Effects of co-patenting across national boundaries on patent quality. An exploration in pharmaceuticals

Acosta, Manuel and Coronado, Daniel and Medina, Jennifer

University of Cadiz

2024

Effects of co-patenting across national boundaries on patent quality. An exploration in pharmaceuticals

Manuel Acosta
Daniel Coronado✉
Jennifer Medina
UNIVERSITY OF CADIZ (Spain)

Abstract: This paper explores three novel research questions. First, is an increase in the number of countries involved in ownership of a co-patent an effective way to enhance patent quality? Second, if the objective is to raise patent quality, which are the right countries to collaborate with? And third, does cooperation with partners located in a tax haven affect patent quality? The empirical methodology relies on forward citations as an indicator of quality, and patent co-ownership as a measure of international collaboration. We estimated several count models with a sample of 143,479 pharmaceutical patents (patent families). Our econometric findings show that, first, the average effect of international collaboration is a 4.9% increase in patent quality compared with those patents for which the assignees come from a single country (once we controlled for patent characteristics). When the number of countries in which the assignees are based increases, the effect of this wider collaboration on patent quality is also greater, though only for up to a maximum of five countries. Second, to produce patents of better quality, the most suitable countries with which to collaborate were found to be the United States, Switzerland, Japan, Germany and the United Kingdom. Finally, collaboration with firms located in a country categorized as a tax haven does not have any significant impact on patent quality.

Key words: patent quality, collaborative patent, international collaboration, pharmaceutical industry.

This is an original manuscript of an article published by Taylor & Francis in Economics of Innovation and New Technology in 2024, available at https://doi.org/10.1080/10438599.2023.2167201

Please, quote as:
Acosta, M., Coronado, D., & Medina, J. (2024). Effects of co-patenting across national boundaries on patent quality. An exploration in pharmaceuticals. *Economics of Innovation and New Technology*, *33*(2), 248-281.

✉ Daniel Coronado
Facultad de Ciencias Económicas y Empresariales
UNIVERSIDAD DE CÁDIZ
C/ Enrique Villegas Vélez, 2
11002 – Cádiz (SPAIN)
e-mail: daniel.coronado@uca.es
Tel. +34 608207679

1. Introduction

The interest of firms in patent quality results from both the positive relationship between patent quality and firm performance (Hirschey and Richardson, 2004; Hall et al., 2005; Chen and Chang, 2010; Patel and Ward, 2011; Harrigan et al., 2018), and the effects of patent quality on a firm's reputation for technological innovation (Henard and Dacin, 2010; Höflinger et al., 2018). Patent quality can also benefit the whole patent system in accomplishing one of its main objectives, which is to confer a net benefit on society by encouraging follow-on inventions. Providing high quality patents on which subsequent inventors can build without infringement serves this purpose (Scotchmer, 1991; Higham et al., 2021). Among the factors affecting patent quality, one key issue that we study in this paper is whether international collaboration in producing joint patents improves patent quality. Joint patents, collaborative patents (co-patents) or co-assigned patents refers to the situation where two or more patent-holders (e.g., companies) own property rights to a registered invention (Hagedoorn et al., 2003; Kim and Song, 2007). A co-patent is international when at least one assignee (owner) is located outside of country A, and at least one other assignee is located within country A.

The need for strengthening international collaboration to produce high-quality patents is particularly relevant because through collaboration in research and development (R&D) activities, organizations may gain access to other countries' resources that firms cannot generate internally, and which help in coping with the increased complexity of innovation (Penner-Hahn and Shaver, 2005; De Beule and Van Beveren, 2019). When firms collaborate with other firms, they are exposed to a larger amount of knowledge and thus higher patent quality is expected. Furthermore, international collaboration can be a more effective strategy to produce quality patents than national or regional collaboration between firms. The main reason for this is that firms located close to one another sometimes use similar knowledge that can overlap. Thus, collaboration across national boundaries is likely to involve a greater variety of knowledge, thus enhancing learning (Molina-Morales and Expósito-Langa, 2013; Mascia et al., 2017).

There are two main methods used to study international collaboration in producing patents. One consists of identifying the location of the patents' inventors, and the other is based on the location of patent owners (assignees). These methods capture two (different) dimensions of geographical technological collaboration. The former reflects the collaboration on inventive activity. The latter represents the economic collaboration produced by innovation (Ma et al., 2009; Lei et al., 2013), and it is also a relevant strategy for companies developing technology jointly (Belderbos et al., 2014). The main advantage of patent co-ownership for firms is that it allows them to overcome individual limitations, in terms of technical or market innovation capabilities (Ponta et al., 2022). However, the analysis of the effect of joint patent ownership on producing quality patents has been neglected. To our knowledge, only Belderbos et al. (2014), Briggs and Wade (2014), Briggs (2015) and Lino et al. (2021) have studied the link between collaboration using patent ownership and patent quality, but only the latter two papers focus on international co-patents. These studies show that quality seems to be higher in joint patents with co-owners in multiple countries. We build on these empirical papers on the effect of co-ownership on patent quality to answer three questions that this literature does not disentangle. In particular, this paper sheds light on the following research questions: first, does an increase in the number of collaborations with partners in different countries, with different regulations, norms and national innovation systems, produce benefits for or have a detrimental impact on patent quality? Second, if the objective is to produce the best performance in terms of patent quality, what are the best countries to engage with in collaboration? And third, patent co-ownership might not be the result of effective collaboration, but simply of patent co-ownership with subsidiaries located in tax havens for fiscal reasons. Thus, to what extent does this affect patent quality?

We address these three main research questions by focusing on patented pharmaceutical technologies. We rely on detailed information for 143,479 pharmaceutical patents (patent families, excluding cosmetics) with assignees from 30 countries between the years 1990-2012. The pharmaceutical industry is characterized by a strong resort to patents because of the high uncertainty, and the high R&D costs of producing technologies, making patents a relevant indicator of firms' technological activities (Chen and Chang, 2010; Hall et al., 2014; Gamba, 2017). Furthermore, pharmaceuticals is one of the sectors where the use of patent co-ownership is more meaningful. Modern pharmaceutical R&D is increasingly complex and requires bringing together a wide range of skills. This can be achieved through co-patents and the collaborations that precede them (Kim and Song, 2007). The pharmaceutical sector is characterized by a great intensity of patent co-ownership because it is more difficult to split inventions into a set of independent components that can be separately patented (Hagedoorn, 2003; Ter Wal and Boschma, 2009).

Findings from the current study are expected to make several contributions. First, rather than focusing on the binary choice of whether or not to collaborate internationally, we analyse the extent to which the breadth of collaboration between patent owners from different countries has a decisive effect on patent quality. Furthermore, we identify whether co-patenting with leading countries in the pharmaceutical industry contributes to obtaining patents of better quality. Second, we investigate these issues in the pharmaceutical sector, a field characterized as being high intensity in R&D, but where the relationship between international collaboration in patent ownership and patent quality remains unexplored. Third, the effect on patent quality of co-ownership with firms located in tax havens is unknown. Finally, by including the variable international collaboration in patent ownership along with other variables, our study contributes to the growing empirical literature on the factors explaining patent quality. Among those factors considered by previous studies are, for example, the use of scientific and technological knowledge developed by other firms and institutions, the breadth of the technological base, the number of patent claims, and the size of the team that developed the patent, (Lanjouw and Schankerman, 2004; Gay et al. 2005; Popp, 2006; Sapsalis et al. 2006; Lahiri, 2010; Nemet and Johnson, 2012; Chang et al., 2018; Acosta et al., 2021).

The paper unfolds as follows. Section 2 reviews the literature on the effect of international collaboration on patent quality. Section 3 presents the data sources and a descriptive analysis of international collaborative patents in the pharmaceutical sector. Section 4 deals with the method, including a brief discussion of patent citations as an indicator of patent quality. This section also describes the variables and the model. The core empirical estimation is presented in Section 5, and we summarize our main conclusions in Section 6.

2. Patent quality and the role of international collaboration

2.1 Patent quality and its measurement

We define the quality of a patent as its impact on subsequent patented inventions. In this respect we follow the same definition as in Argyres & Silverman (2004), Gay et al. (2005), Popp (2006), Sapsalis et al. (2006), Lahiri (2010), Nemet and Johnson (2012), Schmid and Fajebe (2019), and Acosta et al. (2021). Thus, a patent that has an impact in many subsequent patents, in the sense that is used to support other inventions, is considered to have greater quality than others with less impact. This view deals with the technological and economic aspects of patents, for example the underlying capacity of knowledge embedded in patents to promote innovation, encourage the diffusion of technology, and affect economic performance. A related concept used in the literature is patent value, which is a term linked to the extent to which the impact of the patent correlates with any indicator of firm performance and market value (for discussions see, for example, Barberá-Tomás et al. 2011; and de Rassenfosse and Jaffe, 2018). There are clear differences between these concepts, however, there is strong evidence in the literature that indicators of the technological quality of patents are correlated with their economic value (see references in surveys by Hall and Harhoff, 2012; and de Rassenfosse and Jaffe, 2018).

A crucial consideration about patent quality is the issue of how to measure it. Although there are several ways to measure the quality of a patent (for a review, see Squicciarini et al., 2013), in this paper we use the number of forward patent citations. The logic behind the use of forward citations to capture the importance of patents is based on the idea that patents cited by subsequent patents in their 'state of the art' section (or forward citations) include bits of knowledge on which the underlying inventions rely. Therefore, if a patent is cited in many subsequent patents, this means that this particular patent has had a greater technological impact on future inventions, or it is more important than other patents that are less cited. Forward citations may also capture the economic value, as several validation studies have proved. Validation studies have found correlations between forward citations and different measures of patent value, such as social value (e.g., Trajtenberg 1990), values that R&D managers and experts give to patents (e.g., Albert et al. 1991; Harhoff et al. 1999), variation in the stock market value of firms (Hall et al. 2005), the decision to pay renewal fees (Thomas, 1999; Bessen, 2008; Harhoff and Wagner, 2009), measures of performance (Moser et al., 2017), and licensing revenue (Abrams et al., 2018). Some studies, however, cast doubt on forward citations as an indicator of economic value, because the authors did not find such a clear relationship (e.g. Gambardella et al., 2008; Azagra-Caro et al., 2017).

Overall, the use of citations may be justified as a measure of technological impact/value, but it should be acknowledged that this indicator carries significant 'noise' (Hall et al., 2005; Gambardella et al., 2008). This problem can arise from three main sources related to the role of examiners, self-citations, and time truncation. For example, Azagra-Caro and Tur (2018) show that for European Patent Office (EPO) patents, there are different patterns of examiner citations, depending on the examiner's country of residence. Moser et al. (2017) indicates that examiner-added citations are typically unrelated to improvements in performance or a follow-on invention. This study suggests that citations by examiners should be excluded from the number of forward citations. Self-citations might be the most direct procedure to observe follow-on innovations, but as with Higham et al. (2021), we will exclude self-citations in order to isolate the more informative citations. Finally, the truncation problem (the fact that patents continue to be cited over long periods and more recent patents have a lower probability of being cited) can be addressed by considering patents within a window of at least five years from their application date (Lanjouw and Schankerman, 2004; Mariani and Romanelli, 2007; Lahiri, 2010).

2.2 Does a greater number of collaborations between partners from different countries lead to patents of better quality?

Co-patenting across national boundaries indicates some degree of research collaboration, and a joint patent is the result of such collaborative efforts (Kim and Song, 2007). Patent co-ownership shows a strong commitment to the collaborative work from the parties involved, and suggests that the proportion of shared knowledge is relatively high (Hagedoorn et al., 2003; Belderbos et al., 2014; Elvers and Song, 2014). Furthermore, co-owned patents may assume an important role in industries with a strong regime of appropriability, such as the pharmaceutical sector (Hagedoorn, 2003), which is the sector that we analyse in this paper. However, co-patents only reflect a fraction of the firm's collaboration environment, which means that joint patents do not account for all collaborative R&D efforts (Belderbos et al., 2014; Briggs, 2015; Elvers and Song, 2014; Fritsch et al., 2020). Despite this drawback, the analysis of joint patents can provide new insight into the relationship between the cooperation intensity between agents and innovation success measured as patent quality, as the empirical literature has shown (Belderbos et al., 2014; Briggs and Wade, 2014; Briggs, 2015; and Lino et al., 2021).

When collaborative efforts at international level take place, part of which is captured by joint patenting, the theoretical argument explaining why international collaboration in R&D may produce innovative outputs of better quality is straightforward. Through research collaboration, partners can have access to specific knowledge available in other countries, which increases the quality of the research output (Su, 2017; Lee et al., 2020). Network ties positively influence firm innovation by facilitating access to complementary skills, by scale benefits, and by forming a broader knowledge base among the partners that agree on complementary aims (Simar and West, 2006; Knell and Srholec, 2008). Furthermore, collaboration can affect the output by increasing the probability of successful realization (Belderbos et al., 2010).

A key question in our analysis is whether the effect of international collaboration on patent quality could be more positive than for other forms of collaboration at closer geographical distance (e.g., national or regional). It has been widely documented that inter-organizational exchange of flows of knowledge is strongly influenced by the geographical proximity between partners, positively affecting technological and firm performance (e.g., Jaffe et al., 1993; Audretsch and Feldman, 1996). Geographical proximity is beneficial in promoting innovation since learning and knowledge acquisition is facilitated by face-to-face interaction, which is easier at short distances. However, there are several arguments suggesting that collaboration between innovators at larger distances could offer greater benefits than the collaboration between partners at closer geographical distances. First, Boschma (2005) proposed a multidimensional view of proximity. He argued that although geographical proximity facilitates interaction and cooperation for the acquisition of knowledge, other forms of proximity may act as a substitute for geographical proximity. Some empirical papers point in this direction (e.g.

Maggioni et al.; 2007; Basile et al.; 2012; Marrocu et al., 2013). Second, Kotabe et al. (2007), based on an extensive literature review, suggest a number of advantages of international collaboration, such as tapping into different national systems of innovation, gaining access to new lines of technological diversification reflected in local markets, obtaining a more varied flow of ideas, products, processes and technologies, and potential benefits from positive regulatory environments and favourable foreign government incentives. These advantages suggest that firms may reap more benefits in terms of diverse knowledge acquisition from geographically disperse structures (Mascia et al., 2017; van Beers and Zand, 2014). Thus, engaging in inter-organizational relations with geographically distant partners may entail advantages by overcoming the problem of knowledge overlap between two or more actors collaborating at close proximity (Molina-Morales and Expósito-Langa, 2013), which is produced, for example, because the knowledge sources may be the same. Several empirical papers have shown that the capacity for learning when collaborating across international boundaries can be greater than when collaborating over smaller distances because of the access to a greater variety of knowledge, leading to greater quality of innovation (Su, 2021; van Beers and Zand, 2014).

Despite the expected positive effect of international collaboration on patent quality, increasing the number of partners in different countries could have a detrimental impact. The explanation for this is that the potential gains from access to a pool of knowledge from different locations are lessened or neutralized by the difficulty in achieving integration of knowledge across multiple locations (Furman et al., 2006; Singh, 2008), and this problem is aggravated when the number of partners increases. Moreover, collaboration configurations differ in their potential to generate value, meaning that the successful effects of collaborative R&D cannot be generated with just any partner. There should be trust, commitment, and willingness to exchange information between partners (Geum et al., 2013; Broekel and Brachert, 2015). One of the underlying obstacles to knowledge integration with many countries is associated with leakages of knowledge. To obtain knowledge, organizations have to share some parts of their own knowledge with external firms, which motivates the source firm to proceed with caution to prevent the disclosure of crucial knowledge which can then be copied. Laursen and Salter (2014) coined the term "paradox of openness" to describe this problem. Collaborative patents across countries, as a way of formal international collaboration to obtain an innovative output, confront a similar "paradox of openness". On the one hand, firms may obtain advantages from sharing knowledge with other companies and institutions located in different countries, but on the other hand, leakage of knowledge to a potential rival located in a different country might weaken the competitive position of the company (Easterby-Smith et al., 2008; Frishammar et al., 2015). Several papers have warned of the need to proceed with caution in international collaboration, to prevent the risk of opportunistic behaviour, that in turns increases transaction costs and can affect the results of an alliance or lead to failure to achieve its objectives (Delanghe et al., 2009; Santamaría et al., 2021). Although the risk of leakage and opportunistic behaviour is increased in geographically-close firms competing in the same product market (Oxley and Sampson, 2004, and Reuer and Lahiri, 2014), such risk is less, but still remains, when the collaboration is at an international level, particularly between firms which share a similar product market. As a result, in the process of developing a patent, firm A in one country shares its knowledge with another firm B, located in another country, but the latter may use the knowledge of firm A to produce subsequent inventions that compete with those of firm A, the firm that provided the original and crucial knowledge. This fact may prompt firms to only share non-crucial or irrelevant knowledge and this may lead to a co-patent of lower quality than if the patent were produced without collaboration, particularly when the number of collaborators is large and so the probability of knowledge leakage is greater.

If firms are capable of optimally determining the knowledge delivered to other companies, and rationally capturing technological knowledge in the process of developing the collaborative patent, the effect should be an increase in their gains in terms of better patent quality. When there are few countries involved in the collaboration, it is expected that the resulting patent will be of better quality than if the patent were produced alone. In other words, the benefits of collaboration would outweigh the drawbacks of coordination and leakage of relevant knowledge. However, if the number of collaborators from different countries rises, so does the probability of leakage (along with an increase in the cost of coordination), since knowledge is exposed to more firms from different countries. In a context of collaboration with many countries, the firm may still want to collaborate in order to produce a patent for protecting and blocking motives, reputational gains, and the formation of a recombined pool of complementary knowledge to produce follow-on innovations (Blind et al., 2006; Bessen and Maskin 2009; Yang et al. 2010). However, the firm might keep crucial knowledge for itself, rather than openly sharing sensitive information across borders. If all firms involved in the patent adopt a strategy of releasing only non-crucial knowledge, the result will be a decline in patent quality compared to a collaboration in which the firms share all knowledge resources (this is the case analysed, for example, by Acosta et al., 2021).

The above theoretical arguments lead to our first hypothesis:

Hypothesis 1: *Cross-border collaboration exerts a positive and significant effect on patent quality; however, this effect may be limited to a certain breadth of international collaboration, beyond which an increase in the number of collaborators from different countries involved in developing the patent can lead to a decline in quality.*

2.3 Are the leaders in a particular technological domain the right countries with which to establish collaborative relationships to produce patents of better quality?

The number of links between different countries involved in a particular invention captures the breadth of international collaboration, but not the type and quality of knowledge from which firms can benefit by collaborating. Since not all foreign locations have all the specific skills, types of employees and knowledge required for successful collaboration, firms must choose the best countries with which to establish relationships with their inventors. Thus, along with the uncertainty about the effect of the number of countries involved in developing a co-patent, another relevant issue is the choice of the best international partners to produce the greatest result in terms of patent quality.

Developing countries seem to benefit, in terms of obtaining better outputs, from collaborating with developed countries (e.g., Giuliani et al., 2016). This fact seems to confirm the intuitive idea that the most benefit is obtained from partners located in countries that have specialized workers and leading institutions, forming a strong innovation system. Thus, there are two main reasons to collaborate with specific partners. The first is the level of specialization of the partner. To qualify as an attractive partner, apart from the willingness of the firms to collaborate and share knowledge, the partner in the target country should have obvious technological advantages and should offer better knowledge capabilities (Su, 2017; Lee et al., 2020). Thus, the 'supply-oriented' factors that enhance the efficiency of R&D, such as favourable access to skilled technical expertise, could be one of the keys in choosing the right partner to produce patents of better quality. In other words, firms share their knowledge with a partner with higher knowledge capabilities to acquire useful knowledge in return (Guellec and van Pottelsberghe, 2004; Knell and Srholec, 2008).

The second reason is that firms might want to take advantage of different national and sectoral systems of innovation, gaining access to new lines of technological diversification, capturing foreign university knowledge, obtaining more varied flow of ideas and technologies, or even enjoying favourable foreign government incentives (Criscuolo et al., 2005; Kotabe, 2007; Picci and Savorelli, 2018). Lee et al. (2020) claim that to qualify as an attractive partner, a country should have obvious market or technological advantages, and its firms should be willing to collaborate with those in other countries. From this idea and the above discussion, we put forward our second hypothesis:

Hypothesis 2. *Collaborating with partners located in leading countries in a particular domain will produce better performance in terms of patent quality than collaborating with partners in other countries.*

2.4 To what extent can co-ownership with firms located in tax havens affect patent quality?

The fact that patent ownership is assigned to partners in different countries can be the result of effective collaboration, but it may also be that some firms co-locate the legal ownership of patents both in the country where the invention was developed and in tax havens. In these cases, the co-ownership of a patent is not necessarily the result of collaboration in the inventive activity. Tax havens are countries and territories that offer low tax rates and favourable regulatory policies to foreign investors (Hines, 2010). Sharing the ownership of patents with subsidiaries or other collaborating firms located in low corporate tax jurisdictions is apparently an attractive strategy to reduce corporate tax burdens (Karkinsky & Riedel, 2012; Baumann et al., 2020). With a sample that links information on patent applications to European multinationals (more than nine thousand firms), Karkinsky & Riedel (2012) found that multinationals tend to distort the location of their corporate patents in favour of low-tax affiliates. Bauman et al. (2020) reached a similar conclusion using data on multinational entities (MNEs) in Europe. However, some European countries levy tax on the net present value of the expected revenue stream on a patent when it is moved out of the country, and this means it is not worthwhile to relocate to a lower tax jurisdiction (Griffith et al., 2014). Another issue that plays against tax havens as potential locations of patent ownership for inventions developed elsewhere is the implementation in a number of countries of policies allowing special taxation rates for corporate income derived from the ownership of patents. Such tax regimes are also known as "patent boxes" (Bradley et al., 2015; Gaessler et al., 2021).

Given that the lower taxes in tax havens will affect patent income, it is expected that ownership or co-ownership of high-quality patents is more likely to be located in these countries. Thus, low corporate tax jurisdictions could affect not only the location of the co-ownership in these countries, but also patent quality. The scarce empirical research available points in this direction. The results by Baumann et al. (2020) found that propensity to assign patent ownership to a haven economy and separate it from the location of the inventor increases with the value of the patent. Ernst et al. (2014) provide evidence that patent income taxation exerts a significantly negative effect on average patent quality. In line with the previous arguments, we expect that choosing a tax haven as location of patent ownership has a positive and significant impact on patent quality, which leads to the third hypothesis:

Hypothesis 3. *Patents co-owned with firms located in tax havens have greater quality than those co-owned with firms located in other jurisdictions.*

3. Data

3.1 The international context of the pharmaceutical industry

To find answers to our research questions, we investigated international cooperation in pharmaceutical patents for the period 1990–2012. The pharmaceutical industry is a particularly interesting context in which to explore our research questions. It was chosen for the analysis of international collaboration in patents for several reasons. First, the pharmaceutical industry is an industry with high research and development (R&D) intensity (Loschky, 2008). Recent figures show that total R&D costs worldwide per employee are more than twice as high in pharmaceuticals than in any other industry, while in terms of aggregate R&D, the pharmaceutical industry is the second sector in value after the computer and electronic products industry (Lakdawalla, 2018). Second, there is a high likelihood that firms patent their inventions in the pharmaceutical industry (Cohen et al., 2000; Kotabe et al., 2007; Magazzini et al., 2009; Gamba, 2017), thus the study of patent collaboration in this sector can show, better than in any other sector, the international R&D collaboration. Finally, the trade-off between the desire to locate all research in a single location or in multiple countries across the world to take advantage of local spillovers is crucial for multinational pharmaceutical firms, because of their dependence on public research (Furman et al., 2006).

Some figures help to identify the leading countries in the pharmaceutical domain. Table 1 presents the data for countries with the largest firms in the pharmaceutical industry, as obtained from the EU R&D Scoreboard (Hernández et al., 2020)[1]. Note that six countries account for more than 90% of the total R&D expenditure. The United States is at the top, with almost half of the total R&D in pharmaceuticals, followed by Switzerland and the UK. According to the information in the EU R&D Scoreboard, these countries are at the top when using other indicators such as net sales and employees. Although we do not have access to data from before that period, the figures are quite stable, which suggests that firms in those countries have been leaders in R&D expenditure for a long period of time.

[TABLE 1 HERE]

[1] The EU R&D Scoreboard analyses the 2500 companies that invested the largest sums in R&D worldwide. These companies have headquarters in 43 countries. The Scoreboard total R&D is equivalent to approximately 90% of the total expenditure on R&D financed by the business sector worldwide. The whole set of primary data is available at: https://iri.jrc.ec.europa.eu/scoreboard/2019-eu-industrial-rd-investment-scoreboard.

3.2 Pharmaceutical patents. Data and sources

Our unit of measurement is the patent family, which can be defined as the set of patents filed in several countries that are related to each other by one or several common priority filings (Organisation for Economic Co-operation and Development, OECD, 2009; for a detailed discussion, see also Martínez, 2010, 2011; Bakker et al., 2016). In other words, a patent family comprises all patent documents covering the same invention. To ensure that the patent family has a certain quality standard, we retrieved the most important and valuable inventions, following the criterion of patents applied for at least at USPTO and EPO. One of the main advantages of using patent families is the avoidance of duplications in the information contained in patents that cover the same invention in different countries (Martínez 2011; de Rassenfosse et al., 2014). Moreover, the calculated citation indicators may differ substantially depending on the procedures of the patent office where the patent application was submitted. Therefore, patent families reveal the most uniform results, and can be used as a comprehensive measure of inventiveness compared to the simple count of patents (Bakker et al., 2016; van Raan 2017; Tahmooresnejad and Beaudry, 2019).

As patent families contain different dates, and as we considered a window of five years, it is important to clarify the dates. Following de Rassenfosse et al. (2014), to account for time, patent families were sorted by the priority year (when the first application for the family was filed). In order to search the patent families in the pharmaceutical sector, we have used the International Patent Classification (IPC) codes. Pharmaceutical patents are clearly identified by the codes A61K (Preparations for medical purposes) and A61P (Specific therapeutic activity of chemical compounds or medicinal preparations). From the A61K we have excluded the subclass A61K 8/00 (Cosmetics or similar toiletry preparations) because inventions in this subclass do not serve the same purpose as pharmaceuticals. We also dropped the pharmaceutical patents from countries where the number of patents produced may be statistically meaningless, keeping them only for countries with more than 150 patent families over the selected period.

The information was retrieved from the EPO Worldwide Patent Statistical Database (PATSTAT), resulting in a sample of 143,479 pharmaceutical patent families from 30 countries with more than 150 patent families between the years 1990-2012 (see Table A.1 in the Appendix). To identify the international collaboration in generating a collaborative patent, we have classified all the patent families by the country of the assignee. Table 2 presents the number of patent families distributed by the number of countries of the applicants. From the total sample, about 75% are single-owned patents (patent families for which assignees are from a single country, independently of whether there is only one assignee, or the patent includes several assignees from the same country) and 25% are international co-patents: patent families co-owned by assignees from two or more different countries.[2] Note that counting collaboration in this way may include collaboration not only between different companies, but also between parent firms

[2] This high intensity in co-patenting is a characteristic of the pharmaceutical industry. Hagerdorm (2003) suggested the following reasons for this fact. First, having a large proportion of co-patents is a characteristic in industries with strong regimes of appropriability such as chemicals and pharmaceuticals. Hagedoorn (2003) found for US patents that chemicals and pharmaceuticals "are found to have a disproportionate share of joint patenting activities", because in pharmaceuticals it is more difficult to claim for different patents since there are many interdependencies between the various components of a process leading to a product. A second reason pointed out by Hagedoorn (2003) is the experience of applicants with the legal complexities of joint patenting in the pharmaceutical industry.

located in one country and subsidiaries in other countries. Regarding the countries of residence of the assignees, the number of pharmaceutical patent families is rather concentrated. The United States accounts for 47.5% of all patent families, followed by Japan (9.3%), Germany (8.1%), the United Kingdom (5.9%) and France (4.8%) (Table 3).

For each patent family, we tracked the forward patent citations in a five-year window, which is our indicator of quality. Note that the number of citations per patent increases as the number of countries involved in the ownership grows (Table 2). From Table 3, it can be observed that the average number of citations for single-owned patents is 0.95 citations per patent, and 1.26 for co-patents. We have also retrieved the other variables that capture the characteristics of the families, which, according to the literature discussed above, include the backward-cited patents (excluding citations made by examiners), the number of non-patent citations, the number of claims, and the number of different IPC classes to capture the breadth of collaboration involved in a technology.

[TABLES 2 AND 3 HERE]

3.3 International patent collaboration

Although a detailed network analysis is beyond the scope of this paper (the unit of our analysis is the patent family, not the country), some preliminary network indicators help to clarify the extent of the international cross-border relationships between different international partners in the pharmaceutical sector. In this respect, Graph 1 shows the degree centrality, which is a relative measure of the number of direct links between nodes divided by the total number of links. A connection implies that there is a collaborative patent, which means that the patent includes two or more assignees. If the patent includes, for example, the United States and other assignees from 5 countries, the number of connections for each of the assignee countries is 5. In our sample, the number of connections between different countries ranges from 16 to 30 in the net of 30 countries. Countries such as the United States, Germany, Japan and the United Kingdom, for example (those in the middle of the graph), have had connections with all the other 29 countries in the network. However, others such as Taiwan, Russia, Luxembourg and Brazil have collaborated with a lower number of countries. The sizes of the nodes are determined by the degree centrality. The country with the highest degree centrality is the United States with 36.13%, which means that this country accounts for 36.13% of all the countries' connections. The United States is followed by Germany (9.17%), the UK (8.04%) and Switzerland (7.92%).

[GRAPH 1 HERE]

Going back to Table 3, the percentages of collaboration (patent families with applicants from at least two countries) range from 8.2% for Japan, which is the country with the least collaborative patent families, to 99.4% for Bermuda, the country with the highest degree of collaboration. Note that there are substantial differences between countries and, on average, the percentage of cross-border collaborative patents is 24.8%. In this respect, it is necessary to bear in mind that, as we explained in Section 2.3, part of patent ownership is the result of international R&D collaboration, but firms can also use partners in tax havens to reduce corporate tax burdens. Thus, our sample contains six countries considered low-tax jurisdictions by the EU, IMF and Oxfam: Bermuda, the Netherlands, Switzerland, Singapore, Ireland and Luxembourg. All of these countries present percentages of patent co-ownership well above the average.

Regarding quality of patent families by countries, in terms of patent impact, several observations can be drawn from the right part of Table 3. First, on average, the quality of patent families produced through international collaboration is higher than that of patent families produced by teams in a single country: 1.3 forward citations of international co-patents compared to 0.9 forward citations of those applied for by assignees based in one single country. Second, Russia is the country which obtains the most substantial benefit from collaboration in terms of quality (0.11 citations per patent family when there is no collaboration, compared to 0.92 in international collaborative patents). Thus, assuming that forward citations is a good proxy for quality, the collaborative patents involving Russia have a quality that is about seven times higher than for patent families in which the assignees are only from Russia. The same table shows that other countries such as Hungary, Luxembourg, Austria, and China greatly benefit from international collaboration; the average quality of their collaborative patents is more than twice that of those obtained without collaboration.

Third, patent families from the United States present similar values for the indicator of quality when the patent family is owned by partners only from the US or from multiple countries (1.2 forward citations compared to 1.3). In any case, the indicator of quality is always greater for collaborative patents for all countries (Bermuda is the only exception in which the quality of a non-collaborative patent is greater than its collaborative patents, but this country is a rare case as it has only one non-collaborative patent out of 164 total patents).

4. Variables and model

4.1 Dependent variable

Following previous studies, our dependent variable to capture patent quality was the number of forward patent citations (as in, for example, Lerner, 1994; Hall et al., 2005; Sapsalis and van Pottelsberghe, 2007; Sterzi, 2013; Giuliani et al., 2016; Acosta et al., 2009, 2021). As explained in Section 2.1, the main argument for considering the number of forward citations as proxy for quality is based on the idea that patents that are cited by subsequent patents in their 'state of the art' section (or forward citations), include small pieces of knowledge on which the underlying inventions rely. Therefore, if a patent is cited in many subsequent patents, this means that this particular patent has a greater technological impact on future inventions, or that it is more important than other patents which are less cited.

Considering the previous remarks, the dependent variable in this work was the number of times that a focal patent family was cited as relevant state of the art in subsequent patent families filed within a 5-year time window after the first application of the focal patent family. Note that, as we consider patent families as subsequent patents that cite the focal patents, duplicate citations are eliminated from the count. For example, when a subsequent patent family cites two different patents of the same focal family, this counts as one citation. The forward citations in our sample exclude self-citations and examiner citations (*fpc5years*). The most common spans in forward citations to avoid truncation are 5-year (Lanjouw & Schankerman, 2004; Mariani & Romanelli, 2007; Schettino et al.,

2013) and 3-year spans (e.g. Briggs, 2015; Briggs and Wade, 2014). Less frequent is using 10-year spans (Lahiri, 2010; Higham 2021), which requires working with samples too far from the year of the analysis to give time for the latest focal patents in the sample to be cited (within the 10-year span). Squicciarini et al (2013) recommend 5-7 years in the cohort, although they also comment that "almost no gain would be obtained by extending the window of observation for two additional years" (Squicciarini et al., 2013, p. 39). We use a 5-year cohort (and a 3-year to check for robustness) in our main models for two reasons. First, 5-year (and 3-year) spans are the more frequently used in empirical analysis of patent quality. Second, we should not use 7 or 10-year cohorts because our sample consists of patent applications in the period 1990-2012, and there is a risk that, if considering a cohort of 7 or 10 years, the number of forward citations in the final years would decline simply because not all citations have been incorporated into databases yet.

4.2 Independent variables

4.2.1 International collaboration

Our key independent variable is international collaboration. International technological collaboration on patents implies that the invention, the teams generating this invention, and the ownership tend to cross national borders in order to create and share knowledge (Maggioni et al., 2007; Lin et al., 2012; Mazzola et al., 2016; Su, 2017). Thus, there are different ways to measure collaboration on patents. The majority are based on the country of residence of the inventor (Guan and Chen, 2012; von Proff and Dettman, 2013; De Pratto and Nepelski, 2014), the country of residence of the assignee (Briggs, 2015; Su, 2017; Alonso-Martínez et al., 2021), or on both, with a different combination of inventorship and ownership (Ma et al., 2009; Montobbio and Sterzi, 2013; Picci, 2010; Danguy, 2017). Using any of these indicators has advantages and disadvantages (see, for example, Section 7.3 in OECD, 2009, and Bergek and Bruzelius, 2010, for a detailed discussion), but overall, the result will tend to converge because a patent with co-assignees in two countries very often involves inventors from these two countries (de Rassenfosse and Seliger, 2020).

In this paper we use cross-border ownership of the patent (or cross-border co-patent), which means that the organization units (assignees or owners) are located in different countries. Joint patenting or co-patents assume that co-owned patents are the result of inter-firm R&D collaboration and ownership is shared (Hagedoorn, 2003; Belderbos et al., 2014; Briggs, 2015; Alonso-Martínez et al., 2021). Furthermore, co-owned patents are disproportionately important in industries with strong regimes of appropriability such as chemicals and pharmaceuticals (Hagedoorn, 2003).

It should be noted that not all research collaborations will be captured with a co-patent indicator. As is well known, not all collaborative R&D efforts will result in an application for a patent. Even if R&D collaboration does yield a patent application, specific IP arrangements can mean that finally only one partner applies for the patent (Lecocq and Van Looy, 2009), or there may be a division of the invention so that each partner applies for a patent only for the part of the invention that they contributed to producing (Hagedoorn, 2003). Thus, joint patents should be considered a conservative indicator of collaboration since not all collaborative research efforts and subsequent innovation from such efforts are captured by such an indicator (Van Looy, 2009; Briggs, 2015). Besides, as explain above, the co-ownership of a patent might be the result of strategic decisions by firms, such as attempting to reduce the tax burden.

Following this criterion, we have considered different variables to capture whether a patent family was developed in collaboration with partners from different countries:

- Cooperation (*coop*) is a dummy variable that takes value 1 if the assignees of a patent are located in two or more countries, and 0 if the assignees are from a single country. This variable captures the presence of a co-patent owned by assignees in at least two different countries.

- Number of countries (*country*). This is a count variable that captures the number of different countries in which the assignees are based. For example, if a patent was applied for by assignees from a single country, its value is 1. If it was applied for by assignees from, for example, the United States, Germany and the United Kingdom, the value of the variable is 3.

- Dummies for the number of collaborating countries in a patent family (*country2* to *country8*). This is a set of 7 dummy variables to capture whether the patent was owned by two, three, or up to eight countries. The base category is a single country (patent developed without collaboration). We have also considered this way as an alternative to the previous count variable because, considering several dummy variables rather than the count variable *country*, the marginal effect can be compared with the base category (patents developed in a single country) and it varies according to the dummy variable (from two to eight countries). However, in the previous count variable *country*, the marginal effect would be constant, independently of the number of countries. It provides, for example, the increase in quality when the number of countries increases by one unit, independently of the number of countries involved.

- Dummies for the countries involved in collaboration (us-ch-jp-de-uk-fr). In order to identify those countries which are worth collaborating with to enhance patent quality, we have considered a set of dummies for countries with the greatest potential in the pharmaceutical industry. Each variable takes value 1 when the collaborative patent includes the United States (us), Switzerland (ch), Japan (jp), Germany (de), the United Kingdom (uk), or France (fr), and 0 otherwise.

- Location in a tax haven. To capture whether collaboration with partners located in tax havens affects patent quality, we have created a dummy variable when a co-patentee is located in a country considered a low-tax jurisdiction by the European Union (EU), the International Monetary Fund (IMF), or Oxfam.

4.2.2 Other determinants of patent quality

Along with collaboration, it is necessary to control for other factors affecting patent quality. The type and number of patent quality determinants vary widely across studies. These determinants depend on the objectives of each study, and the availability of data. We control in our models for the following factors:

- Number of inventors (*inventors*). This is a rough variable that may increase the cost of an invention, the richness of the knowledge involved in the patent, and the access to a wider and more heterogeneous external network (Guellec and van Pottelsberghe, 2001; Singh 2008; Sun et al., 2020). Some papers confirm that the number of inventors is positively associated with patent quality when the sample is composed mostly of corporate patents (Guellec and van Pottelsberghe, 2001; Singh, 2008), whereas the coefficient is found to be negative or not significant for academic patents (Sapsalis and van Pottelsberghe, 2007; Sterzi, 2013). Our analysis involved corporate patents; thus, a significant and positive sign was expected for the coefficient of this variable.

- Backward patent citations (*back*). This variable includes citations to companies, universities and research centres, capturing the extent to which a patent relies on previous technological knowledge developed in patents owned by these agents (See Jaffe and de Rassenfosse, 2017; and, Aristodemou and Tietze, 2018, for detail reviews). This variable is rather common in studies of patent quality, although its effect is not clear (Jaffe and de Rassenfosse, 2017). Harhoff et al. (2003) and Moaniba et al. (2018) found a positive and significant effect on patent quality. Michelino et al. (2016) also found that patents that do not have backward citations typically have a lower technological and market impact. However, Nemet and Johnson (2012) found positive and negative effects, depending on the type of backward citation.

- Number of claims (*claims*). Claims are the list of 'inventive things' for which the applicant is claiming exclusive rights. The number of claims can be considered a proxy for the patent size (see Rodriguez, 2010, and van Zeebroeck and van Pottelsberghe, 2011, for a discussion). Studies have found a positive correlation between the number of claims and quality for two main reasons. First, the number and content of the claims determine the breadth of the rights conferred by a patent (Lanjouw and Schankerman, 2004). The total number of claims corresponds to the number of variations in the core inventive ideas of the patent. The second reason to expect that patents with more claims are of better quality is the cost; the number of claims is one of the factors that determines the total cost of a patent (Zuniga et al., 2009). The number of claims is frequently correlated with patent quality and value (Gambardella et al., 2008; Chang et al., 2018; Moaniba et al., 2018).

- Citations to non-patent literature (*npl*). The antecedents of a patent include not only citations to other patents (backward citations), but also non-patent citations. Usually known as citation to non-patent literature, this variable encompasses scientific publications, other relevant scientific literature, and firm reports. The rationale for including scientific citations as a determinant of patent quality relies on capturing the complexity and science intensity of the current patent (Cassiman et al., 2008; Squicciarini, 2013; van Raan, 2017). The empirical literature draws mixed conclusions about the effect of *npl* on the number of forward patent citations. For example, Branstetter (2005), and Sorenson and Fleming (2004) found a positive relationship. In contrast, Gittelman and Kogut (2003) demonstrated that important scientific papers are negatively associated with high-impact innovations. Cassiman et al. (2008) found no-relationship, and Harhoff et al. (2003) found a positive effect in some particular sectors but not in other technical fields.

- Scope of the patent (*ipc4*). The scope of a patent captures its technological breadth. Apparently, the larger the number of technologies embedded in a patent, the more the opportunities to be cited. However, the patent scope can be the response to a strategy designed to achieve the exclusion of competitors (Harhoff and Reitzig, 2004). This means that if the number of fields that can be covered by a patent is large, then the possibility of infringement rises, which may reduce the subsequent citations of the patent for risk of infringement. As in Lerner (1994) and Lanjouw and Schankerman (2001), we measured the scope using the number of distinct 4-digit IPC subclasses of a patent family. The the extent to which scope reflects patent quality is ambiguous in empirical analyses. For example, Messeni Petruzzelli et al. (2015) found that patents with a broader scope exert a stronger influence (measured by forward patent citations) on the technological developments outside biotechnology. Other authors, however, have reached different conclusions, although using other indicators of quality. For example, in Harhoff and Reitzig (2004) the coefficient of scope to explain opposition to biotechnology and pharmaceutical patents is non-significant. Lanjouw and Schankerman (2001) found that the effect of the scope variable (number of different four-digit codes of the Standard Industrial Classification) to explain litigation ('the narrower patents tend to be litigated more often') is negative.

4.3 Model

To specify and estimate the model, both the count nature of the dependent variable, and the number of zeros that it might contain have to be considered. A Poisson specification is often the starting point for modelling a count variable following the non-linear form:

$$fpc5years_i = \exp\left(\alpha + \beta_1 international\ collaboration_i + \beta_2 inventors_i + \beta_3 back_i + \beta_4 claims_i + \beta_4 npl_i + \beta_5 ipc4_i + \sum_{j=1}^{t} \lambda_j\, year_{ij} + \varepsilon_i\right),$$

where 'i' is our unit of analysis (patent family). Note that according to Section 3.2.1, international collaboration to produce a patent is measured by several types of explanatory variables. Thus, the variable *international collaboration* can be a dummy variable (*coop*), a count variable (*country*), a set of dummies to account for the number of collaborative countries in the patent family (country2 to country8), a set of dummies to capture the countries of residence of the inventors, and the co-ownership with a firm located in a tax haven. As all of these variables capture international collaboration, sometimes they are highly correlated and are included separately in the empirical models to test the hypotheses and provide answers to our empirical questions.

Once the model is specified, if the data display overdispersion, the standard error of the Poisson model will be biased toward the lower end, resulting in spuriously high values of the t-statistic (Cameron and Trivedi, 1986; Wooldridge, 1999). The most common formulation for considering overdispersion is the negative binomial (NB) model, as it assumes that the variance is a quadratic function of the mean (for a comprehensive discussion of the estimation procedure, see Cameron and Trivedi, 1998). The proposal of the density function, the logarithmic likelihood function and the first-order conditions, etc., are discussed comprehensively in Cameron and Trivedi (1998). An alternative to the NB is applying the Poisson quasi-maximum likelihood estimator (QMLE) (Wooldridge, 1999). When the sample contains many zeros, other usual models are the zero-inflated models (zero-inflated Poisson [ZIP], Lambert, 1992; and zero-inflated negative binomial [ZINB], Heilbron, 1994). In these cases, the zero-inflated distribution can be interpreted as a finite mixture with a distribution whose mass is concentrated at zero. This model contains two sources of overdispersion, one that allows several extra zeros, and another that introduces the individual heterogeneity of the set with positive values. As there are no clear theoretical reasons to think of a mixture of distributions in our data, we have opted to estimate NB models and Poisson QMLE.

5. Results

5.1 The effect of international collaboration on patent quality

Our first empirical analysis focuses on the relationship between international collaboration and the quality of family patents, and particularly on whether the increase in the number of countries has a positive effect on quality. Table 4 provides a brief description of all variables. Tables 5 and 6 present the descriptive statistics and the correlation matrix for the dependent variable (forward patent citation in a 5-year window) and the independent variables. The number of forward citations in each patent family ranges between 0 and a maximum of 174. The mean number of forward citations was 1.02, with a standard deviation 2.77 (variance, 7.70). The correlation matrix shows, on the one hand, that the linear correlation between the dependent variable and those explanatory factors capturing international collaboration is positive, although rather low. On the other hand, variables such as *coop* and *country*, and *coop* and some of the dummy variables capturing the number of countries in collaboration, are highly correlated. This is expected, as these variables measure collaboration in different ways. To avoid collinearity problems, they will be included in separate models.

[TABLE 4 HERE]

Table 7 presents the estimations of negative binomial (NB) models to identify both the extent to which international collaboration affects the quality of patent families and the role of the number of countries in collaboration. We first estimated Poisson MLE (maximum likelihood estimator) (not presented) and then, due to overdispersion, NB models with all the independent variables described in section 3.2 (see short description in Table 4). The models also account for year dummies (22 dummies). To select the best models between Poisson and NB, a likelihood ratio (LR) test of the overdispersion parameter alpha was performed (see the row LR-alpha in Table 5). The null hypothesis alpha=0 is rejected, providing evidence that the NB models are always preferred over the Poisson MLE models.

[TABLES 5 AND 6 HERE]

Models 1 and 2 in Table 7 include the dummy variable *coop,* which captures whether a patent was assigned to partners from at least two countries. Model 1 is a base model that does not control for patent characteristics, and Model 2 includes the control variables. The coefficient of *coop* is positive and statistically significant. On average, when we control for other factors affecting quality such as the size of the patent (variables *claim* and *ipc4*), the size of the team (*inventors*) and the extent to which the patent uses previous technological and scientific citations (variables *back* and *npl*), the effect of international collaboration is, on average, a 4.9% increase in patent quality compared with patent families for which the assignees are from a single country[3].

Models 3 and 4 in Table 7 present the results of the NB estimations when the count variable *country* (number of countries in collaboration) instead of *coop* was included as explanatory factor. When we control for the characteristics of the patent families (Model 4), the results show that when there are assignees from an additional country, the quality increases on average by 4.8%. Finally, Models 5 and 6 present the results using 7 dummies capturing the collaboration between from two to eight countries. These models allow us to identify the effect of international collaboration when partners from different countries are involved in the ownership of the patent family (patent families with assignees from a single country is the base category). Once we control for the patent characteristics (Model 6), the results show that the quality of the patent rises dramatically when the number of countries increases, for up to five countries in collaboration (dummies *country2* until *country5* are positive and statistically significant). However, we did not find significant differences in quality, compared to patenting by assignees from a single country, when there are more than five countries involved in the ownership of a patent. These results provide support for Hypothesis 1, that international collaboration exerts a positive and significant effect on patent quality, but that this effect is limited to a maximum of five countries in collaboration. When there are co-owners from more than five countries involved in patenting, there is no observed benefit from collaborating in the pharmaceutical sector. Note, however, that the number of patents in which there are more than five co-assignees is a small fraction of the sample (only 41 co-patents), which suggests a need to be cautious about this finding.

[TABLE 7 HERE]

Our results showing the positive and significant effect of international collaboration on patent quality are in line with other previous studies (such as Briggs, 2015; and Lino et al., 2021), although the final impact is different. Other studies on a similar topic that used inventors rather than owners also point out a positive and significant effect of cross-border inventions on forward patent citations (e.g., Alnuaimi et al., 2012; Branstetter et al., 2015; Giuliani et al., 2015), but the contexts are so different that their results are hardly comparable to ours.

5.2 What countries should be the best to engage with in collaboration?

According to theory, to benefit from collaboration, the country of a partner in a co-patent should have obvious technological advantages and should offer better knowledge capabilities. The six countries with the greatest potential in the pharmaceutical industry, both in R&D and in other economic variables such as net sales and number of employees, are those presented in Table 1: the United States, Switzerland, Japan, Germany, the United Kingdom and France. This means that, according to the arguments supporting our second hypothesis, collaborating with these countries would allow the harnessing of a

[3] Note that the generic interpretation is that the response has a log-count increase of the dependent variable for a one-unit increase in the value of the predictor, other predictors held at their mean value. As the "log-count increase" is not a very intuitive way to understand the importance of the estimated coefficients, we apply 100x(e^{β}-1), which provides the exact percentage change in the expected count for a unit change in x (Cameron and Trivedi, 2009, p. 336; Long and Freese, 2001, p. 232).

more varied flow of ideas and technological knowledge, which would contribute to improving patent quality.

To identify whether collaborating with these countries has a greater impact on patent quality than collaboration with other countries, we have estimated several negative binomial models using the patent families in collaboration as unit of observation (Table 8). The key variables are dummies capturing the collaboration with the United States (us), Switzerland (ch), Japan (jp), Germany (de), the United Kingdom (uk) and France (fr). For example, the dummy *us* takes value 1 if the co-patent includes assignees from the United States (along with partners from other countries), and 0 otherwise. This same criterion is used to construct the other dummies. Thus, the base category is collaborating with countries other than those specified in these models. As in Table 7, all models include control variables.

Model 1 in Table 8 presents the results of collaborating with the top six countries in pharmaceuticals when the assignees are located in two or more countries. The coefficients of the United States, Switzerland, Japan, Germany and the United Kingdom are all positive and statistically significant. This means that if the patent includes any of these countries in a collaborative patent, the impact of this patent is greater compared to co-patents in which none of these countries is the location of at least one of the assignees. For example, when the co-patent between two countries includes the United States as the location of one of the assignees of the co-patent, the quality in terms of impact in subsequent patents is almost 21.5% greater compared to the base category. Note also that the values of the coefficients become smaller as the potential in terms of R&D of the country decreases. Thus, when one of the partners in the co-patent is located in the US, the coefficient is 0.194. The coefficient of Switzerland is a little smaller (0.187), followed by Japan (0.153), and so on, until the coefficient of France, which is not statistically significant (the co-patents that include these countries –and exclude the other five countries– have similar technological quality as the base category, which is the collaboration with countries other than those included as explanatory variables).

Models 2, 3, 4 and 5 in Table 8 are estimated with co-patents in which there are partners from two, three, four and five countries, respectively. For example, according to Model 2 (results when there are partners from just two countries), those co-patents including the US as location of one of the assignees have on average 21.1% higher quality than those patent families of the base category. Note from Models 3, 4 and 5 that when the number of countries increases, the number of countries from which obtaining benefits in terms of quality becomes fewer. For example, if we look at Models 4 and 5, the only partners that are worth collaborating with when there are assignees from four or five different countries are those located in the United States and Germany, respectively. These results support Hypothesis 2, that collaborating with partners located in leading countries in a particular domain, pharmaceuticals in this case, will produce better performance in terms of patent quality than collaborating with other countries.

5.3 Collaborative patents with firms located in tax havens

As co-patents could be, at least partially, the result of sharing the ownership of patents with subsidiaries located in tax havens to reduce corporate tax burdens, we have constructed a dummy variable for those countries that, according to the EU, IMF and Oxfam, are considered low tax jurisdictions: Bermuda, the Netherlands, Switzerland, Singapore, Ireland and Luxembourg. From this group of countries, Switzerland is, at the same time, one of the countries with the greatest potential in pharmaceuticals, and thus a patent co-ownership with partners in Switzerland can be the result of effective R&D collaboration to benefit from its sectoral innovation system in pharmaceuticals, rather than a mechanism to benefit from lower tax burdens. Thus, Switzerland is excluded from the dummy *haven*.

As shown in Table 8, the coefficient of the dummy variable "haven" is not significant in any model. The correlation coefficients between this variable and the dummies capturing the top leading countries in pharmaceuticals are quite low (between -0.11 and 0.02). Furthermore, the variance inflation factors (VIFs) range between 1.02 and 1.59, which are well below the usual cut-offs, suggesting that the non-significant coefficient of "haven" is not caused by multicollinearity problems. This result suggests that patents co-owned with firms located in tax havens do not have greater quality than patents co-owned with firms located in other jurisdictions, in contrast to what we stated in Hypothesis 3.

[TABLE 8 HERE]

Finally, we discuss the other variables used as determinants of the quality of patent families in both analyses (Tables 7 and 8). Overall, the effect of these variables (patent characteristics) that we included as control is similar to that obtained in the previous literature. The number of inventors (inventors) is statistically significant in all models, pointing to the fact that an increase in the number of inventors significantly affects patent quality, in line with other studies such as Sapsalis et al. (2006), Guellec and van Pottelsberghe (2000, 2002), and Singh (2008). These empirical papers suggest that larger teams are associated with strategic research projects with high expected profits, and consequently higher quality. The variable *claim* is relevant, indicating –as in other papers (Gambardella et al., 2008; Chang et al., 2018; Moaniba et al 2018)– a significant relationship between the size of the patent (proxied for the number of claims) and quality.

The variable *back* (citations to other patents) is highly significant in the majority of our models. The literature, however, is unclear with respect to the effect of this variable on patent quality, as we explained in Section 3.2.2. The reason is probably the difference in origin of the backward citations, which may include citations from university patents, citations to patents from firms in the same and different sectors to the focal patent, etc. This difference in the background of citations would require a disaggregation of citations to further analyse the extent to which backward citations correlate with patent quality.

As for the variable *npl* (citations to non-patent literature), we obtained positive values for the coefficients, but mixed results regarding significance (statistically significant at the 5% level in the models in Table 7 and non-significant in the models in Table 8). Obtaining positive relationships between this variable and patent quality in sectors such as pharmaceuticals, chemistry and biotechnology is quite frequent, due to these sectors' high reliance on science (Harhoff et al., 2003; Arts et al., 2013), but again, the literature offers mixed results on the significance of this variable (see references in Section 3.2.2). The coefficient of the *ipc4* variable points to a non-significant and even negative effect in some models, implying that the number of technologies in patents (measured by the number of IPC codes) is not correlated with quality, or that the relationship could even be negative. This result may be explained by the possibility that a patent with a large number of different codes may not be the result of greater innovativeness, but strategic choices (that might not be correlated with patent quality).

5.4 Robustness checks

In order to check the robustness of our results, we have carried out further analyses. Firstly, as an alternative way to cope with overdispersion, we have estimated the same models as presented in Tables 7 and 8, but applying a Poisson QMLE (quasi-maximum likelihood estimation), which has compelling robustness properties to model overdispersed count data (see for example, Wooldridge, 1999). Note that the negative binomial estimations (Tables 7 and 8) and the Poisson QML estimations (Tables A.2 and A.3 in the Appendix) lead to practically the same results in terms of significance of the coefficients, although there are slight differences in the values.

Secondly, to check whether our results hold using a different cohort for the forward patent citations of each family, we have estimated the same models as in Tables 7 and 8 but using a 3-year window rather than a 5-year cohort. The results of these models are in Tables A.4 and A.5 (Appendix). Again, the results are rather similar in terms of the significance of our key variables, although there are slight differences in values (usually greater when using a 3-year window).

Thirdly, note that the information from the EU R&D Scoreboard, from which we identified the leading countries in pharmaceuticals, refers to the period 2005-2012. To analyse whether considering this period (compared to the period 1990-2012) means any change in the results, we estimated the models in Tables 7 and 8 using this subsample, and no substantial changes in terms of significance of the coefficients were observed.

Fourthly, although international R&D collaboration can be captured by using co-assignees as an indicator, an important part of such collaboration is international cooperation between inventors. In order to check the extent to which our results hold when the countries of the co-inventors are the same as the countries of the co-assignees, we gathered new information about the inventors of each patent and their country of location. Then, we ruled out all patents in which the countries of residence of the assignees do not match the countries of the residence of the inventors. This resulted in a sample of 109,442 patent families. This sample is substantially smaller than our main sample (143,479 patent families). The reason for such a difference is that the new sample is an exact match; this means that all patent families that do not meet the criteria of the same country for all assignees and inventors are excluded. Using this subsample, we estimated the same models as we did with the original sample that included collaboration between assignees (presented in Tables 7 and 8). The new models show that the significant coefficients capturing international collaboration (coop, country and the dummies country2-country8) in Models 1 to 6 in Table 7 (with only assignees) are the same in the new models, which provides (robust) support to the first part of hypothesis 1. The new models also provide support to the second part of hypothesis 1, although this finding must be taken with caution due to the reduced number of patent families in collaboration with more than five inventors/assignees from different countries. The results from the new estimation to test hypothesis 2 are also rather similar in terms of significance of coefficients to those obtained with the original sample, supporting the hypothesis that collaborating with partners located in leading countries in pharmaceuticals results in greater patent quality than collaborating with other countries.

As in Models 3, 4, and 5 in Table 8, the results of the new models show that when the number of collaborating countries increases, the number of countries from which obtaining benefits in terms of patent quality becomes fewer.[4]

Finally, it is important to mention that some papers have raised endogeneity issues on the relationship between collaboration and patent quality. Alnuaimi et al. (2012) point out the risk of reverse causality in the estimations, since teams involved in international collaborations may be assigned to the most promising and valuable projects. Giuliani et al. (2016) argue that their sample can suffer from this same endogeneity problem due to potentially more inventive projects possibly being preassigned to international rather than domestic teams of inventors. This potential endogeneity problem is mitigated in our analysis. First, note the time-related sequence in our models. The dependent variable (patent quality) is measured by the number of forward citations, and the patent can only have citations at the end of the project, once the invention has been developed (with or without R&D collaboration) and the patent has been applied for and published. Second, there is usually a great deal of uncertainty about the results of a project and whether it can lead to a patent of good quality. The number of claims and the scope of the patent can give some idea about the technological impact (number of forward citations) that a patent might have in the future, but our models already controlled for these variables. Third, we focus neither on MNC (as for example in Alnuaimi et al, 2012) nor on firms that have patented repeatedly (as in Giuliani et al., 2016). We gathered information on patent families by filtering by pharmaceuticals IPC codes and institutional applicants. This means that our sample is composed of patent families applied for by a variety of firms with different characteristics and size. In other words, the number of firms which applied for patents is considerably greater and more diverse in their characteristics compared to the sample of large firms used in the cited previous works.

6. Conclusions

The main rationale for collaborating internationally in producing patents relies on the idea that collaborative efforts give access to partners' resources, along with the opportunity to benefit from the innovation environment of the country in which the partners are located. Thus, collaboration may result in better innovation performance, for example, in an increase in patent quality when the co-patent involves partners from several countries. Although an increasing body of empirical literature has stressed the positive role of international collaboration in improving patent quality, there is still research that points in the opposite direction. The reason why international collaboration could reduce patent quality is not only the difficulty in achieving integration of knowledge across multiple locations, but also the fear of leaking knowledge to a potential rival. This paper contributes to this literature by addressing three novel questions. First, to what extent does increasing the number of collaborations with partners in different countries produce benefits in terms of increased patent quality? Second, what are the right countries with which to collaborate when the objective is to achieve patents of better quality? And third, since the co-patents can be the result of sharing the co-ownership of such patents with partners in territories that offer low tax rates, to what extent does this fact affect patent quality? To answer these empirical questions and test three respective hypotheses, we gathered a sample of 143,479 pharmaceutical patent families for the period 1990-2012,

[4] The models estimated in the third and fourth sections of the robustness check are not presented, but they are available upon request.

from which 24.7% are patents with assignees from two or more countries (co-patents). With such a sample, the estimation of several count models leads to the conclusions presented in the following paragraphs.

First, the results show that, controlling for factors affecting quality such as the size of the patent, the size of the team, and the use of previous technological and scientific knowledge, the impact of international collaboration is, on average, a 4.9% increase in patent quality compared with patents with assignees from a single country. When the number of countries in which the assignees are based increases, the effect of a wider collaboration on patent quality is also greater, but we did not find any difference when the number of countries involved is above five (note, however, that this finding must be taken with caution, due to the small number of collaborative patents with more than five assignees). These results provide some evidence for the hypothesis that the effect of collaboration is limited to a certain breadth of cross-border collaboration.

Second, to produce patents of better quality, the appropriate countries with which to collaborate are the United States, Switzerland, Japan, Germany and the United Kingdom. The quality of patents involving one or more of these five countries is substantially higher than that of patents that do not include any of these countries as locations of the assignees. On average, the quality was found to be around 21% higher (compared to patents belonging to partners from a single country) if the co-patent includes the US, 20% for Switzerland, 17% for Japan, 8% for Germany, and 7% higher for the United Kingdom. The significance and values of the coefficients of each country vary depending on the number of countries involved in the co-patent. For example, when there are assignees from four different countries, the only country that is worth collaborating with to get patents of better quality is the US. These results provide evidence for our second hypothesis, that collaborating with countries with greater potential in pharmaceuticals leads to the production of patents of better quality.

Third, according to our findings, there is no effect of co-owning patents with partners in tax havens. Thus, our results do not support the hypothesis that collaborating with partners located in tax havens has a positive effect on patent quality. A plausible explanation for this result is that the tax levied on the expected revenues from patents moved out of the country, and the special treatment by many countries of the taxation of corporate income derived from patent ownership, could offset the benefits of co-assigning patents with partners located in low-tax jurisdictions.

Our results offer some policy implications from both a managerial and a social perspective. From a managerial point of view, the main message of this paper is that international collaboration, apart from providing advantages such as the benefits of collective and organizational learning, can improve the quality of the innovative output (patents) in a technology domain such as pharmaceuticals. However, in order to prevent leakages of knowledge that can result in a co-patent of lower quality than expected, it is recommended that the number of countries in which the assignees are based be maintained at a low number. From a social perspective, it is well known that one of the objectives of the patent system is to encourage innovation by conferring a monopoly over an invention. The other is to achieve greater diffusion of innovation to facilitate follow-on innovations through patent disclosure. Thus, any financial and organizational innovation measure that contributes to encouraging international collaboration with a selected group of leading countries in specific domains can address both perspectives, and contribute to reducing uncertainty around patent quality.

A few caveats must be borne in mind in our study that may give rise to future research. First, our main indicator to capture international collaboration in producing a patent is the country of the assignee. Others have used the country of the inventor, or a combination between the countries of the owner of the patent (assignee) and the inventor. In this paper, we included a robustness check to identify differences between the use of co-assignees and coinventors. In this respect, the analysis of some case studies that allow interviews with patent owners and inventors may shed light on which indicator is the best to capture international collaboration on patents in the pharmaceutical sector. Second, the analysis of more refined indicators of patent quality (for example, using the different codes of relevance of the patent citations) may contribute to improving the measurement of quality. Another relevant factor to take into account in future research is whether our results hold in a more general context. Thus, similar analyses could be carried out for other R&D-intensive sectors, such as aerospace and electronics, and other more traditional industries (e.g., the food sector). Finally, our study focuses on the benefits in terms of patent quality from collaborating with countries with technological advantages in the field of pharmaceuticals, but we do not take into account the level of development of the countries of residence of the co-assignees. Thus, in line with the scarce research on this topic (Alnuaimi et al., 2012; Branstetter et al., 2013; Giuliani et al., 2016; and Herman and Xiang, 2022), analysing the extent to which international patent co-ownership increases opportunities for developing countries is another topic that it is worth exploring.

[APPENDIX HERE]

Acknowledgements: We thanks the support from the regional government (Junta de Andalucía-Spain) [Research Group SEJ-295]. The authors are also very grateful to two anonymous reviewers for their constructive and insightful comments.

References

Abrams, D. S., Akcigit, U., & Grennan, J. (2018). Patent value and citations: Creative destruction or strategic disruption? (No. w19647). New York: National Bureau of Economic Research.

Acosta, M., Coronado, D., & Fernández, A. (2009). Exploring the quality of environmental technology in Europe: Evidence from patent citations. Scientometrics, 80(1), 131–152.

Acosta, M., Coronado, D., Ferrándiz, E., & Jiménez, M. (2022). Effects of knowledge spillovers between competitors on patent quality: what patent citations reveal about a global duopoly. The Journal of Technology Transfer, 47(5), 1451-1487.

Albert, M. B., Avery, D., Narin, F., & McAllister, P. (1991). Direct validation of citation counts as indicators of industrially important patents. Research Policy, 20(3), 251–259.

Alnuaimi, T., Singh, J., & George, G. (2012). Not with my own: Long-term effects of cross-country collaboration on subsidiary innovation in emerging economies versus advanced economies. Journal of Economic Geography, 12(5), 943-968.

Alonso-Martínez, D., González-Álvarez, N., & Nieto, M. (2021). Does international patent collaboration have an effect on entrepreneurship? Journal of International

Entrepreneurship. Advance online publication. doi.org/10.1007/s10843-021-00302-x.
Argyres, N. S., & Silverman, B. S. (2004). R&D, organization structure, and the development of corporate technological knowledge. Strategic Management Journal, 25(8-9), 929–958.
Aristodemou, L., & Tietze, F. (2018). Citations as a measure of technological impact: A review of forward citation-based measures. World Patent Information, 53, 39-44.
Arts, S., Appio, F. P., & Van Looy, B. (2013). Inventions shaping technological trajectories: do existing patent indicators provide a comprehensive picture?. Scientometrics, 97(2), 397-419.
Audretsch, D. B., & Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. The American economic review, 86(3), 630-640.
Azagra–Caro, J. M., & Tur, E. M. (2018). Examiner trust in applicants to the European Patent Office: Country specificities. Scientometrics, 117(3), 1319–1348.
Azagra–Caro, J. M., Barberá–Tomás, D., Edwards–Schachter, M., & Tur, E. M. (2017). Dynamic interactions between university–industry knowledge transfer channels: A case study of the most highly cited academic patent. Research Policy, 46(2), 463–474.
Bakker, J., Verhoeven, D., Zhang, L., & Van Looy, B. (2016). Patent citation indicators: One size fits all? Scientometrics, 106(1), 187–211.
Barberá–Tomás, D., Jiménez–Sáez, F., & Castelló–Molina, I. (2011). Mapping the importance of the real world: The validity of connectivity analysis of patent citations networks. Research Policy, 40(3), 473–486.
Basile, R., Capello, R., & Caragliu, A. (2012). Technological interdependence and regional growth in Europe: Proximity and synergy in knowledge spillovers. Papers in Regional Science, 91(4), 697-722.
Baumann, M., Böhm, T., Knoll, B., & Riedel, N. (2020). Corporate taxes, patent shifting, and anti-avoidance rules: empirical evidence. Public Finance Review, 48(4), 467-504.
Belderbos, R., Cassiman, B., Faems, D., Leten, B., & Van Looy, B. (2014). Co–ownership of intellectual property: Exploring the value–appropriation and value–creation implications of co–patenting with different partners. Research Policy, 43(5), 841–852.
Belderbos, R., Faems, D., Leten, B., & Looy, B. V. (2010). Technological activities and their impact on the financial performance of the firm: Exploitation and exploration within and between firms. Journal of Product Innovation Management, 27(6), 869-882.
Bergek, A., & Bruzelius, M. (2010). Are patents with multiple inventors from different countries a good indicator of international R&D collaboration? The case of ABB. Research Policy, 39(10), 1321-1334.
Bessen, J. (2008). The value of US patents by owner and patent characteristics. Research Policy, 37(5), 932–945.
Bessen, J., & Maskin, E. (2009). Sequential innovation, patents, and imitation. The Rand Journal of Economics, 40(4), 611–635.
Blind, K., Edler, J., Frietsch, R., & Schmoch, U. (2006). Motives to patent: Empirical evidence from Germany. Research Policy, 35(5), 655-672.
Boschma, R. (2005). Proximity and innovation: a critical assessment. Regional studies, 39(1), 61-74.

Bradley, S., Dauchy, E., & Robinson, L. (2015). Cross-country evidence on the preliminary effects of patent box regimes on patent activity and ownership. National Tax Journal, 68(4), 1047-1071.
Branstetter, L. (2005). Exploring the link between academic science and industrial innovation. Annals of Economics and Statistics, 79(80), 119–142.
Branstetter, L., Li, G., & Veloso, F. (2015). The rise of international coinvention. In The changing frontier: Rethinking science and innovation policy (pp. 135-168). University of Chicago Press.
Briggs, K. (2015). Co-owner relationships conducive to high quality joint patents. Research Policy, 44(8), 1566-1573.
Briggs, K., & Wade, M. (2014). More is better: evidence that joint patenting leads to quality innovation. Applied Economics, 46(35), 4370-4379.
Broekel, T., & Brachert, M. (2015). The structure and evolution of inter-sectoral technological complementarity in R&D in Germany from 1990 to 2011. Journal of evolutionary economics, 25(4), 755-785.
Cameron, A., & Trivedi, P. (1986). Econometrics models based on count data: comparisons and applications of some estimators and tests. Journal of Applied Econometrics, 1, 29–53.
Cameron, A., & Trivedi, P. (1998). Regression analysis of count data. New York, NY: Cambridge University Press.
Cameron and Trivedi (2009). Microeconometrics using Stata. Stata Press.
Cassiman, B., Veugelers, R., & Zuniga, P. (2008). In search of performance effects of (in) direct industry science links. Industrial and Corporate Change, 17(4), 611–646.
Chang, S. H., Chang, H. Y., & Fan, C. Y. (2018). Structural model of patent quality applied to various countries. International Journal of Innovation Science, 10(39, 371–384.
Chen, Y. S., & Chang, K. C. (2010). The relationship between a firm's patent quality and its market value—the case of US pharmaceutical industry. Technological Forecasting and Social Change, 77(1), 20–33.
Cohen, W. M., Nelson, R., & Walsh, J. P. (2000). Protecting their intellectual assets: Appropriability conditions and why U.S. manufacturing patent (or not). NBER Working Paper 7552, National Bureau of Economic Research, Cambridge, MA. Available at: https://www.nber.org/papers/w7552.
Criscuolo, P., Narula, R., & Verspagen, B. (2005). Role of home and host country innovation systems in R&D internationalisation: a patent citation analysis. Economics of innovation and new technology, 14(5), 417-433.
Danguy, J. (2017). Globalization of innovation production: A patent-based industry analysis. Science and Public Policy, 44(1), 75-94.
De Beule, F., & Van Beveren, I. (2019). Sources of open innovation in foreign subsidiaries: An enriched typology. International Business Review, 28(1), 135-147.
De Prato, G., & Nepelski, D. (2014). Global technological collaboration network: Network analysis of international co-inventions. The Journal of Technology Transfer, 39(3), 358-375.
de Rassenfosse, G., & Jaffe, A. B. (2018). Are patent fees effective at weeding out low-quality patents? Journal of Economics & Management Strategy, 27(1), 134-148.
de Rassenfosse, G., & Seliger, F. (2020). Sources of knowledge flow between developed and developing nations. Science and Public Policy, 47(1), 16-30.
de Rassenfosse, G., Dernis, H., & Boedt, G. (2014). An introduction to the Patstat database with example queries. Australian Economic Review, 47(3), 395–408.

Delanghe, H., Sloan, B., & Muldur, U. (2009). Transnational collaboration in public research funding and publicly supported research in Europe. In European Science and Technology Policy, Delanghe H, Muldur U., Soete L. (Eds.). Edward Elgar Publishing, 175-192.

Easterby-Smith, M., Lyles, M. A., & Tsang, E. W. (2008). Inter-organizational knowledge transfer: Current themes and future prospects. Journal of Management Studies, 45(4), 677–690.

Elvers, D., & Song, C. (2014). R&D Cooperation and Firm Performance-Evaluation of Partnering Strategies in the Automotive Industry. Journal of Finance and Economics, 2(5), 185-193.

Ernst, C., Richter, K., & Riedel, N. (2014). Corporate taxation and the quality of research and development. International Tax and Public Finance, 21(4), 694-719.

Frishammar, J., Ericsson, K., & Patel, P. C. (2015). The dark side of knowledge transfer: Exploring knowledge leakage in joint R&D projects. Technovation, 41–42, 75–88.

Fritsch, M., Titze, M., & Piontek, M. (2020). Identifying cooperation for innovation—a comparison of data sources. Industry and Innovation, 27(6), 630-659.

Furman, J.L., Kyle, M.K., Cockburn, I. and Henderson, R. (2006) Public & private spillovers, location and the productivity of pharmaceutical research. Annales d'Économie et de Statistique 79-80.

Gaessler, F., Hall, B. H., & Harhoff, D. (2021). Should there be lower taxes on patent income?. Research Policy, 50(1), 104129.

Gamba, S. (2017). The effect of intellectual property rights on domestic innovation in the pharmaceutical sector. World Development, 99, 15-27.

Gambardella, A., Harhoff, D., & Verspagen, B. (2008). The value of European patents. European Management Review, 5(2), 69–84.

Gay, C., Le Bas, C., Patel, P., & Touach, K. (2005). The determinants of patent citations: An empirical analysis of French and British patents in the US. Economics of Innovation and New Technology, 14(5), 339–350.

Geum, Y., Lee, S., Yoon, B., & Park, Y. (2013). Identifying and evaluating strategic partners for collaborative R&D: Index-based approach using patents and publications. Technovation, 33(6-7), 211-224.

Gittelman, M., & Kogut, B. (2003). Does good science lead to valuable knowledge? Biotechnology firms and the evolutionary logic of citation patterns. Management Science, 49(4), 366–382.

Giuliani, E., Martinelli, A., & Rabellotti, R. (2016). Is co-invention expediting technological catch up? A study of collaboration between emerging country firms and EU inventors. World Development, 77, 192-205.

Griffith, R., Miller, H., & O'Connell, M. (2014). Ownership of intellectual property and corporate taxation. Journal of Public Economics, 112, 12-23.

Guan, J., & Chen, Z. (2012). Patent collaboration and international knowledge flow. Information Processing & Management, 48(1), 170-181.

Guellec, D. & van Pottelsberghe de la Potterie, B. (2000) Applications, grants and the value of patent. Economics Letters, 69(1), p. 109–114.

Guellec, D. & van Pottelsberghe de la Potterie, B. (2001), The internationalisation of technology analysed with patent data. Research Policy, 30(8), 1256–1266.

Guellec, D. & van Pottelsberghe de la Potterie, B. (2002) The value of patents and patenting strategies: Countries and technology areas patterns. Economics of Innovation and New Technology, 11(2), 133–148.

Guellec, D., & van Pottelsberghe de la Potterie, B. (2004). Measuring the internationalisation of the generation of knowledge. In Moed, H.F., Glänzel, W.,

Schmoch, U. (Eds.), Handbook of quantitative science and technology research. Springer, Dordrecht, 645-662.
Hagedoorn, J. (2003). Sharing intellectual property rights—an exploratory study of joint patenting amongst companies. Industrial and corporate change, 12(5), 1035-1050.
Hall, B. H., & Harhoff, D. (2012). Recent research on the economics of patents. Annual Review of Economics 4(1), 541-565.
Hall, B. H., & Harhoff, D. (2012). Recent research on the economics of patents. Annual Review of Economics, 4(1), 541–565.
Hall, B. H., Jaffe, A., & Trajtenberg, M. (2005). Market value and patent citations. The RAND Journal of Economics, 36(1), 16–38.
Hall, B., Helmers, C., Rogers, M., & Sena, V. (2014). The choice between formal and informal intellectual property: A review. Journal of Economic Literature, 52(2), 375–423.
Harhoff, D., & Reitzig, M. (2004). Determinants of opposition against EPO patent grants—the case of biotechnology and pharmaceuticals. International Journal of Industrial Organization, 22(4), 443–480.
Harhoff, D., & Wagner, S. (2009). The duration of patent examination at the European Patent Office. Management Science, 55(12) 1969–1984.
Harhoff, D., Henkel, J., & Von Hippel, E. (2003). Profiting from voluntary information spillovers: How users benefit by freely revealing their innovations. Research Policy, 32(10), 1753–1769.
Harhoff, D., Narin, F., Scherer, F. M., & Vopel, K. (1999). Citation frequency and the value of patented inventions. Review of Economics and Statistics, 81(3), 511–515.
Harrigan, K. R., Di Guardo, M. C., & Marku, E. (2018). Patent value and the Tobin's q ratio in media services. The Journal of Technology Transfer, 43(1), 1–19.
Heilbron, D. (1994). Zero–altered and other regression models for count data with added zeros. Biometrical Journal, 36(5), 531–547.
Henard, D. H., & Dacin, P. A. (2010). Reputation for product innovation: Its impact on consumers. Journal of Product Innovation Management, 27(3), 321-335.
Herman, K. S., & Xiang, J. (2022). How collaboration with G7 countries drives environmental technology innovation in ten Newly Industrializing Countries. Energy for Sustainable Development, 71, 176-185.
Hernández, H., Grassano, N., Tübke, A., Amoroso, S., Csefalvay, Z., & Gkotsis, P. (2020). The 2019 EU Industrial R&D Investment Scoreboard; EUR 30002 EN; Publications Office of the European Union, Luxembourg.
Higham, K., De Rassenfosse, G., & Jaffe, A. B. (2021). Patent quality: Towards a systematic framework for analysis and measurement. Research Policy, 50(4), 104215.
Hines Jr, J. R. (2010). Treasure islands. Journal of Economic Perspectives, 24(4), 103-26.
Hirschey, M., & Richardson, V. J. (2004). Are scientific indicators of patent quality useful to investors?. Journal of Empirical Finance, 11(1), 91–107.
Höflinger, P. J., Nagel, C., & Sandner, P. (2018). Reputation for technological innovation: Does it actually cohere with innovative activity? Journal of Innovation & Knowledge, 3(1), 26-39.
Jaffe, A. B., & de Rassenfosse, G. (2017). Patent citation data in social science research: Overview and best practices. Journal of the Association for Information Science and Technology, 68(6), 1360–1374.

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. the Quarterly journal of Economics, 108(3), 577-598.
Karkinsky, T., & Riedel, N. (2012). Corporate taxation and the choice of patent location within multinational firms. Journal of international Economics, 88(1), 176-185.
Kim, C., & Song, J. (2007). Creating new technology through alliances: An empirical investigation of joint patents. Technovation, 27(8), 461-470.
Knell, M. A. R. K., & Srholec, R. (2008). Collaboration in innovation and foreign ownership across industries in Europe. Europe Innova, Innovation Watch.
Kotabe, M., Dunlap-Hinkler, D., Parente, R., & Mishra, H. A. (2007). Determinants of cross-national knowledge transfer and its effect on firm innovation. Journal of international business studies, 38(2), 259-282.
Lahiri, N. (2010). Geographic distribution of R&D activity: how does it affect innovation quality? Academy of Management Journal, 53(5), 1194–1209.
Lakdawalla, D. N. (2018). Economics of the pharmaceutical industry. Journal of Economic Literature, 56(2), 397-449.
Lambert, D. (1992). Zero–inflated Poisson regression, with an application to defects in manufacturing. Technometrics, 34(1), 1–14.
Lanjouw, J. O., & Schankerman, M. (2001). Characteristics of patent litigation: a window on competition. RAND journal of economics, 129-151.
Lanjouw, J. O., & Schankerman, M. (2004). Patent quality and research productivity: Measuring innovation with multiple indicators. The Economic Journal, 114(495), 441–465.
Laursen, K., & Salter, A. J. (2014). The paradox of openness: Appropriability, external search and collaboration. Research policy, 43(5), 867-878.
Lee, S., Lee, H., & Lee, C. (2020). Open innovation at the national level: Towards a global innovation system. Technological Forecasting and Social Change, 151, 119842.
Lei, X. P., Zhao, Z. Y., Zhang, X., Chen, D. Z., Huang, M. H., Zheng, J., ... & Zhao, Y. H. (2013). Technological collaboration patterns in solar cell industry based on patent inventors and assignees analysis. Scientometrics, 96(2), 427-441.
Lerner, J. (1994). The importance of patent scope: An empirical analysis. The RAND Journal of Economics, 25(2), 319–333.
Lin, C., Wu, Y. J., Chang, C., Wang, W., & Lee, C. Y. (2012). The alliance innovation performance of R&D alliances—the absorptive capacity perspective. Technovation, 32(5), 282-292.
Lino, T., Inoue, H., Saito, Y. U., & Todo, Y. (2021). How does the global network of research collaboration affect the quality of innovation? The Japanese Economic Review, 72(1), 5-48.
Long, J. S., & Freese, J. (2001). Regression models for categorical dependent variables using Stata. Stata Press.
Loschky, A. (2008). Reviewing the nomenclature for high-technology trade — the sectoral approach. Technical Report (2008)9. OECD STD/SES/WPTGS.
Ma, Z., Lee, Y., & Chen, C. F. P. (2009). Booming or emerging? China's technological capability and international collaboration in patent activities. Technological Forecasting and Social Change, 76(6), 787-796.
Magazzini, L., Pammolli, F., Riccaboni, M., & Rossi, M. A. (2009). Patent disclosure and R&D competition in pharmaceuticals. Economics of Innovation and New Technology, 18(5), 467-486.

Maggioni, M. A., Nosvelli, M., & Uberti, T. E. (2007). Space versus networks in the geography of innovation: A European analysis. Papers in Regional Science, 86(3), 471-493.
Mariani, M., & Romanelli, M. (2007). 'Stacking' and 'picking' inventions: The patenting behavior of European inventors. Research Policy, 36(8), 1128–1142.
Martínez, C. (2010). Insight into different types of patent families. OECD Science, Technology and Industry Working Papers, No. 2010/02, Paris: OECD Publishing.
Martínez, C. (2011). Patent families: When do different definitions really matter? Scientometrics, 86(1), 39–63.
Marrocu, E., Paci, R., & Usai, S. (2013). Proximity, networking and knowledge production in Europe: What lessons for innovation policy?. Technological Forecasting and Social Change, 80(8), 1484-1498.
Mascia, D., Pallotti, F., & Angeli, F. (2017). Don't stand so close to me: competitive pressures, proximity and inter-organizational collaboration. Regional Studies, 51(9), 1348-1361.
Mazzola, E., Bruccoleri, M., & Perrone, G. (2016). Open innovation and firms performance: state of the art and empirical evidences from the bio-pharmaceutical industry. International Journal of Technology Management, 70(2-3), 109-134.
Messeni Petruzzelli, A., Rotolo, D., & Albino, V. (2015). Determinants of patent citations in biotechnology: An analysis of patent influence across the industrial and organizational boundaries. Technological Forecasting and Social Change, 91, 208–221.
Michelino, F., Cammarano, A., Lamberti, E., & Caputo, M. (2017). Open innovation for start-ups: A patent-based analysis of bio-pharmaceutical firms at the knowledge domain level. European Journal of Innovation Management.
Moaniba, I. M., Su, H. N., & Lee, P. C. (2018). Knowledge recombination and technological innovation: the important role of cross–disciplinary knowledge. Innovation, 20(4), 326–352.
Molina-Morales, F. X., & Expósito-Langa, M. (2013). Overcoming undesirable knowledge redundancy in territorial clusters. Industry and Innovation, 20(8), 739-758.
Montobbio, F., & Sterzi, V. (2013). The globalization of technology in emerging markets: a gravity model on the determinants of international patent collaborations. World development, 44, 281-299.
Moser, P., Ohmstedt, J., & Rhode, P. W. (2017). Patent citations—An analysis of quality differences and citing practices in hybrid corn. Management Science, 64(4) 1926–1940.
Nemet, G. F., & Johnson, E. (2012). Do important inventions benefit from knowledge originating in other technological domains? Research Policy, 41(1) 190–200.
Oxley, J. E., & Sampson, R. C. (2004). The scope and governance of international R&D alliances. Strategic Management Journal, 25(8-9), 723-749.
Patel, D., & Ward, M. R. (2011). Using patent citation patterns to infer innovation market competition. Research Policy, 40(6), 886–894.
Penner-Hahn, J., & Shaver, J. M. (2005). Does international research and development increase patent output? An analysis of Japanese pharmaceutical firms. Strategic Management Journal, 26(2), 121-140.
Picci, L. (2010). The internationalization of inventive activity: A gravity model using patent data. Research Policy, 39(8), 1070-1081.

Picci, L., & Savorelli, L. (2018). The 'inventor balance'and the functional specialization in global inventive activities. Economics of Innovation and New Technology, 27(1), 39-61.
Ponta, L., Puliga, G., Manzini, R., & Cincotti, S. (2022). Sustainability-oriented innovation and co-patenting role in agri-food sector: Empirical analysis with patents. Technological Forecasting and Social Change, 178, 121595.
Popp, D. (2006). They don't invent them like they used to: An examination of energy patent citations over time. Economics of Innovation and New Technology, 15(8), 753–776.
Reuer, J. J., & Lahiri, N. (2014). Searching for alliance partners: Effects of geographic distance on the formation of R&D collaborations. Organization Science, 25(1), 283-298.
Rodriguez, V. (2010). The backlog issue in patents: a look at the European case. World patent information, 32(4), 287-290.
Santamaría, L., Nieto, M. J., & Rodríguez, A. (2021). Failed and successful innovations: The role of geographic proximity and international diversity of partners in technological collaboration. Technological Forecasting and Social Change, 166, 120575.
Sapsalis, E., & van Pottelsberghe de la Potterie, B. (2007). The institutional sources of knowledge and the value of academic patents. Economics of Innovation and New Technology, 16(2), 139–157.
Sapsalis, E., van Pottelsberghe de la Potterie, B. V. P., & Navon, R. (2006). Academic versus industry patenting: An in–depth analysis of what determines patent value. Research Policy, 35(10), 1631–1645.
Schettino, F., Sterlacchini, A., & Venturini, F. (2013). Inventive productivity and patent quality: Evidence from Italian inventors. Journal of policy modeling, 35(6), 1043-1056.
Schmid, J., & Fajebe, A. (2019). Variation in patent impact by organization type: An investigation of government, university, and corporate patents. Science and Public Policy, 46(4), 589-598.
Scotchmer, S. (1991). Standing on the shoulders of giants: cumulative research and the patent law. Journal of economic perspectives, 5(1), 29-41.. 5 (1), 29–4.
Simard, C., & West, J. (2006). Knowledge networks and the geographic locus of innovation. In Chesbrough, H., Vanhaverbeke,W., and West, J., (eds.), Open innovation: researching a new paradigm. Oxford: Oxford University Press, 220-240.
Singh, J. (2008). Distributed R&D, cross–regional knowledge integration and quality of innovative output. Research Policy, 37(1), 77–96.
Sorenson, O., & Fleming, L. (2004). Science and the diffusion of knowledge. Research policy, 33(10), 1615–1634.
Squicciarini, M., Dernis, H., & Crisculo, C. (2013). Measuring patent quality: Indicators of technological and economic value. OECD Science, Technology and Industry Working Papers, No. 2013/03, OECD Publishing, Paris.
Sterzi, V. (2013). Patent quality and ownership: An analysis of UK faculty patenting. Research Policy, 42(2), 564–576.
Su, H. N. (2017). Collaborative and legal dynamics of international R&D-evolving patterns in East Asia. Technological Forecasting and Social Change, 117, 217-227.
Su, H. N. (2017). Collaborative and legal dynamics of international R&D-evolving patterns in East Asia. Technological Forecasting and Social Change, 117, 217-227.
Su, H. N. (2021). How does distant collaboration influence R&D quality?. Technology Analysis & Strategic Management, DOI: 10.1080/09537325.2021.1926965.

Sun, Y., Zhang, C., & Kok, R. A. (2020). The role of research outcome quality in the relationship between university research collaboration and technology transfer: empirical results from China. Scientometrics, 122(2), 1003–1026.

Tahmooresnejad, L., & Beaudry, C. (2019). Capturing the economic value of triadic patents. Scientometrics, 118(1), 127–157.

Ter Wal, A. L., & Boschma, R. A. (2009). Applying social network analysis in economic geography: framing some key analytic issues. The Annals of Regional Science, 43(3), 739-756.

Thomas, P. (1999). The effect of technological impact upon patent renewal decisions. Technology Analysis & Strategic Management, 11(2), 181–197.

Trajtenberg, M. (1990). A penny for your quotes: Patent citations and the value of innovations. The RAND Journal of Economics, 21(1), 172–187.

van Beers, C., & Zand, F. (2014). R&D cooperation, partner diversity, and innovation performance: an empirical analysis. Journal of Product Innovation Management, 31(2), 292-312.

van Raan, A. F. (2017). Patent citations analysis and its value in research evaluation: A review and a new approach to map technology–relevant research. Journal of Data and Information Science, 2(1), 13–50.

van Zeebroeck, N., & van Pottelsberghe de la Potterie, B. (2011). The vulnerability of patent value determinants. Economics of Innovation and New Technology, 20(3), 283–308.

von Proff, S., & Dettmann, A. (2013). Inventor collaboration over distance: a comparison of academic and corporate patents. Scientometrics, 94(3), 1217-1238.

Wooldridge, J. M. (1999). Quasi-likelihood methods for count data. In M. H. Pesaran & P. Schmidt (Eds.), Handbook of Applied Econometrics Volume II: Microeconomics. Oxford: Blackwell Publishers Ltd, 321-367.

Yang, H., Phelps, C., & Steensma, H. K. (2010). Learning from what others have learned from you: The effects of knowledge spillovers on originating firms. Academy of Management Journal, 53(2), 371–389.

Zuniga, P., Guellec, D., Dernis, H., Khan, M., Okazaki, T., & Webb, C. (2009). OECD Patent Statistics Manual. France: OECD Publications.

Table 1. R&D expenditure. Top countries in the pharmaceutical industry

Country	2005		2008		2010		2012	
	€M	%	€M	%	€M	%	€M	%
United States	28,150	47.77	30,175	43.16	30,628	39.17	41,992	43.04
United Kingdom	7,904	13.41	8,005	11.45	8,260	10.56	8,631	8.85
Switzerland	7,888	13.38	11,426	16.34	13,709	17.53	14,555	14.92
France	4,425	7.51	4,924	7.04	4,761	6.09	6,397	6.56
Germany	3,893	6.61	3,501	5.01	4,089	5.23	8,005	8.20
Japan	3,816	6.47	7,563	10.82	11,837	15.14	11,031	11.31
Top-6 countries	56,076	95.15	65,594	93.82	73,284	93.72	90,611	92.88
Others	2,857	4.85	4,315	6.17	4,917	6.29	6,965	7.14
Total	58,933	100	69,909	100	78,201	100	97,575	100
Source: Own elaboration from the EU Scoreboard, available at https://iri.jrc.ec.europa.eu/scoreboard/								

Table 2. Number of patent families according to the number of countries of the assignees (1990-2012)

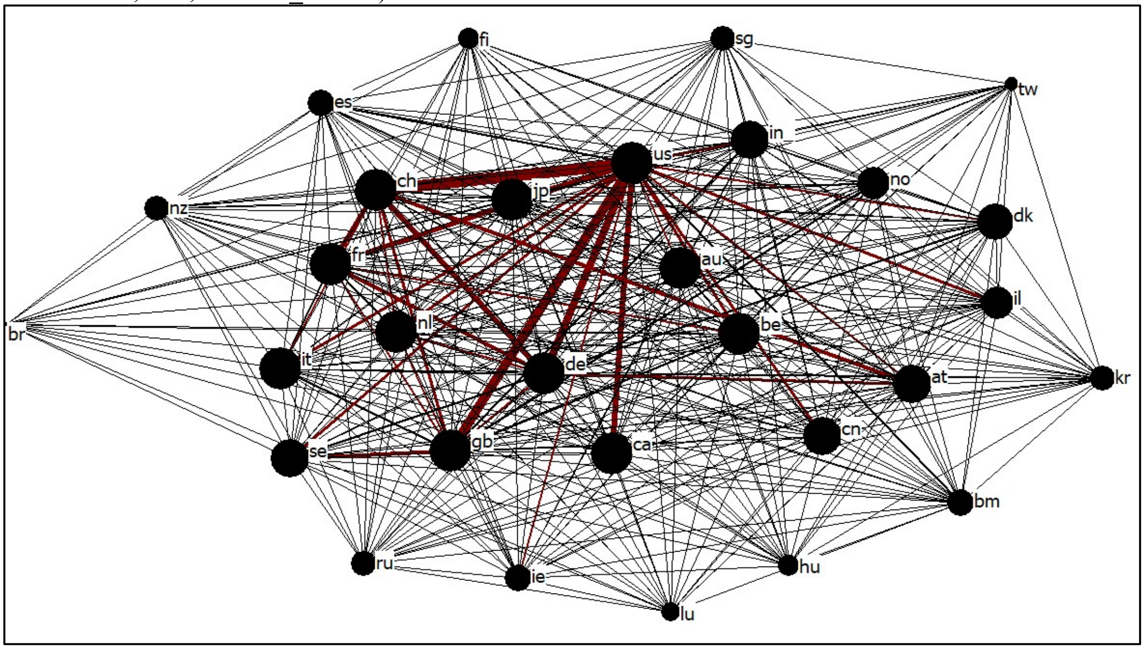
No. different countries of inventors	No. patent families	No. forward patent citations	No. forward citations per patent familiy
Single-owned	107,941	103,012	0.95
Co-patents	35,538	44,689	1.26
2 Countries	27,468	32,479	1.18
3 Countries	6,467	9,024	1.40
4 Countries	1,328	2,410	1.81
5 Countries	234	643	2.75
6 Countries	27	90	3.33
7 Countries	12	33	2.75
8 Countries	2	10	5.00
Total patent families	143,479	147,701	1.03
Single-owned: patent families owned by one or several partners from a single country. Co-patents: sum of patent families with partners from between two and 8 different countries. Source: Patstat and own elaboration.			

Table 3. Distribution of pharmaceutical inventions by countries of the assignees (1990-2012)

ISO	Country	Patent families (1)					Forward patent citations (5-year window) (2)					
		no.	%	Single-owned	In coll.	% coll.	no.	Single-owned	In coll.	Aver.	Aver. Single	Aver. in coll.
us	United States	68,164	47.51	57,887	10,277	15.08	83,657	69,991	13,666	1.23	1.21	1.33
jp	Japan	13,371	9.32	12,281	1,090	8.16	10,031	8,506	1,525	0.75	0.69	1.40
de	Germany	11,752	8.19	8,395	3,357	28.56	10,566	6,061	4,505	0.9	0.72	1.34
uk	United King.	8,491	5.92	4,806	3,685	43.4	7,679	3,414	4,265	0.9	0.71	1.16
fr	France	6,883	4.8	4,724	2,159	31.37	4,757	2,286	2,471	0.69	0.48	1.14
ch	Switzerland	4,799	3.34	1,144	3,655	76.16	5,900	929	4,971	1.23	0.81	1.36
ca	Canada	3,295	2.3	1,978	1,317	39.97	3,771	1,886	1,885	1.14	0.95	1.43
it	Italy	3,208	2.24	2,333	875	27.27	1,987	1,045	942	0.62	0.45	1.08
se	Sweden	2,605	1.82	1,349	1,256	48.21	2,322	811	1,511	0.89	0.6	1.20
nl	Netherlands	2,263	1.58	1,291	972	42.95	1,897	999	898	0.84	0.77	0.92
il	Israel	1,969	1.37	1,373	596	30.25	1,317	764	553	0.67	0.56	0.93
be	Belgium	1,879	1.31	887	992	52.8	1,981	650	1,331	1.05	0.73	1.34
dk	Denmark	1,826	1.27	1,215	611	33.45	2,099	1,201	898	1.15	0.99	1.47
kr	Korea	1,818	1.27	1,638	180	9.89	1,116	914	202	0.61	0.56	1.12
in_	India	1,775	1.24	1,253	522	29.4	1,915	1,119	796	1.08	0.89	1.53
au	Australia	1,705	1.19	1,235	470	27.56	802	455	347	0.47	0.37	0.74
cn	China	1,621	1.13	1,031	590	36.38	1,403	495	908	0.87	0.48	1.54
es	Spain	1,449	1.01	1,061	388	26.77	1,137	736	401	0.79	0.69	1.04
at	Austria	1,071	0.75	336	735	68.64	952	119	833	0.89	0.35	1.13
ie	Ireland	644	0.45	214	430	66.75	662	127	535	1.03	0.59	1.24
no	Norway	464	0.32	224	240	51.68	235	85	150	0.51	0.38	0.63
fi	Finland	446	0.31	331	115	25.83	153	90	63	0.34	0.27	0.55
sg	Singapore	329	0.23	189	140	42.49	237	103	134	0.72	0.54	0.96
hu	Hungary	313	0.22	198	115	36.8	100	34	66	0.32	0.17	0.57
nz	New Zealand	299	0.21	172	127	42.4	161	83	78	0.54	0.48	0.62
tw	Taiwan	252	0.18	98	154	61.12	167	46	121	0.66	0.47	0.79
ru	Russia	239	0.17	110	129	54.06	131	12	119	0.55	0.11	0.92
br	Brazil	202	0.14	156	46	22.92	63	42	21	0.31	0.27	0.45
lu	Luxembourg	184	0.13	31	153	83.18	110	6	104	0.6	0.19	0.68
bm	Bermuda	164	0.11	1	163	99.39	394	3	391	2.4	3	2.40
Total		143,479	100	107,941	35,538	24.77	147,701	103,012	44,689	1.03	0.95	1.26

(1) Number of patent families by countries.
Single-owned means that the owner of a patent is from one single country. In coll. includes the patents in collaboration with two or more countries, and % coll. is the percentage of co-patents (patents in collaboration) over the total patents of the country.
(2) The last three columns of the table present the average forward citations (number of forward citations divided by the number of patents of each country) for the total number of patents of the country, those applied for by a single country, and those applied for in collaboration with other countries.
Source: Patstat and own elaboration.

Graph 1. Network of international collaborative patents in the pharmaceutical sector (degree centrality. Max US: 36,13%; Min BR_ 0.13%)



Source: Patstat and own elaboration.

Table 4. Variables and definitions

Variable	Definition
Dependent variable	
fpc5years	No. forward citations within five years after the first application of the focal patent family.
Independent variables ***Variables capturing international collaboration***	
coop	Dummy variable that takes value 1 if the assignees are located in two or more countries, and 0 if the assignees are from a single country.
country	Number of different countries of the assignees.
country2 to country8	Set of 7 dummy variables to capture whether the patent was owned by a single country or by two, three, or up to eight countries. Each variable takes value 1 for collaborative patents with the number of specified countries, and 0 otherwise (patents with owners from a single country).
us-ch-jp-de-uk-fr	Set of dummy variables that take value 1 when the collaborative patent includes the countries with the greatest potential in the pharmaceutical domain: United States (us), Switzerland (ch), Japan (jp), Germany (de), United Kingdom (uk), France (fr), and 0 for other collaborative patents.
haven	Dummy variable that takes value 1 when the collaborative patent includes the countries considered tax havens by the EU, IMF and Oxfam. The countries in our sample that match with the criteria of these institutions are: Bermuda, the Netherlands, Switzerland, Singapore, Ireland and Luxembourg. As Switzerland is one of the countries with the greatest potential in pharmaceuticals, it is excluded from this dummy.
Other determinants of patent quality (patent characteristics)	
Inventors	No. of inventors in the patent family
claims	No. of claims in the focal patent family.
back	No. of backward patent citations
npl	No. of citations to non-patent literature.
ipc4	No. of different 4-digit subclasses of the IPC (Lerner, 1994).
Control for time	
Year dummies	22 dummies (years 1990 to 2012)
Source: Patstat and own elaboration.	

Table 5. Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max	Obs.
fpc-5years	1.02942	2.77493	0	174	143,479
coop	0.24769	0.43167	0	1	143,479
country	1.31742	0.62352	1	8	143,479
country2	0.19144	0.39344	0	1	143,479
country3	0.04507	0.20746	0	1	143,479
country4	0.00926	0.09576	0	1	143,479
country5	0.00163	0.04035	0	1	143,479
country6	0.00019	0.01372	0	1	143,479
country7	0.00008	0.00914	0	1	143,479
country8	0.00001	0.00373	0	1	143,479
us	0.56109	0.49626	0	1	143,479
ch	0.06959	0.25445	0	1	143,479
jp	0.10196	0.30260	0	1	143,479
de	0.11301	0.31661	0	1	143,479
uk	0.09127	0.28800	0	1	143,479
fr	0.06902	0.25349	0	1	143,479
haven	0.04215	0.20092	0	1	143,479
inventors	3.92743	2.84431	1	56	143,479
claim	15.4628	16.2968	0	383	143,479
back	12.8682	31.1088	0	1,807	143,479
npl	23.0678	54.4426	0	1,861	143,479
ipc4	3.91566	1.74426	1	33	143,479
Source: Patstat and own elaboration.					

Table 6. Correlations

	fpc-5years	coop	country	country2	country3	country4	country5	country6	country7	country8	haven	Inven-tors	claim	back	npl	ipc4
fpc-5years	1.000															
coop	0.047***	1.000														
country	0.057***	0.887***	1.000													
country2	0.027***	0.848***	0.533***	1.000												
country3	0.029***	0.379***	0.586***	-0.106***	1.000											
country4	0.027***	0.168***	0.416***	-0.047***	-0.021***	1.000										
country5	0.025***	0.070***	0.239***	-0.020***	-0.009***	-0.004	1.000									
country6	0.011***	0.024***	0.103***	-0.007*	-0.003	-0.001	-0.001	1.000								
country7	0.006*	0.016***	0.083***	-0.004	-0.002	-0.001	-0.000	-0.000	1.000							
country8	0.005*	0.007*	0.040***	-0.002	-0.001	-0.000	-0.000	-0.000	-0.000	1.000						
haven	0.001	0.227***	0.264***	0.126***	0.165***	0.113***	0.063***	0.030***	0.021***	0.018***	1.000					
inventors	0.153***	0.116***	0.140***	0.065***	0.074***	0.068***	0.051***	0.030***	0.024***	0.012***	-0.005*	1.000				
claim	0.086***	0.020***	0.023***	0.013***	0.007*	0.015***	0.012***	0.002	0.001	0.004	-0.003	0.074***	1.000			
back	0.147***	0.054***	0.057***	0.036***	0.031***	0.016***	0.016***	0.005	0.009***	0.005	0.004	0.086***	0.237***	1.000		
npl	0.123***	0.042***	0.050***	0.023***	0.030***	0.016***	0.020***	0.012***	0.009**	0.006*	0.007*	0.062***	0.272***	0.571***	1.000	
ipc4	0.035***	0.000	0.003	-0.003	0.005*	-0.001	0.004	0.004	-0.003	0.002	0.002	0.067***	0.146***	0.132***	0.237***	1.000

Source: Patstat and own elaboration.
∗ $p < 0.10$; ∗∗ $p < 0.05$; ∗∗∗ $p < 0.01$.

Table 7. Effects of international collaboration on patent quality. Negative binomial estimations

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
coop	0.1620***	0.0481***				
	(0.0130)	(0.0127)				
country			0.1347***	0.0477***		
			(0.0087)	(0.0085)		
country2					0.1143***	0.0282**
					(0.0143)	(0.0140)
country3					0.2320***	0.0758***
					(0.0264)	(0.0257)
country4					0.4617***	0.2020***
					(0.0552)	(0.0534)
country5					0.9318***	0.4458***
					(0.1273)	(0.1223)
country6					1.0642***	0.4873
					(0.3695)	(0.3517)
country7					1.0129*	0.2538
					(0.5589)	(0.5410)
country8					1.2332	0.6547
					(1.3365)	(1.2625)
inventors		0.0947***		0.0939***		0.0938***
		(0.0020)		(0.0020)		(0.0020)
claim		0.0082***		0.0082***		0.0082***
		(0.0004)		(0.0004)		(0.0004)
back		0.0077***		0.0077***		0.0077***
		(0.0003)		(0.0003)		(0.0003)
npl		0.0003**		0.0003**		0.0003**
		(0.0001)		(0.0001)		(0.0001)
ipc4		-0.0034		-0.0033		-0.0034
		(0.0034)		(0.0034)		(0.0034)
_cons	-0.4527***	-1.1159***	-0.5911***	-1.1634***	-0.4559***	-1.1135***
	(0.0273)	(0.0303)	(0.0293)	(0.0318)	(0.0273)	(0.0304)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,479	143,479	143,479	143,479	143,479	143,479
LR alpha=0	198,236.37***	176,032.88***	197,740.71***	175,927.98***	197,653.73***	175,902.21***
Log likelihood	-179,034.53	-175,859.31	-178,988.14	-175,850.77	-178,979.48	-175,846.16
LR chi2	8,636.86***	14,987.30***	8,729.63***	15,004.38***	8,746.96***	15,013.60***

Dependent variable: Forward citation (5-year citation window), examiners' citations and self-citations excluded. Standard errors in parentheses.
∗ $p < 0.10$; ∗∗ $p < 0.05$; ∗∗∗ $p < 0.01$.

Table 8. Effects of collaborating with the top countries in pharmaceuticals on patent quality. Negative binomial estimations

	Model (1) More than one	Model (2) Two countries	Model (3) Three countries	Model (4) Four countries	Model (5) Five countries
us	0.1947***	0.1919***	0.2019***	0.3969***	-0.4684
	(0.0238)	(0.0294)	(0.0567)	(0.1302)	(0.3576)
ch	0.1872***	0.1720***	0.2693***	-0.0209	0.0718
	(0.0248)	(0.0343)	(0.0527)	(0.1304)	(0.3285)
jp	0.1533***	0.1592***	0.1770*	0.0772	0.2477
	(0.0422)	(0.0482)	(0.1021)	(0.2423)	(0.4812)
de	0.0865***	0.0814**	0.0485	0.0809	0.6213**
	(0.0262)	(0.0341)	(0.0555)	(0.1206)	(0.2831)
uk	0.0709***	0.1187***	0.0270	-0.2905**	0.2668
	(0.0269)	(0.0342)	(0.0587)	(0.1276)	(0.2782)
fr	0.0411	-0.0724*	0.1759***	0.1556	0.3318
	(0.0305)	(0.0423)	(0.0610)	(0.1203)	(0.3181)
haven	-0.0260	0.0331	-0.1146*	0.0206	-0.1909
	(0.0330)	(0.0440)	(0.0664)	(0.1306)	(0.3044)
inventors	0.0987***	0.0994***	0.0962***	0.1034***	0.0571*
	(0.0035)	(0.0041)	(0.0076)	(0.0155)	(0.0309)
claim	0.0079***	0.0080***	0.0065***	0.0111***	0.0116
	(0.0007)	(0.0008)	(0.0017)	(0.0034)	(0.0090)
back	0.0066***	0.0070***	0.0072***	0.0012	0.0076*
	(0.0005)	(0.0006)	(0.0010)	(0.0022)	(0.0042)
npl	0.0002	0.0001	0.0002	0.0006	-0.0006
	(0.0002)	(0.0003)	(0.0004)	(0.0010)	(0.0021)
ipc4	-0.0269***	-0.0330***	-0.0091	0.0166	0.1220
	(0.0068)	(0.0079)	(0.0147)	(0.0366)	(0.0845)
_cons	-1.1502***	-1.2005***	-1.3091***	-1.4593***	1.6208
	(0.0715)	(0.0829)	(0.1899)	(0.4888)	(1.3104)
Year dummies	Yes	Yes	Yes	Yes	Yes
Observations	35,538	27,468	6,467	1,328	234
LR alpha=0	49,516.66***	35,896.10***	8,929.07***	2,581.83***	475.73***
Log likelihood	-48,607.27	-36,491.49	-9,374.66	-2,121.26	-403.75
LR chi2	3,961.11***	2,948.31***	801.28***	204.24***	95.95***

Model 1 includes patents applied for by partners from two or more different countries. Model 2 includes patents applied for by partners from just two countries, Model 3 from just three countries, Model 4 from just four countries, and Model 5 from just five countries.

Dependent variable: Forward citation (5-year citation window), examiners' citations and self-citations excluded. Standard errors in parentheses.
$* p < 0.10$; $** p < 0.05$; $*** p < 0.01$.

Appendix

Table A.1. IPC codes used to identify patent families in the pharmaceutical industry (1990-2012).

IPC	Description		Inventions (1)
A61P	**Specific therapeutic activity of chemical compounds or medicinal preparations**		113,218
A61P_1	Drugs for disorders of the alimentary tract or the digestive system		23,400
A61P_3	Drugs for disorders of the metabolism		25,135
A61P_5	Drugs for disorders of the endocrine system		7,824
A61P_7	Drugs for disorders of the blood or the extracellular fluid		14,045
A61P_9	Drugs for disorders of the cardiovascular system		30,486
A61P_11	Drugs for disorders of the respiratory system		17,847
A61P_13	Drugs for disorders of the urinary system		14,475
A61P_15	Drugs for genital or sexual disorders and contraceptives		10,338
A61P_17	Drugs for dermatological disorders		18,293
A61P_19	Drugs for skeletal disorders		18,697
A61P_21	Drugs for disorders of the muscular or neuromuscular system		8,114
A61P_23	Anaesthetics		833
A61P_25	Drugs for disorders of the nervous system		34,809
A61P_27	Drugs for disorders of the senses		13,630
A61P_29	Non-central analgesic, antipyretic or anti-inflammatory agents		26,091
A61P_31	Anti-infectives, i,e, antibiotics, antiseptics, chemotherapeutics		28,379
A61P_33	Antiparasitic agents		4,355
A61P_35	Antineoplastic agents		39,028
A61P_37	Drugs for immunological or allergic disorders		25,483
A61P_39	General protective or antinoxious agents		2,725
A61P_41	Drugs used in surgical methods		944
A61P_43	Drugs for specific purposes, not provided for in groups		46,435
A61K	**Preparations for medical, dental, or toilet purposes**		143,479
A61K_6	Preparations for dentistry		1,953
A61K_9	Medicinal preparations characterised by special physical form		31,689
A61K_31	Medicinal preparations characterised by active ingredients:	Organic active ingredients	93,677
A61K_33		Inorganic active ingredients	5,177
A61K_35		Materials or reaction products with undetermined constitution	12,800
A61K_36		Material from algae, lichens, fungi or plants	4,257
A61K_38		Peptides	42,040
A61K_39		Antigens or antibodies	26,729
A61K_41		Obtained by treating material with wave energy or particle radiation	1,369
A61K_45		Active ingredients not provided for in groups	29,305
A61K_47		Non-active ingredients used	27,259
A61K_48		Medicinal preparations with genetic material, gene therapy	14,749
A61K_49		Genetic material to treat genetic diseases or gene therapy	6,258
A61K_50		Electrically conductive preparations for therapy or testing in vivo	16
A61K_51		Radioactive substances for use in therapy or testing in vivo	4,209

(1) Number of patent families that include the respective IPC class. The total number of patent families in the sample is 143,479, but note that the sum by subclass in (1) is not the total number of patent families (an invention can be classified into several subclasses).
Source: Patstat and own elaboration.

Table A.2. Effects of international collaboration on patent quality. Poisson QMLE

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
coop	0.1742***	0.0720***				
	(0.0154)	(0.0151)				
country			0.1460***	0.0617***		
			(0.0110)	(0.0107)		
country2					0.1239***	0.0484***
					(0.0170)	(0.0167)
country3					0.2482***	0.0995***
					(0.0286)	(0.0286)
country4					0.4838***	0.2419***
					(0.0613)	(0.0594)
country5					0.9035***	0.3992**
					(0.1726)	(0.1764)
country6					1.0839***	0.3266
					(0.2542)	(0.3083)
country7					0.9198**	0.0673
					(0.4619)	(0.4886)
country8					1.3728**	0.3054
					(0.5962)	(0.9678)
inventors		0.0815***		0.0810***		0.0809***
		(0.0020)		(0.0020)		(0.0020)
claim		0.0081***		0.0080***		0.0080***
		(0.0003)		(0.0003)		(0.0003)
back		0.0022***		0.0022***		0.0022***
		(0.0003)		(0.0003)		(0.0003)
npl		0.0013***		0.0013***		0.0013***
		(0.0001)		(0.0001)		(0.0001)
ipc4		-0.0080*		-0.0078		-0.0078
		(0.0048)		(0.0048)		(0.0048)
_cons	-0.4518***	-0.9620***	-0.5979***	-1.0216***	-0.4476***	-0.9569***
	(0.0427)	(0.0456)	(0.0430)	(0.0456)	(0.0428)	(0.0458)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,479	143,479	143,479	143,479	143,479	143,479
Log likelihood	-278,152.72	-263,875.75	-277,858.50	-263,814.76	-277,806.34	-263,797.27
LR chi2	4,309.35***	7,688.36***	4,383.71***	7,722.09***	4,422.31***	7,748.18***

Dependent variable: Forward citation (5-year citation window), examiners' citations excluded. Robust standard errors in parentheses.
∗ p < 0.10; ∗∗ p < 0.05; ∗∗∗ p < 0.01.

Table A.3 Effects of collaborating with the top countries in pharmaceuticals on patent quality. Poisson QMLE

	Model (1) More than one	Model (2) Two countries	Model (3) Three countries	Model (4) Four countries	Model (5) Five countries
us	0.2018***	0.1708***	0.2540***	0.3425**	-0.4291
	(0.0290)	(0.0334)	(0.0669)	(0.1689)	(0.3785)
ch	0.2035***	0.1752***	0.2799***	-0.0556	0.0607
	(0.0291)	(0.0393)	(0.0598)	(0.1448)	(0.3669)
jp	0.1831***	0.1735***	0.2296**	0.0453	-0.2723
	(0.0502)	(0.0582)	(0.1166)	(0.3007)	(0.4503)
de	0.0811***	0.0478	0.1038*	0.0491	0.6390*
	(0.0314)	(0.0399)	(0.0609)	(0.1328)	(0.3365)
uk	0.0685**	0.1094***	0.0781	-0.3980***	0.0821
	(0.0307)	(0.0393)	(0.0643)	(0.1467)	(0.3094)
fr	-0.0139	-0.1642***	0.1015	0.1494	0.3454
	(0.0384)	(0.0506)	(0.0642)	(0.1207)	(0.3079)
haven	-0.0156	-0.0325	-0.0180	0.1524	-0.2547
	(0.0414)	(0.0546)	(0.0712)	(0.1540)	(0.2600)
inventors	0.0825***	0.0879***	0.0772***	0.0950***	0.0797***
	(0.0038)	(0.0036)	(0.0063)	(0.0163)	(0.0309)
claim	0.0072***	0.0071***	0.0067***	0.0104***	0.0018
	(0.0006)	(0.0007)	(0.0012)	(0.0023)	(0.0057)
back	0.0025***	0.0025***	0.0028***	-0.0001	0.0027
	(0.0002)	(0.0002)	(0.0008)	(0.0017)	(0.0034)
npl	0.0008***	0.0008***	0.0008***	0.0007	0.0019
	(0.0002)	(0.0003)	(0.0003)	(0.0007)	(0.0020)
ipc4	-0.0213***	-0.0322***	0.0096	-0.0078	0.1504*
	(0.0071)	(0.0076)	(0.0186)	(0.0377)	(0.0831)
_cons	-1.0054***	-1.0284***	-1.3513***	-1.2461**	1.7180*
	(0.1083)	(0.0951)	(0.2539)	(0.5673)	(0.9037)
Year dummies	Yes	Yes	Yes	Yes	Yes
Observations	35,538	27,468	6,467	1,328	234
Log likelihood	-73,365.60	-54,439.54	-13,839.20	-3,412.17	-641.61
LR chi2	2,536.58***	2,070.26***	702.19***	5,001.70***	2,722.88***

Model 1 includes patents applied for by partners from two or more different countries. Model 2 includes patents applied for by partners from just two countries, Model 3 from just three countries, Model 4 from just four countries, and Model 5 from just five countries.

Dependent variable: Forward citation (5-year citation window), examiners' citations excluded. Robust standard errors in parentheses.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table A.4. Effects of international collaboration on patent quality. Forward citations with a 3-year window (Negative binomial estimations)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
coop	0.1988***	0.0639***				
	(0.0195)	(0.0190)				
country			0.1628***	0.0615***		
			(0.0131)	(0.0128)		
country2					0.1390***	0.0369*
					(0.0216)	(0.0209)
country3					0.2851***	0.1076***
					(0.0398)	(0.0385)
country4					0.5734***	0.2737***
					(0.0836)	(0.0804)
country5					1.0283***	0.4365**
					(0.1947)	(0.1858)
country6					1.1749**	0.5607
					(0.5700)	(0.5396)
country7					1.2765	0.3911
					(0.8526)	(0.8133)
country8					1.4267	0.7525
					(2.0670)	(1.9464)
inventors		0.1169***		0.1158***		0.1157***
		(0.0031)		(0.0031)		(0.0031)
claim		0.0099***		0.0099***		0.0098***
		(0.0006)		(0.0006)		(0.0006)
back		0.0101***		0.0101***		0.0101***
		(0.0004)		(0.0004)		(0.0004)
npl		0.0002		0.0002		0.0002
		(0.0002)		(0.0002)		(0.0002)
ipc4		-0.0022		-0.0019		-0.0021
		(0.0053)		(0.0053)		(0.0053)
_cons	-0.5195***	-1.3350***	-0.6864***	-1.3961***	-0.5227***	-1.3312***
	(0.0389)	(0.0436)	(0.0420)	(0.0458)	(0.0389)	(0.0436)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,479	143,479	143,479	143,479	143,479	143,479
Log likelihood	-128,632.75	-126,505.07	-128,603.00	-126,498.97	-128,598.88	-126,496.79
LR chi2	6,368.51***	10,623.86***	6,428.01***	10,636.05***	6,436.24***	10,640.41***

Dependent variable: Forward citation (3-year citation window), examiners' citations excluded. Standard errors in parentheses.
∗ $p < 0.10$; ∗∗ $p < 0.05$; ∗∗∗ $p < 0.01$.

Table A.5 Effects of collaborating with the top countries in pharmaceuticals on patent quality. Forward citations with a 3-year window (negative binomial estimations)

	Model (1) More than one	Model (2) Two countries	Model (3) Three countries	Model (4) Four countries	Model (5) Five countries
us	0.2222***	0.2173***	0.2149***	0.6029***	-0.8940*
	(0.0345)	(0.0433)	(0.0812)	(0.1796)	(0.5394)
ch	0.2242***	0.2120***	0.2995***	-0.1282	-0.0795
	(0.0360)	(0.0502)	(0.0748)	(0.1849)	(0.4671)
jp	0.2360***	0.2573***	0.2161	0.1787	-0.0051
	(0.0617)	(0.0710)	(0.1475)	(0.3384)	(0.6774)
de	0.1415***	0.1504***	0.0844	-0.0110	0.6397
	(0.0382)	(0.0502)	(0.0790)	(0.1690)	(0.4119)
uk	0.0495	0.1027**	0.0175	-0.4343**	0.2939
	(0.0392)	(0.0504)	(0.0835)	(0.1774)	(0.3836)
fr	0.0491	-0.1223**	0.2586***	0.2516	0.0781
	(0.0443)	(0.0624)	(0.0880)	(0.1675)	(0.4726)
haven	-0.0198	0.0556	-0.1621*	-0.1324	-0.1289
	(0.0481)	(0.0646)	(0.0953)	(0.1855)	(0.4403)
inventors	0.1152***	0.1152***	0.1114***	0.1272***	0.0731*
	(0.0051)	(0.0061)	(0.0111)	(0.0222)	(0.0430)
claim	0.0093***	0.0094***	0.0075***	0.0123**	0.0331**
	(0.0010)	(0.0012)	(0.0025)	(0.0051)	(0.0146)
back	0.0087***	0.0095***	0.0088***	0.0008	0.0054
	(0.0007)	(0.0009)	(0.0016)	(0.0032)	(0.0066)
npl	0.0002	-0.0001	0.0006	0.0015	-0.0026
	(0.0003)	(0.0004)	(0.0007)	(0.0014)	(0.0028)
ipc4	-0.0339***	-0.0400***	-0.0105	0.0121	0.1370
	(0.0102)	(0.0121)	(0.0213)	(0.0530)	(0.1278)
_cons	-1.3833***	-1.4193***	-1.5749***	-1.6847***	1.9950
	(0.1004)	(0.1177)	(0.2602)	(0.6535)	(1.8364)
Year dummies	Yes	Yes	Yes	Yes	Yes
Observations	35,538	27,468	6,467	1,328	234
Log likelihood	-36,888.44	-27,288.33	-7,359.46	-1,716.42	-338.36
LR chi2	2,936.74***	2,182.55***	590.22***	169.66***	72.78***

Model 1 includes patents applied for by partners from two or more different countries. Model 2 includes patents applied for by partners from just two countries, Model 3 from just three countries, Model 4 from just four countries, and Model 5 from just 5 countries.

Dependent variable: Forward citation (3-year citation window), examiners' citations and self-citations excluded. Standard errors in parentheses.
∗ $p < 0.10$; ∗∗ $p < 0.05$; ∗∗∗ $p < 0.01$.