Paper to be presented at

DRUID15, Rome, June 15-17, 2015

(Coorganized with LUISS)

MNC strategies to limit knowledge spillovers: How subsidiaries manage their knowledge source breadth to decrease spillovers

Alessandra Perri
Ca' Foscari University Venice
Management
alessandra.perri@unive.it

Raffaele Oriani
LUISS Guido Carli University
Department of Economics and Business
roriani@luiss.it

Francesco Rullani
Luiss Guido Carli University
Management
frullani@luiss.it

Abstract

The aim of this paper is to investigate the factors influencing the speed at which knowledge flows from foreign to domestic firms. The focus is not on whether a knowledge spillover occurs, but on the time an MNC subsidiary?s knowledge takes to spread in the surroundings. Filling the gap in the literature regarding spillover speed in International Business by means of the insights from Innovation Studies, with particular reference to the literature on search, we propose a conceptual model where the speed of local knowledge diffusion is influenced by the technology sourcing strategies of subsidiaries. We then test our model using a database covering 1394 US patents from foreign MNC subsidiaries in the semiconductors sector. We find that not only does the breadth of the set of subsidiary knowledge sources slow down local knowledge diffusion, but the delay is mainly related to the diversity of global and internal sources used by the subsidiary, hinting at strategies that MNCs can use to further protect their knowledge

Jelcodes:O32,L23

MNC strategies to limit knowledge spillovers:

How subsidiaries manage their knowledge source breadth to decrease spillovers

"Time is the enemy…
Strategies can quickly fall behind,
so the rhythm of planning has to keep pace.
When technologies have disruptive potential,
the stakes are even higher
and the range of strategic implications is wider".
Richard Dobbs
McKinsey, May 2013

Abstract

The aim of this paper is to investigate the factors influencing the speed at which knowledge flows from foreign to domestic firms. The focus is not on whether a knowledge spillover occurs, *but on the time* an MNC subsidiary's knowledge takes to spread in the surroundings. Filling the gap in the literature regarding spillover speed in International Business by means of the insights from Innovation Studies, with particular reference to the literature on search, we propose a conceptual model where the speed of local knowledge diffusion is influenced by the technology sourcing strategies of subsidiaries. We then test our model using a database covering 1394 US patents from foreign MNC subsidiaries in the semiconductors sector. We find that not only does the breadth of the set of subsidiary knowledge sources slow down local knowledge diffusion, but the delay is mainly related to the diversity of global and internal sources used by the subsidiary, hinting at strategies that MNCs can use to further protect their knowledge.

INTRODUCTION

When considering how companies source knowledge from the subsidiaries of foreign multinational firms located in their area (Almeida 1996, Singh 2007, Eapen 2012), a key finding is that the extent of local knowledge outflows critically depends on the characteristics of domestic firms and, more specifically, on their absorptive capacity (Glass and Saggi 1998, Blalock and Simon 2009, Girma 2005, Meyer and Sinani 2009, Spencer 2008).

However, it is important to consider not only *whether* domestic firms are able to absorb knowledge from foreign subsidiaries, but also *the speed* at which they do so. Indeed, rapid knowledge outflows from FDI may allow local firms to build up fast "second-mover" advantages (Lieberman and Montgomery 1988). As fast followers, they can quickly learn from the new technology, thus eroding the first mover's advantage and creating larger distances between themselves and later adopters (Kessler and Chakrabarti 1996). Despite the importance of speed, extant International Business (IB) literature has overlooked the timing of knowledge spillover diffusion from multinational corporation (MNC) subsidiaries to local firms, leaving a gap in the understanding of this phenomenon[1]. Thus, the broader research question we pose in this paper is the following: *what are the determinants of the speed at which subsidiary knowledge diffuses over the host-location?*

In order to address this question, we complement IB literature using an Innovation Studies (IS) perspective, and in particular the literature developed around the concept of search (e.g., Levinthal 1997). In this literature, innovators are conceived as organizations whose current products are constituted of the combination of a number of technological elements. Each combination occupies a specific position on the technological landscape upon which lie all the possible configurations of these elements. The firm innovates, and thus moves along the landscape, searching for new, more profitable combinations of the technological elements.

[1] Very few studies have tackled the issue related to the speed of knowledge diffusion more in general. For example, the work by Phene, Madhok and Liu (2005) focused on the speed of *internal* knowledge transfer within the MNC.

This can be done in the surrounding of its current position on the landscape if the new configurations are close to its current technology, or more extensively, if the search process arrives at configurations (i.e., locations on the landscape) which are remote from the current one (Levinthal 1997). This inclusion of the IS perspective into the IB debate allows us to fill an evident gap in the literature, providing a theoretical explanation for the time MNC subsidiary knowledge takes to spill over onto local firms. Indeed, search literature suggests that, when it comes to the speed at which firms are able to absorb external knowledge, the structure of such knowledge has a crucial role, because it determines the area of the technological landscape to be searched, and thus the length of time spent in exploration (Levinthal and Warglien 1999).

In this paper we develop a set of hypotheses along this line, positing first that a wider breadth of a subsidiary technology sourcing, conceived as the number of different types of sources it draws from, as in Laursen and Salter 2006, slows down the process of local diffusion of its knowledge. Then, we develop the concept of breadth along the organizational (Rosenkopf and Nerkar 2001) and geographic (Almeida and Phene 2004) boundaries of the firm, and identify different types of breadth (internal vs. external; global vs. local). To fully capture this distinction and elaborate on what these boundaries mean in terms of local firms' search, we use two concepts coming from within the search literature: knowledge *interdependence* (Levinthal 1997, Kauffman 1993) and *geographic origin* of knowledge (Phene et al. 2006). When the bits of knowledge to be combined are highly interdependent or coming from geographically distant sources, local firms' search becomes wider and more complex, thus taking more time. Indeed, as predicted by our hypotheses, our data show a slowing-down effect in the case of global sources of knowledge and sources internal to the MNC.

Empirically, we test these ideas using data on a sample of 1394 patents filed by U.S. subsidiaries of foreign MNCs operating in the semiconductor industry. This constitutes an ideal setting given the intense use of patents in this industry and the importance of speed in light of the short technology cycle (Stuart and Podolny 1996). To validate our hypotheses, we analyse the time lag between a subsidiary's patent application date and the application date of the first subsequent patent citing it as prior art. Our results confirm that not only the breadth of knowledge sources (Laursen and Salter 2006), but also the typology of sources included in the breadth index, are fundamental to predict the speed at which spillovers from FDI occur.

Our paper offers several contributions to the existing literature. First and foremost, drawing on a call for more attention to the "time" variable in the IB field (Eden 2009), this paper is one of the few to identify speed of knowledge outflows as an important dimension requiring consideration in order to comprehensively assess the spillover phenomenon. Even if IB has already focused on FDI knowledge spillovers (Almeida 1996, Singh 2007, Meyer and Sinani 2009, Eapen 2012), and IS has shown the strategic importance of the pace of innovative processes (Markman et al. 2005), to the best of our knowledge no study has ever combined these insights and investigated the speed of knowledge flows from foreign subsidiaries to local firms. Second, the paper investigates the drivers of such speed by linking traditional IB literature with an IS perspective, finding that the breadth of a subsidiary's technology sourcing (Laursen and Salter 2006) increases the time it takes for local firms to absorb a subsidiary's knowledge. This relationship has been explained by the introduction of the 'search' mechanism, central to the literature on knowledge diffusion (Sorenson et al. 2006). Third, building on the concept of geographical and organizational boundaries of the firm, our theoretical framework and empirical results, show that not all types of breadth have the same effect on the speed of knowledge diffusion from the subsidiaries. In particular, global (i.e., distribution of knowledge sources among actors in places other than the host location) and internal (i.e., distribution of knowledge sources among different local and global units within the MNC) have a much clearer impact on speed than other types of breadth (i.e., local or external). Finally, this paper offers managers new insights on the mechanisms foreign firms can use to protect their knowledge from rapid external appropriation from local rivals: indeed, combining numerous global or internal sources assures longer search time for local firms.

The remainder of this paper is organized as follows. We first introduce the temporal dimension of the FDI spillover process, relating it to traditional IB literature. Then we develop a theoretical framework in which we build on the IS literature to explain the time patterns of local spillovers, using search as the main theoretical tool, and introducing the concepts of interdependence (Levinthal 1997, Kauffman 1993) and geographic origin of knowledge (Phene et al. 2006) to develop our hypotheses. Finally, we elucidate the empirical strategy and discuss the results and future developments of the analysis.

THEORETICAL BACKGROUND and HYPOTHESES DEVELOPMENT

The breadth of knowledge sourcing and the speed of knowledge outflows from FDI

Innovation capabilities are closely related to a firm's use of external knowledge (Chesbrough 2004, Chesbrough et al. 2006, Laursen and Salter 2006). For example, firms placed in a given region can leverage the set of knowledge resources available in the surrounding local environment (Almeida 1996). Subsidiaries of foreign MNCs constitute a critical source of knowledge for co-located firms, since they embody the MNCs' technology (Hymer 1976) and may themselves be very active in terms of knowledge creation (Almeida and Phene 2004). The presence of foreign firms may help domestic firms to overcome the geographic localization of knowledge diffusion (Branstetter 2006, Singh 2007) by gaining access to competitive technology.

Accessing an MNC subsidiary's knowledge is however not an easy task. Simply being exposed to the subsidiaries' knowledge is not enough for local firms: they need to create the conditions for accessing that knowledge. Indeed, domestic firms are non-passive actors in the FDI spillover process (Glass and Saggi 1998, Meyer and Sinani 2009, Eapen 2012). In order to absorb and make productive use of foreign knowledge, firms need to explore and evaluate alternatives (Cohen and Levinthal 1990), integrate and implement the foreign technology (Meyer and Sinani 2009, Zahra and George 2002), and engage in *active search* (Eapen 2012) allowing them to leverage that knowledge in order to move beyond their current technology.

In order to fully exploit the opportunities arising from the presence of foreign MNCs, domestic firms must not only actively absorb knowledge from foreign subsidiaries, but more importantly, they must do so *quickly*. The ability to accelerate the innovation process is crucial to obtain a competitive advantage (Eisenhardt and Martin 2000). Moreover, speed determines a firm's capability to adapt to external changes, foresee and react to competitors, and enter new markets (Salomon and Martin 2008). Firms compete not only through new knowledge creation, but also by imitating their competitor's technology (Zander and Kogut 1995). The time needed to acquire external knowledge determines the rate at which subsequent innovations, which build upon such knowledge, can be carried out, thus allowing the firm to leapfrog competitors (Lieberman and Montgomery 1988), especially in high-tech industries, where imitation, continuous new discoveries and obsolescence reduce the life span of a given technology (Markman et al. 2005). Thus, the speed at which domestic firms are able to capture knowledge from foreign subsidiaries is a relevant, yet unexplored, aspect of FDI spillovers.

In this respect, not all knowledge is the same. Knowledge creation processes are heterogeneous, as are the knowledge sources that can be used to develop a new technology (Leiponen and 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 knowledge has been built, and from which sources firms have drawn to develop it, the complexity of the tasks required to absorb it may vary, and the time firms need to implement such tasks vary accordingly.

This notion is confirmed by the IS literature, which has already suggested that the technology-sourcing strategies used by firms affect the structure of the newly created knowledge (Teece 1986, Laursen and Salter 2006, Rosenkopf and Nerkar 2001) in ways that may influence the ease with which knowledge spreads to other agents. Zhao (2006) has showed that MNC subsidiaries conducting R&D in countries with weak IPR regimes use strong internal linkages among firm-specific technologies that are dispersed among the other ties of the MNC's internationalised network, thus creating both organizational and geographic barriers to the dissemination of their knowledge within the host-location. Moreover, technology sourcing is a peculiar process, since MNC subsidiaries are simultaneously exposed to very different knowledge environments: the multinational corporation network, composed of the headquarters and other sister units (Bartlett and Ghoshal, 1989); the network of collocated firms (Almeida and Phene, 2004); the network of other firms in the sector, located outside the subsidiary's host region (Phene and Almeida, 2008).

To fully grasp the impact of this step in our argument, we can rely on the literature regarding *search* (Levinthal 1997, Levinthal and Warglien 1999, Rivkin 2000, Kauffman et al. 2000, Fleming and Sorensen 2003, 2004, among others). In this context, organizations are characterised as vectors of attributes. All possible combinations of these attributes can be mapped on a surface, called landscape. Each point on the landscape represents one vector and thus the organization's relative position on the landscape. The landscape can then be used to calculate the performance of each organization (vector) simply by adding an axis to introduce the organization's fitness level with respect to the competitive environment. In this context, innovation can then be grasped easily as a change in the attributes of an organization's current technology: an organization innovates by changing some of its technological attributes, i.e., *searching* for a new technology whose attributes shift it to a new position on the technological landscape, possibly associated with a higher level of fitness. In the literature, this process is called "search" (Kauffman et al. 2000; Fleming and Sorensen 2003), and is broken down into "local search", when organizations change only a few attributes, trying to climb the peaks near their current position on the landscape (Katila and Ahuja, 2002), or "global search" when they radically change numerous attributes, thus acquiring a new position distant from the previous one (Gavetti and Levinthal 2000). The following Figure represents this in a two-dimensional space.

Figure 1 about here

If we conceive organizations as boundedly rational (Simon 1955, Cyert and March 1963, Nelson and Winter 1982, Dosi and Marengo 2007), firms may possess a certain understanding of possible technologies located next to their current one (Winter et al. 2007), but cannot really foresee the possible effect of a radical change in their technology, i.e., "jumping" into further areas of the technological landscape. A firm "*does not have such routines and frames for conducting distant search, [as] it has to deal with many more decision elements, together with alternatives and their consequences. Effectively, distant search may mean more causal ambiguity because the larger number of alternatives and their poorly understood consequences make it more difficult to tell which alternatives result in what level of problem-solving effectiveness*" (Afuah and Tucci, 2012, p. 360). Local search provides the firm with far greater control over the possible outcome of the process, but it also limits the improvements to those which can be achieved in the local area of the landscape. If the landscape is rugged, local search assures only the possibility to reach the closest peak. A higher peak located farther away which is difficult to identify because of bounded rationality is thus out of the search scope of the organizations. And even when it is identifiable, it is not easy to deal with (Katila, 2002, p. 998).

Several strategies can be put into place to facilitate distant search, and thus to extend the reach of the search process to possibly higher peaks. Sourcing outside knowledge, via open innovation (Almirall and Casadesus-Masanel, 2010) or crowdsourcing (Afhua and Tucci, 2012), are examples of this strategy. In our context, a subsidiary's strategy of sourcing technology from many different typologies of knowledge providers (e.g., other local firms, other MNCsubsidiaries, the headquarters, etc.) results in a knowledge basis that occupies a wider area on the technological landscape.

A local firm willing to access this technology must engage in a search process around the position of the newly-created knowledge on the technological landscape. This may allow the firm to explore an area of the landscape which is distant from its current position, thus increasing the odds of climbing to a higher peak. However, the higher the number of different sources the subsidiary has used to develop the new knowledge, the wider the landscape area local firms need to explore in order to assimilate it, and the greater the time local firms will need to successfully absorb foreign subsidiaries' knowledge. The following Figure exemplifies these ideas.

Figure 2 about here

Based on this reasoning, we suggest that a "broad" technology sourcing strategy, encompassing the use of a great number of different sources (Laursen and Salter, 2006), will increase the time it takes for local firms to absorb the subsidiary knowledge, thus exerting a negative effect on the speed of the process of local knowledge outflow. Hence:

Hypothesis 1. *The increase in the breadth of a subsidiary's technology sourcing strategy reduces the speed at which the produced knowledge diffuses over the host-country firms located in the area.*

Unfolding knowledge sourcing breadth: geographic and organizational boundaries

In their search for knowledge, subsidiaries have the inherent opportunity to span both organizational (Rosenkopf and Nerkar, 2001) and geographic boundaries (Almeida and Phene, 2004). The breadth of a subsidiary's technology sourcing may therefore be explored further in order to understand whether any of these boundaries play a role in determining the effect of knowledge source diversity on the speed of local knowledge diffusion. Hence, having looked at the number of different subsidiary technology sources, we investigate the types of sources used. This makes it possible to complement the analysis of the quantity of technology sources made above, with a study of the nature of such sources. In Figure 3, four types of this "second-order" breadth are highlighted, depending on whether the sources are geographically close or distant (the *x*-axis), and whether they are internal or external to the multinational firms (the *y*-axis).

Figure 3 about here

Along the 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 multinational network. Conversely, we identify "external breadth" in technology sourcing as the extent to which the subsidiary obtains knowledge from sources that fall outside the MNC organizational boundaries, either from geographically close or distant locations.

Along the geographic boundaries, "global breadth" in technology sourcing integrates knowledge from geographically distant locations, regardless of whether they belong to the multinational network. "Local breadth", on the contrary, refers to a situation in which the subsidiary builds upon knowledge residing within the host location, either inside its own organization or in other co-located firms.

To investigate the effect of these "second-order" types of breadth, we need to discover how they influence the structure of the resulting knowledge, and how this in turn exacerbates a delay in the process of local diffusion. The rest of this section uses two concepts from within the search literature, knowledge *interdependence* (Levinthal 1997, Kauffman 1993) and *geographic origin* of knowledge (Phene et al. 2006), to illustrate this mechanism.

Sourcing across organizational boundaries

When organizing technology sourcing along the organizational dimension, subsidiaries may choose to rely mainly on external sources or draw from the internal multinational network. What strongly differentiates these two alternatives in terms of the structure of the resulting knowledge is the degree of interdependence between the technology sources used to develop it. Internal sources of technology are highly interdependent. In fact, the technological subunits of the firm operate within the same organizational context, and are likely to develop new technology through the use of firm-specific established routines (Rajan and Zingales, 2001). Knowledge resulting from the use of internal sources is characterized by an idiosyncratic architecture in which each individual piece of technology is integrated with the others through the use of internal linkages (Zhao, 2006). Conversely, external technology sources are not likely to be highly interdependent. Since they are not linked by common organizational structures, but rather arise in distinct organizational contexts, they are likely to be loosely coupled, or even totally independent from each other .

The degree of interdependence among technology sources has a crucial impact on the search process of local firms. Literature on NK modelling (Kauffman 1993, 1995, Levinthal 1997) suggests that the higher the interdependence among the technology sources, the greater the complexity of identifying the right configuration and replication mode within the receiving organization. The higher such complexity, the greater the number of trial and error attempts local firms will need to carry out in order to successfully integrate the foreign knowledge within their own organization. As Afuah and Tucci (2012, p. 362) clearly explain, "*because agents are cognitively limited, it is difficult for the focal agent to accurately articulate a complex problem …, which may cover several different areas of knowledge and have interdependencies that limit understanding of cause and effect. … knowledge complexity is represented by the number of elements, the degree of interactions among elements, and the consequences of the different alternatives. … complexity makes evaluation, transfer, and (re)combination of distant knowledge very challenging*."

In sum, when subsidiaries source broadly, using a great number of technology sources to develop new knowledge, it is important to understand to what extent these sources are interdependent. When interdependence is high, a larger number of sources implies not only a larger area to be searched, but also a more complex search process, thus lengthening the time needed to fully assimilate the subsidiary knowledge.

This is what happens when subsidiaries use a high breadth of internal sources. In this case, after having accomplished a lengthy search and identified the relevant pieces of technology, local firms are left with the challenge of understanding the general configuration of a knowledge basis that is mainly internal to the MNC and thus with a very interdependent structure. The architecture of such knowledge is firm-specific, thereby appearing very opaque to agents external to the organization. As noted by Dosi (1988), even though information about what organizations are doing in their R&D departments spreads relatively quickly, the ability to replicate firm-specific knowledge is much trickier. In the presence of subsidiary internal breadth, local firms may spend a great deal of time trying to discover the correct integration of knowledge sources used by the foreign subsidiary, slowing down their absorption process. Hence, we suggest that:

Hypothesis 2. *The increase in the INTERNAL breadth of a subsidiary's technology sourcing strategy reduces the speed at which the produced knowledge diffuses over the host-country firms located in the area.*

In contrast, external sources are characterized by much lower interdependence as they do not belong to the same organizational structure and therefore are not part of a more general configuration. Consequently, the increase of external breadth should not have a dramatic impact on the complexity of local firms' search activities. We do not expect therefore a significant effect of external breadth on the speed at which the produced knowledge spreads to the host-country firms located in the area.

Sourcing across geographic boundaries

Multinational firms are commonly defined as geographically distributed networks of innovation, whose main ability is to assimilate, create and integrate knowledge on a global scale (Bartlett and Ghoshal 1989). Along the geographic dimension, subsidiaries of these firms can source technology mainly from the host-region where they are established, or rely on technology that is globally dispersed.

The main difference between local and global technology sources lies in their geographic origin. Local sources of technology are geographically proximate to the subsidiary and allow tapping into the specialized pool of knowledge that has accumulated in the host-region over time. Conversely, global sources are geographically distant, and possibly dispersed worldwide. As highlighted by recent literature (Phene et al. 2006), the geographic origin of knowledge is a fundamental dimension in the search processes of firms. On the one hand, knowledge of distant origin may be very useful for innovation, as it provides input that is new and different in terms of the type and content of the technology it embodies. On the other hand, geographically distant knowledge comes with the inherent difficulty of its acquisition and assimilation, precisely because of its diversity.

In the specific case of local firms, this difficulty arises from two main factors. First, as global sources of technology are by definition geographically distant from local firms, the "seeding" of search, that is "*the problem of identifying the starting points of the search process*" (Levinthal and Warglien 1999, p. 349) encompasses the challenge of screening the worldwide technological landscape. Compared to local sources of technology which are located in the immediate surroundings of local firms and hence readily available, global sources can be dispersed and remote, and their screening is likely to take more time. Second, technology developed in a different geographic context bears the systemic and architectural characteristics linked to this context (Phene et al. 2006). Inherently different from those in the context where local firms operate, these characteristics, are likely to reduce the local firm's ability to recognize the very content of the technology. Such is not the case when technology sources are local: in this case the approach to innovation and the pattern of knowledge accumulation are familiar to local firms, making the assimilation process easier and more immediate (Tallmann and Phene 2002). Thus, understanding knowledge arising from the use of a set of technology sources that are geographically distant is likely to be a lengthy process. Overall, this reasoning suggests that:

Hypothesis 3. *The increase in the GLOBAL breadth of a subsidiary's technology sourcing strategy reduces the speed at which the produced knowledge diffuses over the host-country firms located in the area.*

As opposed to global technology sources, technology of local origin tends to follow specific patterns, as geography creates constraints to its evolution (Jaffe et al. 1993). Since "knowledge in the air" (Marshall 1920), local sources of knowledge are not likely to produce very different technologies from those of the local firms. Therefore, the increase in local breadth of a subsidiary's technology sourcing should not have a dramatic impact on the complexity of local firms' search activities. We do not expect therefore a significant effect of local breadth on the speed at which the produced knowledge spreads over the host-country firms located in the area.

METHODS

Data and Sample

We test our hypotheses on a sample of patents developed by US-based subsidiaries of European and Asian multinational firms in the semiconductor industry. This seems to be an appropriate empirical setting for our research. The U.S. semiconductor industry has historically been the target of a large number of inward FDI (Almeida 1996). Therefore, how to profit from knowledge inflows coming from foreign subsidiaries is a fundamental issue for local agents affiliated to this industry. Similarly, for foreign MNCs locating their R&D activities in the US, it is critical to protect their newly created knowledge, since most collocated firms in this specific setting are advanced, and hence may constitute a competitive threat. In addition, the semiconductor sector is characterized by a short technology cycle time (Stuart and Podolny 1996), which makes the speed of knowledge spillover a crucial aspect for a firm's technological performance. Finally, the extensive use of patents that characterizes semiconductor firms allows for the appropriate tracking of knowledge flows.

The use of patent citation data is suitable for studies on the knowledge outflows phenomenon because of the wealth of information provided by patent documents, which includes the geographic location of both the inventor and the "owner" of the innovation, as well as its time 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 importantly for our analysis, the temporal characteristics of the invention. In addition, patent documents incorporate a list of citations to other patents which are useful in identifying the technological antecedents to the particular innovation (Almeida 1996), and whose inclusion is mandatory in the U.S. patent system.

To create our sample, we considered the largest semiconductor companies in terms of sales in 2005 and selected the first 10 European and Asian MNCs. This list of firms was compiled using information provided by Gartner Dataquest and Osiris. For this set of MNCs, we identified 29 U.S. subsidiaries engaged in innovation between 1975 and 2000, and observed their portfolio of semiconductor patents by using the information on the geographic location of the patents. Subsidiaries were mainly concentrated in California, Texas and the New York-New Jersey-Connecticut tri-state area. Since semiconductor companies generally use the U.S. Patent Office to record their innovations (Almeida and Phene 2004), given the aim of this study, we considered only patents filed under this system.

In order 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 is composed of 1,394 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 analysed the filing date and the first inventor's address in order to construct measures on the speed of knowledge outflows and on the possible situation of collocation between the subsidiary and the citing organization. Since our study focuses on the temporal patterns of external knowledge diffusion, we excluded from our analysis those focal patents whose first forward citation was a self-citation, i.e. a citation from a patent assigned to the MNC to which the foreign subsidiary belongs. As this happened for 49 patents, our final sample is composed of 1,345 patents. To make the dataset more manageable, we restricted our analysis to those citing patents whose first inventor was located within the United States. In this way, we were able to compare the speed of knowledge spillover across situations of collocation and non-collocation between the focal patent and the citing patent, but within the same national boundaries. In fact, we define collocation as a situation where the first inventors of the focal and the citing patents are located in the same US metropolitan area. 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 antecedents. However, in approximately 10% of the cases, a US-based organization other than the MNC is able to use the subsidiary's knowledge as prior art in less than 9 months.

To avoid bias due to abnormal patterns of citations over time, we consider only forward citations occurring in the first ten years after the filing date of the focal subsidiary patents (Fabrizio, 2007). Hence, even if we built our sample of focal patents up to 2000, our empirical analysis extends through to 2010. Since the typical life cycle of a semiconductor product is 5 years (Stuart and Podolny 1996), allowing for a 10-year observation window seems a valid choice. In addition, our focus on the speed of knowledge transfer seems to be consistent with the establishment of a limited observation period, a type of censoring that is in any case handled during the estimation by the appropriate use of a duration model.

Overall, our empirical strategy proposes to compare the speed of knowledge outflows across two situations, i.e., when focal and citing patents are co-located vs. when they are not. We are interested in capturing the speed of knowledge spillovers from a subsidiary to co-located firms, but we decided to compare this situation to spillovers to non co-located firms as a reference point. We are thus able to say whether spillovers, which are typically faster when collocation occurs (Jaffe and Trajtenberg 1999), are slowed down by our main regressors compared to more global knowledge flows.

Measures

Main Variables

Speed of Subsidiary Knowledge Transfer. To capture the speed of subsidiary knowledge diffusion, we use the number of months between the subsidiaries 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., taking into account censoring in the estimation). Analysing the timing of the first citation provides us with the 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 a subsidiary knowledge was used in a subsequent innovation (Jaffe and Trajtenberg 1999).

Collocation. In order to test our hypotheses, it is important to have a benchmark for the speed of local knowledge outflows. To this aim, we keep track of whether the first patent citing our focal patent comes from a firm located in the same area of the subsidiary or not. This allows us to use the speed of knowledge outflows between non co-located firms as a benchmark to evaluate the same speed but between co-located firms (our case of interest). This is crucial, as the phenomenon we are examining, i.e., speed of knowledge spillovers, is clearly related to the degree of proximity between the subsidiary and the recipients of its knowledge.

More specifically, we perform this benchmark exercise by building a dummy variable that takes the value 1 if the subsidiary patent and the citing patent belong to the same US metropolitan area, and 0 otherwise[2]. According to the U.S. Census Bureau, a metropolitan statistical area is "*a geographic entity* […] *based on the concept of a core area with a large population nucleus, plus adjacent communities having a high degree of economic and social integration with that core*". Following recent trends in management and IB literature (Tallman and Phene 2007), we chose to identify collocation using the metropolitan area, instead of the state. This choice is based on the observation that many of the relevant U.S. semiconductor clusters span several states (e.g., New York - New Jersey – Connecticut), while some states host more than one cluster (e.g., California).

Breadth of Technology Sourcing. To capture the breadth of technology sourcing of the subsidiary, we draw on Phene and Almeida's (2008) classification of subsidiary knowledge sources into 6 main categories, reflecting the knowledge contexts to which a subsidiary has the opportunity to access: the subsidiary itself, the headquarters, other subsidiaries in the MNC, other organizations in the host location, other organizations in the home country, and other organizations in all other locations. In line with previous research (Leiponen and Helfat 2010, Laursen and Salter 2006), the breadth of a subsidiary's technology sourcing was captured as a combination of these 6 knowledge sources. More specifically, we first 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. Then, the resulting 6 variables are added up, as done by Laursen and Salter (2006). As a result, our breadth term ranges between 0, when the subsidiary has not indicated any prior patented innovation as an antecedent to its newly created knowledge, and 6, when the subsidiary has drawn from all six technology source categories. This measure proxies for a subsidiary's ability to combine the knowledge absorbed from several external and geographically distributed technology sources with the MNC's own knowledge which, in turn, may reside either within the subsidiary's boundaries,

[2] More specifically, we looked at the address (city and state) of first inventor for each of our focal and citing patents, and assigned these patents an MSA/CMSA code (Tallman and Phene 2007).

or within the headquarters and other sister units' organization (Kogut and Zander 1993, Phene and Almeida 2008). The effect of the breadth of subsidiary technology sourcing is captured in our models by interacting this variable with the collocation variable, precisely in order to understand if a higher breath accelerates or slows down the process of local diffusion of knowledge (i.e., local spillovers).

Second-Order Breadth Variables. We followed the same procedure to build our "second-order" breadth types. We used the binary variables previously built for each technology source category whereas for each "second-order" breadth type, we added up only those binary variables belonging to that specific breadth type. For example, along the geographic boundary, "local breadth" was built by adding only the binary variables related to technology sources located within the host-region, i.e. the subsidiary itself and external co-located organizations. On the other hand "global breadth" was built by adding up the binary variables related to global sources, i.e. the headquarters, other subsidiaries in other locations, other organizations in the home-country, and other organizations in other locations. Along the organizational boundary, "external breadth" is constructed as the sum of the binary variables corresponding to sources that fall beyond the boundaries of the MNC organization, i.e. firms in the host-region, in the home-country and in other locations, while "internal breadth" is constructed as the sum of the binary variables associated with internal sources, i.e. the subsidiary itself, the headquarters and other subsidiaries in other locations). As for the first-order measure of breadth, the effect of these second-order breadth types is captured in our models by interacting them with our collocation variable.

Control Variables

A series of subsidiary-level, firm-level, patent-level and region-level controls have been included in this study. First, as suggested by previous literature (Glass and Saggi 1998, Meyer and Sinani 2009, Eapen 2012), when dealing with spillover studies, it is important to control for the absorptive capacity of firms in the local context. Since it is very difficult to gather R&D data at the region-level for the whole period of our analysis, we use patent data, whose technological and geographic information is publicly available along the years. Our proxy for absorptive capacity ("*Abs_capacity*") is therefore constructed as the total number of patents in the focal patent technological class and the region[3] 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 add a measure of technological proximity ("*Tech_proximity*"). This measure is built as a dummy variable with the value of 1 if the citing patent belongs to the same technology class as the focal subsidiary's patent, and 0 otherwise.

Subsidiaries located in a given region for a long time might be more integrated in the local knowledge network, thus allowing for a faster diffusion of their knowledge. To control for this potential effect, we included a variable, subsidiary age ("*Sub_age*"), measured as the number of years between year t and the year of the subsidiary's first patent application.

In addition, since patents of better quality can also be expected to spread more rapidly, we check for this effect by including the number of total forward citations that the patent receives from external organizations, within the 10-year observation window ("*Spillover_potential*"). This control is crucial because it captures the effect of spillovers *themselves*, allowing other regressor coefficients to express impacts only on the timing of spillovers rather than on their presence or magnitude.

Finally, we included a measure for technological breadth of subsidiary semiconductor patents to account for the fact that innovations building on a wide range of technologies may be more difficult to understand, and therefore their diffusion process slower. To construct this measure, we analysed all the backward citations the subsidiary's patents referred to, and

[3] To measure Absortive Capacity, we considered the State-level instead of the MSA-level, due to the availability of more precise data.

classified them according to their main technology class. We then measured our variable ("*Tech_breadth*") through the following formula:

$Tech\_breadth = 1 - \Sigma_j \, p_{ij}^2$

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

We included a measure of the total number of backward citations a subsidiary's patent had reference to, in order to control for the total number of knowledge elements used in the knowledge creation process ("*Source_nbr*").

We also control for the number of inventors involved in the subsidiaries' innovative activities. A large number of scientists may be a telltale sign of the value of the technological project. In addition, inventors can be considered as the most effective channels of knowledge diffusion, as knowledge resides within individuals (Leonard-Barton 1992). The knowledge embedded in patents whose team size is larger may therefore diffuse faster. To account for this effect, we include a measure ("*Inventor_nbr*") calculated as the number of inventors who contributed to the development of subsidiary patents, as highlighted in the patent document. Finally, we cleaned the analysis for firm-level unobserved heterogeneity, by including a set of *firm dummies.*

ESTIMATES AND RESULTS

Our aim is to detect the time it takes for a patent to be cited for the first time. In econometrics, problems like these are usually dealt with using duration analysis, particularly in the case of survival models. In such models, the dependent variable captures the time it takes for a certain event - the first patent citation in our case - to occur. A central measure in this analysis is the *hazard rate*, i.e. the probability that a patent, never cited before t, will be cited within the interval *Δt* starting at *t*. The hazard rate *h(t)* is thus the probability of being first cited at time *t*, and of course it is a function of *t*.

Table 1 about here

Among the models using the hazard rate as their starting point, the Cox model is the most common. The widespread use of this model 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. It is defined as the product between $h_0(t)$ and the exponential function of a vector of *n* variables $exp(\beta_1 x_1+\ldots+\beta_n x_n)$. 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 the logarithm form:

$$\ln[h(t \mid X)] = \ln[h_0(t)] + \beta_1 x_1 + \ldots + \beta_n x_n$$

The Cox model assumes proportional hazards, conceivable as the 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*:

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

which is independent of time *t*. This assumption can be tested for each single variable using Schoenfeld residuals, obtained by comparing the value of the variable for failed cases with its expected value. The tests performed for our main regressors, i.e. collocation and breadth-related variables, do not reject the hypotheses of proportionality, and thus do not suffer from a direct bias due to violation of the assumption. Few control variables, namely *Spillover_potential*, *Tech_breadth*, *Sub_age*, and a *firm dummy*, do instead violate the assumption, resulting in the rejection of the assumption for the whole model. The violation means the effect of these variables is not independent of time. To avoid this bias, we interact them with time, a common-used methodology meant to control for their time-varying effect. The obtained results are thus reliable, and can be read in Table 2. As the table reports, the hazard ratios associated to each regressor (i.e., how the hazard rate changes with respect to the hazard baseline due to the effect of that regressor), a value greater than 1 means that the probability of the event occurring at time *t* (in our case, the citation) increases. A higher probability at each time interval means a higher probability of observing the first citation shortly. In terms of timing, this means increasing the speed at which we expect the first citation to occur. The opposite interpretation is associated to the cases where the hazard ratio is below 1.

Table 2 about here

In Model 1 we can observe the behaviour of the main control variables. As expected, *Spillover potential* increases the speed of knowledge spillovers. Its coefficient is statistically significant and greater than one. On the other hand, the coefficient of *Inventor_nbr* is lower than one and significant, highlighting a slowing-down of knowledge diffusion, due probably to the higher internal heterogeneity of knowledge obtained by the joint work of many people, possibly from diverse backgrounds. This result may also be due to the fact that foreign firms tend to ensure greater protection for those technologies spurring from larger teams, usually characterized by a larger budget and higher expectations. Finally, *Technological breadth* increases the speed of foreign subsidiary knowledge diffusion, as indicated by a coefficient greater than one and statistically significant. This seemingly counterintuitive result may be explained in light of the value of the produced knowledge. Knowledge that builds on a richer universe of technological combinations may indeed have a very high impact in different fields (Singh 2008) and offer the basis for breakthrough innovations (Ahuja and Lampert 2001). Consequently, it is likely to have a greater potential for faster diffusion.

In Model 2, we test *Hypothesis 1*. The results show, first of all, that collocation matters, as the speed of knowledge spillover absorption is higher for co-located than for non co-located firms. The coefficient of the dummy is statistically significant and greater than one. In order to verify whether *Hypothesis 1* is confirmed, we have to analyze the coefficient of the interaction between *Collocation* and *Source breadth*. The coefficient is statistically significant and lower than 1, signalling that *Source breadth* reduces the speed at which knowledge diffuses over the host-location, consistently with *Hypothesis 1*.

In Model 3, we test *Hypothesis 2* by introducing the interaction between *Collocation* and *Internal breadth*. The negative and lower than unity coefficient confirms our expectation that internal breadth reduces the speed at which knowledge diffuses over the host-location. We also report a non-significant coefficient of the interaction between *Collocation* and *External breadth.*

Finally, Model 3 tests *Hypothesis 3*. The statistically significant and lower than unity coefficient of the interaction between *Collocation* and *Global breadth* confirms that global breadth reduces the speed at which knowledge diffuses over the host-location. The other interaction effect, between *Collocation* and *Local breadth* is instead not significant.

To confirm the validity of our results, we also run a series of robustness checks. As far as the second-order types of breadth are concerned, we run a separate regression for each type including only one variable among *Global breadth*, *Local breadth*, *Internal breadth* and *External breadth*, and its interaction with *Collocation* at a time. Each of these four regressions reports results that clearly map our previous findings. Second, we further explored our results relative to first-order breadth. We first introduced *Source breadth* without *Collocation* and without their interaction, and then took into account possible non-linear relationships including its squared term. With these functional forms, we obtain no significant direct effects of *Source breadth* nor of its squared term. Then we introduced the squared term of *Source breadth* into the specification of Model 2, and again obtained no significance for it, not for the direct effect of *Source breadth*, while the coefficient of the interaction between *Source breadth* and *Collocation*, which is what matters for our Hypothesis 1, remains unchanged in sign, size and significance. In other words, our result is robust, while the direct effect of *Source breadth* seems primarily non-significant, despite the 10% significance its coefficient obtains in Model 2. This is confirmed by Models 3 and 4, where the direct effects of each second-order breadth are all non-significant. This validates our choice of building our analysis around the interaction between *Source breadth* (and its second-order variables) and *Collocation*. It shows that the phenomenon under observation, i.e., speed of knowledge spillovers, is intrinsically connected to the proximity between the subsidiary and the absorbing firm, as the simple effect of *Source breadth,* without considering the situation of collocation, results in non-significant effects.

DISCUSSION AND CONCLUSION

IB literature has focused closely on the "why, where and how" of multinational firm behaviour, leaving the "when" factor under-investigated (Eden 2009; p. 535). Drawing on a call for more time-based analyses in the IB field (Eden 2009), this paper is one of the few attempts to include the "time" variable into the literature on the FDI spillover effect, and the first to study the speed of knowledge spillovers from subsidiaries to local firms from the perspective of the subsidiary.

Subsidiaries of foreign MNCs embody an attractive knowledge base upon which local firms can build, especially if they are wholly domestic and hence do not have the chance to overcome the limitations of local search, as multi-location firms do. In this paper, we posit that *the speed* at which local firms are able to capture knowledge from collocated foreign subsidiaries is one critical dimension of the knowledge spillover effect, which is at least as important as *the magnitude* of knowledge spillover to host-location. Our study moves in this direction and contributes to the IB literature on FDI knowledge spillover (Almeida 1996, Singh 2007, Eapen 2012) by investigating the drivers of the temporal patterns of this phenomenon.

Previous research has focused primarily on the absorptive capacity of local firms, as one of the most important factors in determining the likelihood of knowledge spillovers from FDI. Yet, as far as the speed of local spillover is concerned, absorptive capacity is not the only issue to be considered. To shed more light on this issue, we build on two notions from IS literature: first, the notion that innovation stems from search processes; second, that the ease with which these processes unfold is influenced by the underlying characteristics of knowledge. Combining these two notions with insights on subsidiary technology sourcing strategies, we suggest 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 and geographically-distributed sources, a high breadth in technology sourcing increases the time local firms need to carry out search. Recent literature has theoretically highlighted the importance of local firms' search phase for the FDI knowledge spillover effect (Eapen 2012). We contribute to this literature by merging IB literature and IS studies in an empirical analysis, where not only are the mechanisms that relate search to the literature on FDI spillover illustrated, but also the effect of subsidiaries technology sourcing strategies are explicitly taken into account.

Finally, our paper also contributes to the literature on firm technology sourcing (Rosenkopf and Nerkar 2001, Phene et al. 2006). This literature has already looked at how a firm's design of its sourcing strategies along different dimensions (e.g., technological, geographic, organizational) affects the outcome of its innovative process. In this paper, we extend this literature and argue that a firm's use of different typologies of sources to develop new knowledge also heterogeneously affects the search duration of external agents aiming at assimilating such knowledge. More specifically, in order to explore whether the delaying-effect of the breadth in technology sourcing is driven more by specific knowledge sources, we differentiate them along the geographic and the organizational dimensions. We investigate these "second-order" types of breadth looking at two concepts from within the search literature having the potential to affect the speed of spillover: the degree of interdependence between technology sources (Kauffman 1993, Fleming and Sorenson 2001), varying between internal and external sources, and the geographic origin of technology sources (Phene et al. 2006), capturing the differences between local and global sources. Our findings show that, whereas a high breadth in technology sourcing overall slows down the process of local knowledge diffusion, this delaying effect can be exacerbated when subsidiaries use a high breadth of global and of internal sources. Internal sources are all based on the knowledge basis of the MNC, and thus their interdependence is very high. As a consequence, local firms' search becomes an iterative process of trials and errors, as they need to understand the composition of newly created knowledge whose structure is firm specific and highly complex. Global sources, on the other hand, are geographically distant from local firms. This makes their initial identification and subsequent understanding a very lengthy process, as local firms need to screen a worldwide technological landscape to locate the sources of knowledge used by subsidiaries, and then address the challenges of knowledge assimilation from a distance.

Though this paper highlights some interesting findings regarding the factors influencing the temporal patterns of FDI local knowledge outflows, the study has several limitations. As literature has widely documented, there are certainly several potential shortcomings when it comes to using patent citation data to investigate knowledge flows. First of all, patents and patent citations represent by definition the codified part of technology, and do not enable capturing the transfer of tacit knowledge. However, this problem is mitigated by the fact that codified knowledge and tacit knowledge have been found to be correlated and complementary (Mowery et al. 1996). A second issue deals with 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 (Jaffe et al. 1998, Fogarty et al. 2000, Alcacer and Gittelman 2006, Branstetter 2006), and reassures us as to its general pertinence to the aim of this study.

Notwithstanding the limitations of the study, we believe that this paper also provides some interesting managerial implications. First, in the perspective of MNCs, our study informs subsidiary managers regarding the opportunities associated with the strategic use of the knowledge sources they are exposed to, not only in terms of knowledge creation, but also in terms of knowledge protection. Traditional IB literature has looked primarily at knowledge-based FDI as a means through which multinational firms can improve the quality of their innovation, by sourcing new and diverse sets of knowledge from different locations. In this paper, we show that having access to such organizationally and geographically distributed technology sources may benefit multinational firms in one additional way, that is, by helping them maintain the confidentiality of their knowledge for a longer time, thus protecting their competitive assets from expropriation by local firms. Accordingly, our evidence suggests that combining many global or internal sources ensures in fact longer search time for local firms, thus reducing the risk of imitation and second-mover advantages. This latter finding is consistent with previous literature showing that foreign firms develop strong internal linkages to make their innovations less transparent and less appropriable by local firms (Zhao 2006).

In the perspective of local firms, our study offers a more comprehensive evaluation of the potential advantages of being co-located to highly innovative agents like MNC subsidiaries. It shows that, under certain conditions, foreign subsidiaries provide local firms with the opportunity to gain prompt access to recently created knowledge. Being able to absorb newly created knowledge is critical, particularly in dynamic industries because what confers a competitive advantage is not whether a firm eventually manages to acquire a new technology, but whether it can do so faster than its rivals. By showing that the structure of knowledge matters in determining the speed of its local diffusion, our paper also recommends that managers of local firms exposed to the technology of subsidiaries learn that they should look at those MNC technologies based on a lower number of technology sources and yet, possibly focus on those technologies that combine external or local technology sources. More generally speaking, our results seem to suggest that "blindly" investing in absorptive capacity might not be enough when the firm's objective is to access subsidiaries' knowledge faster than rivals. In fact, search duration may depend on how much search experience the local firm holds in specific areas that makes it better positioned to accelerate the process of knowledge assimilation. For example, a local firm that has accumulated experience in screening and using geographically-distributed sources of knowledge might be better equipped to quickly absorb foreign knowledge characterized by a high global breadth, balancing the slowing-down effect due to the unfavourable geographic origin of the subsidiary's knowledge base. Even though future research should explore this issue further, our results seem to suggest that, while investing in absorptive capacity is an essential prerequisite to profiting from external knowledge, a firm's search patterns play an equally important role in determining the speed at which certain types of knowledge can be absorbed.

REFERENCES

Afuah, A., C. L. Tucci. 2012. Crowdsourcing as a solution to distant search. *Academy of Management Review*, 37(3): 355-375.

Ahuja, G., C. M. Lampert. 2001. Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. *Strategic Management Journal*, 22: 521–543.

Alcacer, J., M. Gittelman. 2006. Patent citations as a measure of knowledge flows: the influence of examiner citations. *Review of Economics and Statistics*, 88(4), pp. 774-79.

Almirall, E., R. Casadesus-Masanel. 2010. Open versus closed innovation: a model for discovery and divergence. *Academy of Management Review* 35(1).

Almeida, P. 1996. Knowledge sourcing by foreign multinationals: patent citation analysis in the U.S. semiconductor industry, Strategic Management Journal, 155-165.

Almeida, P., A. Phene. 2004. Subsidiaries and knowledge creation: the influence of the MNC and host country on innovation. Strategic Management Journal; 847-864.

Argyres, N. S., B. S. Silverman. 2004. R&D, organization structure and the development of corporate technological knowledge. Strategic Management Journal, 25(8-9): 929-958.

Bartlett, C. A., S. Ghoshal. 1989. Managing Across Borders, Boston, Mass: Harvard Business School Press.

Blalock, G., D. Simon. 2009. Do all firms benefit equally from downstream FDI? The moderating effect of local suppliers' capabilities on productivity gains. Journal of International Business Studies 40(7): 1095-1112.

Branstetter, L. 2006. Is foreign direct investment a channel of knowledge spillovers? Evidence for Japan's FDI in the United States. *Journal of International Economics*, 68: 325.344.

Chesbrough, H. W. 2004. Managing open innovation. *Research Technology Management*. Vol. January-February 2004. Pp. 23-26.

Chesbrough, H., W. Vanhaverbeke, J. West. (eds.) 2006. *Open Innovation: researching a new paradigm*, Oxford University Press.

Cyert, R. M., J. G. March. 1963. *A behavioral theory of the firm.* Englewood Cliffs, NJ: Prentice-Hall.

Cohen, W. M., D. A. Levinthal. 1989. Innovation and learning: The two faces of R&D, *The Economic Journal*, Volume 99, 569-596.

- 1990. Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly*, 128-152.

Dosi, G. 1988. Sources, procedures, and microeconomic effects of innovation. *Journal of Economic Literature*, 26: 1120-1171.

Dosi, G., L. Marengo. 2007. On the Evolutionary and Behavioral Theories of Organizations: A Tentative Roadmap. *Organization Science*, 18: 491 – 502.

Eapen, A. 2012. Social structure and technology spillovers from foreign to domestic firms, *Journal of International Business Studies,* 43, 244-263.

Eden, L. 2009. Letter from the Editor-in-Chief: time in international business. *Journal of International Business Studies*, 40(4): 535–538.

Eisenhardt, K. M., J. A. Martin. 2000. Dynamic capabilities: what are they?, *Strategic Management Journal*, 1105-1121.

Fabrizio, K., 2007, University Patenting and the Pace of Industrial Innovation, *Industrial and Corporate Change*, Vol 16, No 4, p. 505-534.

Fleming, L., O. Sorenson. 2001. Technology as a complex adaptive system: evidence from patent data. *Research Policy*, 30: 1019-1039.

- 2003. Navigating the technology landscape of innovation. *MIT Sloan Management Review*, 44, 14-23

- 2004. Science as a map in technological search. *Strategic Management Journal*, 25, 909-928.

Fogarty, M., A. Jaffe, M. Trajtenberg. 2000. The meaning of patent citations: report of the NBER/Case-Western Reserve Survey of Patentees. Working Paper.

Gavetti, G., D. A. Levinthal. 2000. Looking forward and looking backward: cognitive and experiential search. *Administrative Science Quarterly*, 45: 113–137.

Glass, A., K. Saggi. 1998. International technology transfer and the technology gap. *Journal of Development Economics*, 55: 369-398.

Girma, S. 2005. Absorptive capacity and productivity spillovers from FDI: a threshold regression analysis. *Oxford Bulletin of Economics and Statistics*, 67(3): 281–306.

Hymer, S. H. 1976. *The International Operations of National Firms*. Cambridge, Mass: MIT Press.

Jaffe, A. B., M. S. Fogarty, B. A. Banks. 1998. Evidence from patents and patent citations on the Impact of NASA and other federal labs on commercial innovation. *Journal of Industrial Economics,* 46(2), 183-205.

Jaffe, A. B., M. Trajtenberg, R. Hendersen. 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly Journal of Economics*, 108: 577-598.

Jaffe, A., M. Trajtenberg. 1999. International knowledge flows: evidence from patent citations, *Economics of Innovation and New Technology*, 105-136.

- 2002. *Patents, Citations & Innovations: A window on the knowledge economy.* MIT Press, Cambridge.

Katila, R. 2002. New product search over time: past ideas in their prime? *Academy of Management Journal*, 45(5): 995-1010.

Katila, R., G. Ahuja. 2002. Something old, something new: a longitudinal study of search behavior and new product introduction. *Academy of Management Journal*, 45(6): 1183-1194.

Kauffman, S. 1993. *The origins of order: self-organization and selection in evolution*. Oxford University Press, New York.

Kauffman, S., J. Lobo, J. Macready. 2000. Optimal search on a technology landscape. *Journal of Economic Behavior and Organization*, Vol. 43, 141–166

Kessler, E. H., A. K. Chakrabarti. 1996. Innovation speed: a conceptual model of context, antecedents, and outcomes. *Academy of Management Review* 21(4): 1143-1193.

Kogut, B., U. Zander. 1993. Knowledge of the firm and the evolutionary theory of the multinational corporation. *Journal of International Business Studies*, 24: 61-90.

Laursen, K., A. Salter. 2006, Open for Innovation: the role of openness in explaining innovative performance among UK manufacturing firms, *Strategic Management Journal*, 131-150.

Leiponen A., C. E. Helfat. 2010. Innovation objectives, knowledge sources, and the benefits of breadth. *Strategic Management Journal*, 31: 224-236.

Leonard-Barton, D. 1992. Core capabilities and core rigidities: A paradox of managing new product development, *Strategic Management Journal*, 13, 111-125.

Levinthal, D. A. 1997. Adaptation on Rugged Landscapes, *Management Science*, 43(7), 934-950.

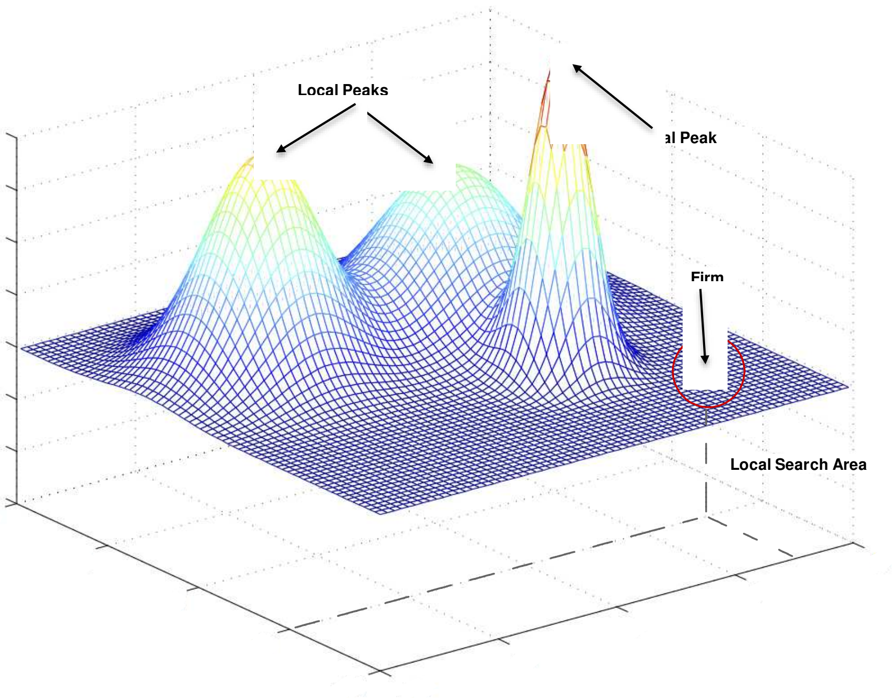
Levinthal, D. A., M. Warglien. 1999. Landscape design: designing for local action in complex worlds, *Organization Science*, 10(3), 342-357.

Lieberman, M., D. Montgomery. 1988. First-mover advantages, *Strategic Management Journal*, Summer 1988, pp. 41-58.

Markman, G. D., P. T. Gianiodis, H.P. Phan, D.B. Balkin. 2005. Innovation speed: transferring university technology to market, *Research Policy*, 1058-1075.
Marshall, A. 1920. *Principles of Economics.* Macmillan: London.
Meyer, K. E., E, Sinani. 2009. When and where does foreign direct investment generate positive spillovers? A meta-analysis. *Journal of International Business Studies*, 40(7): 1075–1094.
Mowery, D., J. Oxley, B. Silverman. 1996. Strategic alliances and interfirm knowledge transfers. *Strategic Management Journal,* 17: 77-91.
Nelson, R. R., S. G. Winter. 1982. *An Evolutionary Theory of Economic Change*. Cambridge, MA: Belknap Press of Harvard University Press.
Phene, A., P. Almeida. 2008. Innovation in multinational subsidiaries: the role of knowledge assimilation and subsidiary capabilities. *Journal of International Business Studies*, 901-919.
Phene, A., K. Fladmoe-Lindquist, L. Marsh. 2006. Breakthrough innovations in the U.S. biotechnology industry: The effects of technological space and geographic origin, *Strategic Management Journal*, 27(4): 369-388
Phene, A., A. Madhok, K. Liu. 2005. Knowledge transfer within the multinational firm: What drives the speed of transfer?, *Management International Review*, 45 (Special Issue 2): 53-74.
Rajan, R., L. Zingales. 2001, The Firm as a dedicated hierarchy: a theory of the origins and growth of firms, *The Quarterly Journal of Economics*, 805-851.
Rivkin, J.W. 2000. Imitation of complex strategies. *Management Science*, 46, 824–844.
Rosenkopf, L., A. Nerkar. 2001. Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management Journal*, Vol. 22, pp. 287-306.
Salomon, R., X. Martin. 2008. Learning, knowledge transfer, and technology implementation performance: A study of time-to-build in the global semiconductor industry, *Management Science*, 1266–1280.
Simon, H. A. 1955. A behavioral model of rational choice. *Quarterly Journal of Economics*, 69: 99–118.
Singh, J. 2007. Asymmetry of knowledge spillovers between MNCs and host country firms, *Journal of International Business Studies*, 764-786.
- 2008. Distributed R&D, Cross-regional knowledge integration and quality of innovative Output, *Research Policy*, 37(1), pp. 77-96.
Sorenson, O., J.W. Rivkin, L. Fleming, 2006. Complexity, networks and knowledge flow. *Research Policy*, 25: 994-1017.
Spencer, J. W. 2008. The impact of multinational enterprise strategy on indigenous enterprises: Horizontal spillovers and crowding out in developing countries. *Academy of Management Review*, 33(2): 341–361.
Stuart, T. E., J. M. Podolny. 1996. Local search and the evolution of technological capabilities. *Strategic Management Journal.* 17 21-38.
Tallman, S., A. Phene. 2002. The effects of regional clusters on knowledge stocks and flows: evidence from the biotechnology industry. AIB Annual Meeting, San Juan, Puerto Rico.
- 2007. Leveraging knowledge across geographic boundaries. *Organization Science*, 252-260.
Teece, D. 1986. Profiting from technological innovation, *Research Policy*, 286-305.
Winter, S., G. Cattani, A. Dorsch. 2007. The Value of moderate obsession: insights from a new Model of organizational search. *Organization Science*, 18(3): 403–419.
Zahra, S. A., G. George. 2002. Absorptive capacity: A review, reconcepualisation, and extension. *Academy of Management Review*, 27(2): 185-203.

Zander, U., B. Kogut. 1995. Knowledge and the speed of the transfer and imitation of organizational capabilities: an empirical test, *Organization Science*, 76-92.
Zhao, M. 2006. Conducting R&D in countries with weak intellectual property rights protection, *Management Science*, 1185-1199.

Figure 1. Landscape representing the level of fit of organizations (2-dimensional surface).



!

!

Figure 2. Two possible search areas on the technological landscape: the subsidiary's number of sources (A and B when they are few, plus C, D and E when many) defines the area to be searched by the host-country firm to leverage the subsidiary's spillovers.

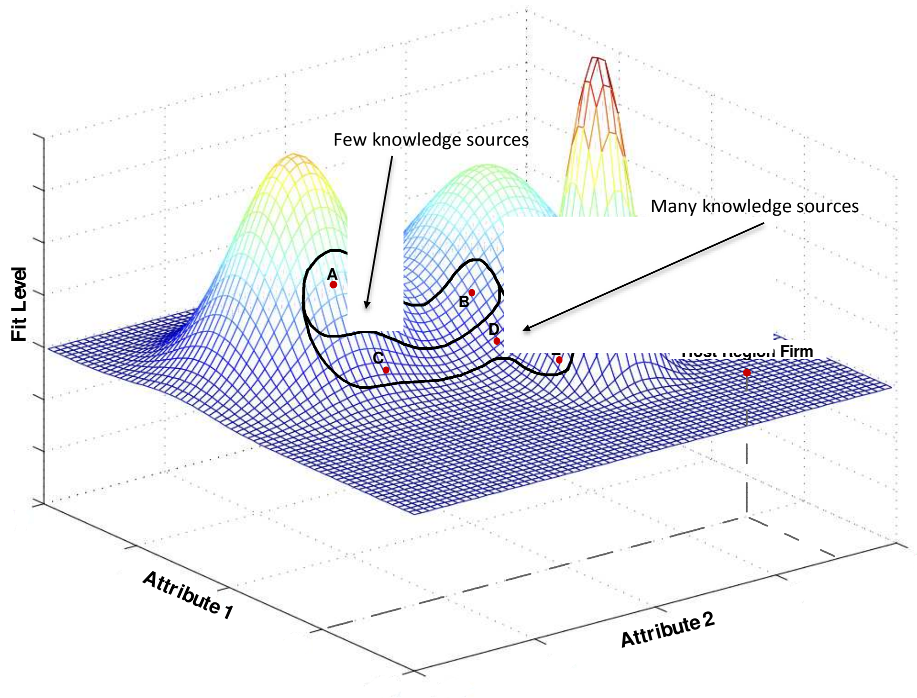


Figure 3. Classification of technology sources along organizational and geographic boundaries.

Geographic boundaries **Organizational boundaries**	***Global***	***Local***
Internal	✓ Headquarters ✓ Other subsidiaries	✓ Focal subsidiary
External	✓ Other firms in the home country ✓ Other firms in other locations	✓ Co-located firms

Table 1. Descriptive statistics and correlation matrix.

Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
1. Citation_Lag	1.000													
2. Co_Location	-0.072	1.000												
3. External_Breadth	-0.041	0.035	1.000											
4. Internal_Breadth	-0.026	-0.069	0.093	1.000										
5. Local_Breadth	-0.049	-0.008	0.590	0.538	1.000									
6. Global_Breadth	-0.019	-0.028	0.523	0.582	0.141	1.000								
7. Source_Breadth	-0.045	-0.023	0.738	0.741	0.763	0.747	1.000							
8. Spill_Potential	-0.339	0.040	0.098	0.055	0.046	0.111	0.103	1.000						
9. Source_N	-0.056	-0.028	0.419	0.371	0.414	0.394	0.534	0.199	1.000					
10. Sub_Age	-0.034	0.097	-0.012	0.090	0.169	-0.092	0.053	0.038	0.022	1.000				
11. Abs_Cap	-0.005	0.199	0.160	-0.075	0.072	0.014	0.057	-0.033	0.001	0.521	1.000			
12. Tech_Prox	-0.207	0.025	-0.029	0.048	0.039	-0.020	0.013	0.003	-0.003	0.072	0.007	1.000		
13. Inventor_nbr	0.043	0.052	0.053	0.038	0.015	0.079	0.062	-0.003	0.021	-0.001	0.024	0.038	1.000	
14. Tech_Breadth	-0.018	-0.061	0.168	0.053	0.070	0.157	0.150	0.075	0.201	-0.048	-0.018	-0.254	0.068	1.000
Mean	38.870	0.144	1.521	0.472	0.662	1.332	1.993	7.789	9.036	12.234	294.854	0.604	1.908	0.297
Std_Dev	29.950	0.351	0.662	0.665	0.659	0.641	0.982	10.786	9.259	6.041	333.878	0.489	1.133	0.273
Min	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000
Max	120.00	1.000	3.000	3.000	2.000	4.000	6.000	99.000	97.000	25.000	1368.000	1.000	10.000	0.884

Table 2. Speed of Local Knowledge Outflows: Cox regression models.

	Model 1	Model 2	Model 3	Model 4
Colloc_Sou_Breadth		0.835**		
		(0.071)		
Source_Breadth		1.071*		
		(0.040)		
Colloc_Int_Breadth			0.747**	
			(0.107)	
Internal_Breadth			1.072	
			(0.053)	
Colloc_Ext_Breadth			0.897	
			(0.105)	
External_Breadth			1.074	
			(0.060)	
Colloc_Glob_Breadth				0.723***
				(0.090)
Global_Breadth				1.054
				(0.062)
Colloc_Loc_Breadth				0.992
				(0.130)
Local_Breadth				1.075
				(0.055)
Collocation		1.646***	1.540**	1.783***
		(0.300)	(0.308)	(0.339)
Spill_Potential	1.022***	1.022***	1.022***	1.022***
	(0.004)	(0.004)	(0.004)	(0.004)
Sources_N	0.999	0.998	0.997	0.999
	(0.003)	(0.004)	(0.004)	(0.004)
Sub_age	1.019*	1.013	1.013	1.013
	(0.011)	(0.010)	(0.010)	(0.010)
Abs_Cap	1.000	1.000	1.000	1.000
	(0.000)	(0.000)	(0.000)	(0.000)
Tech_Prox	1.088	1.054	1.057	1.048
	(0.115)	(0.111)	(0.111)	(0.110)
Inventor_nbr	0.959*	0.957*	0.956*	0.955*
	(0.024)	(0.024)	(0.024)	(0.024)
Tech_Breadth	1.239*	1.230*	1.226*	1.218*
	(0.136)	(0.136)	(0.135)	(0.135)
LR_chi^2	342.61***	348.06***	349.11***	351.69***
N	1336	1336	1336	1336

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each model includes a set of firm dummies, and – to be consistent with the proportional hazard assumption -, interactions between time and *Spill_Potential*, *Tech_Prox*, *Sub_age* and the *firm dummy* identifying the 6th MNC in the sample; model 1 includes also the interaction with the dummy for the 9th MNC. The estimates of the interactions are available from the authors upon request.