SEPTEMBER 2022
BxWP2022-15

BORDEAUX ECONOMICS WORKING PAPERS
CAHIERS D'ECONOMIE DE BORDEAUX

Characterising science-industry patent collaborations: knowledge base, impact and economic value.

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Keywords: University patent, patent value, patent collaboration, Science-Industry.

JEL: O31, O34.

To cite this paper: **RIZZO Ugo and STERZI Valerio** (2022), Characterising science-industry patent collaborations: knowledge base, impact and economic value, Bordeaux Economics Working Papers, BxWP2022-15

https://ideas.repec.org/p/grt/bdxewp/2022-15.html

Characterising science-industry patent collaborations: knowledge base, impact and economic value.

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Abstract

In this article, we analyse the characteristics of science-industry patents with respect to non-collaborative industry patents and industry-industry collaborative patents. This analysis covers patents filed in the years 1978-2015 (and granted up to 2020) at the European Patent Office (EPO) in four large European countries (Germany, France, Italy and the UK) and in the US. We consider three dimensions to assess the characteristics of patents: the knowledge base, the technological impact, and the economic value. Science-industry collaborative patents are averagely more sophisticated and similar or higher impact than other industry patents. However, depending on the proxy chosen, they are of similar or lower economic value compared to non-collaborative industry patents and to industry-industry collaborative patents. When we control for the experience of private companies in collaborating with academic institutions, we observe that more experienced collaborations produce slightly less sophisticated and impactful patents, but with higher economic value. We discuss different explanations of these findings.

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JEL codes: O31, O34

Abstract (FR)

Dans cet article, nous analysons les caractéristiques des brevets collaboratifs science-industrie par rapport aux brevets industriels non collaboratifs et aux brevets collaboratifs industrie-industrie. Cette analyse porte sur les brevets déposés au cours des années 1978-2015 (et accordés jusqu'en 2020) à l'Office européen des brevets (OEB) dans quatre grands pays européens (Allemagne, France, Italie et Royaume-Uni) et aux États-Unis.

Nous considérons trois dimensions pour évaluer les caractéristiques des brevets : la base de connaissances, l'impact technologique et la valeur économique. Les brevets de collaboration science-industrie sont en moyenne plus sophistiqués et ont un impact similaire ou supérieur aux autres brevets industriels. Cependant, selon l'indicateur choisi, leur valeur économique est similaire ou inférieure à celle des brevets industriels non collaboratifs et des brevets collaboratifs industrie-industrie. Lorsque nous contrôlons l'expérience des entreprises privées en matière de collaboration avec les institutions académiques, nous observons que les collaborations plus expérimentées produisent des brevets légèrement moins sophistiqués et moins impactant, mais avec une valeur économique plus élevée. Nous discutons les différentes explications de ces résultats.

1. Introduction[1]

Since at the least the 1990s, an apparent paradox has marked the relationship between science and innovation: corporate investments in basic research have either stagnated or declined (Arora et al., 2018), but the importance of science as a direct source of new products and process has not ceased to increase, witness the rise of biotechnology and information and communications technology (Ahmadpoor & Jones, 2017). How to explain these opposite trends? The answer, or at least part of it, lies in the changing role of universities and public research organisations, which have found themselves uniquely well-positioned for producing prototypes and proofs of concepts derived directly from basic research, but with clear applications for product and process innovation (Baba et al., 2009). This has allowed business companies, especially large ones, to increasingly replace or couple vertically integrated R&D strategies with open-innovation ones and collaborations with academic scientists not only for hunting for new prototypes and proofs of concepts, but also for developing them (Chesborugh, 2003; Arora et al., 2018). However, concerns emerged about whether research conducted by universities can be a good substitute for research performed by larger firms (Arora et al., 2020), especially when coordination and transaction costs (and eventually, conflicting interests) are relevant factors.

In the literature, numerous empirical studies support the idea that the interaction with scientific institutions positively influence the innovativeness of companies (Jaffe, 1989; Mansfield, 1998; Kaufmann and Tödtling, 2001; George, et al., 2002; Lööf and Broström, 2008; Yang, et al., 2009; Eom and Lee, 2010). For instance, Jaffe (1989) proved that university research significantly influences the number of corporate patents, especially in science-based sectors. Mansfield (1998) found that 15% of new products developed in the US would not be developed without support from academic research in the observed period from 1986 to 1994. Yang et al. (2009) found that networking with scientific institutions make new technology-oriented companies localised in scientific parks to innovate more than companies outside the parks.

[1] All our thanks to Laurent Berge, Catalina Martinez, Francesco Lissoni and Ernest Miguelez for their comments and suggestions. We also gratefully acknowledge funding from the CNRS-CSIC 2018 IRP ALLIES - Associated Laboratory on Linkages between Innovation and Environmental Sustainability https://irp-allies.com/ and from the Agence Nationale de la Recherche (ANR) (NPEIE Project, no. ANR-17-CE26-0014-01 https://npeie.org). Some results of the paper have been presented at the table ronde - « L'expérience de la recherche collaborative pour les leaders économiques de demain » during the event organized by the CNRS under the "Présidence française de l'Union Européenne (PFUE) and published in the CNRS booklet "From science to society. The value of European Collaboration".

However, when it comes to estimate the precise role of science-industry collaborations (as a form of interaction), results are less clear. On the one hand, some empirical works point toward a positive effect of science-industry collaborations on the innovativeness of companies. For example, Belderbos et al. (2004) have proven that formal collaboration with universities and research institutes improves technological capabilities of R&D activities within companies, as well as their efficiency. On the other hand, other scholars identified a negative or non-significant impact of science-industry research collaborations, especially if compared to other sources of funding and collaborations. For example, using Italian manufacturing companies' data, Medda et al. (2006) have shown that research collaborations between firms and universities are not associated to a productivity gain (measured as total factor productivity growth), contrary to collaborations involving only firms. A similar result is found by Jaklič et al. (2014) who, by relying on a sample of Slovenian companies participating in the Community Innovation Surveys from 1996 to 2008, found no effect of collaboration with academic institutes on innovation. Finally, these results were confirmed more recently by Raguž and Mehičić (2017) on a study on Croatian firms.

The different conclusions researchers have reached call for further analysis of the phenomenon. To this purpose, in this article, we focus on science-industry patent collaborations. Despite patent data have some important limitations,[2] they allow to directly assess the value of research collaborations - by relying on observably patent characteristics - , rather than to estimate it only indirectly by relying on innovation and performance indicators at firm level. The purpose is to assess the quality, measured in terms of knowledge base, impact and economic value, of *science-industry* collaborative patents by comparing them to both *non-collaborative industry* patents and *industry-industry collaborative* patents. Moreover, we focus on the role of firms know-how in

[2] Patent data have limitations for two reasons. First, patents are not the main channel of science–industry knowledge transfer (Agrawal and Henderson, 2002; Goddard and Isabelle, 2006). For example, by using two different surveys in Austria — one among university departments and one among firms - Schartinger et al. (2001) find that the most frequent and beneficial knowledge transfers occur through the mobility of human capital, for example via the co-supervision of PhDs. Similarly, by exploiting a database that lists more than 1,000 firms having collaborated with the University Louis Pasteur (ULP) between 1990 and 2002, Levy et al. (2009) find that about 18% of ULP's private partners have signed one or several European contract with the university, while only 8% of ULP's private partners are involved in patenting activity (as co-applicants). Second, the propensity to patent varies across industry (Orsenigo and Sterzi, 2010), especially when it comes to collaborations: for example, Arundel and Geuna (2004) show that low tech firms rely more on codified sources (such as publications and patents) and research contracts, whereas high tech firms tend to favour channels allowing the transfer of tacit knowledge whereas.

collaborating with universities and public research centres to investigate the role of experience in collaborating with universities with respect to the quality of the collaboration output.

Our results indicate that when technological quality of the underlying invention is considered, *science-industry* collaborative patents are of higher quality than *non-collaborative* industry patents and *industry-industry* collaborative patents. They appear to be more original, more novel, more general and more cited than *non-collaborative* industry patents. By contrast, when the economic value of the patent is considered, *science-industry collaborative* patents are of lower value or not significantly different from *non-collaborative* industry patents.

However, our results point out an important role played by the experience in collaborating. In particular, we find that higher level of experience in collaborating with academic institutions are associated to lower technological quality and higher economic value compared to collaborations between academic institutions and companies at the first collaborating experience. In a sense, it is as if experience in collaboration makes the research produced by universities more similar (and substitute) to industrial research.

Our findings provide several contributions to the literature on science-industry collaborations, by unveiling how they may result into innovations characterised by many knowledge spillovers (in line with findings by Petruzzelli and Murgia, 2020) but that, however, cannot necessarily substitute research performed by larger firms.

The remainder of the paper is organised as follows. In the next section, we briefly review the background literature on how patent data has been utilised to study economic impact and value of inventive activity. Section 3 presents the data and method. Section 4 reports the main econometric results and finally, Section 5 concludes and describes the main limitations of the paper and the potential directions for future research.

2. Knowledge base, impact and economic value of patented inventions

Innovation can be defined as "a cumulative process, whereby each innovation builds on the body of knowledge that preceded it, and forms in turn a foundation for subsequent advances" (Trajtenberg et al., 1997, p. 20). Patent data provides a rich source of information that makes it possible to investigate a variety of features referred to inventions. In this work we question the characteristics of science-industry collaborations according to three dimensions: the knowledge base, the impact and the economic value. These three features will be proxied by different indicators widely diffused in the literature on patent data. Patents have been widely adopted to study the inventive process and the characteristics of new technologies.

Studying the knowledge components or knowledge base of an invention means to investigate the recombination processes that made the invention came into existence (Weitzman, 1998; Fleming, 2001). Knowledge components can be recombined in different ways, depending on the type of landscape in which the search and combination processes take place (Fleming and Sorenson, 2001). For instance, according to Fleming (2001) and Fleming and Sorenson (2001, 2004), combining similar components through a local search process tend to lead with higher probability to a successful output of the combination effort, however most often producing small improvements with respect to the state of the art. Conversely, moving in a distant search process and combining dispersed and distant knowledge bits have less probability of a successful output, but high probability of leading to a breakthrough invention.

Studying the knowledge base of an invention means therefore to investigate its ex-ante characteristics, or the backword processes that lead to the inventive output. A variety of indicators have been proposed in the literature, some of which applied in the context of science-based inventions. The seminal work by Trajtenberg et al. (1997) stresses the role of the 'importance' of the inventions, and introduce the indicator of originality to measure it. Originality captures the degree of dispersion, across different technological fields, of the knowledge sources on which the invention builds. That is, a higher variety of technological classes belonging to the patents cited in the focal patent indicate the focal invention is of higher complexity (Barbieri et al, 2020). Most of the studies applying this indicator to university patents find that these are averagely more original than industry patents, indicating that public patented research results tend to source knowledge from a higher number of different domains (Thursby et al., 2009). Such findings mirror the consideration that public research tend to be more basic, general and abstract in nature (Arora and Gambardella, 1994; Trajtenberg et al., 1997). In line with these considerations, Fleming (2001) argues that combining more diverse and dispersed knowledge components means to undertake more uncertain research and development projects. Greater uncertainty lead to lower chances of obtaining a successful output, however a higher probability of generating breakthrough inventions. Fleming and Sorenson (2004) argue that more uncertain research project have more chances to end successfully when they benefit from scientific method and knowledge, indicating that scientific research is more prone to generate novel or radical inventions compared to industry research (Thursby et al., 2009; Rizzo et al., 2020).

Studying the impact means to investigate the ex-post technological influence of inventive activity, that is its role for the development of follow-on innovations. Investigating the impact of a technology consists in looking at the technological opportunities that an invention is able to spur (Schoenmakers and Duysters, 2010). Indeed the impact of an invention is measured in terms of its diffusion as prior art in subsequent inventions and by looking at the variety of sectoral applications in which it is exploited (e.g. Barbieri et al., 2020).

Surely the most diffused indicator to measure the impact of an invention is forward citations (Hall and Helmers, 2013; Sorenson and Felming, 2004; Bacchiocchi and Montobbio, 2009; Dechezleprêtre et al., 2017; Dahlin and Behrens, 2005; Schoenmakers and Duysters, 2010; Abrams et al., 2018), widely adopted also to compare university and industry patents (Henderson et al., 1998; Sampat et al., 2003; Thursby et al., 2009; Sterzi, 2013; Sterzi et al., 2019). The extant literature finds different results about which patents receive more citations: some works, especially based on the US, find universities receive higher number of forward citations compared to industry patents (e.g. Trajtenberg et al., 1997; Sampat et al., 2003); other works find no difference (e.g. Sapsalis et al., 2006; Thursby et al., 2009). Another widely adopted indicator of technological impact is the generality index (Hall and Trajtenberg, 2004; Barbieri et al., 2020), introduced by Trajtenberg et al. (1997), which consists in the forward counterpart of originality. It is often adopted to measure the general purposeness of a technology (Bresnahan and Trajtenberg, 1995; Hall and Trajtenberg, 2004). The generality index measures how distributed across different technological fields are the forward citations of an invention. Most studies applying this indicator to compare university and industry patents tend to recognise a premium for the former (Trajtenberg et al., 1997; Henderson et al., 1998), again because of the basic, general and abstract nature of public research activities compared to industrial ones.

Finally, the economic value of an invention concerns those aspects unrelated directly to the characteristics of the invention, but that are expression of the quality with respect to the economic feasibility and success of the invention. As Kline and Rosenberg (1986, p. 278) put it: “it is a serious mistake […] to equate economically important innovations with that subset associated with sophisticated technologies" and "technical success is only a necessary and not sufficient condition in establishing economic usefulness".

The economic value reflects the ability of the patent holder to exploit commercially the invention protected by the patent. More valuable patents tend to be renewed more often and to be extended in a higher number of countries (Lanjouw et al., 1998). Specifically, to the extent that maintaining the patent protection over time is costly, one can assume that any valuable patent pays at least for its own renewal and that the more valuable patents will be renewed for a longer time, conditional on technology-specific differences in knowledge obsolescence (Lanjouw et al., 1998). In turn, the number of renewals has been adopted as an indicator of patent economic value (Higham et al., 2021). Similarly, extending the patent towards more countries, i.e. extending the patent family, is associated with higher costs for the applicant, such as patent office fees, patent attorneys bills and translation costs (Martinez, 2011), and making family size a widely used indicator of the invention economic value (Haroff et al., 2003). These indicators have also been applied to the context of university patents (Sterzi et al., 2019; Cerulli et al., 2021).

In this work we rely on these indicators to study the three dimensions of knowledge base, impact and value in order to investigate the output of science-industry collaborations and to understand in what terms this output is different from non-collaborative inventions, from industry-industry collaborations, and also from non-collaborative science inventions. The same dimensions will be also put in relation to the experience of firms in collaborating with industry.

3. Empirical part

3.1. Data and key figures

In the analysis we rely on patent datasets provided by the OECD (February 2022 version): the HAN Database, the REGPAT Database and the OECD Patent quality database. Further we rely also on PATSTAT (2021 autumn edition) in order to retrieve the DOCDB patent family identifier and to avoid counting more than once those patent applications belonging to the same patent family. Then, in order to associate our patent-application variables to the patent family we follow the same procedure as in, for example, Verhoeven et al. (2016) and Barbieri et al. (2020): we select the highest value within each family.

The analysis focuses on patents applied in the years 1978-2015 (and granted up to 2020) at the European Patent Office (EPO) by industrial firms or public research institutes located in the four largest European countries (Germany, France, Italy and the UK) and in the US. A collaborative patent is defined as a patent with more than one applicant. The applicant is the entity that has the property right to the patent and is responsible (or co-responsible) for the research underlying the patent (or at least its financing). In this analysis, science-industry collaborations are thus defined as collaborative patents involving both firms and academic institutions (universities, public research centres and hospitals). Similarly, industry-industry collaborations are those patents applied by two (or more) different business entities. The type of applicant is retrieved from the EEE-PPAT dataset provided by KU-Leuven.[3]

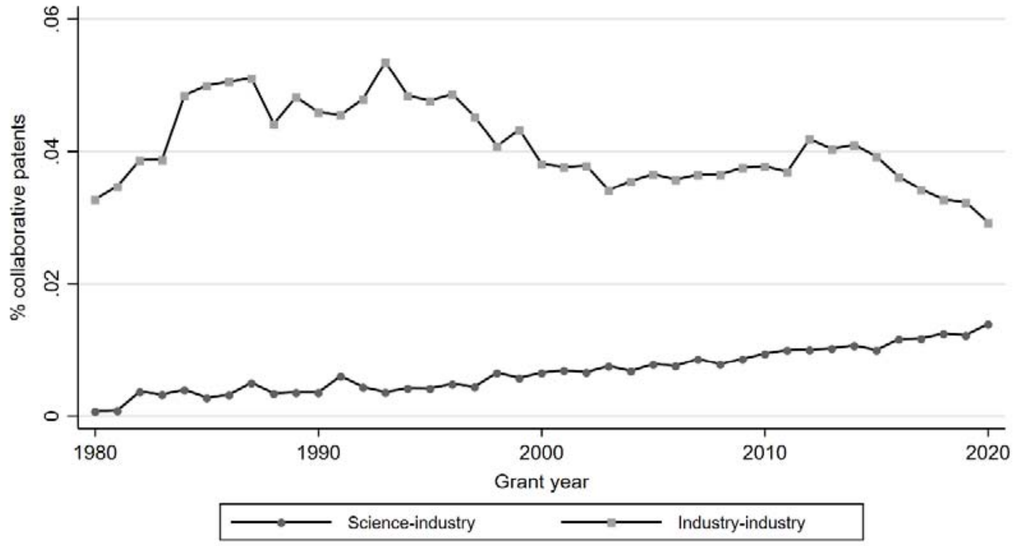
We identify 1,011,147 patent families, of which 917,585 (90.75%) are applied by one firm only ("*non-collaborative patents*")[4], 8,211 (0.8%) are co-applied by firms and universities or public research centres ("*collaborative: science-industry*") and 39,900 (3.95%) are co-applied by two or more firms ("*collaborative: industry-industry*").[5] The remaining 45,451 patents (4.5%) are owned by research institutions only ("*Science only*").

[3] We excluded all patents whose applicants are only individuals or unknown.

[4] Some of these patents may however derive from collaborations between university and firm: this happens whenever a university professor transfers the invention autonomously to the private sector or in case of consultancy activities (Carayol and Sterzi, 2021).

[5] Industry-industry collaborative patents may include both joint ventures and collaborations involving subsidiaries belonging to the same group.

Figure 1. Share of collaborative industry patents by year of grant

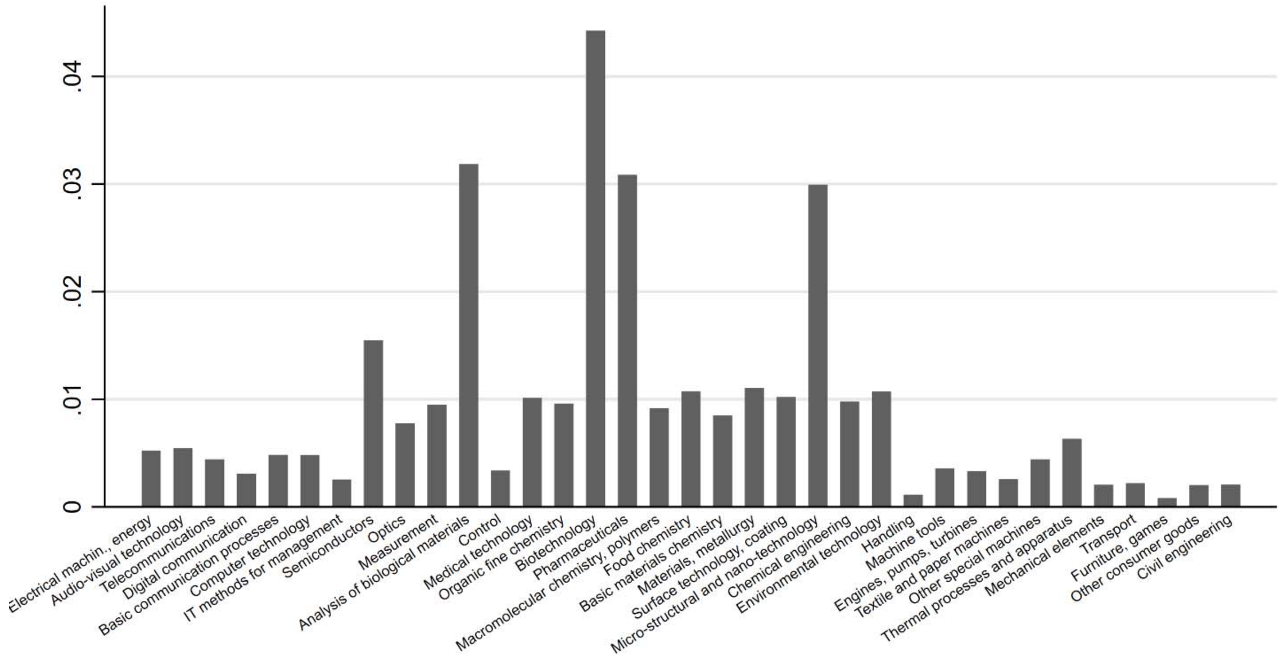


Note. Share of collaborative EPO patent families filed in the years 1978-2015 by industrial firms located in four large European countries (Germany, France, Italy and the UK) and in the US.

Three important facts emerge. First, the weight of science-industry collaborative patents as percentage of industry patents has increased over the last 40 years, starting from around 0.1-0.2% in the early Eighties, growing to 0.6% in early Nineties and reaching 1.5% in 2020 (Figure 1).[6] Meanwhile, the share of industry-industry collaborations is more or less stable, slightly decreasing from the Nineties, but yet twice as science-industry collaborations. This indicates that while collaborations among firms are a rather old phenomenon, collaboration between firms and universities is much newer. Second, the largest shares of collaborative patents are in science-based technological fields: in particular, *Biotechnology*, *Analysis of biological materials*, *Micro-structural and Nano-technology*, and *Pharmaceuticals* are those with the largest share of industry-science collaborative patents, where about 3%-5% of industry patents derive from science-industry collaborations (Figure 2). Third, the share of science-industry collaborative patents varies significantly across the countries considered in the analysis, with France showing the largest share (2%) (Figure 3). The result for France can be in part explained by a relatively large share of French patents owned by universities and public research centers (Martinez and Sterzi, 2019).

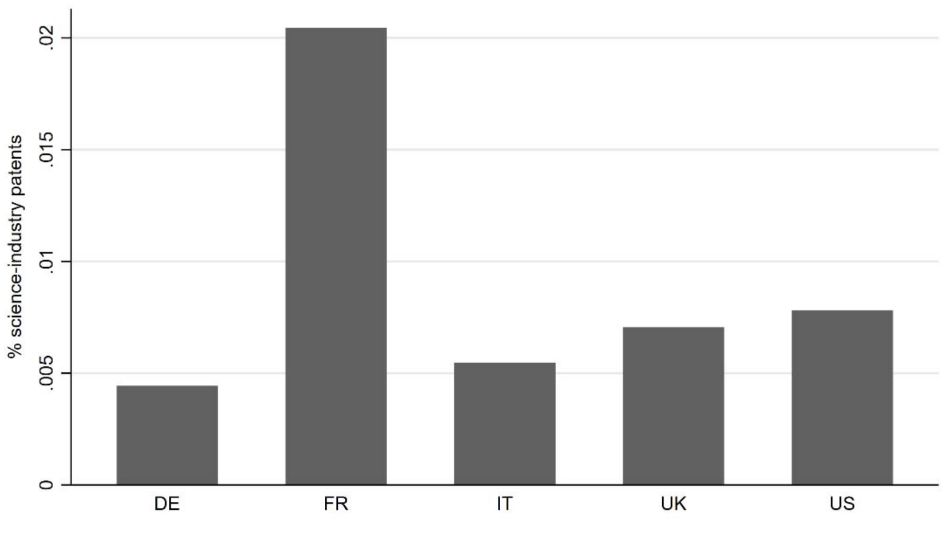
[6] This can be explained both by the increasing propensity of universities and companies to collaborate and by the greater incentive of universities to maintain the intellectual property resulting from the collaborations with the private sector (Martinez and Sterzi, 2020).

Figure 2. Share of science-industry patents by technological fields



Note. Share of science-industry EPO patent families filed in the years 1978-2015 located in four large European countries (Germany, France, Italy and the UK) and in the US. Technological fields are defined according to WIPO 2011, (Squicciarini et al., 2013).

Figure 3. Share of science-industry patents by country



Note. Share of science-industry EPO patent families filed in the years 1978-2015 by country.

3.2. Characterising science-industry collaborations

In order to assess the knowledge base, impact and economic value of science-industry collaborative patents, we estimate the following baseline specification:

$$q_i = \beta_0 + \beta_1[industry - industry] + \beta_2[science - industry] + \beta_3[science\ only] + \beta_4 X + B_{TF} + B_{FY} + B_{GY} + B_c + \varepsilon \quad (1)$$

where q_i is the standardized (z-score) patent family indicators by filing year and technological field (35-macro classes). As delineated in Section 2, we identify two indicators to measure the knowledge base of inventions: originality and novelty in recombination; two indicators to capture impact: 7-year forward citations and generality; and two indicators proxying for the economic value: family size and renewal.[7] Variables *"Industry-Industry"*, *"Science-Industry"* and *"science only"* are dummy variables indicating respectively if the industry patent is co-applied by two or more firms, by (at least) one firm and (at least) one academic institution, or only by one or more academic institutions. The omitted category is the situation in which the patent has been applied for by only one firm (*"Non-collaborative patent"*). Parameters β_1 and β_2 identify the premium value associated with the two types of collaborations with respect non-collaborative industry patents, while β_3 identifies the premium associated to science only patents. Furthermore, we also include a set of patent family level control variables (X): the number of backward citations and the number of IPCs. Finally, with some abuse of notation for simplicity, B_{TF} denotes a set of 35 technological classes fixed effects, B_{FY} a set of filing year fixed effects, B_{GT} a set of grant year fixed effect, B_c a set of country fixed effects. Table 1 report descriptive statistics for the variables used in the analysis.

[7] All indicators but novelty in recombination are derived from the OECD patent quality dataset (Squicciarini et al., 2013); novelty in recombination is a dummy variable taking the value of 1 if the patent is novel and 0 otherwise and is constructed as in Verhoeven et al. (2016). Differently from the other indicators, novelty in recombination has not been standardized by filing year and technological fields.

Table 1. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Non collaborative	1,011,147	.907	.29	0	1
Science only	1,011,147	.045	.207	0	1
Science-industry	1,011,147	.008	.09	0	1
Industry-industry	1,011,147	.039	.195	0	1
Originality	993,445	.666	.241	0	.989
Novelty in recombination	1,011,147	.135	.341	0	1
Generality	420,769	.353	.281	0	.946
Forward citations	1,011,147	1.215	2.877	0	624
Renewal	1,011,147	11.369	4.638	1	29
Family size	1,011,147	6.508	4.547	1	57
Backward citations	1,011,147	5.652	7.511	0	300
Number IPCs	1,011,147	4.275	4.144	1	100

Table 2 shows the regression results based on OLS estimation. Science-industry collaborative patents display 0.09 standard deviations greater in terms of originality, and have 0.8% higher probability of being novel, than non-collaborative industry patents. In terms of knowledge base, science-industry patents reveal to emerge as the outcome of more complex and radical recombinant inventive process compared to non-collaborative patents. Moreover, as it can be seen from the T-test across groups presented in Table 2, science-industry collaborative are also more original and more novel than industry-industry patents, while they are more original but less novel than science-only patents. Overall the collaboration between academic institutions and industry lead to the generation of the most original inventions, and of inventions with a high degree of novelty, second only to pure scientific inventions. The contribution of collaborating with universities in terms of knowledge base is therefore, for collaborating firm, tangible in terms of complexity and novelty of the inventive output.

For what concern the impact of inventions (columns 3 and 4 of Table 2), our results show that science-industry patents receive 0.04 standard deviations more citations and are 0.14 standard deviations more general than non-collaborative industry patents. Science-industry collaborative inventions receive a number of forward citations as high as the one of industry-industry collaborations. Conversely they outperform significantly industry-industry patents in terms of generality, scoring a level for this indicator as high as "Science-only" patents. Again the role of university knowledge is visible and mostly related to the basicness of research, that make these patents to diffuse across a wide range of different sector (higher degree of generality). In terms of diffusion towards following technological developments, the contribution is again visible but align the performance of these patents to the other collaborative patents (industry-industry).

Finally, in terms of economic value, science-industry collaborations reveal to be as valuable as or less valuable than non-collaborative industry patents. Specifically, the coefficient of science-industry patents when the dependent variable is renewals is non-significant, while it is negative (0.05 standard deviations lower than non-collaborative industry patents) when put in relation to family size. From the t-test shown in Table 2 we can note that science-industry patents are not statistically different from industry-industry patents in terms of renewals, while the latter display higher family-size compared to the former. Conversely both indicators score higher coefficients compared to science-only patents.

In summary, our findings indicate that while the output of science-industry collaborations lead to the generation of highly complex and novel inventions that are also able to produce important impact on subsequent inventive activities, the economic value remains rather low.

Table 2. Characteristics of science-industry collaborations (OLS regression)

	Knowledge base		Impact		Economic value	
	(1)	(2)	(3)	(4)	(5)	(6)
	Originality	Novelty in recombination	Forward citations	Generality	Renewal	Family size
Industry-industry (β_1)	0.0396***	-0.00986***	0.0524***	0.0166**	-0.0113**	0.0603***
	(0.00485)	(0.00159)	(0.00532)	(0.00768)	(0.00495)	(0.00505)
Science-industry ($\boldsymbol{\beta_2}$)	**0.0888*** **	**0.00775** **	**0.0443*** **	**0.138*** **	**0.00567**	**-0.0530*** **
	(0.0107)	**(0.00329)**	**(0.0127)**	**(0.0165)**	**(0.0105)**	**(0.0106)**
Science only (β_3)	0.0538***	0.0163***	-0.0283***	0.134***	-0.114***	-0.254***
	(0.00511)	(0.00153)	(0.00484)	(0.00777)	(0.00495)	(0.00448)
Backward citations	0.216***	0.00182***	0.106***	0.0228***	0.0265***	0.0485***
	(0.00155)	(0.000342)	(0.00245)	(0.00138)	(0.000922)	(0.00119)
Number IPCs	0.183***	0.121***	0.119***	0.158***	0.0283***	0.146***
	(0.000944)	(0.000426)	(0.00156)	(0.00143)	(0.000932)	(0.00118)
Constant	-0.00980***	0.134***	-0.00115	-0.0294***	0.00551***	0.00946***
	(0.00101)	(0.000318)	(0.00102)	(0.00161)	(0.00101)	(0.00102)
T-test: $\beta_1 = \beta_2$	17.8***	23.8***	0.35	45.9***	2.16	95.4***
T-test: $\beta_2 = \beta_3$	9.0***	5.8**	29.4***	0.06	110***	323***
Filing year FE	Yes	Yes	Yes	Yes	Yes	Yes
Grant year FE	Yes	Yes	Yes	Yes	Yes	Yes
Technology FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	993,445	1,011,147	1,011,142	420,767	1,011,147	1,011,145
R-squared	0.096	0.207	0.037	0.038	0.062	0.066
F	12635***	16427***	1729***	2705***	504.3***	4222***

Note. Estimated parameters $\hat{\beta}_1$and $\hat{\beta}_2$ from the baseline specification (1); robust standard errors in parenthesis: Sign: ***99%, **95%, *90%. All patent indicators, except novelty, are standardized by 35-class technological fields and filing years. The omitted category consists of non-collaborative industry patents.

3.3. Experience in science-industry collaborations

One possible explanation of the fact that science-industry patent collaborations are not of a particularly high economic value is that firms may lack of routines and experiences in collaborating with academic institutions (Petruzelli, 2011). In fact, in order to be effective, science-industry collaborations require strong investments for both firms and academic institutions that can be achieved only by routines. Firms should invest in absorptive capabilities (for example, by hiring managers whose role it is to interact with academia) and communicate the firm's technological needs. Academic institutions, should invest in facilitating the transfer of tacit knowledge ("know-how") in the development process.

In order to consider whether experience in collaboration matters and, more in general, what is the role of such experience in respect to the knowledge base, impact and especially economic value of science-industry collaborations, we estimate the following model where we distinguish first experiences in collaboration from further collaborations:

$$q_i = \beta_0 + \beta_1[industry - industry] + \beta_2[science - industry\ first\ collab] + \beta_3[science - industry\ further\ collab] + \beta_4[science] + \beta_5 X + B_{TF} + B_{FY} + B_{GY} + B_c + \varepsilon \qquad (2)$$

where our main parameters of interest are β_2 and β_3 that identify the premium value associated with the science-industry collaborations with respect non-collaborative industry patent respectively when firms collaborate with academic institutions for the first time ever or, on the contrary, when firms have already collaborated with academic institutions in the past; β_1 identifies the premium value associated with the industry-industry collaborations with respect to non-collaborative industry patents, while β_4 the premium associated to the scientific patent with respect to non-collaborative industrial patents.

OLS estimated parameters are shown in Table 3. The economic value of science-industry collaborations when it measured by renewals (column 5) tends to remain stable, independently from the experience of the firm in collaborating with academic institutions. Conversely, moving from the first to further experience, the value of science-industry collaborations measured throughout the indicator of family size tend to increase (column 6). Indeed, while first experience science-industry patents have lower family size than non-collaborative industry patents, further collaborations lead to patents with the same level of family size of non-collaborative industry patents.

Overall it is plausible to conclude that science-industry collaborations tend to show higher economic value when the firm has already matured some experience in collaborating with an academic institution.

Looking at the indicator of the knowledge base, our results point out that science-industry collaborations at the first experience are more original than science-industry collaborations that involve firms having already maturated some experience in collaborating with academic institutions in the past (column 1). A similar result is also obtained when looking at the novelty in recombination indicator (column 2), although the difference is less significant.

For what concern the impact, science-industry collaborations appear also to be more general when they involve firms at the first experience in science-industry collaborations with respect to firms having already maturated some experience in the past (column 4). However, science-industry collaborations that derive from experienced firms display a higher level of generality with respect both industry-industry collaborations and non-collaborative industry patents. By contrast, experience in science-industry collaboration does not appear playing a significant role when the impact is proxied by the number of 7-year forward citations (column 3): forward citations of science-industry collaborations are higher than non-collaborative patents, however there is no difference in coefficient between science-industry collaborations, independently of the experience of the firm, and industry-industry collaborations.

Table 3. Characteristics of science-industry collaborations (OLS regression)

	Knowledge base		Impact		Economic value	
	(1)	(2)	(3)	(4)	(5)	(6)
	Originality	Novelty in recombination	Forward citations	Generality	Renewal	Family size
Industry-industry (β_1)	0.0395***	-0.00986***	0.0523***	0.0164**	-0.0114**	0.0603***
	(0.00485)	(0.00159)	(0.00532)	(0.00768)	(0.00495)	(0.00505)
Science-industry first collab ($\boldsymbol{\beta_2}$)	**0.103*** **	**0.00988** **	**0.0313** **	**0.161*** **	**0.00922**	**-0.101*** **
	(0.0133)	**(0.00416)**	**(0.0152)**	**(0.0201)**	**(0.0127)**	**(0.0124)**
Science-industry further collab ($\boldsymbol{\beta_3}$)	**0.0618*** **	**0.00441**	**0.0378* **	**0.0777*** **	**-0.0186**	**0.0227**
	(0.0184)	**(0.00531)**	**(0.0195)**	**(0.0291)**	**(0.0187)**	**(0.0191)**
Science only (β_4)	0.0538***	0.0163***	-0.0286***	0.134***	-0.114***	-0.254***
	(0.00511)	(0.00153)	(0.00484)	(0.00777)	(0.00495)	(0.00448)
Backward citations	0.216***	0.00182***	0.106***	0.0228***	0.0265***	0.0485***
	(0.00155)	(0.000342)	(0.00245)	(0.00138)	(0.000922)	(0.00119)
Number IPCs	0.183***	0.121***	0.119***	0.158***	0.0283***	0.146***
	(0.000944)	(0.000426)	(0.00156)	(0.00143)	(0.000932)	(0.00118)
Constant	-0.00979***	0.134***	-0.00105	-0.0294***	0.00557***	0.00950***
	(0.00100)	(0.000318)	(0.00102)	(0.00161)	(0.00101)	(0.00102)
T-test: $\beta_1 = \beta_2$	20.3***	19.9***	1.71	45.7***	2.31	146***
T-test: $\beta_1 = \beta_3$	1.38	6.69***	0.52	4.19**	0.14	3.66*
T-test: $\beta_2 = \beta_3$	3.30*	0.66	0.07	5.64**	1.52	29.9***
Filing year FE	Yes	Yes	Yes	Yes	Yes	Yes
Grant year FE	Yes	Yes	Yes	Yes	Yes	Yes
Technology FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	993,445	1,011,147	1,011,142	420,767	1,011,147	1,011,145
R-squared	0.096	0.207	0.037	0.038	0.062	0.067
F	10529***	13689***	1441***	2254***	420.5***	3524***

Note. Estimated parameters $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\beta}_3$ and $\hat{\beta}_4$ from specification (2); robust standard errors in parenthesis: Sign: ***99%, **95%, *90%. All patent indicators, except novelty, are standardized by 35-class technological fields and filing years. The omitted category consists of non-collaborative industry patents.

4. Conclusions

In this paper we analyse whether science-industry patent collaborations are associated with a premium in quality with respect non-collaborative industry patents and industry-industry collaborative patents. Three dimensions of patent quality are considered: knowledge base, impact, and economic value.

The analysis shows that science-industry patent collaborations cover inventions that ground on more complex and novel knowledge bases, show higher impacts on follow-on innovation, but that do not reflect in a higher economic value. Inexperience in science-industry collaborations explains only partially this last result: science-industry collaborations involving firms that have already experienced at least one collaboration with academics in the past display a slightly higher economic value with respect to non-collaborative industry patents. Conversely, the knowledge base and impact tend to reduce when firms involved in the science-industry collaborations are involved. These findings reveal that firms that approach a collaboration with an academic institution for the first time tend to generate very valuable inventions from a technical point of view but lacking economic value. In turn, when they gain experience in collaborating with the science partner, the technicalities tend to decrease in favour of an increased economic value.

The non-correspondence between the technological impact and the economic value of science-industry collaborative patents can be explained by different hypothesis. First, patents are nowadays used for many reasons in addition to protecting an invention from imitation, especially in case of science-industry collaborations, where they may reflect the necessity to clarify the ownership of the invention and to facilitate the knowledge transfer (Helman, 2007). Accordingly, the decision to patent an invention depends often more on the university side (rather than on the company), as universities aim to obtain economic returns from public agencies that view patents as a performance indicator (Sterzi et al., 2019; Martinez and Sterzi, 2021). Second, firms may prefer to avoid to collaborate with universities for core strategic projects, and that what they do in collaborations is more exploratory: in this case they may renew less (or extend patents in fewer countries) because these patents open new lines of research and lead to subsequent patenting but not to protection of inventions in the market. Further research is however necessary to validate these interpretations.

In terms of policy implications, these results suggest that corporate research conducted in collaboration with academic institutions can lead to breakthrough innovation in the long term but that may be an imperfect substitute for research performed by firms in the short term, especially when coordination and transaction costs (and eventually, conflicting interests) are relevant factors. Firms should keep investing in in-house basic research rather than simply rely on knowledge acquired from outside to fuel their growth.

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