The Inverted U-Shaped Relationship between Broadband Penetration and International R&D Collaboration: Evidence from 19 OECD Countries

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The Inverted U-Shaped Relationship between broadband penetration and International R&D Collaboration: Evidence from 19 OECD Countries

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Abstract

This paper investigates the relationship between ICT and international R&D collaborations among 19 OECD countries from 2000 to 2015. More specifically, it looks at the impact of broadband penetration on the number of *international co-inventions measured through patents*. Poisson and Negative binomial regression models are employed for estimation. The results reveal a non-linear association between broadband access and international R&D collaborations, characterized by an inverted U-shaped curve. Additionally, the insights show that broadband penetration increased the concentration of existing and new collaboration ties. Subsequent analysis is undertaken, splitting the overall country-pairs sample into seven technology areas using the OST7 classification. Consistent with the overall findings, Electronics, Instruments, Chemicals, and Pharma exhibit the same inverted U-shaped relationship. However, the relationship is non-significant for Industrial and Mechanical Processes, while Civil engineering displays a positive linear association. These results also underline how crucial it is to consider particular technology areas when assessing how technology adoption affects international R&D collaboration.

KEYWORDS: Broadband penetration, International R&D Collaboration, Negative Binomial

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1 Introduction

More broadly, the Internet and information and communication technologies (ICT) have changed many aspects of how people and businesses interact and collaborate. This includes how inventors work and join forces in research and development activities within and across borders. Stemming from the field of scientific research at CERN, the world wide web was initially designed specifically to help researchers share questions, methods and results. Through the past two decades, one particular stream of research has focused on how ICT contribute to the geographical distribution of innovation activities within and across firms (Macher and Mowery, 2008). Via survey data on 204 Austrian firms, Kaufmann et al. (2003) showed that the Internet allows firms to interact with distant partners more easily and tends to reinforce existing collaboration networks. This latter result concurs with Laudel (2001), who found that while face-to-face interactions initiate scientific collaborations, the Internet sustains and strengthens existing connections over time. Using firm-level data, Forman and Zeebroeck (2012) found that adopting basic Internet technology could significantly reduce the costs of coordinating research teams and increase R&D collaboration between distant establishments within US firms. These studies have looked at a relatively basic version of the Internet (generally basic Internet access), and the question remains about the impact of broadband connectivity across a country on R&D collaborations. Surprisingly, little evidence is available to date on the geographical distribution of R&D collaborations between countries due to faster and more widely accessible Internet connectivity.

This question speaks to at least to significant streams of literature. First, it speaks to studies on the geography of innovation. Suppose broadband Internet access can support more advanced and intensive forms of collaborations (think, for instance, of videoconferencing and collaborative online tools using the cloud). In that case, one should expect innovation networks across countries to be intensified, reshaped, or both. It also speaks to the literature on the business value of ICT since deeper and broader collaborative networks might enhance the productivity of R&D investments and positively contribute to more or better innovation globally. In the present work, we will primarily focus on the geography of collaborative networks in R&D and how it is influenced by broadband penetration across countries.

Some recent studies have looked at the contribution of broadband penetration to productivity growth, sometimes highlighting a positive effect. Koutroumpis (2009) suggested that broadband infrastructure and growth in the UK are significantly causally linked. Atif et al. (2012) found that broadband penetration positively impacts economic growth based on an annual panel of 31 OECD countries from 1998 to 2010. They discovered that a 10% increase in broadband penetration growth caused economic growth per employee of around 0.035 percentage points. Similarly, Czernich et al. (2011) claimed that greater broadband coverage effects yearly per capita growth favorably in OECD countries. More broadly, in their review of the empirical literature on ICT and productivity, Cardona et al. (2013) notice that most studies find a positive effect of ICT on productivity. However, empirical methods and countries matter significantly, with the most positive impacts being observed with US rather than European data.

Beyond ICT, extant evidence exists on the contribution of innovation to productivity (see, e.g. Grossman and Helpman 1990, 1993). This has motivated numerous studies on the drivers of innovation. Multiple works have emphasized the importance of (international) R&D collaborations[1] in generating high-quality innovation output (e.g. Wuchty et al., 2007). Actors with a high absorptive capacity are particularly attractive for forming collaborations, as their ability to identify, internalize, and utilize knowledge from external sources greatly influences the collaborative process (Cohen and Levinthal, 1990).

At the interface of these two currents, Choi and Yi (2018) have shown how the Internet enhances the contribution of R&D spending to economic growth. Regrettably, little is known about how ICT contributes to innovation and productivity.

In this study, we examine the role of ICT on international R&D collaborations among OECD countries. Specifically, we first analyze how the penetration of broadband connectivity, by reducing the cost of distant coordination and communication, may influence R&D collaborations among countries. Second, we investigate in which direction the broadband penetration affects the concentration of R&D collaboration. We hypothesize that broadband Internet access provides inventors with greater access to a vast network of potential collaborators, which can lead to new inventions (Wernsdorf et al., 2020). By exploring the relationship between broadband penetration and international R&D collaboration, this study aims to shed light on the transformative effects of IT technologies on the geography of innovation.

We use a panel of 19 OECD countries from 2000 to 2015 to study how broadband penetration influences international R&D collaborations, measured by the number of international co-inventions. Our empirical research study unexpectedly reveals an inverted U-shaped relationship between broadband penetration and international R&D collaborations. As broadband penetration increases, international R&D collaborations are enhanced. Nevertheless, beyond a certain threshold, further broadband penetration may exhibit declining returns or even a negative impact on international R&D collaborations. This suggests decreasing marginal returns to broadband penetration. We speculate that this pattern may be due to the potential challenges and barriers related to information security, intellectual property protection or a preference for local collaboration.

Our findings contribute to the literature on the business value of ICT and the geography of innovation in two ways. First, we highlight an aggregate effect of broadband penetration on international R&D collaborations. Second, we show that the relationship between broadband penetration and international

[1] International collaboration in R&D occurs when a patent has several inventors residing in different countries (Guellec and van Pottelsberghe de la Potterie, 2001).

R&D collaborations is curvilinear. Last, we find that broadband penetration enhances the concentration of new and existing collaborative ties.

The reminder of this paper is organized as follows. Section 2 provides the theoretical background on the patterns and drivers of international R&D collaboration and the relationship between broadband penetration and international R&D collaboration. Section 3 presents empirical facts about international R&D collaboration and the recent changes in R&D collaboration patterns. Section 4 shows empirical facts about digital broadband penetration by describing technological facts and trends. Next, the methodological framework and the empirical results are presented in Section 5. Finally, Section 6 offers a discussion and conclusion to the paper.

2 Theoretical background and hypotheses

2.1) International R&D collaboration patterns and drivers

***International R&D* Collaboration patterns**. In the last decades, *international R&D* collaboration has increased significantly. Many studies have shown a substantial rise in the number of co-inventions and co-inventors (Cronin et al., 2004; Glänzel, 2002; Adams et al., 2005; Wuchty, Jones & Uzzi, 2007). In their paper, Guellec and Van Pottelsberghe (2001) presented three new indicators to measure internationalization of technology in the OECD area from 1985-1995. They found an increasing trend of *international R&D* collaboration, indicating a significant growth in the pace at which knowledge is produced and circulated. By examining the *international R&D* collaboration status in the solar cell industry for the period 1971-2010, Lei et al. (2013) showed that the collaboration of inventors and assignees has been intensified and that the average number of inventors has progressively enhanced, suggesting that *international R&D* collaboration is a necessity and that invention has shifted from single inventors or organizations to more collaborative work. Ma and Lee 2008, used patent data from the eight most inventive OECD countries and two Asian countries to show a pattern of an important and increasing international R&D collaboration in inventive activities worldwide between 1980-2005. They have used the term "Techno-globalism" (Archibugi and Michie, 1995) to describe the globalization of technology due to the increasing collaborative efforts in invention. In point of fact, by promoting international R&D collaboration, governments and policymakers recognize the value of fostering international R&D collaboration to facilitate the exchange and flow of expertise and knowledge among countries, thereby maintaining a competitive advantage. Mainly, Winkler et al. (2011) found that US-International collaborations rose from 9% to 23% from 1991-2007. However, these collaborations are lower for economics (and higher for physics) than for the other natural science subfields since economics research is more focused at the national level than research in natural sciences, pointing out the field disappearances in the way research is conducted (Jones et al., 2008). Finally, by using a new indicator of collaboration intensity[2] for countries with rapidly growing research for 1999-2018, Pohl (2020) investigated whether an entity collaborates with rapidly growing research countries. The findings indicated that rapid changes in the academic world force us to become more proactive in collaboration efforts, fostering links rapidly with developing research countries and therefore promoting proactive development of international research collaboration.

Why do firms or countries collaborate in R&D? International R&D collaborations have become increasingly prevalent in many fields, such as technology and science. These collaborations enable partners to share knowledge, skills, and technologies, improving productivity (Katz and Martin, 1997). Moreover, research has shown that collaborative R&D efforts yield high-quality and high-impact outcomes, as evidenced by higher citation rates compared to solo efforts (Nomaler et al., 2013; Wuchty et al., 2007; Persson et al., 2004). Many previous studies showed that multi-country joint patent ownership positively impacts patent quality (Narin, 1991; Briggs, 2015; Belderbos et al., 2014; Briggs and Wade, 2014). Indeed, international R&D collaborations improve the dissemination of relevant knowledge acquired to innovate in many technological fields but often available in different places. It is also a way to compensate for national technological weaknesses (Danguy, 2017). Montobbio and Sterzi (2013) stated that joint research efforts and collaboration help create various opportunities to learn from each other. Above and beyond, collaboration creates social networks that promote mutual learning, motivating individuals and companies to be more innovative (Breschi & Lissoni, 2009; Hoekman, Frenken, & Van Oort, 2009; Singh, 2005).

On the other hand, Sonnenwald (2007) reported three main factors that helped increase collaboration. First, *scientific factors*: since researchers are motivated by discovering new knowledge and are becoming more and more specialized, teams with narrower expertise are encouraged to collaborate with other researchers to compensate for the lack of expertise and knowledge they might have. In other words, collaboration is motivated by combining multiple knowledge and expertise to solve complex problems and issues. Increased specializations within science fields are a key factor for international collaboration (Persson et al., 2004). Secondly, *socio-economic factors*, as collaborations promote economic growth by spreading the financial risk of research for companies and providing access to local and scientific markets. Thirdly, *accessibility of resources*: by facilitating access to expensive materials and scarce resources, data is increasingly available as materials and data are easily shared between actors.

To finish, Moaniba, et al., (2019) argued that since countries aim to maximise their economic growth through innovation, international R&D collaboration and technological diversity must be highly associated with higher innovation and economic growth. For this reason, countries choose to be more technological diversified and internationally collaborative.

[2] This new index is the Normalised Collaboration Intensity Index, that was developed based on co-publications to reflect the collaboration portfolio of a country or another entity.

<u>What influences the propensity of firms or countries to collaborate in R&D?</u> Collaboration in R&D can be facilitated by various factors that enable successful partnerships between entities. When evaluating potential collaborators, firms should carefully consider specific criteria. The drivers of R&D collaboration identified by Prato & Nepelski (2012) include inventive capacity, technological specialization, openness to international collaboration, and economic potential of technology (Archibugi & Iammarino 2002; Dunning 1994; Sachwald 2008). Moreover, it has been shown that sharing a common language promotes bilateral international collaboration, while the cultural distance between countries has a discernible impact on collaboration and innovation (Siegel et al., 2013). Additionally, Danguy (2014) found that countries with similar industry-specific technological knowledge, as measured by technological proximity, tend to collaborate more effectively in generating innovation. When the knowledge bases of two countries are closer, the likelihood of cooperation in knowledge production increases (Guellec and Van Pottelsberghe, 2001; Cantner and Meder, 2007; Montobbio, 2012).

On the other hand, Guellec and Van Pottelsberghe (2001) have found that the geographical proximity of partnering countries plays a role in determining collaborations. International R&D collaboration tends to be negatively affected by distance. However, several barriers to international collaboration have been reduced in recent decades. This is primarily due to the decrease in travel and telecommunication costs andthe introduction of communication tools that enable the sharing of tacit knowledge (Picci, 2010). In particular, the emergence of information and communication technologies (ICT) has facilitated collaboration (Sachwald, 2008). ICT applications such as email, instant messaging, videoconferencing, and voice-over IP have enhanced the sharing of resources, data, and knowledge among researchers from different entities. The relationship between broadband penetration and international R&D collaboration will be discussed in more detail in the following section.

2.2) Digital technologies and international R&D collaboration

Information and communication technology (ICT) is changing how inventors collaborate. With the significant reduction in communication costs, inventors and researchers now find it easier to collaborate, share data, and exchange knowledge. Numerous studies have argued that ICT facilitates the exchange of codified knowledge (Ding et al., 2010).

Wernsdorf et al. (2020) examined the adoption of Bitnet, an early version of the Internet, across U.S. universities between 1981 and 1990. They found that adopting Bitnet had a more substantial impact on collaborative patents among new teams that had not previously collaborated. Bitnet facilitated the identification of potential collaborators with complementary capabilities through communication tools such as email and discussion forums. This effect was particularly pronounced in fields where knowledge is easily codifiable, such as Chemistry and Instruments. Bitnet made it easier for collaborators to exchange knowledge in written forms.

Forman and van Zeebroeck (2012) examined the impact of basic Internet technology on research collaborations within firms from 1992 to 1998, focusing on within-firm industrial collaborations. They found that the deployment of essential Internet technologies encouraged the creation of collaborative patents by teams from different locations part of the same firm. In other words, there was a noticeable rise in the likelihood of researcher collaboration when two locations within a company both implemented basic Internet technology. Furthermore, the study highlighted the shifting nature of scientific research, with an increasing emphasis on collaborative efforts rather than individual inventors. This shift is attributed to researchers' growing knowledge burden as knowledge accumulates over time. The authors argued that specialization and division of labor among scientists can enhance research productivity, and adopting Internet technologies may further amplify the benefits of collaborative work. By reducing coordination costs, basic Internet technology slightly improved the productivity of larger geographically dispersed research teams compared to other research collaborations.

Winkler et al. (2011) investigated the impact of IT diffusion, measured by the number of years since an institution adopted a domain name, on collaboration patterns across institutional and national borders between 1991 and 2007. They found that IT exposure positively and significantly affected multi-institution collaborations. This effect became even stronger as the size of the network increased, indicating that IT facilitated collaboration among a more significant number of institutions. Similarly, Ding et al. (2010) examined the direct impact of IT adoption on collaboration between individual researchers. They analyzed a random sample of 3114 research-active life scientists from 314 U.S. institutions over 25 years. Their findings revealed that access to IT enhanced collaboration, measured by co-authorship. IT played a crucial role in expanding co-authors since the 1980s, as it facilitated access to resources and reduced communication costs. IT provided researchers with improved access to materials and equipment, allowing them to request materials online and engage in remote interactions with other researchers. As a result, IT fostered knowledge and idea sharing at a low cost, promoting collaboration among scientists.

In a study published in the Journal of electrical engineering, Agrawal and Goldfarb (2008) investigated the effects of decreased collaboration costs brought about by the deployment of BITNET on institutional-pair collaboration patterns. The study used a difference-in-differences approach to examine the data, focusing on the years 1977 to 1991. They categorized authors' institutional affiliations into three tiers: lower, medium, and elite. They found that adopting Bitnet connectivity led to a significant increase of 50% in collaboration between connected universities. Notably, middle-tier universities experienced the most significant benefit from this technology, as they observed a substantial increase in collaboration with top-tier universities. The authors suggested that the most important effect of this sharp decrease in communication costs (through the adoption of Bitnet) may have been facilitating gains from trade through specialization and collaboration. By reducing communications costs, Bitnet adoption facilitated collaboration between connected institutions and enabled them to engage in more productive research collaborations.

Butler, Butler and Rich (2008) conducted a study to examine the impact of the Internet on inter-departmental collaboration in the fields of political science and economics. Specifically, they investigated the differential effect of the Internet on researchers outside of top-tier departments. The study period spanned from 1980 to 2003. Their study used a review of National Bureau of Economic Research (NBER) series during the 1990s to measure IT availability. They found that before January 1997, the e-mail of an author was never mentioned in the paper, but as of January 1999, all papers include an e-mail address. Using this indicator to measure Internet access, they found that the Internet increases collaboration (co-authorships) and that the impact is higher at lower-ranked universities. In contrast, Jones et al. (2008) examined data from 662 US universities and 4.2 million research papers published between 1975 and 2005, they found that even if multi-university collaborations were the fastest-growing type of co-authorship, these collaborations were driven by factors that existed before the widespread adoption of the Internet.

To conclude, these studies provide evidence of the transformative impact of information and communication technology (ICT) on collaboration in different research settings. The findings emphasize the significant role of ICT in fostering collaboration, enhancing productivity, and facilitating knowledge sharing in research and innovation activities. As technology continues to evolve, it is expected that ICT will further transform collaboration patterns and enable new forms of research cooperation.

2.3) Theoretical framework

This section will develop our theoretical framing by conceptualizing how broadband penetration enhances international R&D collaboration across countries. Our approach involves two key steps. First, we examine the nature of the relationship that might exist between broadband penetration and international R&D collaboration. Second, we intend to principally examine how broadband penetration may influence the concentration of international R&D collaboration. In this study, we build upon existing literature to explore the impact of broadband penetration on international R&D collaboration among countries. While previous research has examined the linear relationship between basic Internet usage and research collaboration within firms or academic institutions, our study extends the analysis to the macro level by investigating the relationship between broadband penetration and international R&D collaboration among countries. To measure international R&D collaboration, we use co-invented patents, known as "Co-inventions," as a proxy, aiming to determine the relationship between broadband penetration and international R&D collaboration. It is important to note that, in the subsequent sections of this paper, the term "*Co-inventions*" refers explicitly to international co-inventions. At the same time "*R&D collaboration*" is specifically used to denote international R&D collaboration.

The national Broadband Taskforce established by the Canadian government defined broadband as "*a high-capacity, two-way link between an end-user and access network suppliers capable of supporting full-motion, interactive video applications*" (Grosso, M., 2006). Additionally, the International Telecommunication Union (ITU) defines fixed broadband internet subscription as a high-speed access subscription to the public Internet, with downstream speeds equal to or greater than 256 kbit/s. Broadband has several advantages compared to narrowband, including higher data transfer rates, faster and more efficient internet access and data transmission, support for simultaneous activities without compromising connection speed, and the ability to handle modern applications and services such as cloud computing, video conferencing, and virtual reality (Armenta et al. (2012)). The faster internet speed of broadband allows for quicker data downloads, uploads, and communication, ultimately leading to increased productivity (Cardona et al., 2013; Kongaut & Bohlin, 2017). The faster internet speed of broadband facilitates quicker data downloads, uploads, and communication, leading to increased productivity (Kongaut & Bohlin, 2017).

Conversely, as the burden of knowledge increases, researchers tend to specialize in specific tasks, resulting in higher coordination costs[3] when collaborating (Jones, 2009; Becker and Murphy 1992; Adams et al., 2005). However, the emergence of broadband internet has significantly lowered unit search and communication costs (Abualghanam, 2019), encouraging inventors to work together and increase the co-production of inventions. By adopting a transaction cost framework, we argue that technology, specifically broadband penetration, enhances R&D collaboration among countries by reducing transaction and coordination costs within and across entities (Frieden, R., 2005; Forman & Van Zeebroeck, 2012; Chen and Kamal, 2016). Additionally, Chen and Kamal (2016) show that the adoption of communication technology reduces internal and external coordination costs, lowering communication and search costs and economic incentives costs regarding moral hazards and opportunistic behavior. The development of information technology had also increased trade in differentiated goods and services after the 1970s when international communications became more affordable (Tang, 2006), and we anticipate a similar positive effect on the number of co-invented patents between countries in the innovation market. In light of our conceptual framework, we propose the following hypotheses to be tested:

Hypothesis 1. Broadband penetration positively impacts R&D collaboration by reducing transaction and coordination costs between entities. It mitigates the higher coordination costs caused by the burden of

[3] Coordination costs are defined as costs that are associated with physical flow and the direct costs of managing the coordination (Xu et al. (2006)).

knowledge accumulation and the increasing specialization of research tasks, fostering collaboration between inventors and researchers and improving the co-production of inventions.

Conversely, we mainly examine how broadband penetration may influence the concentration of R&D collaboration. In other words, we search to investigate if the increasing trend in R&D collaboration, triggered by broadband penetration, is due either to an expanding number of new collaborations caused by the cost reduction of new collaborations, or simply to a rise in R&D collaboration concentration (intensity) of existing partners through reinforcing existing ties. Specifically, we search if broadband penetration leads to a homogeneous increase of R&D collaboration cross all countries or, on the contrary, will lead to a more substantial agglomeration of R&D collaborations since broadband penetration can help reduce transaction and coordination costs.

Empirical studies argued that innovation activity is concentrated in large cities as they have a locational advantage compared to smaller cities (Feldman and Kogler 2010; Carlino and Kerr, 2015; Glaeser and Hausman, 2019). Paunov et al. (2019) examined how digital technologies have shaped the concentration of inventive activity in cities across 30 OECD countries from 2010 and 2014. They showed that digitalization tends to favor agglomeration more than dispersion meaning that regions that are among the top benefit more from digitalization. The concentration of innovation in a few top geographical regions is due to the complexity of sharing complex knowledge and the advantages of col-location innovators critically need (Paunov et al., 2019). Danguy (2014) by studying the globalization of innovation between 1988 and 2005 among OCED countries, found that the globalized word of innovation is made of a growing number of partner countries that intensively collaborate together. His study suggests that the number of international collaborators increased intensively in the same way as the collaboration intensity.

On the contrary, Fritsch and Wyrwich (2021) examined and compared the geographic concentration of patents in 14 developed market economies over the 2000-2015 period. They found no general trend of an increase in the geographic concentration. Their study showed that there are more countries where patent concentration in large metropolitan regions is decreasing than countries where the concentration of patents is increasing. Hence, they conclude that agglomeration economies do not play an essential role in innovation activities as transportation and communication costs (key argument behind agglomeration economies drivers) have fallen (Glaeser, 2010). Based on the previous finding, we formulate our second hypothesis as follows:

Hypothesis 2. broadband penetration *increases the concentration of existing and new international R&D collaboration ties*.

3 Empirical facts about international R&D collaboration

3.1) Co-inventions as a measure of international R&D collaboration[4]

In this paper, we exploit various data sources to examine collaborations across 19 OECD most innovative countries from 2000 to 2015.

Although patent data are associated with several drawbacks and shortcomings (Bergek and Bruzelius 2010), they are broadly used as a measure of R&D collaboration (Danguy, 2014; Thomson, 2013; Picci and Savorelli, 2012; De Prato and Nepelski, 2012; Winkler et al., 2011; Guellec and van Pottelsberghe, 2001; Almeida, 1996; Cantwell, 1995; Patel and Pavitt, 1991; Chen et al. 2013; Petruzzelli, 2011; Lei et al. 2013; Ma and Lee 2008). As patent data provide geographical, sectoral, organizational and temporal dimensions of innovation, it is an excellent measure to analyze collaborative efforts at macro and micro levels over time (Yoon, 2015). Therefore, we use patent data from the European Patent Office (EPO) Worldwide Patent Statistical Database 2019 named PATSTAT. This database covers records of patent applications submitted to around 90 Patent Offices in the world. Patent data are particularly suitable for analyzing the relationship between geographical collaboration and inventive activities. It represents a valuable information source for technological development and collaboration. One of the key advantages of patent data is that they contain detailed address information related to inventors and assignees, which is very appropriate for analyzing technological collaboration patterns in geographical areas (Lei Xiao et al., 2013). In addition, Bergek and Bruzelius (2010) argued that cross-country patents ould be used as an indicator of international collaboration despite some limitations. Finally, the international and collaborative characteristics of patents with several inventors from different countries make them an excellent international R&D collaboration indicator (Bergek and Bruzelius, 2010; Ma and Lee, 2008; Almeida and Phene, 2004; Guellec and van Pottelsberghe de la Potterie, 2001; Patel and Vega, 1999).

This study considers only "priority" applications instead of granted patents filed at EPO office. We also use the priority filing[5] dates instead of application dates. This choice has the advantage of permitting the analysis of recent data as many years could elapse between filing and granting a patent. Moreover, using patent applications is common practice in the literature. The period considered covers from January 1st, 2000 to December 31st, 2015. To compare collaborations across different technological areas, we further use the International Patent Classification at 4 digits (IPC4) to compute our main indicators. IPC codes are manually assigned to each patent by patent office examiners. They typically attribute each patent with a main code linked to its content and sub-codes that refine the description. This nomenclature, set up in 1968, is used in many patent offices worldwide. The advantage of this

[4] According to Guellec and van Pottelsberghe de la Potterie, 2001 international collaboration in R&D occurs when a patent has several inventors residing in different countries.

[5] A priority filing is the first patent application protecting an invention

method based on IPC classification is that the examiners are the ultimate arbiters of assigning patent classes, which minimizes the risk of misclassifying patents (Sampson, 2007).

Finally, since we are interested in the incidence of collaborations rather than in actual counts of innovative or collaborative output, we use the "whole count" method instead of the "fractional count" method (de Rassenfosse et al., 2013). The former method counts the collaborative patents between any two countries as 1, while the later methodology counts it as 1 divided by the number of countries involved in one patent. We attribute patents to countries based on the inventor's country of residence (Picci, 2010). In other words, when a given patent only involves inventors residing in the same country, the patent is considered "national". Otherwise, the patent is qualified as "international". We use the inventor criterion to assign patents to countries (De Prato and Nepelski, 2012; de Rassenfosse et al., 2013; Turlea et al., 2011) as it reflects the actual location of inventive activity better than applicant (assignee) addresses, which may instead reflect IP strategies – especially among multinational companies. Overall, in our panel dataset, our observation unit is a pair of countries in a given technological area.

As previously mentioned, it is essential to note that our study is based on patent data from the European Patent Office (EPO), which may not capture the full extent of patent activity due to the home advantage bias. Furthermore, for the purpose of our research, we collect economic and institutional data from different sources.

Our sample consists of 19 OECD countries, namely Austria (AT), Australia (AU), Belgium (BE), Canada (CA), Switzerland (CH), Germany (DE), Denmark (DK), Spain (ES), Finland (FI), France (FR), the Great-Bretagne (GB), Ireland (IE), Israel (IL), Italy (IT), Japan (JP), the Netherlands (NL), Norway (NO), Sweden (SE), the United-States (US). By including these countries, we aim to provide a diverse and representative set of economies for our analysis.

3.2) Changes in patterns of international R&D collaboration

Main international R&D collaboration partners

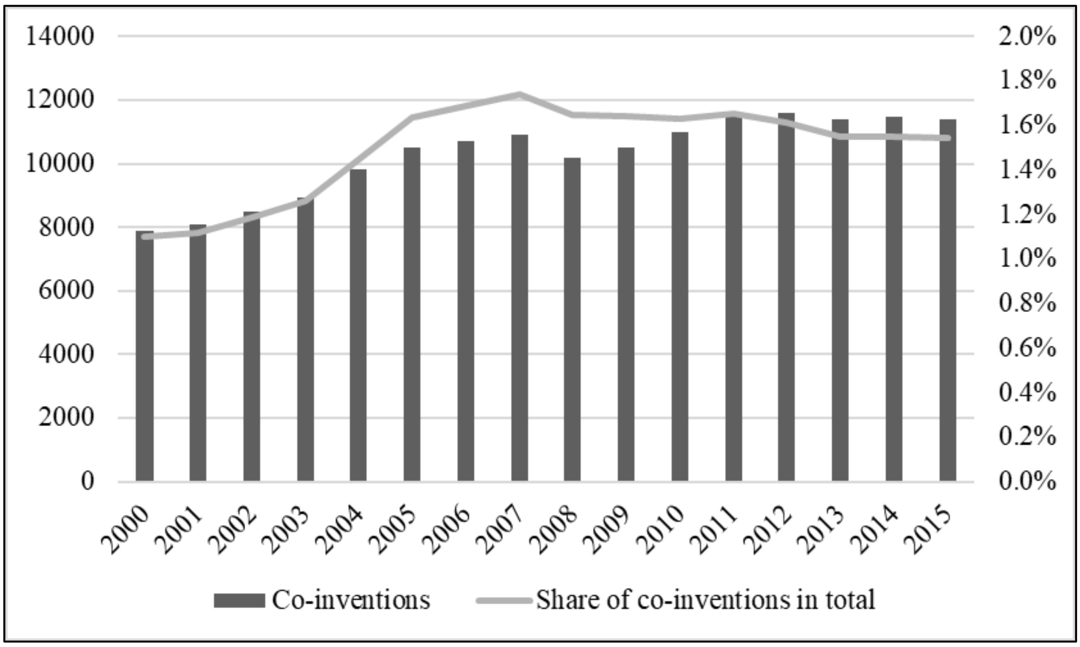
This paper adopts an aggregated approach at the country level to examine the relationship between broadband penetration and R&D collaboration. While this approach may not capture firm-industry specific issues, it is considered exhaustive as it encompasses all inventions regardless of ownership (Guellec and van Pottelsberghe, 2001).

Figure 1 illustrates the significant changes in R&D collaborations evolution in terms of the share and counts of co-inventions between 2000 and 2015. In 2000, out of 715,475 inventions, there were 7,871 co-inventions. Among these co-inventions, 51% were initiated by the United States. Germany, the United Kingdom, Canada, France, Japan, and Switzerland emerged as the United States' primary collaborative partners, also ranking among the top collaborative countries. The average number of co-inventions per country pair was 49.5 co-invented patents.

By 2007, the total number of co-inventions increased to 10,919 out of 626,553 inventions, while the average number of co-inventions per country pair rose to over 68.2. The United States maintained its position as the largest producer of co-inventions, accounting for a 43% share. Countries like Germany and the United Kingdom were also emerging as significant collaborative partners. However, in 2008, co-inventions experienced a substantial decline in year-to-year growth, reaching its lowest point at -7.8%, reflecting the impact of the 2008 financial crisis.

In 2015, there was only a slight increase of 0.4% in the average number of co-inventions per country pair compared to 2007, reaching 69.2 co-inventions. While the total number of co-inventions showed a modest average growth of 0.8%, these figures suggest that collaboration in technology is entering a phase of weak growth in terms of partners and volume.

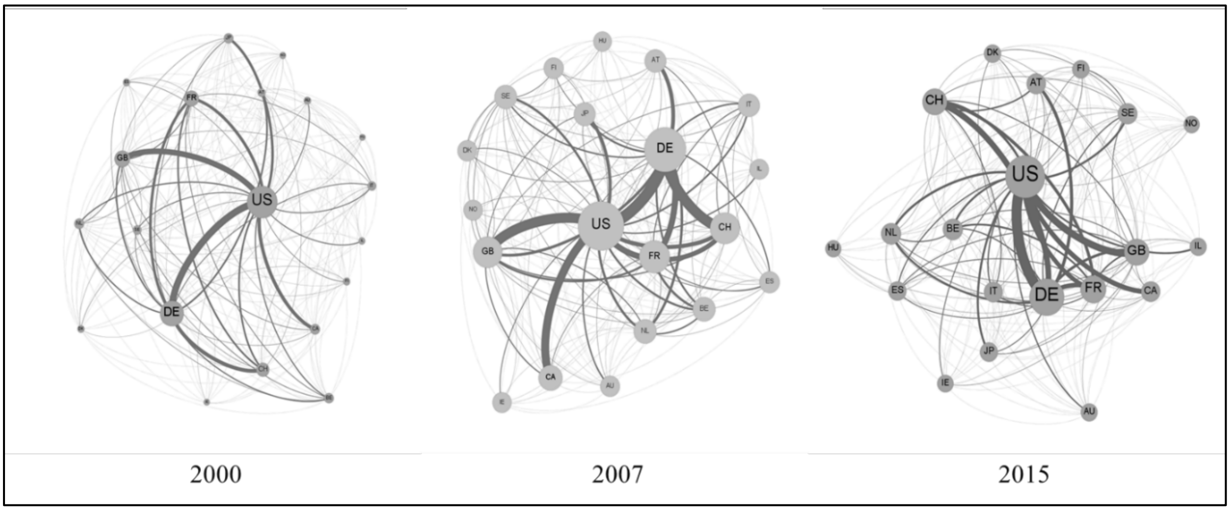
Figure 1. Evolution of co-inventions share within the total between 2000 and 2015



Source: Own calculations using the inventor/applicant criterion based on PATSTAT Database, version 2019

Figure 2 provides a visualization of the primary R&D collaboration partners. This visualization algorithm is used to represent the full international R&D collaboration network. Each country is represented with a circle and the bubble sizes reflect the magnitude of international co-inventions counts for each country in a given year. The thickness of the lines represents the concentration of R&D collaboration between countries (the number of co-invented patents between each pair). We represented links between the 19 OCDE countries of our sample for three distinct years: 2000, 2007 and 2015. By visually representing the links and collaboration patterns, the figure further supports and confirms previous insights regarding the changing dynamics of R&D collaboration over time.

Figure 2. Main international R&D collaboration partners



Source: Own calculations using the inventor/applicant criterion based on PATSTAT Database, version 2019

4 Empirical facts about digital technology

The main objective of this paper is to investigate the influence of broadband penetration on international R&D collaboration. To achieve this, we utilize the broadband penetration rate, measured by the number of broadband subscribers per 100 inhabitants.

Broadband penetration includes various internet technology connections such as cable modem, Digital Subscriber Line (DSL, ADSL, SDSL and VDSL), fiber-to-the-home, fixed wireless (WIMAX) technologies, satellite broadband and terrestrial fixed wireless broadband excluding mobile wireless Internet technologies (mobile broadband). The data for our study is sourced from the OECD library and ITU World Telecommunication/ICT Indicators (WTI) Database for the year 2020[6].

This section will mainly present major facts and information related to the broadband penetration.

4.1) Digital technology has become cheaper and more effective

Recently, prices for communications products have fallen significantly, accompanied by a remarkable improvement in the quality of communications equipment (as shown in Figure A.1. in the appendix). The result is a more efficient exchange of data and knowledge between different locations. In addition,

[6] As per ITU's definition, a fixed BB Internet subscriber refers to a subscriber who pays for high-speed access to the public Internet (a TCP/IP connection), at speeds equal to, or greater than, 256 kbit/s, in one or both directions.

Cooper's Law, also known as the Law of Spectral Efficiency, suggests that the maximum number of voice conversations or equivalent data transactions that can be conducted in the available radio spectrum doubles every 30 months[7]. This law indicates that technology continues to anticipate and meet the current growth of our interconnected society. In summary, we observe a continuous decline in the cost of exchanging information and knowledge remotely, supported by enhancement in the quality of technology services. These trends contribute to the facilitation and affordability of communication, therefore fostering increased collaboration, innovation and knowledge sharing in R&D field.

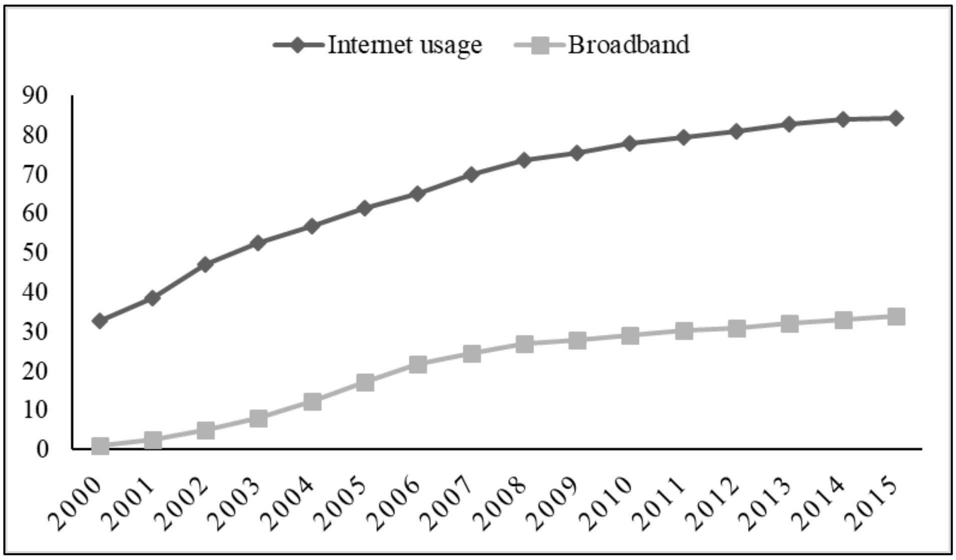
4.2) The increasing trend of broadband penetration

The creation of the World Wide Web in 1989 marked a significant milestone in the history of communication. Initially, the Internet served to interconnect laboratories engaged in government research. Still, since 1994, it has been expanded to help millions of users and a myriad of purposes worldwide[8]. In addition, the deployment and the penetration of Broadband connection to the Internet significantly increased the capacity of transmitting data and knowledge through the same channel with high performance (Nandi and Subramaniam, 2012). Therefore, it has enabled global connectivity, opened up new possibilities for collaboration and innovation, and enhanced the efficiency and effectiveness of communication in the digital era.

Figure 3 presents the Internet usage and fixed broadband subscriptions trends between 1990-2015. It shows that in 1990, there were zero broadband subscriptions by 100 inhabitants while Internet usage was barely 0.25%. By 2015, the number of broadband subscriptions per 100 inhabitants had increased to 34, indicating a substantial expansion of high-speed internet access. The internet usage rate had also risen significantly, surpassing 80% of the population. These figures demonstrate the remarkable growth in digital connectivity and the increasing importance of the internet in people's lives. Therefore, the principal factor for this broadband growth is its capability to serve remote areas at a moderately lower cost than landlines and its ability to stream information from anywhere in the world, contributing to the expansion of digital connectivity (Nandi and Subramaniam, 2012).

[7] "Antennas Get Smart," Scientific American, June 9, 2003
[8] Internet World stats, Usage and Population Statistics

Figure 3. Internet users per 100 inhabitants and fixed broadband subscriptions, 19 OECD countries, 2000-2015



Source: ITU WTID 2020

5 Impact of broadband penetration on international R&D collaboration

This section aims to determine whether broadband penetration has fostered R&D collaborations among the most innovative OECD countries using econometric models. The estimation sample spans from 2000 to 2015, a crucial period for studying the impact of broadband penetration on R&D collaboration. This timeframe encompasses the development and the adoption of various technological systems and applications, including instant messaging, online collaboration tools and voice-over-IP communication.

5.1) Dependent variable

Since we aim to analyze the role that broadband penetration has played in influencing R&D collaboration across OECD countries, we proxy collaboration with account variable that is the number of "*Co-inventions*" per technology area by residents of country i in collaboration with foreign researchers from country j formed in a specific year t. Many studies (Picci, 2010;; Picci and Savorelli, 2012; De prato and Nepleski, 2012; Thomson, 2013) used the count of dyadic patents to identify the determinants of R&D collaboration. Whereas Danguy (2014) and Guellec and van Pottelsberghe de la Potterie (2001) considered a ratio variable as an index of revealed collaboration intensity per dyad countries that controls for the size effect of a country to measure R&D collaboration. In this study, we will not use the ratio variable, the number of collaborative patents to total patents, since there is a risk of overestimating the preference of collaboration among countries with a low frequency of collaboration. In this case the risk of overestimation biases is high (Hwang, 2020). Therefore, we will only focus on the count of dyad "*Co-inventions*" (De Prato and Nepelski, 2012).

Our data set defines an observation as a pair of countries within a specific technology area. As a result, the matrix per technology area representing the count of "*Co-inventions*" between country i and country j is perfectly symmetric. This symmetry arises from the fact that co-inventions between country i and country j are equivalent to co-inventions between country j and country i. This observation highlights the reciprocal nature of R&D collaboration, where bilateral collaborations are mutually beneficial and symmetrical in co-inventions.

5.2) Explanatory variable

Our key independent variable of interest is the fixed broadband penetration ($BB.pen.$). This variable is measured by the number of broadband subscriptions by 100 inhabitants in each country. To capture the dyad broadband penetration, we calculate the average of fixed broadband penetration of the pair countries (i and j) at period t ($BB.pen_{ij_{t-1}} = (BB.pen_{i_{t-1}} + BB.pen_{j_{t-1}})/2$). This average is measured at the country-pair level. Moreover, to account for the potential nonlinear relationship between broadband penetration and R&D collaboration, we include the square term of broadband penetration ($BB.pen_{ij_{t-1}}{}^2$) in our econometric specifications. This allows us to assess the curvature of the relationship and examine any inverted U-shaped pattern that may exist.

On the other hand, our analysis aims to investigate the influence of broadband penetration on the concentration of R&D collaboration, explicitly focusing on the benefits observed within dyad-countries. To explore this relationship, we introduce an interaction term between broadband penetration and the R&D collaboration concentration index ($Con_{coll_{ijt}}$). Therefore, we defined an R&D collaboration concentration index. This index captures the extent to which R&D collaborations are concentrated among fewer partners. The formula used to calculate the index is as follows:

$$Con_{coll_{ijt}} = {}^{co_{inventions_{ijt}}}/{}_{co_{inventions_{wt}}}$$

It is calculated between two countries (i *and* j), at time t, as the ratio of co-inventions ($co_{inventions_{ijt}}$) between country (i) *and* country (j) to the total co-inventions in the world ($co_{inventions_{wt}}$). It takes values in the interval [0.1]; the index is equal to 1 if all inventions are co-invented by only one country-pair, and it is equal to 0 if no patent is co-invented by the country-pairs. In other words, this index indicates the weight of each country-pair in the total co-inventions. In essence, this index represents the relative weight of each country-pair in the total co-inventions.

We incorporate this interaction to show how broadband penetration influences the concentration of R&D collaboration among dyad-countries. Furthermore, we recognize the time required for the effects of broadband implementation to manifest in the form of co-inventions. To account for this lag, we incorporate a one-year lag in our analysis, considering the time needed between broadband implementation and co-inventions application.

5.3) Other explanatory variables

To ensure that our analysis considers the impacts of other significant drivers of collaboration, we include additional variables in our specification models. These variables are selected based on previous research and literature on the topic. By including these variables, we aim to account for other factors that may affect collaboration and provide a more comprehensive analysis of the relationship between broadband penetration and R&D collaboration.

5.3.1) Technological proximity

Cunningham and Werker (2012) found that collaborations benefit from different types of proximity, particularly technological proximity, have a high magnitude of effect on R&D collaboration. Other studies showed that technological overlap of the potential partners enhances the probability to cooperate (Mowery et al. 1998; Sorenson et al. 2005; Canter and Meder, 2007). Collaborators need technological proximity to effectively communicate and understand new knowledge (Boschma, 2005). In other words, partners need to have a similar knowledge base to see directly the benefits of sharing their knowledge base (Colombo, 2003). Consequently, technological proximity facilitates R&D collaborations between different teams as they share a similar knowledge base and technological experience (Nooteboom, 2000; Knoben and Oerlemans, 2006). We then add technological proximity ($\boldsymbol{Prox_{ijst}}$) variable to our model. The latter measures the degree of sharing the same knowledge or technology between two countries. We calculated this indicator based on the formula proposed by Jaffe (1986), Capron and Cincera (1998) and MacGarvie (2006), which uses the share of patent portfolios that fall within the same technological classes (See appendix C). Moreover, several studies (Mowery et al. 1998; Sampson 2007; Petruzzelli 2011; Lin et al. 2012) established an inverted U-shape relationship between technological proximity and international collaboration outcome. We, therefore, include the square term of technological proximity ($\boldsymbol{Prox}^2$).

5.3.2) Technological specialization

In our analysis of R&D collaboration, we include technological specialization as a measure of the burden of knowledge. Technological specialization refers to the concentration of patents within specific technological fields, indicating the degree to which countries focus their innovation activities on a narrow range of sectors. Hence, in our methodological framework, we use the average degree of specialization ($Tech.Spec_{av_{ijst}}$) between the dyad countries to account for this factor. Considering the phenomenon of R&D collaboration, technological specialization is one of its relevant drivers (De Prato & Nepelski, 2012). Moreover, Moaniba et al. (2019) found that countries need to concentrate their innovation activities within a narrow scale of technological domains to enhance their innovation performance and improve their economic efficiency. Moreover, Chen et al., (2011) argued that technological competency and the life cycle of potential partners have an essential role in forming partnerships and alliances. We compute each country's technological specialisation degree using a Herfindhal index (see Appendix C).

5.3.3) Control variables

According to the Schumpeterian hypothesis on the relation between country size and innovation (Inyoung, 2020), many studies found that the economic size of a country facilitates R&D collaborations and increases the attractiveness of collaborative inventions (De Prato and Nepelski, 2012; Picci, 2011; Guellec and Van Pottelsberghe, 2001). However, we do not control for country dyad *economic size*[9] as it is highly correlated (0.85) with our primary variable of interest, "Broadband penetration", which would create multicollinearity issues. In fact, through infrastructure investment and technological advancement, larger economies tend to have higher levels of broadband penetration, and smaller economies tend to have lower levels of broadband penetration (Atif et al., 2012; Choiand Yi, 2018).

Instead, we control for the level of technological endowment by using the research intensity. Research intensity is represented by R&D expenditures as a percentage of GDP (Guellec & van Pottelsberghe, 2001). In this study, the *research intensity* of dyad countries ($R\&D\ Int_{t-1}$) is calculated by taking the average R&D intensity of country i and country j. Subsequently, as current collaborations ($Co-inventions_t$) are influenced by previous collaborations, we include past collaboration ($Co-inventions_{t-1}$) in our specification model by including the one-year lag of co-inventions.

Apart from all the above reported variables, we also include a series of calendar dummies (t) in our econometric specifications to avoid unobserved heterogeneity in our data panel. We use the one-year lagged variables research intensity to consider lagged effects and avoid potential endogeneity problems. The statistical details of all our variables are reported in Table 1.

Table 1. Descriptive statistics

Variable name	Obs	Mean	Std.Dev.	Min	Max
Co-inventions	19152	11.23	28.60	0	384
Coll_Con.	19152	.59	1.28	0	10.71
BB. pen.	19152	21.44	11.83	0	43.44
Tech. prox.	19152	.74	.19	.04	1
Tech. spec.	19152	.07	.06	.01	.29
R&D int.	19152	6.87	2.29	2.90	16.96
Priority years	19152	2007.50	4.61	2000	2015
Techno. area	19152	4	2	1	7

Source: Authors' own elaboration.

[9] Economic size is measured by the average of GDP in millions dollar of the dyad countries,

We do not detect any problem of multicollinearity based on the results of variance inflation factors (VIF) for the independent variables and correlation matrix (Table A.1 in Appendix A)

5.4) Econometric specifications

In this section, we are aiming to estimate the production function of technology collaboration. Our dependent variable is the number of co-inventions ($Co - inventions_{st}$) by the country dyads per technology area, which is, by definition, a count variable. Since the econometric literature provides us with numerous models that deal explicitly with count outcomes, in this paper, we will estimate two "count" models: the Poisson Regression Model (PRM)[10] and the Negative Binomial (Negbin), which is an extension of the Poisson that permits inequality of mean and variance, and it is also a robust estimation technique. A simple linear regression model could be biased, inefficient and inconsistent when the outcome is a discrete variable (Chen, 2014; Long and Freese, 2014).

The simple Poisson regression model (PRM) is the most basic econometric model where the mean of the distribution is a function of the independent variables, and the conditional mean of the outcome is equal to the conditional variance. Moreover, as the Poisson model is in the linear exponential family, the estimators remain consistent on the condition that the mean of dependent variable is specified correctly.

However, when dealing with panel data, the conditional mean differs across individuals, leading to unobserved heterogeneity. In general, failing to account for heterogeneity may lead to "overdispersion", i.e. conditional variance exceeds conditional mean (Winkelmann and Zimmermann, 1995; Cincera, 1997). Therefore, the Poisson model might not fit given the equality between its two first moments, as its estimates might be consistent but inefficient, and the standard errors will be biased downward,resulting in spuriously large z-values. Besides, a critical hypothesis of a Poisson process is that events are independent; meaning that when an event occurs it does not impact the probability of an event occurring in the future, which is not the case in our study as past collaborations influence current collaborations. Hence, we explore a more general econometric model, the Negative Binomial (NegBin), an extension to the Poisson that permits inequality of mean and variance and is also a robust estimation technique (see Appendix B).

In light of the above, the production function of technology collaboration between countries takes the following form:

[10] Ding et al. 2010 used a Poisson model to examine how the Broadband adoption influences collaboration.

$$Co-inventions_{ijst} = \exp\Big(\alpha + \beta_1 BB\ Pen_{\ av_{ij(t-1)}} + \beta_2 BB\ Pen^2_{\ av_{ij(t-1)}} + \beta_3 BB\ Pen_{\ av_{ij(t-1)}} * Coll\_Con_{ijt} + \beta_4 R\&D.Coll_{ijst-1} + \beta_5 Prox_{ijst} + \beta_6 Prox^2_{ijst} + \beta_7 Spec_{av_{ijst}} + \beta_8 R\&D\ Int_{ij(t-1)}\Big) + t + \varepsilon_{ijst}$$

To estimate the functions described above, we employ regression analysis with fixed effects to account for any country-dyad-specific omitted variables that do not change over time. In addition, we use robust standard errors clustered within country-dyad to address the significant variation in the dependent variable "*Co-inventions*" and account for heteroskedastic errors, as detected by additional testing (Kleis, 2012). Our analysis incorporates a one-year time lag model to account for any time delay between collaboration and the independent variables. This allows us to capture the potential lagged effects of the independent variables on collaboration.

5.5) Econometric analyses

To select the appropriate model, we conducted fixed effect regressions using three specifications: Poisson, Negative Binomial, and Ordinary Least Squares (OLS). The results were directionally consistent for the negative binomial but not significant at the usual level for Poisson and OLS (Table D.1). Moreover, based on the likelihood ratio test (Gof), the negative binomial model outperformed both the Poisson and OLS models in terms of goodness of fit and model selection (TableD.2).

The overdispersion test results in the appendix Figure D.1.2 reveal the presence of significant overdispersion in the *Co-inventions* data, conditional on Broadband penetration ($P > |t| = 0.000$). This indicates that the variance of the Co-inventions is larger than what would be expected under a Poisson distribution, where the mean and variance are equal. Given this significant overdispersion, it is more appropriate to use an estimation model that can account for the unequal mean and variance. The negative binomial regression model is well-suited for such situations, as it relaxes the assumption of equal mean and variance and provides more robust results (Wooldridge, 2002).

Based on the significant overdispersion in the Co-invention data and the better fit provided by the negative binomial model compared to other models, we select the negative binomial model as our main estimation approach. This choice allows us to analyze the relationship between broadband penetration and R&D collaboration more accurately and obtain more reliable estimations.

5.5.1) Curvilinear relationship test between broadband penetration and international R&D collaboration

Since the linear and the quadratic term of broadband penetration are highly correlated, testing the significance of their coefficients based only on the regression results presented in Table 3 could be misleading. In our Poisson model, only the effect of the quadratic term of broadband penetration is statistically significant, whereas the coefficient of the linear term is not. Consequently, to confirm the existence of an inverted-U shape relationship between broadband penetration and R&D collaboration, we carried out, for each quadratic model (Poisson, Negbin and OLS) presented above, the post-estimation test developed by Lind and Mehlum (2010). They presented a general framework developed by Sasabuchi (1980) to test for a U-shape or an inverted U-shape relationship. It tests the composite null hypothesis (H_0) that the relationship is decreasing at low values of the broadband penetration and increasing at high values (a U-shape relationship where $\beta_1 < 0 \; and \; \beta_2 > 0$) or the monotone relationship between broadband penetration and R&D collaboration. The alternative hypothesis (H_1) consists of testing the presence of an inverted U-shape pattern reflecting that the relationship between broadband penetration and R&D collaboration is increasing at low levels and decreasing at high levels ($\beta_1 > 0 \; and \; \beta_2 < 0$).

In addition, Li (2018) suggested three steps procedure to evaluate an inverted U-shape relationship. First, the coefficient β_2 needs to be significant and of the anticipated sign. Second, the slopes should be significant on both sides of the turning point[11]. Third, the turning point should be located inside the data range (Haans et al. (2016)). Besides, we use the Fieller (1954) confidence interval for the estimated extreme point to ensure that the inverted-U relationship is not only a marginal phenomenon (Benayed and Gasbi, 2020). This test is provided in Stata through the command *utest* and Table 4 presents the results.

Table 2. Test of an inverted-U shape relationship between broadband penetration **and R&D collaboration**

Dependent variable: ***Co-inventions***	**NegBin**
Data range [BB_{min}; ; BB_{max}]	[0 ; 42.217]
Slope at BB_{min}	.0146***
Slope at BB_{max}	-.0092***
Sasabushi-Lind-Mehlum test for inverse U-shaped relationship	2.37***
Extremum point	25.812
95% Confidence interval, Fieller method	[12.619, 36.780]

Source: Authors' own elaboration.
t-statistics are in parentheses

[11] "Turning point" is a point at which the curve attains its maximum or minimum.

The Broadband minimum (BB_{min}) slope is positive and significant at 10% for the Poisson model and at 1% for the Negative Binomial model. On the other hand, the Broadband maximum (BB_{max}) slope is negative and statistically significant at 10% for the Poisson model and at 1% for the Negative Binomial model. This indicates that Lind and Mehlum (2010) test supports an inverted-U shape relationship between broadband penetration and R&D collaboration (Poisson and Negative Binomial). However, it is important to note that this inverted-U shape relationship is insignificant in the OLS model, indicating that the test is not valid for this particular model.

5.5.2) Results

We report the full fixed effect regression model results[12] using the negative binomial in Table 5. These models include control variables separately to mitigate potential biases arising from highly correlated variables.

In the baseline model (1), the quadratic term for broadband penetration is omitted. Contrary to previous research findings, the linear form for broadband penetration is statistically not significant. Only by introducing the quadratic term for broadband penetration in the second model (model 2), this becomes significant at 1% in the negative binomial model and at 10% in the Poisson model. An inverted-U shape requires that the coefficient of the linear term should be positive ($\beta_1 > 0$) while the coefficient of the quadratic term should be negative ($\beta_1 < 0$) (Li (2018)). This is precisely what model 2 shows. The signs of both coefficients are, thus, consistent with the evidence that an inverse-U relationship exists between broadband penetration and R&D collaboration. Hence, the latter model does not confirm our first hypothesis as the relationship between the R&D collaboration and penetration of broadband follows an inverted U-shape curve. This means that at low broadband penetration levels, technology positively influences R&D collaboration through increasing the number of co-inventions between twee collaborative countries. The more institutions (firms, universities, etc.) adopt technology, the more they collaborate by implementing new applications and systems to facilitate communication, the exchange of knowledge and access to new data. However, our specifications show that from a certain level of broadband penetration (${}^{-\beta_1}/_{(2.\beta_2)}$), the penetration of broadband is not positively impacting collaboration as R&D collaboration degree is decreasing with the level of broadband penetration. This means that at a certain level of technology, R&D collaboration requires face-to-face interactions no matter the technological level.

The results from the model (3) support hypothesis 2, which posits that broadband penetration increases the concentration of existing and new R&D collaboration ties. Specifically, the coefficient for the interaction term between broadband penetration and the R&D collaboration concentration index is

[12] Table D.1. and Table D.2. in appendix D report the results using the Poisson regression model

statistically significant and positive at a significance level of 1%. This implies that as countries adopt technology, it stimulates the formation of new collaborative relationships between dyad collaborative countries.

In model (4), the coefficient of R&D collaboration in the previous year (t-1) is positive and statistically significant, indicating that R&D collaborations established in the previous year positively impact R&D collaboration in the current year. This finding suggests a reinforcing effect, where existing collaborations contribute to forming new collaborations and further enhance R&D collaboration. The results from model 5 reveal a significant U-shaped relationship between technological proximity and R&D collaboration. This suggests that the intensity of collaboration decreases for low levels of technological proximity. However, beyond a certain threshold, an increase in technological proximity positively impacts R&D collaboration. In other words, when countries have a limited technological overlap, their collaboration intensity is lower. However as they share a more similar knowledge and technology base, their collaboration intensity increases. This finding underscores the importance of having a sufficient level of technological similarity between collaborating countries to foster effective communication and knowledge sharing, ultimately leading to enhanced R&D collaboration. As expected, technological specialization shows a positive, highly significant coefficient suggesting that country-pairs with a high average specialization level tend to collaborate more intensively in innovation production (model 6). This model supports our first hypothesis, suggesting that the burden of knowledge accumulation positively influences R&D collaboration. In addition, when including technological specialization, the effect of broadband penetration becomes more significant (at the 1 per 100 level). This finding suggests that despite the higher coordination costs associated with knowledge specialization, technology adoption, such as the Internet, helps mitigate these costs by reducing search and communication expenses. As a result, inventors and researchers are encouraged to collaborate more closely, leading to a higher level of co-production of inventions. The results from model 7 indicate that R&D intensity has a significant negative effect on R&D collaboration. This suggests that larger innovative countries tend to collaborate less with other countries. The higher the level of R&D intensity, the lower the likelihood of R&D collaboration. This finding is consistent with previous literature that suggests that countries with high R&D intensity may rely more on their internal capabilities and resources for innovation, leading to reduced collaboration with other countries. In addition, the results reveal that the effect of broadband penetration on R&D collaboration is significantly enhanced in the presence of high R&D intensity. This implies that countries with high R&D intensity experience more significant benefits from broadband penetration in terms of facilitating R&D collaboration.

In the final model (Model 8), which includes all the variables, the relationship between technology adoption and R&D collaboration remains consistent with an inverted U-shape. This suggests that there is an optimal level of broadband penetration that maximizes R&D collaboration, beyond which further adoption may have diminishing returns. The coefficient for broadband penetration remains statistically significant at a level of 1%, indicating that it has a robust and significant impact on R&D collaboration. Furthermore, the inclusion of the other explanatory variables in the model does not alter the significance of the relationship between broadband penetration and R&D collaboration. This suggests that the influence of broadband penetration on collaboration outcomes is independent of the effects of other factors considered in the model.

Table 3: Effect of Broadband penetration on inter. R&D collaboration – Negative Binomial

Dep. Var. *Co-inventions*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BB. Pen. (t-1)	-0.001	0.015**	0.013**	0.012**	0.014**	0.017***	0.019***	0.016***
	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
BB. Pen^2. (t-1)		-3.10^{-3}***	-3.10^{-3}***	$-3.\ 10^{-3}$***	$-3.\ 10^{-3}$***	$-3.\ 10^{-3}$***	$-5.\ 10^{-3}$***	$-5.\ 10^{-3}$***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Coll. Con.			0.001***					$-4.\ 10^{-3}$**
			(0.000)					(0.000)
R&D. Coll (t-1)				0.006***				0.005***
				(0.000)				(0.000)
Tech. Prox.					-1.655***			-0.475
					(0.391)			(0.414)
Tech. Prox^2					1.542***			0.655**
					(0.276)			(0.291)
Tech. Spec.						3.003***		2.374***
						(0.331)		(0.348)
R&D Int.(t-1)							-0.057***	-0.054***
							(0.007)	(0.007)
Constant	2.090***	2.090***	2.076***	2.012***	2.355***	1.922***	2.476***	2.159***
	(0.038)	(0.038)	(0.038)	(0.039)	(0.146)	(0.042)	(0.060)	(0.165)
Obs.	18004	18004	18004	17172	18004	18004	17172	17172
Log likelihood	-34768	-34764	-34240	-33972	-34217	-34211	-34212	-33893

Standard errors are in parenthesis
**** p<0.01, ** p<0.05, * p<0.1*

Subsequently, we analyze the impact of broadband penetration on R&D collaboration within different technology areas. We divide our dyad country sample into seven sub-samples based on the OST7 classification[13]: Electronics, Instruments, Chemicals, Pharmaceuticals, Industrial procedures, mechanical engineering and civil engineering. For each technology area, we estimate a separate negative binomial model. Table 6 illustrates the results of the seven and the results from the previous model for comparison purposes. The findings reveal an inverted U-shaped relationship between broadband penetration and R&D collaboration in Electronics, Instruments, Chemicals, and Pharma (columns 2, 3, 4, and 5). This suggests that as broadband penetration increases, the level of R&D collaboration initially rises, reaches a peak, and then starts to decline. The significant positive coefficients on the linear term

[13] We use the OECD Science and Technology (S&T) field of technology classification sourced from the European Patent Office

of broadband penetration indicate that the initial increase in broadband penetration positively affects R&D collaboration in these sectors. However, no significant impact of broadband penetration on R&D collaboration is observed in industrial procedures, mechanical engineering, and civil engineering (columns 6, 7, and 8). This shows that broadband penetration does not affect R&D collaboration levels in these particular technology areas. Furthermore, compared to the full model (column 1), the results in columns 2, 3, 4, and 5 indicate a significant increase in the linear term of broadband penetration for Electronics, Instruments, Chemicals, and Pharma. This implies that broadband penetration has a stronger positive impact on R&D collaboration in these sectors compared to the overall sample.

Table 4. Effect of Broadband penetration on R&D collaboration per industry – Negative Binomial

Dep. Var. *Co-inventions*	(1) Full	(2) Electronics	(3) Instruments	(4) Chemicals	(5) Pharma	(6) Ind. Proc.	(7) Mech. Eng.	(8) Civil Eng.
BB. pen. (t-1)	0.019***	0.030**	0.051***	0.032**	0.034***	-0.016	-0.012	-0.016
	(0.006)	(0.015)	(0.014)	(0.013)	(0.013)	(0.015)	(0.017)	(0.023)
BB. pen². (t-1)	-5. 10^{-3}***	-5. 10^{-3}*	-0.001***	-0.001***	-0.001**	4. 10^{-3}	-5. 10^{-3}	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D Coll. (t-1)	0.005***	0.004***	0.006***	0.006***	0.004***	0.007***	0.004***	0.013***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
Tech. Proximity	-0.859**	1.637	-2.567*	-0.739	-29.426**	2.206	0.501	0.993
	(0.401)	(1.183)	(1.384)	(1.210)	(13.497)	(1.729)	(0.917)	(1.087)
Tech. Proximity²	0.920***	-0.261	1.630*	1.254	16.277**	-0.741	0.518	-0.154
	(0.282)	(0.792)	(0.893)	(0.814)	(7.328)	(1.142)	(0.706)	(0.889)
Tech. Spec.	2.160***	10.270***	2.335	4.729***	-0.964	9.247***	8.368***	3.797***
	(0.334)	(1.784)	(1.519)	(1.214)	(1.003)	(3.259)	(1.814)	(1.203)
RD Int. (t-1)	-0.057***	-0.107***	-0.077***	-0.037**	-0.027	-0.082***	-0.033	-0.033
	(0.007)	(0.017)	(0.017)	(0.017)	(0.017)	(0.020)	(0.021)	(0.024)
Constant	2.333***	0.804	3.853***	2.047***	15.974**	1.360*	1.582***	1.110***
	(0.161)	(0.500)	(0.588)	(0.487)	(6.224)	(0.726)	(0.387)	(0.415)
Obs.	18004	2636	2652	2581	2623	2623	2508	2381
Log likelihood	-33893	.-5761	-5043	-5414	-5489	-4550	-3985	-3255

Standard errors are in parenthesis
****p<0.01, **p<0.05, *p<0.1*

To further explore the relationship between broadband penetration and R&D collaboration in specific technology areas, we also examine the industrial procedures, mechanical engineering, and civil engineering models without the square term to test for a linear relationship. The results are presented in Table 7. The findings indicate a positive linear relationship between broadband penetration and R&D collaboration in the Civil engineering sector. This suggests that as broadband penetration increases, the level of collaboration in Civil engineering also increases linearly. However, for the Industrial procedures and Mechanical engineering sectors, we do not observe a significant impact of broadband penetration on R&D collaboration. This implies that the relationship between broadband penetration and collaboration in these sectors may not follow a linear pattern either.

These results suggest that the electronics, instruments, chemicals and pharmaceuticals sectors have derived substantial benefits from broadband penetration in R&D collaboration. In contrast, the impact of broadband penetration is less pronounced in the industrial procedures and mechanical engineering sectors. The positive linear relationship observed in civil engineering highlights its unique response to broadband penetration compared to other sectors. These findings align with the research conducted by Wernsdorf et al. (2020), which also highlighted the more substantial effect of broadband penetration in fields where knowledge is easier to codify, such as Instruments and Electronics.

Table 5. Effect of Broadband penetration on R&D collaboration industrial procedures, mechanical engineering and civil engineering

	(1) Ind. Proc.	(2) Mech. Eng.	(3) Civ. Eng.
BB. pen. (t-1).	-0.007	0.002	0.023**
	(0.006)	(0.007)	(0.010)
Constant	2.736***	2.201***	1.689***
	(0.128)	(0.142)	(0.140)
Obs.	2623	2508	2381
Log Likelihood	-3287	-4018	-4595

Standard errors are in parenthesis
**** p<0.01, ** p<0.05, * p<0.1*

5.5) Robustness Checks

In this section, we conduct three additional estimation analyses to validate the robustness of our earlier findings regarding the inverted U-shaped relationship between broadband penetration and R&D collaboration.

First, we divide our data into two subsamples based on broadband penetration: one with broadband penetration lower than 27 subscriptions per 100 inhabitants and the other with broadband penetration higher than 27 subscriptions per 100 inhabitants. Using fixed-effects negative binomial estimation, we examine the impact of broadband penetration on collaboration in each subsample. The results (Appendix Table E.1.) reveal that in the subsample with lower broadband penetration, broadband penetration has a significant positive impact at a level of 1% on R&D collaboration. Conversely, in the subsample with higher broadband penetration, broadband penetration has a significant negative (or nonsignificant) impact at a level of 10% on collaboration. These findings confirm the presence of an inverted U-shaped relationship, wherein the effect of broadband penetration initially increases until reaching a peak, after which it starts to decrease.

By conducting this robustness analysis, we provide further evidence supporting an inverted U-shaped relationship between broadband penetration and R&D collaboration. These findings highlight the importance of reaching an optimal level of broadband penetration to maximize collaboration outcomes.

Second, we conduct a falsification test further to confirm the effect of broadband penetration on R&D collaboration. The test involves running a fixed-effects negative binomial regression where the dependent variable "Co-inventions" is lagged by one, two, and three years. We aim to examine whether future broadband penetration levels influence past R&D collaboration by lagging the dependent variable. If there is a significant effect, it would suggest a causal relationship between broadband penetration and collaboration. However, if the results do not indicate any significant effect when the dependent variable is lagged, it would support the curvilinear relationship between broadband penetration and collaboration.

The results of the falsification test (Appendix Table E.2.) do not show any significant effect of Broadband penetration when the dependent variable "Co-inventions" is lagged. This finding suggests that future broadband penetration levels do not influence past R&D collaboration. This result further reinforces a curvilinear relationship between broadband penetration and collaboration, supporting our earlier findings.

Third, we explore an alternative measure of broadband penetration, using Internet usage ($Net\ Usage$) as a proxy, to examine its impact on R&D collaboration. We employ fixed-effects negative binomial models, similar to previous analyses, including the new variable.

To incorporate Net Usage into our specification model, we calculate the average share of internet users in the total population of the dyad countries i and j ($net\_usage_{av_{t-3}} = (net\_usage_{i_{t-3}} + net\_usage_{j_{t-3}})/2$). Additionally, we include the square of the average share of Internet users, considering the inverted U-shaped relationship between Internet usage and R&D collaboration. It is important to note that Internet access predates broadband, as it was introduced in early 1994, while broadband emerged in the early 2000s. Internet access refers to entities to connect to the Internet, regardless of the type and the speed of the connection.

The results of the models are presented in Appendix Table E.3. and Table E.4. Overall, the findings confirm our main results, indicating that the relationship between broadband penetration and R&D collaboration follows an inverted U-shape pattern regardless of the specific measure used. This suggests that further increases in broadband penetration beyond a certain threshold may not yield significant additional benefits in R&D collaboration. By considering alternative measures of broadband penetration, we provide robustness to our findings and emphasize the consistent nature of the inverted U-shape relationship. These findings have relevant implications for policymakers and organizations seeking to optimize their strategies for fostering R&D collaboration in the digital age.

6 Discussion and conclusion

This paper examines collaborations across 19 OECD countries for 2000-2015 using patent data from the European Patent Office (EPO) Worldwide Patent Statistical Database 2019.

Among the main findings for our sample, the association between R&D collaboration and broadband penetration is a nonlinear inverted U-shaped relationship. This U-shaped relationship between broadband penetration and R&D collaboration suggests that at low technology levels, technology positively influences the degree of R&D collaboration since many institutions (firms, universities, etc.) are increasingly using new applications and systems that facilitate communication, the exchange of knowledge and the access to new data. As from a certain level of broadband penetration, technology does not boost any more R&D collaboration as partnership ties are already formed. At this stage, face-to-face interaction is required to have a smooth collaboration to facilitate the sharing of tacit knowledge.

Previous research has demonstrated a significant positive between technology adoption and collaboration, specifically across multiple universities (Agrawal and Goldfarb (2008), Ding et al. 2010, Winkler et al. (2011), Forman & van Zeebroeck (2012)). Technology has its most significant impact on co-authorship and not on individual productivity. Notably, technology may provide a higher advantage in the social sciences as researchers can easily collaborate at a distance (Winkler et al. 2010 & Ding et al. 2010). Nevertheless, Gray et al. (2015), showed that Internet adoption did not reduce the importance of face-to-face interaction and may not lower the benefits from co-location between R&D activities and manufacturing. Lastly, Kleis (2012) wrote, "... *information technology contributes to the firm innovation process by enabling innovation knowledge management, innovation production, and external innovation collaboration. The end result is a collaborative innovation process, enabled through IT, that creates new value-added innovations in a productive manner*" (Kleis et al., 2012, p.46).

The current research suggests that technology, proxied by broadband penetration, may boost R&D collaboration. Indeed, telecommunications, e-mail systems and corporate IP networks facilitate the transfer of data and knowledge between collaborators (Klies et al., 2012). Rice (1994) showed that electronic mail applications is an effective communications and information sharing tool between agents in an R&D network and can complement face-to-face communication. The study shows that technological specialization increases the significant effect of broadband penetration on collaboration. It indicates that countries with a high degree of technological specialization tend to collaborate more when they adopt technology. In addition, our main specifications confirm the U-shape relationship between technological proximity and R&D collaboration and show that even when two countries are technologically close, technology's effect remains significant. Focusing on within-firm industry collaborations, Forman and van Zeebroeck (2012) found that Basic Internet only increased collaborations of research teams sharing the same technology base rather than collaborations across specialized teams.

Furthermore, these findings suggest that broadband penetration is crucial in improving the concentration of R&D collaboration ties. By reducing transaction and coordination costs, broadband penetration enables countries to establish closer and more focused collaborative relationships with their counterparts. The positive dynamics of technology, particularly in terms of cost reduction, create an environment conducive to the formation of concentrated and impactful R&D collaborations. In addition, the positive and significant coefficient of R&D collaboration in t-1 underlines the importance of past collaborations in shaping current collaboration patterns. Collaborations established in the previous year provide a foundation for knowledge sharing, resource pooling, and joint research efforts, fostering new collaborations and facilitating ongoing R&D collaboration.

The sectorial results show that the electronics, instruments, chemicals and pharmaceuticals sectors have derived substantial benefits from broadband penetration regarding R&D collaboration. However, the impact of technology adoption is less pronounced in the industrial procedures and mechanical engineering sectors. The positive linear relationship observed in civil engineering highlights its unique response to broadband penetration compared to other sectors. These findings emphasise the importance of considering sector-specific dynamics when examining the relationship between broadband penetration and R&D collaboration. Similarly, Rosenblat and Mobius (2004) found that, as communication costs fall, researchers in economics seek to collaborate with distant colleagues with the same interests.

Based on our empirical results, the following policy recommendations can be drawn. First, policymakers should encourage broadband penetration up to the point where it maximizes R&D collaboration. Beyond a certain threshold, additional investment may not translate into a significant benefit in terms of R&D collaboration. Second, when broadband penetration reaches its maximum level, policymakers should explore other channels for R&D collaboration. This could involve leveraging communication technologies such as video conferencing systems and virtual collaboration platforms to enhance collaboration without relying solely on broadband penetration. In addition, the COVID-19 pandemic highlighted the essential role of the Internet in sustaining economic activity through teleworking, virtual research and e-learning. Policymakers should heed this experience and recognize the importance of a robust broadband infrastructure for the resilience and continuity of different sectors. Finally, policymakers should address the obstacles and challenges that may arise with increased broadband penetration, focusing on information security and intellectual property protection issues. Furthermore, the sectoral insights can help shape targeted policies and initiatives to promote successful sectoral collaboration.

We conclude by discussing the important limitations of our study. First, we use only aggregated data at a country-level by taking into consideration industry-sector specifications. It is important to deepen this analysis by looking at a more granular level by identifying which firms are collaborating the most and benefit from technology. Second, while our study finds that over the last 15 years, there has been an inverted U-shaped relationship (Increase/ Decrease) between broadband penetration and R&D collaboration, our study is unable to show anything about the extent to which this relationship will continue or whether at higher levels of broadband penetration this association will be U-shaped. We leave these puzzles for future research.

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9 Appendix

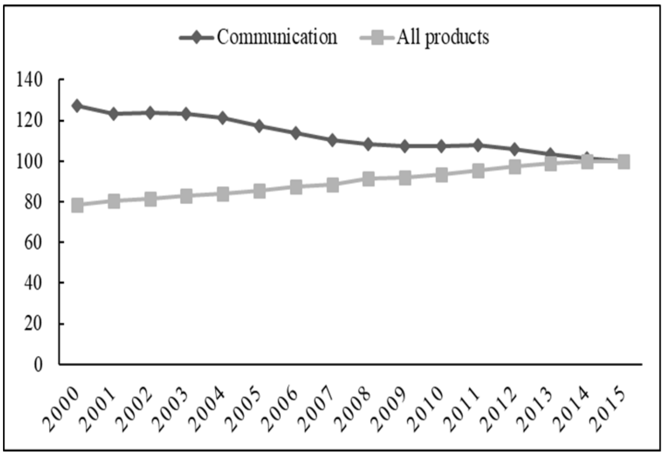
Appendix A: Descriptive statistics, figures and tests

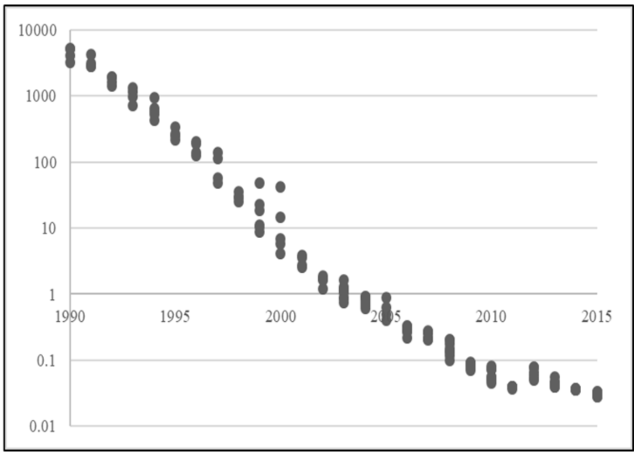
Table A.1. Collinearity diagnostics and correlation

			Correlations				
	Variables	VIF	1	2	3	4	5
1	Co-inventions		1				
2	BB penetration	1.01	0.018*	1			
3	Tech. Proximity	1.27	0.275*	-0.0670*	1		
4	Tech. Spec.	1.27	0.071*	0.0372*	0.4579*	1	
5	R&D Int.	1.00	0.025*	0.0248*	0.0171*	0.0367*	1
	VIF Mean	1.14					

Source: Authors' own elaboration.

Figure A.1. Consumer price indices of all products and ICT goods and services14, 20 OECD countries, 2000-2015 and Cost of storage (Log scale and Gb) Index 2015 = 100[15]





[14] Source OECD Consumer Price Inc-dices (CPIs) Database (June, 2021)
[15] "Disk drive prices 1955-2021", www.jcmt.net/deskprice.htm, June, 2021

Appendix B: Poisson regression model (PRM) and Negative Binomial regression model (NegBin)

Poisson regression model (PRM):

The simple Poisson regression model (PRM) is the most basic econometric model where the mean of the distribution is a function of the independent variables and the conditional mean of the outcome is equal to the conditional variance. Moreover, as the Poisson model is in the linear exponential family, the estimators remain consistent on condition that the mean of dependent variable is properly specified.

$$\lambda_{ijt} = E(y_{ijt}|x_{ijt}) = \exp(x_{ijt}\beta)$$

Where y_{ijt} is a count variable that represents the number of co-inventions by country i and country j at time t. This discrete variable has a Poisson distribution with parameter $\lambda_{ijt} > 0$ and $P(y_{ijt}|\lambda_{ijt}) = \frac{e^{-\lambda_{ijt}}\lambda_{ijt}}{\lambda_{ijt}!}$ where $y_{ijt} = 1,2,3, \dots$

This model suggests that conditional mean is equal to the conditional variance, i.e. $E(y_{ijt}|x_{ijt}, \beta) = V(y_{ijt}|x_{ijt}, \beta) = \lambda_{ijt}$. Therefore, after including all explanatory variables, our estimated Poisson model has the following form:

$$\begin{aligned} Co - inventions_{ijst} &= \exp\Big(\alpha + \beta_1 BB\ Pen_{\ av_{ij(t-1)}} + \beta_2 BB\ Pen^2{}_{av_{ij(t-1)}} + \beta_3 BB\ Pen_{\ av_{ij(t-1)}} * Coll\_Con_{ijt} \\ &+ \beta_4 R\&D.Coll_{ijt-1} + \beta_5 Prox_{ijst} + \beta_6 Prox^2_{ijst} + \beta_7 Spec_{av_{ijst}} + \beta_8 R\&D\ Int_{ij(t-1)}\Big) + t \\ &+ \varepsilon_{ijst} \end{aligned}$$

However, when dealing with panel data the conditional mean differs across individuals leading to unobserved heterogeneity. In general, failing to account for heterogeneity may lead to “overdispersion”, i.e. conditional variance exceeds conditional mean (Winkelmann and Zimmermann, 1995). Therefore, the Poisson model might not fit given the equality between its two first moments as its estimates might be consistent but inefficient and the standard errors will be biased downward resulting in spuriously large z-values. Besides, a critical hypothesis of a Poisson process is that events are independent; meaning that when an event occurs it does not impact the probability of an event occurring in the future, which is not the case in our study as current collaborations are influenced by past collaborations. Hence, we implement a more general econometric model which is the Negative Binomial (NegBin) which is an extension to the Poisson that permits inequality of mean and variance and is also a robust estimation technique.

Negative Binomial regression model (NegBin)

To consider unobserved heterogeneity, and hence allowing the conditional variance to exceed the conditional mean, the Poisson model is extended by including individual specific effects ε_{ij} into the λ_{ijt} parameters:

$$\widetilde{\lambda_{ijt}} = \exp\,(x_{ijt}\beta + \varepsilon_{ij})$$

Where ε_{ij} is a random error[16] that is assumed to be uncorrelated with the independent variables. In this case, the conditional mean is still λ_{ijt}, but the variance will be greater because of the error term ε_{ij}. According to Winkelmann and Zimmermann (1991), the relationship between the variance and the mean of the negative binomial (Negbin) model is set as:

$$V(y_{ijt}|x_{ijt}) = (\sigma^2 - 1)E(y_{ijt}|x_{ijt})^{k+1} + E(y_{ijt}|x_{ijt})$$

Where σ^2 represents the dispersion parameter and k is the non-linearity in the variance-mean relationship. These two parameters are of course independent of β. Depending on the values of σ^2 and k we get the following models: when σ^2=1 we get the Poisson model, negative binomial models such as Negbin I when $\sigma^2 > 1$ and $k = 0$, and Negbin II when $\sigma^2 > 1$ and $k = 1$. Note that the model parameters are estimated by the maximum likelihood estimation method.

The negative binomial model has the advantage of correcting several sources of poor fit that are related to the Poisson distribution; namely, the variance of the Negbin distribution is larger than the variance of the Poisson distribution for a given mean, and thus Negbin allow for overdispersion.

The estimated Negative binomial model has the following form:

$$\widetilde{\lambda_{ijt}} = E(y_{ijt}|x_{ijt}) = \exp\,(\alpha + X_{ijt}\beta \quad + \varepsilon_{ij})$$

In light of the above, the production function of technology collaboration between countries takes the following form:

$$\begin{aligned} Co - inventions_{ijst} \\ &= \exp\Big(\alpha + \beta_1 BB\ Pen_{\ av_{ij(t-1)}} + \beta_2 BB\ Pen^2{}_{av_{ij(t-1)}} + \beta_3 BB\ Pen_{\ av_{ij(t-1)}} * Coll\_Con_{ijt} \\ &+ \beta_4 R\&D.Coll_{ijst-1} + \beta_5 Prox_{ijst} + \beta_6 Prox^2{}_{ijst} + \beta_7 Spec_{av_{ijst}} + \beta_8 R\&D\ Int_{ij(t-1)}\Big) + t \\ &+ \varepsilon_{ijst} \end{aligned}$$

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[16] You can think of ε as either the combined effects of unobserved variables that have been omitted from the model or as another source of pure randomness

Appendix C:

Technological proximity

We calculated this indicator based on Jaffe (1986) and MacGarvie (2006) formula that uses the share of patent portfolios that fall in the same technological classes. More specifically, within our panel dataset, the technological proximity between country i and country j is computed as:

$$Prox_{ijst} = \frac{\sum_{k=1}^{K} P_{ikst} P_{jkst}}{\sqrt{(\sum_{k=1}^{K} P_{istk}^2)(\sum_{k=1}^{K} P_{jstk}^2)}}$$

Where P_{jkt} is the total number of patents of country i in 4-digit IPC class k and K is the total number of technological classes considered at priority year t. $Prox_{ijt}$ takes values between 0 and 1 for all dyad countries (individuals). It is equal to one when both countries have the same share shares of patent applications across technological classes and it tends to zero when both vectors of patents are totally different. In other words, the more the value of this indicator is close to 1, the closer are the dyad countries and the more the indicator is close to 0, the farther the dyad countries.

Technological specialization

We compute the degree of technological specialization of each country using a Herfindhal index. The Herfindahl index is given by:

$$H_{ist} = \sum_{c=1}^{C} s_{ict}^2$$

Where:

- $s_{ict} = N_{ict}/N_{it}$ is the share of patents applied for by country i in period t that fall in the j^{th} technological class
- N_{ict} is the number of patents applied for by country i in period t that fall in the c^{th} technological class
- N_{it} is the number of patents falling into C class

The resulting score ranges between 1, if all patents are concentrated in a single class, and 0 if all patents belong to different classes. To account for the average degree of specialization ($Spec_{av_{ijst}}$) we take the average of Herfindahl indices H_{ist} and H_{jst} of country i and j respectively.

Appendix D: Regression analysis

Table D.1. Analysis of parametric estimates

Dep. Var. *Co-inventions*	NegBin (C)	NegBin (D)	Poisson (A)	Poisson (B)	OLS (E)	OLS (F)
BB pen. (t-1)	-0.001	0.015**	-0.002	0.023	-0.065	0.098
	(0.003)	(0.006)	(0.007)	(0.015)	(0.085)	(0.131)
BB pen^2. (t-1)		-0.0003***		-0.0005*		-0.003
		(0.000)		(0.000)		(0.002)
Constant	2.090***	2.090***			10.213***	10.185***
	(0.038)	(0.038)			(0.321)	(0.317)
Obs.	18004	18004	18004	18004	18669	18669
R^2/Log LL	-32470	-32466	-35378	-35342	0.004	0.005

Table D.2. Criteria for Assessing Goodness of Fit "*Gof*"

Criterion	Model		
	Poisson	***NegBin***	***OLS***
Log Likelihood (higher is better)	-37370.53	-34251.14	-62802.95
AIC (smaller is better)	74775.06	68538.29	125641.9
BIC (smaller is better)	74907.63	68678.66	125782.9

Source: Authors' own elaboration. Data processed within Stata 15.1

The test results, in table D.2, underline that both the Poisson and Negative Binomial models better fit the data compared to the OLS regression. The likelihood ratio test statistics, ($LR_{Poisson-OLS} = -50964.49\ and\ LR_{NegBin-OLS} = 57203.27$), are significantly higher than the theoretical threshold value ($\chi^2_{2\alpha;2} = 4.605$). Furthermore, when comparing the Poisson model and the Negative Binomial model, the Negative Binomial model exhibits a higher log-likelihood ($LL_{Poisson} = -37370.53 < LL_{NegBin} = -34251.14$), indicating a better fit. These findings are further supported by the information criteria, such as AIC and BIC, which are the lowest for the Negative Binomial model. This suggests that the Negative Binomial model outperforms both the Poisson and OLS models in terms of goodness of fit and model selection.

Figure D.1. Overdispersion test

Overdispersion test (H0: equidispersion) Number of obs = 19,152

Co-inventions	Coef.	Std.Err.	t	P>t	[95%Conf.	Interval]
uhat	6.377	0.290	22.020	0.000	5.809	6.944

Table D.3. Effect of Broadband penetration on international R&D collaboration – Poisson

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BB. Pen. (t-1)	-0.002	0.023	0.023	0.019**	0.024	0.027**	0.027*	0.029***
	(0.007)	(0.015)	(0.016)	(0.008)	(0.015)	(0.013)	(0.015)	(0.003)
BB. Pen^2. (t-1)		-5.10^{-3}*	-5.10^{-3}*	-4.10^{-3}***	-5.10^{-3}*	-5.10^{-3}**	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Coll. Con. (t-1)			-3.10^{-3}					1.10^{-3}
			(0.000)					(0.000)
R&D. Coll (t-1)				0.004***				0.003***
				(0.000)				(0.000)
Tech. Prox.					-2.149***			-0.191
					(0.671)			(0.281)
Tech. Prox^2					1.440***			0.240
					(0.493)			(0.189)
Tech. Spec.						6.767***		5.747***
						(0.931)		(0.263)
R&D Int.(t-1)							-0.097***	-0.077***
							(0.012)	(0.005)
Obs.	18004	18004	18004	17172	18004	18004	17172	17172
Log Likelihood	-37406	-37371	-37365	-34396	-37337	-36968	-35017	-34039

Standard errors are in parenthesis

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

Table D.4. Effect of Broadband penetration on international R&D collaboration per technology area – Poisson

Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Co-inventions	Full	Electronics	Instruments	Chemicals	Pharma	Ind. Proc.	Mech. Eng.	Civil Eng.
BB. Pen. (t-1)	0.013***	0.007	0.033***	0.012	0.014	0.011	0.009	-0.014
	(0.004)	(0.008)	(0.008)	(0.007)	(0.009)	(0.007)	(0.009)	(0.013)
BB. Pen^2. (t-1)	-0.000***	0.000	-0.000***	-0.000**	-0.000**	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D. Coll.(t-1)	0.003***	0.002***	0.002**	0.003***	0.002***	0.003***	0.001	0.005**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
Tech. Prox.	-0.126	4.374**	-2.779**	0.242	-22.453	1.950	0.239	1.121
	(0.575)	(1.735)	(1.193)	(1.482)	(14.320)	(1.844)	(0.799)	(1.132)
Tech. Prox^2	0.192	-2.228**	1.531**	0.396	12.550	-0.787	0.513	-0.473
	(0.400)	(1.105)	(0.777)	(0.970)	(7.757)	(1.188)	(0.577)	(0.932)
Tech. Spec.	5.841***	17.084***	1.891	4.551***	-1.226	8.447**	8.233***	3.347**
	(0.730)	(2.795)	(1.868)	(1.526)	(1.332)	(3.472)	(1.530)	(1.341)
R&D Int.(t-1)	-0.063***	-0.110***	-0.074***	-0.023	-0.023	-0.064***	-0.069**	-0.083***
	(0.010)	(0.025)	(0.019)	(0.019)	(0.018)	(0.021)	(0.031)	(0.027)
Obs.	17172	2517	2532	2461	2503	2504	2388	2267
Log Likelihood	-34068	-5911	-4952	-5392	-5469	-4401	-3867	-3180

Standard errors are in parenthesis

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

Appendix E: Robustness checks

Table E.1. Effect of Broadband penetration on inter. R&D collaboration – Negative Binomial

Dep. Var. *Co-inventions*	BD. pen. < 27 subscrip. Per 100 inhab.		BD. pen. > 27 subscrip. Per 100 inhab	
	(1)	(2)	(3)	(4)
BB. Pen. (t-1)	0.008*	0.010**	-0.011*	-0.011*
	(0.005)	(0.005)	(0.006)	(0.006)
Co-inventions (t-1)		0.004***		0.003***
		(0.000)		(0.000)
Tech. Proximity		-0.099		0.447
		(0.672)		(0.620)
Tech. Proximity^2		0.569		0.260
		(0.461)		(0.436)
Tech. Spec.		0.009		3.005***
		(0.475)		(0.684)
RD Int. (t-1)		-0.086***		-0.013
		(0.012)		(0.010)
Constant	2.533***	2.623***	3.024***	2.195***
	(0.058)	(0.277)	(0.150)	(0.281)
Obs.	9629	9629	7726	7726
Pseudo R^2	-16296	-16188	-13951	-13871

Standard errors are in parenthesis
**** p<0.01, ** p<0.05, * p<0.1*

Table E.2. Falsification test – Negative Binomial

Dep. Var. *Lagged Co-inventions*	(1) One year lag	(2) Two years lag	(3) Three years lag	(4) Three years lag
BB. pen. (t-1)	0.008	0.002	-0.005	0.000
	(0.006)	(0.006)	(0.006)	(0.006)
BB. pen^2. (t-1)	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Tech. Proximity				-1.504***
				(0.447)
Tech. Proximity^2				1.230***
				(0.317)
Tech. Spec.				2.238***
				(0.401)
RD Int. (t-1)				-0.039***
				(0.007)
Constant	2.000***	2.030***	2.081***	2.561***
	(0.039)	(0.043)	(0.051)	(0.179)
Obs.	17992	17145	16072	16072
Pseudo R^2	-33967	-31899	-29560	-29514

Standard errors are in parenthesis
**** p<0.01, ** p<0.05, * p<0.1*

Table E.3. Effect of Internet Usage on R&D collaboration – Negative Binomial

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Net Usage (t-1)	--2.10^{-3}	0.009***	0.008***	0.007***	0.010***	0.009***	0.008***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Net Usage ^{2} (t-1)		-1.10^{-3}***	-1.10^{-3}***	-1.10^{-3}***	-1.10^{-3}***	-1.10^{-3}***	-1.10^{-3}***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tech. Coll (t-1)			0.006***				0.005***
			(0.000)				(0.000)
Tech. Proximity				-1.591***			-0.798**
				(0.390)			(0.401)
Tech. Proximity^2				1.489***			0.870***
				(0.276)			(0.282)
Tech. Spec (Av.)					3.039***		2.184***
					(0.331)		(0.334)
R&D Int. (log av. in t-1)						-0.053***	-0.049***
						(0.007)	(0.007)
Constant	2.086***	1.920***	1.862***	2.200***	1.726***	2.291***	2.123***
	(0.046)	(0.060)	(0.060)	(0.152)	(0.065)	(0.076)	(0.167)
Obs.	18480	18480	18004	18004	18004	18004	18004
Log Likelihood	-34767	-34756	-33968	-34213	-34204	-34213	-33895

Standard errors are in parenthesis
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table E.4. Effect of Internet Usage on R&D collaboration per technology area – Negative Binomial

Dep. Var. *Co-inventions*	(1) Full	(2) Electronics	(3) Instruments	(4) Chemicals	(5) Pharma	(6) Ind. Proc.	(7) Mech. Eng.	(8) Civil Eng.
Net Usage (t-1)	0.008***	0.004	0.031***	0.005	0.013**	0.000	0.003	-0.010
	(0.002)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.010)
Net Usage ^{2} (t-1)	-0.000***	0.000	-0.000***	-0.000*	-0.000***	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tech. Coll (t-1)	0.005***	0.004***	0.006***	0.006***	0.004***	0.007***	0.004***	0.013***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
Tech. Proximity	-0.798**	2.039*	-2.914**	-0.714	-28.128**	1.892	0.352	1.228
	(0.401)	(1.185)	(1.374)	(1.216)	(13.465)	(1.729)	(0.911)	(1.089)
Tech. Proximity^2	0.870***	-0.541	1.806**	1.268	15.488**	-0.510	0.570	-0.354
	(0.282)	(0.794)	(0.887)	(0.818)	(7.312)	(1.142)	(0.705)	(0.889)
Tech. Spec (Av.)	2.184***	10.112***	1.972	4.727***	-1.073	8.773***	8.000***	3.815***
	(0.334)	(1.676)	(1.521)	(1.214)	(1.002)	(3.269)	(1.801)	(1.240)
R&D Int. (log av. in t-1)	-0.049***	-0.101***	-0.055***	-0.025	-0.025	-0.074***	-0.023	-0.047**
	(0.007)	(0.017)	(0.016)	(0.016)	(0.016)	(0.019)	(0.021)	(0.024)
Constant	2.123***	0.536	3.289***	1.833***	15.255**	1.425*	1.550***	1.307***
	(0.167)	(0.503)	(0.587)	(0.498)	(6.213)	(0.738)	(0.413)	(0.455)
Obs.	18004	2636	2652	2581	2623	2623	2508	2381
Pseudo R^2	.z	.z	.z	.z	.z	.z	.z	.z

Standard errors are in parenthesis
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

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