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Dipartimento Economia e Statistica Cognetti de Martiis

Working Paper Series

22/14

THE CONTRIBUTION OF ACADEMIC KNOWLEDGE TO THE VALUE OF INDUSTRY INVENTIONS: MICRO LEVEL EVIDENCE FROM PATENT INVENTORS

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UNIVERSITÀ DEGLI STUDI DI TORINO

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

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Work in progress, comments most welcome. V10 - 21/7/2014

Acknowledgments
The authors are grateful to Jenny Kuan, Pai-Ling Yin and Arvids Ziedonis for comments and suggestions. Particular thanks go to Francesco Lissoni for access to the EP-INV database produced by CRIOS-Bocconi. We thank Guido Romano and Andrea Gavosto for access to CERVED data. Thanks are due to Paolo Checchelli for his contribution to creation of the PIEMINV database. The paper has benefited from comments and suggestions received during the following seminar and conference presentations: EPIP conference, Paris, September 2013, SIEPI Conference, Naples, February 2014, Seminar at the Department of Economics, University of Trieste, March 2014, DRUID Conference, June 2014. We are grateful for financial support from the IAMAT Project coordinated by Fondazione Rosselli, from the European Union (FP7) Project "An Observatorium for Science in Society based in Social Models – SISOB" Contract no.: FP7 266588 and the Collegio Carlo Alberto Project "Researcher Mobility and Scientific Performance".

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Abstract

There is little evidence on the specific characteristics of the process of university-industry knowledge transfer leading to the generation of valuable inventions. Using the results of an original survey of industry inventors of European patents, resident in the Italian region of Piedmont, we analyze what determines the value of inventions that have benefited from academic knowledge. We find that inventors with greater cognitive proximity to the university and higher patenting output are more likely to interact with universities and to benefit from university knowledge. After controlling for the characteristics of firms and technologies, we find that it is the transfer of theoretical academic knowledge rather than solutions to more technical and specified problems that leads to more valuable inventions. We found some evidence that knowledge transfer processes involving direct personal collaboration between the company inventor and the university researcher (which are characterized by higher trust as a result of social network embeddedness) are conducive to relatively higher value inventions.

Key words: Academic knowledge, university-industry knowledge transfer, invention value, inventor survey, patent value, collaborations

JEL codes: O31 - Innovation and Invention: Processes and Incentives; O32 - Management of Technological Innovation and R&D; O34 - Intellectual Property Rights.

1. Introduction

Since the 1990s in particular, a great deal of evidence has emerged showing that the transfer of academic knowledge to industry leads to economically valuable outcomes. Several macroeconomic studies have estimated the elasticity of technological progress, measured in terms of variations in total factor productivity (TFP), to investment in public research (Guellec and van Pottlesberghe de la Potterie (2002), or the impact of academic research on TFP (Adams, 1990) and found positive and significant values. Other works investigated the impact of expenditure on academic research, on the innovation performance (in terms of research expenditure, patents produced, or new products announced) of firms localized in the same region and found 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 which, in the absence of available university research results, would have been developed much later or not at all (Mansfield, 1991, 1998). Finally, several studies have focused on how and why academic knowledge contributes to firm innovation, exploring the direct links between firms' innovation performance and their reliance on scientific research (Fleming and Sorenson, 2004; Gittelman, 2005). However, much of this research, to capture the use of academic knowledge by firms, used indirect proxies such as patent citations to the scientific literature, employment of researchers previously affiliated to scientific institutions, or co-authorship of publications with academic scientists (Cockburn and Henderson, 1998; Zucker et al., 2002; Cassiman et al., 2008, 2012). Very little is known about the specific processes through which academic research increases the productivity of business innovation.

An 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. Since the mid 1990s, much research has focused on the determinants of the value of patented inventions (see reviews in Reitzig, 2003, Sapsalis and van Pottlesberghe de la Potterie, 2003, and Gambardella et al., 2008). However, there is very little evidence on the contribution of academic knowledge to their value. Some studies explored the contribution of academic knowledge to the quality of patents, measured by number of forward citations, but the contribution of academic knowledge to the direct economic value of inventions remains largely unexplored.

In this paper we investigate the conditions under which reliance on academic knowledge in the invention process, contributes to the development of more valuable inventions. First, we introduce a new measure of patent value based on the inventor's estimate of the economic value of an invention that has benefited from the contribution of academic knowledge, in relation to the most valuable invention in the inventor's portfolio. This proxy for the (relative) value of a patent is built on the responses to a survey of patent inventors; it does not suffer from the problems traditionally associated with inventors' estimations since it only requires the inventors to know the relative ranking of the value of their patents. Second, we shed light on the specific processes through which academic research contributes to invention value. Most studies assume that this occurs through the exploitation of research findings (often captured by indirect proxies such as patent citations to the scientific literature); here, our aim is to test directly what type of academic knowledge and what organizational set up of university-firm interactions lead to more valuable inventions. Based on the results in the literature we control for individual and firm characteristics that might affect the value of an invention.

The study relies on an original survey (PIEMINV survey - Cecchelli et al., 2012) of industry inventors residing in the Italian region of Piedmont, one of the most economically prosperous regions of Italy. According to the latest Regional Innovation Scoreboard (EC, 2014), Piedmont is the only Italian region that can be described as an "Innovation follower", with scientific and technological performance close to the average for 22 EU member countries, for most indicators (and higher than the average for innovation by small and medium sized enterprises - SMEs). Inventors were asked a range of questions on their interactions with academic research. They were asked to estimate the monetary value of the invention with the highest economic impact, and the invention that benefited most from the contribution of academic knowledge. These questions avoid the problem of subjectivity in the quantification of invention value since the responses allow us to calculate the value of the invention that benefited most from academic knowledge in relation to the inventor's most valuable invention.

Checking a variety of model specifications and controlling for selection bias and endogeneity, we find that the transfer of theoretical academic knowledge has a significant positive impact on the relative value of the invention, compared to the transfer of technological knowledge. In relation to the knowledge transfer process, those involving a personal contractual collaboration (private contract with an individual researcher) are correlated to relatively more valuable inventions (after instrumenting for the social network at the basis of the selection of personal contracts) than those involving an institutional collaboration (contract signed with the university). Inventors with greater cognitive proximity to the university (more educated, with experience of working in a university) and with greater patenting experience, have higher absorptive capacity and are more likely to collaborate with a university and use academic knowledge; however, their absorptive capacity is not correlated to the relative value of inventions that rely on academic knowledge. Finally, firm characteristics also are relevant: technological capabilities are positively related to the invention's value, and especially for micro firms the contribution of academic knowledge enables higher-value inventions, which suggests that large firms are able independently to produce more valuable inventions compared to those developed with academic knowledge because large firms invest more in internal invention activities.

The paper is structured as follows. Section 2 provides a brief review of the literature on the economic contribution of academic research, focusing particularly 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 individual and firm characteristics. In Section 4 we discuss the data and in Section 5 we describe our empirical strategy. Section 6 presents and interprets the empirical results and Section 7 provides some conclusions and implications for policy.

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

There is a wealth of evidence suggesting that academic knowledge enhances the innovation process in industry. The nature and extent of these contributions have been explored from several perspectives, using macroeconomic data at national or regional level, and firm-level data obtained from ad-hoc surveys or patent and publications databases. We briefly discuss the literature building upon firm-level evidence, 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 which showed that 11% of the new products and 9% of the new processes introduced by these firms over a ten-year period would either not have been developed without academic research, or would have been developed with substantial delay. In a later study, Mansfield (1998) found that the importance of academic research for industrial innovation processes had increased, and that the average time lag between publication of research results and their commercial exploitation was much shortened. Subsequent studies provided evidence that firms' collaboration or interaction with universities increased their innovation performance, measured in terms of investment in research and development (R&D) (Adams et al., 2003), innovation productivity (Zucker et al., 2002; Cassiman et al., 2012) and sales (Belderbos et al., 2004) .

The channels of interaction conducive to such improved performance vary. Based on 62 case studies of firms in the medical devices industry, MacPherson (2002) found that innovative manufacturers interacted with the academic sector more closely than their less innovative counterparts, and that formal and informal linkages were equally important. A quantitative study by Grimpe and Hussinger (2013) of 2,092 German firms similarly found that firms' innovation performance increased with formal and informal relations with universities compared to only one type of interaction. In addition to direct interactions with academic scientists, employment links also act as important conduits for academic knowledge to increase industry innovation: Ejsing et al. (2013) used panel employment data at firm level and found that newly hired former university researchers contributed more to innovative activity than newly hired recent graduates or joiners from other firms.

A substantial body of work has tried to assess the influence of scientific knowledge on the *quality* of industry patents - measured generally in terms of number of forward citations to the patent over time. A patent is considered more valuable if cited by a large number of other patents since this indicates its contribution to the development of many other inventions (Lerner, 1994; Hall et al., 2007). Several studies have also assessed the presence of links to scientific knowledge based on the inclusion in a patent of backward citations to the scientific literature. Narin et al. (1997) showed that citations in US patents to scientific papers generally grew rapidly during the 1980s and the 1990s, although patterns varied across technological fields (Callaert et al., 2006). In a study of over 16,000 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. Fleming and Sorenson argued that when firms tried to develop more complex new knowledge by recombining many knowledge sources, the existing scientific knowledge and methods served as a "map" which helped them to structure a more systematic search process. Cassiman et al. (2008) analyzed 1,186 European patents granted to 79 Flemish firms in 1995-2001 and found that patents citing the scientific literature tended to generate forward citations in a broader range of technological fields, indicating that scientific knowledge contributed to development of inventions with wider applicability. However, Cassiman and colleagues reported that citations to the scientific literature did not increase the number of forward citations per se, similar to the result in Reitzig (2003). These contradictory findings for the importance of citations to scientific papers for patent quality might depend on the fact that citations to scientific papers are not a reliable measure of a technology's dependence on science. Based on a survey of Dutch industry-based inventors of international patents, Tijssen (2002) found that around 20% of these patents depended on scientific knowledge but less than half included citations to the scientific literature. Citations to scientific papers may be an indication of the general background knowledge involved, but may not be critical for the development of the technology.

To investigate the link between academic knowledge and patent quality, some studies exploited ad-hoc surveys, or information on patent ownership and invention. Scandura (2013) found that the number and quality (measured in terms of forward citations) of the patents invented by a sample of industry inventors in various European countries increased if the inventor drew knowledge from both scientific and "market" (e.g. clients and customers, direct competitors, or suppliers) sources rather than only one of these sources. Gittelman (2005) found that patents whose development involved scientists with previous experience of working in a public lab before joining a biotechnology firm, received more citations than other patents. Cassiman et al.'s (2012) study suggested that patents whose inventors had links with a scientific institution were more valuable, particularly if they were assigned to a company that collaborated with the scientific institution. These findings emphasize the role of "boundary crossing" inventors who span the divide between academia and industry, and the further importance of working in a company that is supportive of interactions with scientific institutions.

An argument for why patents that exploit links with academia are more valuable may be 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 granted to public research institutions (considered 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 tended to be incremental and less valuable.

The above works, like many others that 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; they simply measured whether there was a link with scientific or academic[1] knowledge or not, and whether this link affected the value of the patent. In the present study, we try to identify what features of academic knowledge, among other factors, affect the value of an invention relative to the most valuable invention in their inventor's portfolio. Our survey data allow us to provide detailed insight into the specific contribution of academic knowledge by distinguishing among the types of academic knowledge used by inventors for the development of their inventions, considering a) theoretical knowledge, b) methodologies, instruments, prototypes, c) solutions to technological problems, and d) information about other potential sources of knowledge.

3. How does academic knowledge contribute to the value of industry inventions?

We study the main determinants of the relative value of industry inventions that have benefited from the contribution of academic knowledge (e.g. through the inventor's collaboration with university researchers or her access to open academic knowledge). We expect that the capacity to translate academic knowledge into more valuable innovations by integrating it with the firm's internal knowledge will depend mainly on: i) the specific characteristics of the academic knowledge that is transferred, ii) the organization of the process of knowledge transfer, and iii) the characteristics of the inventor. In line with the literature, we expect also that iv) firm and industry specificities will be relevant.

i) Academic knowledge characteristics

It has been argued that theoretical scientific knowledge, compared to more applied technological knowledge, increases the efficiency of private research by contributing to the development of inventions that are more likely to constitute radical breakthroughs from existing knowledge (Carpenter et al., 1980). In turn, radical inventions are usually more valuable than incremental inventions since they are likely to find application in a broad range of technological domains, and hence can be exploited commercially in a variety of fields (Reitzig, 2003). Moreover, radical innovations face less potential competition in the final product market (Sapsalis and van Pottlesberghe de la Potterie, 2003). At the same time, scientific knowledge helps to guide inventors through the technological landscape and to find

[1] Only very infrequently was the author of a non-patent literature citation identified as strictly academic (e.g. Malo and Geuna, 2000).

more useful combinations of previously unrelated knowledge domains, and reduces efforts expended on fruitless research (Fleming and Sorenson, 2004). Firms blocked by their technological developments or locked into obsolete technologies can benefit from more general knowledge to resolve their practical and specific technological problems (Cassiman et al., 2012).

Universities enjoy competitive advantage in the production of theoretical knowledge (and methods) as opposed to more applied knowledge. If their contribution concerns precisely the type of knowledge that they specialize in, they are more likely to support the development of a valuable invention. If the universities' involvement concerns specific knowledge about technologies and applied processes, their competitive advantage vis a vis other providers may disappear and they may not add much to the invention's value. Therefore, we expect invention processes that exploit more theoretical scientific knowledge to generate more valuable inventions.

ii) Organization of the knowledge transfer process

The possibility to successfully exploit academic knowledge for commercial purposes should be enhanced when the knowledge transfer channel enables the transmission of the academics' tacit knowledge which is generally necessary for the application of most codified pieces of knowledge (Dasgupta and David, 1994). This applies particularly to complex and cutting edge knowledge; blueprints and manuals provide only a partial picture, and the involvement of the knowledge creator is fundamental to ensuring successful implementation. The importance of tacit knowledge for the development of valuable inventions implies that forms of university-industry knowledge transfer that enable more effective transmission of tacit academic knowledge should lead to more valuable inventions.

Although all forms of knowledge transfer (including more "formal" ones such as patent licensing) to some extent are accompanied by interpersonal interactions between academics and industry researchers, certain channels such as direct collaboration, are more conducive to the transmission of tacit knowledge (Perkmann and Walsh, 2008). Thursby et al. (2001), in a survey of 62 US universities, found that 71% of the inventions licensed from universities to firms required personal interaction with the inventor (usually in the form of a consultancy contract) to enable subsequent commercialization, suggesting that the successful implementation of patented inventions for commercial purposes relies on tacit knowledge that can be harnessed effectively only through direct collaboration with university researchers.

The governance of collaboration may play a role in the extent to which transfer of tacit academic knowledge is facilitated. The relationship between university and industry personnel may be mediated by the involvement of the university institution or may rely on personal relationships (contractually regulated) between the individual academic and the firm (Geuna and Muscio, 2009). While both forms of governance constitute important channels for the transfer of knowledge, personal contractual collaborations have been shown to be particularly useful for small firms with fewer resources to cope with more cumbersome institutional channels (Bodas Freitas et al., 2013). Personal contractual collaborations are more likely to occur between academic and industry researchers belonging to the same social, local, or educational (alumni) networks which increases mutual trust (Bodas Freitas et al., 2014). Since mutual trust facilitates the transfer of tacit knowledge (Santoro and Saparito, 2003; Inkpen and Tsang, 2005; Bruneel et al., 2010), we expect inventors to benefit particularly from academic knowledge and to generate more valuable inventions if the transfer of this knowledge occurs through a personal contractual collaboration.

iii) Inventor's characteristics

The inventor's individual characteristics may affect the ability to effectively exploit academic knowledge to develop more valuable inventions. The efficient transfer of academic knowledge requires the recipient of the knowledge to have the appropriate cognitive resources to absorb and utilize the knowledge in the process of invention (Cockburn and Henderson, 1998). The capacity to absorb academic knowledge may increase with level of education, previous exposure to certain concepts or methods, and broader experience due for example, to higher career mobility, and experience of learning by doing. Individual absorptive capacity will affect the probability of collaborating with a university researcher and the benefit derived from such collaboration. More highly educated firm inventors (Bodas Freitas et al., 2014) tend to engage in more frequent collaboration with universities. Among firm inventors, active personal engagement in science is an important dimension of their absorptive capacity and ability to exploit scientific knowledge. Engagement in scientific research improves the inventor's ability to identify and absorb relevant sources of academic knowledge. It allows its integration in the firm's knowledge processes, which leads to faster translation of research into new technologies (Fabrizio, 2009; Cassiman et al., 2008). Boundary spanning inventors with strong personal connections to scientific research through coauthorship with academic scientists (Cockburn and Henderson, 1998), collaboration with scientific institutions (Cassiman et al., 2012), or previous employment in a scientific institution (Gittelman, 2005; Bjerregaard, 2010), may be better able to transform academic knowledge into valuable innovation. Therefore, we expect inventors with higher absorptive capacity to collaborate more often with academic scientists and be more successful at translating academic knowledge into valuable inventions.

iv) Firm and industry specificities.

Much of the literature discussing the importance of absorptive capacity for knowledge transfer focuses on firm-level rather individual variables. This is due in part to data availability although it has been argued that some firm characteristics are important for the ability of employees to exploit academic knowledge to develop innovations. In particular, the firm's exposure to and engagement in research activities are important predictors of its ability to exploit scientific knowledge. To study the contribution of academic knowledge to invention value we need to control for the firm's technological capability. It is important also to control for sectoral and/or technological specificities. Although there seems to be increased reliance on scientific knowledge among innovative firms, the opportunities for successful exploitation of scientific research is concentrated in certain fields such as biotechnology and pharmaceuticals, information and communication technology, and nanotechnology (Callaert et al., 2006), where firms are more likely to benefit from academic research to produce valuable inventions (Mansfield, 1991; Cohen et al., 2002; Laursen and Salter, 2004; Abreu et al., 2008). Thus, we need to consider the specificities of these sectors. Also, firm size is positively correlated to the development of collaborations with universities (Mohnen and Hoareau, 2003; Laursen and Salter, 2004; Fontana et al., 2006) but insignificant for predicting the value of patents (Cassiman et al., 2008).

4. Industry inventors in Piedmont: the PIEMINV survey

Piedmont is one of the most technologically advanced regions in Italy with scientific and technological performance in line with the EU average (EC, 2014), and much higher investment in R&D compared to the rest of Italy (Bodas Freitas et al., 2013). The region has an important manufacturing base with a relevant presence in both R&D intensive industries such as automotive (e.g. FIAT Group), aeronautics and aerospace (e.g. Alenia Aeronautica, Thales Alenia Space, Avio, Selex Galileo, Microtecnica), and telecommunications (e.g. Telecom Italia research centre), and traditional industries such as food (e.g. Ferrero, Lavazza), and fashion (e.g. Ermengildo Zegna, Fila). It hosts three important universities. Two are in Torino, the region's largest city. The University of Torino is one of the oldest and most prestigious Italian universities, and is a large (ca 63,000 students) multidisciplinary institution. The Politecnico of Torino has almost 29,000 students and is one of the three elite technical universities in Italy. The more recently (1998) established University del Piemonte Orientale is a smaller university (almost 10,000 students) with campuses in three small Piedmont towns. All three universities have small campuses in minor urban centers in the region. These characteristics make Piedmont an interesting case study to explore how university research contributes to the process of industry innovation.

The PIEMINV survey targeted the population of inventors resident in the region, named on at least one European Patent Office (EPO) patent application between 1998 and 2005 (about 4,000 patents and 3,000 inventors in Piedmont).[2] After cleaning the address list, and excluding inventors working at universities and public research centers, the PIEMINV questionnaire was administered in autumn 2009 and spring 2010 to 2,916 inventors; it resulted in 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 on the inventor (age, gender, education, mobility) and her inventive activity (age at first patent, office where patents first filed, ratio of invention to innovation); (ii) evaluation of the overall importance of university knowledge for the development of inventions and the relative importance of different interaction channels; (iii) evaluation of the effectiveness, frequency, and nature of university-industry interaction channels to pursue different firm objectives; (iv) assessment of the economic impact of university knowledge.

Additional information on the firm employing the inventor (number of employees, revenue, head office location, number of branches, year of foundation, sector, legal status, industry) was collected from the CERVED database of Italian companies' accounts and other public

[2] For a detailed analysis of the PIEMINV survey see Cecchelli et al. (2012). Data available on request.

online sources.[3] This information was available for 298 of the 363 firms in the sample (or 738 inventors); availability was lower for non-public small/micro firms. We collected the number of patents filed by the inventor's firm during 1998 to 2005, from the Derwent Innovations Index. For each inventor we collected the number of patent applications and of granted patents between 1998 and 2005, the most common type of assignee, the average number of backward citations, the average number of forward citations, the average number of citations to academic papers, the date of first patent application, the most common technology class.[4] Twenty-three inventors were removed from the database because at the time of patent filing they were employed by a public institution (university, public research organization, government agency), leaving 915 industry inventors for our analysis.

The mean age of the whole sample is 48.1 years, with most in the 41-50 cohort (36.7%). The mean age is lower for women (41.6 years) who constitute 8.2% of the sample.[5] Younger inventors are more highly educated on average: 76.8% of under-40s have a tertiary degree (sample average is 59%) and 5.6% have a PhD (sample average 3.8%). Inventors are characterized by low education 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 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 education attainment: more highly educated inventors are more mobile.

Most (60.8%) inventors work in large firms (more than 250 employees), and in five manufacturing sectors: manufacture of fabricated metal products (except machinery and equipment); manufacture of computer, electronic and optical products; manufacture of electrical equipment; manufacture of machinery and equipment n.e.c.; manufacture of motor vehicles, trailers and semi-trailers.

Almost two-thirds of inventors patented fewer than five inventions during their career; the average is 1-2 patented inventions each. The share of inventors with more than 16 patented inventions is 8%. The number of non-patented inventions is almost double the number of patented inventions (ca 3-5 non-patented inventions). This is in line with evidence for other regions and countries (Acs and Audretsch, 1988; Arundel and Kabla, 1998). Although most

[3] Firm-related information classifications are according to United Nations ISIC (Rev.4) (UN, 2008).
[4] Classification by macro-technology classes is according to OST-DT7 (OST, 2004).
[5] The share of women in the PIEMINV survey is higher than the Italian (2.7%) and the European (2.8%) shares, reported by the PatVal survey (Giuri et al., 2007).

inventors (849) responded to the question about the number of patented inventions, information on non-patented inventions was provided by only 286 inventors.

After a first cleaning of the original dataset for missing observations, incomplete answers, and missing information about the inventor's employing firm, we were left with a sample of 657 observations including both inventors who collaborated with a university and benefited from university knowledge, and inventors who did not declare any substantial contribution from university knowledge. The 657 inventors that accounted for complete questionnaires, and are used for the empirical analysis, are not significantly different from the overall sample of 915 respondents. Mean age is 48.5 years, and the share of men is 92.7%; 58% of inventors have a tertiary degree or a PhD (*HEducation*) and 8.7% have experience of working at a university (*University Work Experience*). Each inventor was involved, on average, in 2.2 EPO applications between 1998 and 2005 measured by the proxy variable *Technological Productivity*.

5. Empirical strategy

5.1. Measuring the value of inventions

As discussed previously, the literature that investigates the impact of academic knowledge on patent value relies almost exclusively on the measure of forward citations. Forward citations are easy to retrieve from patent databases but suffer from several limitations (van Zeebroeck, 2011; Squicciarini et al., 2013) There are other proxies for the economic value of patents in the general patent literature including patent opposition and renewal data, where patent value is captured by the extent to which companies find it worthwhile to spend resources on litigation or patent renewal (Priest and Klein, 1984; Pakes and Simpson, 1989; Bebchuk, 1994; Lanjouw and Schankerman, 2004), patent claims or the extent of the protection sought in a patent application (Lanjouw and Schankerman, 2004; Beaudry and Kananian, 2012), company start-up activity, capturing creation or not of a high-tech start-up on the basis of the patent (Shane, 2001), probability of a patent being granted, which captures the quality of the underlying invention (Guellec and van Pottelsberghe de la Potterie, 2000), and composite indicators (Lanjouw and Schankerman, 2004; van Zeebroeck, 2011).

None of these variables is a direct measure of economic value, and all are poorly correlated with one another, suggesting that they capture different aspects of a patent's importance or quality. A few studies ask respondents to provide estimates of the monetary value of their patents (Harhoff, 2000; Reizig, 2003; Gambardella et al., 2005).[6] This approach has some shortcomings related mainly to data accuracy and reliability since estimating the commercial value of a patent is extremely difficult, especially for the large share of patents that are not traded but are developed internally or used strategically (e.g. blocking patents). Patent inventors, who are the usual targets of these surveys, may not be best placed to answer questions about patent value (this information is often the preserve of product/R&D managers or executives - Mansfield, 1991). On the other hand, inventors are better able to answer questions about the invention process. Thus, survey designers may be faced with a tradeoff when attempting to link patent value to the features of the invention process.

The present study proposes a new measure of patent value that should overcome some of the limitations of survey-based approaches. The PIEMINV survey asked inventors to identify and provide information on two specific inventions - patented or not: the invention that benefited the most from academic knowledge,[7] and the invention that had the highest economic impact. For each invention, respondents were asked to provide information on its monetary value (€'000 at current prices).[8] Among the sample of inventors with two or more patented inventions, 164 (24.9%) stated that at least some of their inventions had benefited from academic knowledge and provided information on the two inventions.[9]

Since it can be difficult for the inventor to estimate the exact value of an invention, and some might overestimate and others underestimate this value, we do not use the directly reported economic value but instead construct two relative measures. First, we count how many inventors stated that the invention that had benefited most from academic knowledge was also the invention that had the highest economic impact. Figure (1) shows a graphical representation of our variable of interest (a dummy variable that we called *Huniecon* which is equal to 1 if the inventions coincide): 53 out of 164 respondents (26.9%) stated that the invention that had received the greatest contribution from academic knowledge was also their

[6] Scherer and Harhoff's (2000) survey asks: "If in 1980 you knew what you now know about the profit history of the invention abstracted here, what is the smallest amount for which you would have been willing to sell this patent to an independent third party, assuming that you had a bona fide offer to purchase and that the buyer would subsequently exercise its full patent rights?" Similarly, the PatVal project asked "What is your best guess of the minimum price at which the owner of the patent would sell the patent right to an independent party on the day the patent was granted?", offering a choice of 10 value intervals (Gambardella, et al.,, 2008).

[7] About 85% of inventions that had benefited greatly from academic knowledge had been patented.

[8] The question was based on a question in Patval (see Gambardella et al,, 2008) and asked: "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?"

[9] When we consider the total sample, 33% stated that at least some of their inventions had benefited from academic knowledge.

most valuable invention, suggesting an important role of academic knowledge in the process of value creation.

<< FIGURE 1 ABOUT HERE>>

We also calculate the ratio of value of the invention with the highest contribution from academic knowledge, and value of the invention with the highest economic impact. This variable, *Ratio,* takes values between zero and 1. Using a relative measure of invention value overcomes the problem of lack of comparability of invention values across inventors since it only requires the assumption that each inventor's evaluations of her two inventions are consistent. This ratio also eliminates unit of measurement problems (common in relation to this type of question) and provides, regardless of the subjective and heterogeneous measures used by inventors, an indication of the value of the invention that benefited most from academic knowledge with respect to the most valuable invention in the inventor's portfolio. The value of invention with the highest economic impact allows us to net out from our estimates the intrinsic quality of inventors, which clearly is correlated with the value of their invention.

The variables *Huniecon* and *Ratio* are our main dependent variables. Table 1 shows that *Ratio* has fewer observations than the binary variable *Huniecon* since not all the inventors who identified the two inventions were able or willing to provide specific monetary values.[10] Figure 2 plots the distribution of the (logs of) the values of the invention with the highest university contribution. As expected, the distribution is extremely skewed and displays a large range of values, in line with the findings in the patent value literature.

<< TABLE 1 ABOUT HERE>>

<<FIGURE 2 ABOUT HERE>>

[10] Among the 164 inventors who indicated that the two inventions coincided, 77 did not provide the economic value of one or both inventions. In those cases we cannot calculate the *Ratio* variable. Among these 77 individuals, 54 had uniecon=0 and 23 had uniecon=1. This means that in this restricted subsample of excluded inventors the share of uniecon=1 is 29%, which is in line with the overall average of 27% (53 inventors over 164, see Figure 1). Therefore, we believe that the inventors for whom we cannot compute *Ratio* represent a fairly random subsample of non-respondents.

The relative measures of the contribution of academic research to the value of industry inventions proposed in this paper are designed to overcome the principal limitations of 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 capture the most important impact and may not be representative of the whole spectrum of contribution of academic knowledge to all the inventive activities of firm inventors. However, the literature shows that the value of patents is highly skewed with a very small number of patents relating to important innovations with high economic value, and a large number of patents being unexploited. Therefore, our measures should provide good insights into those inventive processes that result in significant economic impact.

5.2. The econometric model

Our aim is to explain what factors are correlated to the value of those inventions with an important academic knowledge contribution, relative to the most valuable invention in the inventor's portfolio, paying particular attention to: i) the specific characteristics of the academic knowledge transferred, ii) the organization of the process of knowledge transfer, and iii) the characteristics of the inventor and several firm and industry specificities. We propose the following linear model:

$$y_i = c + \sum_j \beta_j KNOW_{ij} + \sum_k \chi_k ORG_{ik} + \sum_l \delta_l INV_{il} + \sum_m \gamma_m FIRM_{im} + \sum_n \phi_n TECH_{im} + v_i \qquad (1)$$

where y_i is a proxy for the value of inventor *i*'s invention which benefited most from the contribution of university knowledge, relative to the inventor's most valuable invention; *KNOW* denotes a set of variables capturing the type of academic knowledge the inventor used to develop the inventions; *ORG* is a set of variables capturing the organizational processes to access academic knowledge; *INV* is a set of variables capturing some inventor characteristics; *FIRM* and *TECH* are sets of firm and technological control variables; and v_i is an idiosyncratic error term.

In order to estimate equation (1) we need to avoid selection bias. Only those inventors who said they benefited from university research were able to evaluate the contribution of academic knowledge to the value of their inventions. Hence, we need first to control for whether this subset of inventors is significantly different from the rest of the sample. Also, some of the features influencing the value of the contribution of academic knowledge are likely to influence the probability of having benefited from university research; in the absence of a selection equation the effect of these variables would be overestimated.

Hence, we estimate a selection equation which indicates whether inventors were able to benefit from university knowledge, and an intensity equation to measure the effect of different variables on the relative economic value of inventions with an academic knowledge contribution. The selection equation is written as:

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

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

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

In the empirical analyses we 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 estimate a probit model with sample selection, and in the second case we estimate a Tobit type II model (Amemiya, 1984).

5.3. The selection equation

Our preferred selection variable (*Contribution*) is a dummy that is equal to 1 if at least some of the inventor's inventions received important contributions from academic knowledge.[11]

[11] This variable is based on 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. *Contribution* is equal to 1 if at least "less than a half" was selected by the respondents..

However, in order to check the robustness of our findings we also used the alternative selection variable *Cooperation*, which is equal to 1 if the inventor has had experience of cooperation with a university institution or an individual university professor.[12] This variable is used in the literature to analyze university-industry relationships. We prefer the first selection variable (*Contribution*) because we believe it is a better measure of the individual ability of the inventors to benefit from academic knowledge. In the selection equation we are interested in understanding the characteristics that allow inventors to exploit university knowledge successfully, while cooperating or not with a university is mainly influenced by the characteristics of the firm employing the inventor (e.g. large companies cooperate more).

For the selection equation we use a set of independent variables which, according to the literature, are likely to influence the probability that an inventor collaborated with a university researcher in the development of her invention.

Table 2 reports the descriptive statistics for the variables used in the first stage selection equation for 657 observations. First, we control for inventor's absorptive capacity which should facilitate the establishment of collaboration with a university researcher. More educated inventors (*HEducation* captures whether the inventor has a bachelors, masters or doctoral degree) and those with experience of working in a university (*University Work Experience*) might be more inclined to consult a source of academic knowledge, and might be better able to understand the academic literature and communicate with university scientists. This type of inventor might also have a well developed network of contacts with university researchers. More productive inventors (*Technological Productivity*) may be more experienced and also more likely to benefit from academic knowledge. Finally, we control for *Age* (and its square) and gender.

Second, a number of firm characteristics affects the probability of interacting with a university. The literature shows that larger, research-intensive firms are better able to benefit from academic research due to their better absorptive capacity (Mohnen and Hoareau, 2003; Arundel and Geuna, 2004; Laursen and Salter, 2004; Fontana et al., 2006). We therefore consider firm size through a set of dummies: micro-companies with less than 10 employees, and individual inventors; small companies with between 10 and 49 employees; medium firms with between 50 and 250 employees; large firms with more than 250 employees. Table 2 shows that the majority (68%) of inventors work in large companies, with the remaining 32%

[12] The specific question in the PIEMINV survey is: "Have you had any experience of collaborations with a university and contracts with individual staff? (Yes / No)"

fairly evenly distributed among micro, small, and medium firms. We control also for the technological level of each firm using the variable *Technological capability* which measures the firm-level number of EPO granted patents in the period 1998 to 2005. The average number of patents per firm is 262 with large firms accounting for around 2000 patents, and some firms registering zero patents in the time-window. We include a dummy indicating whether the company's ownership is not Italian (*Foreign companies)*, which shows that some 10% of firms are foreign-owned.[13]

Finally, we include several dummies to capture the most common technology class in the inventor's portfolio among electrical engineering and electronics, process engineering, instruments, chemicals, pharmaceutical, mechanical engineering, and consumer goods. Compared with firms' codes of economic activity, these variables more precisely capture the types of technologies the inventors work on, especially in the case of large multiproduct firms where industry affiliation might be too generic.[14] Table 2 shows that electrical engineering and mechanical engineering are the most common technology classes indicated by inventors. This is consistent with the industry specialization in the Piedmont region and serves to distinguish the present study from most previous studies which focus on the biomedical and pharmaceutical industries.

<< TABLE 2 ABOUT HERE>>

5.4. The main equation

The following independent variables are used in the main equation (Table 3 reports the descriptive statistics relating to the variables used in the main equation on 164 observations).

Inventors were asked to identify the kind of academic knowledge that they considered most important for the development of their inventions. This information allows us to build dummy variables to capture: scientific theorems and principles (*Theories*), methodologies, techniques, and instruments (*Methods*), solutions to technological problems/support for prototyping (*Applied*), and information about other relevant sources of knowledge/about other

[13] These firms are either Italian subsidiaries of foreign companies or are headquartered just outside the Italian border, e.g. some Swiss firms are very close to the Italian border. Since the PIEMINV survey targeted inventors resident in the Piedmont region, the sample does not include inventors who worked for foreign companies located at a distance from the Italian border.

[14] Two inventors working in the same large company, e.g. the car manufacturer FIAT, might be specialized in very different technological fields (e.g. electronics, and mechanical engineering). Using only a sectoral dummy would be misleading since different technological disciplines are likely to have different university knowledge needs.

organizations (*Contact*). Among our 164 respondents, university knowledge was exploited mainly to obtain information about other relevant sources of knowledge (61.3%) and in order to obtain solutions to technological problems (60.7%); theoretical knowledge was declared important by 56.3% of respondents and methodologies, techniques, and instruments by 51.2%.

Several variables describe the organization of knowledge transfer from the university. We include a variable (*Collabo*) which indicates whether the development of the invention with the highest academic knowledge contribution involved any form of contract-based collaboration with university researchers. There are two main modes of governance of research collaborations: personal contractual collaborations, and institutional relationships. We coded two variables for whether the research contract was signed directly by the researcher (*PContracts*) or by the university administration (*Institutional*). Table 3 shows that 23% of the inventions with the highest contribution from university knowledge are the result of personal contractual collaboration with an individual researcher, and 28% are based on an institutional relationship. The choice of governance may be affected by the expected value of the invention process since personal contractual collaborations are characterized by easier appropriability for the firm (Bodas Freitas et al., 2013). To control for endogeneity we instrument our variable of interest *PContracts*. Following Bodas Freitas et al. (2014), we expect that the choice of governance of the relationship with the university depends on the inventor's social network and routines.

To capture inventor's absorptive capacity, we use a variable for ability to master academic knowledge, proxied by the number of the inventor's scientific publications in the Scopus database (*Publications*). Finally, we control for inventor's age (and age squared) and gender. We use the same firm and technology controls as in the selection equation.

<< TABLE 3 ABOUT HERE>>

6. Results

Table 4 presents the results of the selection models using the two selection variables described in Section 5 in order to examine the characteristics of inventors able to benefit from university knowledge or to collaborate actively with an academic institution. Table 4 column (1) presents the results of a probit regression with the dependent variable *Contribution*:[15] it shows a positive and significant effect of higher education (*HEducation*), of having spent at least one month working at a university (*University Work Experience*), and of the number of patent applications to the EPO in the period 1998-2005 (*Technological Productivity*). Firm-size dummies are not significant, suggesting that for capability to benefit from academic knowledge there are no substantial differences among small and large companies. Also, the variable *Technological capability* at firm level is not significant, indicating that the individual characteristics of the inventor are better predictors than firm characteristics of the ability to use academic knowledge. Though not reported in the table, some of the technology class dummies are significant, confirming the existence of relevant differences across technologies for the propensity to collaborate.

<< TABLE 4 ABOUT HERE>>

In column (2) the dependent variable is the probability of having collaborated with a university (*Cooperation*). The results are similar to the previous estimation, although the coefficients of firm size are different. In line with the literature on university-industry interactions if probability to cooperate is the dependent variable, large firms have a positive and significant coefficient.

Given the similarity of the results across specifications we prefer *Contribution* as our selection variable, since we believe it more precisely captures the capacity of inventors to benefit from university knowledge.

<< TABLES 5 AND 6 ABOUT HERE>>

Table 5 presents the results for the value equation (1), correcting for the selection bias explained in equation (3). We start with the dummy variable *Huniecon* as our dependent variable, and hence opt for a probit model which accounts for selection bias.[16] Since the

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[15] We tried another specification in which *Contribution* is modeled as an ordinal variable following the formulation of the question in the survey. In this estimation, the coefficients of age and age squared are significant suggesting the existence of a U-shaped relationship between age and the capacity to benefit from university knowledge.

[16] We use the Stata routine *heckprobit* which accounts for the selection bias problem in models where the dependent variable is dichotomous

selection equation is the same as in Table 4, we do not report it in Table 5. Table 5 column (1) reports the marginal effects relative to the value equation. The coefficient of *Theories* which indicates that inventors use university knowledge in order to access scientific theorems and principles, is positive and significant (at the 10% level). In the case of other types of university knowledge the coefficients are not significant.

The coefficient of *Collabo* which indicates whether the invention involved institutional or personal collaboration with a university researcher is positive but not significant. Columns (5) and (6) distinguish between personal contractual collaborations with a university researcher (*PContract*) and institutional collaboration with the university organization (*Institutional*): the results show that the coefficient of collaborations with individual researchers is bigger than the coefficient of institutional collaborations, however, in both cases the coefficients are not significantly different from zero. The age variable and its squared term indicate a U-shaped relationship between age and the probability of achieving an economically valuable invention that benefited from academic knowledge. More specifically, given the coefficients of -0.059 of age and of 0.001 of age-squared, we find that after 29.5 years of age the effect of age becomes positive, and becomes increasingly positive as age increase. The coefficient of number of publications is negative but not significantly different from zero, showing that higher levels of absorptive capacity do not increase the relative value of inventions with a high university contribution.

Among the control variables, we find that firm size, especially large size, has a negative but not significant coefficient, while the coefficient of firm technological capability (measured by number of patents granted) is positive and significant. The model includes technology dummies (not reported in the tables), which are never significant. The rho coefficient is small and not significant, meaning that when the dummy variable *Huniecon* is the dependent variable there are no serious selection bias problems.

Table 6 presents the results of a Tobit type II model (Amemiya, 1984) where the variable *Ratio* is the dependent variable in the value equation. Table 6 column (1) shows that *Theories* is still positive and significant, while *Collabo* is positive but not significant. Column (2) distinguishes between the two types of collaboration, and as before, only personal contractual collaborations with individual researchers (*PContract*) is positively (and significantly) correlated with the relative value of the invention with the highest contribution of academic knowledge, while institutional collaboration (*Institutional*) is negative but not significant.[17] In this specification firm's technological capability is positive and significant indicating that research active (inventive) firms are more able to transform academic knowledge into invention value. We find also that the coefficient of large firms is negative and significant, similar to the results in Table 5. This negative effect for large firms can be explained by the fact that large corporations rely mostly on internal resources for the development of their innovations, in line with the corporate model of knowledge generation (Antonelli and Fassio, 2014). Therefore, it is less likely that collaboration with a university will lead to a relatively high economic impact invention by an employee in a large firm. However, micro companies and engineering consultancies which usually do not possess all the competences needed for the development of innovations, will gain comparatively more from collaborating with a university. Inventions developed with the contribution of academic knowledge will be more frequent among the most valuable inventions developed by inventors working in micro-firms or small engineering consultancies. Technology dummies (not reported in the tables) are weakly significant. The rho coefficient is always positive and significant, meaning that, in this specification, a selection equation was needed.

Overall, the results of the estimations of equation (1) provide some support for academic theoretical knowledge being the type of knowledge that is positively correlated with the relative value of inventions that benefited from academic knowledge. Although inventors used most often applied university knowledge, is the theoretical academic knowledge that is significantly correlated with higher value inventions.

6.1. Contractual relations and causality

A possible problem with the estimation of equation (1) is that the unobserved and idiosyncratic quality (economic value) of an invention might be correlated with the specific

[17] Careful analysis of the ways in which industrial inventors interact with academic institutions shows that the channels of interactions are often very complex, and often involve different types of formal and informal collaborations simultaneously. Inventors indicated that they often exploited several types of channels. Personal and institutional collaborations commonly occurred in tandem, based on supervision of masters and doctoral students or shared laboratory space in the university. Given the high number of possible combinations of interaction forms we ran a Principal Components Analysis (PCA) on all the possible types indicated by the inventors and extracted some factors that represent stylized ways of interacting with universities. The results of the PCA identified three main components: the first corresponds closely to personal contractual collaboration, the second mostly refers to institutional collaborations, and the third refers to ways of benefiting from academic knowledge that do not involve personal interactions. When we included the three factors in our value equation we found that only the factor corresponding to personal contractual collaboration was positive and significant, confirming the robustness of our preferred specification in Tables 5 and 6.

channel of interaction chosen by the inventor for its development. It might be that if an invention has a very high expected economic value firms prefer personal contractual collaboration to allow higher approriability by the firm since the property rights to the invention will be assigned directly to the firm. It negates the need to negotiate with the university over sharing of patent rights.

This results in a typical problem of reverse causality, which would bias estimates of the coefficient measuring the impact of personal contractual collaborations on the value of the invention. To overcome this, problem we resort to an instrumental variable strategy aimed at identifying whether there is a true causal link between choosing personal contractual collaboration and the value of the invention.

A suitable instrument for this analysis is a variable that influences the treatment status, that is, that an inventor prefers personal contractual collaboration with an individual researcher, but which is not correlated with the economic value of the specific invention analyzed in the value equation. Building on previous work using the same sample of inventors (Bodas Freitas et al., 2014) we know that different factors influence the use of personal contractual collaborations. An important determinant of the use of personal contractual collaborations is that the inventor completed secondary education in Piedmont. Given low mobility patterns present in the region, it is possible that both the inventor and the university employee were educated in Piedmont, which increases their social, relational, and cultural proximity, which is supposed to increase mutual trust. The embeddedness of inventors in local networks of relationships should increase the probability of personal contractual collaboration as the preferred means to access academic knowledge. Our first instrument is a variable *Local* which is equal to 1 if the inventor's highest educational attainment is a second degree earned in Piedmont and if she generally considers personal contractual relationships important for the development of her inventions.

Another factor that has been shown to increase the probability of inventors exploiting personal contractual relationships (Bodas Freitas et al., 2014) is the interaction between the inventor and researchers in the university that awarded the inventor's highest degree (alumni interactions). Again, it is likely that the inventor will have greater social, relational, and cultural proximity to university researchers in her alma mater. We build a variable named *Alumni_polito* which is equal to 1 if the inventor graduated from the Politecnico di Torino (Piedmont's elite engineering university) and claims to have frequent professional interaction with that institution.

The PIEMINV survey specifically asked inventors with which university personal contractual collaboration had been established; the geographic pattern of these collaborations shows that collaborations are frequent with other Italian university researchers outside of Piedmont. We believe this is determined by the alumni connections of inventors who graduated from universities outside Piedmont, or by the existence of a professional network built in the course of the inventor's career which allows privileged personal interaction with individual researchers in other Italian regions. Data on the inventors' scientific publications (extracted from Scopus) were used to build a third variable *Share Italy* which measures the share of Italian coauthors outside of Piedmont in the inventor's total number of coauthors. After controlling for regional social network, the share of Italian coauthors not resident in Piedmont will be higher, as will be the likelihood that inventors will have professional networks that include researchers outside of Piedmont and will choose personal collaborations. Table (3) presents the main descriptive statistics of the three selected instruments for the sample of inventors included in the value equation.

To sum up, we hypothesized that in our sample of inventors treatment status is changed by three instruments which account for differentiated stylized types of inventors. This led us to adopt an over-identified instrumental variable strategy with three instruments for one endogenous variable. Following Angrist (2001), and considering also the limited size of our sample, we adopted the simplest possible specification in order to focus explicitly on identifying the causal effect of treatment on the treated: we used Two Stage Least Squares (2SLS) to estimate equation (1), without correction for selection bias. Our choice is supported further by the fact that in Table 5 columns (1) and (2) the rho coefficient indicates that there is no selection bias in the estimation of equation (1). Column (3) table (5) presents the results of the 2SLS with personal contractual collaborations (*PContract*) instrumented by the three variables outlined above.

The underidentification test of the first stage statistics shows that the excluded instruments are relevant, as shown also by the positive and significant coefficients of the first stage. In addition, the Hansen test suggests that the model is correctly identified and the excluded instruments are not correlated with the error term. Finally, the Angrist and Pischke (2009) test for weak instruments rejects the hypothesis of weak instruments and confirms that the 2SLS coefficients are reliable and not biased. Looking at the results in the value equation in table (5) we see that *Pcontract* is positive and significant, while all the other coefficients are unchanged. More specifically we find that the effect of *Theories* and age and age squared are positive and significant. Columns (3) and (4) in table (6) show the results of 2SLS estimation of equation (1) with *Ratio* as the dependent variable. Again, the results show that *PContracts* is positive and significant when instrumented, and that the coefficient of *Theory* remains positive and significant. The first stage statistics with *Ratio* as the dependent variable show that while the *Local* instrument is still strongly relevant, the other two instruments lose most of their significance: this results in lower F-statistics and a potential problem of weak instruments. This is because if *Ratio* is the dependent variable half of the observations are lost and these likely include inventors who choose personal contractual collaborations because of the alumni effect or because of professional networks outside the region. The only instrument in column (4) is *Local*: the results do not change and we find that in this new specification the instrument is no longer weak, as shown by the F-statistic.

Overall, the results show the existence of a true positive causal effect of personal contractual interactions on the relative value of an invention developed with a large contribution of university knowledge. These results confirm our expectation that the mutual trust characteristics of personal contractual collaboration facilitate the transfer of tacit knowledge allowing for achievement of higher value inventions based on academic knowledge.

<< TABLE 7 ABOUT HERE>>

7. Conclusions

Since the mid 1990s, 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 assumption underlying this perspective is that academic knowledge is a fundamental component of the invention process in private firms, and that companies with access to academic knowledge will be able to introduce more valuable innovations and increase their economic performance. The university-industry linkage literature includes a large amount of evidence on the positive effect of academic knowledge on the performance of those firms able to access it (Mansfield 1991; Jaffe, 1989). While the macro-economic literature frequently focuses on the effect of university knowledge on the economic performance of regions or countries, mostly measured by the increase in TFP (Adams, 1990; Haskel and Wallis, 2010), at the micro-level most analyses measure the impact of academic research on the technological performance of firms, using patent data and related measures (Cockburn and Henderson, 1998; Fleming and Sorenson, 2004; Cassiman et al., 2008). Few studies track the contribution of university knowledge to specific inventions, and most importantly, none assess to what extent the contribution of university knowledge increases the economic value of an invention.

This paper addresses both issues for a sample of non-academic inventors resident in the Piedmont region of Italy. Taking advantage of an original survey (PIEMINV) designed to study the relationships between industry inventors and academia, we asked inventors about the economic value of their inventions which had a relevant contribution from academic research. In order to deal with problems related to inventors' subjective measures of value, we devised a relative measure that compares the value of the inventor's invention with a high contribution from university knowledge with the invention with the highest economic impact in the inventor's portfolio. Extrapolating from the monetary value, we built a measure that captures how much the value of the patent that benefited from academic knowledge matches the highest value invention of the inventor, that is, the maximum economic value of the inventor's invention. To avoid comparing oranges and apples, we controlled for various firm, knowledge, and invention characteristics and for selection bias; we found that firm technological capability and firm size affect the process of transformation of academic knowledge into economic value, which confirms previous results related to the characteristics of firms and inventors collaborating with universities.

Our results show that the transfer of theoretical academic knowledge rather than solutions to more technical and specified problems, from university researchers, leads to more valuable firm inventions. It is general theoretical academic knowledge that enables firms to resolve technological problems and produce more valuable inventions. Also, the way that the knowledge exchange is governed is relevant to the extraction of economic value. Knowledge transfer processes involving direct personal collaboration between the company inventor and the university researcher, forged on the basis of social network embeddedness, are characterized by higher trust. This characteristic enables easier transfer of tacit knowledge, making personal contractual collaborations more conducive to production of higher relative value inventions.

Our results show also that inventors with greater cognitive proximity to the university, that is, with higher levels of education, or with experience of working at a university even for a short time, and high patenting productivity are more likely to interact with university researchers and benefit from university knowledge. However, these characteristics and the publication output of inventors, which can be considered proxies for inventor's absorptive capacity, are not correlated with more valuable inventions. Only inventor's age is associated weakly with higher relative value.

These results highlight an important issue that should be considered by policy-makers keen to increase the effectiveness of the channels of knowledge transfer from academia to private firms. Among the many possible contributions from universities to invention activity, those that involve the transfer of basic principles and theories are the most effective for increasing the economic value of the inventions. Our results indicate that the most effective academic knowledge contributions are not applied knowledge: inventors benefit more from more theoretical academic knowledge in which the university is specialized. Policy action in the last 20 or so years has tried to steer universities toward producing more applied knowledge which it was assumed is more useful to companies. This study challenges the rationale for this policy action.

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Figure 1. Construction of the dependent variable *uniecon*

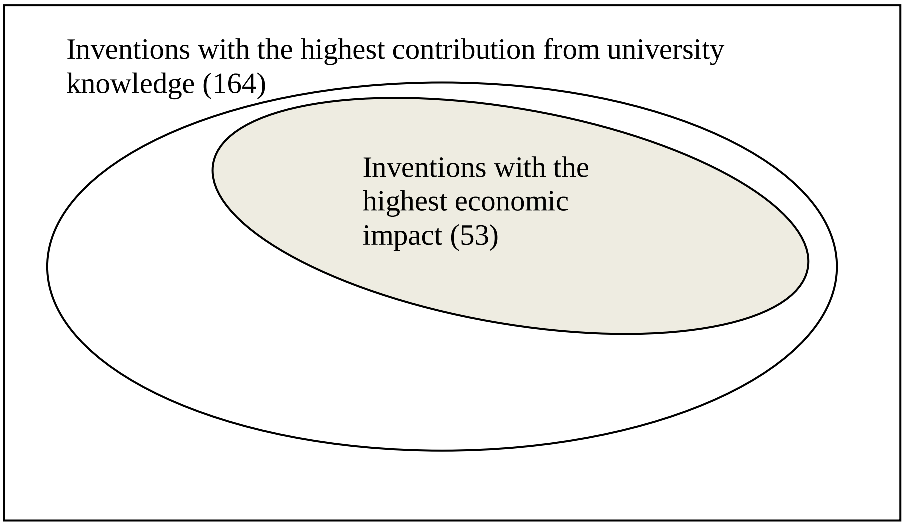

Figure 2. Distribution of the value of the invention with highest university contribution

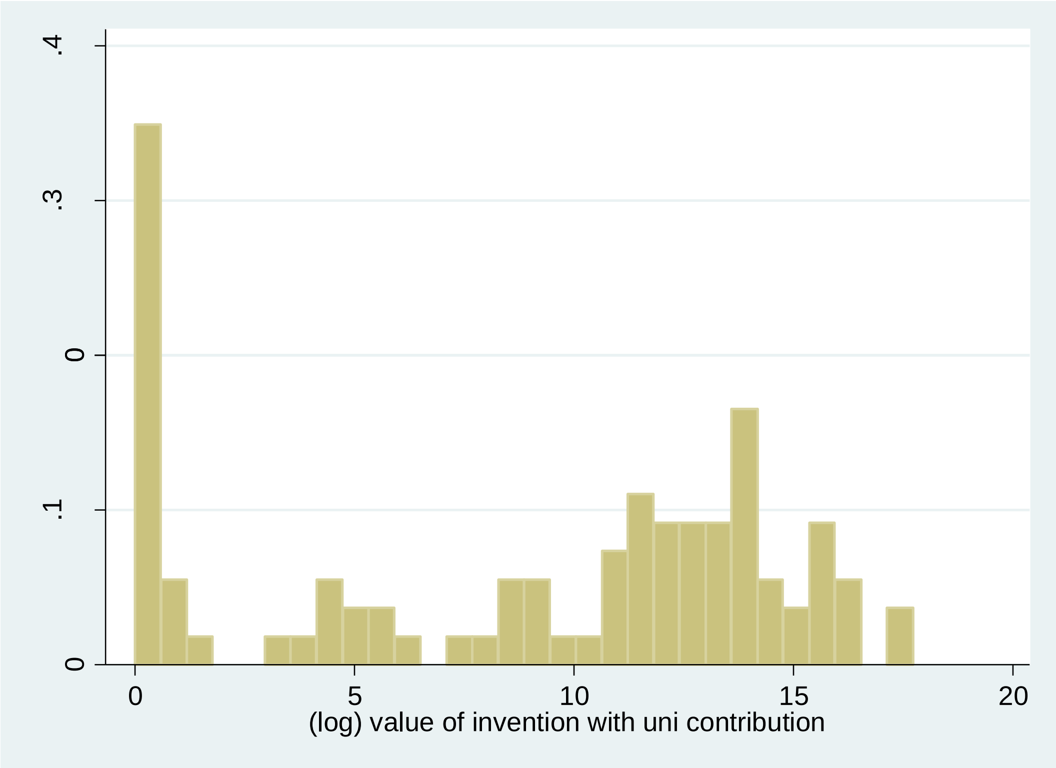

Table 1. Distributions of variables capturing invention value

	Huniecon	*Ratio*	Economic value of inventions with highest contribution from university knowledge	Economic value of inventions with highest economic impact
Observations	164	87	87	87
Mean	0.304	0.53	2,158,749	6,044,990
St. deviation	0.461	0.43	7,741,929	24,700,000
Minimum	0	0		
Maximum	1	1	50,000,000	200,000,000
Skewness	0.85	-0.05	5.55	6.51
Kurtosis	1.71	1.26	34.35	48.3

Table 2. Descriptive statistics. All inventors

Variable	Obs	Mean	Std. Dev.	Min	Max
Contribution	657	0.250	0.433	0	1
Cooperation	657	0.452	0.498	0	1
Individual Characteristics					
Male	657	0.927	0.260	0	1
Age	657	48.521	9.940	30	88
HEducation	657	0.583	0.493	0	1
University work experience	657	0.087	0.282	0	1
Technological productivity	657	2.213	2.498	0	24
Firm Characteristics					
Micro firms	657	0.102	0.303	0	1
Small Firms	657	0.082	0.275	0	1
Medium Firms	657	0.132	0.339	0	1
Large Firms	657	0.683	0.466	0	1
Foreign companies	657	0.107	0.309	0	1
Technological capability	657	262.938	511.852	0	4808
Technological dummies					
Electrical engineering	657	0.251	0.434	0	1
Instruments	657	0.100	0.301	0	1
Chemicals	657	0.065	0.248	0	1
Pharmaceuticals	657	0.014	0.116	0	1
Process Engineering	657	0.131	0.338	0	1
Mechanical Engineering	657	0.368	0.483	0	1
Consumer goods	657	0.070	0.255	0	1

Table 3. Descriptive statistics, restricted sample

Variable	Obs	Mean	Std. Dev.	Min	Max
Types of academic knowledge					
Theories	164	0.549	0.499	0	1
Methods	164	0.506	0.501	0	1
Applied	164	0.610	0.489	0	1
Contact	164	0.598	0.492	0	1
University-industry governance					
Collabo	164	0.488	0.501	0	1
PContract	164	0.232	0.423	0	1
Institutional	164	0.287	0.454	0	1
Individual Characteristics					
Male	164	0.909	0.289	0	1
Age	164	48.5	10.573	31	88
HEducation	164	0.793	0.407	0	1
University work experience	164	0.183	0.388	0	1
Publications	164	5.859	15.168	0	144
Technological productivity	164	2.665	3.203	0	24
Firms Characteristics					
Micro firms	164	0.085	0.280	0	1
Small Firms	164	0.067	0.251	0	1
Medium Firms	164	0.098	0.298	0	1
Large Firms	164	0.750	0.434	0	1
Technological capability	164	296	565.504	0	2869
Technological dummies					
Electrical engineering	164	0.287	0.454	0	1
Instruments	164	0.146	0.355	0	1
Chemicals	164	0.104	0.306	0	1
Pharmaceuticals	164	0.024	0.155	0	1
Process Engineering	164	0.091	0.289	0	1
Mechanical Engineering	164	0.311	0.464	0	1
Consumer Goods	164	0.037	0.188	0	1
Instruments					
Local	164	0.030	0.172	0	1
Alumni_polito	164	0.103	0.305	0	1
Share Italy	164	0.180	0.296	0	1

Table 4. Selection equations

VARIABLES	(1) *select*	(2) *coll.*
HEducation	0.184***	0.303***
	(0.035)	(0.042)
University Work Experience	0.230***	0.248***
	(0.074)	(0.077)
Age	-0.023	0.035*
	(0.015)	(0.019)
Age^2	0.000*	-0.000*
	(0.000)	(0.000)
Technological Productivity	0.013*	0.030***
	(0.007)	(0.009)
Male	0.046	-0.080
	(0.056)	(0.080)
Firm characteristics		
Small Firms	-0.082	0.181*
	(0.065)	(0.108)
Medium Firms	-0.071	0.137
	(0.065)	(0.097)
Large Firms	0.009	0.246***
	(0.060)	(0.076)
Foreign	-0.027	-0.011
	(0.054)	(0.071)
Technological capability	-0.001	0.001
	(0.000)	(0.000)
Technological dummies	***yes***	***yes***
Observations	657	657
pseudo-Rsquared	0.105	0.165
Log-likelihood	-330.3	-377.5

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. Mechanical 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 and IV on *Huniecon*

	(1) probit	(2) probit	(3) IV
Theories	0.169*	0.169*	0.154*
	(0.092)	(0.094)	(0.083)
Methods	-0.009	-0.007	-0.006
	(0.084)	(0.083)	(0.070)
Applied	-0.106	-0.105	-0.072
	(0.095)	(0.095)	(0.090)
Contact	0.074	0.067	0.060
	(0.094)	(0.093)	(0.085)
Collabo	0.106		
	(0.083)		
Pcontracts		0.155	0.597*
		(0.102)	(0.308)
Institutional		0.024	0.098
		(0.096)	(0.102)
Age	-0.059**	-0.055**	-0.056**
	(0.029)	(0.027)	(0.023)
Age^2	0.001**	0.001**	0.001***
	(0.000)	(0.000)	(0.000)
Publications	-0.006	-0.006	-0.003
	(0.004)	(0.004)	(0.002)
Male	-0.092	-0.109	-0.139
	(0.162)	(0.165)	(0.153)
Firm Characteristics			
Small Firms	-0.044	-0.061	-0.114
	(0.206)	(0.198)	(0.197)
Medium Firms	0.058	0.039	-0.042
	(0.196)	(0.196)	(0.201)
Large Firms	-0.146	-0.151	-0.233
	(0.165)	(0.169)	(0.167)
Technological capability	0.001**	0.001**	0.001*
	(0.000)	(0.000)	(0.000)
constant	-	-	1.731***
	-	-	(0.628)
Technological dummies	***yes***	***yes***	***yes***
First stage			
Local			0.458**
			-0.196
Alumni_polito			0.239*
			(0.122)
Share Italy			0.324**
			(0.153)
Underid. test (Kleibergen-Paap rk LM statistic):			9.184
p-value			0.026
Angrist-Pischke F test of excluded instruments:			4.02
Prob>F			0.008
Hansen J statistic (overid. test of all instruments):			0.092
χ^2 P-value			0.954
athanrho	-0.192	-0.165	-
	(0.403)	(0.393)	-
Observations	657	657	164
Uncensored obs.	164	164	-

Equations in columns (1) and (2) are estimated with a probit model with sample selection. The reference category for the size dummies are micro companies and individual inventors. In columns (1) and (2) marginal effects (at the sample mean) are displayed. In column (3) the coefficients of a 2SLS instrumental variable estimation are displayed, first stage coefficients are reported . 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 and IV on the *Ratio* of the two values

	(1) tobit	(2) tobit	(3) IV	(4) IV
Theories	0.175*	0.178*	0.180*	0.180*
	(0.095)	(0.091)	(0.097)	(0.097)
Methods	0.114	0.141	0.186*	0.186*
	(0.113)	(0.106)	(0.104)	(0.106)
Applied	0.011	0.007	0.021	0.022
	(0.108)	(0.108)	(0.124)	(0.122)
Contact	0.045	0.043	0.017	0.016
	(0.100)	(0.100)	(0.110)	(0.112)
Collabo	0.055			
	(0.089)			
Pcontracts		0.163*	0.470*	0.478*
		(0.094)	(0.283)	(0.279)
Institutional		-0.090	-0.023	-0.021
		(0.094)	(0.129)	(0.129)
Age	-0.040	-0.043	-0.049	-0.050
	(0.041)	(0.041)	(0.040)	(0.043)
Age^2	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Publications	-0.003*	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Male	0.184	0.221	0.250	0.252
	(0.272)	(0.239)	(0.235)	(0.234)
Firm Characteristics				
Small Firms	-0.027	-0.090	-0.146	-0.147
	(0.182)	(0.183)	(0.195)	(0.190)
Medium Firms	-0.182	-0.254	-0.288	-0.290
	(0.184)	(0.190)	(0.206)	(0.204)
Large Firms	-0.256*	-0.311*	-0.377**	-0.380**
	(0.153)	(0.162)	(0.192)	(0.192)
Technological capability	0.001*	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.909	1.017	1.523	1.531
	(1.243)	(1.168)	(1.013)	(1.082)
Technological dummies	***yes***	***yes***	***yes***	***yes***
First stage				
local			0.795***	0.688***
			(0.202)	(0.183)
alumni_polito			0.334	-
			(0.203)	-
Share Italy			0.116	-
			(0.224)	-
Underid. test (Kleibergen-Paap rk LM statistic):			6.172	3.996
p-value			0.103	0.045
Angrist-Pischke F test of excluded instruments:			5.28	14.00
Prob>F			0.003	0.00
Hansen J statistic (overid. test of all instruments):			0.086	0.912
χ^2 P-value			0.958	0.633
athanrho	0.867*	0.788**	-	-
	(0.480)	(0.356)	-	-
Observations	580	580	87	87
Uncensored obs.	87	87	-	-

Equations in columns (1) and (2) are estimated with a Tobit Type II model with sample selection. The reference category for the size dummies are micro companies and individual inventors. In columns (3) and (4) the coefficients of a 2SLS instrumental variable estimation are displayed, first stage coefficients are reported. All models include OST7-based technological dummies. Standard errors are robust to heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1