increase the number of forward citations per se, a result also found by Reitzig (2003). Perhaps one of the reasons for the contradictory findings on the importance of citations to scientific papers for patent quality is that the former are not a reliable measure of a technology's dependence on science. Indeed, based on a survey of Dutch industry-based inventors of international patents, Tijssen (2002) found that about 20% of these patents depended upon scientific knowledge, but that less than half of these contained citations to the scientific literature. Citations to scientific papers are not necessarily key for the development of the technology but may just indicate general background knowledge, and only capture the codified knowledge embedded in a patent, neglecting the transfer of tacit knowledge (Meyer, 2000).

To investigate the link between academic knowledge and patent quality, other studies have exploited ad-hoc surveys or information about patent ownership and inventorship. Scandura (2013) found that the amount and quality of the patents invented by a sample of industry inventors in various European countries increased when inventors drew their knowledge jointly from scientific and “market” (e.g. clients and customers, direct competitors, or suppliers) sources, rather than from only one of these. Gittelman (2005) found that patents whose development involved scientists who had worked in a public lab before later joining a biotechnology firm, received more citations than other patents. Cassiman et al. (2012) found that patents whose inventors had links with a scientific institution were more valuable, particularly if the patent assignee was a company that was a partner of that scientific institution. These findings emphasize the role of “boundary crossing” inventors who span the divide between academia and industry. A possible argument explaining why patents building upon links with academia are more valuable is that the contribution of scientific knowledge increases the novelty of the invention. Sapsalis and van Pottlesberghe de la Potterie (2003) found that patents with a higher share of backward citations to patents applied for by public research institutions (considered as a measure of the novelty of an invention) were more valuable, while patents with a high share of backward citations to patents invented by the same firm were more incremental and less valuable.

These authors, like many others who attempted to identify the contribution of academic knowledge to patent value, did not delve into the type of knowledge used in the development of the invention, but simply measured whether a link with scientific knowledge was present or not. Thanks to our survey data, we are able to distinguish the type of academic knowledge that inventors used for the development of their inventions into a) theoretical knowledge, b) methodologies, instruments, prototypes, c) solutions to technological problems and c) information about other potential sources of knowledge, thus providing detailed insight into the specific contribution of academic knowledge.

2.1 Measuring the value of inventions

While this literature has provided substantial insight into the impact of academic knowledge on patent value, one limitation is the almost exclusive reliance upon forward citations as a measure of patent quality, or value. Forward citations are easily retrieved through patent databases, but they suffer from several limitations: a high number of forward citations may simply indicate that the patent involves a very crowded area of research (Czarnitzki et al., 2008); moreover, citation standards can be different across technology classes, which biases comparisons between patents in different classes.

The economic value of patents is notoriously difficult to measure, and a variety of proxies can be found in the literature. Besides forward citations, other widely used proxies of patent value include:

- patent opposition and renewal data, where patent value is captured by the extent to which companies find it worthwhile to spend resources in order to litigate it or renew it (Priest and Klein, 1984; Pakes and Simpson, 1989; Bebchuk, 1994; Lanjouw and Schankerman, 2004);
- patent claims, that is the extent to which protection is sought in a patent application (Lanjouw and Schankerman, 2004; Beaudry and Kananian, 2012)
- company start-up activity, capturing whether a high-tech start-up has been created or not on the basis of the patent (Shane, 2001);
- the probability to get a patent granted, capturing the quality of the underlying invention (Guellec and van Pottelsberghe, 2000); and composite indicators (Lanjouw and Schankerman, 2004; van Zeebroeck, 2011).

None of these proxies are direct measures of economic value. This problem was addressed by a few studies such as Scherer and Harhoff (2000), Reizig (2003) and Gambardella et al. (2005) which relied on targeted surveys asking respondents to provide estimates of the monetary value of their patents. These approaches also have some limitations mainly having to do with data accuracy and reliability, as estimating the commercial value of a patent is extremely difficult, especially for the large share of patents that are not traded but developed internally or used as strategic tools (such as blocking patents). Patent inventors who are the usual target of these surveys may not be best placed to answer questions about patent value (this information may be more available to product/R&D managers or executives) but on the other hand they are better able to answer questions about the invention process so survey designers are often faced with a tradeoff when attempting to link patent value to the features of the invention process. The present study adopts the latter approach, targeting a sample of inventors of European patent application and asking them to identify, among other things, their most valuable invention and the invention that received the maximum contribution from academic knowledge, and the monetary value of each.

3. How does academic knowledge contribute to the value of industrial invention?

To analyze how academic knowledge contributes to the value of industrial invention, we need to develop a framework that allow us to explain what are the characteristics of academic knowledge, and the individual and organizational factors that influence the inventors' ability to exploit academic research to generate more valuable inventions. We would expect that the capacity to translate academic knowledge into valuable innovations integrating it with the internal knowledge of the company mainly depends upon: a) the specific characteristics of the academic knowledge that is transferred, b) the characteristics of the inventor involved and c) the way in which the process of exchange is organized.

a) Characteristics of academic knowledge. It has been argued that scientific knowledge increases the efficiency of private research, as it is contributes to the development of inventions that are more likely to constitute radical breakthroughs from existing knowledge (Carpenter et al., 1980). This could be due to scientific knowledge being able to better guide inventors through the technological landscape, helping them to find more useful combinations of previously unrelated knowledge domains, and eliminating fruitless paths of research (Fleming and Sorenson, 2004). In turn, radically new innovations are usually more valuable than incremental ones. Radically new inventions can find applications in a broad range of technological domains, and hence can be commercially exploited in a variety of fields, while incremental inventions are usually applicable in a few specific domains (Reitzig, 2003). Morever, more radical innovations face less potential competition on the final product market (Sapsalis and van Pottlesberghe de la Potterie, 2003). Therefore we expect processes of invention that exploit more basic scientific knowledge to generate more valuable inventions.

b) Characteristics of the inventor involved. The inventor's individual characteristics may affect his or her ability to effectively exploit academic knowledge in order to develop more valuable inventions. For academic knowledge to be transferred effectively, the individual that is the recipient of the knowledge transfer needs to have the appropriate cognitive resources to be able to absorb such knowledge and utilize it in the process of innovation in an effective way. Usually, absorptive capacity increases with one's level of education, previous exposure to certain concepts or methods, broader experience due for example to higher career mobility and experience in the interaction that via learning by doing improves the effectiveness of knowledge exchange. For company inventors who attempt to exploit scientific knowledge, it has been shown that active personal engagement in science is an important dimension of absorptive capacity: by engaging in scientific research, inventors improve their ability to identify relevant sources of academic knowledge and to absorb it and integrate it in their knowledge processes, which in turn leads to faster translation of research into new technologies (Fabrizio 2009; Cassiman et al., 2008). Indeed, more valuable inventions are more likely to involve boundary spanning inventors, who have strong personal connections to scientific research, for example thanks to having co-authored publications with academic scientists (Cockburn and Henderson, 1998), having collaborated with scientific institutions (Cassiman et al., 2012) or having worked for a scientific institution before joining the company (Gittelman, 2005). We would expect that the capacity of an inventor to transform academic knowledge in innovative value would therefore increase with an inventor's education, previous exposure to the methods and practices of academic research, and experience in collaborations with other industrial and especially academic researchers.

c) Organization of the knowledge transfer process. The possibility to successfully implement academic knowledge for commercial purposes should be enhanced when the knowledge transfer channel allows for the transmission of the academics' tacit knowledge, which is necessary for the application of most codified pieces of knowledge (Dasgupta and David, 1994). This is particularly so for forms of knowledge that are complex and cutting edge, where reading blueprints and manuals can only provide a partial picture and the involvement of the knowledge creator is fundamental in order to ensure success in implementation. The importance of tacit knowledge for the development of valuable inventions should imply that forms of university-industry knowledge transfer where the academics' tacit knowledge is transmitted more effectively should lead to more valuable inventions. Although to some extent all forms of knowledge transfer, including more "formal" ones like patent licensing, are accompanied by interpersonal interactions between academics and industrial researchers, certain channels such as direct collaborations are more conducive to interactions which are very often explicitly designed as part of the knowledge transfer process (Perkmann and Walsh, 2008). Indeed, Thursby et al. (2001), in a survey of 62 US universities, found that

71% of the inventions licensed from the university to firms required personal interactions with the inventor in order to be subsequently commercialized, suggesting the successful implementation of patented inventions for commercial purposes relies upon tacit knowledge that can only be harnessed effectively through direct collaboration with the academic inventor. Therefore, we expect that inventors who organize their interactions with academics in ways that are best suited to allow transmission of tacit knowledge, are more likely to generate more valuable inventions with the contribution from academic knowledge.

Firm and industry specificities. Much of the literature that discusses the importance of absorptive capacity for knowledge transfer is actually focused on firm-level variables, rather than individual ones. While this is in part due to data availability, several arguments suggest that some characteristics of the firm are important in driving their employees' ability to exploit academic knowledge to develop innovations. In particular, firms' exposure and engagement in research activities are important predictors of its ability to fruitfully exploit scientific knowledge. Being active in research, especially basic research, allows the firm to develop the capabilities to better search for, monitor and evaluate useful scientific knowledge. It has in fact been found that firms that invest more in internal R&D, firms that have developed more patents (Leten et al., 2013), and larger firms (Arora and Gambardella, 1994; Dornbrusch and Neuhäusler, 2013) are more likely to interact with universities and/or to rely upon external academic knowledge. In turn, firms that collaborate more with academia are more likely to have better research performance (Cockburn and Henderson, 1998; Leten et al., 2013) and to generate more valuable patents, even when those patents are not directly exploiting academic research findings (Cassiman et al., 2008).

Another argument explaining the better innovation performance of firms that are active in research and in collaboration with science is that these firms, by setting up a science-friendly environment, are more likely to attract employees who are interested in engaging with universities (Stern, 2004) and thus act as boundary spanners with the world of academia.

Finally, in studies exploring the contribution of academic research on firms' innovation performance it is important to control for sectoral and/or technological specificities. Despite a general increase in firms' reliance upon scientific knowledge, the opportunities for successful exploitation of scientific research appear to be particularly concentrated in several fields such as biotechnology and pharmaceuticals, information and communication technologies, nanotechnologies (Callaert et al., 2006), whose specificities must therefore be taken into account. It has been shown that firms in certain industries are more likely to benefit from academic research in order to produce valuable inventions (Mansfield, 1991; Cohen, Nelson and Walsh, 2002; Laursen and Salter, 2004; Abreu et al., 2008).

4. Industrial inventors in Piedmont

The PIEMINV survey targeted the population of inventors resident in the region of Piedmont who were named in at least one EPO patent application between 1998 and 2005 (about 4,000 patents and 3,000 inventors in Piedmont) (Cecchelli et al., 2012). After cleaning the address list, and excluding inventors working at universities and public research centres, the PIEMINV questionnaire was sent out in autumn 2009 and spring 2010 to 2,916 inventors, who returned 938 valid responses (31% response rate).

The questionnaire was designed to investigate various aspects of university-industry interactions, and to enable quantitative measurement of the local universities' contribution to the invention process. It included four sections: (i) general information about the inventors and their inventive activity; (ii) overall evaluation of the importance of university knowledge in the development of inventions and of the relative importance of different interaction channels; (iii) evaluation of the effectiveness, frequency and nature of university-industry interaction channels used to pursue different firm objectives; (iv) assessment of the economic impact of university knowledge.

Additional information on the firms for which inventors worked (number of employees, revenue, location of head office, number of different premises, year of foundation, sector, legal status, industry) was collected from the CERVED database of Italian companies' accounts and other public online sources. This information was available for 298 out of 363 firms in the sample (or 738 inventors); it was difficult to find information about non-public small/micro firms. We also collected the number of patents filed by the inventors' respective companies during the 1998 to 2005 period, from the Derwent Innovations Index. Information was gathered on inventors' patents. These data were available for all inventors. 23 inventors were removed from the database because, when the patent was filed, they were not employed in industry, but at a public institution (university, public research organization, government agency), which left us with 915 industry inventors for the analysis.

The mean age in the survey sample is 48.1, with most falling within the 41-50 cohort (36.7%); mean age is lower among women (41.6), who constitute 8.2% of the sample. Younger inventors are on average more educated, as 76.8% of under-40s have a tertiary degree (the sample average is 59%) and 5.6% have a PhD (sample average 3.8%). Inventors are characterized by low educational and career mobility: 79.5% completed their primary and secondary education in Piedmont and 31.5% have worked for only one organization throughout their career. 60.7% of the inventors have worked for less than five different organizations and only 7.8% have had more than five different employers. Inventor mobility is correlated with educational attainment: more educated inventors are more mobile.

After a first cleaning of the original dataset, due to missing observations, incomplete answers and missing information about the firms for which the inventors work, we end up with a full sample of 651 observations, which include both inventors who collaborated with the university and benefited from university knowledge and inventors who, on the contrary, did not claim to have received any substantial contribution from university knowledge.

The sample of 651 inventors who fully answered the set of questions that we need for our empirical analysis is not significantly different from the overall sample of 915 respondents. The mean age (*age*) is 48.5 and the share of men (*male*) is 92.7%. 58% of inventors hold a higher education degree or a Phd (*hedu*) and 8.7% have experience of working within a university (*workuni*, a dummy indicating whether the inventor has ever worked at a university). Each inventor was involved, on average, in 2.2 European Patent applications between 1998 and 2005 (*pat9805*), a variable that proxies an inventor's patenting experience. Table 1 presents the descriptive statistics for the sample of 651 inventors.

<< TABLE 1 ABOUT HERE>>

5. Empirical strategy

Inventors, being the source of the invention process, can clearly identify those inventions to which university research contributed. We aim to explain what are the factors that affect the value of inventions with an important contribution from academic knowledge, paying particular attention to the (i) ability of the inventor to exploit academic knowledge and (ii) a set of firm and industry characteristics. In order to do so we use the following linear model:

$$y_i = c + \sum_k \beta_k INV_{ik} + \sum_m \gamma_m FIRM_{im} + \sum_n \delta_n IND_{im} + v_i \qquad (1)$$

where y_i is a proxy for the value of inventor *i*'s invention which has benefited from the maximum contribution of university knowledge; *INV* denotes a set of variables capturing the ability of the inventor to exploit academic knowledge in order to generate valuable inventions (these relate to: (a) the type of academic knowledge the inventor uses to develop her inventions, (b) the inventor's absorptive capacity/competence, and (c) the organizational processes she sets up in order to access academic knowledge); *FIRM* and *IND* indicate a set of firm and industry level control variables and v_i is an idiosyncratic error term.

In order to estimate equation (1) we must avoid any selection bias. Only those inventors who said that they benefited from university research were able to evaluate the contribution of academic knowledge to the value of their inventions. Hence, we first need to control whether this subset of inventors is significantly different from the rest of the sample. Moreover some of the features influencing the value of contribution from academic knowledge are also likely to influence the probability to have a contribution from university research itself, so if we did not include a selection equation the effect of these variables would be overestimated.

5.1. Measuring the value of inventions: Dependent variables

In this paper we are interested in understanding the contribution of academic knowledge to the value of innovation developed by industrial inventors. We are not aiming to provide an exact monetary estimation of this contribution; the final value of an invention depends on many factors that might not be clearly available to inventors. R&D managers that have information about specific innovative products, such as in the case of the survey done by Mansfiled (Mansfield, 1991), should be surveyed to gather that information. However, R&D managers may not have access to the right information regarding the contribution of university research, information that instead is available to inventors. We therefore decided to collect information from inventors, who are very familiar with the process of knowledge creation and knowledge sourcing from universities, and develop specific measures of the contribution of academic knowledge based on the economic value of the invention (as perceived by the inventors) but not using absolute values that could be biased.

In the PIEMINV survey, inventors were asked to identify and provide specific information about two of their inventions: (a) the invention that had received the highest contribution from academic knowledge, and (b) the invention with the highest economic impact (whether these inventions had been patented or not). For each of these two inventions, respondents were asked to provide information about the monetary value of the invention (in thousand euro, at current prices)[1], as well as several other questions that have been used to construct our independent and control variables. 158 inventors (or 24.2% or our complete sample) answered these questions. In Table 2 we present the descriptive statistics for this subset of 158 inventors. Compared to the overall sample of 651 inventors, the share of inventors with a Masters degree or Phd (*hedu*) and the share of inventors who have experience of working within a university (*workuni*) are higher (respectively, 79% and 18.9%).

<< INSERT TABLE 2 ABOUT HERE>>

Since for an inventor it may be very difficult to estimate the exact value of one of his or her inventions, with some inventors possibly greatly overestimating such a value and others underestimating it, we did not use directly the reported economic value but we constructed two relative measures. First, we counted how many inventors stated that their invention with the highest academic knowledge contribution was also their invention with the highest economic impact. Figure (1) shows a graphical representation of our variable of interest (a dummy variable that we called *uniecon,* and is equal to 1 when the two inventions coincide): 48 out of the 158 respondents to this specific question (30.4%) stated that their invention that received the greatest contribution from academic knowledge was also their most valuable invention.[2] Almost one third of the inventors that indicated academic knowledge as important for their innovative process said that those inventions that had highest university contribution were also their most valuable ones, suggesting a non negligible role for academic knowledge in the process of value creation.

<< FIGURE 1 ABOUT HERE>>

As second measure we calculated the ratio between the value of the invention with the highest contribution from university knowledge and the value of the invention with the highest

[1] The question was modeled on the Patval questionnaire (see Gambardella, Harhoff and Verspagen, 2005). It was formulated as follows: "Suppose that, on the day in which the invention was completed (or, if the invention has been patented, on the day in which the patent was granted) a potential competitor had expressed an interested in purchasing it: what is the minimum price that the invention's owner would have asked for it?"

[2] When building the variable *uniecon* we had to eliminate inventors who had only one patent, since in that case the two inventions would coincide by definition.

economic impact; a variable we called *ratio* with values comprised between zero and one. Using a relative measure of invention value allows us to overcome the problem of lack of comparability of invention values across inventors, as it only requires us to assume that each inventor's evaluations of the two inventions are consistent. Moreover, by taking the ratio of the two inventions' estimated values, unit of measurement problems (common in this type of questions) are eliminated and we obtain a measure that, regardless all the subjective and heterogeneous measures used by the inventors, gives an indication of how valuable the invention with the highest contribution of academic knowledge was with respect to the most valuable invention in the inventors' portfolio.

The variables *uniecon* and *ratio* are our main dependent variables. As Table (3) shows, the variable *ratio* has fewer observations than the binary variable *uniecon*, since not all the inventors who identified the two inventions were able or willing to provide their specific monetary values. Their distributions are extremely skewed and display a large range of values, in line with the findings from the literature on patent value.

<< TABLE 3 ABOUT HERE>>

The relative measures of the contribution of academic research to the value of industrial inventions proposed in this paper try to overcome the principal limitations of previous survey-based measures. Focusing only on the inventions with the highest contribution of university research and assessing their value compared to the most valuable inventions clearly limits the validity of our measures to capturing the most important impact and it may not be representative of the whole spectrum of contribution of academic knowledge to all inventive activities of company inventors. However, previous literature has clearly shown that the value of patents is highly skewed with very few patents resulting in important innovations with high economic value and a large majority of patents ending up unused. Our measures should therefore be able to provide good insight about those inventive processes that result in important economic impact.

5.2. The selection equation

Our preferred selection variable (*select*) is a dummy that is equal to 1 if at least some of the inventor's inventions have received an important contribution from academic knowledge.[3] However in order to check for the robustness of our findings we also used the alternative selection variable *coll*, a dummy equal to 1 if the inventor states that s/he has direct experience of having collaborated with a university institution or with an individual university professor; this is the variable traditionally used when analyzing university industry relationships. We prefer the first selection variable (*select*) because we believe it is a better measure of the individual ability of the inventors to benefit from academic knowledge. Indeed in the selection equation we are interested in understanding the characteristics that allow inventors to exploit university knowledge successfully. Collaborations instead are not necessarily related to the inventor's ability, they are sometimes influenced by characteristics of the company in which inventors are employed (large companies collaborate more).

For these two selection variables we use a set of independent variables that capture the usual set of firm and inventor characteristics used in the literature that are likely to influence the probability that an inventor has collaborated with a university researcher in the development of her invention.

In the literature it is often found that larger, research-intensive firms are better able to benefit from academic research, thanks to their greater absorptive capacity (Arundel and Geuna, 2004). We have therefore considered the firm's size, using a set of dummies: *size1* indicates micro-companies, with less than 10 employees, and individual inventors; *size2* indicates small companies with between 10 and 49 employees; *size3* indicates medium firms with between 50 and 250 employees; *size4* indicates large firms with more than 250 employees; and *foreign* is a dummy that controls whether the company's ownership is not Italian. As Table 1 shows the majority (68%) of inventors work in large companies, while the remaining inventors are quite uniformly distributed among micro, small and medium firms. About 11% of the firms are foreign-owned.

Second, we also control for some inventor characteristics. Inventors who are more educated (*hedu* is a dummy that captures whether the inventor holds a bachelor, a master or a PhD

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[3] This variable was based on the inventors' answers to the following question: "*How many of your inventions have received an important contribution from academic knowledge? By "contribution" we mean any resource, idea, clarification, assessment provided (formally or informally) by a university, which has been instrumental in order to realize an invention*". The possible answers were: None / less than half / more than half / All. The *select* dummy is equal to 1 if at least "less than a half" was select by the respondents. To check whether our results are driven by our specific choice about the selection mechanism we also have experimented with a categorical variable (*ord_select*), built on the four categories of the questions obtaining similar results.

degree) and those who have experience of working at a university (*workuni*) may be more inclined to consult academic knowledge sources, and may be better equipped to understand academic literature and to communicate with university scientists. Also, they may have developed a network of contacts with university researchers. More productive inventors (*pat9805*) may be more experienced and also more likely to benefit from academic knowledge. We also control for age and gender (*age* and its square *age2* and *male*). Finally, we use several dummies which capture the most common technology class in the inventor's portfolio: electrical engineering and electronics (*electr*), process engineering (*proceng*), instruments (*instr*), chemicals (*chem*), pharmaceutical (*pharma*), mechanical engineering (*mech*), consumer goods (*consumer*). Compared with the firm's codes of economic activity, these variables capture more precisely the types of technologies in which the inventors are actually engaged, especially in the case of large multiproduct firms where the sectoral affiliation might be too generic.

5.3. Determinants of the contribution of academic knowledge to the value of inventions

The theoretical framework identified three main set of inventor-related factors that can affect the contribution of academic knowledge to the value of invention: a) the specific characteristics of the academic knowledge that is transferred, in particular the inventor's exploitation of basic scientific knowledge; b) the characteristics of the inventor involved, in particular her absorptive capacity; c) the way in which the process of exchange is organized, in particular the extent to which the organizational setup facilitates the transmission of tacit knowledge.

To capture the first factor, we use four variables describing the kind of academic knowledge that the inventor considered most important for the development of her inventions: scientific theorems and principles (*theories*), methodologies, techniques and instruments (*meth*), solutions to technological problems / support to prototyping (*applied*), information about other relevant sources of knowledge / about other organisations (*contact*). Our expectation is that knowledge transfer processes involving the transmission of more basic knowledge like theorems and scientific principles would favor the development of more novel inventions while those involving the transmission of more applied knowledge would be related to more incremental developments. Among our 158 respondents, university knowledge was mostly used in order to obtain information about other relevant sources of knowledge (*contact*, 61.3%) and in order to obtain solutions for technological problems (*applied*, 60.7%); theoretical knowledge (*theories*) was deemed important by 56.3% and methodologies, techniques and instruments (*meth*) by 51.2%.

To capture the second factor, the inventor's absorptive capacity, we use a variable capturing the inventor's experience: his or her patent productivity (*pat9805*) and age (*age, age2*).

Finally, we include a set of variables that describe the organization of the knowledge transfer process with the university. Research collaborations between university scientists and industry researchers, based on face-to-face interactions, favor the transmission of tacit knowledge to a greater extent than indirect exchanges based on, for example, the joint supervision of master and doctoral students, the sale and licensing of intellectual property, or the reading of publications. Direct collaborations can also favor the emergence of novelty by allowing a broader exploration of the search space and the integration of different competences: it is the opportunities for direct interactions provided by collaborations which open up possibilities for the emergence of unexpected outcomes and for the integration of different sources of knowledge. We hence include a variable (*collabo*) which indicates whether the development of the invention with the highest contribution of academic knowledge involved any form of contract-based collaboration with university researchers. Research collaborations can be governed by two main modes: institutional relationships and contractual personal collaboration (Bodas Freitas, Geuna, Rossi, 2013). We coded two variables that specify whether the research contract was directly signed by the researcher (*reser*) or a university organization (*inst*). Table 2 shows that 24% of inventions with the highest contribution from university knowledge resulted from a personal contractual collaboration with a single researcher and 28% from an institutional relationship.

We also use the same firm and industry controls used in the selection equation.

5.4 Econometric specification

Our strategy is to adopt an estimation procedure that includes estimating both a selection equation, which indicates whether inventors were able to benefit from university knowledge, and an intensity equation in which we will measure the specific effect of different variables on the relative economic value of inventions with academic knowledge contribution. The selection equation will hence be as follows:

$$SEL_i = \begin{cases} 1 & if \quad sel_i^* = z_i^{'}\gamma + e_i > c \\ 0 & if \quad sel_i^* = z_i^{'}\gamma + e_i \le c \end{cases} \qquad (2)$$

where *SEL* is a binary variable which equals 1 if an inventor declares to have benefited from university knowledge and *sel** is a latent variable which measures the general ability of an inventor to use the university as a source of knowledge. If such an ability exceeds a certain threshold level *c* then the inventor will claim that his/her invention do benefit from university activities. The value of inventions with university contribution *y*, which depends on the set of variables *x* that we have already mentioned in equation (1), will be observed only if SEL_i is equal to 1:

$$y_i = \begin{cases} y_i^* & if \quad SEL_i = 1 \\ 0 & if \quad SEL_i = 0 \end{cases} \quad \leftrightarrow \quad y_i = \begin{cases} y_i^* = x_i^{'}\beta + \varepsilon_i & if \quad SEL_i = 1 \\ 0 & if \quad SEL_i = 0 \end{cases} \qquad (3)$$

In our empirical analyses we will use two specifications of the model: one in which the dependent variable *y* is a dummy variable (0/1) and one in which the dependent variable is a continuous variable: in the first case we will estimate a probit model with sample selection, while in the second case we will estimate a Tobit Type II model (Anemiya, 1984). Our preferred selection variable (*select*) is a dummy that is equal to 1 if at least some of the inventor's inventions have received an important contribution from academic knowledge.

6. Results

In Table (4) we present the results of selection models using the two selection variables that we have identified in Section (5), in order to examine the characteristics of the inventors who were able to benefit from university knowledge or to actively collaborate with academic institutions. Column (1) present the results of a probit regression with the dependent variable *select*: it shows a positive and significant effect of higher education (*hedu*), of having spent at least one month working at the university (*workuni*), and of the number of patent applications at the EPO in the period 1998-2005 (*pat9805*). We also include technology class dummies: the results indicate that inventors specialized in Chemicals, Pharmaceutical and Electrical Engineering, as well as those that patent in technologies like optics and technologies for control and medical engineering (*Instruments*) benefit more from university knowledge with respect to the reference technology class, which is Process Engineering. The firm-size dummies instead are not significant, suggesting that for what concerns the capability to benefit from academic knowledge, there aren't substantial differences among small and large companies.

<< TABLE 4 ABOUT HERE>>

In Column (2) we use as a dependent variable the probability of having collaborated with the university (*coll*). Again we find that inventors that are educated and who have worked for some time at the university are more likely to collaborate with the university, as well as those inventors with a higher number of patent applications at the EPO (*pat9805*). Also technological dummies show the same signs of the coefficients of the previous specifications. The main difference between Columns (1) and (2) is in the coefficients of the firm-size dummies. When the probability to collaborate is the dependent variable large firms have a positive and significant coefficient. This results is in line with the literature on university-industry interactions (Arora and Gambardella, 1994; Dornbrusch and Neuhäusler, 2013).

Given that the results are quite similar across specifications we chose to use *select* as our preferred selection variable, since we believe it captures more precisely the capacity of inventors to benefit from university knowledge.

<< TABLE 5 AND 6 ABOUT HERE>>

Table (5) present the results for the value equation (1), with the correction for the selection bias explained in equation (3). We start with the dummy variable *uniecon* as dependent variable, and hence we adopt a probit model that accounts for selection bias. In columns (1) and (2) we present the selection equation, which is the same as the one showed in Table (4), while in columns (3) and (4) are reported the coefficients and the marginal effects relative to the value equation. The results in columns (3) and (4) show a positive and significant (at the 10% level) coefficient of *theory*, the variable that indicates that inventors use university knowledge in order to have access to scientific theorems and principles. This is not the case for other types of knowledge that university can provide, such as information and contacts about other relevant sources of knowledge or about other organizations (*contact*), methodologies, techniques and instruments (*meth*) and solutions to technological problems, or support to prototyping (*applied*).

The coefficient of the *collabo* variable which indicates whether the invention involved an institutional or personal collaboration with a university researcher is instead positive but not significant. In columns (5) and (6) we further distinguish between personal contractual collaborations with a university researcher (*reser*) and institutional collaboration with a university organization (*inst*): the results show that the positive coefficient of the *collabo* variable in columns (2) and (3) was driven mainly by collaborations with individual researchers, which indeed are positive and significant at the 10% level, while institutional collaborations are still positive but not significantly different from zero. Also in column (5) the coefficient of *theories* is positive and significant at the 5% level. The age variable with its squared terms indicates a U-shaped relationship between age and the probability to have an economically valuable invention with academic contribution: more specifically, given the coefficients of -0.059 of age and of 0.001 of age-squared we find that after 29.5 years the effect of age starts to be positive, and increasingly so as the age increase. The other variables that we use as controls are not significant, including the firm-size dummies, indicating that these are factors that do not have strong effects on the value of inventions with an academic contribution. The rho coefficient is small and not significant, meaning that when we use the dummy variable *uniecon* as dependent variable we do not face serious selection bias problems.

In Table (6) we present the results of a Tobit Type II model (Anemyia, 1984) where the *ratio* variable is the dependent variable in the value equation. In column (3) we find that *theories* is still strongly positive and significant (at the 5% level), while the *collabo* variable is again positive but not significant. In column (4) again we distinguish among the two different types of collaborations and, consistently with the previous results, we find that only personal contractual collaborations with individual researchers (*reser*) have a positive and significant effect on the relative value of inventions with the highest contribution from university knowledge, while institutional collaborations (*inst*) are negative but not significant. Here we notice that the *rho* coefficient is always positive and significant, meaning that the decision to include a selection equation was appropriate.

<< TABLE 7 ABOUT HERE>>

6.1. Robustness checks

Another problem with the estimation of equation (1), beyond the already mentioned selection bias, is that the unobserved and idiosyncratic quality of an invention might be correlated with the specific channel of interaction chosen by an inventor to develop it and of course with its economic value. This would result in a typical problem of omitted variable bias, which would produce an upward bias in the estimates of our coefficients of interest (in particular we are concerned about the variables measuring the collaboration with the university).

A way to overcome this problem is to provide a measure of the "potential value" of the invention with the highest contribution from university knowledge: in the PIEMINV survey inventors were asked a set of question that provide a tentative and indirect measure of this potential value. Specifically we define a dummy variable equal to 1 if the invention opened new lines of research in the company of the inventor (*newline*), another dummy equal to 1 if the invention had the highest number of potential uses (*potential*) and a dummy equal to 1 if the invention was at an early stage of development (*early*). These measures allow us to control for the potential value of the invention and their inclusion should solve most of the problems related with the presence of unobserved heterogeneity concerning the quality of inventions.

The three additional variables (newline, *potential* and *early*) are introduced in the value equation, both when the dependent variable is *uniecon* and when it is the ratio of the two inventions' value (*ratio*). We estimate our models checking for the usual selection bias problems and hence we include also the selection equation. The results are shown in Table (7). In columns (3) and (4) we introduce the three variables with *uniecon* as the dependent variable. None of the variables shows significant coefficients. The coefficient of newline is large and positive, but not significant. The coefficient of *potential* is still positive but relatively smaller, while *early* has a negative and not significant coefficient. We find that including these variables does not affect the coefficients of the main variables of interest, *theories* and *reser*: on the contrary the coefficient of *theories* becomes even slightly larger and more significant. When we include the three variables in the equation of ratio in column (7), we find that potential and early are not significant, while newline is positive and significant at the 1% percent level, showing that in the restricted subsample of inventors who answered the question on the specific value of their inventions the possibility to open new research areas is positively associated with the value of invention with high university contribution. Again the coefficient of *theory* is left unaffected by the inclusion of these additional variables as well as the coefficient of *reser*. Especially in the case of personal contractual collaborations with university researcher (*reser*) these last results reassure us about the fact that the positive coefficient found in Tables (5) and (6) is not due to a positive correlation between these variables and the unobserved heterogeneity in the quality of inventions.

7. Conclusions

In the last 20 years, great emphasis has been put on the role of academia as a fundamental driver of technological change and of the level of competitiveness of regional and national economic systems. The underlying assumption is that academic knowledge is a fundamental component of the inventive process within private firms, and that companies that have access to it will be able to introduce more valuable innovations and increase their economic performance. However few studies have been able to track the contribution of university knowledge to specific inventions and, most importantly, none of them has assessed the extent to which the contribution of university knowledge increases the economic value of an invention.

In this paper we address both issues for a sample of non-academic inventors resident in the Piedmont region in Italy. We put forward three main hypotheses. The first is that, since more radical innovations face less potential competition on the final product market and are thus likely to provide higher economic returns, situations in which universities contribute basic theoretical advances, rather than applied incremental knowledge, should lead to more "radically new" inventions and hence to more profitable ones. The second hypothesis examines the impact of inventor absorptive capacity on her ability to transform and integrate academic knowledge to produce valuable inventions. The third hypothesis is that the possibility to successfully implement academic knowledge for commercial purpose should be enhanced when the knowledge transfer channel allows for the transmission of the academic researchers' tacit knowledge. We hence expect that the successful implementation of inventions that rely upon tacit knowledge can be better achieved through direct collaboration with academic researchers.

Our results show that the transfer from university researchers of theoretical academic knowledge, rather than solutions to more technical and specified problems, leads to more valuable inventions. Knowledge transfer processes involving a direct collaboration between the inventor and the university (and particularly individual researchers) are positively associated with the relative value of inventions. Furthermore our results show that inventors with greater cognitive proximity to the university, that is with a higher level of education, or with an experience of working at the university for a limited time period and with high patenting productivity are more likely to benefit from university knowledge (and more likely to interact with university researchers). However, these characteristics are not correlated to more valuable inventions, only the seniority of the inventor is associated to on higher relative value.

These results highlight two policy-relevant issues. The first is that among the many possible contributions provided by the university to the activity of inventors, those that involve the transfer of basic principles and theories are the most effective in increasing the economic value of inventions. Hence, the best contributions from academic knowledge are not applied in nature: inventors benefit from the more theoretical academic knowledge in which the university is specialized. The key finding of this paper challenges the rationale for policy actions which, in the last twenty or so years, have tried to stir the university toward producing more applied knowledge supposedly because more useful to companies. The second finding is that although indirect types of access to university knowledge (such as the participation to conferences, or the reading of academic papers) are useful and frequently used by company inventors, and as such should be supported by public funding, only the direct collaboration between inventors and university researcher lead to the development of inventions with a high economic value. Company inventors needsto interact directly with university researchers to appropriate and transform codified and tacit academic knowledge, and to most successfully integrate it in their knowledge creation processes, resulting in more valuable inventions.

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Figure 1. Construction of the dependent variable *uniecon*

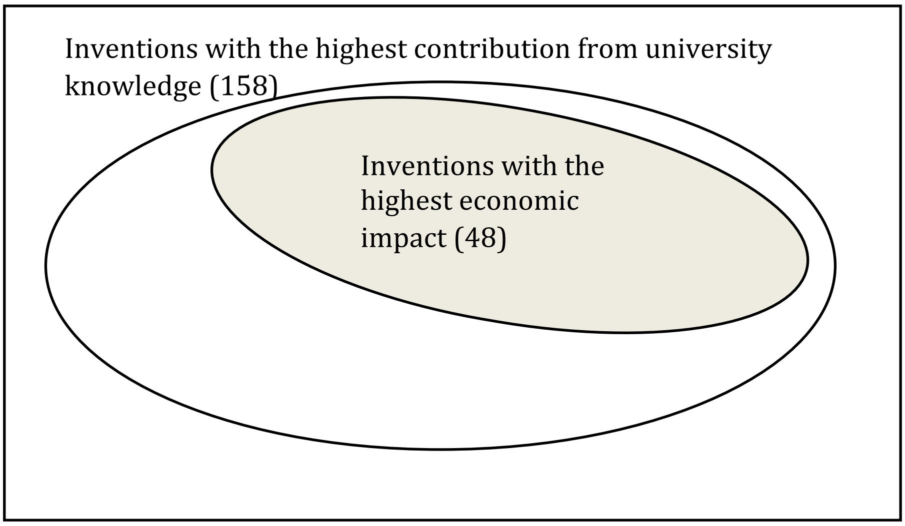

Table 1. Descriptive statistics. All inventors

Variable	Obs	Mean	Std. Dev.	Min	Max
select	651	0.24	0.43	0	1
coll	651	0.45	0.49	0	1
male	651	0.93	0.26	0	1
age	651	48.45	9.90	30	88
hedu	651	0.58	0.49	0	1
workuni	651	0.09	0.28	0	1
pat9805	651	2.21	2.51	0	24
Mechanical Engineering	651	0.37	0.48	0	1
Electrical engineering	651	0.25	0.43	0	1
Process Engineering	651	0.13	0.33	0	1
Instruments	651	0.10	0.30	0	1
Chemicals	651	0.06	0.24	0	1
Consumer goods	651	0.07	0.26	0	1
Pharmaceuticals	651	0.02	0.12	0	1
micro companies & individual inventors	651	0.10	0.31	0	1
size: 10-49 employees	651	0.08	0.27	0	1
size: 50-250 employees	651	0.13	0.34	0	1
size: >250 employees	651	0.68	0.47	0	1
foreign	651	0.11	0.32	0	1

Table 2. Descriptive statistics, restricted sample (*select*)

Variable	Obs	Mean	Std. Dev.	Min	Max
uniecon	158	0.30	0.46	0	1
collabo	158	0.49	0.50	0	1
reser	158	0.24	0.43	0	1
inst	158	0.28	0.45	0	1
theories	158	0.56	0.50	0	1
meth	158	0.51	0.50	0	1
applied	158	0.61	0.49	0	1
contact	158	0.61	0.49	0	1
male	158	0.91	0.29	0	1
age	158	48.20	10.40	31	88
hedu	158	0.79	0.41	0	1
pat9805	158	2.67	3.25	0	24
Electrical engineering	158	0.29	0.46	0	1
Instruments	158	0.15	0.36	0	1
Chemicals	158	0.10	0.30	0	1
Pharmaceuticals	158	0.03	0.18	0	1
Mechanical Engineering	158	0.31	0.46	0	1
Consumer goods	158	0.04	0.19	0	1
Process Engineering	158	0.08	0.27	0	1
micro companies & individual inventors	158	0.09	0.29	0	1
size: 10-49 employees	158	0.07	0.26	0	1
size: 50-250 employees	158	0.09	0.29	0	1
size: >250 employees	158	0.75	0.44	0	1
foreign	158	0.14	0.35	0	1

Table 3. Distributions of variables capturing invention value

	Observations	Mean	St. deviation	Maximum	Skewness	Kurtosis
uniecon	158	0.3	0.46	1	0.85	1.73
ratio	86	0.55	0.43	1	-0.11	1.27
Economic value of inventions with highest contribution from university knowledge	86	2,186,175	7,783,126	50,000,000	5.52	33.96
Economic value of inventions with highest economic impact	86	5,951,474	24,800,000	200,000,000	6.501	48.008

Table 4. Selection equations

Variables	(1) *select*	(2) *coll*
hedu	0.172***	0.319***
	(0.035)	(0.042)
pat9805	0.013**	0.029***
	(0.007)	(0.009)
workuni	0.233***	0.247***
	(0.074)	(0.078)
male	0.052	-0.061
	(0.055)	(0.080)
age	-0.020	0.033*
	(0.014)	(0.019)
age_squared	0.000	-0.000
	(0.000)	(0.000)
Firm-size dummies		
10-49 employees	-0.057	0.164
	(0.068)	(0.107)
50-250 employees	-0.062	0.103
	(0.065)	(0.097)
>250 employees	-0.006	0.232***
	(0.058)	(0.074)
foreign	0.007	0.000
	(0.054)	(0.068)
Electrical engineering	0.124*	0.091
	(0.073)	(0.078)
Instruments	0.252***	0.231***
	(0.093)	(0.084)
Chemicals	0.191*	0.287***
	(0.104)	(0.094)
Pharmaceuticals	0.343**	0.266*
	(0.170)	(0.157)
Mechanical Engineering	0.088	0.048
	(0.063)	(0.072)
Consumer goods	-0.028	0.012
	(0.088)	(0.105)
Observations	651	651
pseudo-Rsquared	0.112	0.164
Log-likelihood	-319.3	-375.0

Reported coefficients are marginal effects (at the sample means) from a probit. The reference category for the size dummies are micro-companies and individual inventors. Process Engineering is the reference category for technological dummies. Standard errors robust to heteroskedasticity. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5. Probit on uniecon with selection equation

	(1)	(2)	(3)	(4)	(5)	(6)
	selection equation		value equation		value equation	
	coeff.	*marg. effects*	*coeff.*	*marg. effects*	*coeff.*	*marg. effects*
theories			0.487*	0.167*	0.524**	0.177*
			(0.256)	(0.098)	(0.260)	(0.100)
meth			0.028	0.010	0.032	0.011
			(0.227)	(0.080)	(0.228)	(0.079)
applied			-0.292	-0.104	-0.279	-0.098
			(0.262)	(0.098)	(0.265)	(0.097)
contact			0.192	0.067	0.189	0.065
			(0.258)	(0.091)	(0.258)	(0.090)
collabo			0.247	0.087		
			(0.228)	(0.081)		
reser					0.459*	0.167*
					(0.262)	(0.102)
inst					0.043	0.015
					(0.259)	(0.091)
age	-0.068	-0.020	-0.181**	-0.063**	-0.169**	-0.059**
	(0.049)	(0.014)	(0.090)	(0.030)	(0.086)	(0.028)
age2	0.001	0.000	0.002**	0.001**	0.002**	0.001**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
pat9805	0.046**	0.013**	0.025	0.009	0.025	0.009
	(0.023)	(0.007)	(0.041)	(0.014)	(0.039)	(0.013)
male	0.188	0.052	-0.301	-0.111	-0.391	-0.145
	(0.217)	(0.055)	(0.420)	(0.165)	(0.424)	(0.169)
Firm-size dummies						
10-49 employees	-0.212	-0.057	0.052	0.019	0.010	0.003
	(0.272)	(0.068)	(0.574)	(0.207)	(0.573)	(0.200)
50-250 employees	-0.230	-0.062	0.442	0.166	0.377	0.140
	(0.258)	(0.065)	(0.544)	(0.217)	(0.550)	(0.216)
>250 employees	-0.019	-0.006	-0.032	-0.011	-0.057	-0.020
	(0.198)	(0.058)	(0.420)	(0.149)	(0.426)	(0.150)
foreign	0.022	0.007				
	(0.182)	(0.054)				
hedu	0.613***	0.172***				
	(0.138)	(0.035)				
workuni	0.678***	0.233***				
	(0.202)	(0.074)				
Constant	0.076		3.788*		3.503*	
	(1.231)		(2.190)		(2.109)	
Observations	651	651	651	651	651	651
Uncensored obs			158	158	158	158
athanrho			-0.047	-0.047	-0.033	-0.033
			(0.426)	(0.426)	(0.407)	(0.407)
Log-likelihood	-407.0		-407.0		-406.1	

The equations are estimated with a probit model with sample selection. Coefficients and marginal effects (at the sample mean) are displayed. The reference category for the size dummies are micro-companies and individual inventors. In column (1) and (2) the dependent variable is select, in columns (3) to (6) the dependent variable is uniecon. All models include OST7-based technological dummies. Standard errors are robust to heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1

Table 6. Tobit Type II on the ratio of the two values

	(1)	(2)	(3)	(4)
	selection equation		value equation	
	coeff.	*marg. Effects*	*coeff.*	*coeff.*
theories			0.220**	0.231***
			(0.094)	(0.088)
meth			0.123	0.152
			(0.109)	(0.099)
applied			0.049	0.047
			(0.112)	(0.112)
contact			0.064	0.042
			(0.107)	(0.105)
collabo			0.049	
			(0.093)	
reser				0.177*
				(0.093)
inst				-0.128
				(0.106)
age	-0.054	-0.011	-0.040	-0.037
	(0.063)	(0.013)	(0.035)	(0.035)
age2	0.001	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
pat9805	0.029	0.006	0.000	-0.012
	(0.029)	(0.006)	(0.017)	(0.018)
male	0.640**	0.094***	0.119	0.094
	(0.310)	(0.030)	(0.324)	(0.262)
Firm-size dummies				
10-49 employees	-0.207	-0.038	-0.071	-0.130
	(0.279)	(0.047)	(0.165)	(0.158)
50-250 employees	-0.279	-0.052	-0.245	-0.300
	(0.280)	(0.045)	(0.192)	(0.186)
>250 employees	-0.349*	-0.079	-0.243*	-0.269**
	(0.210)	(0.050)	(0.133)	(0.129)
foreign	0.178	0.052		
	(0.209)	(0.052)		
hedu	0.614***	0.115***		
	(0.148)	(0.030)		
workuni	0.742***	0.217***		
	(0.222)	(0.076)		
Constant	-0.749		1.072	1.095
	(1.584)		(0.977)	(0.908)
Observations	580	580	580	580
uncensored obs			86	86
athanrho			0.690**	0.605**
			(0.341)	(0.272)
Log-likelihood			-253.0	-250.0

The equations are estimated with a Tobit Type II model (Anemyia, 1984) with sample selection. The reference category for the size dummies are micro companies and individual inventors. In column (1) and (2) the dependent variable is *select* and coefficients and marginal effects (at the sample mean) are displayed. In columns (3) and (4) the dependent variable is *ratio.* All models include OST7-based technological dummies. Standard errors are robust to heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1

Table 7. Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	selection equation		uniecon		selection equation		ratio
VARIABLES	*coeff.*	*marg. effects*	*coeff.*	*marg. effects*	*coeff.*	*marg. effects*	*coeff.*
theories			0.585**	0.208**			0.276***
			(0.268)	(0.102)			(0.082)
meth			-0.013	-0.005			0.124
			(0.230)	(0.084)			(0.104)
applied			-0.258	-0.095			0.070
			(0.265)	(0.100)			(0.105)
contact			0.220	0.079			-0.010
			(0.264)	(0.097)			(0.093)
reser			0.491*	0.186*			0.151*
			(0.270)	(0.105)			(0.090)
inst			0.050	0.018			-0.161*
			(0.267)	(0.098)			(0.094)
newline			0.284	0.104			0.272***
			(0.271)	(0.103)			(0.097)
early			-0.320	-0.117			0.043
			(0.259)	(0.100)			(0.098)
poten			0.048	0.017			0.040
			(0.254)	(0.093)			(0.090)
age	-0.068	-0.020	-0.172*	-0.063*	-0.052	-0.011	-0.047
	(0.049)	(0.014)	(0.093)	(0.033)	(0.063)	(0.013)	(0.033)
age2	0.001	0.000	0.002**	0.001**	0.001	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
pat9805	0.046**	0.013**	0.009	0.003	0.030	0.006	-0.027
	(0.023)	(0.007)	(0.039)	(0.014)	(0.029)	(0.006)	(0.017)
male	0.188	0.052	-0.369	-0.141	0.641**	0.094***	0.021
	(0.216)	(0.055)	(0.434)	(0.172)	(0.310)	(0.030)	(0.218)
Firm-size dummies							
10-49 employees	-0.214	-0.057	-0.160	-0.056	-0.201	-0.038	-0.203
	(0.272)	(0.068)	(0.584)	(0.199)	(0.280)	(0.047)	(0.138)
50-250 employees	-0.232	-0.062	0.331	0.126	-0.279	-0.052	-0.282
	(0.258)	(0.065)	(0.568)	(0.224)	(0.281)	(0.045)	(0.180)
>250 employees	-0.019	-0.006	-0.109	-0.040	-0.351*	-0.079	-0.310***
	(0.198)	(0.058)	(0.434)	(0.162)	(0.211)	(0.050)	(0.119)
foreign	0.017	0.007			0.235	0.052	
	(0.184)	(0.054)			(0.205)	(0.052)	
hedu	0.611***	0.172***			0.583***	0.115***	
	(0.137)	(0.035)			(0.154)	(0.030)	
workuni	0.683***	0.233***			0.763***	0.217***	
	(0.198)	(0.074)			(0.218)	(0.076)	
Constant	0.082		3.612		-0.779		1.322
	(1.230)		(2.300)		(1.595)		(0.822)
Observations	651	651	651	651	580	580	580
Uncensored obs			158	158			86
athanrho			-0.129	-0.129			0.466
			(0.403)	(0.403)			(0.288)
Log-likelihood			-404.7	-404.7			-245.9

Equations in columns (1) to (4) are estimated with a Probit model with sample selection. Equations in columns (5) to (7) are estimated with a Tobit Type II model (Anemyia, 1984) with sample selection. Coefficients and marginal effects (at the sample mean) are displayed. The reference category for the size dummies are micro companies and individual inventors. In the selection equations the dependent variable is select. All models include OST7-based technological dummies. Standard errors are robust to heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1