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REGULAR ARTICLE

The effects of limited exhaustibility of knowledge and geographical distance on the quality of R&D collaborations: The European evidence 2000–2012

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Abstract
Much evidence exists of the increasing levels of research cooperation and globalization in the knowledge generation process. This paper aims to assess the determinants of the quality of research collaborations, using a sample of joint patent applications to the European Patent Office between 2000 and 2012. The results of the empirical analysis show that the limited exhaustibility of knowledge and the geographical distance among research partners are crucial determinants of research quality. Specifically, the non-exhaustible character of knowledge and cross-border knowledge creation enhance patent quality. Moreover, the distance among research partners exerts a curvilinear effect, as the quality of innovation increases when partners are either in spatial proximity or distant among each other.

Keywords Knowledge limited transferability · Cross-border collaborations · Patent quality · Patent co-ownership

JEL Classification O32 · O33

1 Introduction

Several studies show that the production of new technological knowledge requires a growing quantity of knowledge and researchers, representing a "burden" to further economic growth (Jones 2009). Research productivity is believed to have fallen over time, implying that "ideas are getting harder to find" (Bloom et al. 2020; Boeing

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and Hünermund 2020). For these reasons, firms might develop alternative strategies, such as looking for external knowledge beyond internal and local knowledge pools.

Growing empirical evidence shows that international technological collaborations have increased over the last several decades (Dachs and Pyka 2010; Briggs 2015; Danguy 2017). Lower transport costs and advances in information and communication technologies (ICTs) have facilitated the implementation of research collaborations at distances through more accurate long-range searching and screening, and reducing communication costs, which help identify and absorb external knowledge at longer distances (Antonelli 2017).

This paper hypothesizes that the geographical variety of knowledge collaborations and the non-exhaustibility of knowledge improve the efficiency of the knowledge generation process. Specifically, the paper tests whether and how previous technological knowledge and cross-border collaborations enhance the quality of knowledge output, measured by the number of forward citations received by joint patents.

Analyzing a sample of co-owned patents, I find that cross-country technological collaborations are conducive to patents of better quality. I measure the geography of collaborations in several ways. The first bundle of results highlights that patent quality increases with the number of inventors and applicants from different countries. I then show that the geographical distance among the co-applicants positively affects patent quality. Finally, I hypothesize that a U-shaped relationship characterizes patent quality and distance among co-patenting firms. Firms in spatial proximity benefit from the high frequency of face-to-face interactions and occasional meetings that facilitate the transmission of sticky and tacit knowledge. However, sharing property rights also increases the quality of the innovative output when firms reside far from each other. Indeed, cross-country knowledge creation allows the combination of different knowledge bases that nurture the recombinant generation of new technological knowledge. Therefore, the quality of the innovative output increases both with local and distant collaborations.

The empirical analysis is based on a sample of co-owned patents applied at the European Patent Office (EPO). The links between patent co-ownership and the characteristics of innovative output have received little consideration from the existing literature. The first stage of this sparse literature has interpreted joint ownership as a second-best option or an outcome of informal and unintentional research collaborations (Hagedoorn 2003; Belderbos et al. 2010). Conversely, recent empirical evidence highlights an increase in the share of co-owned patents over the number of total patents and a positive effect of co-ownership on the quality of the research output and several measures of firms' performance (Belderbos et al. 2014; Briggs 2015). These results acknowledge co-patents as formal and structured knowledge interactions to enhance patent quality.

The paper's rationale is that the generation of new technological knowledge is a cumulative process that recombines internal knowledge accumulated by firms in the past with external knowledge (Weitzman 1996, 1998). The notion of recombinant technological progress extended to incorporate external knowledge flows provides the underpinnings to identify co-patents as structured knowledge interactions allowing firms to access external knowledge that complements the internal knowledge base. Limited transferability characterizes knowledge as an economic good since firms must incur substantial absorption costs to scan, select, and integrate external knowledge (Cohen and Levinthal 1990). Research collaborations reduce absorption costs in obtaining external knowledge possessed by other firms and foster the recombination of distinct varieties of knowledge with the ultimate effect of improving the quality of the knowledge output.

Previous literature has devoted much attention to exploring the role of technological distance in implementing research cooperation (Boschma 2005) and little attention to analyzing the effects exerted by the geographical distance among co-applicants on the quality of a patent. However, the new mechanisms of generation and exploitation of knowledge associated with the augmented levels of global competition and interactions have undermined the prerequisite of geographical proximity to local knowledge clusters to acquire external knowledge. As a result, firms have expanded their boundaries of external knowledge acquisition beyond national ones to widen the recombination of heterogeneous varieties of knowledge (Berchicci et al. 2016; Giuliani et al. 2016; Kerr and Kerr 2018). Therefore, cross-border collaborations help the firm bring together diverse knowledge bundles that increase the efficiency and quality of knowledge output. These theoretical results complement the findings in evolutionary economic geography that knowledge variety is a strong driver of economic growth through Jacobs' increasing returns (Frenken et al. 2007; Quatraro 2010).

The econometric model examining patent applications to the EPO for a subset of European countries along the years 2000–2012 shows that existing technological knowledge and cross-country collaborations improve patent quality, measured in terms of forward citations received. Moreover, the geographical distance among co-applicants exerts a U-shaped effect on patent quality. The results are robust to different specifications and an instrumental variable strategy that reduces endogeneity concerns of cross-country collaboration variables. Further, to corroborate the hypothesis that close and distant collaborations affect patent quality through the recombination of different knowledge bases that improve the originality of the knowledge output, a final test is carried out and confirms the U-shaped effect of distance among research partners and the positive effect of cross-border collaborations on an indicator of patent originality.

These findings may have implications for designing public policies to enhance cross-border knowledge collaborations. Increased cooperation in performing research activities and exploiting their output may be an effective tool to contrast the apparent decline of research productivity.

The rest of the paper is structured as follows. Section 2 briefly surveys previous empirical studies on patent co-ownership and outlines the testable hypotheses. Section 3 presents the data and econometric methodology. Section 4 discusses the results of the baseline empirical analysis and implements several robustness checks, whereas Section 5 summarizes the conclusions.

2 Interpretative framework

2.1 Co-patents and the limited transferability of knowledge

The economics of innovation has extensively discussed systematic and structured interactions between users and providers as a mechanism to access external knowledge (Lundvall 1988 Von Hippel 1998). Firms acquire external knowledge with structured interactions in several ways. For example, they form strategic knowledge alliances to access new capabilities (Mowery et al. 1996; Rosenkopf and Almeida 2003), exploit the mobility of inventors belonging to specific research networks to increase the rate of technological change (Miguelez and Moreno 2013), or acquire smaller knowledge-intensive firms through M&As (Orsi et al. 2015).

Inter-organizational knowledge alliances represent structured interactions aimed at accessing the core competencies of other firms. For example, interactions between firms, scientific organizations, and universities allow access to mutual tacit knowledge and competencies (Antonelli and Scellato 2013). The 'resource-based' theory emphasizes that firms differ in their knowledge bases, resources, and routines (Penrose 1959). Within this line of reasoning, technological alliances among firms become a tool for recombining these heterogeneous resources. Indeed, rich literature on the economics of complexity has investigated how social interactions complement market transactions as an engine of new and better technological knowledge (Hanusch and Pyka 2007).

Technological alliances provide the firm with a tool to access external knowledge and reduce the burden of internal research activities. As a result, they represent a means to internalize pecuniary knowledge externalities, reducing absorption costs and increasing the efficiency of the knowledge generation process. Moreover, the implementation of knowledge alliances is a powerful tool to increase the levels of knowledge appropriability by impeding imitation from other parties, erecting barriers to entry into product markets, and reducing the harmful effects of their knowledge dissipation.

Much case study evidence has focused on the implementation of knowledge alliances with the purpose of accessing external knowledge. Carnabuci and Operti (2013) confirm that the strategies of knowledge co-creation differ widely across firms, and the extent to which firms are integrated within an intra-organizational network affects the nature of recombination, which is more oriented to refining existing combinations for new uses when the firms lie within an integrated network. The detailed case study of L'Oréal shows that the company acquires knowledge similar in scope to its knowledge base to reinforce specialization patterns (Sedita et al. 2022). Similar results emerge in the automotive technology class by using co-citation analysis (Castriotta and Di Guardo 2016).[1]

A joint patent represents a documented trace of a research collaboration between the firm and other partners to access external knowledge. The collaboration with other firms is a strategic tool to integrate external knowledge that otherwise would not be accessible. Joint patents represent a subset yet a relevant proportion of R&D collaborations with other firms (Belderbos et al. 2014; Acosta et al. 2023).

This paper analyzes patents with joint ownership. A co-patent is a single patent that shares ownership between two or more entities. For example, the applicants of a joint patent can be firms, research institutions, or individuals that, in virtue of joint ownership, maintain the same property rights over the patent's use. As a result, joint patents differ from other multiparty agreements, such as cross-licenses, pooled

[1] For other specific case studies, see also Mogee and Kolar (1999) and Barirani et al. (2013).

patents, or patent infringement agreements. Firms develop joint patents with subsidiaries, suppliers, universities, public research organizations (PROs), and competitors. Since the co-owned application is, per se, a complex legal activity that requires high levels of trust of the parties involved, previous experiences of co-patenting positively affect the probability of subsequent co-patent applications with the same partners of previous co-applications or new joint applications with other firms (Hagedoorn, Kranenburg and Osborn 2003; Murgia 2021).

According to Hagedoorn (2003), joint patents are especially important in sectors with strong appropriability regimes, such as pharmaceuticals and chemicals. A few studies have analyzed the behavior of specific firms and industries in developing co-patent applications. For example, Agostini and Caviggioli (2015) analyze the automotive industry and find that co-inventions with allies, suppliers, and subsidiaries generated by the most important firms in the sector are more complex and human capital-intensive than inventions developed singularly. Su, Lin and Chen (2016) focus on three leading high-tech firms and show highly differentiated strategies across firms. For example, IBM has often collaborated directly with foreign competitors to access new expertise and knowledge; Hitachi collaborates especially with local partners and subsidiaries to share risk and production costs; finally, Bayer has collaborated extensively with foreign partners to expand its market share globally.

The analysis of the patent applications to the EPO reveals that the proportion of co-patents over total patent applications has been growing steadily (Briggs 2015). The rationale behind using co-patents has been discussed extensively. Two views can be identified in the existing literature. According to a strand of research predominant during the early 2000s, co-owned patents often resulted from small-scale and informal inter-firm research collaborations, in which it was complicated to allocate intellectual property rights among partners. Therefore, joint patenting was seen as a suboptimal strategy, and firms preferred to apply for a standard patent instead of a joint one (Hagedoorn 2003). Therefore, a joint patent was an unintended outcome of a collaboration strategy not aimed at developing patents of better quality. Different appropriability regimes across countries could also increase uncertainty and discourage firms from engaging in joint patents. Given the traditional linkage between knowledge inputs, such as R&D efforts, and knowledge outputs, such as patent applications (Griliches 1998; Hall et al. 2010), one should expect a positive association between R&D partnerships and joint patenting. However, Hagedoorn et al. (2003) investigate such a possibility but do not find any statistical relation between R&D collaborations among companies and their probability of applying for a joint patent.

Later, another view arose from the empirical evidence that joint patents improve patent quality more than single-owned patents and enhance a firm's value (Belderbos et al. 2014; Briggs and Wade 2014; Briggs 2015). Therefore, the theoretical literature has advanced the hypothesis that co-owned patents originate from intentional and structured collaboration efforts among firms with different knowledge bases, leading to an innovation output of high quality. Briggs and Wade (2014) find that patent quality, measured by forward patent citations received within 3 years, increases with the number of owners and is positively affected by joint ownership. Briggs (2015) extends the analysis and provides evidence that the multicountry ownership of a patent and having a university co-owner positively affect the quality of the patent. Interestingly, by analyzing a sample of European, US and Japanese R&D-intensive firms between 1996 and 2003, Belderbos et al. (2014) distinguish between intra-industry and inter-industry partners involved in a joint patent and find that co-patenting with other firms operating in the same technological domain decreases a firm's performance. On the contrary, patenting with firms operating in different product markets raises a firm's value. Looking at university–industry collaborations, Messeni Petruzzelli (2011) shows that technological relatedness exerts a U-shaped effect on innovation value, whereas prior ties and geographical distance have a positive impact. Funk (2013) demonstrates that the quality of university joint patents varies with the type of co-assignee and shows that university–corporate collaborations are of high quality.

The more recent evidence highlighting the positive and intentional effects of jointly owned patents on the quality of the research output aligns with the hypothesis that structured knowledge interactions are a powerful tool to improve the transferability of knowledge among economic agents. Knowledge as an economic good possesses limited transferability. Transferring knowledge as an economic good is a peculiar case compared to other economic goods. Arrow (1969) is the first to highlight the difficulties associated with the transmission of knowledge among economic agents.[2] Specifically, the inability of the information's user to understand the content of the piece of information received is the main constraint to knowledge transmission.

Effective knowledge transmission engenders absorption costs, such as learning efforts, which burden the user (Cohen and Levinthal 1990). The competence and learning efforts required to use knowledge are substantial compared to other standard and tangible economic goods. As a result, the transferability of knowledge is lower than the average of standard economic goods, especially when technological knowledge possesses high degrees of tacitness that cannot be eradicated. Overall, the implementation of R&D collaborations reflected in joint patent applications represents a strategy to acquire external knowledge from other firms and reduce the absorption costs deriving from transferring external knowledge.

The following section discusses the determinants of the research quality of joint patents and articulates the testable hypotheses.

2.2 Testable hypotheses

This section focuses on the determinants of the quality of R&D collaborations, leading to the development of three testable hypotheses.

2.2.1 Knowledge recombination and patent quality

Recent advances in the economics of innovation have been directed to explore the consequences of the limited exhaustibility of knowledge and, hence, its effects in terms of indivisibility and cumulability. These properties imply that knowledge can be reused repeatedly as input both in the production of further technological

[2] Arrow writes: "…, *every piece of information can be regarded as transmitted in a code and can only be used if decoded.*"

knowledge and in producing other economic goods alongside capital and labor (Griliches 1979).

The analysis of the characteristics of knowledge enables us to grasp the knowledge generation process as a recombinant activity of existing knowledge items (Weitzman 1996, 1998). The same blueprint can be leveraged over larger output volumes with slow obsolescence rates (Haskel and Westlake 2017; Antonelli et al. 2022). The stock of knowledge generated by the firm and characterized by limited exhaustibility contributes to generating further technological knowledge and changing its composition. Firms benefit from a large amount of knowledge not only in terms of the quantity of new knowledge generated but also in terms of efficiency in the knowledge generation process (Antonelli and Fusillo 2023; Klüppel and Knott 2023).

Moreover, the external knowledge generated but not fully appropriated by other parties enters as input alongside the stock of internal knowledge and the current R&D expenditures to produce new knowledge (Crépon et al. 1998; Antonelli and Colombelli 2017). Knowledge is only limited exhaustible but also partially appropriable. The part of knowledge not appropriated by its inventors spills over the system and benefits third parties. External knowledge has become an indispensable input into the knowledge generation process, both in terms of sheer size and composition.

Further studies have recognized the importance of the variety of knowledge inputs as a driver of the generation of new technological knowledge (Frenken et al. 2007; De Noni et al. 2017). Therefore, a larger accession to external knowledge provides the firms with a large stock of knowledge to draw upon and a large variety of knowledge to recombine with the current knowledge base. All the sources of codified knowledge, such as scientific publications and existing technological knowledge incorporated in patent documents, represent valuable resources the firms use to develop technological knowledge of greater quality. Moreover, firms benefit from the quality and size of existing human capital, both within its boundaries and externally available in the geographical area where the firm operates. A larger team size in developing an invention brings more ideas and different capabilities, improving the efficiency of the knowledge generation process.

Recent decades have been characterized by a growing global division of knowledge generation based on international technological collaborations. Knowledge spillovers in the global market allow countries to imitate and interact with other countries at the technological frontier in different product markets. Moreover, learning opportunities from international knowledge spillovers improve the firms' absorptive capacity. According to several studies, the larger the exposure to global markets, the greater the opportunities to imitate and interact with other competitors on knowledge frontiers (Branstetter 2001, 2006). Therefore, the larger the openness to global trade, the higher the opportunities for recombination and, in turn, the greater the research quality.

Therefore, the stock of knowledge, both internal and external, is an essential input upon which the generation of new knowledge builds. The firm's internal stock of knowledge, the number of collaborators, and the available external resources contribute to improving the quality of the patent. Therefore, the first testable hypothesis is:

Hypothesis 1 The size of existing knowledge, internal and external, increases patent quality.

2.2.2 International collaborations and patent quality

Little consideration has been devoted to the geographical variety of research partners in analyzing the innovation outcome, except for some contributions that focused only on co-inventorship ties (Messeni Petruzzelli and Murgia 2020; Su and Moaniba 2020; Su 2021). The original contribution of Jacobs (1969) emphasized the increasing returns stemming from the variety of activities localized within a geographical space. Jacobs' increasing returns apply when the output of the innovation process increases with the variety of knowledge inputs.

The variety of knowledge items allows firms in a geographical cluster to access the external stock of quasi-public knowledge at costs below equilibrium. The recombination of heterogeneous knowledge items because of Jacobs' increasing returns produces positive effects on regional economic growth, next to the sheer size of the internal stock of knowledge and the dedicated research efforts (Antonelli et al. 2017). Moreover, the variety of knowledge also relates to differences in skills and levels of the researchers' human capital that contribute to the innovative process.

In the new global knowledge economy, access to external knowledge through cross-border knowledge creation is becoming a crucial source of competitive advantage. The openness to international markets has increased competitive pressure and has encouraged firms to search for new knowledge-creation mechanisms (Audretsch et al. 2014). In addition, firms in developed countries benefit from outsourcing part of their production processes abroad, so R&D activities are increasingly carried out internationally (Montobbio and Sterzi 2013). The exploitation of co-inventorship and co-application strategies represent helpful tools to integrate external knowledge within firm boundaries. Recent decades have been characterized by increasing collaborations with cross-border research partners (Briggs 2015; De Rassenfosse and Seliger 2020). Cooperation among firms has become increasingly global because of the openness to international trade, which has affected the creation and transmission of knowledge across borders for both developed and developing countries (Picci 2010; Montobbio and Sterzi 2011; Branstetter et al. 2015; Giuliani et al. 2016). In addition, the increase in competition has motivated firms to collaborate with global partners to access a greater variety of knowledge through inter-firm networks.

One reason behind the firm's choice to look for partners abroad is the opportunity to find diverse knowledge bases that can be integrated with the existing ones. Indeed, persistent local exposure to knowledge spillovers may hinder the ability to generate novel ideas, constraining the firm from pursuing knowledge exploration strategies and hampering the development of breakthrough innovations (Byun et al. 2021). On the contrary, firms may access specific technological areas available in other countries through international research collaborations. The influx of new capabilities and the access to different environments provide firms with novel resources to use to generate new technological knowledge (Nathan and Lee 2013; Nathan 2015).

Even though foreign firms are little cognitively proximate, Berchicci et al. (2016) notice that knowledge structure, that is, how firms organize and combine knowledge in several elements, differs among firms and provides opportunities for generating novel creations through the unique combinations of resources and tacit competencies. Nonetheless, searching for knowledge at a great distance prompts deeper knowledge scrutiny and more substantial learning efforts to outweigh its higher transmission costs compared to local knowledge collaborations. In the case of distant collaborations, firms search for the best partner and maximize the collaboration efforts to compensate for the costs (Mansfield 1995).

Therefore, the extent to which an international collaboration occurs, and the number of international collaborations should positively affect patent quality in terms of co-inventorship and co-ownership (Briggs 2015; Su 2021 Acosta et al. 2023). The explanations articulated in this section are conducive to testing the following hypothesis:

Hypothesis 2 International R&D collaborations, proxied by multicountry co-inventorship and co-ownership ties, increase patent quality.

2.2.3 The U-shaped effect of the distance among patent applicants on patent quality

Albeit the previous subsection explains why one expects that cross-border international collaborations improve patent quality, the existing literature has articulated two contrasting arguments explaining the links between the geographical distance among patent co-applicants and the patent value.

According to the first bundle of hypotheses, acquiring external knowledge through multiple and distant partners may have detrimental effects on knowledge value. First, evolutionary economics literature argues that the development of a set of routines limits the further creation of technological knowledge within technological trajectories (Nelson and Winter 1982). Here, firms are little incentivized to integrate external knowledge when too dissimilar from internal knowledge, as characterized by standardized routines and practices. Firms benefit from technological collaborations only when the cognitive distance of the external knowledge from internal practices is short, and the novelty value of new knowledge combines with the absorptive capacity made up by internal knowledge stock (Kim and Song 2007; Nooteboom et al. 2007). The stronger the dissimilarity between internal and external knowledge, the larger the scope and the absorption costs required to combine them. As explained in the previous subsection, distant partners are more likely to be characterized by different knowledge structures, increasing the absorption costs, particularly for firms with well-defined routines and practices.

Furthermore, as evidenced by Jaffe et al. (1993), knowledge flows “leave a paper trail” through patent citations and are geographically localized and constrained by geographical distance. Some argued that the exchange of tacit knowledge benefits from proximity and, hence, collaborations between close partners are likely to generate an output of higher value (McKelvey et al. 2003). Specifically, when knowledge is sticky and tacit, interaction among economic agents is highly dependent on spatial proximity. The localization of firms within a geographical cluster facilitates knowledge exchange since it reduces communication costs and increases the frequency of face-to-face contacts, providing access to tacit knowledge that otherwise is difficult to transmit. The spatial clustering of economic activities results in an interactive environment in which actors combine both similar and dissimilar knowledge that is often sticky and tacit (Malmberg and Maskell 2002; Bathelt et al. 2004). Firms acquire new knowledge serendipitously 'by just being there' (Gertler 1995). Urbanization economics refers to the local 'buzz' as the learning environment in which knowledge is transmitted with both frequent and incidental contacts, creating the basis for the emergence of cultural values and typical interpretative schemes among the firms participating in the cluster (Storper and Venables 2004). This process is supported by the mobility of human capital with skills and capabilities that contribute to form inter-firm relationships (Almeida and Kogut 1999). As a result, the development of reciprocal trust and the emergence of communities of localized learning develop inter-organizational relationships that constitute the basis for successful research collaborations (Tubiana et al. 2022). Therefore, according to this first bundle of evidence, proximity should favor the quality of knowledge collaborations.

According to a second argument, access to new knowledge does not result only from local and regional interactions; it can also be acquired through cross-border collaborations that occur via global pipelines. In fact, global pipelines open new opportunities with the access to different environments and complement the favorable effects of local knowledge clusters (Owen-Smith and Powell 2004; Bathelt et al. 2004). A greater distance among firms is associated with a greater exchange of knowledge resources, increasing the value of the knowledge output because of the positive effects of Jacobs' increasing returns in variety (Zucker and Darby 2001). Local collaborations often involve sharing similar knowledge bases, common values, and interpretative schemes. However, sharing similar resources may also lead to accessing redundant knowledge. As a result, complementing local knowledge bases with extra-local linkages may be highly beneficial to the firm.

Boschma (2005) first recognized that geographical proximity is neither necessary nor sufficient for collaboration, and other forms of proximity, such as cognitive proximity, matter. De Jong and Freel (2010) demonstrate that firms investing in absorptive capacity are weakly dependent on geographical proximity. Firms may look for partners at a greater distance to access non-redundant knowledge inputs. Knowledge alliances between distant partners become the mechanism to access external knowledge directly and exploit economies of scope because of the recombination of distinct yet complementary varieties of knowledge (Bertrand and Mol 2013).

Moreover, alliances among firms operating in different product markets or parts of the value chain yield greater benefits than collaboration among firms that share the same product markets. Indeed, two different layers can be identified according to the partnering relationship. First, in vertical cooperation, firms collaborate in distinct segments of the same value chain. These relationships are found in either supplier–costumer relationships within the same value chain but in different parts, or collaborations among different research segments of the same global corporation. On the other hand, in horizontal collaborations, firms are in the same part of the value chain and, therefore, might compete in identical product markets. The latter case poses challenges to the appropriability of the final product.

Firms' interactions can also bring competition for appropriating the same resources and hinder knowledge spillovers within regions, reducing innovative output (Drivas 2021). The limits to the appropriability of the returns from knowledge output substantially reduce the incentives for firms to commit resources and invest in learning efforts for knowledge interactions (Acosta et al. 2022). In addition, a great distance among firms acts as a barrier to entry into their respective product markets, particularly regarding vertical cooperation, within which firms operate along the same value chain but in different parts. Here, firms can keep their control in the respective market areas.

The augmented levels of risk that stem from missing the returns from the research outcome reduce the general efforts applied to the knowledge partnership and lower the incentives to undertake them (Abramovsky et al. 2009; Cantabene and Grassi 2019). Moreover, firms are reluctant to collaborate with rival firms since tacit competencies and routines that compose a firm's competitive advantage can leak out to the rival (Bloom et al. 2013; Ryu et al. 2018). As a result, firms collaborating with partners abroad are less exposed to appropriability challenges. Indeed, they can retain control of their respective product markets and exploit the benefits of recombining different knowledge bases.

In line with this line of reasoning, I postulate the existence of a quadratic U-shaped relationship between applicants' geographical distance and knowledge value. When distance is low, firms benefit from the advantages of spatial proximity in developing new research projects. Conversely, accessing knowledge structures in different geographical contexts represents a further opportunity to integrate non-common and novel external knowledge. Following the theory of knowledge clusters (Bathelt et al. 2004; Gertler and Levitte 2005), the spatial proximity to other firms is complemented and reinforced by the construction of global pipelines that represents an opportunity to combine firms' respective knowledge bases, enhancing the value of knowledge. The last hypothesis that will be tested is the following:

Hypothesis 3 The geographical distance among co-applicants exerts a U-shaped effect on patent quality.

3 Empirical analysis

3.1 Research setting and sample data

This paper examines the quality of knowledge collaborations, assuming that, as in the extant literature, joint patent applications represent a portion of all the R&D collaborations (Danguy 2017; De Rassenfosse and Seliger 2020; Acosta et al. 2023). For this purpose, the empirical analysis uses the number of forward citations to measure the quality of inventions, as extensive literature does (Trajtenberg 1990; Hall et al. 2005; Arts and Fleming 2018). The count of patent citations to measure patent quality is based on the premise that not all the inventions protected by a patent possess the same value. Patents receiving more citations by subsequent patents are believed to possess a greater technological impact. Indeed, there is much evidence of the fact that measures of technological quality are related to a firm's performance and market value (Hall et al. 2005).

However, using forward citations to measure the quality of an invention can be subject to several criticisms. First, one concern regards the extent to which we conceive patents as a measure of technological progress, since patent applications represent only a subset of all the inventions produced by a firm. Indeed, other tools can be used to appropriate the returns from innovation, for example, secrecy. Second, the examiner always decides which citations to include in the patent document. Therefore, many citations, especially from the US patent office, could be of low quality (Michel and Bettels 2001). However, this concern may be mitigated by considering only patent applications to the EPO, in which the examination process delivers patent citations that are more reliable than those contained in USPTO patent documents (Breschi and Lissoni 2009).

Therefore, it must be acknowledged that patents may capture only a part of all the inventions a firm develops. Similarly, the citations received by such inventions may represent an imperfect measure of research quality. Yet, the count of patent citations provides one of the most accurate measures of technological quality, mainly when targeted to discriminate between high- and low-quality patents (Gay and Le Bas 2005).

To test the propositions above, I analyze a sample of co-owned patents applied at the EPO (European Patent Office). Using patents filed with the EPO presents several advantages. First, it reduces the “home advantage effect”, which arises when domestic firms file patents more frequently at their country patent office. Second, since the patent application process to the EPO is more costly than those at domestic offices, patents filed with the EPO usually possess greater value than domestic patents and are more comparable across countries.

The dataset used in the analysis is combined by exploiting several complementary sources: (i) the OECD REGPAT database, from which information on patent applications submitted to the EPO is retrieved; (ii) the OECD CITATIONS database, which contains data on both backward and forward citations made and received by the patent; (iii) the OECD HAN database that provides a unique identifier for each applicant firm linked to a patent in the OECD REGPAT database obtained after a process of cleaning and harmonization of all the applicants’ names; (iv) the OECD PATENT QUALITY INDICATORS, which collects a series of quality indicators related to the patent.

The OECD REGPAT database contains patent applications assigned to regions by exploiting each patent document’s owners’ and inventors’ addresses. The sample includes patent applications, regardless of whether the patent has been granted. Moreover, the sample comprises patent applications submitted to the EPO by assignees in five European countries (France, Germany, Italy, Netherlands, and Spain) plus the United Kingdom. These countries cover the body of the European economic structure, possess most patent applications to the EPO and share the same patent protection regime. Hence, all patents are assigned to applicants from one of the six countries mentioned above. Restricting the sample to this bundle of countries enables examining a comparable group of joint patents. Hence, the analysis excludes cross-country patents (with the US, for instance) by firms located, for example, in Luxembourg or Switzerland, which possess an enormous number of joint patent applications mainly for fiscal reasons, or Sweden, in which only two firms, Eriksson and AstraZeneca, possess a large majority of Sweden patent applications (Dachs and Pyka 2010).

The sample period ranges from 2000 to 2012, where the year refers to the priority date of the patent application.[3] I choose the year 2000 as the beginning period since, as documented by several studies (Hagedoorn 2003; Briggs 2015), the number of co-patent applications has grown since the 2000s. The analysis considers only those patents jointly owned by two or more entities. Thus, after merging the four datasets, the final sample comprises 44,037 joint patent applications. Table 8 in the Appendix shows the distribution of owners per patent. It emerges that the large majority of co-patents have two owners.

3.2 Econometric methodology

3.2.1 Econometric model

The foregone discussion of the complementary role of internal and external knowledge on the efficiency of the knowledge generation process provides the underpinnings to articulate an empirical analysis in which the quality of innovation depends on a bundle of internal and external factors. Specifically, the non-exhaustible character of knowledge and its limited appropriability suggest that the stock of knowledge capitalized by the firm and incorporated in intellectual property products of other parties provides an indispensable source upon which firms impinge to generate new technological knowledge.

Second, access to external knowledge through knowledge interactions takes place at different geographical layers, according to the distance among research partners. Consequently, I examine whether the joint research quality depends on the research partners' location.

The model can be formalized as follows:

$$Quality_i = f(\boldsymbol{InternalKnowledge_i}, \boldsymbol{ExternalKnowledge_i}, \boldsymbol{CollaborationsDistance_i}) \tag{1}$$

Therefore, the patent quality is explained by variables that proxy for internal knowledge, external knowledge, and collaborations' distance.

I use the number of forward citations as the dependent variable. The number of forward citations takes on non-negative and integer values, violating the assumption of normal distribution of the classical linear model. Therefore, it is necessary to adopt count models instead of standard OLS techniques. The most used count models are the Poisson and the negative binomial. However, valid statistical inference requires equi-dispersion of the dependent variable, which occurs when the conditional variance and the conditional mean are equal, a rare event, particularly in cross-sectional models. Indeed, unobservable heterogeneity among units induces over-dispersion, which occurs when the conditional variance exceeds the conditional mean, as in

[3] As highlighted in Maraut et al. (2008), the priority date represents the date of the first filing for a patent, and it should be used when patent indicators reflect technological achievements since it represents the closest date to the time of the original invention.

this case.[4] Violating equi-dispersion is equivalent to violating the homoskedasticity assumption in the standard OLS linear model. Therefore, to correct the bias caused by heteroskedasticity, the two most adopted methods are the Poisson regression model estimated with the quasi-maximum likelihood estimator with corrected standard errors and the negative binomial count model (Cameron and Trivedi 2013). The negative binomial requires more restrictive assumptions than the Poisson, but it can lead to more efficient estimation. However, with cross-sectional settings, the gains in efficiency may be relatively minor, and the Poisson estimated with the quasi-maximum likelihood is the baseline model adopted in this paper. However, I show that using the negative binomial model does not alter the results significantly.[5]

Therefore, I estimate the following model:

$$cit3_i = \exp(\alpha + \boldsymbol{InternalKnowledge}_i^{\prime} \beta_1 + \boldsymbol{ExternalKnowledge}_i^{\prime} \beta_2 + \boldsymbol{CollaborationsDistance}_i^{\prime} \beta_3 + e_i) \tag{2}$$

3.2.2 Variables

This subsection describes the variables used in the econometric model. Table 9 in the Appendix reports a description of the variables used in the analysis and some descriptive statistics.

Dependent variable The dependent variable *cit*3 is the number of forward citations received by a patent within 3 years after the publication date. I include all the citations made to a patent from EPO or PCT (Patent Cooperation Treaty) publications, besides other national or regional publications. Measuring forward citations within a fixed time window allows for overcoming the truncation bias that arises when older patents are more cited than recent patents, simply because they have had a longer period to do so.[6]

CollaborationsDistance Regarding the role of geography in the knowledge generation process, I analyze the geographical variety of knowledge collaborations using the following variables. First, I measure the geographical distance among applicants. For this purpose, I use the distance in km among the regions where the applicants reside, *GeoDist*. To do so, first, I take the centroid of each TL2 (Territorial Level 2) region of the six European countries chosen. Then, I calculate the distance from the centroid of the region or country of the other partner.[7] Finally, when the patent is

[4] Notice that I can only infer the degree to which the unconditional variance, not the conditional one, exceeds the unconditional mean from simple descriptive statistics. However, overdispersion likely persists even after controlling for other factors when the unconditional variance is two times larger than the unconditional mean (Cameron and Trivedi 2013).

[5] See Table 12 in the Appendix.

[6] Table 13 in the Appendix shows that the results are robust to using all the citations received from a patent over its life. When the total number of citations received over the life of the patent is used, year fixed effects capture the truncation effect (Briggs and Wade 2014; Sterzi 2013).

[7] Notice that I take the region's centroid (at the TL2 level) in which the applicant is located when available in the OECD REGPAT database. If not, I include the centroid of the country.

assigned to more than two entities, I compute the average distance among the combination pairs.[8]

Moreover, to measure the extent of international collaborations, I also consider the number of inventors' and assignees' countries represented in each patent, *No. Inv. Countries* and *No. App. Countries,* respectively. More countries would reveal that the patent builds on distinct knowledge items from different places. Indeed, the descriptive evidence in the following section shows that the higher the number of countries represented in the patent document, the higher the number of forward citations received. Finally, I also insert two dummy variables to identify patents with multicountry ownership, in which one applicant comes from one of the six European countries chosen, and at least one other comes from another country, *MultiCountry*, and, second, patents with extra-region ownership, in which the applicants come from different regions within the same country, *MultiRegion*.

Even though the geographical distance among applicants has been already used in this empirical literature (Briggs 2015; Briggs and Wade 2014; Santoalha 2019), it is also necessary to highlight that this operationalization of international collaborations presents some drawbacks. For instance, a multinational firm may assign a patent to the headquarters, but a subsidiary developed the patent in another country. If this is the case, we are underestimating the extent of international collaborations. At the same time, the parent company may choose to co-apply the patent with a subsidiary, even though the invention has been developed in the focal firm's laboratories or elsewhere. Here, we would overestimate the extent of international collaborations.

Even though these limitations must be assessed for interpreting the results, De Rassenfosse and Seliger (2020) argue that a patent co-applied by firms in two countries often implies that the inventors come from these two countries. Moreover, the bias in measuring international collaborations with patent data also arises when the inventor' location is considered, with different measurement errors but not less relevant (Bergek and Bruzelius 2010). The results of the baseline empirical analysis and several robustness checks confirm that looking at the inventor's or applicant's side does not contradict the main findings that international collaborations do increase patent quality.

InternalKnowledge and ExternalKnowledge The limited exhaustibility of knowledge implies that firms can rely on existing internal and external knowledge to generate new technological knowledge. I use various proxies for the internal and external knowledge that a firms use and that could affect patent quality. First, I include

[8] Therefore, taking the centroid of the regions where the applicants are located means that co-patents between Piedmont and Lombard firms are all characterized by the same geographical distance regardless of whether the firms are located, for example, in Cuneo or Torino, two Piedmont cities. This concern should not represent an issue for the theoretical framework, as the interest is in the product markets in which firms operate, extending beyond city boundaries. Therefore, the regional level should represent the appropriate reference. However, one may legitimately argue that taking the city level should reduce the measurement error in the econometric exercise. For this reason, I address this concern by redoing the analysis using the recent update of OECD REGPAT (July 2021 edition) that allows us to allocate patent applications even at the city level for most patents. In this case, I geocoded all the cities listed in the dataset and, when not available, firm's address. The main results are not affected by using this more granular measurement level.

the number of backward citations made to other patents as an influential prior art to build upon, *Backward*, and the number of non-patent references, *NonPatLit*, to control the bundle of scientific knowledge to which the patent refers. Second, the size of the research team could enhance the innovative performance of the partners, as it can help manage larger and more heterogeneous knowledge items. Hence, I include the number of inventors listed on each joint patent (*NumberInv*).

Third, I construct a variable that measures the amount of technological capital stock to draw upon to generate new technological knowledge, *TechCapital*. Indeed, the knowledge accumulated by the firm strengthens the absorptive capacity to internalize external and dissimilar knowledge (Cohen and Levinthal 1990; Nooteboom et al. 2007). For this purpose, I exploit the OECD HAN database, which harmonizes the applicant names listed on each patent and collects a unique identifier for each applicant. Therefore, I sum up the number of patent applications each applicant made in the five years before the patent application date. Even though it does not help distinguish between the type of applicant (i.e., firm, public organizations, universities), this measure enables discrimination among applicants based on their innovative capabilities. Moreover, it might help capture unobservable characteristics among units.

Fourth, I consider the number of three-digit International Patent Classification (IPC) codes listed on each patent, *TechFields*. The number of technology fields reveals the scope of the patent, defined as the number of landscapes to which the patent contributes, noticing that each patent can fall into over one technology class. Hence, the greater the patent scope, the higher the probability of the patent being cited.

I also consider whether country-specific factors could influence knowledge quality. For this purpose, I include the average levels of human capital *AvHum* and openness *AvOpen* (imports plus exports as a percentage of GDP) across the applicants' countries of each co-patent.[9] Human capital is expected to impact knowledge quality positively since the larger the endowment of human capital in each region, the higher the intensity of investment in knowledge and research. On the other hand, openness should capture the extent of knowledge spillovers from other countries. The larger the exposure to international product markets, the greater the opportunities to imitate and interact with other competitors on knowledge frontiers (Branstetter 2001, 2006). Therefore, the larger the sum of trade over GDP, the higher the opportunities for recombination and, in turn, the greater the research quality.

Moreover, as in Briggs (2015), I assume that income differences among countries could implicitly capture differences in the propensity to collaborate with other partners attracted from different patent protection regimes or legal benefits. Hence, I include the average logarithmic difference between the GDP of all the applicants' countries of origin, *GDPDiff*.[10]

[9] Human capital data are taken from the Penn World Table, version 10.0. Specifically, the PWT constructs an index of human capital based on years of schooling and returns to education (Feenstra et al. 2015). The openness indicator is taken from OECD repositories.

[10] Unfortunately, the patent protection indexes constructed in the literature are available only for a limited number of countries or just for some years, reducing the sample size used in the empirical analysis and making comparisons unpractical.

Fixed effects I insert country dummies for the six European countries to which the patent is assigned, year dummies to control for unobservable common factors affecting all the patents in a year and technological classification dummies to account for specific differences in quality across technology areas. Technology dummies correspond to the standard classes defined by the WIPO classification scheme measured at the one-digit IPC level. The eight classes are Human necessities; Performing operations, transporting; Chemistry, metallurgy; Textiles, paper; Fixed construction; Mechanical engineering, lighting, heating, weapons, blasting; Physics; Electricity.

4 Results

4.1 Preliminary evidence

This section reports preliminary descriptive evidence. Figure 1 shows the evolution of the number of co-patents applied at the EPO between 2000 and 2012 and the shares of co-patents and multicountry co-patents over the total number of patent applications. The number of co-applications has sharply increased over the 2000–2012 period, as indicated by the bar graph. However, the share of overall co-patents and co-patents involving applicants from at least two different countries over the total number of patents has also increased. In 2012, almost 9.5% of patents were owned by two or more owners, compared to about 7.5% in 2000. The share of multi-country co-patents has increased from 3.8 to 4.9% in the period 2000–2012.[11]

Table 1 shows preliminary empirical evidence of the slowdown in research quality, which is proxied by the average number of citations received by each patent within 3 years of the publication date (Arora et al. 2018). The table unfolds interesting results. First, the average number of citations received by all the sample patents (single or joint patents) declined between 2000 and 2012. Second, co-patent applications (second to fourth row) decrease, even though they receive more citations during the entire period. Third, the declining trend in citations received by co-patents reversed after the 2007 crisis. Indeed, the quality of co-patents held by co-applicants from over two different countries has increased from 2007, almost returning to 2000 levels.

These findings signal that the decline in technological knowledge quality is less pronounced, or does not occur at all, for all the co-patents and, particularly, co-patents held by applicants from different countries.[12]

[11] On the other hand, the share of multicountry co-patents over the total number of co-patents has increased from 50.8% in 2000 to 53% in 2012.

[12] I implement a simple econometric test to support this proposition. Considering both single-owned and joint patents in my sample, I regress the number of forward citations received within 3 years on a dummy indicating whether the patent is co-owned, a dummy indicating whether the patent is co-owned by applicants in different countries, and patent controls and fixed effects described in Section 3.2, using a Poisson model. The results of this test, available from the author upon request, confirm that cross-country collaborations increase patent quality when the sample considers both single-owned and co-owned patents, confirming the descriptive evidence provided in Table 1.

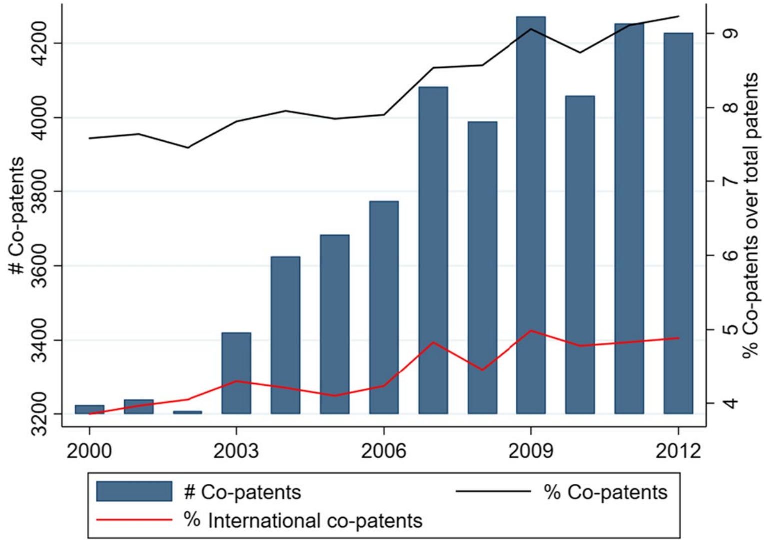

Fig. 1 Co-patents evolution

4.2 Baseline results

This section discusses the results. Table 10 shows that pairwise correlations among variables fall below the 0.70 threshold, which is commonly acceptable to avoid multicollinearity issues.

Table 2 reports the results for the Poisson regression model, in which the number of forward citations received within 3 years is the dependent variable. In addition, the table shows the estimation coefficients across different specifications. All the models include technology class, country, and time dummies.

Column (1) displays the estimation coefficients when including all variables except for country and geographical controls. In column (2), I add the number of assignees and inventor countries for each patent. Column (3) shows the results when the geographical distance among research partners is included. Column (4) tests the U-shaped effect of distance on knowledge quality. Finally, column (5) replaces the geographical distance among assignees by dummies for multicountry and multiregion ownership, as specified previously.

Across all columns, the variables referring to internal and external knowledge exert a positive and statistically significant impact (at high levels of confidence) on patent quality, confirming the Hypothesis 1. Specifically, a greater knowledge base improves the patent quality, as more technological capital increases firms' absorptive capacity and provides more significant benefits from research collaborations. In addition, the number of inventors, the patent scope, and references to both patents and non-patent documents improve the patent quality, confirming the results found in the literature (Messeni Petruzzelli 2011; Belderbos et al. 2014).

Column (2) reveals that the number of assignee and inventor countries is positively and significantly related to patent quality. Research collaborations among

Table 1 Forward citations (within 3 years) distributed by type of patent

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
All patents	1.02	1.00	0.99	1.01	0.95	0.93	0.84	0.79	0.81	0.83	0.81	0.81	0.79
Co-patents	1.62	1.37	1.29	1.37	1.39	1.26	1.20	1.03	1.02	1.11	1.10	1.11	1.08
Multicountry co-patents	1.97	1.53	1.54	1.44	1.49	1.45	1.34	1.16	1.15	1.26	1.29	1.26	1.29
Multicountry co-patents (with over two different countries)	2.88	1.76	1.89	1.53	1.92	1.31	0.97	0.80	0.80	1.39	1.24	1.09	2.12

Table 2 Main regression results

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Cit3	Cit3	Cit3	Cit3	Cit3
Backward	0.212***	0.193***	0.197***	0.195***	0.194***
	(0.0212)	(0.0209)	(0.0210)	(0.0210)	(0.0209)
NumberInv	0.345***	0.291***	0.277***	0.286***	0.294***
	(0.0170)	(0.0187)	(0.0186)	(0.0186)	(0.0188)
TechFields	0.254***	0.247***	0.239***	0.240***	0.251***
	(0.0678)	(0.0676)	(0.0674)	(0.0675)	(0.0676)
NonPatLit	0.0669***	0.0774***	0.0754***	0.0754***	0.0779***
	(0.0191)	(0.0188)	(0.0188)	(0.0188)	(0.0188)
TechCapital	0.0714***	0.0738***	0.0752***	0.0778***	0.0750***
	(0.00478)	(0.00480)	(0.00476)	(0.00476)	(0.00474)
No. Inv Countries		0.131***	0.170***	0.144***	0.130***
		(0.0256)	(0.0240)	(0.0245)	(0.0249)
No. App Countries		0.240***			
		(0.0379)			
AvHum		1.043***	1.149***	1.115***	1.060***
		(0.0910)	(0.0876)	(0.0867)	(0.0884)
AvOpen		0.000660	0.00151**	0.00318***	0.000587
		(0.000603)	(0.000593)	(0.000590)	(0.000605)
GDPDiff		0.0117	0.0122	0.0115	0.0117
		(0.00819)	(0.00838)	(0.00827)	(0.00821)
GeoDist			0.0175***	– 0.0488***	
			(0.00382)	(0.0117)	
GeoDistSq				0.00796***	
				(0.00136)	
MultiCountry					0.100**
					(0.0165)
MultiRegion					– 0.109***
					(0.0252)
Country dummies	Yes	Yes	Yes	Yes	No
Year dummies	Yes	Yes	Yes	Yes	Yes
Tech. dummies	Yes	Yes	Yes	Yes	Yes
Obs.	44,037	44,037	44,037	44,037	44,037

Poisson pseudo-maximum likelihood estimation with robust standard errors (in parenthesis)

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

partners from different places promote the recombination of heterogeneous resources and enhance research quality. Therefore, Hypothesis 2 is widely confirmed, both at the inventor's and applicant's side.

Column (3) reports the results when I include the natural logarithm of the average geographical distance among applicants. The coefficient turns out to be positive and statistically significant ($p < 0.01$). Indeed, holding other factors fixed, a greater distance between research partners is associated with having a high-quality patent. This result confirms that the heterogeneity in the knowledge bases of the different owners residing in different countries favors the recombinant process of new knowledge, leading to knowledge output of higher quality.

However, in column (4), I add the squared term of distance. Here, the non-squared term turns out to be negative and remains statistically significant ($p < 0.01$). The squared term is positively associated with the quality of the patent ($p < 0.01$), confirming Hypothesis 3. These findings signal a convex function between the patent quality and geographical distance among applicants. At low levels of distance, the impact is positive. As distance increases but under a certain threshold, the quality declines. Over a certain threshold, the increase in distance positively affects the quality of innovative output. Applying the prescribed calculations of Haans et al. (2016),[13] I find that the turning point of the U-shaped relationship is about 3.07, well within the range of the geographical distance variable (which has a min of 0 and a max of 9.856). Moreover, Table 11 in the Appendix applies the U-shaped test of Lind and Mehlum (2010). The scope of the test is to evaluate whether the slope is sufficiently steep at both ends of the data range. The results of the test in Table 11, performed on the extreme value point of 3.07, confirms that a U-shaped relationship does exist.

This result supports the validity of the Hypothesis 3 stated. Patent quality is higher both with local and extra-local collaborations. Therefore, both spatial proximity and the construction of distant collaborations are beneficial to the quality of knowledge output.

The results that appear in column (5) also support this conclusion. The dummy *MultiCountry* enters with a positive and statistically significant coefficient ($p < 0.01$), showing that collaborations with foreign firms positively affect research quality. However, collaborating with firms within the country but located in different regions affects patent quality negatively, as the coefficient for *MultiRegion* shows ($p < 0.01$).

From columns (2) to (5), the model also includes the average logarithmic difference in GDP, level of human capital and openness across all applicants' countries. Differences in GDP across applicants' countries do not affect knowledge quality. On the other hand, the larger the endowment of human capital and the greater the exposure to international trade in the applicants' country of origin, the greater the patent quality. Furthermore, including these controls does not alter neither the magnitude nor the significance of the other estimation coefficients.

4.3 Robustness tests

This section addresses some concerns about the baseline estimation. The Appendix includes several robustness checks that challenge the validity of the baseline results by using a different estimation method and alternative dependent variables.

[13] Precisely, given a relationship of the form $y = \beta_0 + \beta_1 X + \beta_2 X^2$, the turning point may be obtained as $\beta_1/2\beta_2$.

First, Table 12 in the Appendix shows that the results are robust to using a negative binomial model instead of the Poisson. On the other hand, Tables 13 and 14 show that the main results are unaltered if forward citations over the patent's life and within 5 years are used as dependent variables, respectively. Therefore, the results of the analysis are not sensitive to the use of longer time windows to define patent citations. On the other hand, Tables 15 and 16 use the number of claims and the family size as alternative proxies for patent quality. The number of claims represents the legal breadth of the patent and reflects a higher firm's market value and a greater patent's expected value (Lanjouw and Schankerman 2004). On the other hand, the family size indicates the number of patent offices in which the inventors sought legal protection. Hence, it defines the geographical scope of the patent and is related to its value (Harhoff et al. 2003). Results in Table 15 and 16 align with previous findings, showing a positive impact of international collaborations and the U-shaped effect of the geographical distance among co-applicants on these alternative patent quality proxies.

Then, I also implement other robustness checks regarding the conceptualization of cross-border collaborations. First, there may be issues in accurately defining the applicants' location. Especially in the case of multinational firms, a patent may be co-applied by the focal firm and one of its subsidiaries. However, the patent can be fully developed in either the focal firm's R&D laboratories or the subsidiary. The joint patent may not reflect a true R&D collaboration in this case. For these reasons, I drop from the sample all the patents owned by the applicants in the top 25% of the patent distribution each year. In this way, I exclude top firms (more likely to be multinational corporations) from the sample. After this elimination, the sample size reduces to 33,355 patents. Despite this drop, Table 3 shows that the results essentially mimic Table 2.

Second, to check whether the applicant's location bias is relevant to my results, I limit the sample to patents owned by two applicants in which the multicountry ownership and the multicountry inventorship coincide. In other words, I focus only on patents co-applied and co-invented in the same European country or patents co-invented and co-owned by two firms located in different countries. In this case, we are more reassured to capture inter-country R&D collaborations. Table 4 shows that the results are almost unaltered by using this specification.

4.4 Instrumental variable analysis

Endogeneity issues may affect the link between the geographical distance among the assignees and patent quality. At least two reasons may be identified for the endogeneity of the distance among research partners. First, one argument may be that the owner of a high-quality patent may be a valuable partner with whom another firm may choose to collaborate. The regression controls for the applicants' technological capabilities, but other unobservable factors may influence the choice of collaborating with distant partners. Second, firms working on specific and complex technologies may find only a few partners with whom to collaborate. To the extent to which these partners are uncommon and located at

Table 3 Regression results – Excluding large firms

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Cit3	Cit3	Cit3	Cit3	Cit3
Backward	0.234***	0.214***	0.219***	0.217***	0.215***
	(0.0244)	(0.0239)	(0.0242)	(0.0240)	(0.0239)
NumberInv	0.352***	0.289***	0.275***	0.284***	0.294***
	(0.0200)	(0.0220)	(0.0219)	(0.0219)	(0.0221)
TechFields	0.241**	0.241**	0.236**	0.237**	0.246**
	(0.0815)	(0.0811)	(0.0809)	(0.0810)	(0.0812)
NonPatLit	0.0538**	0.0656**	0.0626**	0.0631**	0.0662**
	(0.0225)	(0.0223)	(0.0223)	(0.0222)	(0.0222)
TechCapital	0.0853***	0.0863***	0.0871***	0.0900***	0.0869***
	(0.00602)	(0.00606)	(0.00602)	(0.00603)	(0.00602)
No. Inv Countries		0.144***	0.191***	0.162***	0.142***
		(0.0304)	(0.0277)	(0.0284)	(0.0292)
No. App Countries		0.222***			
		(0.0449)			
AvHum		1.094***	1.201***	1.168***	1.110***
		(0.0985)	(0.0941)	(0.0932)	(0.0949)
AvOpen		0.000462	0.00118*	0.00294***	0.000401
		(0.000679)	(0.000668)	(0.000677)	(0.000679)
GDPDiff		0.0102	0.0108	0.00982	0.0101
		(0.0100)	(0.0103)	(0.0101)	(0.0101)
GeoDist			0.0130**	– 0.0499***	
			(0.00414)	(0.0135)	
GeoDistSq				0.00775***	
				(0.00162)	
MultiCountry					0.102***
					(0.0204)
MultiRegion					– 0.0914**
					(0.0278)
Country dummies	Yes	Yes	Yes	Yes	No
Year dummies	Yes	Yes	Yes	Yes	Yes
Tech. dummies	Yes	Yes	Yes	Yes	Yes
Obs.	33,355	33,355	33,355	33,355	33,355

Poisson pseudo-maximum likelihood estimation with robust standard errors (in parenthesis)

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

long distances, the firm needs purposely to search for those partners and maximize the collaboration efforts.

To account for endogeneity, one must choose an instrument correlated with the geographical distance among research partners but not related to the error term in the explanatory regression. For this purpose, I instrument the geographical distance

Table 4 Regression results – Dyadic patents in which the multicountry ownership and the multicountry inventorship coincide

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Cit3	Cit3	Cit3	Cit3	Cit3
Backward	0.185***	0.174***	0.174***	0.174***	0.174***
	(0.0276)	(0.0274)	(0.0275)	(0.0274)	(0.0274)
NumberInv	0.390***	0.287***	0.276***	0.283***	0.293***
	(0.0268)	(0.0288)	(0.0288)	(0.0288)	(0.0290)
TechFields	0.163**	0.149*	0.152*	0.147*	0.153*
	(0.0817)	(0.0820)	(0.0822)	(0.0822)	(0.0821)
NonPatLit	0.0695**	0.0758***	0.0753***	0.0726**	0.0760***
	(0.0228)	(0.0224)	(0.0225)	(0.0224)	(0.0224)
TechCapital	0.0706***	0.0773***	0.0767***	0.0787***	0.0777***
	(0.00676)	(0.00662)	(0.00662)	(0.00662)	(0.00662)
No. Inv Countries		0.141**	0.267***	0.209***	0.137**
		(0.0651)	(0.0361)	(0.0434)	(0.0652)
No. App Countries		0.239**			
		(0.0979)			
AvHum		0.971***	1.007***	1.006***	0.987***
		(0.123)	(0.125)	(0.123)	(0.123)
AvOpen		0.00125	0.00133	0.00302***	0.00128
		(0.000890)	(0.000910)	(0.000914)	(0.000890)
GDPDiff		0.0234*	0.0240*	0.0230*	0.0233*
		(0.0129)	(0.0131)	(0.0130)	(0.0129)
GeoDist			0.00133	– 0.0462**	
			(0.00545)	(0.0149)	
GeoDistSq				0.00659***	
				(0.00200)	
MultiCountry					0.128*
					(0.0701)
MultiRegion					– 0.0745**
					(0.0343)
Country dummies	Yes	Yes	Yes	Yes	No
Year dummies	Yes	Yes	Yes	Yes	Yes
Tech. dummies	Yes	Yes	Yes	Yes	Yes
Obs.	21,688	21,688	21,688	21,688	21,688

Poisson pseudo-maximum likelihood estimation with robust standard errors (in parenthesis)

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

among applicants and the multicountry collaboration dummies with a dummy variable that takes value one if one applicant is registered in a country that has a corporate income tax rate below the 25th percentile[14] of the distribution of corporate income tax rate.[15] For instance, this variable takes a value equal to one if the co-applicant comes from a country such as Switzerland, Ireland, Bermuda, Luxembourg or other countries with low taxes. The choice of this instrument is motivated by referring to a strand of literature showing that countries with low corporate income tax rates or preferential fiscal regimes may attract more investments in R&D (Lokshin and Mohnen 2012; Mohnen et al. 2017; Skeie et al. 2017). Hence, applicants from these countries may be more attractive as collaboration partners. Furthermore, this instrument should satisfy the abovementioned conditions of being correlated with the endogenous regressor but uncorrelated with the explanatory equation.

Since the dependent variable is a count variable, the instrumental variable strategy cannot implement a two-stage least squares (2SLS) estimator. Instead, I use the control function approach developed by Wooldridge (2010, 2015). The strategy consists of estimating a first stage in which the suspected endogenous variable is regressed by OLS on the control variables and the instrument, and then taking the residuals of this regression. In the second step, the residuals of the first step are added as a further control variable in the count data regression of the dependent variable on the endogenous regressor and the control variables. Standard errors are then adjusted with the bootstrap procedure (Cameron and Trivedi 2010).[16] This method has the advantage of getting rid of the endogeneity of the geographical distance variable, while allowing in the second stage to estimate the quadratic specification without the need to find a second instrument for the squared term.

Table 5 shows the results of the instrumental variable procedure. Specifically, column (1) in Table 5 endogenizes the geographical distance among applicants with the tax dummy. Column (2) reports the results for the quadratic specification, whereas, in column (3), the instrumented variable is the number of inventor countries. The results of Table 5 confirm the previous findings fully. In column (1), the linear geographical distance among co-applicants exerts a positive and statistically significant effect ($p < 0.01$). Column (2) confirms the U-shaped effect of the distance on patent quality (it is worth remembering that for the existence of the U-shaped relationship, it is required that only the squared term would be significant and of the expected sign). Finally, column (3) supports the hypothesis that inventors' cross-border collaborations increase patent quality.

As a test for the validity of the exclusion restriction, I regress the number of forward citations on the average income corporate tax rate for each patent only on the sample of non-cross-border patents. If the exclusion restriction holds, one should not find any relationship between the corporate income tax rate and patent quality. Indeed, the average income corporate tax rate coefficient is not distinguishable from zero.[17]

[14] Considering different thresholds does not alter the results.

[15] Data on corporate income tax rates are taken from OECD and KPMG.

[16] The estimation uses 100 bootstrap replications.

[17] Results are available upon request.

Table 5 Regression results – Instrumental variable estimation

	(1)	(2)	(3)
Dependent variable:	Cit3	Cit3	Cit3
Backward	0.184***	0.189***	0.188***
	(0.0239)	(0.0239)	(0.0246)
NumberInv	0.318***	0.325***	– 0.0981
	(0.0183)	(0.0184)	(0.0888)
TechFields	0.237***	0.240***	0.205***
	(0.0767)	(0.0767)	(0.0784)
NonPatLit	0.0854***	0.0817***	0.0485**
	(0.0176)	(0.0176)	(0.0209)
TechCapital	0.0583***	0.0681***	0.103***
	(0.00477)	(0.00524)	(0.00816)
AvHum	1.005***	1.027***	1.032***
	(0.097)	(0.0952)	(0.0935)
AvOpen	0.00267***	0.00421	0.000682
	(0.000641)	(0.000625)	(0.000641)
GDPDiff	0.0112	0.0108	0.0105
	(0.00882)	(0.00861)	(0.00955)
$\widehat{GeoDist}$	0.896***	– 0.0183	
	(0.0164)	(0.0274)	
$\widehat{GeoDistSq}$		0.00933***	
		(0.00169)	
$No.\widehat{InvCountries}$			1.503***
			(0.308)
Country dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Tech. dummies	Yes	Yes	Yes
Obs.	44,289	44,289	44,289
Endogeneity test (p value)	0.000	0.061	0.000

Control function approach. Bootstrapped standard errors are in parenthesis (100 replications)

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

4.5 Mechanism

This section investigates one of the mechanisms behind which a higher distance among assignees leads to patents of better quality. According to the theoretical hypotheses, the value of the output increases when firms can integrate diverse and original pieces of knowledge. Novel knowledge may be acquired through multi-country co-inventorship and co-applicant ties, and both local and distant collaborations, following the U-shaped effect described in the previous section. Therefore, to gauge whether past technological knowledge and co-applicant distance are conducive to greater originality of research output, I investigate whether partners make patents that build in a broader array of technology fields. I use the originality index constructed by Squicciarini et al. (2013) extracted from the OECD Patent Quality Indicators database. The originality index is equivalent to the following formula:

$$Originality_i = 1 - \sum_{j}^{n_i} s_{ij}^2 \tag{3}$$

where s_{ij} is the percentage of backward citations made by a patent i to a patent class j measured at the IPC 4-digit level. The higher the originality index, the higher is the technological breadth of the patent, meaning that the invention protected by the patent is built by recombining a wider range of technological domains. Hence, this variable quantifies the magnitude of the recombination process since a higher value of the index is conducive to greater knowledge recombination. The index of patent originality takes values between zero and one, so a linear model would produce biased estimates (Wooldrige 2010). Thus, I use a quasi-maximum likelihood (QML) fractional logit regression. Even in this case, I run an instrumental variable regression in which I instrument the variables for international technological collaborations with the tax dummy. In this case, I use a simple OLS with a two-stage least squares regression. This method is frequently used albeit the variables are not continuous (Wooldridge 2010; Giuliani et al. 2016).

Table 6 reports the results. The findings are very similar to those for forward citations. Column (1) show that international co-inventorship collaborations increase patent originality, whereas the number of assignee countries does not improve patent originality. Column (2) shows that the linear geographical distance does not enhance patent originality. These findings suggest that to enhance patent originality, the geographical heterogeneity of inventors is more relevant, which brings to the organization more distinct knowledge. However, the geographical distance maintains a curvilinear effect on originality, as evidenced in column (3). In columns (5)–(7), I adopt the same Instrumental Variable specification as in Table 5, adopting a two-stage least-squares estimation method. The results show that, correcting for endogeneity, international technological collaborations as multicountry co-inventorship and multicountry co-ownership, and the geographical distance among applicants, exert a positive effect on patent originality, supporting the findings of Table 5.

4.6 Geographical vs. technological distance

The paper focuses on the distance among research partners based on the location where they reside. Therefore, it articulates the argument that firms located in different countries possess heterogeneous knowledge bases that might be recombined together to produce patents of better quality. As a result, collaborating with partners abroad provides access to non-redundant and original knowledge different from the firm's resources and practices. Therefore, when firms collaborate with partners abroad, they do not simply integrate knowledge that is diverse in content, but also in its structure (Berchicci et al. 2016). The knowledge structure refers to the practices through which different knowledge items are connected and organized in mental models. While the knowledge content may be similar across firms residing in different countries, the

Table 6 Regression results – Originality index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	Cit3	Cit3	Cit3	Cit3	Cit3	Cit3	Cit3
Method:	GLM Fract. Logit	GLM Fract. Logit	GLM Fract. Logit	GLM Fract. Logit	2SLS	2SLS	2SLS
Backward	0.557***	0.557***	0.556***	0.557***	0.109***	0.109***	0.109***
	(0.0124)	(0.0124)	(0.0124)	(0.0124)	(0.00249)	(0.00247)	(0.00252)
NumberInv	0.0785***	0.0774***	0.0823***	0.0808***	0.0166***	0.0168***	– 0.0111
	(0.00953)	(0.00944)	(0.00946)	(0.00957)	(0.00192)	(0.00193)	(0.0123)
TechFields	0.828***	0.828***	0.829***	0.830***	0.154***	0.155***	0.151***
	(0.0317)	(0.0317)	(0.0317)	(0.0317)	(0.00562)	(0.00557)	(0.00605)
NonPatLit	0.0856***	0.0855***	0.0850***	0.0859***	0.0153***	0.0150***	0.0131***
	(0.00875)	(0.00875)	(0.00875)	(0.00875)	(0.00168)	(0.00167)	(0.00191)
TechCapital	0.0198***	0.0199***	0.0217***	0.0198***	0.00341***	0.00391***	0.00669***
	(0.00261)	(0.00260)	(0.00261)	(0.00260)	(0.000598)	(0.000525)	(0.00129)
No. Inv Countries	0.0415**	0.0439**	0.0253*	0.0396**	– 0.00226	0.00293	
	(0.0138)	(0.0133)	(0.0136)	(0.0137)	(0.00502)	(0.00323)	
No. App Countries	0.0155						
	(0.0174)						
AvHum	0.249***	0.253***	0.230***	0.248***	0.0224	0.0396***	0.0174
	(0.0442)	(0.0437)	(0.0440)	(0.0439)	(0.0149)	(0.00971)	(0.0172)
AvOpen	– 0.000254	– 0.000192	0.000721**	– 0.000281	0.000106	– 0.0000435	– 0.000126
	(0.000312)	(0.000313)	(0.000349)	(0.000311)	(0.0000795)	(0.0000629)	(0.0000811)
GDPDiff	– 0.00104	– 0.00103	– 0.00121	– 0.00106	– 0.000292	– 0.000233	– 0.000351
	(0.00442)	(0.00442)	(0.00443)	(0.00443)	(0.000876)	(0.000876)	(0.000896)
GeoDist		0.00139	– 0.0335***				
		(0.00192)	(0.00623)				

Table 6 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GeoDistSq			0.00437***				
			(0.000734)				
MultiCountry				0.00414			
				(0.00937)			
MultiRegion				– 0.0231*			
				(0.0133)			
$\widehat{GeoDist}$					0.00557**		
					(0.00245)		
$\widehat{MultiCountry}$						0.00906**	
						(0.00399)	
$No.\widehat{InvCountries}$							0.102**
							(0.0423)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tech. dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	42,017	42,017	42,017	42,017	42,017	42,017	42,017

Columns (1)–(4) estimate a GLM conditional fractional logit. Columns (5)–(7) estimate a 2SLS model. Standard errors are in parentheses

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

knowledge structure and the cognitive distance among firms vary as a function of geographical distance (Bertrand and Mol 2013). As the distance increases, the knowledge structure does so. Firms embedded in geographical clusters are characterized by peculiar interpretative schemes, leading to localized learning processes highly dependent on spatial proximity and transferable across space only to a limited extent. The knowledge structure embedded in researchers is essentially tacit and varies with the location, making it spatially dependent (Hautala 2011).

Therefore, although two firms belong to the same industry and are cognitively proximate, they might be characterized by different knowledge structures linked to their respective locations. However, it may be interesting to distinguish between the geographical distance among partners in R&D collaborations from their technological distance in terms of the technological sector in which they mainly operate. Therefore, to disentangle the effects of the distance in the knowledge sectors or fields from the geographical distance among co-applicants, I adopt the following procedure. First, building on the strategy of Belderbos et al. (2014), I distinguish firms based on the main sectors in which they operate. To do this, I assign patents to a specific sector via the concordance table of Schmoch (2008). The table assigns a four-digit technological class in the patent document to 35 main sectors. Therefore, I can assign each firm to a specific Schmoch sector by observing the technological field of each patent. A firm is thus assigned to one of the 35 sectors if it filed most of its patents in that sector during the period 2000–2012. Second, I restrict the attention to firms with at least 15 patent applications (corresponding to about the first quartile of the distribution of patent applications) to more accurately assign firms to technological sectors. Then, I generate a dummy equal to one if at least one firm belongs to a different sector from the other partner/s. Therefore, the dummy indicates whether the collaboration is among firms operating in different industries.

Table 7 shows the results of the exact specifications adopted in Table 2 but adds the dummy proxying for inter-industry co-patenting. Its coefficient is negative but not distinguishable from zero from columns (2) to (5). More importantly, the results obtained for the various proxies for geographical distance among co-applicants are not affected by the inclusion of the inter-industry dummy, confirming that geographical distance exerts a role in affecting patent quality that extends beyond technological distance.

5 Conclusions

This paper intends to contribute to the current debate on the decline of technological opportunities and the reduced value of knowledge (Bloom et al. 2020; Jones 2009). Faced with a decline in technological opportunities, firms expanded their boundaries to search actively for external knowledge. While patterns of R&D internationalization have been investigated since the last decades of the last century (Gassman and Von Zedtwitz 1999), it is only recently that economics of innovation has started to study R&D collaborations through co-patent applications. Moreover, patent documents show an increase in the globalization of innovation since the 2000s. De Rassenfosse and Seliger (2020) study patent applications filed in 52 patent offices and document that only 1.2% of total patents were co-applied between European firms and firms located in other regions in 1990, while this share increased to about 6.7% in 2010. Briggs (2015) shows that the share

Table 7 Regression results – Including technological distance

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Cit3	Cit3	Cit3	Cit3	Cit3
Backward	0.164***	0.152***	0.153***	0.153***	0.152***
	(0.0253)	(0.0251)	(0.0251)	(0.0251)	(0.0250)
NumberInv	0.357***	0.315***	0.308***	0.316***	0.317***
	(0.0213)	(0.0234)	(0.0230)	(0.0230)	(0.0233)
TechFields	0.261**	0.253**	0.245**	0.251**	0.255**
	(0.0830)	(0.0827)	(0.0827)	(0.0826)	(0.0826)
NonPatLit	0.0168	0.0346	0.0340	0.0363*	0.0351
	(0.0222)	(0.0221)	(0.0222)	(0.0220)	(0.0221)
TechCapital	0.0403***	0.0555***	0.0568***	0.0617***	0.0562***
	(0.00957)	(0.00958)	(0.00957)	(0.00981)	(0.00956)
Inter-industry	– 0.0960***	– 0.0151	– 0.0275	– 0.0215	– 0.00662
	(0.0232)	(0.0234)	(0.0236)	(0.0234)	(0.0233)
No. Inv Countries		0.139***	0.155***	0.137***	0.138***
		(0.0317)	(0.0300)	(0.0304)	(0.0314)
No. App Countries		0.158**			
		(0.0501)			
AvHum		1.435***	1.504***	1.428***	1.444***
		(0.147)	(0.138)	(0.140)	(0.145)
AvOpen		– 0.000903	– 0.0000438	0.00219**	– 0.000922
		(0.000974)	(0.000950)	(0.00108)	(0.000970)
GDPDiff		0.000252	0.000446	0.000337	0.000194
		(0.00932)	(0.00939)	(0.00934)	(0.00933)
GeoDist			0.0145**	– 0.0429**	
			(0.00505)	(0.0171)	
GeoDistSq				0.00723***	
				(0.00206)	
MultiCountry					0.0667**
					(0.0225)
MultiRegion					– 0.0791**
					(0.0363)
Country dummies	Yes	Yes	Yes	Yes	No
Year dummies	Yes	Yes	Yes	Yes	Yes
Tech. dummies	Yes	Yes	Yes	Yes	Yes
Obs.	26,739	26,739	26,739	26,739	26,739

Poisson pseudo-maximum likelihood estimation with robust standard errors (in parenthesis)

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

of patents with a multicountry ownership remained relatively stable over the period 1978–2000, even though a slight increase is observed after 2000. Therefore, the pattern of international collaborations in patent documents is a relatively new phenomenon.

Patent applications are regarded as an imperfect and incomplete measure of the amount of technological knowledge generated by economic agents, as patent counts underestimate the portion of knowledge with a strong tacit content, which is the outcome of learning processes. However, patents may provide a reliable proxy for a consistent portion of knowledge that can be codified and formalized. At the same time, patent citation counts represent the value of the knowledge generated and credit the quality of the research efforts. That said, the study of co-patent applications represents a valuable tool to investigate the determinants of R&D collaborations.

Economics of innovation has put little effort into providing a theoretical and empirical analysis of the phenomenon of joint patent ownership. However, motivated by the increase in co-owned patents over the last two decades, recent empirical studies have investigated the consequences of co-ownership on qualitative measures of innovative output (Messeni Petruzzelli 2011; Briggs and Wade 2014; Belderbos et al. 2014; Briggs 2015).

This paper focused on how geography and knowledge properties affect the quality of R&D collaborations measured through co-patent applications. The analysis of the value of patent applications to the EPO for six countries of the European area from 2000 to 2012 provides new insights into the literature on co-patents. First, the stock of internal and external knowledge remains a crucial source to build high-quality knowledge. Indeed, the stock of applicant's past knowledge, citations to other patent documents and scientific publications, the team size, and the patent scope increase patent quality. Second, patent quality is higher when inventors and applicants belong to different countries and when the number of represented countries increases. Finally, the distance among applicants exerts a U-shaped effect on patent quality, signaling that both local and distant collaborations increase collaborations quality.

The findings of this paper contribute to a wider literature studying the relationship between geographical distance and innovation value. Empirical studies have found evidence that geographical proximity helps to foster knowledge flows, especially in university–industry collaborations (De Jong and Freel 2010). However, in the new global knowledge economy, the determinants of knowledge flows extend beyond geographical proximity, including the concept of cognitive distance, as defined by Boschma (2005). Acquiring external knowledge aims to gain different knowledge bases partners possess in different areas (Messeni Petruzzelli 2011). I contributed to this debate by showing that both geographical proximity and long distances among partners matter for patent quality. This result points to a double positive effect from co-operating with partners located close and abroad.

The results of the empirical analysis confirmed that multicountry collaborations are an important tool to acquire novel and different varieties of knowledge, complementing available sources of codified knowledge. More specifically, firms benefit from implementing both local and distant collaborations. These results widely confirm previous literature finding that collaborations with firms and inventors located in different countries contribute to increase patent quality (Briggs 2015; Berchicci et al. 2016; Giuliani et al. 2016; Su and Moaniba 2020). Moreover, the U-shaped effect of distance on patent quality provides support to the theory of knowledge clusters, which sees extra-local interactions with suppliers, subsidiaries, and firms abroad, occurred through global pipelines, as a complementary valuable strategy to the beneficial effect of being located within local clusters (Owen-Smith and Powell 2004; Bathelt et al. 2004).

Even though measuring R&D collaborations by joint ownership has several limitations, the robustness of the analysis to different specifications and potential drawbacks clarified that the quality of innovative output increases when the research partners, whether inventors or applicants, belong to different countries. Overall, the results are robust to using alternative measures of patent quality and different measures of cross-border collaborations. Moreover, to reduce endogeneity concerns of cross-border collaborations, I used an instrumental variable analysis based on the implementation of low corporate income tax rates that attract foreign R&D investment. In this way, the presence of low taxes on corporate income positively influences the implementation of cross-border collaborations, while being unrelated to factors influencing the citation received by the patents 3 years later.

Finally, the paper investigated a possible channel through which collaborations affect patent quality. Indeed, the theoretical framework predicts that the patent quality increases when partners share distinct knowledge bases in local or multicountry collaborations. As a result, I found that patent originality is greater with multicountry collaborations and with both local and distant co-applications, confirming the results found for patent quality.

Furthermore, this discussion has substantial policy implications. It may provide valuable suggestions for designing public policies that could enhance innovative joint efforts, looking at knowledge from the input and output sides.

Appendix

Table 8 Number of applicants per patent

Number of applicants	Frequency	Percentage	Cumulative percentage
2	37,249	84.59	84.59
3	4085	9.28	93.86
4	2003	4.55	98.41
5	419	0.95	99.36
6	117	0.27	99.63
7	66	0.15	99.78
8	36	0.08	99.86
9	26	0.06	99.92
10	14	0.03	99.95
11	5	0.01	99.96
12	1	0.00	99.96
13	7	0.02	99.98
14	1	0.00	99.98
15	3	0.01	99.99
16	1	0.00	99.99
17	1	0.00	99.99
18	1	0.00	100.00
61	1	0.00	100.00
62	1	0.00	100.00

The total number of patents is 44,037

Table 9 Descriptive statistics

	Variable	Description	Obs.	Mean	Std. Dev.	Min	Max
1	Cit3	Citations received within 3 years	44,037	1.214	2.528	0	90
2	BackCit	Number of backward citations (Ln)	44,037	1.482	0.548	0	3.738
3	NumberInv	Number of inventors (Ln)	44,037	1.079	0.619	0	4.127
4	TechFields	Number of three-digit IPC codes (Ln)	44,037	0.901	0.273	0.693	2.398
5	NonPatLit	References to non-patent literature (Ln)	44,037	0.46	0.696	0	3.829
6	TechCapital	Sum of the number of patent applications in the previous 5 years made by all the co-applicants (Ln)	44,037	5.617	2.521	.693	9.982
7	GeoDist	Average geographical distance among co-applicants (Ln)	44,037	5.274	2.941	0	9.856
8	GeoDistSq	Squared of the average geographical distance among co-applicants (Ln)	44,037	36.468	25.771	0	97.138
9	NumberAppCountries	Number of assignee countries (Ln)	44,037	0.426	0.387	0	2.303
10	NumberInvCountries	Number of inventor countries (Ln)	44,037	0.234	0.437	0	2.639
11	GDPDiff	Average log difference in GDP across co-applicants' countries.	44,037	0.015	1.136	-5.963	6.562
12	AvHum	Average level of human capital across co-applicants' countries	44,037	3.345	0.264	2.061	3.719
13	AvOpen	Average level of openness across co-applicants' countries	44,037	72.693	23.166	25.624	333.053

Table 10 Pairwise correlation among variables

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1.	1.000												
2.	0.035*	1.000											
3.	0.129*	−0.066*	1.000										
4.	0.082*	0.009	0.112*	1.000									
5.	0.050*	−0.399*	0.185*	0.100*	1.000								
6.	0.068*	−0.044*	0.095*	−0.038*	0.024*	1.000							
7.	0.065*	0.054*	0.066*	0.011*	−0.047*	0.163*	1.000						
8.	0.070*	0.046*	0.063*	0.022*	−0.027*	0.085*	0.945*	1.000					
9.	0.107*	−0.014*	0.399*	0.068*	0.091*	−0.064*	0.269*	0.300*	1.000				
10.	0.074*	0.078*	−0.026*	−0.039*	−0.086*	0.277*	0.686*	0.684*	0.328*	1.000			
11.	0.010*	−0.000	0.004	0.002	−0.004	0.005	0.010*	0.011*	0.005	0.012*	1.000		
12.	0.083*	0.082*	0.028*	−0.021*	−0.119*	0.092*	0.192*	0.155*	0.067*	0.154*	0.004	1.000	
13.	0.003	0.048*	−0.091*	−0.104*	−0.081*	0.302*	0.011*	−0.113*	−0.041*	0.256*	0.008	0.210*	1.000

* shows significance at the 0.05 level. Numbers indicate the same variables used in Table 9

Table 11 U-shaped test for the relationship between patent quality and distance

	Lower bound	Upper bound
Interval	0	9.856
Slope	–0.0488	0.108
t value	–4.160	6.739
P>|*t*|	0.000	0.000

The extreme point is 3.06633. Overall test for the presence of a U-shaped relationship: t value = 4.16, P>|t|=0.000

Table 12 Regression results – Forward citations with negative binomial model

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Cit3	Cit3	Cit3	Cit3	Cit3
Backward	0.222***	0.204***	0.207***	0.204***	0.204***
	(0.0192)	(0.0187)	(0.0190)	(0.0190)	(0.0187)
NumberInv	0.291***	0.248***	0.284***	0.283***	0.253***
	(0.0152)	(0.0170)	(0.0153)	(0.0153)	(0.0172)
TechFields	0.240***	0.254***	0.256***	0.252***	0.255***
	(0.0634)	(0.0624)	(0.0630)	(0.0625)	(0.0624)
NonPatLit	0.0856***	0.101***	0.102***	0.102***	0.101***
	(0.0166)	(0.0163)	(0.0163)	(0.0163)	(0.0163)
TechCapital	0.0867***	0.0817***	0.0770***	0.0812***	0.0826***
	(0.00546)	(0.00546)	(0.00542)	(0.00546)	(0.00548)
No. Inv Countries		0.130***			0.127***
		(0.0233)			(0.0233)
No. App Countries		0.258***			0.107*
		(0.0322)			(0.0645)
AvHum		0.899***	1.026***	0.981***	0.901***
		(0.0840)	(0.0824)	(0.0819)	(0.0839)
AvOpen		0.000791	0.00205***	0.00397***	0.000718
		(0.000569)	(0.000566)	(0.000613)	(0.000569)
GDPDiff		0.0107	0.0119	0.0113	0.0107
		(0.00770)	(0.00784)	(0.00780)	(0.00770)
GeoDist			0.0258***	– 0.0524***	
			(0.00344)	(0.0111)	
GeoDistSq				0.00941***	
				(0.00127)	
MultiCountry					0.0617**
					(0.0300)
MultiRegion					– 0.0838**
					(0.0255)
Country dummies	Yes	Yes	Yes	Yes	No
Year dummies	Yes	Yes	Yes	Yes	Yes
Tech. dummies	Yes	Yes	Yes	Yes	Yes
Obs.	44,037	44,037	44,037	44,037	44,037

Negative binomial estimation with robust standard errors (in parenthesis).
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 13 Regression results – Forward citations over the life of the patent

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	CitLife	CitLife	CitLife	CitLife	CitLife
Backward	0.203***	0.185***	0.189***	0.187***	0.185***
	(0.0164)	(0.0160)	(0.0162)	(0.0161)	(0.0160)
NumberInv	0.299***	0.254***	0.236***	0.245***	0.256***
	(0.0138)	(0.0150)	(0.0148)	(0.0148)	(0.0150)
TechFields	0.278***	0.273***	0.265***	0.266***	0.277***
	(0.0515)	(0.0511)	(0.0510)	(0.0511)	(0.0511)
NonPatLit	0.0582***	0.0689***	0.0664***	0.0666***	0.0690***
	(0.0149)	(0.0146)	(0.0146)	(0.0145)	(0.0145)
TechCapital	0.0399***	0.0404***	0.0424***	0.0455***	0.0424***
	(0.00381)	(0.00377)	(0.00374)	(0.00373)	(0.00372)
No. Inv Countries		0.0989***	0.152***	0.122***	0.101***
		(0.0206)	(0.0196)	(0.0200)	(0.0202)
No. App Countries		0.318***			
		(0.0290)			
AvHum		1.002***	1.147***	1.104***	1.033***
		(0.0739)	(0.0720)	(0.0707)	(0.0720)
AvOpen		0.000590	0.00175***	0.00363***	0.000542
		(0.000470)	(0.000462)	(0.000454)	(0.000472)
GDPDiff		0.00866	0.00932	0.00852	0.00874
		(0.00677)	(0.00696)	(0.00687)	(0.00681)
GeoDist			0.0233***	– 0.0517***	
			(0.00298)	(0.00906)	
GeoDistSq				0.00899***	
				(0.00107)	
MultiCountry					0.134***
					(0.0131)
MultiRegion					– 0.124***
					(0.0198)
Country dummies	Yes	Yes	Yes	Yes	No
Year dummies	Yes	Yes	Yes	Yes	Yes
Tech. dummies	Yes	Yes	Yes	Yes	Yes
Obs.	44,037	44,037	44,037	44,037	44,037

Poisson pseudo-maximum likelihood estimation with robust standard errors (in parenthesis)

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

Table 14 Regression results – Forward citations within 5 years

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Cit5	Cit5	Cit5	Cit5	Cit5
Backward	0.109**	0.0831**	0.0886**	0.0870**	0.0856**
	(0.0370)	(0.0360)	(0.0364)	(0.0363)	(0.0361)
NumberInv	0.304***	0.246***	0.215***	0.230***	0.248***
	(0.0225)	(0.0241)	(0.0225)	(0.0232)	(0.0246)
TechFields	0.757***	0.758***	0.737***	0.740***	0.764***
	(0.133)	(0.132)	(0.130)	(0.131)	(0.132)
NonPatLit	0.0825**	0.0963**	0.0912**	0.0923**	0.0972**
	(0.0378)	(0.0376)	(0.0372)	(0.0373)	(0.0375)
TechCapital	0.0435***	0.0412***	0.0446***	0.0480***	0.0450***
	(0.00679)	(0.00663)	(0.00659)	(0.00643)	(0.00662)
No. Inv Countries		0.0954	0.184***	0.143**	0.119**
		(0.0659)	(0.0505)	(0.0528)	(0.0594)
No. App Countries		0.543***			
		(0.0908)			
AvHum		1.215***	1.395***	1.360***	1.325***
		(0.130)	(0.126)	(0.121)	(0.128)
AvOpen		-0.000737	0.00146	0.00392**	-0.000805
		(0.00157)	(0.00135)	(0.00125)	(0.00161)
GDPDiff		0.0122	0.0132	0.0123	0.0126
		(0.0141)	(0.0147)	(0.0145)	(0.0144)
GeoDist			0.0462***	– 0.0521**	
			(0.00666)	(0.0171)	
GeoDistSq				0.0116***	
				(0.00198)	
MultiCountry					0.193***
					(0.0287)
MultiRegion					– 0.221***
					(0.0469)
Country dummies	Yes	Yes	Yes	Yes	No
Year dummies	Yes	Yes	Yes	Yes	Yes
Tech. dummies	Yes	Yes	Yes	Yes	Yes
Obs.	44,037	44,037	44,037	44,037	44,037

Poisson pseudo-maximum likelihood estimation with robust standard errors (in parenthesis).
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 15 Regression results – Number of claims

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Claims	Claims	Claims	Claims	Claims
Backward	0.0350***	0.0335***	0.0336***	0.0335***	0.0331***
	(0.00685)	(0.00685)	(0.00684)	(0.00684)	(0.00684)
NumberInv	0.0782***	0.0628***	0.0618***	0.0639***	0.0628***
	(0.00538)	(0.00551)	(0.00544)	(0.00549)	(0.00558)
TechFields	0.0951***	0.0954***	0.0948***	0.0947***	0.0949***
	(0.0212)	(0.0212)	(0.0212)	(0.0212)	(0.0212)
NonPatLit	0.0518***	0.0531***	0.0530***	0.0530***	0.0529***
	(0.00550)	(0.00549)	(0.00549)	(0.00548)	(0.00550)
TechCapital	– 0.00448**	– 0.00369**	– 0.00361**	– 0.00309**	– 0.00369**
	(0.00145)	(0.00149)	(0.00148)	(0.00148)	(0.00148)
No. Inv Countries		0.0560***	0.0582***	0.0514***	0.0493***
		(0.00907)	(0.00888)	(0.00913)	(0.00905)
No. App Countries		0.0171*			
		(0.0102)			
AvHum		0.143***	0.146***	0.140***	0.127***
		(0.0283)	(0.0278)	(0.0277)	(0.0280)
AvOpen		0.000821***	0.000895***	0.00124***	0.000779***
		(0.000202)	(0.000198)	(0.000214)	(0.000200)
GDPDiff		– 0.000313	– 0.000298	– 0.000423	– 0.000375
		(0.00287)	(0.00288)	(0.00286)	(0.00286)
GeoDist			0.00170	– 0.0122***	
			(0.00114)	(0.00360)	
GeoDistSq				0.00171***	
				(0.000430)	
MultiCountry					0.0255***
					(0.00556)
MultiRegion					0.00858
					(0.00755)
Country dummies	Yes	Yes	Yes	Yes	No
Year dummies	Yes	Yes	Yes	Yes	Yes
Tech. dummies	Yes	Yes	Yes	Yes	Yes
Obs.	40,190	40,190	40,190	40,190	40,190

Poisson pseudo-maximum likelihood estimation with robust standard errors (in parenthesis)

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

Table 16 Regression results – Family size

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Family Size	Family Size	Family Size	Family Size	Family Size
Backward	0.0181**	0.0103	0.0130*	0.0120*	0.0115
	(0.00721)	(0.00712)	(0.00716)	(0.00712)	(0.00711)
NumberInv	0.116***	0.101***	0.0897***	0.0974***	0.110***
	(0.00619)	(0.00668)	(0.00662)	(0.00664)	(0.00672)
TechFields	– 0.00974	– 0.0106	– 0.0144	– 0.0145	– 0.00298
	(0.0209)	(0.0209)	(0.0209)	(0.0209)	(0.0208)
NonPatLit	– 0.0400***	– 0.0350***	– 0.0371***	– 0.0368***	– 0.0333***
	(0.00670)	(0.00661)	(0.00664)	(0.00659)	(0.00658)
TechCapital	0.0278***	0.0271***	0.0287***	0.0310***	0.0279***
	(0.00176)	(0.00177)	(0.00177)	(0.00179)	(0.00175)
No. Inv Countries		0.0366***	0.0740***	0.0492***	0.0450***
		(0.0100)	(0.00945)	(0.00975)	(0.00983)
No. App Countries		0.173***			
		(0.0124)			
AvHum		0.235***	0.323***	0.298***	0.278***
		(0.0305)	(0.0309)	(0.0300)	(0.0301)
AvOpen		– 0.0000182	0.000523**	0.00189***	– 0.0000386
		(0.000222)	(0.000223)	(0.000228)	(0.000223)
GDPDiff		– 0.00156	– 0.00131	– 0.00185	– 0.00161
		(0.00299)	(0.00306)	(0.00302)	(0.00299)
GeoDist			0.00835***	– 0.0462***	
			(0.00149)	(0.00429)	
GeoDistSq				0.00665***	
				(0.000483)	
MultiCountry					0.0306***
					(0.00611)
MultiRegion					– 0.154***
					(0.00904)
Country dummies	Yes	Yes	Yes	Yes	No
Year dummies	Yes	Yes	Yes	Yes	Yes
Tech. dummies	Yes	Yes	Yes	Yes	Yes
Obs.	40,190	40,190	40,190	40,190	40,190

Poisson pseudo-maximum likelihood estimation with robust standard errors (in parenthesis)

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

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Conflict of interest The author has no competing interests to declare that are relevant to the content of this article**.**

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