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Unlocking the technological diversification among top R&D performers: the role of the international breadth and depth of inventive activities and technological dissimilarity with foreign R&D host regions

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ABSTRACT

This aim of this paper is to investigate the relationship between the international geographical scope of inventive activities and the technological diversification of top R&D performers into related and unrelated technological fields. Further, this study addresses a critical gap in understanding how specific contextual factors, that is the technology dissimilarity of companies with the foreign R&D host (sub-national) regions, can affect the corporate technological diversification. Employing a survey sample consisting of 1,125 top R&D performers, that have applied for 803,066 priority patent applications over the period of 2000-2018, our empirical analysis, using a fixed-effects panel regression model, unveils significant findings. Firstly, while the breadth in the geographic distribution of foreign inventive activities serves as a catalyst for companies to expand and diversify their patent portfolio, the depth discourages it. Secondly, there is positive and significant relationship between technology dissimilarity and technological diversification. Moreover, we discover that expanding R&D activities into increasing number of foreign locations with a more dissimilar technological base tends to hinder the corporate technological diversification efforts, whereas technological dissimilarity with R&D foreign host regions positively moderates the relationship between the depth of foreign inventive activities and technological diversification, particularly in unrelated domains.

Key-words: top R&D performers; international breadth; international depth; technology dissimilarity, technological diversification, knowledge sourcing.

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1. Introduction

The increasing complexity in products and processes push companies to invest in a wider range of technologies over time and diversify their technological base (Granstrand & Sjölander, 1990; Cantwell and Piscitello, 2000; Breschi et al., 2003). Technological diversification refers to the firm capability to combine and recombine accumulated knowledge into new ideas and expands the existing technological competencies across different technological fields (Garcia-Vega, 2006; Quintana-Garcia and Benavides-Velasco, 2008; Corradini et al., 2016). In imperfectly competitive markets, firms can protect from the risk of imitation by diversifying their technological base and becoming less vulnerable to economic depreciation and obsolescence phenomenon.

According to the organizational learning theory and knowledge-based arguments, technological diversification can feed firm innovativeness and push for more R&D investments, stimulating novel methods, materials and solutions and accelerating the rate of invention, avoid a lock-in effect in a particular technological specialization and promote gains in economies of scope (Granstrand and Oskarsson, 1994; Garcìa-Vega, 2006; Quintana Garcìa and Benavides-Velasco, 2008; Cincera and Ravet, 2014). Furthermore, technologically diversified companies can achieve economy of scale lowering the R&D average costs, exploit learning and experience curve effects and take advantage of speed in R&D (Cantwell and Piscitello, 2000).

Technological diversification can occur in related technological fields, when new technologies, sharing principles of proximity, commonality, and complementarity of knowledge with the previous ones, are recombined through a cross-fertilization process (Breschi et al., 2003), while unrelated technological diversification can be attained by combining knowledge domains that were previously unconnected.

Whereas an extensive theoretical and empirical literature has studied the impact of technological diversification on corporate performance and innovation output (Granstrand, 1998; Gambardella and Torrisi, 1998; Garcìa-Vega, 2006; Miller, 2006; Leten et al., 2007; Quintana Garcìa and Benavides-Velasco, 2008; Chen et al., 2012; Appio et al., 2019; Choi and Lee, 2021), little is known yet about the determinants of technological diversification. A limited number of studies has investigated how the R&D organizational structure of multinational companies could impact the technological diversification, in particular considering the R&D internationalization (Cantwell and Piscitello, 2000; Le Bas and Patel, 2005) and intra-firm R&D networks such as the strength of ties between inventors (Cecere and Ozman, 2014) and the presence of international inventor teams (Damioli et al., 2023). We aim to contribute to this current scant literature by investigating the role of the geographic distribution of cross-border placed inventive activities in shaping the technological diversification patterns of top R&D multinationals across related and unrelated fields. Indeed, despite there is empirical evidence showing that the international expansion of leading R&D performers can enhance their R&D productivity (Cincera and Ravet, 2014), productivity levels (Castellani et al., 2017), product diversification and international performance (Tang et al., 2019), innovation output (Iwasa and Odagiri, 2004; Singh, 2008; Lahiri, 2010; Nieto and Rodriguez, 2011; Rahko, 2016; Zhang et al., 2019; Wen and Zheng, 2020), its impact on technological diversification has still been neglected so far.

In line with a consolidated approach used in IB research (Kafourous et al., 2012; Castellani et al., 2017; Tang et al., 2019), we distinguish between the breadth and depth in the geographic distribution of foreign based inventive activities: breadth pertains to the extent to which companies disperse the R&D activities across multiple foreign locations, whereas depth dimension relates to how intensely companies concentrate their efforts in each foreign location where R&D activities are placed. These two different aspects characterize together the geographic scope of R&D portfolios across different locations and within each of them. Building on the concept of multiple embeddedness of the geographically dispersed companies (Meyer et al., 2011), we suggest that spreading R&D activities can be a means through which to diversify the patent portfolio: the spatial distribution of innovative activities entails the absorption of globally dispersed knowledge and can lead to new combinations, promoting cross-fertilization across different technological fields (Wen and Zheng, 2020). Hence, as starting point of this work, we hypothesize that companies that distribute R&D activities across foreign markets can benefit in terms of increasing innovation capacity and appropriability from a larger and more diverse pool of knowledge, borrowing and exploiting new ideas, know-how and technologies from the different contexts in which they are embodied (Kafouros et al., 2008). Conversely, the depth dimension should weaken companies' ability to diversify their patent portfolios as it may be associated with the access to and exploitation of limited globally dispersed knowledge.

We also want to investigate whether the technological dissimilarity of multi-technology companies with their foreign R&D host locations, that is the difference in their technological bases, can affect their diversification of patent portfolio. This analysis provides an original contribution to the literature that lacks in studying how the contextual factors related to the host locations could enhance firms' ability to diversify their technological base. We argue that increased technological dissimilarity with host locations, i.e. the gap existing in their technology expertise, could encourage the corporate technological diversification as breaking the path of dependency of innovation process (Dosi et al. 1990) requires the absorption of knowledge that is relatively distant compared to the existing knowledge base (Dosso and Vezzani, 2015).

Furthermore, we propose to investigate the role of some moderating forces. First, we question whether the technological dissimilarity with foreign host regions may play a negative moderating role between the breadth of international inventive activities and technological diversification as there could be high costs associated with absorbing knowledge from different locations with different technology base compared to that already available in the organization (Kafouros et al., 2018). Besides, we investigate whether technological dissimilarity is expected to mitigate the adverse impact of the concentration of foreign inventive activities. Specifically, companies with greater technological dissimilarity relative to the host regions are likely to experience lower diminishing returns on their capability to diversify the technologies from the depth of foreign inventive activities.

We estimate these research questions through fixed-effects panel regression model, using a survey sample consisting of 1,125 top R&D performers, which are mainly headquartered across the most developed OECD countries[3] and have applied for 803,066 priority patent applications during the time period from 2000 to 2018 years. Starting from the technology vector of sample companies and exploiting the different levels of the technological classes defined by International Patent Classification (IPC) classification, we derive the entropy measure of technological diversification and distinguish between related and unrelated diversification. We capture the breadth and depth in the geographic distribution of foreign inventive activities considering respectively the number of foreign locations where R&D activities are placed (breadth) and the adjusted Herfindahl index as a measure of geographic concentration (depth). Then, we build a measure of technological dissimilarity relying on the angular separation measure between the companies and the foreign host locations vectors of patent shares across different technological fields. An additional novelty of this paper is also that of conducting a sub-national analysis: following the OECD territorial classification, we take into account the distribution of inventive activities across Territorial Level 2 (TL2) large regions where the sampled companies are based and where knowledge is created. Building upon the literature on economic geography (Jaffe et al., 1993; Audretsch & Feldman, 2004; Iammarino and McCann, 2013), we assume that R&D facilities of multinationals could easily absorb knowledge and technology spillovers and benefit from agglomeration effects unfolding in the regional innovation system hosting them (Criscuolo et al., 2005; Cantwell and Piscitello, 2005). We observe that the breadth of foreign inventive activities across different geographic locations encourages organizations to diversify into both related and unrelated technological fields while the depth discourages it. Secondly, as expected, our results show that technology dissimilarity with R&D host locations fosters the corporate technological diversification. Last, there is a negative/positive moderating role of technological dissimilarity in the relationship between breadth/depth of foreign inventive activities and technological diversification. Furthermore, significant differences emerge when we split our sample between frontier and laggard companies with respect to their main industrial competitor. The paper is organized as follows. In Section 2, we establish the theoretical framework and develop the research hypotheses. Section 3 proceeds with the description of data and the methodology applied. Our findings are detailed in Section 4, while Section 5 provides additional checks and robustness estimates. The last Section concludes with a general discussion on the main findings, contributions, implications and limitations of the analysis and future research.

2. Theoretical framework and research hypotheses development

2.1 Related and unrelated technological diversification

The diversification of corporate technological activity can be defined as the firm ability to extend technological competence into a broader range of technological areas (Granstrand and Oskarsson, 1994). Technological diversification allows companies to enhance their absorptive capacity and resilience in the face of disruptive technological changes incentivizing their long-term survival capability and may allow to enter more easily into a new technological domain, avoiding the negative lock-in effect in single and less profitable technologies (Kim et al., 2021). According to knowledge-based view, adopting technological diversification strategies allows companies to experience a growth in their innovativeness (Wen and Zheng, 2020) and expand upon the knowledge and principles that inform both their products

[3] Top R&D performers from Asian countries have been excluded from this study due to their limited representation in the sample and potentially different technological characteristics compared to those headquartered in the EU and US, as they are highly specialized in ICT technologies (Dernis et al., 2015).

and production methods (Appio et al., 2019). Through the exploitation of the experience curve and learning effects, technologically diversified firms can effectively reduce average R&D costs while simultaneously enhancing their technological knowledge. Additionally, the integration of various technologies, known as the cross-fertilization effect, facilitates the development of new and revolutionary innovations across a wide spectrum of technological domains (Garcìa-Vega M., 2006; Quintana-Garcia and Benavides-Velasco, 2008; Chen et al., 2012).

Related technological diversification occurs when companies exploit the cross-fertilization effect across related technology fields grounded in common scientific principles (Chen et al., 2012). This strategy not only enables firms to enhance their R&D competencies by learning from related technological domains but also reduces R&D unit costs through economies of scale and take advantage of speed in R&D (Cantwell and Piscitello, 2000). Furthermore, it facilitates R&D support across various related technological domains due to the interconnected knowledge base (Breschi et al. 2003; Miller 2006; Chen et al., 2012).

It is well-established that firms are more likely to diversify technologies in related fields rather than unrelated ones, primarily due to the significant transaction and information costs associated with unrelated technological diversification, that could outweigh the benefits (Breschi et al., 2003; Chen et al., 2012). Since it is beyond the scope of the paper to discuss about the trade-off that exists between related and unrelated technological diversification, we want to focus attention on both the strategies. Indeed, our sample consists of large top R&D performers who have fewer constraints on facing the higher costs of unrelated technological diversification, compared to small and medium-sized enterprises that could be more likely to develop related technological capabilities (Corradini et al., 2016).

2.2 The impact of breadth and depth in the geographic distribution of foreign inventive activities on technological diversification

While technological diversification has been acknowledged as a significant characteristic of large multinational corporations with extensive technology portfolios (Zander, 1997; Zander, 1999; Leten et al., 2007), the innovation generation process of multinationals increasingly stems from their cross-border knowledge-generating activities (Dunning and Lundan, 2009). The extensive embedding of multinationals in different local contexts (Meyer et al., 2011) implies that the geographic spread of inventive activities can be regarded as a source of technological diversification: the benefits related to innovation in geographically dispersed R&D subsidiaries can extend to the parent company and have implications on the corporate technological diversification. Indeed, extensive research indicates that companies expanding their research activities across different locations can leverage the cross-fertilization of ideas through knowledge spillovers among subsidiaries and parent companies, leading to increased innovativeness (Almeida and Phene, 2004). The rationale behind this strand of literature is that companies, absorbing and integrating knowledge from their R&D units located in various geographic sites, can manage to combine existing knowledge and ideas with local knowledge of host locations to create novel combinations and further innovation (Singh, 2008). Hence, we support the idea that globally distributed R&D subsidiaries can operate as a source and vehicle of knowledge and technology by leading parent companies towards more exploratory paths of recombinant knowledge through intra MNEs and inter-unit knowledge sharing and transferring mechanism (Zhang et al, 2019). Based on this outlined framework, it can be assumed that R&D distant units, connecting the knowledge and competences of the host context with the internal network of MNEs (Dunning and Lundan, 2009), exert positive spillovers effects to their headquarters and other affiliates facilitating the knowledge recombination and the development of new technologies. Few studies have specifically addressed the dimension of technological diversification for companies that leverage knowledge and technologies from multiple sources. A notable exception is a recent study by Damioli et al. (2023). Analyzing a large sample of 454 multinational enterprises over the period 2007–2014, they have provided evidence for a positive association between the involvement of international inventor teams and both related and unrelated technological diversity. This paper complements this research as we want investigate the potential role of a greater R&D international expansion, i.e. the breadth in the geographical distribution of foreign inventive activities, in shaping the technological diversification across related and unrelated technological domains. We aim to address empirically this issue by testing the following hypothesis:

H1.a The international breadth of inventive activities promotes the corporate technological diversification of top R&D performers.

Conversely, the previous arguments lead us to assume that, as companies increase the concentration of foreign related inventive activities, i.e. the depth in the geographical distribution of such activities in foreign locations, the internal knowledge of the MNEs organization can become more bounded to that of a few foreign locations, thereby limiting their capability to access, integrate and recombine diverse external sources of novel knowledge. In other words, leveraging more in-depth R&D foreign activities can incentivize the path dependency of innovation and the technological specialization, reducing the diversification capabilities. Hence:

H1.b The international depth of inventive activities discourages the corporate technological diversification of top R&D performers.

2.3 The impact of technological dissimilarity with foreign R&D host locations on technological diversification

While prior research has focused largely on the determinants of technological diversification relying only on the organizational attributes of companies, we want to analyze to what extent context-related factors can affect it. Technological diversification can be determined not only by specific firm and industry characteristics that can push for the exploration of new technological opportunities (Pavitt et al. 1989), but also by contextual factors associated with the specific context in which the R&D units are locally embedded. Indeed, according to the knowledge-based theory, companies can be seen as "open system" that incorporate internal and external sources of knowledge. The benefits of geographical distribution of inventive activities across different locations may be contingent on to the distinct knowledge base that the company can access by locating the R&D unit in a specific location. The spillovers unfold upon demonstration effects, targeted knowledge searches, reverse engineering, employee mobility, collaborative agreements, and various other forms of inter-organizational interaction (Audretsch and Feldman, 1996; Kafourous et al., 2018). Therefore, we propose that the technological dissimilarity with target locations, that can be reflected into the different background of knowledge, competences, resources and technologies, may impact the firm ability to reach and exploit diverse ideas, skills and competences. Thanks to their proximity to the locations where certain technologies are developed, R&D employees can promptly recognize their potential and comprehend their underlying rationale by engaging in innovation practices specific to those locations (Nieto and Rodriguez, 2011). The local knowledge assimilated from the host context differs from the type of knowledge already integrated in the organization, and it has the potential to expand the knowledge and technological capabilities of companies as the dissimilarity increases. The localization in contexts with a different technological base can lead the organization to tap into new and unexplored knowledge and recombine it with the existing knowledge. According to the arguments outlined above, we can hypothesize a positive relationship between technological dissimilarity with the foreign host locations and corporate technological diversification. Thus, we test the following hypothesis:

H2. The technology dissimilarity with foreign R&D host locations promotes the corporate technological diversification of top R&D performers.

2.4 The moderating effects of technological dissimilarity on the relationship between breath/depth of foreign inventive activities and corporate technological diversification

Most of the empirical studies have tested the role of some internal corporate attributes in moderating the relationship between the geographic dispersion of inventive activities and the innovation performance of multinational corporations: while Singh (2008) gives evidence to the role of the cross-regional innovation knowledge sourcing, collaboration and mobility of inventors within multinationals in explaining such relationship, in a similar manner Lahiri (2010) emphasizes the importance of intra-organizational linkages between R&D units located at multiple network positions. Our contribution lies in examining how technological dissimilarity with foreign R&D host regions moderates the impact of geographical distribution of inventive activities, whether by expanding (breath) or concentrating (depth) them across various foreign locations, on corporate technological diversification. Although expanding inventive activities to diverse foreign locations should increase the possibility of exploring new knowledge trajectories, the literature suggests that the costs of international breadth may outweigh the benefits in terms of innovation (Lahiri, 2010; Alcácer and Zhao, 2012). We propose here that this effect may be contingent upon the negative moderating effect of technological dissimilarity with the host regions: greater international expansion of R&D locations that are more technologically dissimilar could exacerbate the complexity associated with the management of diversity, thereby potentially reducing the marginal contribution of such diverse external knowledge to the firm's capability to diversify their technological base. Moreover, it may overstretch the overall absorptive capacity of a firm by making the integration of global knowledge more challenging (Kafouros et al., 2018). Consequently, the gain in terms of technological diversification from leveraging distant external knowledge could diminish with an increasing number of foreign host R&D locations. This leads us to formulate the following hypothesis:

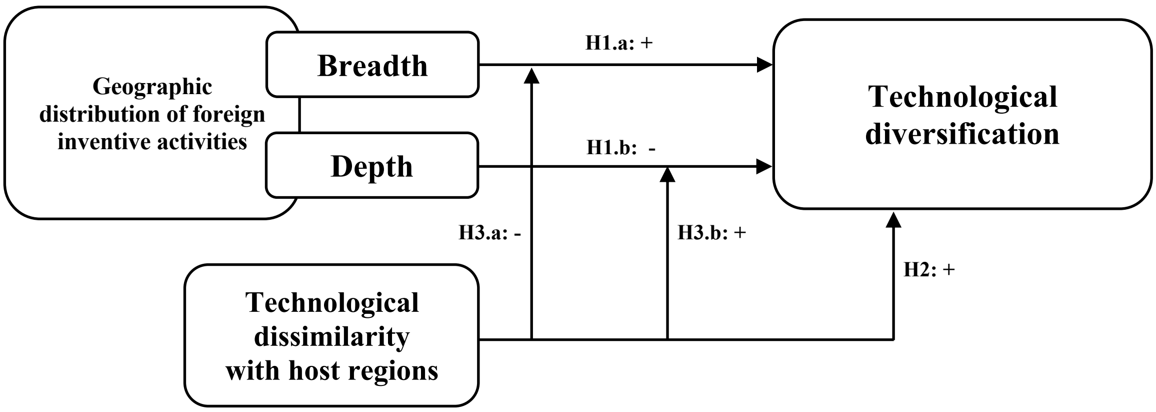
H3.a The technological dissimilarity with foreign R&D host locations negatively moderates the positive effects of the international breadth of inventive activities on the corporate technological diversification of top R&D performers.

Further, we propose that if the companies experience an increase of the international depth of inventive activities in more technologically different contexts, they can exploit the opportunity to engage with the local actors of the host locations and concentrate their efforts on interacting with more heterogeneous and distant knowledge from that which already exists in their own organization, searching more deeply for novel combinations, as a result of a stronger embeddedness (Kafouros et al., 2012; Kafouros et al., 2018). Indeed, the exploitation of knowledge from each R&D host location can stimulate the efficiency in learning and adaptation processes and strengthen the overall absorptive capacity of companies leading to more exploration opportunities (Cohen & Levinthal, 1990). Therefore, we suggest that increasing levels of technology dissimilarity with foreign R&D host regions can positively moderate the relationship between the depth of foreign inventive activities and technological diversification, such that the threshold level after which the negative returns of depth on corporate technological diversification manifest will be lower. Hence:

H3.b The technological dissimilarity with foreign R&D host locations positively moderates the negative effects of the international depth of inventive activities on the corporate technological diversification of top R&D performers.

Based on the outlined theoretical background and research hypotheses developed, we design our research framework in the following figure (Fig.1).

Figure 1 – Theoretical framework and research hypotheses development



Source: Authors' elaboration.

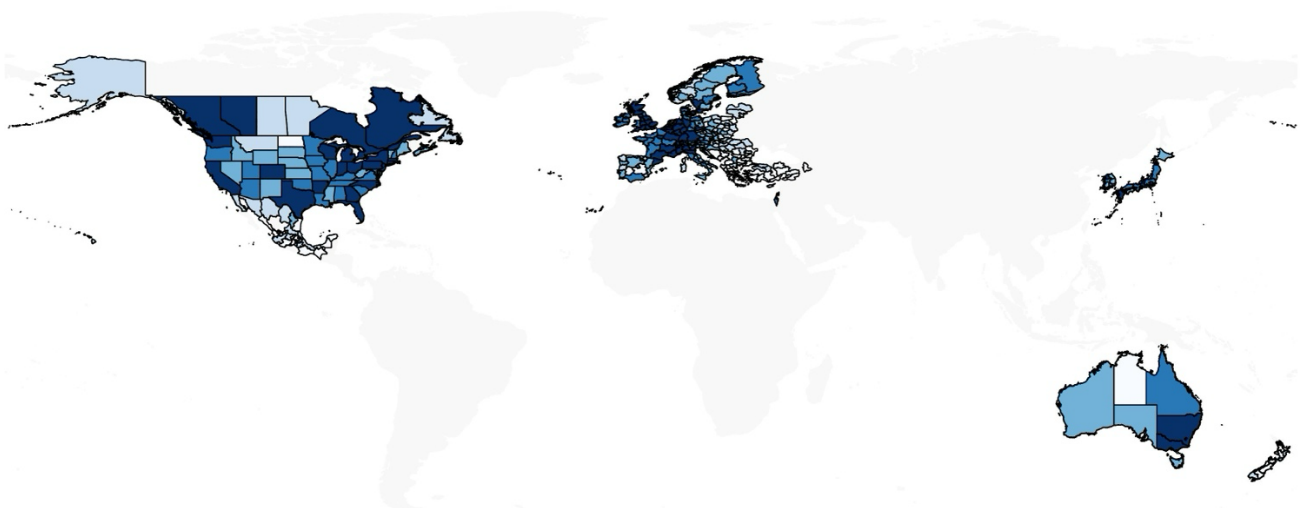
3. Data and empirical strategy

3.1 Data description

The main data source used for our study is the RISIS CIB/CinnoB dataset developed by Risis Core Facility, that collects data on about 2,000 worldwide largest R&D corporate performers, which are responsible of over 90% of world corporate industrial R&D. This database combines different firm-level information extracted from the Industrial R&D Investment Scoreboard (EU Commission), RISIS Patent database and ORBIS by Bureau van Dijk database (Laurens P., 2020). It releases data on the priority patent applications by applicants and inventor place of residence, applying in at least 2 of the 5 largest IP offices in the world[4]. We employ a final dataset of 1,125 multinational companies with 803,066 priority[5] patent applications observed during the period 2000-2018 and headquartered mainly in Europe and North America. This sample of companies is very suitable for our analysis as they are considered as world-leading corporate innovators and have a multi-unit geographically dispersed organizational structure (Dernis et al., 2015). Rather than limiting the analysis at the country level, we are conducting a study at the sub-national level.

Following the OECD territorial classification, we manually allocate our sample companies to Territorial Level 2 (TL2) regions (when this information is missing from the original data). The reason for adopting this strategy lies in the fact that adopting a granular approach can yield more benefits allowing to detect better how the specific local context in which firms are located can influence corporate dynamics and patterns of technological diversification. Further, the strong regional disparities in the localization of knowledge within and between the countries under investigation are well known and aggregating the analysis at the national level results in the loss of this heterogeneity. We capture when an invention originates from a different location than the one where the parent company is headquartered. The headquarters are primarily located in a relatively small set of few sub-national regions, mainly in the United States (27%) and Germany (9%). We plot the spatial distribution of R&D units where the inventive activities take place across of the entire sample of companies, over the period covered: we can see that they are strongly concentrated in few regions of the United States and in some European countries such as Germany, Great Britain, France and Netherlands (see Figure 1 below). We can observe a clear overlap between the number of R&D units and the number of patents in each hosting region over the period under analysis (see Figure 2 below).

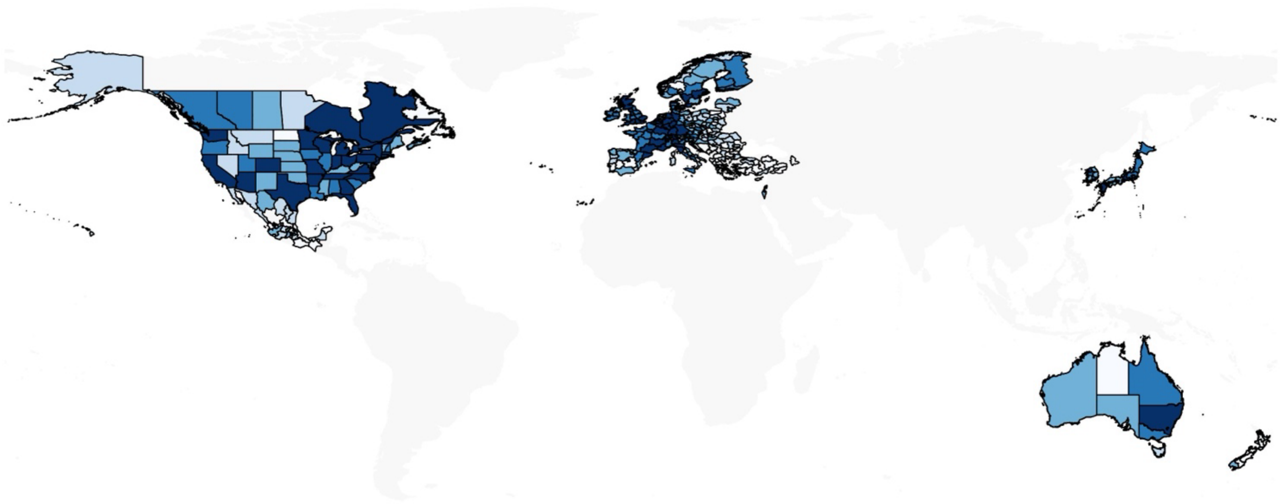
Figure 1 – Spatial distribution of the total number of R&D units across host locations (OECD TL2 regions)



Note: The values have been divided based on quantile distribution (5 classes).
Source: Authors' elaboration.

[4] The five offices, known as the IP5, are the European Patent Office (EPO), Korean Intellectual Property Office (KIPO), Japan Patent Office (JPO), China National Intellectual Property Administration (CNIPA) and United States Patent and Trademark Office (USPTO).
[5] The priority date corresponds to the first filing of an application for a patent.

Figure 2 – Spatial distribution of total number of patent applications across host locations (OECD TL2 regions) – average values for 2000-2018 years



Note: The values have been divided based on quantile distribution (5 classes).
Source: Authors' elaboration.

3.1.1 Dependent variables

In line with the most relevant literature (Palepu, 1985; Granstrand and Oskarsson, 1994; Zander, 1997; Appio et al., 2019), we use the so-called Jacquemin-Berry entropy indicator to capture the level of corporate diversification of patent portfolio. The entropy-based measure appears to be the most suitable indicator to assess the within-group variance and for distinguishing between related and unrelated diversification (Chen et al., 2012; Damioli et al., 2023). This paper adopts the same methodology outlined by Chen et al. (2012) to compute the entropy measure of technological diversification and split it into related and unrelated technological diversification. Taking in account the distribution of patent vectors by IPC grouped technological classes of our sample companies, the first step entails the calculation of the technological diversification as follows:

$$\mathrm{TECH\_DIV}_{\mathrm{i,t}} = \sum_{s=1}^{K} P_s * \ln\,(1/P_s)$$

where P_s is the share of patents in each technical field *s*, out of the *K* total ones, by IPC sub-classes (at 4-digits level). Then, we calculate the unrelated technological diversification:

$$\mathrm{UT\_DIV}_{\mathrm{i,t}} = \sum_{k=1}^{M} P_k * \ln\,(1/P_k)$$

where P_k is the share of patents in each technical field *k,* out of the *M* total ones, by IPC classes (at section level).

Since technological diversification is the sum of related and unrelated diversification, we derive the related diversification in this way:

$$\mathrm{RT\_DIV}_{\mathrm{i,t}} = TECH\_DIV_{i,t} - \ UT\_DIV_{i,t}$$

These indicators range from zero to infinity. The $TECH\_DIV_{i,t}$ indicator assumes a value equal to 0 when a company focus on both related and unrelated diversification, while it approaches infinity whether it spreads across various related or unrelated patent classes. $UT\_DIV_{i,t}$ takes value of zero when a company focus on one unrelated patent class, infinite values when diversifying the portfolio across various unrelated patent classes. $RT\_DIV_{i,t}$ equals 0 if the company's patent portfolio concentrates on a single related patent class and it tends to infinity when the company the company's patent portfolio spreads across different related patent classes (Chen et al., 2012).

3.1.2 Explanatory variables

The focal regressors of our analysis are given by the geographical dispersion (breadth) and concentration (depth) of inventive activities across different foreign R&D active locations and the technology dissimilarity with them. Following prior research (Kafourous et al., 2012; Castellani et al., 2017; Tang et al., 2019), we measure the international breadth of inventive activities using the total number of foreign host locations taking into account the inventor place of residence of patent applications[6] ($\text{INT\_BREADTH}_{i,t}$). We use the common Herfindahl-Hirschman index as a measure of concentration to calculate the international depth of inventive activities and adjust it using the bias correction (N/N- 1) to consider that this indicator could be distorted when companies place their inventive activities in few locations (Hall, 2005).

$$\text{INT\_DEPTH}_{i,t} = \sum_{r=1}^{N} P_r^2 * \left(\frac{N}{N-1}\right)$$

Where P_r is the share of patents to inventors in a given location *r* and N is the total number of foreign host locations from which patents originate. This indicator takes on values between 0 and 1 and it is higher the more geographically concentrated the patent portfolio of each company is. Lower values of the indicator suggest that the patent portfolio is more dispersed across different host locations.

We rely on the angular separation measure introduced by Jaffe (1986) to capture to what extent the companies and foreign host regions differ in their technological base. We first calculate the cosine of the angle, that is the uncentred correlation coefficient, between the technology vector of patent distribution of companies and that of each region from which inventions are drawn:

$$\text{ANG\_SEP}_{i,host} = \frac{\sum_{c=1}^{N}(P_{c,i} * P_{c,host})}{\sqrt{\sum_{c=1}^{N} P_{c,i}^2 * \sum_{c=1}^{N} P_{c,host}^2}}$$

Where $P_{c,i}$ and $P_{c,host}$ indicate the share of patents within each c technological field, as defined according to the Schmoch classification based on 35 grouped technological domains[7]. This indicator ranges between 0 and 1: when $AngularSep_{i,host} = 0$, there is orthogonality between the two vectors, indicating the complete technology dissimilarity between firm and each R&D host region; in the opposite case ($AngularSep_{it} = 1$), the two vectors overlap, resulting that the pair of units have the same identical position in the technological space. The advantage of using this symmetric measure is that of considering whether the two vectors align in the same direction while also adjusting for vector length based on the number of total patents within that dimension. This ensures also that its computation is not affected by a greater dimension of technology vectors (Jaffe, 1986). Then, for each company *i*, we calculate the average angular separation, considering all the regions where the inventive activities take place in each year. Additionally, as our focus lies in identifying the technological dissimilarity with foreign R&D active locations, we derive the inverse of this indicator as follows:

$$\text{TECH\_DISS}_{i,t} = 1 - \left(\frac{\sum_{r=1}^{N} AngularSep_{i,host}}{N}\right)$$

Where *N* is the total number of R&D active (sub-national) regions where knowledge is created.

[6] Given that multinational corporations are used to apply for patents in their headquarters, we don't rely on the location of applicants.
[7] We employed the World Intellectual Property Organization (WIPO) concordance table linking the IPC classes to the 35 technological fields outlined by Schmoch's classification in order to identify them. Refer to Appendix – Section A for more details on this classification. The implementation of this taxonomy makes more suitable the comparison of knowledge bases across diverse geographical entities (Schmoch, 2008).

3.1.3 Controls

We need to control for firm-level attributes that can affect the corporate technological diversification.

R&D intensity. Since R&D represents the key input to the innovation process (Pakes and Griliches, 1984), we add the R&D intensity of companies as the R&D expenditure over the total assets (in thousands of euros) (Miller, 2006; Wen and Zheng, 2020). Missing values are replaced with zeros, and a dummy variable is introduced to flag these observations (Singh, 2008; Rahko, 2016).

Number of employees. The (log-transformed) number of employees is a proxy for the size of the firm ~~(Singh, 2008);~~ : we anticipate it to positively influence technological diversification.

Production value. The production value of companies, expressed in logarithm, concerns the sales of goods and services and changes in stock. Greater resources could fuel innovation and push for greater inventions in different fields.

*Return on Asset (ROA).*The Return on Asset (ROA) after taxes measures the profitability of a companies, given by the net income in relation to their total assets.

Patent stock. The (log-transformed) number of total patents accumulated by the companies in the previous year serves as a proxy of their knowledge stock (Corradini et al., 2016) and to account for experience curve effects.

Technological internationalization. We control for the level of technological internationalization, that has been proven to be a leading factor for the corporate technological diversification (Cantwell and Piscitello, 2000; Rahko, 2016) including the share of international patents on the total ones of their portfolio. We retrieve this information by looking at the residence of inventors and applicants for each patent application in order to discern when they have or don't have the same nationality of the headquarter.

Intra-organizational linkages. Collaboration and connections within an organization could incentivize the sharing and transfer of knowledge, facilitating the exploration of novel inventions (Lahiri, 2010). We proxy the strength of intra-organizational linkages by the (log-transformed) number of co-patent applications that result from the collaboration between different R&D units.

3.1.4 Descriptive statistics

In the Appendix – Section B we report the descriptive statistics of the variables used in our empirical analysis (Table B2). On average, the companies included in our sample show higher values of related technological diversification compared to unrelated one. Additionally, their inventive activities are intensely dispersed geographically. The technological dissimilarity with R&D host locations is relatively small, with an average index of 0.35. Furthermore, regarding specific firm characteristics, our sample consists of large and profitable companies, with an average workforce of around 34 thousands of employees, a high production value averaging about 11 millions of euros and average ROA (net) of around 3%. They exhibit a wide innovation capacity, with an average of 670 patents accumulated. Moreover, a significant portion of the sample have a high share of international patents out of the total ones, and on average, there are 7 co-patented patent applications per company. The share of patents from foreign locations stands on average at 0.5. In the Appendix – Section B we also include the correlation matrix (Table B3) and correlation plots that show the linear relationship of the technological diversification variables and our exploratory variables (Figure B4-B5-B6).

3.2 Empirical strategy

In our empirical analysis, we employ a two-way fixed-effects panel regression with unit and time fixed effects in order to test empirically the relationship between the international breadth and depth of inventive activities and corporate technological diversification (H1), as specified by the following equation, in which the dependent variable $Y_{i,t}$varies based on whether we're examining the overall technological diversification ($\mathrm{TECH\_DIV}_{i,t}$), related ($\mathrm{RT\_DIV}_{i,t}$) or unrelated ($\mathrm{UT\_DIV}_{i,t}$) diversification.

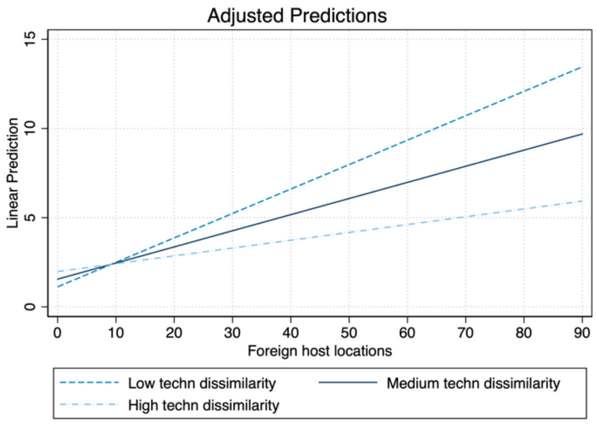
$$\mathrm{Y}_{i,t} = \beta_1(\mathrm{INT\_BREADTH}_{i,t-1}) + \beta_2(\mathrm{INT\_DEPTH}_{i,t-1}) + \varphi(\mathrm{X'}_{i,t-1}) + \gamma_i + \delta_t + \varepsilon_{i,t} \qquad (1)$$

Where *i* indicates firms in our sample (i= 1…1,125), and t accounts for our time span of 2000-2018 years. $\mathrm{X'}_{i,t-1}$, is a vector of control variables that encompass several corporate characteristics, as discussed above, γ_i and δ_t stand respectively for firm and year fixed effects, accounting for firm-level and time-variant unobserved features. Then, on the right-side of our equation, we include the technological dissimilarity with foreign host locations ($\mathrm{TECH\_DISS}_{i,t-1}$) in order to test its impact on the corporate technological diversification (H2). Ultimately, the inclusion of interaction terms serves to examine to what extent the technological dissimilarity can play a moderating role in the relationship between the international breadth/depth and technological diversification (H3). All the regressors are lagged by one year in order to mitigate the potential reversed causality and unobserved heterogeneity.

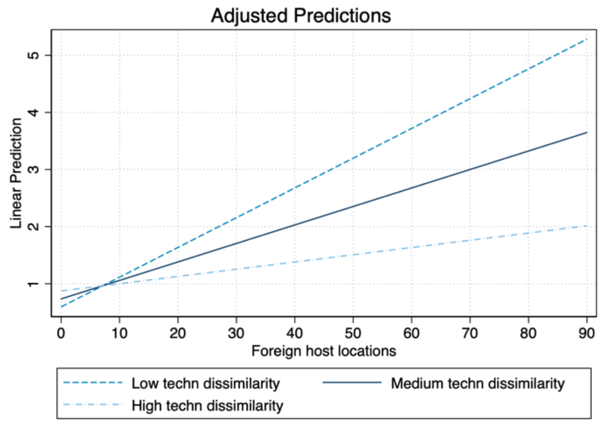
4. Results

In this section, we report the results of our empirical analysis, running fixed-effect panel regression model on different specifications for our dependent variables of overall (Table 1), related (Table 2) and unrelated (Table 3) technological diversification. First, in each model specification, we include our proxy for the international breadth of inventive activities, that is the total number of foreign R&D host locations. We obtain that the coefficient estimated is positive and significant at 1% level: as expected, the dispersion of patents across different foreign host locations affects positively and significantly the capability of companies to diversify their technologies, both in related and unrelated domains. Then, we test the impact of international depth of inventive activities, and the results lead us to confirm that a greater concentration of patent portfolio discourages the technological diversification. So, we can largely confirm our first research hypothesis. We introduce our last focal regressor of technological dissimilarity of companies with R&D host regions. In line with the second research hypothesis, the positive and significant coefficient across all the models strongly supports the existence of a positive relationship between technological dissimilarity and technological diversification. Finally, in the last two columns of our model specifications we add the interaction terms respectively between the international breadth/depth of inventive activities and technological dissimilarity, in order to assess the role of the technological dissimilarity in moderating the effects of international breadth/depth on technological diversification (H3). The coefficient of the interaction term between international breadth and technological dissimilarity is negative and statistically significant at 1%. As we formulated in our third hypothesis, there is a negative moderating effect of technological dissimilarity in the relation between international breadth and corporate technological diversification. Firms dispersing inventive activities across more dissimilar locations tend to achieve lower positive returns in technological diversification performance as the number of foreign host locations increases (Figure 3). Testing the potential role of technological dissimilarity in shaping the direction of the relationship between international depth and technological diversification, we obtain mixed evidence across the different models. We find that a greater technological dissimilarity with host locations can mitigate the negative impact of international depth on the overall technological diversification, even though the effect is slight, as indicated by the coefficient of the interaction term being positive and significant at the 10% level. While this effect does not hold when testing the related diversification, it emerges with a statistical significance level of 5% in the case of unrelated diversification. This evidence leads us to only partially confirm our last hypothesis, but also to interesting insights: a higher technological dissimilarity with the host regions, combined with a greater exploitation of such locations, allow companies to diversify into unrelated technological fields rather than in related ones. Figure 4 suggests that higher levels of technological dissimilarity with host locations augment the effect of international depth standing at low degrees and mitigate the negative impact of high levels of international depth. Regarding the other regressors included in the specifications, we have found others interesting results. While the R&D intensity influence positively and significantly the overall and related technological diversification, it has no effect on the unrelated technological diversification. Conversely, production value has a positive and significant impact only on the capability of companies to diversify into unrelated technological fields. The firm size, proxied by the number of employees is positively and significantly associated with the overall capacity to diversify technologies, and specially into related domains. The profitability of companies, captured by the ROA indicator, doesn't seem to affect the corporate technological diversification as its estimated coefficient does not hold statistical significance from 0 across all the specifications. As expected, the stock of patents has a positive and strong effect on corporate technological diversification. Surprisingly, we discover that the corporate technological diversification is negatively affected by a greater share of international patents, which retains a negative sign and high statistical significance across all the specifications[8]. Last, there is not a clear and distinct direction in the relationship between corporate internal collaboration and technological diversification as the estimated coefficient doesn't remain statistically significant across all specifications. This is particularly evident whether the number of foreign host locations is included in the specifications, meaning that the international breadth can explain the variability of the phenomenon under analysis to a greater extent rather than the collaboration within the organization.

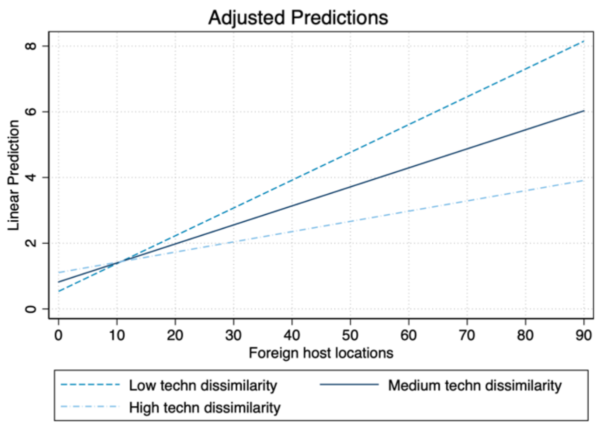
Figure 3 – Moderating effect of technological dissimilarity on the linear relationship between technological diversification and international breadth



(a) Overall



(b) Related

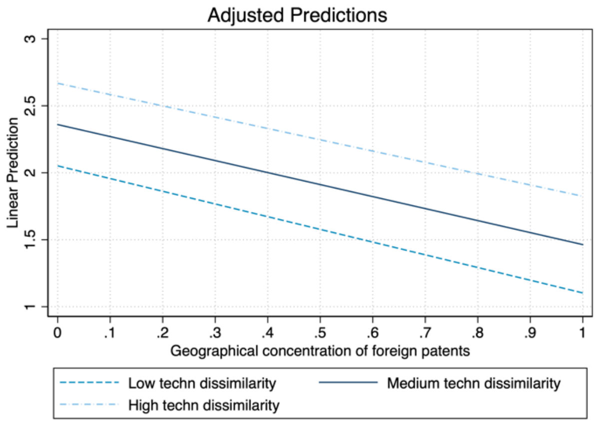


(c) Unrelated

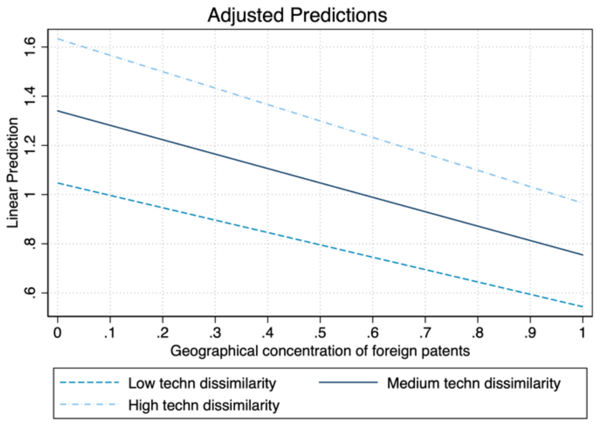
Note: Low technological dissimilarity is defined as one standard deviation below the mean, Medium as the mean, High technological dissimilarity as one standard deviation above the mean.
Source: Authors' elaboration.

[8] Following Castellani and Pieri (2013), we compute the share of foreign patents out of the total ones above which the marginal effect on technological diversification is negative, finding evidence that it manifests when the share is above the 75th percentile of the distribution. This suggests that few firms in the sample should experience negative returns from higher technological internationalization. It should be subject to further investigation.

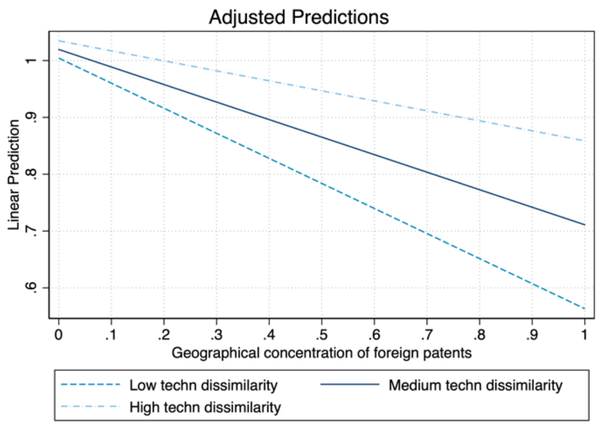
Figure 4 – Moderating effect of technological dissimilarity on the linear relationship between technological diversification and international depth



(a) Overall



(b) Related



(c) Unrelated

Note: Low technological dissimilarity is defined as one standard deviation below the mean, Medium as the mean, High technological dissimilarity as one standard deviation above the mean.
Source: Authors' elaboration.

4.1 Additional estimates and robustness checks

Drawing insights from various research contributions (Cantwell and Kosmopoulou, 2001; Almeida and Phene, 2004), we want further to explore to what extent firm heterogeneity can affect our findings. We seek to investigate the debated question of whether technologically more advanced firms might be better positioned to assimilate knowledge spillovers from dispersed R&D locations and explore new patterns of innovation, or whether less advanced ones might be more inclined to capitalize on the resources available in their host locations in order to bridge their technological gap. We first define the technological frontier as the technological level of companies relative to their main competitor operating in the same industry in order to distinguish between firms that are close to or lag behind it. Indeed, we calculate the distance to the technology frontier as the distance of the innovation output between firm *i* and the best/worst performing in the same field[9]. We split the sample based on a dummy variable that captures when firms have a distance to frontier score from the technological frontier greater or less than the median of the distribution. We find that our main results are driven by "frontier" firms, which operate closer to or at the technology frontier (see Table 4) compared to the "laggards" firms (see

[9] Proceeding with the methodology outlined by World Bank to compute the economy's distance to frontier score (2014), we calculate the distance to frontier indicator for each sample company employing this formula: (worst - Total_patents) / (worst - best), where worst and best are respectively the lowest and highest level of innovative output defined for each industry. This indicator takes a value between 0 and 1: the closer it is to 1, the more the firm is able of to catch up with the technological frontier.

Table 5). We can observe that the positive relationship between international breadth of inventive activities and corporate technological diversification holds true for both the sub-samples. However, the international depth of inventive activities does not affect significantly the technological diversification of laggards. We also find that greater international depth in regions with a more dissimilar knowledge base has a positive and significant effect on the overall and unrelated diversification only among the frontiers (with even greater significance and magnitude compared to the results obtained from models estimated across the entire sample). This evidence suggest that absorptive capacity and innovative capabilities of companies play a fundamental role in enhancing their capability to take advantage of a greater diversity of R&D host locations. Furthermore, we assess the robustness of our baseline model by excluding US based companies, representing half of the sample, that might introduce bias into our findings (Damioli et al., 2023) but our main results persist largely[10]. (see Appendix - Section C – Table C1). Our results remain largely robust when lagging all our focal regressors and control variables by two years in our baseline estimation in order to account for the delay in patenting following the learning process and subsequent R&D activities in geographically dispersed multiple R&D units (see Appendix. - Section D – Table C2). Last, following previous research (Lahiri, 2010; Corradini et al., 2016), we test our baseline specification using the inverse of the adjusted Herfindahl-Hirschman index as a proxy variable for the corporate technological diversification and our findings remain consistent (see Appendix. - Section D – Table C3).

[10]Although we do not find support for the hypothesis of a moderating role of technological dissimilarity in the negative relationship between international depth and technological diversification, leading us to assume that non-US headquartered multinational companies may not have the absorptive capacity necessary to acquire external knowledge when they concentrate their own efforts in a given host location.

Table 1 – Baseline: the impact of international breadth and depth and technological dissimilarity with foreign host regions on the overall technological diversification

VARIABLES	(1) TECH_DIV$_{i,t}$	(2) TECH_DIV$_{i,t}$	(3) TECH_DIV$_{i,t}$	(4) TECH_DIV$_{i,t}$	(5) TECH_DIV$_{i,t}$	(6) TECH_DIV$_{i,t}$
INT_BREADTH$_{i,t-1}$	0.0164***			0.0117***	0.0416***	0.0125***
	(0.00223)			(0.00215)	(0.00509)	(0.00213)
INT_DEPTH$_{i,t-1}$		-0.0879***		-0.0519***	-0.0317**	-0.0796***
		(0.0121)		(0.0123)	(0.0124)	(0.0215)
TECH_DISS$_{i,t-1}$			0.398***	0.294***	0.427***	0.352***
			(0.0509)	(0.0509)	(0.0590)	(0.0632)
INT_BREADTH$_{i,t-1}$ *TECH_DISS$_{i,t-1}$					-0.0506***	
					(0.00824)	
INT_DEPTH$_{i,t-1}$*TECH_DISS$_{i,t-1}$						0.0909*
						(0.0486)
RD_INTENS$_{i,t-1}$	0.289*	0.318**	0.322**	0.289*	0.300*	0.293*
	(0.162)	(0.160)	(0.156)	(0.158)	(0.154)	(0.158)
Dummy(RD_INTENS$_{i,t-1}$)	-0.000763	0.00112	0.00639	7.72e-05	-0.00406	0.000775
	(0.0555)	(0.0550)	(0.0553)	(0.0534)	(0.0525)	(0.0534)
Log(EMPLOYEES$_{i,t-1}$)	0.0501***	0.0547***	0.0567***	0.0447***	0.0428***	0.0455***
	(0.0173)	(0.0176)	(0.0176)	(0.0167)	(0.0165)	(0.0167)
Log(PROD_VALUE$_{i,t-1}$)	0.0180	0.0171	0.0179	0.0167	0.0175	0.0166
	(0.0110)	(0.0110)	(0.0113)	(0.0108)	(0.0107)	(0.0108)
ROA_NET$_{i,t-1}$	0.000452	0.000667	0.000675	0.000448	0.000446	0.000448
	(0.000589)	(0.000599)	(0.000601)	(0.000595)	(0.000593)	(0.000595)
Log(PAT_STOCK$_{i,t-1}$)	0.0447***	0.0564***	0.0525***	0.0386***	0.0373***	0.0387***
	(0.0130)	(0.0133)	(0.0133)	(0.0128)	(0.0128)	(0.0128)
TECH_INT$_{i,t-1}$	-0.256***	-0.239***	-0.178***	-0.234***	-0.249***	-0.236***
	(0.0359)	(0.0358)	(0.0346)	(0.0352)	(0.0349)	(0.0351)
Log(CO_PAT$_{i,t-1}$)	0.0120*	0.0226***	0.0204***	0.00877	0.0111*	0.00900
	(0.00709)	(0.00717)	(0.00709)	(0.00695)	(0.00667)	(0.00694)
Constant	0.923***	0.840***	0.752***	0.897***	0.853***	0.875***
	(0.187)	(0.193)	(0.193)	(0.182)	(0.181)	(0.183)
Observations	10,818	10,818	10,818	10,818	10,818	10,818
R-squared	0.818	0.817	0.817	0.819	0.820	0.819
R-squared adj.	0.796	0.795	0.795	0.798	0.799	0.798
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
N_clust	1125	1125	1125	1125	1125	1125

Note: Clustered standard errors at firm level are in parentheses. The significance levels of the statistical test are given by the p-value, that is: *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' elaboration.

Table 2 – Baseline: the impact of international breadth and depth and technological dissimilarity with foreign host regions on related technological diversification

VARIABLES	(1) $RT\_DIV_{i,t}$	(2) $RT\_DIV_{i,t}$	(3) $RT\_DIV_{i,t}$	(4) $RT\_DIV_{i,t}$	(5) $RT\_DIV_{i,t}$	(6) $RT\_DIV_{i,t}$
$INT\_BREADTH_{i,t-1}$	0.0135***			0.0102***	0.0268***	0.0104***
	(0.00176)			(0.00173)	(0.00395)	(0.00172)
$INT\_DEPTH_{i,t-1}$		-0.0630***		-0.0327***	-0.0215**	-0.0373**
		(0.00888)		(0.00891)	(0.00892)	(0.0154)
$TECH\_DISS_{i,t-1}$			0.310***	0.228***	0.302***	0.238***
			(0.0362)	(0.0360)	(0.0429)	(0.0441)
$INT\_BREADTH_{i,t-1}$ *$TECH\_DISS_{i,t-1}$					-0.0280***	
					(0.00651)	
$INT\_DEPTH_{i,t-1}$* $TECH\_DISS_{i,t-1}$						0.0151
						(0.0352)
$RD\_INTENS_{i,t-1}$	0.153*	0.177**	0.180**	0.153*	0.159*	0.154*
	(0.0856)	(0.0864)	(0.0851)	(0.0837)	(0.0829)	(0.0836)
Dummy($RD\_INTENS_{i,t-1}$)	-0.0436	-0.0417	-0.0378	-0.0428	-0.0451	-0.0427
	(0.0360)	(0.0371)	(0.0377)	(0.0359)	(0.0354)	(0.0359)
Log($EMPLOYEES_{i,t-1}$)	0.0317**	0.0364***	0.0375***	0.0279**	0.0269**	0.0281**
	(0.0134)	(0.0137)	(0.0139)	(0.0130)	(0.0128)	(0.0130)
Log($PROD\_VALUE_{i,t-1}$)	0.00507	0.00452	0.00503	0.00413	0.00458	0.00412
	(0.0101)	(0.0101)	(0.0102)	(0.00994)	(0.00982)	(0.00994)
$ROA\_NET_{i,t-1}$	5.18e-06	0.000190	0.000193	2.01e-06	9.12e-07	2.02e-06
	(0.000398)	(0.000406)	(0.000405)	(0.000398)	(0.000396)	(0.000398)
Log($PAT\_STOCK_{i,t-1}$)	0.0294***	0.0398***	0.0363***	0.0248***	0.0241***	0.0248***
	(0.00878)	(0.00922)	(0.00906)	(0.00865)	(0.00864)	(0.00865)
$TECH\_INT_{i,t-1}$	-0.142***	-0.125***	-0.0794***	-0.124***	-0.132***	-0.124***
	(0.0259)	(0.0257)	(0.0249)	(0.0253)	(0.0252)	(0.0253)
Log($CO\_PAT_{i,t-1}$)	0.00654	0.0158***	0.0138**	0.00411	0.00542	0.00415
	(0.00542)	(0.00568)	(0.00563)	(0.00532)	(0.00516)	(0.00532)
Constant	0.502***	0.427***	0.362**	0.480***	0.455***	0.476***
	(0.140)	(0.147)	(0.147)	(0.137)	(0.136)	(0.138)
Observations	10,818	10,818	10,818	10,818	10,818	10,818
R-squared	0.804	0.803	0.803	0.806	0.806	0.806
R-squared adj.	0.781	0.779	0.780	0.783	0.783	0.783
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
N_clust	1125	1125	1125	1125	1125	1125

Note: Clustered standard errors at firm level are in parentheses. The significance levels of the statistical test are given by the p-value, that is: *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' elaboration.

Table 3 – Baseline: the impact of international breadth and depth and technological dissimilarity with foreign host regions on unrelated technological diversification

VARIABLES	(1) $UT\_DIV_{i,t}$	(2) $UT\_DIV_{i,t}$	(3) $UT\_DIV_{i,t}$	(4) $UT\_DIV_{i,t}$	(5) $UT\_DIV_{i,t}$	(6) $UT\_DIV_{i,t}$
$INT\_BREADTH_{i,t-1}$	0.00283***			0.00145*	0.0147***	0.00211**
	(0.000904)			(0.000875)	(0.00264)	(0.000871)
$INT\_DEPTH_{i,t-1}$		-0.0248***		-0.0191***	-0.0102	-0.0419***
		(0.00706)		(0.00726)	(0.00733)	(0.0136)
$TECH\_DISS_{i,t-1}$			0.0859***	0.0635**	0.123***	0.111***
			(0.0289)	(0.0294)	(0.0325)	(0.0368)
$INT\_BREADTH_{i,t-1}$ * $TECH\_DISS_{i,t-1}$					-0.0224***	
					(0.00402)	
$INT\_DEPTH_{i,t-1}$ * $TECH\_DISS_{i,t-1}$						0.0746**
						(0.0317)
$RD\_INTENS_{i,t-1}$	0.138	0.142	0.143	0.138	0.142	0.140
	(0.123)	(0.122)	(0.121)	(0.122)	(0.120)	(0.122)
Dummy($RD\_INTENS_{i,t-1}$)	0.0428	0.0428	0.0441	0.0428	0.0410	0.0434
	(0.0420)	(0.0415)	(0.0416)	(0.0413)	(0.0412)	(0.0415)
Log($EMPLOYEES_{i,t-1}$)	0.0179*	0.0178*	0.0188*	0.0163	0.0155	0.0170
	(0.0104)	(0.0105)	(0.0104)	(0.0104)	(0.0105)	(0.0105)
Log($PROD\_VALUE_{i,t-1}$)	0.0130**	0.0127*	0.0130**	0.0126*	0.0130*	0.0126*
	(0.00658)	(0.00658)	(0.00660)	(0.00658)	(0.00666)	(0.00658)
$ROA\_NET_{i,t-1}$	0.000461	0.000490	0.000497	0.000460	0.000459	0.000460
	(0.000382)	(0.000382)	(0.000383)	(0.000384)	(0.000384)	(0.000384)
Log($PAT\_STOCK_{i,t-1}$)	0.0146*	0.0159**	0.0155**	0.0131*	0.0125	0.0132*
	(0.00788)	(0.00778)	(0.00784)	(0.00787)	(0.00786)	(0.00785)
$TECH\_INT_{i,t-1}$	-0.111***	-0.111***	-0.0965***	-0.108***	-0.115***	-0.109***
	(0.0219)	(0.0218)	(0.0213)	(0.0217)	(0.0217)	(0.0217)
Log($CO\_PAT_{i,t-1}$)	0.00550	0.00684*	0.00667*	0.00475	0.00579	0.00494
	(0.00361)	(0.00353)	(0.00353)	(0.00359)	(0.00354)	(0.00358)
Constant	0.428***	0.420***	0.397***	0.424***	0.405***	0.406***
	(0.111)	(0.111)	(0.111)	(0.110)	(0.111)	(0.111)
Observations	10,818	10,818	10,818	10,818	10,818	10,818
R-squared	0.681	0.681	0.681	0.681	0.682	0.682
R-squared adj.	0.643	0.643	0.643	0.643	0.644	0.644
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
N_clust	1125	1125	1125	1125	1125	1125

Note: Clustered standard errors at firm level are in parentheses. The significance levels of the statistical test are given by the p-value, that is: *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' elaboration.

Table 4 – Additional checks – the impact of international breadth and depth and technological dissimilarity with foreign host regions on the overall, related and unrelated technological diversification in frontier firms

VARIABLES	(1) TECH_DIV$_{i,t}$	(2) TECH_DIV$_{i,t}$	(3) RT_DIV$_{i,t}$	(4) RT_DIV$_{i,t}$	(5) UT_DIV$_{i,t}$	(6) UT_DIV$_{i,t}$
INT_BREADTH$_{i,t-1}$	0.0331***	0.0103***	0.0225***	0.00875***	0.0106***	0.00154*
	(0.00539)	(0.00207)	(0.00440)	(0.00170)	(0.00266)	(0.000867)
INT_DEPTH$_{i,t-1}$	-0.0281*	-0.101***	-0.0143	-0.0339	-0.0138	-0.0680***
	(0.0149)	(0.0326)	(0.0110)	(0.0227)	(0.00865)	(0.0211)
TECH_DISS$_{i,t-1}$	0.385***	0.349***	0.285***	0.212***	0.102**	0.139***
	(0.0831)	(0.0896)	(0.0625)	(0.0623)	(0.0444)	(0.0531)
INT_BREADTH$_{i,t-1}$ * TECH_DISS$_{i,t-1}$	-0.0391***		-0.0229***		-0.0162***	
	(0.00893)		(0.00725)		(0.00405)	
INT_DEPTH$_{i,t-1}$ * TECH_DISS$_{i, t-1}$		0.154**		0.0272		0.128***
		(0.0657)		(0.0457)		(0.0436)
RD_INTENS$_{i,t-1}$	-0.216	-0.249	-0.0377	-0.0605	-0.178	-0.189
	(0.436)	(0.437)	(0.337)	(0.337)	(0.168)	(0.168)
Dummy(RD_INTENS$_{i,t-1}$)	-0.0216	-0.0197	-0.0482	-0.0470	0.0265	0.0272
	(0.0564)	(0.0562)	(0.0428)	(0.0428)	(0.0434)	(0.0436)
Log(EMPLOYEES$_{i,t-1}$)	0.0676***	0.0716***	0.0466**	0.0482**	0.0213**	0.0237**
	(0.0240)	(0.0241)	(0.0211)	(0.0213)	(0.0108)	(0.0109)
Log(PROD_VALUE$_{i,t-1}$)	0.0246	0.0236	0.0188	0.0182	0.00560	0.00510
	(0.0183)	(0.0184)	(0.0166)	(0.0168)	(0.00747)	(0.00732)
ROA_NET$_{i,t-1}$	3.57e-05	5.94e-05	0.000289	0.000289	-0.000237	-0.000212
	(0.000761)	(0.000763)	(0.000541)	(0.000545)	(0.000447)	(0.000445)
Log(PAT_STOCK$_{i,t-1}$)	0.0346*	0.0360**	0.0196*	0.0204*	0.0142	0.0148
	(0.0181)	(0.0181)	(0.0113)	(0.0114)	(0.0113)	(0.0112)
TECH_INT$_{i,t-1}$	-0.263***	-0.250***	-0.141***	-0.131***	-0.118***	-0.115***
	(0.0561)	(0.0568)	(0.0420)	(0.0424)	(0.0336)	(0.0334)
Log(CO_PAT$_{i,t-1}$)	0.00783	0.00636	0.00525	0.00420	0.00269	0.00227
	(0.00771)	(0.00798)	(0.00634)	(0.00653)	(0.00364)	(0.00364)
Constant	0.794***	0.797***	0.246	0.271	0.551***	0.528***
	(0.300)	(0.299)	(0.229)	(0.231)	(0.156)	(0.156)
Observations	5,916	5,916	5,916	5,916	5,916	5,916
R-squared	0.866	0.865	0.859	0.859	0.756	0.756
R-squared adj.	0.849	0.848	0.842	0.841	0.725	0.725
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
N_clust	627	627	627	627	627	627

Note: Clustered standard errors at firm level are in parentheses. The significance levels of the statistical test are given by the p-value, that is: *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' elaboration.

Table 5 – Additional checks – the impact of international breadth and depth and technological dissimilarity with foreign host regions on the overall, related and unrelated technological diversification in laggard firms

VARIABLES	(1) TECH_DIV$_{i,t}$	(2) TECH_DIV$_{i,t}$	(3) RT_DIV$_{i,t}$	(4) RT_DIV$_{i,t}$	(5) UT_DIV$_{i,t}$	(6) UT_DIV$_{i,t}$
INT_BREADTH$_{i,t-1}$	0.0418***	0.0274***	0.0227**	0.0188***	0.0188**	0.00841**
	(0.0118)	(0.00638)	(0.00880)	(0.00467)	(0.00751)	(0.00394)
INT_DEPTH$_{i,t-1}$	-0.0163	-0.0239	-0.0213	-0.0175	0.00452	-0.00665
	(0.0195)	(0.0286)	(0.0148)	(0.0213)	(0.0129)	(0.0195)
TECH_DISS$_{i,t-1}$	0.248***	0.168*	0.139**	0.106*	0.105*	0.0588
	(0.0937)	(0.0906)	(0.0641)	(0.0614)	(0.0579)	(0.0573)
INT_BREADTH$_{i,t-1}$ * TECH_DISS$_{i,t-1}$	-0.0381		-0.00909		-0.0284*	
	(0.0252)		(0.0187)		(0.0160)	
INT_DEPTH$_{i,t-1}$ * TECH_DISS$_{i, t-1}$		0.00896		-0.0240		0.0318
		(0.0898)		(0.0668)		(0.0624)
RD_INTENS$_{i,t-1}$	-0.209***	-0.209***	-0.120***	-0.120***	-0.0882***	-0.0877***
	(0.0437)	(0.0438)	(0.0315)	(0.0315)	(0.0298)	(0.0299)
Dummy(RD_INTENS$_{i,t-1}$)	0.419***	0.421***	0.173***	0.173***	0.247**	0.248**
	(0.106)	(0.105)	(0.0645)	(0.0646)	(0.110)	(0.110)
Log(EMPLOYEES$_{i,t-1}$)	-0.0672	-0.0652	-0.0959	-0.0956	0.0285	0.0302
	(0.115)	(0.116)	(0.0734)	(0.0738)	(0.0687)	(0.0690)
Log(PROD_VALUE$_{i,t-1}$)	0.00992	0.0107	-0.00494	-0.00475	0.0146	0.0151
	(0.0243)	(0.0242)	(0.0186)	(0.0186)	(0.0174)	(0.0174)
ROA_NET$_{i,t-1}$	0.0122	0.0125	0.00111	0.00120	0.0116	0.0118
	(0.0136)	(0.0136)	(0.0111)	(0.0111)	(0.00991)	(0.00990)
Log(PAT_STOCK$_{i,t-1}$)	0.000654	0.000640	-0.000226	-0.000226	0.000900	0.000887
	(0.000805)	(0.000804)	(0.000543)	(0.000543)	(0.000556)	(0.000554)
TECH_INT$_{i,t-1}$	0.0361	0.0351	0.0220	0.0215	0.0133	0.0127
	(0.0245)	(0.0246)	(0.0171)	(0.0172)	(0.0150)	(0.0150)
Log(CO_PAT$_{i,t-1}$)	0.0218	0.0207	0.0100	0.00968	0.0116	0.0108
	(0.0147)	(0.0148)	(0.0107)	(0.0106)	(0.00868)	(0.00868)
Constant	0.967***	0.983***	0.636***	0.643***	0.333**	0.341**
	(0.220)	(0.218)	(0.163)	(0.162)	(0.152)	(0.152)
Observations	4,728	4,728	4,728	4,728	4,728	4,728
R-squared	0.691	0.691	0.651	0.651	0.586	0.586
R-squared adj.	0.630	0.630	0.583	0.583	0.504	0.504
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
N_clust	751	751	751	751	751	751

Note: Clustered standard errors at firm level are in parentheses. The significance levels of the statistical test are given by the p-value, that is: *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' elaboration..

5. Discussion and conclusions

5.1 Discussion on the main findings and contribution

This paper contributes to the advancement of the existing literature in several ways. Firstly, we attempt to examine the factors influencing the corporate technological diversification, exploring both related and unrelated variety, an area that has received limited attention so far (Damioli et al., 2023). Building on the idea that the geographically dispersed structure of companies can act as a crucial technology transfer vehicle within the organization (Singh, 2008; Lahiri, 2010; Wen and Zheng, 2020), we distinguish between two dimensions of international expansion of inventive activities, breadth and depth, and discussing how each contributes to different stages of technological diversification. Using data on 1,125 multinational companies, which are observed during the 2000-2018 years, our results confirm that dispersing the patent portfolio overseas enables a firm to gain proximal access to external knowledge pools across different locations, tap into diverse contexts and facilitating knowledge recombination (Singh, 2008; Lahiri, 2010). Conversely, a greater in-depth exploitation of host locations is associated with a lower ability to diversify the technological base. Additionally, to our knowledge, this is the first contribution that sheds light on how specific contextual factors, such as differences in knowledge and technology bases with R&D host regions, can influence the technological diversification performance of the leading innovative companies. We find that the dissimilarity from sources of new knowledge can affect positively the development of technological capabilities of companies. Additionally, our study addresses a current gap in understanding by examining the moderating influence of technological dissimilarity with host regions on the relationship between the geographic distribution of foreign inventive activities and technological diversification. First, the capability to enter into new technological domains is undermined when companies disperse inventive activities in an increasing number of locations and technological dissimilarity with them increases. We explain this evidence by arguing that the firm's absorptive capacity from multiple and dissimilar knowledge sources could be compromised with higher costs and complexity associated with it (Singh, 2008; Lahiri, 2010; Alcácer and Zhao, 2012). Furthermore, our results indicate that the technology dissimilarity with host regions helps companies to overcome the negative effects of the international depth of inventive activities, augmenting the opportunity to draw on and explore new knowledge from a greater exploitation of host locations (Kafouros et al., 2012; Kafouros et al., 2018), on technological diversification, especially in unrelated domains. Therefore, we offer empirical support for the well-established notion in the IB literature that companies can enhance their knowledge base by capitalizing on advantageous locations with distinct knowledge base (Le Bas and Patel, 2005). However, while the technological dissimilarity with the host regions turns out to be an important predictor of corporate technological diversification, it can reduce the capability to absorb diverse and non-overlapping knowledge, compared to that already integrated in the organization, in the presence of a more dispersed geographical structure of R&D activities. Then, our results suggest that a more in-depth internationalization of inventive activities causes the firm to acquire redundant knowledge and does not increase technological diversification, but this effect can be mitigated when the firm localizes these activities in regions with a more distinct technological footprint. Multinational companies should take into account both the breadth and depth simultaneously and weigh the geographic distribution of patents against technological dissimilarity with foreign R&D host regions as these components could impact each other mutually in determining the possibility of diversifying the patent portfolio. Further, splitting the sample between frontiers and laggards, based on what extent they operate close to the technological frontier relative to their industry, our hypotheses are proved to be consistent for companies with higher innovative capabilities being better positioned to absorb external heterogeneous knowledge and connect it with internal knowledge (Cohen & Levinthal, 1990). Then, we state that internal absorptive capacity matters to ensure that companies are able identify and integrate external knowledge and exploiting the benefits from foreign-based inventive activities (Kafouros et al., 2012).

5.2 Implications

This study raises relevant implications for management practice and policy. From a managerial point of view, our research should provide useful insights for R&D managers on how to structure geographically the patent portfolio in a way that enhance their technological diversification. Indeed, our findings support the corporate decisions on R&D location choice: the adoption of vertical integration strategies of their foreign inventive activities needs to be aimed at leveraging the geographical expansion across diverse knowledge hubs thanks to the exploitation and absorption of local knowledge and technology spillovers. Multinational companies should identify ideal levels of international breadth and depth that optimize the technological diversification performance taking into account the distinct technological profile of the location to which they have accessed. Particularly, we suggest to consider the trade-off between the breadth and depth in the geographical distribution of inventive activities on the level of technological dissimilarity with the host regions. The greater exploration of foreign markets should incentivize technological diversification but the exploitation of host locations should be adopted when accessing a more technologically dissimilar location. However, we posit that strengthening the internal absorptive capacity and innovative performance is critical to achieve such outcome. Then, policy makers can obtain empirical support to design national incentive policies to push the most domestic advanced companies to distribute their R&D activities across diverse target locations in order to benefit from it in terms of national technological base upgrading, that is, to move forward the national technological frontier towards new specializations.

5.3 Limitations and future research

Future research should focus on explaining how external knowledge absorbed by geographically dispersed R&D units can effectively flow into the organizational network and lead to a break in the innovation process of companies, which is characterized by path-dependency and cumulative nature and constrained by organizational routine (Cohen and Levinthal, 1990; Dosi et al. 1990). Indeed, this analysis is limited from the non-automatic nature of knowledge and technology transfer, even within the same organization: several obstacles can come into play, related to the tacit nature of the technological knowledge being transferred, the existing knowledge and the degree of absorptive capacity in the receiving unit as well as the motivation of the R&D units to share knowledge with other parts within the organization (Criscuolo, 2003). Only a study that captures the flows of knowledge within the organisational network of companies and test how they contribute to corporate technological diversification could disentangle the mechanisms underlying the evidence presented in this paper.

Turning to our future research agenda, an important robustness checks involves better addressing the estimation of the causal relationship between the corporate technological diversification and geographic distribution of inventive activities that entails endogeneity issues: firms that diversify their technology base may be more likely to expand their activities into more geographic sites to recoup their massive R&D investment efforts (Stephan, 1997). In addition, given that technological diversification affects learning behaviors, recombinant capabilities, and managerial efficiency (Garcia-Vega, 2006), geographically dispersed companies may self-select to identify valuable external technologies from their host locations (Ardito et al., 2019). It must also be taken into account that unobservable characteristics can influence firms' decisions to geographically distribute their inventive activities and their ability to diversify their technological base. Applying specific econometric techniques, such as instrumental variable approach, Heckman two-step selection method and/or contrafactual identification strategies, could help to deal with the endogeneity problems in our analysis and provide for more robust estimates. This study also calls for further investigation into how specific characteristics of the host environment can influence firms' capacity to pursue new knowledge trajectories. Furthermore, this research neglects that external sources of knowledge to the organization, such as collaborations with external partners, can incentivize the recombination of new knowledge and technological diversification: a future analysis could investigate this aspect in more detail.

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Appendix

Section A – Notes on the construction of the angular separation variable

Table A1 - Schmoch's technology classification

	Area, field	IPC code
I	**Electrical engineering**	
1	Electrical machinery, apparatus, energy	F21#, H01B, H01C, H01F, H01G, H01H, H01J, H01K, H01M, H01R, H01T, H02#, H05B, H05C, H05F, H99Z
2	Audio-visual technology	G09F, G09G, G11B, H04N-003, H04N-005, H04N-009, H04N-013, H04N-015, H04N-017, H04R, H04S, H05K
3	Telecommunications	G08C, H01P, H01Q, H04B, H04H, H04J, H04K, H04M, H04N-001, H04N-007, H04N-011, H04Q
4	Digital communication	H04L
5	Basic communication processes	H03#
6	Computer technology	(G06# not G06Q), G11C, G10L
7	IT methods for management	G06Q
8	Semiconductors	H01L
II	**Instruments**	
9	Optics	G02#, G03B, G03C, G03D, G03F, G03G, G03H, H01S
10	Measurement	G01B, G01C, G01D, G01F, G01G, G01H, G01J, G01K, G01L, G01M, (G01N not G01N-033), G01P, G01R, G01S; G01V, G01W, G04#, G12B, G99Z
11	Analysis of biological materials	G01N-033
12	Control	G05B, G05D, G05F, G07#, G08B, G08G, G09B, G09C, G09D
13	Medical technology	A61B, A61C, A61D, A61F, A61G, A61H, A61J, A61L, A61M, A61N, H05G
III	**Chemistry**	
14	Organic fine chemistry	(C07B, C07C, C07D, C07F, C07H, C07J, C40B) not A61K, A61K-008, A61Q
15	Biotechnology	(C07G, C07K, C12M, C12N, C12P, C12Q, C12R, C12S) not A61K
16	Pharmaceuticals	A61K not A61K-008
17	Macromolecular chemistry, polymers	C08B, C08C, C08F, C08G, C08H, C08K, C08L
18	Food chemistry	A01H, A21D, A23B, A23C, A23D, A23F, A23G, A23J, A23K, A23L, C12C, C12F, C12G, C12H, C12J, C13D, C13F, C13J, C13K
19	Basic materials chemistry	A01N, A01P, C05#, C06#, C09B, C09C, C09F, C09G, C09H, C09K, C09D, C09J, C10B, C10C, C10F, C10G, C10H, C10J, C10K, C10L, C10M, C10N, C11B, C11C, C11D, C99Z
20	Materials, metallurgy	C01#, C03C, C04#, C21#, C22#, B22#

	Area, field	IPC code
I	**Electrical engineering**	
21	Surface technology, coating	B05C, B05D, B32#, C23#, C25#, C30#
22	Micro-structure and nano-technology	B81#, B82#
23	Chemical engineering	B01B, B01D-000#, B01D-01##, B01D-02##, B01D-03##, B01D-041, B01D-043, B01D-057, B01D-059, B01D-06##, B01D-07##, B01F, B01J, B01L, B02C, B03#, B04#, B05B, B06B, B07#, B08#, D06B, D06C, D06L, F25J, F26#, C14C, H05H
24	Environmental technology	A62D, B01D-045, B01D-046, B01D-047, B01D-049, B01D-050, B01D-051, B01D-052, B01D-053, B09#, B65F, C02#, F01N, F23G, F23J, G01T, E01F-008, A62C
IV	**Mechanical engineering**	
25	Handling	B25J, B65B, B65C, B65D, B65G, B65H, B66#, B67#
26	Machine tools	B21#, B23#, B24#, B26D, B26F, B27#, B30#, B25B, B25C, B25D, B25F, B25G, B25H, B26B
27	Engines, pumps, turbines	F01B, F01C, F01D, F01K, F01L, F01M, F01P, F02#, F03#, F04#, F23R, G21#, F99Z
28	Textile and paper machines	A41H, A43D, A46D, C14B, D01#, D02#, D03#, D04B, D04C, D04G, D04H, D05#, D06G, D06H, D06J, D06M, D06P, D06Q, D99Z, B31#, D21#, B41#
29	Other special machines	A01B, A01C, A01D, A01F, A01G, A01J, A01K, A01L, A01M, A21B, A21C, A22#, A23N, A23P, B02B, C12L, C13C, C13G, C13H, B28#, B29#, C03B, C08J, B99Z, F41#, F42#
30	Thermal processes and apparatus	F22#, F23B, F23C, F23D, F23H, F23K, F23L, F23M, F23N, F23Q, F24#, F25B, F25C, F27#, F28#
31	Mechanical elements	F15#, F16#, F17#, G05G
32	Transport	B60#, B61#, B62#, B63B, B63C, B63G, B63H, B63J, B64#
V	**Other fields**	
33	Furniture, games	A47#, A63#
34	Other consumer goods	A24#, A41B, A41C, A41D, A41F, A41G, A42#, A43B, A43C, A44#, A45#, A46B, A62B, B42#, B43#, D04D, D07#, G10B, G10C, G10D, G10F, G10G, G10H, G10K, B44#, B68#, D06F, D06N, F25D, A99Z
35	Civil engineering	E02#, E01B, E01C, E01D, E01F-001, E01F-003, E01F-005, E01F-007, E01F-009, E01F-01#, E01H, E03#, E04#, E05#, E06#, E21#, E99Z

Source: WIPO IPC-Technology Concordance Table.

Section B – Descriptive statistics

Table B1 – Detailed description of variables

Variables	Description	Unit of measure	Type	Source
Technological diversification (TECH_DIV)	Entropy index of technological diversification at subclass level.	Index	Dependent	Authors' elaboration on RISIS CIB database.
Unrelated diversification (UT_DIV)	Entropy index of technological diversification at IPC section level.	Index	Dependent	Authors' elaboration on RISIS CIB database.
Related diversification (RT_DIV)	Difference between technological diversification and unrelated diversification.	Index	Dependent	Authors' elaboration on RISIS CIB database.
International breadth (INT_BREADTH)	Total number of foreign host locations.	Count	Independent	Authors' elaboration on RISIS CIB database.
International depth (INT_DEPTH)	Adjusted Herfindahl concentration index of patent distribution, across total number of foreign host locations.	Index	Independent	Authors' elaboration on RISIS CIB database.
Technological dissimilarity (TECH_DISS)	Technological dissimilarity between companies and foreign host locations, as measured by the inverse of the angular separation indicator.	Index	Independent	Authors' elaboration on OECD REGPAT database.
R&D intensity (RD_INTENSITY)	R&D expenditure scaled to total assets.	Share (%)	Control	ORBIS Bureau Van Dijk database.
R&D intensity, dummy (Dummy(RD_INTENS))	Whether missing values of R&D intensity are replaced by 0.	Binary	Control	ORBIS Bureau Van Dijk database.
Number of employees (EMPLOYEES)	Total number of employees.	Thousands of people	Control	ORBIS Bureau Van Dijk database.
Production value (PROD_VALUE)	Total production value.	Thousands of euros	Control	ORBIS Bureau Van Dijk database.
Return on Assets, net (ROA_NET)	Return on Total Assets (net, after taxes).	Share (%)	Control	ORBIS Bureau Van Dijk database.
Patent stock (PAT_STOCK)	Firms' knowledge stock measured by the number of total patent applications accumulated in the previous year.	Count	Control	Authors' elaboration on RISIS CIB database.
Technological internationalization (TECH_INTERN))	Share of international patent applications out of the total ones.	Share(%)	Control	Authors' elaboration on RISIS CIB database.
Intra-organizational linkages (CO_PAT)	Total number of co-authored patent applications.	Count	Control	Authors' elaboration on RISIS CIB database.

Source: Authors' elaboration.

Table B2 – Descriptive statistics

	Obs	Mean	Std. Dev.	min	max	p25	Median	p75	p90
TECH_DIV	10,818	1.848	0.908	0	4.509	1.205	1.806	2.47	3.059
RT_DIV	10,818	1.025	0.642	0	2.873	0.548	0.983	1.451	1.919
UT_DIV	10,818	0.825	0.425	0	1.955	0.562	0.824	1.151	1.373
INT_BREADTH	10,818	6.088	8.803	0	89	1	3	7	15
INT_DEPTH	10,797	0.164	0.302	0	1	0.005	0.024	0.111	0.779
TECH_DISS	9,539	0.335	0.194	0	0.799	0.187	0.349	0.485	0.588
RD_INTENS	10,818	0.055	0.087	-0.004	1.372	0.009	.027	0.067	0.128
EMPLOYEES	10,754	34,410.667	67,823.052	1	2,300,000	3,580	11,047	35,864	95,359
PROD_VALUE	10,785	11,105,311	2.30e+07	-7.713	4.296e+08	790,528.63	2,571,167.4	9,392,100	27,857,200
ROA_NET	10,773	3.347	12.580	-99.235	95.336	1.547	5.036	8.534	12.871
PAT_STOCK	10,818	673.116	1,940.377	1	29,852	48	140	464	1524
TECH_INT	10,818	0.493	0.333	0	1	0.211	0.455	0.8	1
CO_PAT	10,818	7.13	35.958	0	687	0	0	2	12

Source: Authors' elaboration.

Table B3 – Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) TECH_DIV	1.000												
(2) RT_DIV	0.906***	1.000											
(3) UT_DIV	0.765***	0.421***	1.000										
(4) INT_BREADTH	0.534***	0.550***	0.309***	1.000									
(5) INT_DEPTH	-0.471***	-0.408***	-0.384***	-0.265***	1.000								
(6) TECH_DISS	0.532***	0.538***	0.315***	0.558***	-0.415***	1.000							
(7) RD_INTENS	-0.199***	-0.136***	-0.220***	-0.045***	0.096***	-0.074***	1.000						
(8) Log(EMPLOYEES)	0.509***	0.470***	0.377***	0.461***	-0.266***	0.467***	-0.460***	1.000					
(9) Log(PROD_VALUE)	0.493***	0.457***	0.362***	0.442***	-0.263***	0.459***	-0.497***	0.922***	1.000				
(10) ROA_NET	0.158***	0.139***	0.127***	0.131***	-0.136***	0.177***	-0.492***	0.331***	0.425***	1.000			
(11) Log(PAT_STOCK)	0.574***	0.573***	0.358***	0.646***	-0.385***	0.663***	-0.059***	0.510***	0.524***	0.170***	1.000		
(12) TECH_INT	-0.113***	-0.109***	-0.078***	0.132***	0.054***	-0.237***	-0.081***	-0.003	-0.018*	-0.004	-0.088***	1.000	
(13) Log(CO_PAT)	0.428***	0.441***	0.247***	0.633***	-0.211***	0.478***	0.005	0.372***	0.382***	0.069***	0.579***	0.058***	1.000

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

Source: Authors' elaboration.

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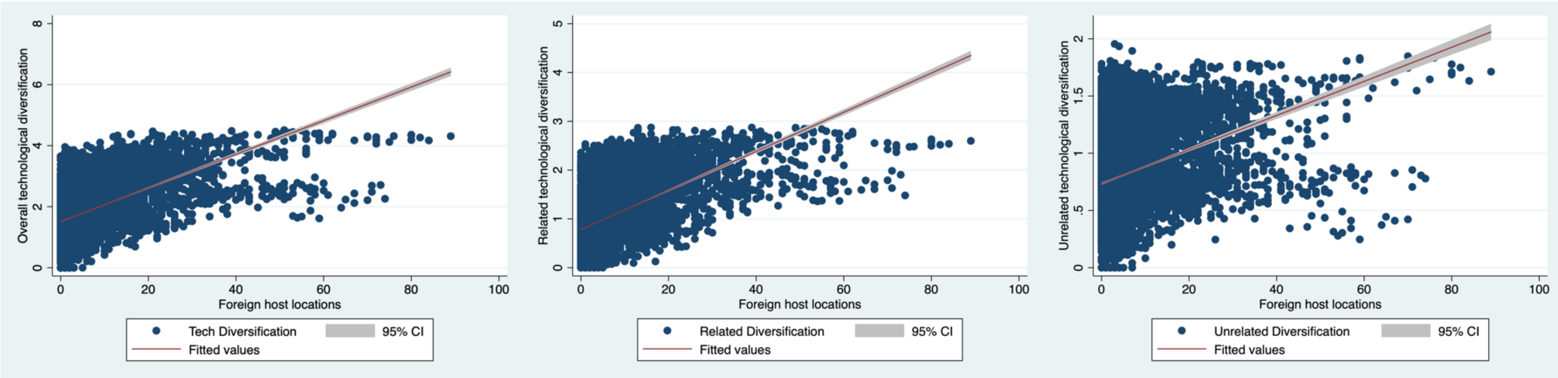
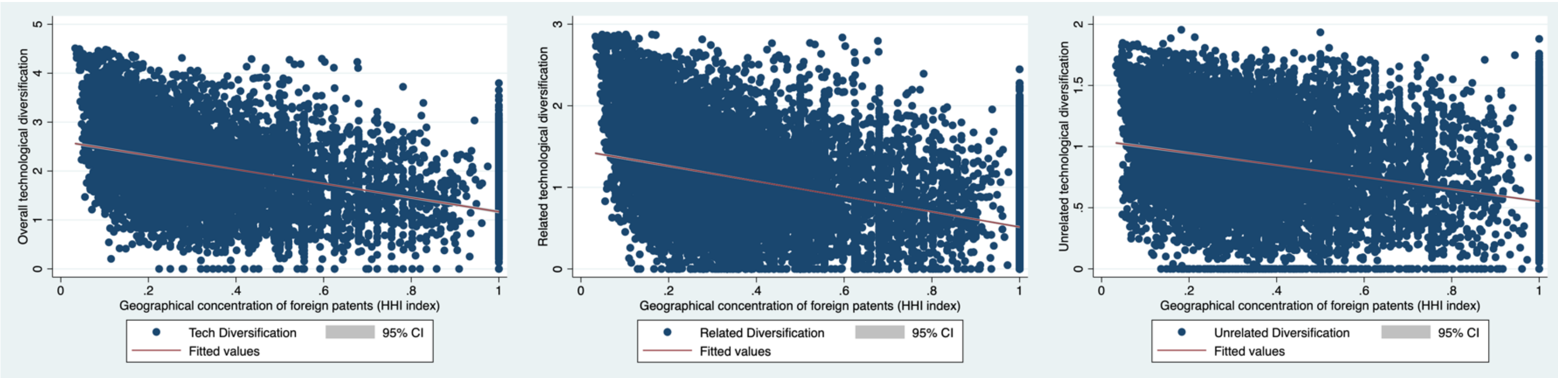
Figure B4 – Correlation plots between technology diversification and international breadth (with 95% confidence intervals)



(a) Overall (b) Related (c) Unrelated

Source: Authors' elaboration.

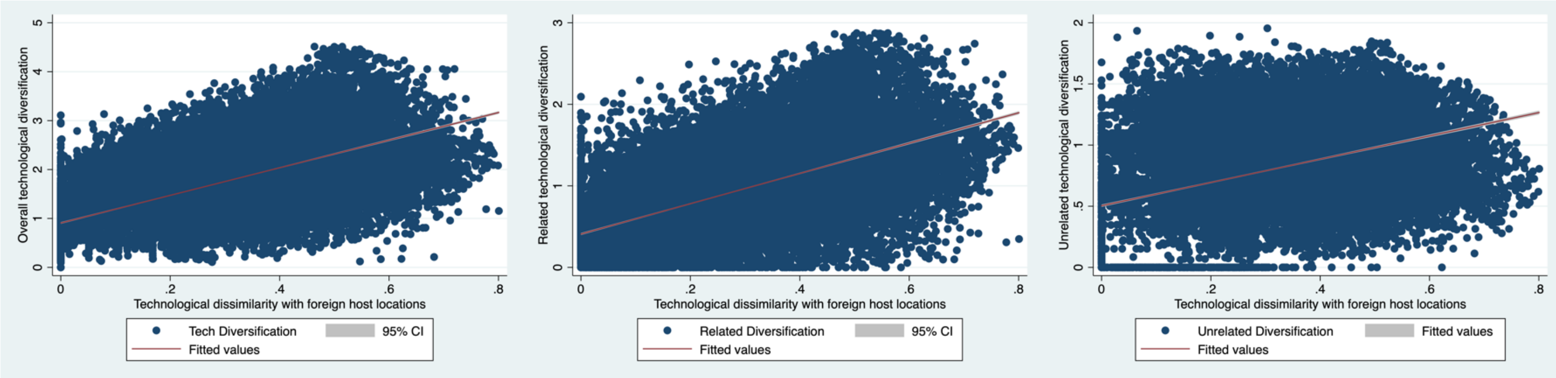
Figure B5 – Correlation plots between technology diversification and international depth (with 95% confidence intervals)



(a) Overall (b) Related (c) Unrelated

Source: Authors' elaboration.

Figure B5 – Correlation plots between technology diversification and technological dissimilarity (with 95% confidence intervals)



(a) Overall (b) Related (c) Unrelated

Source: Authors' elaboration.

Section C – Robustness checks

Table C1 – Robustness checks: excluding US based companies

VARIABLES	(1) TECH_DIV$_{i,t}$	(2) TECH_DIV$_{i,t}$	(3) RT_DIV$_{i,t}$	(4) RT_DIV$_{i,t}$	(5) UT_DIV$_{i,t}$	(6) UT_DIV$_{i,t}$
INT_BREADTH$_{i,t-1}$	0.0377***	0.0141***	0.0221***	0.0112***	0.0155***	0.00286**
	(0.00662)	(0.00259)	(0.00534)	(0.00202)	(0.00345)	(0.00127)
INT_DEPTH$_{i,t-1}$	-0.0380**	-0.0641**	-0.0277**	-0.0318*	-0.0105	-0.0329*
	(0.0177)	(0.0285)	(0.0124)	(0.0192)	(0.0105)	(0.0182)
TECH_DISS$_{i, t-1}$	0.409***	0.326***	0.292***	0.234***	0.118**	0.0934*
	(0.0838)	(0.0921)	(0.0602)	(0.0626)	(0.0470)	(0.0541)
INT_BREADTH$_{i,t-1}$ * TECH_DISS$_{i,t-1}$	-0.0421***		-0.0192**		-0.0229***	
	(0.0105)		(0.00861)		(0.00536)	
INT_DEPTH$_{i,t-1}$ * TECH_DISS$_{i, t-1}$		0.0398		-0.00873		0.0497
		(0.0643)		(0.0441)		(0.0435)
RD_INTENS$_{i,t-1}$	-0.231	-0.248	-0.118	-0.126	-0.105	-0.115
	(0.287)	(0.290)	(0.210)	(0.211)	(0.156)	(0.156)
Dummy(RD_INTENS$_{i,t-1}$)	0.0357	0.0328	-0.0252	-0.0276	0.0614	0.0610
	(0.118)	(0.118)	(0.0405)	(0.0405)	(0.119)	(0.119)
Log(EMPLOYEES$_{i,t-1}$)	0.0389*	0.0408*	0.0202	0.0207	0.0186	0.0201
	(0.0235)	(0.0238)	(0.0185)	(0.0187)	(0.0133)	(0.0134)
Log(PROD_VALUE$_{i,t-1}$)	0.00270	0.00126	-0.00135	-0.00195	0.00407	0.00323
	(0.0159)	(0.0163)	(0.0150)	(0.0151)	(0.00696)	(0.00690)
ROA_NET$_{i,t-1}$	0.000268	0.000245	-0.000642	-0.000653	0.000895	0.000884
	(0.000958)	(0.000957)	(0.000593)	(0.000594)	(0.000631)	(0.000630)
Log(PAT_STOCK$_{i,t-1}$)	0.0168	0.0181	0.00718	0.00777	0.00888	0.00959
	(0.0180)	(0.0181)	(0.0124)	(0.0124)	(0.0108)	(0.0109)
TECH_INT$_{i,t-1}$	-0.191***	-0.182***	-0.0651*	-0.0607	-0.123***	-0.119***
	(0.0523)	(0.0525)	(0.0375)	(0.0375)	(0.0325)	(0.0325)
Log(CO_PAT$_{i,t-1}$)	0.00570	0.00401	0.00325	0.00241	0.00272	0.00186
	(0.0100)	(0.0106)	(0.00781)	(0.00809)	(0.00527)	(0.00540)
Constant	1.178***	1.211***	0.644***	0.666***	0.538***	0.549***
	(0.258)	(0.263)	(0.205)	(0.208)	(0.146)	(0.148)
Observations	5,773	5,773	5,773	5,773	5,773	5,773
R-squared	0.824	0.823	0.817	0.816	0.669	0.669
R-squared adj.	0.801	0.800	0.793	0.793	0.627	0.626
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
N_clust	630	630	630	630	630	630

Note: Clustered standard errors at firm level are in parentheses. The significance levels of the statistical test are given by the p-value, that is: *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' elaboration.

Table C2 – Robustness checks: baseline estimation with 2-year lags for the independent variables

VARIABLES	(1) $TECH\_DIV_{i,t}$	(2) $TECH\_DIV_{i,t}$	(3) $RT\_DIV_{i,t}$	(4) $RT\_DIV_{i,t}$	(5) $UT\_DIV_{i,t}$	(6) $UT\_DIV_{i,t}$
$INT\_BREADTH_{i,t-2}$	0.0260***	0.0104***	0.0193***	0.00927***	0.00651**	0.00108
	(0.00495)	(0.00199)	(0.00398)	(0.00164)	(0.00263)	(0.000841)
$INT\_DEPTH_{i,t-2}$	-0.0244*	-0.0623***	-0.00951	-0.0167	-0.0147*	-0.0442***
	(0.0129)	(0.0234)	(0.00919)	(0.0176)	(0.00794)	(0.0153)
$TECH\_DISS_{i,t-2}$	0.343***	0.316***	0.254***	0.202***	0.0816**	0.106**
	(0.0626)	(0.0689)	(0.0459)	(0.0507)	(0.0365)	(0.0419)
$INT\_BREADTH_{i,t-2}$ * $TECH\_DISS_{i,t-2}$	-0.0274***		-0.0169**		-0.0102**	
	(0.00827)		(0.00667)		(0.00400)	
$INT\_DEPTH_{i,t-2}$ * $TECH\_DISS_{i,t-2}$		0.0812		0.000748		0.0774**
		(0.0537)		(0.0414)		(0.0333)
$RD\_INTENS_{i,t-2}$	-0.0574	-0.0707	0.00899	-0.000934	-0.0658	-0.0691
	(0.177)	(0.177)	(0.132)	(0.132)	(0.113)	(0.113)
Dummy($RD\_INTENS_{i,t-2}$)	0.0472	0.0502	0.00843	0.0102	0.0391	0.0403
	(0.0505)	(0.0510)	(0.0483)	(0.0486)	(0.0331)	(0.0332)
Log($EMPLOYEES_{i,t-2}$)	0.0574***	0.0599***	0.0351**	0.0361**	0.0224*	0.0238*
	(0.0208)	(0.0209)	(0.0163)	(0.0164)	(0.0130)	(0.0131)
Log($PROD\_VALUE_{i,t-2}$)	0.00671	0.00521	0.00308	0.00229	0.00386	0.00318
	(0.0153)	(0.0153)	(0.0122)	(0.0123)	(0.00886)	(0.00891)
$ROA\_NET_{i,t-2}$	0.000410	0.000412	6.75e-05	7.04e-05	0.000357	0.000357
	(0.000638)	(0.000639)	(0.000467)	(0.000468)	(0.000396)	(0.000396)
Log($PAT\_STOCK_{i,t-2}$)	-0.0271*	-0.0262*	-0.0241**	-0.0238**	-0.00303	-0.00251
	(0.0150)	(0.0150)	(0.0104)	(0.0105)	(0.00908)	(0.00909)
$TECH\_INT_{i,t-2}$	-0.187***	-0.178***	-0.110***	-0.103***	-0.0776***	-0.0757***
	(0.0397)	(0.0397)	(0.0287)	(0.0286)	(0.0248)	(0.0246)
Log($CO\_PAT_{i,t-2}$)	0.00804	0.00691	-0.00150	-0.00234	0.00951***	0.00922***
	(0.00688)	(0.00702)	(0.00532)	(0.00542)	(0.00356)	(0.00356)
Constant	1.315***	1.328***	0.725***	0.747***	0.590***	0.582***
	(0.238)	(0.239)	(0.171)	(0.172)	(0.137)	(0.137)
Observations	8,424	8,424	8,424	8,424	8,424	8,424
R-squared	0.838	0.838	0.824	0.824	0.716	0.716
R-squared adj.	0.818	0.818	0.802	0.802	0.681	0.681
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
N_clust	888	888	888	888	888	888

Note: Clustered standard errors at firm level are in parentheses. The significance levels of the statistical test are given by the p-value, that is: *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' elaboration.

Table C3 – Robustness checks: baseline estimation with the inverse of the adjusted Herfindahl-Hirschman index as dependent variable

VARIABLES	(1) TECH_DIV_HH$_{i,t}$	(2) TECH_DIV_HH$_{i,t}$	(3) TECH_DIV_HH$_{i,t}$	(4) TECH_DIV_HH$_{i,t}$	(5) TECH_DIV_HH$_{i,t}$	(6) TECH_DIV_HH$_{i,t}$
INT_BREADTH$_{i,t-1}$	0.00218***			0.00123***	0.00868***	0.00174***
	(0.000460)			(0.000454)	(0.00138)	(0.000445)
INT_DEPTH$_{i,t-1}$		-0.0186***		-0.0147***	-0.00967***	-0.0322***
		(0.00355)		(0.00364)	(0.00373)	(0.00758)
TECH_DISS$_{i,t-1}$			0.0519***	0.0341**	0.0673***	0.0708***
			(0.0166)	(0.0168)	(0.0193)	(0.0225)
INT_BREADTH$_{i,t-1}$ * TECH_DISS$_{i,t-1}$					-0.0126***	
					(0.00220)	
INT_DEPTH$_{i,t-1}$ * TECH_DISS$_{i, t-1}$						0.0572***
						(0.0169)
RD_INTENS$_{i,t-1}$	0.158***	0.161***	0.163***	0.158***	0.161***	0.160***
	(0.0394)	(0.0391)	(0.0389)	(0.0392)	(0.0385)	(0.0393)
Dummy(RD_INTENS$_{i,t-1}$)	0.00786	0.00784	0.00880	0.00774	0.00671	0.00818
	(0.0125)	(0.0126)	(0.0127)	(0.0125)	(0.0123)	(0.0124)
Log(EMPLOYEES$_{i,t-1}$)	0.0110**	0.0110**	0.0119**	0.00986*	0.00941*	0.0104**
	(0.00515)	(0.00518)	(0.00516)	(0.00516)	(0.00518)	(0.00519)
Log(PROD_VALUE$_{i,t-1}$)	0.00110	0.000849	0.00108	0.000794	0.000995	0.000753
	(0.00370)	(0.00370)	(0.00372)	(0.00369)	(0.00370)	(0.00371)
ROA_NET$_{i,t-1}$	-0.000144	-0.000121	-0.000114	-0.000144	-0.000145	-0.000144
	(0.000220)	(0.000222)	(0.000222)	(0.000222)	(0.000222)	(0.000222)
Log(PAT_STOCK$_{i,t-1}$)	0.0106**	0.0116***	0.0116***	0.00969**	0.00937**	0.00977**
	(0.00440)	(0.00437)	(0.00436)	(0.00437)	(0.00435)	(0.00435)
TECH_INT$_{i,t-1}$	-0.0697***	-0.0696***	-0.0594***	-0.0687***	-0.0725***	-0.0697***
	(0.0121)	(0.0120)	(0.0118)	(0.0120)	(0.0120)	(0.0120)
Log(CO_PAT$_{i,t-1}$)	0.00127	0.00233	0.00241	0.000826	0.00141	0.000976
	(0.00179)	(0.00177)	(0.00178)	(0.00177)	(0.00173)	(0.00176)
Constant	0.574***	0.567***	0.551***	0.573***	0.562***	0.559***
	(0.0590)	(0.0589)	(0.0588)	(0.0587)	(0.0586)	(0.0591)
Observations	10,818	10,818	10,818	10,818	10,818	10,818
R-squared	0.641	0.642	0.641	0.642	0.643	0.643
R-squared adj.	0.599	0.599	0.598	0.600	0.601	0.600
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
N_clust	1125	1125	1125	1125	1125	1125

Note: Clustered standard errors at firm level are in parentheses. The significance levels of the statistical test are given by the p-value, that is: *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' elaboration.