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ABSTRACT

This paper explores the integration of emerging countries into the global system of innovation, as a channel for their technological catch-up. Using data on the innovative activity in the Chinese pharmaceutical industry, we analyze the geographic dispersion of inventor networks linked to China, as a function of the characteristics of the innovative actors that coordinate their inventive work.

Keywords: Emerging Countries, Technological Catch-Up, FDI.

JEL Classification Numbers: M16.

1. INTRODUCTION

Emerging countries local systems of innovation are increasingly developing. Although in recent years scholars have shown renewed interest in the technological advancement of emerging economies (e.g. Cuervo-Cazurra and Genc, 2008; Hobday, 2010; Kumaraswamy, et al. 2012; Lorenzen and Mudambi, 2013), the catch-up process that allows these contexts to upgrade their capabilities is not yet fully understood. This study aims at shedding light on this subject by studying innovation in the Chinese pharmaceutical industry. More specifically, we look at the international connectivity (Lorenzen and Mudambi, 2013) of Chinese inventors in this sector, defined as the extent to which Chinese inventors collaborate with peers located in foreign countries. Assuming that knowledge flows more effectively through direct interaction and personal contacts (Saxenian, 1994), emerging country inventors collaborating with international teams should act as a channel for the acquisition of advanced technology and knowledge creation practices, thus ultimately fostering the development of superior innovation capabilities.

Inventors' scientific work is usually coordinated by organizations such as private companies, state-owned firms, universities and research labs, originating from both local (Chinese) and foreign geographic contexts. Because organizations differ in terms of their objectives and incentives, their willingness to foster the international connectivity of their research teams can vary. In order to explore this phenomenon, in this study we ask the following research question: *How do the geographic origin and institutional type of innovative actors 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.

2. KNOWLEDGE NETWORKS AND INTERNATIONAL CONNECTIVITY

The concept of connectivity is rooted in the idea of linkages. Linkages can be defined as channels that allow for the exchange of different types of resources (Lorenzen and Mudambi, 2013). Because technological advances have fostered the disaggregation of value chains into specialized activities (Mudambi and Venzin, 2010), linkages have become increasingly global over time. This has generated prominent opportunities to participate to global value chains for emerging countries (Meyer et al., 2011). Entering global value chains helps emerging economies to get "closer" to the developed world. On one hand, emerging country actors become more familiar with the context of advanced economies, and may more easily consider investing in these locations in order to gain access to cutting-edge technologies and business practices. On the other hand, developed world organizations increasingly recognize the role that emerging countries play in the international organization of economic activities, thereby seeking to exploit potential business opportunities related to these contexts. These bi-directional mechanisms generate higher awareness and mutual interdependence, which in turn reinforce the process of interaction and linkages creation between emerging countries and the rest of world. This dynamic is crucial for the catch-up process of emerging countries, as linkages frequently carry knowledge. Knowledge plays a critical role in countries' innovativeness and economic growth, but it is often difficult to acquire from a distance (Singh, 2005), because its diffusion process tends to be geographically localized (Jaffe et al., 1993). However, literature shows that the complexity of knowledge acquisition can be overcome through personal interaction between those who are willing to learn and those who have generated or master the knowledge to be transmitted (Breschi and Lissoni, 2001).

Geographically dispersed inventor networks, through which scientist from different countries interact and share pieces of their own knowledge, may thus offset distances and foster the effective transmission of technology, thereby allowing Chinese inventors to learn and ultimately catch-up.

3. THEORY AND HYPOTHESES

3.1 Geographic origin: Chinese vs. foreign institutions

In the context of the Chinese pharmaceutical industry, the dynamics of interaction and mutual recognition involving local and foreign actors have been particularly evident, thereby giving rise to an increasing number of collaborations, business opportunities as well as to a relevant flow of inward and outward investment. This has fostered the development of knowledge linkages with innovative actors located abroad, thus connecting the country to the rest of the world. On the whole, it appears that there are two drivers of connectivity: local innovative actors reaching out, and foreign innovative actors reaching in. *Local innovative actors* are Chinese-based organizations that are able to reach out and develop connections with foreign inventors, in order to use their scientific work to innovate. This can be obtained, for instance, by means of knowledge-intensive FDI in advanced countries (Piscitello et al. 2014). Many Chinese pharmaceutical companies are increasingly investing overseas not only for seeking knowledge and technology, but also for building brand awareness and global legitimacy in order to increase their market share and compete more effectively with advanced MNEs (KPMG, 2011). Although obtaining drug certification from the European or US market is a major challenge, Chinese companies strive to achieve this objective as it also encompasses a series of positive outcomes on both the home-market and other foreign markets, such as promoting reputation and brand image as signaling drug quality. Knowledge-based FDI helps emerging country organizations to develop collaborations with local investors, thus accessing to diverse pools of knowledge.

The second source of connectivity is represented by *foreign innovative actors*. *Foreign innovative actors* are foreign-based institutions that reach in, and involve local inventors in the organization of their research activities. Typically, this happens through the offshoring of innovation and knowledge-intensive activities to emerging countries (Lewin et al., 2009). In the case of China, the *Open Door Policy* has of course played a role in the activation of a substantial flow of direct investment from advanced economies. Specifically, foreign organizations have by now realized the importance of being involved in the Chinese pharmaceutical industry, not only for the size of the market, but also in the light of its innovative potential.

While both foreign and domestic innovative actors may drive connectivity, we are interested in understanding whether systematic differences in their ability to spawn geographically dispersed inventor networks exist. Because of the increased globalization of human capital (Florida, 2005), developed world actors are starting to face a global race for talent (The Economist, 2006), which drives them to source knowledge and high value-added resources worldwide, in order to exploit the best available opportunities and increase efficiency. 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). At least 80000 Chinese PhDs from Western institutions have return to China to work in industry or in academic institutions, positing China as a leader in the knowledge-intensive outsourcing industry (KPMG, 2011). Accordingly, an increasing number of Chinese drug companies are turning to contract research organizations (CROs), and their market is expected to growth annually by 33% (KPMG, 2011). Chinese CROs offer research services at significantly lower costs and are increasingly able to meet Western standards (KPMG, 2011). Under these conditions, foreign organizations are likely to develop frequent linkages with Chinese inventors. Conversely, due to their *liability of emergingness* (Madhok and Keyhani, 2012), Chinese actors are likely to face barriers when attempting to connect to foreign inventors. In spite of the increasing international openness of the Chinese pharmaceutical industry, cultural, institutional and technological distances may hinder Chinese-based organizations' ability to develop collaborations with foreign inventors thereby limiting the geographic dispersion of their inventor network. We therefore expect that:

> *HP1. In emerging markets, domestic innovative actors spawn less internationally dispersed inventor networks than foreign innovative actors*

3.2 Institutional type of innovative actors

The geographic origin of innovative actors is not the only variable that may influence the geographic dispersion of inventor networks. Organizations that involve in innovative activities are heterogeneous in terms of their institutional types. Since different types of institutions are driven by heterogeneous objectives, their incentive to stimulate the international collaboration of their research teams may vary. In order to explore this issue, we distinguish between MNEs, single-location firms and university and research centers, and elaborate on their ability to drive connectivity. More specifically, assuming MNEs as the benchmark to which comparing the other institution types, we develop hypotheses on universities and research centers and single-location firms.

Compared to MNEs, universities and research centers are characterized by an "open" approach to science and technology (Balconi et al. 2004). While MNEs have a strong incentive to protect the outcomes of their innovation, as they represent a source of rents, inventors operating in universities and research centers pursue research with the goal of advancing the knowledge frontier, and are often driven by their individual motivation. Moreover, the social and professional environment to which they belong stimulates their willingness to share the results of their innovative processes, as this increases their reputation. Universities and research centers are not interested in the commercialization of their ideas, as this falls beyond the scope of their activity. Therefore they have no need to keep them secret. 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.

Single-location firms have limited opportunities in terms of resource access. While MNEs have a network of subsidiaries established worldwide, and may therefore access to pools of localized knowledge and resources in different host-regions (Almeida and Phene, 2004), single-location firms can only acquire resources available in their own locality. Access to resource is not the only aspect on which single-location firms are constrained. Compared to MNEs, which can exploit firm-internal networks and develop substantial internal linkages (Alcacer and Zhao, 2012; Meyer et al., 2011), single plant firms tend to rely more on their local cluster for linkages creation, thus being isolated from international networks (Henderson, 2003). We therefore expect that:

> *HP2a. Compared to MNEs, universities and research centers spawn more internationally dispersed inventor networks*
>
> *HP2b. Compared to other innovative actors, single location firms spawn less internationally dispersed inventor networks*

3.3 Combining the geographic origin and institutional type of innovative actors

In order to fully appreciate the impact of the geographic origin of innovative actors and their institutional type, it is important to consider these factors jointly. In fact, the effects predicted in HP2a and HP2b could behave differently in the case of domestic innovative actors.

On 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). Compared to their foreign peers, universities and research centers from emerging countries are likely to be marginalized, peripheral components of the scientific community, thus being less able to connect to the global academic network. On the other hand, compared to foreign single location firms, those located in emerging countries tend to be endowed with a narrower capability base, which decreases their already low ability to connect to the rest of the world. The relative backwardness and peripheral position of their locality also plays a role in reducing the opportunities for the creation of knowledge linkages with partners from more technologically advanced regions. Compared to their foreign peers, they should therefore drive a lower degree of connectivity. Based on this reasoning, we expect that:

HP3a. The higher connectivity of universities and research centers compared to MNEs is less accentuated in the case of domestic innovative actors than in the case of foreign innovative actors.

HP3b. The lower connectivity of single location firms compared to MNEs is more accentuated in the case of domestic innovative actors than in the case of foreign innovative actors.

4. THE EMPIRICAL SETTING

We test our hypotheses in the Chinese pharmaceutical industry. The industry is characterized by inefficiencies arising from the difficulty to exploit economies of scale. In fact, R&D and manufacturing activities are geographically distributed throughout the territory and scattered across several (especially domestic) manufacturers, which lack competences and financial resources. Most local manufactures are engaged in imitation and repetitive production of low value-added molecules. Although in 2009 the Chinese government has started to reorganize the industry by favoring the integration with foreign firms, compared to their local counterparts, domestic companies are still at a disadvantage (Yuanjia et al., 2007).

5. DATA AND METHODOLOGY

5.1 Sample

In order to study inventors' collaborations and the relative geographical distribution, we employed patent data. Patent co-invertorship has been previously employed to study the collaboration patterns of inventors (e.g. Breschi and Lissoni, 2009; Cano-Kollman et al., 2013; Ejermo and Karlsson, 2006). We decided to focus on United States Patent and Trademark Office (USPTO) data considering that it represents the most reliable and used foreign patent office, so this should be the best way to capture collaboration of Chinese inventors with foreign inventors. The choice of the only use of USPTO data is also related to the well-known issues arising from the lack of consistent quality across national patent systems and homogeneity in approval procedures and time. Further, inventions patented in foreign patent offices are in general more valuable, especially in the case of USPTO (Archibugi and Coco, 2005).

In order to build our sample, we selected all USPTO patents that: (1) have at least one Chinese inventor; (2) were granted between 1975 and 2010; (3) are representative of the pharmaceutical industry, referring to the Drug and Medical technological fields defined by

Hall et al., 2001[1]. USPTO design patents mentioning the technological class “Pharmaceutical Devices” (D24) were also included. The sample thus generated consists of 1251 patents. We excluded from the initial sample patents that were unassigned or assigned to individuals (255 patents, 20.38% of the initial sample). Hence, our final sample accounts for 996 patents.

For information about inventors (i.e. name and address), we complemented our dataset merging the disambiguated inventors and co-authorship data provided by the Harvard Dataverse database (Li et al., 2014), which contains information on the USPTO patents granted between 1975 and 2010.

5.2 Variable definitions

5.2.1 Dependent variable

The dependent variable, *Geo_disp*, is the geographical dispersion of the network of inventors measured following the approach of Cano-Kollmann and colleagues (2013). The construction of *Geo_disp* 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 Geo_disp_i for patent *i* is constructed as follows:

$$Geo\_disp_i = 1 - \sum_{n=1}^{N} (Inv_{i,n}/Inv_i)^2$$

[1] 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).

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.

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 becomes more dispersed across different countries.

5.2.2 Independent variables

In order to test our first hypothesis, we built the independent variable *Domestic_innovative_actor*, which is a dummy variable equal to 1 if the assignee is domestic, i.e. Chinese, and 0 otherwise[2]. Since we are interested in the home-country of the innovative actors included in our sample, if the assignee was an MNE's foreign subsidiary, we built the variable using the location of its headquarters (Almeida and Phene, 2004; Phene and Almeida, 2008). In doing so, we used BvD Orbis and rely on the information on firms' global ultimate owners.

The second set of independent variables is related to the institutional type of the assignee. We distinguished between universities and research centers, MNEs and single-location firms. For each assignee mentioned in the patent document, we analyzed first the institutional typology, and then, in the case of firms, the ownership structure, using information from BvD Orbis and companies' websites. We defined as MNE any firm that has at least one subsidiary located abroad; otherwise firms were categorized as single-location. The categorization of the assignee type is time variant[3] in order to take into account changes in the firm ownership

[2]Our sample includes 12 patents co-assigned by a Chinese and one or more foreign institution. In these cases the variable Insider take the value of 1, because we applied an inclusive criterion as at least one of the assignees is domestic.

[3] We checked the status of each assignee in correspondence to the year of the patent application.

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 *MNE* as the benchmark. 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.

5.2.3 Control variables

In order to control for the possibility that the most innovative actors generate the most dispersed inventor network, we included a dummy variable, *Leader,* which takes the value of 1 for assignees in the upper quartile of the global pharmaceutical industry in terms of patent production in the year previous to the patent application (*t-1*). We measured patent production as the natural logarithm of the cumulative number of USPTO pharmaceutical patents[4] issued by each assignee in the period 1975 - *t-1*. Data come from Harvard Dataverse database (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.

Innovative actors from wealthier countries may have more resources to spawn globally dispersed inventors network. To control for this effect, we included the variable *GDP pp,* measured as the average of the natural logarithm of GDP per capita of the countries of all the assignees the focal patent in year *t-1*. GDP per capita data was obtained from the World Bank

[4] Defined as describes in Section 4.1.

database. If the company is an MNE's foreign subsidiary, we used the GDP per capita of the country of the global ultimate owner.

We also controlled for the number of inventors for each patent, as captured by the variable *Team_size*.

Moreover, we introduced the variable *Design*, a dummy that 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/).

We also accounted for the technological characteristics of patents. *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 4.1; otherwise it takes the value of 0.

Moreover, we built the variable *Tech composition* adapting 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:

$$H\_tech_i = \sum_{m=1}^{M} (Tech\_class_{i,m})^2$$

where $Tech\_class_{i,m}$ 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:

$$Tech\_composition_i = F[(Tech\_class_{i,l})/(H\_tech_i - Tech\_class_{i.l}{}^2)^{1/2}]$$

[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 $Tech\_class_{i,l}$ is the percentage of the technological class most representative in patent *i*[6].

In order to measure the amount of knowledge sources used to generate the patented innovation, we introduce the variable *Know_source*, which was calculated as the natural logarithm of the count of the patents that were cited by the focal one.

Since we pool patent data over a 30-year period characterized by strong regulatory turbulence in Chinese IP regime, we control for the years of the discontinuity adding 2 dummy variables in 2002 and 2005 (*Year t* for t = 2002, 2005). These years represent two main changes in the Chinese institutional and international landscape: the ratification by the Chinese government of WTO entry and full compliance with the requirements of the TRIPS agreement, respectively.

5.3 Model and methodology

Given that our dependent variable is censored, taking a minimum value of and an upper limit asymptotically approaching 1, we adopted a robust Tobit regression model, which allows controlling for heteroskedasticity of the sample. To facilitate the interpretation of the results, we standardized all the continuous predictor variables before entering them in the different regression models (Aikne and West, 1991).

In order to test our fist hypothesis we started from the following basic equation model 1 (*Model 2*):

$$(1) \qquad Geo\_disp_{\,i} = \beta_0 + \beta_1 Domestic\_innovator\_actor_i + \beta_2 Controls_i + \varepsilon_i$$

[6] 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, $Tech\_class_{i,l} = 90\%$.

where *i*=1,2, 3, …, 996 are the Chinese pharmaceutical patents included in our sample; *Geo_disp* is the dependent variable, which represents the geographical dispersion of the inventor team of patent *i*; *Domestic_innovative_actor* is the dummy variable taking the value of 1 if the assignee is domestic (i.e. Chinese); *Controls* are the control variables described above, and ε is the error term.

To test our HP2a and HP2b, we employed equation model 2 (*Model 3*):

$$(2) \qquad Geo\_disp_{\,i} = \beta_0 + \beta_1 Domestic\_innovator\_actor_i + \beta_2 University_i + \beta_3 Single\_location_i + \beta_4 Controls_i + \varepsilon_i$$

where we added to equation model 1 the dummy variables *University* and *Single_location,* which are equal to 1 if the assignee is a university or research center, or a single location firm, respectively.

Finally, to test the third set of hypotheses (HP3a and HP3b), we interacted the dummy *Domestic_innovative_actor* with the variables *University* and *Single_location*, i.e. *Model 4 and 5*. In order to isolate the two different interaction effects, we introduced the interactions in separated equations (*equation model 3 and 4*), as it is shown in the following:

$$(3) \qquad Geo\_disp_{\,i} = \beta_0 + \beta_1 Domestic\_innovator\_actor_i + \beta_2 University_i + \beta_3 Single\_location_i + \beta_4 University_i * Domestic\_innovator\_actor_i + \beta_5 Controls_i + \varepsilon_i$$

$$(3) \qquad Geo\_disp_{\,i} = \beta_0 + \beta_1 Domestic\_innovator\_actor_i + \beta_2 University_i + \beta_3 Single\_location_i + \beta_4 Single\_location_i * Domestic\_innovator\_actor_i + \beta_5 Controls_i + \varepsilon_i$$

Table 1 reports the descriptive statistics and correlations of the analyzed variables. The table shows that the control variable *GDP pp* is strongly correlated (-0.9355) with the independent variable *Domestic_innovator_actor*. The high correlation is due to the propensity of Chinese institutions to collaborate internationally with innovative actors located in high-income countries. Hence, in order to avoid multicollinearity issues, we decided to exclude the control variable from our models.

[Insert Table 1 about here]

6. RESULTS

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

[Insert Table 2 about here]

All models produced statistically significant results (LR chi^2=285.92 and $p<.0$ in Model 1, LR chi^2=703.93 and $p<.0$ in Model 2, LR chi^2=727.38 and $p<.0$ in Model 3, LR chi^2=728.18 and $p<.0$ in Model 4, LR chi^2=733.16 and $p<.0$ in Model 5).

We employed Model 1 as baseline that includes all our controls. In order to test our HP1, we ran Model 2 and we found confirmation of our first hypothesis. As predicted, the dummy variable *Domestic_innovative_actor* exhibits a positive and significant coefficient ($p<.001$ also in Model 3, 4 and 5), thus showing that domestic innovative actors spawn less internationally dispersed inventor networks compared to foreign innovative actors.

In order to test our second set of hypotheses, we employed Model 3 which shows positive and significant coefficient ($p<.001$ in Model 3, 4 and 5) for the dummy variable *University*, and negative and significant loading ($p<.1$ in Model 3, $p<.05$ in Model 4, $p<.01$ in Model 5) for the dummy variable *Single_location.* These two results support our HP2a and HP2b. They suggest that compared to MNEs, universities and research centers establish more internationally dispersed investor networks; on the contrary, single location firms present less internationally connected networks with respect to MNEs.

As regards our H3a and H3b, Model 4 and 5 include, respectively, the interaction terms that reflect our theoretical argumentations, i.e. *University*Domestic_innovative_actor* and *SinglelLocation*Domestic_innovative_actor*. We calculated the marginal effects shown in Table 3 and we also present a graphical analysis (Figure 1 and 2) as suggested by Hoetker (2007). In fact, in non-linear models, the relation of the interaction term with the dependent variable may be more or less pronounced at varying level of the interacted variables, and the overall effect only refers to the average values. Therefore, the probability of an outcome cannot be directly discerned from the variable's coefficient (Hoetker, 2007). In our specific case, in Model 4 the coefficient of the interaction between *University* and *Domestic_innovative_actor* seems to be not statistically significant. On the other hand, the interaction between *Single_location* and *Domestic_innovative_actors* turns out to be significant ($p<.05$) in Model 5. Therefore, we review the marginal effects of the interaction terms and the interaction plots in order to obtain a richer and more informative interpretation of the results.

Table 3 exhibits that all the marginal effects are statistically significant ($p<0.001$), and they are positive only when the variable *Domestic_innovative_actor* is equal to 0, and negative otherwise. Further, Figures 1 and 2 show the different impact of *Domestic_innovative_actor* on the dependent variable *Geo_disp* when innovative actors are universities and research centers and single location firms, respectively. In both cases (universities and single location firms), the connectedness turns out to be higher when the innovative actors are foreign, and lower when they are domestic. These results provide support for our HP3a and HP3b.

[Insert Table 3 about here]

[Insert Figure 1 and 2 about here]

Of the control variables, *Leaders* and *Team_size* show a positive and significant effect ($p<0.001$) in all the tested models. This means that patents by innovation leader assignees are more connected than the ones by laggard innovative actors, because the former better leverage their ability to recombine knowledge that is diffused among different inventors. Further, and not surprisingly, we find that the larger the inventor team of a patent, the higher the connectedness, because it is higher the chance that one or more of the inventors is located in a different country. Also *Know_sources* is positively and significantly ($p<.001$ in Model 1, $p<.1$ in Model 2, 3 and 4, p,<0.5 in Model 5) associated with the dependent variable *Geo_disp*, meaning that patents that source more from previous innovations tend to be more globally connected. Conversely, the control variable *Design* presents a negative and significant effect ($p<.05$ in Model 1 and 2, $p<.1$ in Model 3, 4 and 5). This is in line with the finding of Cano-Kollmann and colleagues (2013), confirming that design patents tend to be less geographically dispersed compared to utility patents. Finally, the variable *Tech_composition* shows a negative coefficient, but it turns out to be significant only in Model 1 ($p<.5$). It suggests that the higher the concentration in a specific technological class, the lesser the international connectedness of the patent.

7. LIMITATIONS

The use of patent data comes with a series of well-known limitations (Alcacer and Gittelman 2006). In the specific case of this paper, the choice of employing USPTO data may under-estimate the connectivity of the Chinese innovation system, especially with other emerging countries. Yet, USPTO patents are likely to capture high quality Chinese innovation, rather than the questionable inventiveness of repeated patents granted by emerging markets' local patent offices (Hu and Mathews, 2005). Moreover, because our focus is on the catch-up process of emerging economies, connectivity with other emerging markets, which by definition have less to offer in terms of learning opportunities, is less relevant to the objective of our study. Finally, it is worth noting that pharmaceutical patents do not represent - per se - innovations of commercial value, given the several stages that the patented drug has to undergo before reaching the market.

8. DISCUSSION AND CONCLUDING REMARKS

Big pharma perform different activities in different emerging markets, some of them being used only as sales platforms due to the fear of knowledge leakage. This paper explores the role of emerging markets as locations for innovative activities in the pharmaceutical industry. As demonstrated by the considerable flow of inward investment that has targeted the country in the last decade, China is a very attractive location for R&D to advanced economy. In fact, in spite of the relatively low standards of intellectual property protection, MNEs have learned to implement effective strategies to avoid the risks of knowledge spillovers, for instance through the creation of strong internal linkages among technologies (Zhao, 2006). We focus on the catch-up process of the Chinese innovative system in the pharmaceutical industry. We argue that a key aspect of this process is integration into global value chains and the global innovative system. There are two drivers of integration into global innovation systems: foreign actors undertaking innovative activities in the local (Chinese) economy and domestic actors undertaking innovative activities in foreign (typically advanced economy) locations. We examine the extent of integration into the global innovation system by looking at knowledge networks that are linked to China, either through organizations or individual inventors. We find that, compared to domestic innovative actors, foreign innovative actors generate more globally dispersed knowledge networks involving Chinese inventors, thereby sustaining the integration of China into the global innovation system. Moreover, the institutional type of the innovative actor matters for the connectivity of emerging markets. In fact, universities and research centers are responsible for the highest connectivity, while single location firms spawn less dispersed innovative networks. Finally, our results show that these latter effects vary with the geographic origin of innovative actors.

It is interesting to note that we are able to replicate the findings of Balconi et al. (2004), that relate to an advanced economy (Italy), for an emerging economy. In other words, universities and research centers have more dispersed innovative networks than commercial organizations. These non-commercial organizations have even more widely dispersed innovative networks than foreign MNEs.

This finding has important implications for the institutional audience. Since a greater dispersion can be traced to foreign universities and research centers, we suggest that attracting advanced economy universities and research centers is particularly valuable for emerging economy catch-up processes, even more important than attracting high knowledge FDI. It may also be the case that non-commercial actors are less sensitive to issues of knowledge spillovers than commercial actors like MNEs.

We find that single location firms have less dispersed innovative networks and amongst these firms, domestic Chinese firms have particularly low connectedness. This suggests that in the emerging economy context, smaller local firms are less promising as sources of catch-up innovation. This could be because such firms have lower absorptive capacity and tend to rely on their local cluster also for knowledge sourcing, given that are not able to develop knowledge linkages with the global innovative system. Thus, highly innovative international new ventures (INVs) may be mainly an advanced economy phenomenon.

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TABLES AND FIGURES

Table 1. Descriptive statistics and correlation matrix of the variables employed in the analysis

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	*Geo_disp*	1											
(2)	*Single_location*	-0.2519	1										
(3)	*University*	-0.0451	-0.4387	1									
(4)	*MNE*	0.2743	-0.4908	-0.4313	1								
(5)	*Domestic_inn_actor*	-0.6602	0.1578	0.2598	-0.3452	1							
(6)	*Leader*	0.4673	-0.4288	-0.0482	0.4989	-0.4623	1						
(7)	*GDP pp*	0.6629	-0.1611	-0.275	0.3975	-0.9355	0.5152	1					
(8)	*Team_Size*	0.1381	-0.1066	0.0723	0.1361	-0.0788	0.1322	0.0973	1				
(9)	*Design*	-0.1165	0.2157	-0.2313	-0.0284	0.0632	-0.1306	0.0057	-0.2206	1			
(10)	*Pharma*	-0.0497	0.161	-0.0984	-0.0291	0.0159	-0.0302	0.0065	0.0567	0.1696	1		
(11)	*Tech_composition*	-0.1046	0.0204	-0.0157	0.0043	0.0891	-0.0818	-0.0863	-0.1243	0.1564	0.042	1	
(12)	*Know_Sources*	0.1212	0.0434	-0.2158	0.1873	-0.2015	0.0669	0.21	-0.0412	0.1495	-0.0205	0.0338	1
	Mean	0.204	0.37	0.361	0.334	0.456	0.327	8.902	3.885	0.0863	0.686	0.939	1.547
	Std. Dev.	0.236	0.483	0.481	0.472	0.498	0.469	1.716	3.099	0.281	0.464	0.075	1.134
	Min	0	0	0	0	0	0	5.206	1	0	0	0.673	0
	Max	0.82	1	1	1	1	1	11.135	31	1	1	1	6.196
	N. Obs	996	996	996	996	996	996	996	996	996	996	996	996

Table 2. Robust Tobit Regressions (dependent variable = Geo_disp)

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Leader	0.428***	0.150***	0.112***	0.105***	0.100***
	(0.0307)	(0.0256)	(0.0282)	(0.0292)	(0.0286)
Team_Size	0.0530***	0.0413***	0.0420***	0.0436***	0.0409***
	(0.0144)	(0.0118)	(0.0116)	(0.0118)	(0.0115)
Design	-0.118*	-0.119*	-0.0909†	-0.0918†	-0.0976†
	(0.0597)	(0.0511)	(0.0517)	(0.0513)	(0.0507)
Pharma	-0.0381	-0.0415†	-0.0283	-0.0271	-0.0271
	(0.0308)	(0.0251)	(0.0249)	(0.0249)	(0.0248)
Tech_composition	-0.0292*	-0.0119	-0.0144	-0.0143	-0.0146
	(0.0142)	(0.0116)	(0.0115)	(0.0114)	(0.0114)
Know_Sources	0.0641***	0.0141†	0.0217†	0.0215†	0.0230*
	(0.0141)	(0.0115)	(0.0114)	(0.0114)	(0.0113)
Domestic_inn_actor		-0.597***	-0.628***	-0.602***	-0.682***
		(0.0326)	(0.0341)	(0.0438)	(0.0418)
University			0.0978***	0.111***	0.107***
			(0.0284)	(0.0319)	(0.0285)
Single_location			-0.0574†	-0.0638*	-0.0956**
			(0.0306)	(0.0314)	(0.0343)
University Domestic_inn_actor*				-0.0536	
				(0.0598)	
*Single_location *Domestic_inn_actor*					0.140*
					(0.0576)
Year dummies	Yes	Yes	Yes	Yes	Yes
_cons	-0.0902**	0.264***	0.264***	0.265***	0.278***
	(0.0311)	(0.0269)	(0.0318)	(0.0318)	(0.0320)
N	996	996	996	996	996
LR chi^2	285.92	703.93	727.38	728.18	733.16
p	0.00	0.00	0.00	0.00	0.00
Pseudo R^2	0.2127	0.5236	0.5411	0.5417	0.5454

Note: Variables have been standardized. Standard errors in parentheses.
† p, <. 1, * p<.05, ** p<.01, *** p<.001.

Table 3.Marginal effects of the interactions (Model 4 and 5)

	Domestic_inn_actor=0	*Domestic_inn_actor=1*
University	0.3902***	-0.3438***
	(0.0271)	(0.0367)
Single_location	0.2399***	-0.3423***
	(0.0276)	(0.0416)

† p, <. 1, * p<.05, ** p<.01, *** p<.001.

Figure 1. Interaction plot: University Domestic_inn_actor (University=1)*

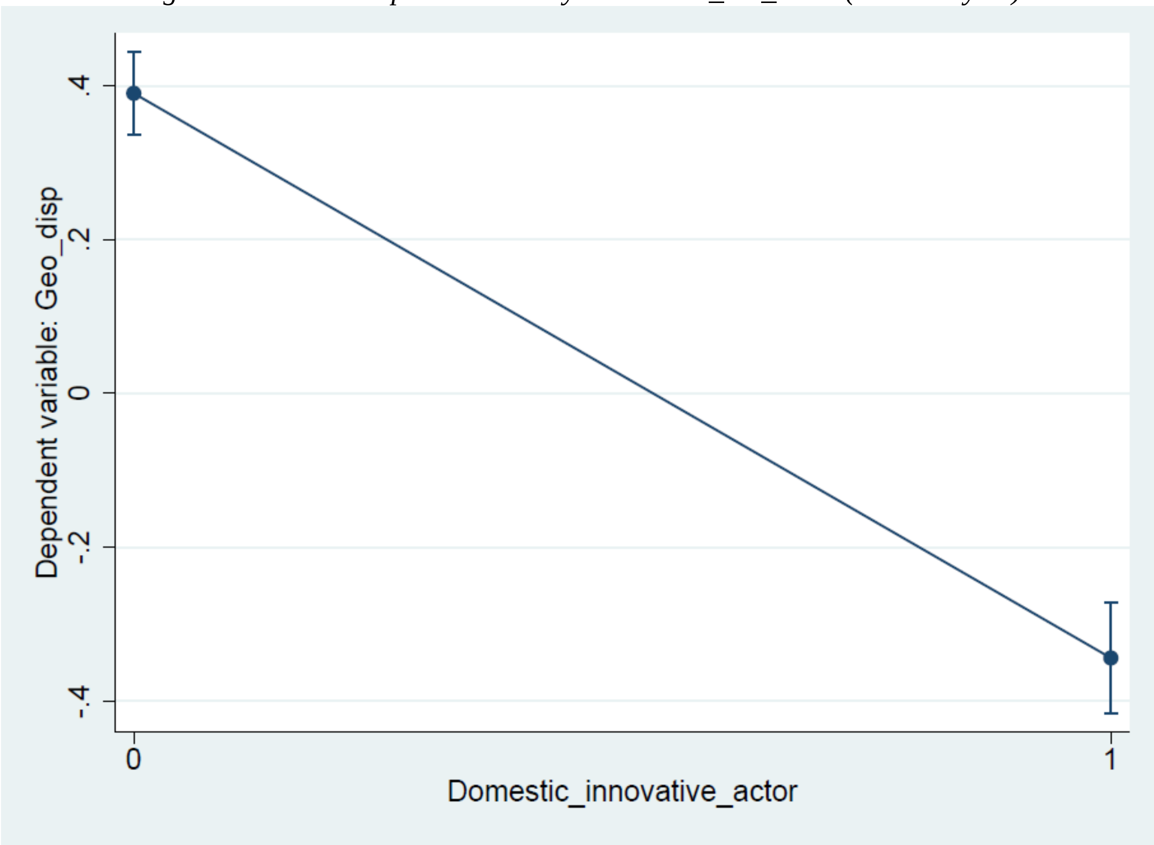

*Figure 2. Interaction plot: Single_location *Domestic_inn_actor (Single_location=1)*