An analysis of the co-inventor networks associated with the Chinese pharmaceutical industry

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

Vittoria Giada Scalera
Politecnico di Milano
Department of Management, Economics and Industrial Engineering
vittoriagiada.scalera@polimi.it

Ram Mudambi
Fox School of Business - Temple University
Department of Strategic Management
rmudambi@temple.edu

Abstract
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1. Introduction

Emerging market multinational enterprises (EMNEs) have risen to occupy important positions in a wide range of global industries (Cuervo-Cazurra and Genc, 2008; Hobday, 2010; Kumaraswamy, et al. 2012; Lorenzen and Mudambi, 2013). A key to understanding the rapid pace with which many of these EMNEs have achieved such significant positions on the global stage is to distinguish between output and innovation capabilities (Bell and Pavitt, 1993). While output capabilities depict a firm’s expertise in delivering the current generation of products and services, innovation capabilities refer to its inherent proficiency in extending and enriching existing technological knowledge. In this regard, recent studies have demonstrated that emerging country firms are quick in catching up on output capabilities, but not as quick in terms of innovative capabilities (Awate et al., 2012).

While this finding confirms that the process behind the development of output and innovation capabilities is inherently different, it also reveals that our understanding of how innovation catch-up happens is underdeveloped. Innovation capabilities are critical for EMNEs, as a persistent lack of such skills would prevent these firms from fully participating in the creation of knowledge-based intangibles that account for the bulk of all value creation in today’s global economy (Mudambi, 2008; Corrado and Hulten, 2010). Aggregating up from the firm level, this implies that a failure of EMNEs to develop innovation capabilities will hinder the overall catch-up process of the economy at large (Abramovitz, 1986). Indeed, the contrast between South Korean firms’ development of innovation capabilities and Brazilian firms inability to do the same has been highlighted as one of the causes underlying the different catch-up experiences of these two economies (Moreira 1995; Hannigan et al, 2013).
The foregoing discussion emphasizes the critical importance of the development of innovation capabilities for emerging economies. Our principal objective in this study is to address the core research question related to this phenomenon to wit, what are the most promising organizational conduits for emerging economy knowledge sourcing? Recent research has analyzed this phenomenon in the context of EMNEs (Awate et al., 2015), showing that these firms seek to access the knowledge required for innovation catch-up from their acquisitions in advanced countries. In this study, we widen our lens beyond multinational enterprises (MNEs) to include other actors that may play a critical role in the build-up of innovation capabilities: domestic firms, as well as domestic and foreign universities and research centers.

A basic requisite of international knowledge sourcing is connectivity, the full range of potential linkages between one location and all other global locations. In other words, connectivity provides the basis for the potential recombination of ideas from diverse locations. It occurs through the activation of a variety of global linkages that may serve as conduits for valuable knowledge inflows (Lorenzen and Mudambi, 2013). Several studies suggest that it may play a central role in emerging countries’ technological catch-up (Amin, 2002; Davenport, 2005; Gertler and Levitte, 2005; Martin and Sunley, 2006).

Knowledge is context-specific (Nelson & Winter, 1982) and tends to develop in co-evolution with distinct national characteristics (Phene et al., 2006). Hence, relying only on local resources for innovation catch-up would expose emerging countries to the risk of being locked into their poor and low-quality knowledge base (Martin and Sunley, 2006). Conversely, infusions of external knowledge may provide actors in these countries with the novelty and variety that are needed to feed and enrich local innovation processes, especially if
the knowledge sources reside in foreign countries (Malmberg and Maskell, 2002; Bathelt et al., 2004).

Our research context in this study is the Chinese pharmaceutical industry. We use patent data to examine the extent to which inventor networks linked to China are geographically dispersed. We consider an inventor network to be “linked to China” either when it includes one or more Chinese inventors, or when it refers to a patent that has been assigned to a Chinese organization. The phenomenon of international connectivity through geographically dispersed inventor networks is especially relevant given the decrease in communication and transportation costs and the notable upgrades in digital technologies, which enable real time collaborations with peers located at great distance (Saxenian, 2005; McCann, 2005). If knowledge flows more effectively through direct interaction and personal contacts (Saxenian, 1994), collaborating with international teams should act as a channel for the acquisition of advanced technology and knowledge creation practices, and increase the likelihood of knowledge sharing across locations in the future (Haas & Hansen, 2005), thus ultimately fostering the development of innovation capabilities.

Inventors’ scientific work can be coordinated by different types of innovative organizations, referred to as “patent assignees”, which may originate from both advanced and emerging geographic contexts. Because organizations may differ in terms of their resource endowment, objectives and incentives depending on they geographic origin (advanced versus emerging countries) and typology (e.g., multinational firms, universities, research centers, single-location firms), their ability and willingness to foster the international connectivity of their research teams can vary. In order to explore this phenomenon, this study seeks to understand
how the geographic origin and institutional type of innovative organization affect the international connectivity of inventor networks in the Chinese pharmaceutical industry.

To answer this question, we collected the population of pharmaceutical patents issued by the USPTO between 1975 and 2010 and granted to both Chinese and foreign assignees utilizing the scientific work of Chinese inventors. We analyze the geographic dispersion of the inventor networks and classified patent assignees based on their geographic origin, as well as on a comprehensive taxonomy of assignee types.

We believe the empirical setting of our research is appropriate for several reasons. First, the pharmaceutical industry one of the most technology intensive sector, but simultaneously displays a significant gap, in terms of knowledge-based activities, between advanced and emerging countries (National Science Board, 2014), thus representing an interesting field for exploring innovation catch-up strategies of emerging countries. Second, agents affiliated to this industry extensively use patents as a way to protect their innovation output and intellectual property (IP), thus making patent information a reliable and rather comprehensive data source. Finally, due to both the increasing interest of foreign multinational firms and the manifold reforms that have occurred in the industry in the last decades, the Chinese pharmaceutical sector is populated by various types of actors – both domestic and foreign – that actively participate in the innovation process (Thomson Reuters, 2010). This provides us with the opportunity to investigate the role that different organizational, institutional and geographic characteristics of the innovative agents may play in a country’s innovation catch-up process.
Our paper contributes to the literature on the technological catch up of emerging countries by focusing on innovation catch-up, the most sophisticated component of the catch-up process. It does so by investigating the specific channel of international co-inventor networks. Building on previous research suggesting that internationalization is critical for the upgrade of emerging countries (Chittoor, et al., 2009), we focus on the internationalization of inventors’ collaborative activities. Specifically, we analyze the geographic reach of collaboration behaviors in emerging countries, under different organizational arrangements. We also add to the research stream on the networking behavior of inventors (Balconi et al. 2004), by simultaneously accounting for the role of the geographic origin and institutional type of innovative actors in a previously unexplored economic context, i.e. the emerging country context. We discuss both institutional and managerial implications of our study.

2. Conceptual framework and research

2.1 International knowledge sourcing through global linkages and connectivity

Firms attempt to develop their knowledge internally, but often they also leverage external sources using formal and informal arrangements. Internal R&D and external knowledge sourcing are often complementary parts of an organization’s innovation strategy (Cassiman and Veugelers, 2006). External knowledge sourcing occurs through numerous mans, including direct channels like acquisitions and alliances, as well as indirect ones like spillovers, personal relationships, scientist mobility in the labor market, buyer-supplier relationships, and other means (Chung and Yeaple, 2008; Laursen and Salter, 2004).
Considering that innovation activities and knowledge resources differ across countries, firms can increase their knowledge base by sourcing technical capabilities internationally (Cantwell, 1989; Kuemmerle 1999). The disaggregation of global value chains has accelerated geographically dispersed knowledge sourcing as organizations increasingly use their foreign subsidiaries to tap into global centers of excellence. The orchestration of fine sliced value chains by orchestrating organizations has played a key role in the creation of global linkages between firms and individuals located in both advanced and emerging economies (Jensen and Pedersen, 2011; Mudambi, 2008; Mudambi and Venzin, 2010). As value chains increasingly span national borders, national systems of innovation have become interconnected in global innovation networks (Narula and Guimón, 2010).

Global value chains have not only created and intensified global linkages, but they have also changed the configuration of the social networks. Traditionally global innovation networks were concentrated in advanced market economies with relatively low levels of geographical dispersion. However, both these characteristics of global innovation networks are rapidly changing. MNEs based in emerging economies are increasingly entering global innovation networks, so the dominance of advanced market economies is declining. Further, the extent of global innovation networks’ geographical dispersion is rising, driven by two processes. First, MNEs based in advanced market economies are offshoring knowledge creation to subsidiaries in emerging market economies in order to leverage the high quality, low cost resources available there (D’Agostino et al., 2013; Govindarajan and Ramamurti, 2011). Second, EMNEs are implementing “catch-up” processes by strategically acquiring knowledge assets in advanced market economies (Awate et al., 2012; Athreye and Kapur, 2009; Deng, 2009; Li
et al., 2012). Both of these processes lead to geographically dispersed innovation networks spanning advanced and emerging economies.

In this context, global linkages can be defined as channels that allow for the efficient transmission of different types of resources from geographically dispersed locations. Lorenzen and Mudambi (2013) distinguish between two forms of global linkages: pipelines, which are “organization-based linkages” (Bathelt et al., 2004) and personal relationships that are often leveraged through global diasporas. This latter form of global linkage is particularly important for the diffusion of knowledge, since extant literature demonstrates that the complexity of knowledge acquisition and transfer can be overcome through personal interactions between those who are willing to learn and those who have generated the knowledge to be transmitted (Breschi and Lissoni, 2001).

The concept of connectivity is defined by integrating the nature of global linkages with their network structure. It has been proposed that the connectivity that arises a decentralized network structure is most conducive to knowledge creation and innovation in emerging economies. Since a network structure is characterized by the lack of a strong “gatekeeper” controlling access into and out of emerging economy locations so that local inventors and scientists can interact and share knowledge. International connectivity facilitates external knowledge infusions that can nourish (local) internal innovative activities, especially because it encourages the recombination of knowledge from different sources and countries (Bathelt et al., 2004).
2.2 Emerging economies and technological catch-up

Firms from emerging economies often lack the competencies and knowledge to successfully compete with their counterparts from advanced economies (Awate et al., 2015; Luo and Tung, 2007). EMNEs tend to lag behind in terms of technological expertise (Kumar and Russell, 2002), and therefore cannot rely only on their own resources to reduce the gap. Although the literature has documented the ongoing process of technological upgrading and the relatively large pools of high skilled human capital in emerging economies (Athreye and Cantwell, 2007; Lewin et al., 2009), progress seems to be slow. Moreover, it is primarily focalized on output capabilities (Awate et al., 2012).

Extant literature has shown that foreign direct investment (FDI) from advanced economies often generates knowledge spillovers (Blomstrom and Kokko, 1998). More importantly, it is the genesis of spillover processes that work through the joint activities of MNE subsidiaries and local firms (Mudambi, 2008) and these processes are typically the spark that ignites wide-ranging technological catch-up (Li et al. 2012, Wei and Liu, 2006). Personal relationships and the mobility of skilled workers act in concert with inter-organizational ties as knowledge channels that operationalize spillovers (Filatotchev et al., 2011). Given that knowledge flows more effectively through direct interaction and personal contacts (Saxenian, 1994), emerging country inventors collaborating with international teams should act as an efficient channel for the acquisition of advanced technology and knowledge creation practices. This should ultimately promote the development of superior innovative capabilities.

This discussion suggests that international connectivity has a critical role in fostering the technological catch-up process of emerging economies. It activates global linkages that
conduct knowledge inflows from worldwide sources (Amin, 2002; Davenport, 2005; Gertler and Levitte, 2005), offsetting distances and allowing inventors from emerging countries to learn and ultimately to implement catch-up processes. It is important to recognize that connectivity is bi-directional, and generates higher awareness and mutual interdependence.

In the context of emerging economies, it appears that there are two drivers of international connectivity: institutions from emerging markets “reaching out”, and foreign organizations from advanced economies “reaching in”. The major modalities for reaching out are technology licensing and joint ventures, followed by cross-border acquisitions. The goals of these knowledge-seeking acquisitions are both R&D knowledge (technology and know-how) and marketing knowledge (brand building and global legitimacy) (Buckley et al., 2007; Luo and Tung, 2007). R&D-based FDI in particular helps emerging countries organizations to develop collaborations with foreign inventors, thus accessing diverse pools of knowledge and cutting-edge technologies.

The second driver of connectivity is embodied in foreign-based institutions that reach into emerging economies. Typically, this happens through the offshoring of manufacturing activities, production processes, and services (Contractor et al., 2010). Asian countries, such as China, offer a substantial pool of qualified workers and expertise at a competitive cost, to which firms from other countries are increasingly willing to access (Lewin et al., 2009). As a result, emerging economies are the preferred offshoring location for R&D activities (D’Agostino et al., 2013). Thus, the presence of advanced institutions in emerging economies promotes the involvement of local inventors in their knowledge networks, facilitating the chances of cooperation and transfer of ideas and know-how (Lorenzen and Mudambi, 2013).
While both emerging countries institutions reaching out and advanced market organizations reaching in generate connectivity, we claim that there is a systematic difference between these two sets of actors in their ability to create effective connectivity, and so to spawn geographically dispersed inventor networks. In particular, we posit that emerging economies innovative institutions more likely generate less internationally dispersed networks, compared to their advanced economy counterparts.

Geographic origin, in fact, is crucial in determining access to knowledge, resources and networks (Bartholomew, 1997; Phene et al., 2006; Porter, 1990). Advanced economy innovative institutions are traditionally recognized as the engine of innovation and have been the major players in the production of cutting-edge R&D for a long period of time (Cantwell, 1989). The leading innovators from advanced economies possess complex and established organizational capabilities that they leverage to orchestrate geographically dispersed activities effectively (Cantwell and Mudambi, 2011; Tallman and Chacar, 2011). Such firms are able to transmit and integrate even the most tacit knowledge across borders and over long distances (Cantwell and Santangelo, 1999). Conversely, emerging economy organizations have only recently started to invest in innovation and the globalization of their R&D is nascent (UNCTAD, 2005). In contrast to their counterparts from advanced economies, emerging economies innovative institutions have been positioned in the peripheries of international innovative networks, playing supporting role in the exchange and creation of knowledge at international level (Awate et al., 2012).

Hence emerging economy institutions are likely to face higher barriers when attempting to connect to inventors or institutions from advanced markets (Madhok and Keyhani, 2012). In
spite of their increasing international openness, cultural and institutional distances may hinder the ability of emerging market organizations in developing collaborations with foreign inventors and thereby limit the international connectivity of their networks. Further, emerging markets innovative institutions may not possess enough international experience to manage the complexity associated with international knowledge networks, which embrace a range of different sources of heterogeneity (Hansen, 2002). Further, they typically lack a knowledge base that is strong enough to be leveraged in the support of effective R&D collaborations with more skilled partners (Deng, 2009; Lane et al., 2001). In fact, they may not even possess sufficient know-how to successfully interact with their peers and to orchestrate dispersed and heterogeneous networks.

We therefore expect that:

Hypothesis 1 (H1): In emerging economies, domestic innovating organizations (and those based in other emerging economies) spawn less internationally dispersed networks than innovating organizations based in advanced economies.

2.3 The role of university and commercial knowledge pipelines

The geographic origin of innovative actors is not the only variable that may influence the international dispersion of inventor networks. Organizations involved in innovative activities are highly heterogeneous in terms of their institutional types. Since different types of organizations differ systematically in terms of their objectives, leading to differences in their patterns of knowledge sourcing and knowledge creation. In order to explore this issue, we
distinguish between (foreign) MNEs, (domestic) single-location firms and universities and research centers, and elaborate on their ability to drive connectivity. More specifically, assuming single-location firms as the benchmark to which comparing the other institutional types, we develop hypotheses on the role of MNEs and universities and research centers.

Single-location firms have limited opportunities in terms of resource access. In fact, as suggested by existing literature, they tend to rely almost exclusively on their local cluster for linkages creation, thus being isolated from international networks (Henderson, 2003).

Conversely, MNEs have the potential to access to two different knowledge networks (Almeida and Phene, 2004), both of which are geographically dispersed. First, MNEs by definition are organized as networks of subsidiaries established worldwide. Hence, they can exploit firm-internal networks and develop substantial internal linkages (Alcacer and Zhao, 2012; Meyer et al., 2011). Second, by embedding in their localities (Andersson et al., 2002), foreign subsidiaries develop external linkages that grant access to pools of localized knowledge and resources in different host-regions (Almeida and Phene, 2004).

As far as universities and research centers are concerned, previous literature has demonstrated that inventors working for this type of institutions are better in “connecting individuals and network components” (Balconi et al. 2004, p. 144) compared to non-academic inventors. Universities and research centers act as the sources of basic knowledge for industrial scientists (Cohen et al., 2000) but, unlike the latter, they are characterized by an “open” approach to science and technology (Balconi et al. 2004). While industrial innovators have a strong incentive to protect the outcomes of their innovative activities as these represent a source of
rents, scientists operating in universities and research centers are typically not interested in the commercialization of ideas, as this falls beyond the scope of their activity.

In other words, academic inventors are driven by “primacy” while commercial inventors are driven by “secrecy” (Mudambi and Swift, 2009). Rather, they pursue research with the goal of advancing the knowledge frontier, often driven by their individual motivation. In addition, the social and professional environment to which they belong stimulates their willingness to share the results of their innovative processes, as this increases their personal reputation (Siegel et al., 2003). The dissemination of the research results is in fact a central component of universities’ and research centers’ scientific activity (Fabrizio, 2007), which for this reason is often referred to as “public science”. In sum, contrary to what happens in commercial firms, inventors working for universities and research centers retain strong incentives to collaborate over long geographical distances as they seek linkages with experts and the broadest possible diffusion of their ideas. It follows that the community of scientists tends to be highly connected in spite of geographic distance, which stimulates the collaboration among inventors located worldwide.

We therefore expect that:

Hypothesis 2 (H2). In emerging economies, both MNEs and universities and research centers spawn more internationally dispersed inventor networks compared to (domestic) single-location firms.

In an advanced country context, one could argue on which institutional type, among MNEs and universities and research centers, is able to drive the most internationally dispersed
inventor networks. The innovative activities of MNEs in advanced economies tend to be central and linked to their widely dispersed subsidiary networks. Conversely, MNE innovation occurring in emerging countries is usually peripheral since it is rooted in a local context where the industrial knowledge base is backward and the institutional infrastructure, including the intellectual property protection system, is rather poor. As MNEs are strongly committed to protect their proprietary knowledge from external appropriation (Mariotti, Piscitello, & Elia, 2010; Perri and Andersson, 2014), they can be expected to have lower incentives to develop internationally dispersed inventor teams in such locations. Giving a central role to innovation teams in these locations could decrease the control over their assets while granting access to low-quality knowledge.

In contrast, as we have argued, universities and research centers are less sensitive to knowledge protection imperatives (Balconi et al., 2004), and are thus less concerned about threats arising from weak intellectual property rights protection. Combining these arguments, we suggest that, in emerging country contexts, universities and research centers generate higher international connectivity than MNEs do:

Hypothesis 2a (H2a). In emerging economies, inventor networks coordinated by universities and research centers are more internationally dispersed than inventor networks coordinated by MNEs.

2.4 The impact of geographic origin on the role of universities and firms pipelines

In order to fully appreciate the impact of the geographic origin of innovative organizations and their institutional type, it is important to consider these factors jointly. In fact, the effects
predicted in H1a and H2a may be sensitive to whether the innovative organization coordinating the scientific work of the inventor team is based in an advanced or an emerging country.

As far emerging country MNEs and universities are concerned, the literature suggests that they can rely on the return migration of skilled graduate students and engineers educated in advanced countries and returned to their home economies endowed with critical professional linkages to peers in their former host-countries (Saxenian, 2005; Jonkers and Tijssen, 2008). While this is an important channel for enabling these actors to connect to international networks, their counterparts from advanced countries have many other critical advantages that may place them in privileged position to spawn internationally dispersed inventor teams.

On the one hand, in spite of the idea of the academic community as a small world characterized by high interconnectedness, not all actors belonging to this world are likely to be equally central or to share the same privileged position within the network (Newman, 2000; 2001; Fleming and Marx, 2006). Compared to their foreign peers, universities and research centers from emerging countries are likely to be marginalized, peripheral components of the scientific community, less able to connect to the global academic network.

On the other hand, compared to advanced country MNEs, those originating from emerging countries are likely to have a less geographically dispersed network of foreign affiliates and their internal linkages may be hampered by the opportunism of acquired subsidiaries (Awate et al., 2015). Moreover, EMNEs tend to be endowed with a narrower capability base (Mathews, 2006), which decreases their ability to connect to the rest of the world. The relative backwardness and peripheral position of their locality may also play a role in reducing the
opportunities for the creation of knowledge linkages with partners from more technologically advanced regions.

Compared to their advanced counterparts, they should therefore drive a lower degree of connectivity. Based on this reasoning, we expect that:

Hypothesis 3a (H3a). In emerging economies, the higher connectivity of universities and research centers is less accentuated when they originate from emerging countries.

Hypothesis 3b (H3b). In emerging economies, the higher connectivity of MNEs is less accentuated when they originate from emerging countries.

3. Empirical analysis

3.1 Empirical setting

Traditionally regarded as a highly profitable context (Ghemawat, 2010), the global pharmaceutical sector has experienced a number of major changes in the last decades, which have strongly modified the industry’s competitive dynamics leading to a gradual shrinking of profit opportunities (Scalera et al., 2015). After the discovery of important “blockbuster” drugs which have fed the big pharmaceutical companies for several decades, the odds of coming up with new high-potential molecules decrease over time, as those “easy targets are being steadily exhausted” (Bruche, 2012; p.5). Major institutional changes also contributed to modify the industry’s structure and competitive approaches, inducing the rise of a generic
market segment and, accordingly, of an increasing number of imitative manufacturers (Bruche, 2012). Finally, starting from the early 1980s, the successful emergence of biotechnology and genetics demanded incumbent firms to develop new skills in terms of rational drug design, as opposed to traditional trial and error discovery processes, thus making the exploitation of external technology sources compelling (Cockburn, 2004).

Faced with these competitive challenges, big pharmaceutical companies had to significantly amend their business model over time. One opportunity for managing these challenges arise from emerging countries, whose enormous populations, growing awareness of the importance of healthcare, and increasing GDP have readily attracted companies by then used to deal with mature and stagnant markets. Originally regarded exclusively as final markets where Western pharmaceutical companies could manufacture and sell their products, emerging countries have progressively become the target of knowledge intensive FDI, hosting an increasing number of foreign MNEs’ R&D facilities (Scalera et al., 2015). Among these locations, emerging markets like India and China take the lead. In these geographical contexts, the pharmaceutical industry tends to be a turbulent and discontinuous environment. In fact, the effects of the economic liberalization process and IP reforms combine with the specificities of a highly regulated industrial setting. Internal heterogeneity is also a major issue in these countries, as there are profound gaps in terms of access to healthcare services among rural and more central geographic areas.

We choose the Chinese pharmaceutical industry as the empirical setting of our study, as China represents an ideal test-bed for our hypotheses. China is one of the largest pharmaceutical markets in the world, but its prominence arises from the size of its population, rather than
from the sophistication of its offer. Although in the last decades it has experienced a reform of the healthcare system and a gradual transformation of local pharmaceutical industry, which is increasingly populated by research-based companies, the market is still highly fragmented, and characterized by a complex system of sub-national segments dominated by small to medium-sized generics and over the counter drugs (OTC) manufacturers. Moreover, in spite of China’s adhesion to the World Trade Organization (WTO) in 2001, the country is still regarded as an unsafe context for intellectual property rights protection (Zhao, 2006).

3.2 Data

In order to study innovative activities in the Chinese pharmaceutical industry, we used patent data as a proxy for innovative output. Accordingly to other studies about innovative activities in China (e.g. Branstetter et al., 2013; Scalera et al., 2015; Zhao, 2006), we focus on the United States Patent and Trademark Office (USPTO) data, in order to assure the originality and high quality of the innovations analyzed (Archibugi and Coco, 2005). Extant literature has already explored collaboration patterns of inventors employing patent co-inventorship (e.g. Ejermo & Karlsson, 2006). In fact, patents provide detailed information on the team of inventors, favoring the identification of collaborations among inventors and their geographical distribution. In addition, patents represent a more refined measure of the efficient utilization of human capital, compared to input measures. Finally, they also give the

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1 We decided to not consider data from the State Intellectual Property Office of the Public Republic of China (SIPO) for an array of reasons. First, the Chinese patent system has been frequently changed over time, and so Chinese data may be inconsistent in our time horizon. Second, it is common practice to use data from a single patent office in order to avoid problems related to lack of consistent quality across national patent systems (Jaffe and Trajtenberg, 2002).
possibility to account only for innovations considered valuable by the innovative organizations that make the application to the patent office (Griliches, 2000; Zhao, 2006).

In order to build our sample, we selected all USPTO patents granted between 1975 and 2010, that report at least one Chinese inventor or applied for by a Chinese organization. From the initial sample, we only included patents representative of the pharmaceutical industry, so referring to the Drug and Medical technological fields defined by Hall et al. (2001)\(^2\). We also included design patents containing the technological class “Pharmaceutical Devices” (D24). Finally, we exclude patents assigned to individuals, or unassigned. The sample thus generated consists of 1026 patents, emanating from 516 different assignee organizations.

In order to ensure the validity of our analysis, it is crucial that we identify each individual inventor and determine their address. To do so, we complemented our patent data gathered directly from USPTO website using the “Disambiguation and co-authorship networks of the U.S. patent inventor database (1975 - 2010)” distributed by The Harvard Dataverse Network (see Li et al., 2014). In particular, we used this database to source the information concerning the inventors, since the database focuses on USPTO patent data and disambiguates each patent inventor, providing – among other information – their addressees, together with cities’ ZIP codes and latitude and longitude\(^3\).

3.3 Variables and model

3.3.1 Dependent variable: Geographical dispersion

\(^2\) The Drug and Medical category as defined by Hall et al. (2001) includes four sub-categories: Drugs (sub-category code 31); Surgery and Medical Instruments (32); Biotechnology (33); and Miscellaneous – Drugs and Medicine (39).

\(^3\) As “Disambiguation and co-authorship networks of the U.S. patent inventor database (1975 - 2010)” does not include all the USPTO design patents, we manually checked the address information of the inventors of the design patents not found in the database.
To measure the degree of connectedness of the innovative actors we employ the geographical dispersion of their inventors’ team, using the UPSTO and “Disambiguation and co-authorship networks of the U.S. patent inventor database (1975 - 2010)” location data of the address of patent inventors. In fact, often an invention underlying a patent assigned to a company or a university may be the result of R&D activities distributed in different locations. The focus on inventors’ location enables us to determine the actual geographic origin of the knowledge\(^4\) (Lahiri, 2010).

Thus, the dependent variable, *Geographical dispersion*, is the geographical dispersion of the network of inventors measured at patent level, following the approach of Cano-Kollmann and colleagues (2014). The construction of *Geographical dispersion* is based on the Herfindahl index, also known as Herfindahl–Hirschman Index, which is commonly used in industrial organization to measure of concentration of an industry (e.g., Tallman and Li, 1996). Since we are interested in the dispersion (and not in the concentration) of the inventor network at patent level, the *Geographical dispersion*\(_i\) for patent \(i\) is constructed as follows:

\[
Geographical\ dispersion_i = 1 - \sum_{n=1}^{N} \left(\frac{Inv_{i,n}}{Inv_i}\right)^2
\]

where \(Inv_{i,n}\) is the number of inventors of patent \(i\) located in country \(n\) (\(N\) is the total number of inventors’ locations mentioned in patent \(i\)), \(Inv_i\) is the total number of inventors of patent \(i\).

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\(^4\) The locations are identified at country level.
As a result, we obtained a censored dependent variable, which takes the minimum value of 1 when all inventors are located in the same country (i.e. China in our analysis), and an upper limit asymptotically approaching 1 as the inventors network is more dispersed across different countries.

We employ a multiple regression approach to test our hypotheses. Given that our dependent variable is censored, taking a minimum value of 0 and an upper limit asymptotically approaching 1 (the maximum value is 0.82), we adopted a robust Tobit regression model, which allows controlling for heteroskedasticity of the sample (Greene, 2000: 905-926).

The baseline model to be tested is the following:

$$\text{Geographical dispersion}_i = f(\text{Emerging}_i; \text{University}_i; \text{MNE}_i; \text{controls}_i)$$

where \( i = 1, \ldots, 1026 \) patents.

To test our HP3a (HP3b) we add to the baseline model the interaction effect between \( \text{Emerging} \) and \( \text{University (MNE)} \), as follows:

$$\text{Geographical dispersion}_i = f(\text{Emerging}_i; \text{University}_i; \text{MNE}_i; \text{University}_i \ast \text{Emerging}_i; \text{controls}_i)$$

$$\text{Geographical dispersion}_i = f(\text{Emerging}_i; \text{University}_i; \text{MNE}_i; \text{MNE}_i \ast \text{Emerging}_i; \text{controls}_i)$$

3.3.2 Explanatory variables
3.3.2.1 Emerging economies innovative institutions

In order to test our first hypothesis, we introduced the independent variable *Emerging*, which is a dummy variable equal to 1 if the assignee is located in an emerging country (mostly in China), and 0 otherwise. For the purposes of the current work, we have relied on the World Bank classification of emerging countries, which is based on the level of per capita income. Consequently, all countries belonging to the lower and upper middle-income groups have been classified as emerging (http://data.worldbank.org/about/country-and-lending-groups).

If the assignee is an MNE’s foreign subsidiary, we built the variable using the location of its headquarter (Almeida and Phene, 2004; Phene and Almeida, 2008). We used BvD Orbis to identify the locations of the MNE headquarter.

Further, our sample includes 108 (10.53%) co-assigned patents, i.e. patents that have more than one assignee. In these cases, the variable Emerging takes the value of 1, if at least one of the assignee is from an emerging country.

3.3.2.2 Typology of innovative institutions

In order to categorize the organization contributing to the innovative activities in emerging economies, we distinguished between (1) universities and research centers, (2) MNEs and (3) single-location firms. We have carried out a thorough work of cleaning and standardizing assignees’ names and addresses. Assignees have been identified first by assigning a unique code to all assignees with the same name and address. Then, using *BvD Orbis*, we consolidated the code to assignees with the same address and with very similar names, when
inconsistences arise from misspelling, presence/absence of extensions, or presence/absence of spaces between parts of the names.

For each assignee mentioned in the patent document, and univocally identified, we analyzed first the institutional typology and then, in the case of commercial firms, the ownership structure, manually inspecting the assignees’ name and relying on information from *BvD Orbis*, companies’ websites and other on-line resources, i.e. Bloomberg website. As regards the commercial firms, we defined as MNE any firm that has at least one foreign subsidiary by looking at the family tree for every firm in our sample. Because patents may be assigned either to the MNE parent company or to one of its subsidiaries for unobservable reasons (Cantwell and Mudambi, 2005), we considered each multiunit firm as an integrated strategic agent, following the approach of Zhao (2006).

The categorization of the assignee type is time variant, since we checked the status of each assignee in correspondence to the year of the patent application. This procedure enables us to take into account changes in the firm ownership structure (e.g. merge and acquisitions), which are very frequent especially in the pharmaceutical industry.

After the assignees’ categorization, for each patent we created three dummy variables: *University*, if the patent’s assignee is a university or a research center, *MNE*, in case the patent has been assigned to an MNE or one of its subsidiaries, and *Single_location*, otherwise. For the analysis, we used *Single location* as the benchmark. Finally, in case of co-assigned patents, we take into consideration the categories of all the co-assignees. For instance if a patent has been assigned to a university and an MNE, both *University* and *MNE* take the value of 1.
3.3.2.3 Controls

Assignee innovative leadership: The dummy variable Leader takes the value of 1 for assignees that are in the upper quartile (or 75th percentile) of the pharmaceutical patent pool in terms of patent production in the year previous the patent application (t-1). To determine the pharmaceutical patent pool we considered all UPSTO patents granted in Drug and Medical technological fields defined by Hall et al. (2001). We measured patent production as the natural logarithm of the cumulative number of USPTO pharmaceutical patents issued by each assignee in the period 1975 – (t-1). Data come from “Disambiguation and co-authorship networks of the U.S. patent inventor database (1975 - 2010)” (Li et al., 2014). If the company is part of a group or is the subsidiary of an MNE, we used the pharmaceutical patent stock of its global ultimate owner to calculate the variable. In case of co-assigned patent, Leader takes the value of 1, if at least one of the co-assignees is in the upper quartile.

Number of inventors of the inventor team: Team size represents the number of inventors for each patent.

Design patent: the variable Design is a dummy and takes the value of 1, if the patent is classified by the USPTO as a design patent and 0 in case it is a utility patent. Relying on the USPTO definition, “[...] “utility patent” protects the way an article is used and works, while a “design patent” protects the way an article looks. The ornamental appearance for an article includes its shape/configuration or surface ornamentation applied to the article, or both” (http://www.uspto.gov/).
Primary pharmaceutical technological class: *Pharma* is a dummy variable equal to 1, if the first technological class of the focal patent is included in the pharmaceutical category, as defined in section 3.2; otherwise it takes the value of 0.

Technological composition of the patent: The variable *Tech composition* is built adapting to the Cubbin-Leech index (Cubbin and Leech, 1983) to the case of the patents’ technological composition\(^5\). First, we computed the Herfindal index of the patent technological concentration \((H_{tech})\), using the three digit technological classes to which the USPTO has assigned the patent:

\[
H_{tech} = \sum_{m=1}^{M} (Tech_{class_{i,m}})^2
\]

where *Tech composition\(_{i,m})* is the percentage of the technological class \(m\) represented in patent \(i\) on the total number of technological classes mentioned in patent \(i\), i.e. \(M\). *Tech composition* is defined as follows:

\[
Tech_{composition_{i}} = F[(Tech_{class_{i,1}})/(H_{tech} - Tech_{class_{i,1}}^2)^{1/2}]
\]

\(^5\) For a different approach measuring the ownership concentration shares in a firm, see Mudambi and Nicosia (1998).
where $F[.]$ is the standard normal distribution function and $Tech\_class_{it}$ is the percentage of the technological class most representative in patent $i^6$.

Co-assigned patent: *Co-assigned* is a dummy variable that takes the value of 1 if the patent has more than one assignee, and 0 otherwise.

IP policy changes: Since we pool patent data over a 35-year period characterized by regulatory turbulence in Chinese IP regime, we include a year dummy that is equal to 1 if the patent has been applied for from 2005 onwards. Since 2005, in fact, the Chinese government fully has fully complied with the requirements of the TRIPS agreement.

4. Findings

Table 2 shows the estimated coefficients of the Tobit regressions applied to the equation models described above.

[Insert Table 2 about here]

All models produced statistically significant results (LR $\chi^2=283.05$ and $p<.0$ in Model 1, LR $\chi^2=726.35$ and $p<.0$ in Model 2, LR $\chi^2=744.09$ and $p<.0$ in Model 3, LR $\chi^2=747.29$ and $p<.0$ in Model 4, LR $\chi^2=744.56$ and $p<.0$ in Model 5).

---

* For patent with only one technological class, so with highest level of technological concentration, we proxy the limit case for which it is possible to calculate a compute value of Tech composition, i.e, $Tech\_class_{it} = 90\%$. 
We employed Model 1 as the baseline that includes all our controls. As expected, the technological leadership of innovative organizations (*Leader*) has a positive (0.446) and significant effect (p<.001) on inventor teams’ geographic dispersion, as technologically advanced actors are endowed with appropriate knowledge and relational resources to develop global linkages. Moreover, larger inventor teams are also more likely to encompass a higher geographic dispersion, as highlighted by the positive (0.021) and significant (p<.001) coefficient of the *Team size* control.

In order to test our HP1, we ran Model 2 and found confirmation of our first hypothesis. As predicted, the dummy variable identifying emerging economies innovative institutions (*Emerging*) exhibits a negative and significant coefficient (p<.001 also in Model 3, 4 and 5), thus showing that local innovative actors spawn less internationally dispersed inventor networks compared to advanced economy innovative actors.

In order to test our second set of hypotheses, we employed Model 3 and added the variables for universities and research centers and multinational firms. The *University* dummy variable shows positive and significant coefficient (p<.001 in Model 3, 4 and 5), confirming the central role of this type of innovative institution in the technological catch-up process of emerging economies. The *MNE* dummy variable is also positive, but much less significant across the different specifications (p<.05 in Model 3, p<.05 in Model 4, p<.1 in Model 5). Overall, these results suggest that, compared to single-location firms, both universities and research centers and MNEs establish more internationally dispersed investor networks, thus offering support for HP2. Moreover, further analysis (Table 3) rejects the hypothesis of
equality of the *University* and *MNE* coefficients, confirming our HP2a and providing evidence of the higher connectivity associated with University patents.

[Insert Table 3 about here]

To test HP3a and HP3b, Model 4 and 5 include, respectively, the interaction terms that reflect our theoretical argumentations, i.e. *University*\(^*\)Emerging and *MNE*\(^*\)Emerging. In particular, in Model 4 the coefficient of the interaction between *University* and *Emerging* (emerging innovative institutions) is negative and statistically significant, although at a low level (p<.1). This lends some support to HP3a. On the other hand, in Model 5, the interaction between *MNE* and *Emerging* (emerging innovative institutions) turns out to be non significant. Hence, HP3b is not supported.

To further explore the effects of geographic origin on the institutional type of innovative organizations, we split our original sample between patents developed by emerging economies institutions and patents developed by advanced economies institutions, and run regressions including both the University and MNE dummy variables (results are available upon request). The analyses performed on the two subsamples seem to confirm our expectations that both universities and research centers and MNEs are capable of driving international connectivity when they originate from advanced countries. In fact, the coefficients of the *University* (p<0.001) and *MNE* (p<0.05) variables are significant in the
advanced economy subsample. Conversely, they turn out to be non-significant in the subsample of patents belonging to emerging economy organizations.

5. Discussion and conclusions

Our results show that innovative organizations from emerging countries spawn less internationally dispersed inventor networks than innovative organizations from advanced countries. This suggests that, in spite of the economic growth that many emerging economies have achieved in the last years, their process of technological catch-up still hinges upon innovative actors from the “advanced world”, at least when it comes to the channel of international connectivity. Hence, these contexts are not independent as regards the development of innovation capabilities.

Moreover, contrary to the expectations that ascribe to MNEs a central role in the technological development of emerging countries, in the context of our analysis, it is the institutional category of universities and research centers to act as the most effective pipeline to connect China to global knowledge networks. This finding confirms the critical role universities play as growth engines (Charles, 2003; Cooke, 2001; Dasgupta and David, 1994; Kitagawa, 2004; Lundvall, 1992; Nelson, 1993, 2004; Salter and Martin, 2001). Our result pointing to the major contribution universities and research centers can offer to the development of innovation capabilities in emerging countries is also consistent with previous research suggesting that these actors are seldom able to impact directly on commercial firms’ creation of new products and services (Pavitt, 2001). In fact, while firms are successful on this
latter dimension, given their strong motivation toward the accumulation of financial wealth, universities and research centers are further from markets and, due to their focus on fundamental investigation, provide a greater contribution to the development of more sophisticated, long-term innovation capabilities, by offering a better understanding of underlying phenomena (Fleming and Sorenson, 2004; Fabrizio, 2007). Not surprisingly, previous research has shown that only firms that adopt very “open” search strategies and invest in R&D draw upon university knowledge for their innovative activities (Laursen and Salter, 2004).

Overall, our results offer renewed support for the statement according to which “at best, foreign investment from the core might contribute to the incremental mastery of manufacturing techniques and upgrading of local suppliers. Even the most successful newly industrializing countries are destined to remain imitators as long as leading-edge skill and technology reside in the corporate research labs and universities in the core.” (Saxenian, 2005; p. 38).

Of course, it should be noted that universities and research centers play a primary role in fostering internationally dispersed inventor networks mainly when they originate from advanced countries, suggesting that the periphery’s scientific environment has not yet developed the required skills to continually connect with the core. This finding is also consistent with research suggesting that, among the different emerging countries, China has been the least successful in fostering the return migration of its skilled scientist and knowledge workers (Jonkers and Tijsse, 2008), likely due to an ineffective return incentives policy (Cao, 1996).
These results have some implications for both local and global policy-makers aiming to expedite the process of technological catch-up of emerging countries, who should (1) continuously engage innovative actors from advanced countries, and (2) design incentive policies involving universities and research centers, along with FDI attraction strategies. Moreover, our results have some bearings also for emerging country firms. First, they should be aware that connecting to global knowledge networks is a very complex activity for organizations that are not familiar with the global innovation system. Second, they should consider that in order to gain access to global knowledge, they may choose between two alternative strategies: the pursuit of internationally distributed inventor networks, or the leverage of global cities’ inventors. The latter strategy may result easier, as it does not require geographic dispersion, but rather focuses on “selected” locations.
References


Corrado, C. and C. Hulten (2010), ‘How do you measure a technological revolution?’


Perri, A. and U. Andersson (2014), ‘Knowledge outflows from foreign subsidiaries and the
tension between knowledge creation and knowledge protection: evidence from the semiconductor industry,’ *International Business Review*, 23, 63-75.


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Obs.          | 1026 | 1026 | 1026 | 1026 | 1026 | 1026 | 1026 | 1026 | 1026 | 1026 | 1026 |
Mean          | 0.199 | 0.340 | 0.361 | 0.472 | 0.319 | 3.845 | 0.086 | 0.682 | 0.940 | 0.324 | 0.105 |
Std. Dev.     | 0.235 | 0.474 | 0.480 | 0.499 | 0.466 | 3.073 | 0.280 | 0.466 | 0.075 | 0.468 | 0.307 |
Min           | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.673 | 0.000 | 0.000 |
Max           | 0.82  | 1     | 1     | 1     | 1     | 31    | 1     | 1     | 1     | 1     | 1     |
Table 2. Tobit regression results (Dependent variable = Geographical dispersion).

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Note: Standard errors in parentheses
† p<0.1, * p<0.05, ** p<0.01, *** p<0.001
Table 3. Test on the equality of MNEs and Uni_Rc coefficients.

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