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Time is the enemy: The speed of proximity-based knowledge diffusion

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Abstract

Does knowledge spread more quickly when firms are geographically closer? Focusing on knowledge diffusion from multinational enterprises (MNEs) subsidiaries in the context of the US semiconductor industry, our analysis suggests that the broader MNE patents are, in terms of the knowledge sources they draw on, the slower the speed of knowledge diffusion to more spatially proximate firms, compared to more distant ones. Moreover, our findings suggest that this outcome could be attributed to a greater reliance on knowledge sources that are internal to the MNE network or located geographically distant. We provide interpretative cues for these findings and provide policy recommendations in line with our results.

KEYWORDS

knowledge diffusion, knowledge spillover, patent, subsidiary, time

1 | INTRODUCTION

Research in economic geography has been increasingly interested in multinational enterprises (MNEs), that is, companies controlling value-added activities in multiple countries (Dunning & Lundan, 2008). MNEs are conceived as nodes connecting local to global knowledge (Amendolagine et al., 2018; Bathelt & Cohendet, 2014; Cantwell & Iammarino, 2003; Cantwell & Piscitello, 2005; Castellani, 2002; Crescenzi et al., 2014; Iammarino & McCann, 2013; among many others). Evidence regarding MNEs playing this role at the local level is mixed (Almeida, 1996; Driffield et al., 2002; Gorg, 2004; Javorcik & Spatareanu, 2008, 2011; Jindra et al., 2009), and studies have demonstrated that proximate interactions and local factors matter the most (LeSage et al., 2007), so that, for example, the absorptive capacity of domestic firms determines the extent to which subsidiaries of MNEs impact the area where they operate (Blalock & Simon, 2009; Girma, 2005; Glass & Saggi, 1998; Kemeny, 2010; Meyer & Sinani, 2009; Spencer, 2008; Zhang et al., 2010). While much of the earlier research focused on whether domestic firms are able to absorb knowledge from MNE subsidiaries, the *speed* at which MNE knowledge flows to other firms remains relatively under-researched (Kim, 2016; Phene et al., 2005). Indeed, investigating this dimension is important because fast followers can quickly learn from new technology, thus creating a larger distance between themselves and later adopters (Kessler & Chakrabarti, 1996; Lieberman & Montgomery, 1988), with positive repercussions on the general innovative capacity of the local area (Merlevede & Purice, 2016).

In this paper we investigate some determinants of the speed at which knowledge from an MNE subsidiary diffuses within the surrounding area, as compared to more distant locations in the host country. At the same time, we account for the fact that an innovation (as captured by a patent) can have different knowledge structures depending on the variety of knowledge sources it draws on (Frost, 2001). This can be classified along two dimensions: (a) *organizational breadth*, distinguishing between intra-MNE and extra-MNE knowledge sources (see e.g., Rosenkopf & Nerkar, 2001) and (b) *geographical breadth*, which instead focuses on the distinction between knowledge sourced within the local area and distant knowledge (see Almeida & Phene, 2004).

Using a sample of 1394 granted patents developed by US-based subsidiaries of foreign MNEs operating in the US semiconductor industry, we analyzed the time lag between an MNE subsidiary's patent application date (i.e., focal patent) and the application date of the first subsequent patent that cites it as prior art in the US. This citation link signals that the subsidiary's knowledge has been used as input in the invention process of other local firms (Almeida, 1996; LeSage et al., 2007). We seek to identify whether this time lag is shorter if a subsidiary's patents are cited by firms colocated within the same subnational area, empirically captured via a metropolitan statistical area (MSA),[1] and whether and how the subsidiary knowledge sourcing strategy—distinguishing between organizational and geographical breadth— affects the speed at which these patents get cited. Our analysis suggests that a high level of breadth in technology sourcing slows down the process of knowledge diffusion (observed in the lag in patent citations) for colocated firms more than it does for distant ones within the larger country. This result seems to be driven mainly by the "distant breadth" of MNE patents (when the patented technology builds heavily on distant knowledge sources) and by "internal breadth" (when it builds heavily on intra-MNE knowledge sources).

2 | THEORY

2.1 | From knowledge flows to their speed

Research has shown that MNEs may work as representatives (Sigler et al., 2023), linking two distant locations, or even as brokers, acting as knowledge gatekeepers (Giuliani & Bell, 2005; Morrison, 2008), thus allowing firms colocated in the same area to access knowledge generated elsewhere and transferred to the host location. In parallel, subsidiaries of foreign MNEs constitute a critical source of knowledge for colocated firms (Hymer, 1976), especially in the case of subsidiaries that are themselves active in terms of knowledge exploitation and creation and that therefore have a potential to transfer—incidentally or voluntarily—technological knowledge to their host locations (Almeida, 1996; Dellestrand & Kappen, 2012; Marin & Bell, 2006). As a result, there is currently little debate regarding the fact that the MNE network of subsidiaries can act as international conduits of knowledge

[1]In our case a metropolitan statistical area (MSA) is to be understood as a subnational, geographically defined area. A growing focus on this level, as highlighted by Cunningham & O'Reilly (2018), is crucial to understand the forces governing innovation and knowledge dissemination, even though a critical reflection on the potential benefits of looking at this intermediate dimension is needed, as pointed out by Iammarino (2005).

(Bartlett & Ghoshal, 1989; Branstetter, 2006; Singh, 2007) for local host country firms. However, the circumstances that make knowledge transfer more or less likely to occur are less clear.

One area where research has been especially lacking concerns the *speed* at which knowledge flows out from MNEs to other actors in the host country and finally becomes part of the endowment of local firms' innovative outputs, as indicated, for instance, in their patents (Kim, 2013; Zander & Kogut, 1995). The underlying assumption in this case is that knowledge diffusion occurs more rapidly at shorter distances, a concept supported by the studies of Agrawal et al. (2008) and Merlevede and Purice (2016). Therefore, proximity becomes crucial, as closely situated entities are more likely to benefit from rapid knowledge spillovers (Jaffe & Trajtenberg, 1999; Maurseth & Verspagen, 2002). The rationale behind this lies in the increased accessibility of face-to-face interactions for firms located close to the source of knowledge, facilitating accelerated learning processes (Aldieri, 2011; Comin et al., 2012; Keller & Yeaple, 2013). Proximity is thus expected to facilitate knowledge transfer between firms, mitigating potential transfer barriers (Dellestrand & Kappen, 2012; Szulanski, 1996).

The time needed to acquire knowledge impacts the rate of subsequent innovations (Lieberman & Montgomery, 1988). The faster local firms absorb knowledge from MNE subsidiaries, the sooner they can develop innovative outputs (e.g., patents). Overall, this could be beneficial for local firms and the area where the subsidiary is located, leading to technological progress (Almeida, 1996), even though this may occur at the expense of the MNE, which could experience larger knowledge outflows than inflows (Mariotti et al., 2010) These considerations are especially true in high-tech industries, where the pace of innovation is so high that time is the real enemy (Markman et al., 2005). For this reason, the context of our research is ideal for investigating this matter.

2.2 | Knowledge source breadth

Not all knowledge is the same. Knowledge creation processes are heterogeneous, and so are the knowledge sources that can be used to develop a new technology (Leiponen & Helfat, 2010). According to Cohen and Levinthal (1989, p. 570), "the ease of learning [...] depends upon the characteristics of the underlying technological and scientific knowledge." Hence, depending on how diverse the knowledge sources constituting a piece of technological knowledge or a patent are, the complexity of the tasks required to absorb it may vary, and so will the time firms need to implement such tasks.

The idea that firms' knowledge sourcing affects the structure of newly created knowledge in ways that may influence the ease with which knowledge spreads to other agents is not entirely new in innovation studies (Kim, 2016; Laursen & Salter, 2006; Rosenkopf & Nerkar, 2001; Teece, 1986; Zhao, 2006). MNE subsidiaries draw on multiple knowledge sources to develop their patents, because they are simultaneously exposed to very different knowledge environments. More precisely, one of these environments is the MNE internal network, composed of the headquarters and other sister subsidiaries, which are generally in distant locations, although subsidiaries may also rely on their own, locally-developed knowledge (Bartlett & Ghoshal, 1989); the other is the external network, which in turn can include local firms or other actors (Almeida & Phene, 2004), as well as those located outside of the subsidiary's host region or country (Phene & Almeida, 2008). Drawing on earlier research, we use the notion of knowledge breadth and we refer to "broad" technology sourcing when a firm uses a variety of technology sources to innovate (Laursen & Salter, 2006). There can be different knowledge structures, depending on their source configurations and therefore on whether the sources are internal or external to the MNE, and on whether they are geographically close (i.e., in the surrounding area where the subsidiary is located) or more distant.

In terms of organizational boundaries, we conceive "internal breadth" in technology sourcing as the extent to which the subsidiary utilizes knowledge from different geographic domains but situated within the boundaries of the MNE network. Conversely, we identify "external breadth" in technology sourcing as the extent to which a subsidiary obtains knowledge from sources that fall outside the MNE's organizational boundaries, whether from geographically close or distant locations.

In terms of geographical boundaries, "distant breadth" in technology sourcing integrates knowledge from geographically distant locations (i.e., beyond the surrounding subnational area where the subsidiary is located), regardless of whether they belong to the MNE network. "Local breadth," on the contrary, refers to a situation in which the subsidiary builds upon knowledge residing within the subnational surrounding area, either inside its own organization or in other colocated firms. We elaborate further on these dimensions below.

2.3 | Organizational breadth

When developing technology sourcing along the organizational dimension, subsidiaries may rely on sources both from within and from outside their MNE internal network. Depending on this origin, the resulting innovation may contain more or less MNE-specific knowledge.

Indeed, as the technological subunits of the MNE operate within the same organizational environment, any new technology they develop is likely created through routines that are firm-specific (Rajan & Zingales, 2001). Pieces of knowledge built in this way are consequently likely to exhibit a certain degree of homogeneity. As a result, new technology developed based on them, as opposed to a more heterogenous knowledge base, is likely to be easier to understand for other firms, and faster to absorb.

However, in line with Dosi (1988), we also expect that identifying and understanding firm-specific knowledge related to MNE routines will be difficult for other firms. The organizational routines of an MNE – the "DNA" of a firm according to Feldman and Pentland (2003) – are often opaque and deeply embedded in an organizational environment (Feldman & Pentland, 2003; Iwao, 2015), and consequently the knowledge produced through them ends up being very firm-specific and thus very distant from the knowledge base of other firms. As a consequence, in the presence of high internal breadth, firms may spend a great deal of time trying to overcome the cognitive distance (Nooteboom et al., 2007) between their knowledge base and the knowledge base of the subsidiary's patent, which slows down absorption (Kim, 2013; Mahoney & Pandian, 1992). In sum, the final effect that heavy reliance on knowledge sources internal to an MNE network has on the diffusion speed of a subsidiary's knowledge depends on the interplay between knowledge homogeneity and cognitive distance.

Conversely, when a subsidiary combines pieces of knowledge generated outside an MNE internal network, these external pieces of knowledge form a mixture of the various other organizational environments from which they originate. They are organizationally *extraneous* to each other, so to speak. Thus, these pieces of knowledge are not linked to a single organizational structure, but rather are built in different organizational environments, with different routines and no shared tacit knowledge. As a result, there is no firm-specific background knowledge embedded in the recombination of such sources, and therefore firms interested in using the resulting patent have no specific organization to target when trying to reduce the cognitive distance (Nooteboom et al., 2007). This suggests that an increase in the external breadth of a subsidiary's technology sourcing strategy might have no significant effect on the speed at which the knowledge produced will diffuse to other firms.

2.4 | Geographical breadth

MNE subsidiaries source technology from the area where they are established in their host country, as well as from areas that are more distant or even globally dispersed. As highlighted by the extant literature (e.g., Phene et al., 2006), the geographic origin of knowledge is a fundamental dimension in the innovation processes of firms. Knowledge with distant origins may contribute to innovation via its diversity and newness, but at the cost of being less fine-grained and less rich than locally embedded knowledge. In the case of distant knowledge, the "seeding" of search, that is, "the problem of identifying the starting points of the search process" (Levinthal & Warglien, 1999, p. 349), faces the challenge of screening the worldwide technological landscape. Compared to local sources of technology that are located in the immediate surroundings of local firms and hence readily available, distant sources can be dispersed and remote, and their screening is likely to take more time. Moreover, technology developed predominantly in a different geographic context bears systemic and architectural characteristics linked to that context (Phene et al., 2006), which are inherently different from those in the area where the subsidiary and local firms operate. Making sense of these differences may take time and slow down the absorption process.

In contrast, when technology sources are mainly locally generated, they are likely to be more familiar to colocated firms, decreasing cognitive distance (Nooteboom et al., 2007) from the subsidiary. For example, colocated firms may be able to relate directly to some of the subsidiary's routines, something that allows them to create "common ground" with it (Srikanth & Puranam, 2011, 2014) and easing understanding of the subsidiary's technology, thus making the absorption process easier and more immediate (Broekel & Boschma, 2011; Tallman & Phene, 2002). In other words, inasmuch as geographic proximity between local firms and the subsidiary can fill the gap in their cognitive distance, knowledge generated predominantly by combining local sources should not suffer the same low speed of spillover knowledge diffusion that occurs with distant sources.

2.5 | Speed, proximity, and types of knowledge breadth: The research question

While the speed at which MNE subsidiaries' knowledge seeps out of their boundaries toward colocated firms is a relatively under-investigated subject in economic geography, it is not an untapped terrain in other fields. Jaffe and Trajtenberg (1999), for instance, suggest that, since knowledge is expected to follow a diffusion process through geographic, institutional and technological spaces, "researchers that are nearby along each of these dimensions would be particularly likely to benefit disproportionately in the period immediately after the antecedent innovation occurs" (p. 107).

Moreover, in their study of the patterns of citations among patents developed by inventors in the United States, the United Kingdom, France, Germany, and Japan, they find that patents whose inventors are from the same country cite each other systematically more than inventors from other countries, and that these citations occur quicker. This happens because recently created knowledge is highly tacit (Bathelt et al., 2004; Lawson & Lorenz, 1999; Rodriguez-Pose & Crescenzi, 2008), which makes face-to-face interactions arising from proximity extremely important for its transfer (Audretsch & Feldman, 1996; Polanyi, 1958). Moving ahead with its life cycle, knowledge becomes more explicit and easier to transfer even without the need for intensive personal communication; as a consequence, as time goes by, its dissemination is less bounded by geography, and it travels internationally with greater ease.

Thus, when investigating the impacts that different knowledge structures have on knowledge diffusion speed, we examined whether this speed varies depending on the geographical proximity of domestic firms and an MNE subsidiary. We ask the following: *does knowledge breadth (both organizational and geographical) affect diffusion speed differently, depending on whether actors are geographically close to or distant from the MNE subsidiary?* Although we have taken an exploratory approach, conventional understanding of diffusion processes (e.g., Jaffe & Trajtenberg, 1999), which we discussed earlier in this section, prompts us to suggest that knowledge spreads more quickly among more proximate firms. We contribute to this debate by exploring how this conclusion is affected by the breadth of knowledge sourcing undertaken by MNE subsidiaries.

3 | METHODS

3.1 | Data and sample

We conducted our empirical analysis on a sample of granted patents developed by MNE subsidiaries originating in Europe and Asia, located in the United States and belonging to the semiconductor industry. We focused on the semiconductor industry for the following reasons: (a) it has historically been the target of a large number of inward foreign direct investments (Almeida, 1996) oriented towards conducting R&D activities in the United States; (b) the semiconductor sector is characterized by a short technology cycle time (Stuart & Podolny, 1996), which makes the speed of knowledge flows a crucial aspect in a firm's technological performance; and (c) as patents are extremely widespread in this industry, they are suitable for measuring innovation and tracking knowledge flows. More importantly, even with some caveats (see the discussion on this topic in the concluding section of this paper), the use of patent citation data is apt for studying knowledge outflows because of the wealth of information provided by patent documents, which includes the geographic location of the inventor of the innovation, as well as its timing and technology. Thanks to this information, patents make it possible to identify the *locus* of the innovative activity, the organization to which the patent is assigned, and, most important for our analysis, the temporal characteristics of the invention. In addition, patent documents incorporate a list of citations to other patents, whose inclusion is mandatory in the US patent system, and these are useful to identify the technological antecedents of a particular innovation (Almeida, 1996).

To build our sample, we were inspired by Almeida and Phene (2004) and Phene and Almeida (2008), and consequently collected data on the patents of 29 US-based subsidiaries of the largest non-US semiconductor MNEs, selected from Gartner Dataquest information for 2005.[2] For this set of MNEs, we identified 29 US subsidiaries engaged in innovation between 1975 and 2000[3] and examined their portfolio of semiconductor patents by using the information on the geographic location of the patents' first inventor (hUallacháin, 2012). Since semiconductor companies generally use the US Patent Office to record their innovations (Almeida & Phene, 2004), and since we focus on R&D activities taking place in the United States, we only considered patents filed under this system.

The selected time frame (1975–2000) is particularly relevant as it encompasses the period when, according to the Semiconductor Industry Association (SIA), the United States held a pivotal role in the industry. Indeed, during the 1980s, half of all semiconductor firms were from the United States (Malerba, 1985), and in 1999 the United States was the world's largest semiconductor end-user. More generally, since its establishment in 1958, the semiconductor industry has experienced cyclical patterns marked by alternating phases of rapid growth and decline. Notably, from 1975 to 2000, the industry demonstrated a remarkable annual growth rate, as reported by Semiconductor Industry Association (SIA) (2004). However, a substantial downturn occurred in 2001 (Chen et al., 2016). Subsequently, the significant growth of the Asian market from the late 1990s resulted in a trend where Asia gained increased significance compared to the United States in the semiconductor industry (Hobday, 1990; Kumar & Krenner, 2002). The timeframe chosen allows us to capture the liveliest period of the industry in the geographic location of the study.

To identify a subsidiary's semiconductor patents, we used Derwent's technological classification. We retained only patents belonging to the four Derwent patent classes included in the primary section of the "Semiconductors and Electronic Circuitry" category: U11 (semiconductor materials and processes), U12 (discrete devices), U13 (integrated circuits), and U14 (memories, film and hybrid circuits). Our final sample was composed of 1344 patents, which were filed over a 26-year period.

For each of these focal patents, we identified the first subsequent patent citing it as prior art. This was done to infer the existence of a knowledge flow between the organization to which the focal patent was assigned (i.e., the subsidiary) and the citing organizations. For each citing patent, we analyzed the first inventor's address and the address of the first inventor of the citing patent. We then constructed a measure of the physical proximity between

[2]We started by selecting the 10 largest non-US semiconductor MNEs in 2005. However, one of these firms was established as a joint venture in 2003. Since our empirical analysis ends in 2000, that is, before the joint venture formation, we considered the two parent companies as separate entities for the purpose of this study.

[3]To identify these subsidiaries, we first downloaded the US patents of the MNEs. Then we matched the geographic location of their first inventor with information on the location of their US-based subsidiaries, which we could find on their websites, company reports and specialized press. We then excluded from our analysis all MNE patents whose first inventor was located in MSAs in which we could not verify the existence of a subsidiary. While these patents indicate that the MNE is carrying out local innovative activities, for instance through the hiring of US-based inventors, they are not necessarily suggestive of the presence of a subsidiary.

the subsidiary and the citing organization based on the inventors' co-location in the same MSA. More specifically, proximity is captured by a dummy variable, taking the value of 1 if inventors are colocated in the same MSA and 0 if they are in different MSAs.

The choice of MSAs as the subnational unit of analysis is intentional, and in line with recommendations by Kang and Dall'erba (2016) and Agrawal et al. (2008). In fact, Audretsch and Feldman (2004) stated that measuring localized knowledge spillovers in countries poses significant challenges due to their extensive surface area, a point particularly true for US states. While analysis at the subnational level in Europe is conducted on regions or even regional clusters, as discussed by Bell et al. (2009), data at this level in the United States are usually gathered using MSAs as analytical units. As the fundamental notion behind an MSA is the presence of a central area housing a significant population nucleus, alongside surrounding communities characterized by a strong level of economic and social integration with the core (Office of Management and Budget [OMB], 2023), their boundaries very closely map the actual interaction occurring among their inhabitants. Indeed, Kang and Dall'erba (2016) show that face-to-face interactions, among the most effective means of diffusing knowledge (Polanyi, 1958), do support localized spillovers within a range of 50 to 75 miles maximum from the center of the MSA (Kang & Dall'erba, 2016). Given the average surface area of the MSAs considered in this paper (~7166 square miles, corresponding to an average distance of 48 miles from the center), we argue that MSAs are an appropriate unit of analysis that can capture spillovers due to proximity-based interaction.

Moreover, and importantly, MSAs do not function as legal administrative divisions like counties or as separate entities like US States, whose boundaries are the result of political processes that sometimes have little to do with actual interactions between their populations. In addition, the reference offered by the US OMB, rather than of each different legal entity, ensures a harmonized and comparable data source for all MSAs, making the exploration of the semiconductor industry dynamics in the United States better aligned with the criteria outlined by Maggioni (2002).

We then recorded the filing date of the focal patent and of the citing patent, and we considered the difference between the two moments to be a measure of the speed of knowledge diffusion. To avoid bias due to abnormal patterns of citations over time, we considered only forward citations occurring in the first 10 years after the filing date of the focal subsidiary patents (Fabrizio, 2007). Hence, even if we built our sample of focal patents up to the year 2000, our analysis extends through to 2010. There is no agreement in the literature on the period of time during which semiconductor products can be considered to be the leading edge of their technology; according to Moore's law (1965), the lifecycle of a semiconductor invention is 3 years, while Stuart and Podolny (1996) use a window of 5 years to analyze technological change in this sector, though they argue that for certain inventions this window might not be sufficient to account for time-to-manufacture, which could be a critical aspect to consider when looking at the dynamics of local knowledge outflows. To be fully conservative, we allowed for a 10-year observation window. In addition, our focus on the speed of knowledge flows seems to be consistent with the establishment of a limited observation period, a type of censoring that can, in any case, be handled during the estimation through the appropriate use of a duration model.[4]

3.2 | Variables

3.2.1 | Dependent variable

Speed. To capture the speed of MNE subsidiary knowledge flows, we used the number of months between the subsidiary patent application date and the application date of the first patent that cites it as prior art (citation lag), also recording the fact that a certain patent may be never cited (i.e., considering censoring in the estimation).

[4]More precisely, the applied Cox model and the AFT model distinguish between patents whose citation time lies within the 120 observed periods and patents whose citation time is the maximum number of periods (120) simply because no citation has occurred in the window of observation (i.e., they are censored).

Analyzing the timing of the first citation provided us with an assessment of the minimum time lag between the filing of the subsidiary patent and that of the citing patent, thus indicating the pace at which an instance of subsidiary knowledge was used in a subsequent innovation (Jaffe & Trajtenberg, 1999).

Our study aims to reveal the role of physical proximity in knowledge diffusion. To pinpoint this effect properly, we needed to control for the heterogeneity of our sample. More specifically, we needed to make sure that the only difference between our observations depended on whether citing inventors were physically proximate or distant from the inventor of the focal patent; other conditions had to be controlled for.

To ensure this situation, we employed two strategies. The first was when defining the sample and the second was when choosing the estimation model. In accordance with the sample, we limited our interest to citing patents produced in the host country, that is, patents whose first inventor was in the United States, recording whether she/he was within versus outside the same MSA as the first inventor of the patent cited. Focusing on the United States allowed us to minimize problems of institutional, cultural, and innovative heterogeneity across countries (Freeman, 1995; Nelson, 1993), as these factors could influence our dependent variable. Following the estimation model, we applied propensity score matching (PSM), as elaborated further in the estimation section.

Our sample reveals that, on average, it takes about 39 months for the first subsequent US-based patent to cite a subsidiary's patent as its technological antecedent, and in 14% of these cases the first citation detects a knowledge flow (as proxied by a patent citation) occurring within the same MSA.

3.2.2 | Independent variables

Source_Breadth. To begin our study on the organizational and geographical breadth of knowledge sources, we first captured the breadth of the technology sourcing of the subsidiary *in general*. We drew on Phene and Almeida's (2008) classification of subsidiary knowledge sources in semiconductors into six main categories, reflecting the knowledge contexts to which a subsidiary would have access: (i) the subsidiary itself, (ii) the headquarters, (iii) other MNE subsidiaries,[5] (iv) other organizations in the MSA, (v) other organizations in the home country, and (vi) other organizations in all other locations.[6] We then followed Laursen and Salter (2006) and coded each source as a binary variable, with the value of 1 if the subsidiary has drawn upon that specific technology source and 0 otherwise. We used backward citations to detect the knowledge sources that the focal patent had used. In particular, for each patent cited by our focal patents, we used information on the address of the first inventor to assign patents to different geographic locations, and information on the patent assignee to determine whether the patent had been developed by the MNE or by an external organization. Thus, patents whose assignee was the focal MNE were classified as headquarters' patents if their first inventor was located in the MNE home country, as the focal subsidiary if their first inventor was located in the subsidiary MSA, or as other MNE subsidiaries in all remaining cases. On the other hand, a patent whose assignee was an organization other than the focal MNE was assigned to other organizations in the MSA if its first inventor was located in the subsidiary MSA, to other organizations in the home country if its first inventor was located in the MNE home country, or to other organizations in all other locations in all remaining cases. Then, in line with previous research (Leiponen & Helfat, 2010), the breadth of a subsidiary's technology sourcing was captured as a combination of these six knowledge sources. More specifically, the six variables created above were summed, as foreseen by Laursen and Salter (2006). As a result, our breadth term ranges from 0, when the subsidiary had not indicated any prior patented innovation as an antecedent to its newly created knowledge, to 6, when the subsidiary had drawn from all six knowledge sources. This measure ("*Source_Breadth*") proxies for a subsidiary's ability to combine the knowledge absorbed from several distributed

[5]This category includes both MNE subsidiaries located in other US MSAs and MNE subsidiaries located in other countries (different from the home country).

[6]This category includes both other firms located in other US MSAs and other firms located in other countries (different from the home country).

technology sources within or beyond the MNE, independent of their location (Kogut & Zander, 1993; Phene & Almeida, 2008).

As a further step, we refined our measures and moved from a general account of source breadth to an analysis of different kinds of *organizational* and *geographical* breadth. We implemented this idea by building the following variables:

- *Local_Breadth* measures the extent to which the focal patent draws on knowledge sources originating in its local area, including the patent owner itself. It is determined by counting the number of different knowledge sources cited by the focal patent that are from its MSA. It ranges from 0 (when no sources from the same MSA are used) to 2 (when the focal patent cites other subsidiary patents and also patents from other external organizations in the same MSA).
- *Distant_Breadth* measures the extent to which the focal patent draws on knowledge sources that come from outside the boundaries of its MSA, and this is built by adding all the binary variables related to distant sources, that is, its headquarters, other subsidiaries in other locations, other organizations in its home country, and other organizations in other locations.
- *External_Breadth* measures the extent to which the focal patent draws on knowledge sources other than the MNE the subsidiary belongs to, and it is constructed as the sum of all the binary variables corresponding to sources that fall beyond the boundaries of the MNE, that is, other firms in the same MSA, other firms in the home country and other firms in other locations.
- *Internal_Breadth* measures the extent to which the focal patent draws on knowledge sources within the subsidiary's MNE, and it is constructed as the sum of all the binary variables associated with the subsidiary itself, its headquarters, and other subsidiaries in all other locations.

Table 1 reports the relationships between the variables and the six knowledge sources derived before.

Proximity. Following earlier research (e.g., Tallman & Phene, 2007), we built a dummy variable that takes the value of 1 if the first inventor of the subsidiary's patent belongs to a location within the same US metropolitan area (MSA/CMSA code) as the one corresponding to the address of the first inventor of the citing patent, and of 0 if the two are instead located in different areas of the US. *Interactions*: The effect produced by breadth of subsidiary technology sourcing is captured in our models by interacting with *Proximity*, general *Source_Breadth* and specific *Local_Breadth*, *Distant_Breadth*, *Internal_Breadth* and *External_Breadth*. The idea is to capture whether a wider breadth of knowledge sourcing slows down the process of the local diffusion of knowledge flows more among proximate inventors (i.e., in the same MSA) than among more distant inventors in the United States.

3.2.3 | Control variables

A series of subsidiary-level, patent-level and MSA-level controls have been included in this study. First, as suggested by previous literature (Blalock & Simon, 2009; Eapen, 2012; Girma, 2005; Glass & Saggi, 1998; Meyer & Sinani, 2009; Spencer, 2008), when dealing with knowledge flows, it is important to control for the absorptive capacity of firms in the

TABLE 1 Classification of technology sources along organizational and geographic boundaries.

Geographic boundariesorganizational boundaries	Distant	Local
Internal	✓ Headquarters ✓ Other subsidiaries	✓ Focal subsidiary
External	✓ Other firms in the home country ✓ Other firms in other locations	✓ Colocated firms

local context. Since it is very difficult to gather R&D data at that level for the whole period of our analysis, we used patent data, whose technological and geographic information is publicly available over the years. Our proxy for absorptive capacity (*Absorptive_cap*) was therefore constructed as the stock of patents that have been applied for in the focal patent's technological class by inventors located in the area[7] as of the first citing patent, up to the patent's application year (Singh, 2008).

To control for the fact that patents belonging to the same technological class may cite each other earlier, we added a measure of technological relatedness (*Tech_Relatedness*). This measure was built as a dummy variable with the value of 1 if the citing patent belongs to the same technological class as the focal subsidiary's patent and 0 otherwise.

Subsidiaries located in a given area for a long time might be more integrated in the local knowledge network, thus allowing for faster diffusion of their knowledge. To control for this potential effect, we included a variable, *Subsidiary_Age*, measured as the number of years between year *t* and the year of a subsidiary's first patent application. We also included a measure of the total number of backward citations a subsidiary's patent had reference to, to control for the total number of knowledge elements used in the knowledge creation process (*Source_n*).

To account for the fact that innovations building on a wide range of technologies may be more difficult to understand, slowing down the diffusion process, we analyzed all the backward citations the subsidiary's patent referred to and classified them according to their main technology class. We then measured technological complexity using the following formula:

$$Tech\_Complexity = 1 - \sum_j p_{ij}2,$$

where p_{ij} is the proportion of citations made by the subsidiary's patent i to the technology class j[8] (Argyres & Silverman, 2004; Jaffe & Trajtenberg, 2002).

We also controlled for the number of inventors involved in the subsidiaries' innovative activities. A large number of scientists may be a sign of the value of a technological project. Yet even more than that, since knowledge resides within individuals (Leonard-Barton, 1992), inventors can be considered to be the most effective channels of knowledge diffusion, especially when physical proximity is at play. The knowledge embedded in patents with larger team sizes may consequently diffuse faster. To account for this effect, we included a measure (*Inventors_n*) calculated as the number of inventors who contributed to the development of subsidiary patents, as highlighted in the patent document.

We cleaned our analysis for firm-level unobserved heterogeneity by including a set of dummies identifying the subsidiaries.

Finally, since patents of higher quality can also be expected to be a source of knowledge that spreads more rapidly, we checked for this effect by including the number of total forward citations that a patent receives from external organizations, within the 10-year observation window (*Spread_Potential*). This control is crucial because it captures the effect of knowledge spreading per se, allowing other regressor coefficients to express impacts only in terms of the *timing* of knowledge diffusion rather than the presence or magnitude of the diffusion itself.

Tables 2a and 2b report descriptive statistics and correlations between the variables mentioned.

3.3 | Estimation

3.3.1 | Empirical strategy

Our aim is to detect the time it takes for a patent to be cited for the first time. Problems of this type are usually dealt with using duration analysis, particularly using survival models. In such models, the dependent variable

[7]To measure absorptive capacity, we considered the US State level instead of the MSA level.

[8]For patents with no backward citations, we set this variable equal to 0.

TABLE 2a Descriptive statistics ($N = 1344$).

Variables	*N*	Mean	St. Dev	Median	Min	Max
Speed	1344	38.905	29.935	31	1	120
Proximity	1344	0.144	0.352	0	0	1
Distant_Breadth	1344	1.331	0.641	1	0	4
Local_Breadth	1344	0.661	0.659	1	0	2
Internal_Breadth	1344	0.472	0.666	0	0	3
External_Breadth	1344	1.521	0.662	1	0	3
Spread_Potential	1344	7.793	10.788	4	0	99
Source_n	1344	9.04	9.262	7	0	97
Subsidiary_Age	1344	12.233	6.043	13	0	25
Absorptive_cap	1344	294.834	334.002	197	0	1368
Tech_Relatedness	1344	0.604	0.489	1	0	1
Inventors_n	1344	1.908	1.134	2	1	10
Tech_Complexity	1344	0.296	0.273	0.278	0	0.884

captures the time it takes for a certain event—the first patent citation in our case—to occur. The choice of models has sparked discussions regarding the best way to fit the available data (see, for instance, Box-Steffensmeier et al., 2015; Cader & Leatherman, 2011; Lopes et al., 2023). The Cox proportional hazard model (Cox, 1972) is commonly used for modeling survival data, while accelerated failure time (AFT) models offer a well-known alternative to it (Newby, 1988; Wei, 1992). Although extensively employed in biostatistics, the Cox model has also been applied in different fields, such as finance, management, and political sciences (Xue & Schifano, 2017). In multivariate survival analysis, the Cox model is often favored, yet it assumes multiplicative effects of covariates on the hazard, and its constant hazard assumption can lead to misinterpretations and reduced statistical test power. Its widespread use is due to the fact that it does not require a specification of the theoretical distribution of the baseline hazard rate $h_0(t)$, but rather it estimates it empirically.

The Cox model is defined as the product of $h_0(t)$ and the exponential function of a vector of n variables exp $(\beta_1 x_1 + \cdots + \beta_n x_n)$. The idea behind this formulation is that $h_0(t)$ is the starting point to define the hazard rate of a generic observation, which then becomes idiosyncratic to each actual observation in the sample thanks to the additional intervention of the n variables. The model is usually operationalized in this logarithm form:

$$\ln[h(t|X)] = \ln[h_0(t)] + \beta_1 x_1 + \cdots + \beta_n x_n.$$

The coefficient associated with each regressor represents how the baseline hazard rate changes due to the effect of that regressor. A positive coefficient implies that the relative hazard rate is higher than the baseline hazard rate, which means that the probability of an event occurring at time t (in our case, the citation) increases. A higher probability of citation at each time interval means a higher probability of observing the first citation earlier. In terms of timing, this means increasing the speed at which we expect the first citation to occur. The opposite interpretation is associated with a negative coefficient, which implies a smaller hazard rate than baseline, a longer period of time before the first citation, and thus the slowing down of the knowledge diffusion process.

The Cox model assumes proportional hazards, conceivable as invariance with respect to t, of the effects of the variables in the exponential. In more analytical terms, and considering the hazards of observations i and j, it is

TABLE 2b Correlation matrix (N = 1344).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Speed	1.000												
(2) Proximity	−0.072*	1.000											
(3) *Distant_Breadth*	−0.018	−0.027	1.000										
(4) *Local_Breadth*	−0.049	−0.007	0.140*	1.000									
(5) *Internal_Breadth*	−0.026	−0.068*	0.581*	0.538*	1.000								
(6) *External_Breadth*	−0.040	0.035	0.523*	0.590*	0.093*	1.000							
(7) *Spread_Potential*	−0.339*	0.040	0.111*	0.046	0.055*	0.098*	1.000						
(8) *Source_n*	−0.057*	−0.029	0.394*	0.414*	0.372*	0.419*	0.198*	1.000					
(9) *Subsidiary_Age*	−0.034	0.097*	−0.093*	0.169*	0.090*	−0.012	0.039	0.022	1.000				
(10) *Absorptive_cap*	−0.005	0.199*	0.014	0.072*	−0.075*	0.159*	−0.033	0.001	0.521*	1.000			
(11) *Tech_Relatedness*	−0.206*	0.025	−0.021	0.039	0.048	−0.030	0.004	−0.003	0.072*	0.007	1.000		
(12) *Inventors_n*	0.043	0.052	0.079*	0.015	0.038	0.053	−0.003	0.021	−0.001	0.024	0.037	1.000	
(13) *Tech_Complexity*	−0.017	−0.060*	0.156*	0.070*	0.053	0.168*	0.075*	0.201*	−0.049	−0.018	−0.255*	0.068*	1.000

*Shows significance at the 0.05 level.

$$\frac{h_i(t)}{h_j(t)} = \frac{h_0(t)\exp[\beta_1 x_{1i} + \ldots + \beta_n x_{ni}]}{h_0(t)\exp[\beta_1 x_{1j} + \ldots + \beta_n x_{nj}]} = \exp[\beta_1(x_{1i} - x_{1j}) + \ldots + \beta_n(x_{ni} - x_{nj})],$$

which is independent of time t. Time independence is an assumption that must be tested. It is possible to test it for each single variable using Schoenfeld residuals, obtained by comparing the value of the variable for failed cases with its expected value. The violation means the effect of these variables is not independent of time, undermining the reliability of the estimations. To avoid this bias, we interacted the violating variables with time, a commonly used methodology meant to take their time-varying effect into account.

This assumption is not needed in an AFT model, which therefore proves to be a valuable alternative to the Cox model, especially when the impact of treatment (in our case proximity) is that of accelerating or delaying the event of interest (in our case the citation). AFT models explain a linear relationship between the logarithm of the survival time and the covariates (Zou et al., 2011). Despite these benefits, AFT models come with assumptions about the event-time distribution, posing challenges in selecting the appropriate parametric distribution. Nevertheless, when underlying distribution assumptions are met, AFT models better describe the evolution of time-to-event (Majeed, 2020). Moreover, when implementing AFT models, one does not necessarily have to check the proportional hazards assumption a priori.

Using an AFT model, the covariate effects are assumed to be constant and multiplicative on the time scale (Folorunso & Osanyintupin, 2018), meaning that the covariates have an impact on survival by a constant factor, called an acceleration factor. Hence, the corresponding logarithm form of an AFT model with respect to time is given by

$$\log T_i = \mu + \alpha_1 X_{1i} + \alpha_2 X_{2i} + \cdots + \alpha_p X_{pi} + \sigma\varepsilon_i.$$

In this paper, we employed both AFT and Cox proportional hazard models—all with robust standard errors to avoid misspecification biases—to see whether we obtain convergent results. In addition, to correct for possible endogeneity, we applied propensity score matching (PSM), using pairwise nearest neighbor methodology, and then estimated both the Cox and the AFT models again. Specifically, we aligned patents from the treatment (proximity) and control groups based on their propensity scores, estimated using certain patent-level and MSA-level variables, namely absorptive capacity, technological relatedness, inventors, and spread potential. Given that the number of treated cases (patents cited in the same MSA) is smaller than potential observations from the control group (>50%), we adopted a 1:n matching ratio, specifically choosing a 1:3 ratio to strike a balance between being neither excessively large nor too sparse. For instance, McAfee et al. (2006) opted for a 1:4 matching ratio due to a larger number of control subjects than test subjects to improve study power. Other studies propose stricter ratios, such as 2 or 3, as optimal, with the lowest biases observed in the nearest neighbor scheme (Rassen et al., 2012, 2013). Additionally, as is common practice, PSM was conducted without replacement, ensuring that each subject would be included in only one matched set.

4 | RESULTS

Table 3 presents the outcomes of our comprehensive analysis with twelve distinct regression models, providing a nuanced examination of key variables. We begin by reporting the estimates provided by the three AFT-based models, followed by those from the three Cox-based models. We then provide the results of the three Cox models post-PSM and the outcomes from the three AFT models post-PSM. We think that this sequential arrangement not only enhances the clarity of our results but also ensures coherent understanding of the diverse modeling strategies applied in our study.

TABLE 3 The speed of local knowledge outflows.

	Aft Model			Cox Model			Aft Model post-PSM			Cox Model post-PSM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Proximity	−0.34***	−0.37***	−0.28**	0.45***	0.49***	0.38**	−0.23*	−0.28**	−0.18	0.33*	0.42**	0.29
	(0.12)	(0.12)	(0.13)	(0.17)	(0.17)	(0.18)	(0.13)	(0.14)	(0.14)	(0.19)	(0.2)	(0.21)
Source_Breadth	−0.04*			0.05			−0.02			0.4		
	(0.03)			(0.04)			(0.04)			(0.06)		
Prox*Source_Breadth	0.11**			−0.15**			.08			−0.14*		
	(0.05)			(0.08)			(0.06)			(0.08)		
Spread_Potential	−0.03***	−0.03***	−0.03***	0.02***	0.02***	0.02***	−0.03***	−0.03***	−0.03***	0.03***	0.03***	0.03***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0.01)	(0.01)	(0.01)
Source_n	0	0	0	0	0	0	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0.01)	(0)	(0.01)	(0.01)	(0.01)	(0.01)
Subsidiary_Age	0.01	0.01	0.01	−0.01	−0.01	. −0.01	.01	0.01	0.01	−0.01	−0.01	.−0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Absorptive_cap	0	0	0	0	0	0	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Tech_Relatedness	−0.36***	−0.36***	−0.36***	0.05	0.05	0.02	−0.49***	−0.49***	−0.49***	0.26*	0.28*	0.23
	(0.04)	(0.04)	(0.04)	(0.1)	(0.1)	(0.1)	(0.06)	(0.06)	(0.06)	(0.15)	(0.15)	(0.15)
Inventors_n	0.04**	0.04**	0.05**	−0.03	−0.03	−0.03	0.04*	0.04*	0.04*	−0.06	−0.06	−0.07
	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Tech_Complexity	−0.12	−0.12	−0.12	0.15	0.14	0.15	−0.1	−0.1	−0.1	0.08	0.22	0.08
	(0.08)	(0.08)	(0.08)	(0.11)	(0.11)	(0.11)	(0.1)	(0.1)	(0.1)	(0.15)	(0.15)	(0.15)

TABLE 3 (Continued)

	Aft Model			Cox Model			Aft Model post-PSM			Cox Model post-PSM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Prox*Distant_Breadth		0.16**			−0.23**			0.17*			−0.26**	
		(0.08)			(0.11)			(0.09)			(0.13)	
Distant_Breadth		−0.05			0.06			−0.08			0.12	
		(0.04)			(0.06)			(0.06)			(0.1)	
Prox*Local_Breadth		0.05			−0.07			0			−0.01	
		(0.09)			(0.12)			(0.09)			(0.14)	
Local_Breadth		−0.04			0.04			0.02			−0.04	
		(0.04)			(0.05)			(0.05)			(0.08)	
Prox*Internal_Breadth			0.19**			−0.24**			0.16*			−0.2
			(0.08)			(0.12)			(0.09)			(0.14)
Internal_Breadth			−0.05			0.07			−0.03			0.05
			(0.03)			(0.05)			(0.05)			(0.07)
Prox*External_Breadth			0.05			−0.09			0.03			−0.08
			(0.07)			(0.11)			(0.08)			(0.12)
External_Breadth			−0.04			0.03			−0.01			0.01
			(0.04)			(0.06)			(0.05)			(0.08)
Observations	1344	1344	1344	1344	1344	1344	693	693	693	693	693	693
subsidiary dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

We first considered the AFT estimation with the full sample ($n = 1344$; models 1, 2 and 3). In model 1 we introduced the interaction between *Proximity* and *Source_Breadth* and found that, while the coefficient of *Proximity* is significant and negative, the coefficient of the interaction term is positive and significant, suggesting that high levels of *Source_Breadth* moderate the higher speed at which proximate firms absorb knowledge spillovers vis-à-vis distant firms. The interaction plot presented in Figure 1 highlights precisely this point.

In model 2 we reach precisely the same conclusion for *Distant_Breadth*, as the positive and significant coefficient of the interaction between *Proximity* and *Distant_Breadth* suggests that building on many distant knowledge sources reduces a higher speed in knowledge diffusion among proximate compared to distant firms (see Figure 2). We also considered *Local_Breadth* and its interaction with *Proximity*, but we obtained nonsignificant coefficients.

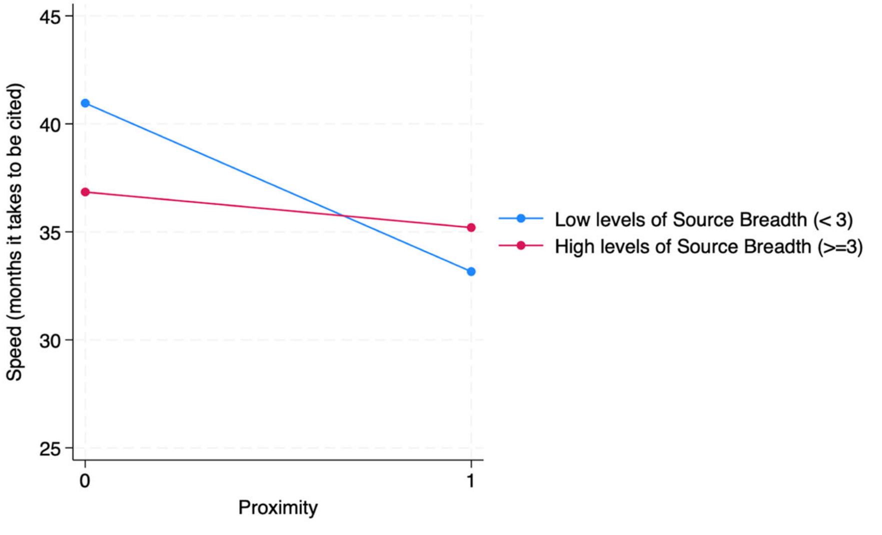

FIGURE 1 Interaction Plot Proximity*Source Breadth. [Color figure can be viewed at wileyonlinelibrary.com]

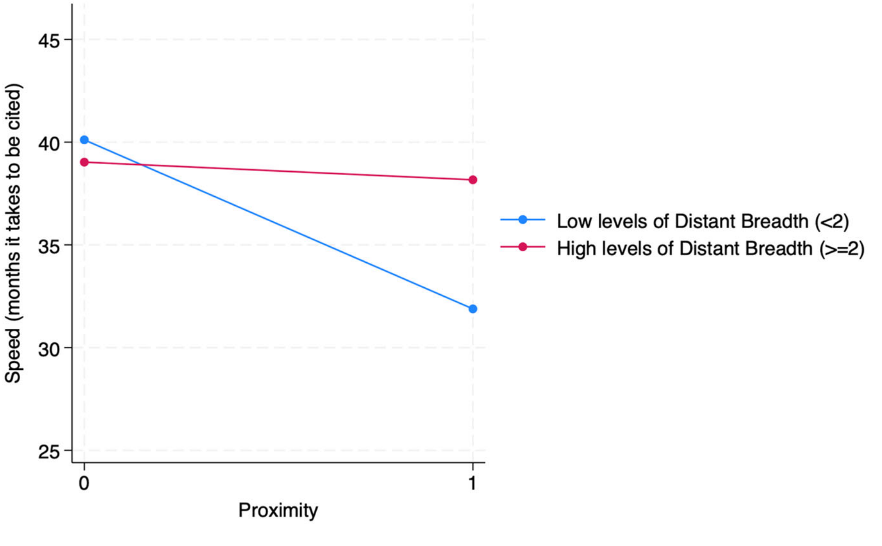

FIGURE 2 Interaction plot Proximity*Distant Breadth. [Color figure can be viewed at wileyonlinelibrary.com]

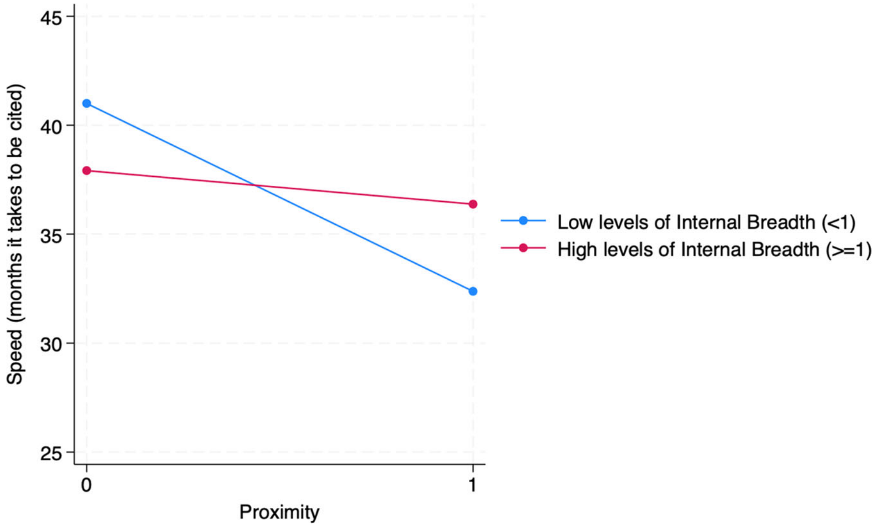

FIGURE 3 Interaction plot Proximity*Internal Breadth. [Color figure can be viewed at wileyonlinelibrary.com]

In model 3, we introduced the interaction between *Proximity* and *Internal_Breadth*. Again, the coefficient is both positive and significant, meaning that building on a larger number of internal sources reduces the higher speed at which knowledge diffuses among proximate firms vis-à-vis distant firms (see Figure 3). It is also useful to note the nonsignificant coefficients for *External_Breadth* and its interaction with *Proximity*.

When computing the Cox model with the full sample, our results remained consistent (coefficients have the opposite sign than AFT due to the differences in the underlying estimation strategies), with negative and statistically significant coefficients for the interactions between *Proximity* and *Source_Breadth* (model 4), *Distant_Breadth* (model 5), and *Internal_Breadth* (model 6).

Upon computing the same models for the PSM sample (the further six models in Table 3), results remained by and large the same. Some of the interactions did show weaker results (namely between *Proximity* and *Source_Breadth* and *Internal_Breadth*) but when considering the results across all models in Table 3, these same interactions preserve the significance of their coefficients in three specifications out of four, thus supporting our overall conclusions. The opposite can be said for the direct effect of *Source_Breadth*, whose coefficient turns out to be barely significant (10% level) only for model 1 and nonsignificant in all three of the other models in Table 3. The strongest finding is the one for *Proximity*, whose coefficient is significant in 10 models out of the 12 presented in Table 3.

4.1 | Robustness checks

To corroborate the validity of our results, we also ran a series of robustness checks for all the models presented in Table 3 (AFT and Cox, both full sample and PSM sample). We first focused on the way time was captured, considering days rather than months, and thus obtained a measure that resembles a continuous measurement of time. We re-estimated the 12 models and found consistent results, even though, in model 10, the coefficient for *Proximity*Source_Breadth* has the expected sign, but it turned out to be nonsignificant.

We reverted to the month-based measure of time and tried to substitute the fixed effect for each subsidiary with the one for each MNE, to see whether accounting for effects at this higher level might change our findings. We confirmed our results once again, but in this case also, model 10 exposed a weak coefficient for *Proximity* Source_Breadth*, confirming the sign, but making it nonsignificant.

We then tried a different specification for the key independent variables. We divided *Distant_Breadth* and *Internal_Breadth* by *Source_Breadth* and used the resulting ratios to give a relative account of the number of distant and internal sources used. All coefficients bear signs in line with our results, and even though *Distant_Breadth* turned out to be nonsignificant, *Proximity*Internal_Breadth* remained significant for the full sample.

We then focused specifically on the definition of *Source_Breadth*, *Distant_Breadth* and *Internal_Breadth*. We integrated two weighting schemes into our analysis. The first assigned weight of 0.5 to distant and external sources and the second also introduced intermediate weights of 0.75 for internal and distant sources and for local and external sources. The idea was to weigh lesser knowledge sources that were progressively less centered on the subsidiary and its surroundings. The estimations confirm our results with both weighting schemes, even though some weaknesses appear related to the role of *Internal_Breadth* and *Source_Breadth*.

We then considered a "broader" definition of our *Proximity* variable, giving it the value of 1 if the first inventor of the subsidiary's patent and the first inventor of the citing patent are located within the same MSA *or in contiguous MSAs*, and 0 otherwise. The outcome of this exploration confirmed our main results, and provided intuitions that strengthen the general approach we applied.[9]

We eventually estimated a new model, different from Cox and AFT, for the full sample, focusing on the event of either being cited or not being cited. Specifically, we reshaped our data into a panel format and estimated a logit detecting the passage from "no citations (yet)" to "cited." We re-ran the models and again confirmed our findings. Overall, robustness checks did not expose any specific weakness across any estimations, even though at times one effect or another lost significance. We can thus, by and large, confirm our conclusions.

5 | DISCUSSION AND CONCLUSION

This paper is one of the few attempts to include the "time" variable in the literature on MNE knowledge outflows into host countries, by considering the perspective of the MNE subsidiary and the structure of its patents' knowledge sources. Subsidiaries of foreign MNEs embody an attractive knowledge base upon which local firms can build, especially if they are wholly domestic and thus have more restricted chances to overcome the limitations of a local search, compared to multi-location firms. In this paper, we posited that the speed at which local firms are able to capture knowledge from colocated foreign subsidiaries is one of the critical dimensions of the knowledge spillover effect.

Previous research had considered the absorptive capacity of local firms as one of the most important factors in determining the likelihood of knowledge outflows from MNEs. Indeed, for these firms to absorb and make productive use of foreign knowledge, they need to explore and evaluate alternatives (Cohen & Levinthal, 1990), integrate and implement foreign technology (Meyer & Sinani, 2009; Zahra & George, 2002), and engage in active searches (Eapen, 2012), allowing them to leverage that knowledge to move beyond their current technology. Yet, as far as the speed of local spillover is concerned, absorptive capacity is not the only issue to be considered. If innovation stems from search processes (Fleming & Sorenson, 2003, 2004; Kauffman et al., 2000; Levinthal & Warglien, 1999; Levinthal, 1997; Rivkin, 2000, among others), then the ease with which these search processes unfold is influenced by the underlying knowledge structure (i.e., their breadth), which, in turn, reflects MNE subsidiary technology sourcing strategies. Along this line of reasoning, we would expect that the larger the breadth of a subsidiary's technology sourcing, the slower the process of knowledge diffusion. Because a subsidiary may draw knowledge from a variety of diverse sources, high breadth in technology sourcing increases the time local firms need to carry out searches. In particular, as Yan et al. (2022) explain, "*Dispersing and decentralizing information*

[9]Specifically, results relative to *Proximity*Source_Breadth* persist, but other results are weakened. However, this strengthens our analysis by proving that spillover effects can mainly be observed within MSAs, that is, within the perimeter predicted by Kang et al. (2016), where – according to the definition of an MSA provided by the OMB (2023)—most direct interaction occurs. All these checks are available from the authors upon request.

can raise imitators' search costs, making it difficult to understand and merge from different sources" (p. 1930) and resulting in slower imitation.

In our empirical investigation we found almost no evidence of such a conclusion. We saw that breadth in technology sourcing had a very weak direct effect on the speed of knowledge diffusion (observed by way of patent citations, LeSage et al., 2007). However, we did observe the role that breadth in technology sourcing acquires when considered in conjunction with geographical proximity of the subsidiary and local firms. In particular, higher breadth in technology sourcing has a larger *slowing down* effect on more proximate firms than for more distant ones. This is a counter-intuitive result that contrasts with our expectation that the speed of MNE-domestic knowledge flows would be higher among colocated firms than among distant ones (e.g., as per Merlevede & Purice, 2016).

Next, we found this result to hold both when we considered *Distant_Breadth* and *Internal_Breadth* as independent variables, suggesting that the local slow-down effect that we observed takes place both when the focal patent draws on distant knowledge sources and when it draws on internal MNE knowledge, which we have suggested to be, respectively, more diversified or more subsidiary-specific. This latter finding is at once consistent with the previous literature, showing that foreign firms develop strong internal linkages to make their innovations less transparent and less appropriable by local firms (Yan et al., 2022; Zhao, 2006), but it also shows they are developmental, which implies that geographical proximity among local firms and a subsidiary does not generate enough cognitive proximity to compensate for the slowing down of spillovers from patents produced by recombining internal knowledge, that is, based on MNE routines and tacit knowledge (Dosi, 1988; Nelson & Winter, 1982; Rajan & Zingales, 2001).

We can provide interpretative cues regarding our unexpected results. We envisage two kinds of mechanisms that could explain them. First, the close proximity of firms to the knowledge source they seek to absorb may generate a "chillout effect." Since we are measuring knowledge flows in terms of patent citations, and therefore through a well-codified means of knowledge appropriation, it is possible that colocated firms pause and reflect when they face knowledge sources that are more complex to appropriate, either because they are more diverse and distant (as in the case of *Distant_Breadth*), or because they are largely MNE-specific (*Internal_Breadth*). Hence, rather than rushing off to use that piece of knowledge to produce the next invention, these firms could follow Merlevede and Purice's (2016) intuition and take advantage of their geographical proximity to gather additional insights, and dig further, via informal channels (face-to-face interactions, demonstration effects, informal chit-chat), into the relevant knowledge base, trying to close the gaps in their cognitive proximity with the subsidiary. This practice can ease absorption but also slow down the timing of the patent's application date. This strategy may lead to positive implications regarding the quality of the filed patent, a dimension that we did not investigate here but which is suggestive of the fact that the observed slowdown may potentially pay off in the longer run.

An alternative mechanism to explain the observed slowdown could be related to the existence of a "liability of foreignness" effect (Hymer, 1976; Zaheer, 1995) in MNEs. MNE liability of foreignness is a well-known international business construct which was developed to refer to "all additional costs a firm operating in a market overseas incurs that a local firm would not incur" (Zaheer, 1995: pp. 342–343). It more broadly refers to the difficulties MNEs encounter when operating abroad simply due to being foreign, which places them at a certain disadvantage vis-à-vis domestic firms, since they have more limited knowledge of, for example, the foreign market's characteristics, culture, and institutional apparatus. This results in them struggling to do business and make a profit. Liability of foreignness is also sometimes associated with legitimacy deficits, skepticism or even repulsion (Eden & Miller, 2001; Fiaschi et al., 2017) on the part of domestic audiences and firms, which may endanger, at least temporarily, MNE embeddedness processes in a local context (Merlevede & Purice, 2016). Such legitimacy deficits are socially constructed and they are often tied to a number of fears or emotional barriers domestic firms and their human resources may have regarding foreign investors—for instance, the fear of being outcompeted, of being deprived of their own proprietary assets via imitation, of being perceived as technologically inferior to the MNE subsidiary, or simply of having their competitive space somewhat disturbed by "outsiders." Clearly, these kinds of negative reactions are likely to be salient when the potential threat is real and tangible, as occurs when it is close by.

Geographical proximity may thus explain why domestic firms take more time, when they are closer compared to when they are distant, to take up knowledge pieces (in the form of patent citations) from an MNE subsidiary. This observation is especially true when these pieces are composed of knowledge from internal and/or distant sources. On the one hand, they may be more circumspect vis-à-vis the subsidiary and its background knowledge and routines, and it may therefore take even longer for them to scrutinize what they discover about it; on the other hand, the potential emotional barriers and skepticism may increase when they see that the subsidiary has produced knowledge by recombining, in an original way, elements from distant knowledge sources, far from the local context in which the human resources of the colocated firms operate.

Unfortunately, our data do not allow us to dig deeper into these mechanisms and ascertain which one prevails, or to provide additional insights on the functioning of these mechanisms. What is interesting, however, is that the slowing down of spillovers toward colocated firms compared to faraway firms, due to higher breadth of subsidiary knowledge sourcing, is mainly due to more extensive us of distant and internal sources, at least as far as we could observe in our patent data. These considerations open up interesting questions for further research, which could investigate more deeply the conditions that lead to a slower spread of local knowledge, possibly with the help of more qualitative research. This further research could also consider informal knowledge sharing and the extent to which it overlaps with the spread of codified knowledge in the form of patent citations.

More broadly, our work seeks to contribute to the growing economic-geography literature on the importance of regional openness to distant sources of knowledge and, more specifically, on the role played by MNEs to foster local development processes (Bathelt & Cohendet, 2014; Bathelt et al., 2018; Crescenzi et al., 2014; Iammarino & McCann, 2013; Phelps & Fuller, 2016, among others). Our original contribution to this agenda is, firstly, the consideration that knowledge diffusion speed is one of the dimensions that is often overlooked but that can have important implications for the competitiveness of host regions, especially in cases in which firms miss out on opportunities to be first- or second-movers in the innovation market. Focusing on speed, as we have shown, can lead to interesting results, making it clear that, when *time* is at stake, mechanisms other than those normally observed— such as the "the chillout effect" or "liability of foreignness"—may play a key role. Second, our work connects the timing dimension with the firm-specificity of MNE knowledge, as reflected in the internal breadth of patents, and with its intrinsic diversity and heterogeneity, as reflected in the distant breadth of its patents. Our work consequently refines scholarly understanding of the heterogenous capacity of MNEs to contribute to knowledge diffusion, innovation and potential growth in host locations (Marin & Bell, 2006).

Should more research find similar results, it could inform regional development policy agendas in interesting ways. One possible recommendation for policymakers could be to have a cautious approach towards foreign investment attraction policies, especially depending on the intended goals of these policies. If the goal is that of sparking rapid growth in the host region where the MNE is located, then greater consideration should be given to the type of knowledge that these companies can really bring to the host locations and to the issue of whether they are more or less likely to spill over quickly to the local area. This point is particularly relevant to regional policy actors who may compete with the policymakers of other regions for resources and foreign investments. Therefore, our observed "greater speed of MNE knowledge diffusion in distant locations" finding may not be good news for them, because distant rivals could be in a position to outcompete their own regional firms despite the greater distance from the knowledge source. These considerations should warn against policies that expect immediate spillover effects to appear from MNE investments in a host region. This caveat by no means implies that MNEs are not important actors in creating a global-local nexus, but it certainly calls for a more informed implementation of foreign investment attraction policies and for a wiser consideration of their potential unintended downsides.

This study has certain limitations that might warrant taking our results with caution. As the literature has widely documented, there certainly are many potential shortcomings when it comes to using patent citation data to investigate knowledge flows (see, e.g., Arora et al., 2018). First of all, patents and patent citations are by definition the codified part of technology and do not enable us to capture the transfer of tacit knowledge. A second issue regards the examiner-added citations, which might create noise in the quantification of knowledge flows, since not all citations contained in the patent document are spontaneously indicated by the inventor. Notwithstanding this limitation, empirical spillover analysis has long recognized the effectiveness of the citation measure (Alcácer & Gittelman, 2006; Branstetter, 2006; Fogarty et al., 2000; Jaffe et al., 1998), and this reassures us as to its general pertinence to the aim of this study. Additionally, in our study we were not able to investigate MNE subsidiaries' own strategies and investment motivations, and hence our understanding of how other potential MNE-level dimensions could impact knowledge transfer speed remains limited, which certainly points to an area for future research.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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