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# Innovation, Création de connaissance et réseaux de recherche : le cas des multinationales Chinoises

Anran Mao

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# Innovation, Knowledge creation and Research Networks: evidence from Chinese MNEs

*Innovation, Création de connaissance et réseaux de recherche :  
le cas des multinationales Chinoises*

## Thèse de doctorat de l'université Paris-Saclay

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Professeur des universités, Université Paris Saclay

Thèse soutenue à Sceaux, le 15 décembre 2023, par

**ANRAN MAO**

## Composition du Jury

<b>Fabrice LE GUEL</b> Professeur, Université Paris Saclay	Président
<b>Julie LE GALLO</b> Professeur, Agro Dijon	Rapporteure
<b>Nadine MASSARD</b> Professeur, Université Grenoble Alpes	Rapporteure
<b>Muge OZMAN</b> Professeur, Institut Mines Telecom, Business School	Examinatrice
<b>Lorenzo CASSI</b> Maître de Conférence HDR, Université Panthéon Sorbonne	Examineur

**Titre :** *Innovation, Création de connaissance et réseaux de recherche : le cas des multinationales Chinoises*

**Mots clés :** Innovation technologique, Réseaux d'inventeurs, Brevets, Multinationales Chinoises

**Résumé :** La thèse étudie la manière dont les entreprises multinationales chinoises innovent en acquérant des connaissances en dehors de leurs frontières géographiques par le biais de centres de recherche et des collaborations à travers le monde.

La thèse est composée de quatre chapitres. Le premier présente la construction d'une base de données de brevets de 51 groupes multinationaux chinois, leurs caractéristiques technologiques, leurs inventeurs en Chine et en dehors dans leurs centres de recherche. Ces données sont exploitées dans les chapitres 2 et 3.

Le second chapitre étudie comment les centres de recherche à l'étranger innovent en s'intéressant à l'intégration des inventeurs dans les réseaux de co-invention internes à la multinationales et externe par les partenariats.

Le troisième chapitre étudie plus spécifiquement les réseaux internes à l'entreprise et explore dans quelle mesure des « gatekeepers », autrement dit des inventeurs à l'intersection entre les inventeurs de l'entreprise et ceux des centres de recherche à l'étranger facilitent l'intégration de connaissance externes (processus de transfert inverse) permettant à la multinationale d'explorer de nouvelles technologies. Le dernier chapitre s'appuie sur des données de brevets USPTO et étudie dans quelle mesure les multinationales chinoises peuvent bénéficier d'une implantation dans les aires métropolitaines américaines en distinguant le rôle de différents stocks de connaissance (aire métropolitaine, les réseaux d'inventeurs et l'entreprise) dans la production d'innovation.

**Title:** Innovation, Knowledge creation and Research Networks: evidence from Chinese MNEs

**Keywords:** Technological innovation, networks of inventors, Patents, Chinese multinational enterprises

**Abstract:** The main objective of this research is to investigate how multinational enterprises from emerging markets (EM MNEs) innovate by sourcing knowledge outside their geographical boundaries through research units and collaborations all over the world. The knowledge-sourcing and diffusion mechanism and their specific impact on the innovation outcome are studied through the role of overseas inventors and their relationships with home company inventors by focusing on Chinese MNEs.

This thesis is composed of four chapters. The first chapter describes the construction of a patent database used in chapters 2 and 3. The database includes information on patents produced by a group of 51 Chinese MNEs, their technological characteristics, their inventors within the home company, and their foreign research units.

The second chapter focuses on the respective influence of internal and external embeddedness of Chinese MNEs' inventors on their innovation outcomes. The third chapter concentrates on the role of Chinese MNEs' internal networks and specific inventors, namely gatekeepers, in the reverse knowledge transfer process and knowledge absorption. This chapter explores how gatekeepers contribute to new knowledge creation. The final chapter uses UPSTO patent data and investigates the local environment of Chinese MNEs' overseas inventors and unboxes how knowledge stocks at different levels (metropolitan area, network, and firm) affect their innovation outcomes.

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---

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## RESUME EN FRANÇAIS

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L'objectif principal de cette recherche est d'étudier les mécanismes par lesquels les entreprises multinationales des pays émergents innovent en acquérant des connaissances en dehors de leurs frontières géographiques par le biais de centres de recherche et des collaborations à travers le monde. La thèse étudie les mécanismes d'acquisition et de diffusion des connaissances et leur impact sur l'innovation en considérant le rôle des inventeurs de ces centres de recherche et leur relation avec les inventeurs de la multinationale dans le pays d'origine.

La thèse est composée de quatre chapitres. Le premier présente la construction d'une base de données de brevets qui est ensuite exploitée aux chapitres 2 et 3. La base de données porte sur les brevets de 51 groupes multinationaux chinois, leurs caractéristiques technologiques, leurs inventeurs en Chine et en dehors dans leurs centres de recherche. Le second chapitre s'intéresse à l'innovation des inventeurs des centres de recherche hors de la Chine en considérant leur intégration dans des réseaux de partenariats externes à l'entreprise et leur intégration dans les réseaux internes à l'entreprise. Le troisième chapitre étudie plus spécifiquement les réseaux internes à l'entreprise et explore dans quelle mesure des gatekeepers, autrement dit des inventeurs à l'intersection entre les inventeurs de l'entreprise et ceux des centres de recherche permettent des processus de transfert inverse permettant à la multinationale d'explorer de nouvelles technologies. Le dernier chapitre s'appuie sur des données de brevets USPTO et étudie dans quelle mesure les multinationales chinoises peuvent bénéficier d'une implantation et de l'environnement local dans les villes américaines en distinguant le rôle de différents stocks de connaissance (aire métropolitaine, les réseaux d'inventeurs et l'entreprise) dans la production d'innovation.

## **Chapitre 1 : Construction d'une base de données de brevets et inventeurs :**

### **Méthodologie et contenu**

Ce chapitre décrit la construction d'une base de données originale de brevets et d'inventeurs de 51 multinationales chinoises. L'objectif principal est de collecter des informations sur les centres de recherche d'entreprises chinoises à travers le monde, l'entreprise et leurs relations afin d'étudier les mécanismes d'acquisition de connaissance et d'intégration permettant l'innovation et les processus de rattrapage. Cette base offre des informations sur les firmes multinationales chinoises et leur activité d'innovation. Elle comprend 149 570 brevets de 51 entreprises entre 2005 et 2020. La construction de la base s'appuie sur les étapes suivantes :

1. Identification des multinationales chinoises ayant des centres de recherche à l'étranger ainsi que leur localisation ;
2. Extraction des brevets de la base Lens ;
3. Traitement de données et identification des inventeurs et des brevets associés à ces centres.

## **Chapitre 2 : Performance à l'innovation en dehors des frontières : le rôle de l'intégration duale**

Les performances à l'innovation des entreprises multinationales de pays émergents sont étroitement liées à la performance de leurs inventeurs à l'étranger. Le chapitre explore comment ces inventeurs innovent et explorent de nouvelles technologies. L'étude s'appuie sur les collaborations entre, d'une part, les inventeurs des centres et les inventeurs de l'entreprise dans le pays d'origine et, d'autre part, les réseaux externes à l'entreprise, autrement dit, l'intégration interne et externe. Les réseaux de co-invention sont construits pour étudier comment ils affectent la productivité et l'exploration des inventeurs à l'étranger. Les résultats mettent en évidence les aspects structurels et relationnels des réseaux internes à l'entreprise plus que les liens externes qui restent secondaires.

## **Chapitre 3 : Le rôle du réseau intragroupe et des « gatekeepers » dans le rattrapage technologique**

Le chapitre explore les mécanismes de transfert inverse dans le processus de rattrapage en mettant l'accent sur l'innovation de l'entreprise dans le pays d'origine. Il s'agit d'explorer

comment l'entreprise s'approprié les connaissances explorer à l'étranger dans les centres de recherche. Le chapitre met l'accès sur les mécanismes d'acquisition de connaissance, à savoir les relations directes avec des inventeurs à l'étranger par le réseau de co-invention interne et s'intéresse aux gatekeepers qui sont des inventeurs qui font le lien entre les deux et représentent une capacité d'absorption. L'impact des gatekeepers est étudié à travers leur impact sur la nouveauté des brevets. Une estimation fondée sur des variables instrumentales permet de réduire l'endogénéité associée aux données de brevets. Les résultats confirment le rôle des gatekeepers comme mécanisme d'intégration entre les centres de recherche et l'entreprise dans le pays d'origine. Les collaborations directes et la proximité de réseaux sont des facteurs déterminants qui facilitent l'absorption de connaissances externes et la création de nouvelles technologies.

#### **Chapitre 4 : A la recherche de la toison d'or : la dynamique de connaissance des inventeurs de multinationales chinoises à l'étranger**

Ce dernier chapitre explore les déterminants de la performance des entreprises chinoises à l'étranger. A partir de données de l'USPTO, le chapitre étudie l'innovation des inventeurs qui brevètent pour des entreprises chinoises aux Etats-Unis. Il s'agit d'estimer l'impact de trois sources d'innovation : l'aire métropolitaine, les réseaux de co-invention et l'entreprise. Il s'agit d'examiner comment ces différents stocks de connaissance influencent la productivité des inventeurs. Les résultats indiquent que les entreprises multinationales bénéficient des réseaux de co-invention et de la proximité géographique aux inventeurs locaux au sein des aires métropolitaines. L'estimation exploite de nombreux effets fixes pour corriger l'hétérogénéité non observée. Le rôle du stock de connaissance de l'agglomération semble moins déterminant.

## GENERAL INTRODUCTION

---

Innovation stands as the lifeblood of a company, driving its ability to adapt, evolve, and remain competitive in dynamic markets. It can be regarded as a problem-solving process through the exploration of knowledge (Choi et al., 2018). The accumulation of knowledge significantly boosts companies' ability to create new concepts and apply their knowledge to drive further innovations (Cohen & Levinthal, 1990). Despite this, a substantial amount of knowledge remains closely tied to local contexts (Asheim, 1999). Seeking knowledge from overseas is a widely recognized driver behind the globalization of research and development (Cantwell & Mudambi, 2005). Multinational enterprises (MNEs) often acquire foreign knowledge that is not readily available in their home country by accessing the local knowledge pool (Kuemmerle, 1999). Thus, in today's rapidly evolving landscape of innovation and technology, the globalization of R&D has emerged as an important trend, which is especially the case for MNEs from emerging markets (EM) (Awate et al., 2015). For EM MNEs, acquiring knowledge from developed countries serves as a strategic approach to narrow the gap with established industrial incumbents (Verbeke, 2009). To achieve this objective, they establish overseas research units and position researchers in other countries to act as bridgeheads to source knowledge from foreign sources (Wang et al., 2018).

However, benefiting from external knowledge sourcing for innovation is undeniably challenging. First, seeking knowledge in foreign environments offers benefits but also faces obstacles, including geographical and cultural distances (Shimizutani & Todo, 2008), alongside barriers imposed by domestic incumbents (Cantwell and Mudambi, 2011). Following the external acquisition of knowledge, EM MNEs encounter challenges when integrating this newly acquired knowledge into their existing knowledge base, a process often observed to be difficult (Amighini et al., 2015) due to the lack of knowledge absorptive capacity. Hence, the primary aim of this thesis is to explore how EM MNEs acquire knowledge from foreign environments, absorb this knowledge, and leverage it to drive innovation. Inventors play a central role in this process, sourcing and transferring knowledge through both internal and external networks. The overseas inventors of EM MNEs serve as the interfaces between inter- and intra-firm networks. However, existing literature often overlooks their role, as most analytical models encompass them within the broader structure of internal inventors. In order

to enhance the understanding of the knowledge dynamics within EM MNEs, this thesis focuses on the overseas inventors of Chinese MNEs. It delves into their interactions with collaborators in foreign environments, as well as their engagement with inventors from the home company in various innovation activities.

The thesis is composed of four chapters. The chapters are summarized as follows:

The first chapter describes the construction of an original database of patents and inventors from 51 Chinese MNEs. In pursuit of comprehensively exploring the mechanisms of knowledge acquisition and creation within EM MNEs, the existing databases prove inadequate due to their lack of information regarding the internal structures of these companies. While recognizing the significant role of overseas inventors and their affiliated research units in the innovation processes of EM MNEs, the specific nature of their contribution, particularly the dynamics of knowledge exchange between these inventors and the internal and external partners, remains unclear. Thus, the main objective is to collect detailed information on Chinese MNEs' overseas research units, home company, and their relationships, as well as information on their inventors in order to investigate their sourcing and integration mechanisms in their innovation and catching-up process. This database offers an overview of Chinese MNEs' overseas inventors' innovation activities. It comprises 149,570 patent applications from 51 Chinese MNEs from 2005 to 2020. The construction of the database is carried out through the following steps: 1. Identification of leading Chinese MNEs that have established research units in foreign countries and the location of these units. 2. Extraction of the patent applications of these MNEs from the Lens database. 3. Data processing and the identification of the inventors and the patent applications related to these units. The work in this chapter lays a solid foundation for empirical analysis in the second and third chapters.

It is increasingly emphasized that MNEs' innovation performance in foreign environments is tightly related to the performance of inventors in their overseas divisions. The second chapter contributes to this discussion by exploring ***MNEs' overseas inventors' innovation and their exploration of new technologies***. Ever since Granovetter (1985) introduced the concept of

“embeddedness” within the context of new economic sociology, this term has found widespread application in innovation analysis. Previous examinations at the organizational level have concentrated on the internal and external knowledge networks of MNEs, defining the involvement of MNE subsidiaries in both spheres as “dual embeddedness” (Figueiredo, 2011). Some scholars have adopted this conceptual model for analyzing MNEs’ innovation (Athreye et al., 2016; Ferraris et al., 2020). However, their continued emphasis remains on the organizational level, with a noticeable absence of substantial evidence at the inventor level. Thus, this chapter focuses on the ***collaborations of these inventors within their home company and with external partners, namely the dual embeddedness***. Co-inventor networks are constructed to capture the details of overseas inventors’ innovation activities for empirical analysis at the inventor level. Practically, the internal and external embeddedness of inventors is categorized into structural and relational aspects following the framework established by Zukin and DiMaggio (1990). This categorization aims to provide a more comprehensive understanding of knowledge dynamics within both environments. The results highlight the importance of intra-firm networks and the complex mixed impact of both internal and external embeddedness on overall innovation outcomes and explorative patents.

The third chapter explores the ***mechanisms of reverse knowledge transfer in EM MNEs’ technological catch-up process***. EM MNEs acquire knowledge from diverse foreign locations and subsequently transfer a significant portion back to their home company, aiming to achieve technological catch-up with industrial incumbents (Najafi-Tavani et al., 2015). Focusing on the innovation activities of the home company, the aim is to investigate ***whether and how they benefit from the knowledge sourced by their overseas research units***. The absorption of knowledge also plays a crucial role in producing innovation based on the new knowledge sourced externally (Mathews, 2002). In the process of knowledge transmission and absorption, emphasis has been placed on the significance of internal networks (Alnuaimi et al., 2012) and the specific contributions of individual inventors (Le Gallo and Plunket, 2020). Thus, the chapter focuses on specific sourcing and absorption mechanisms, namely direct relationships of home company inventors with overseas inventors through intra-firm

networks and highlights the role of specific inventors, namely home company gatekeepers, in enhancing knowledge absorptive capacity. A detailed analysis of patents from Chinese MNEs' overseas research units, and home companies is used to investigate the impact of gatekeepers and intra-firm networks on the novelty of patents. A 2SLS approach is adopted to cope with network endogeneity. Findings indicate the role of gatekeepers through their intermediation role as knowledge sourcing and integration mechanisms between units and the home company. Direct collaborations with units and network proximity emerge as essential moderators, facilitating the absorption of diverse external knowledge and the creation of novelty.

The fourth chapter "In search of Golden Fleece: The knowledge dynamics of Chinese MNEs' inventors in foreign environment" investigates the local determinants of Chinese MNEs' foreign inventors' performance. While the analysis in the first chapter delves into the external embeddedness of inventors within Chinese MNEs' overseas research units, capturing essential features of their knowledge creation mechanism, the focus on external relationships primarily centers around collaboration at the company level. However, it is crucial to **analyze the origin of knowledge among overseas inventors** in foreign environments to gain a deeper understanding of their external knowledge sourcing mechanisms. Tubiana et al. (2022) offer an exemplary multi-level analysis that provides an ideal model for studying the knowledge dynamics of individuals. Based on their model, the chapter explores the respective impact of **three sources of knowledge for innovation: the metropolitan level, the co-inventor level, and the firm level**, based on USPTO data and focusing on inventors located in the United States and patenting for Chinese companies. The aim is thus to examine how knowledge stocks at different levels influence inventor productivity. By adding various fixed effects to control for unobserved heterogeneity, the chapter uncovers the importance of knowledge in co-inventor networks for inventors' productivity, while the role of metropolitan stock of knowledge is less relevant. The results also highlight the positive impact of technological proximity within geographically co-located peers in metropolitan areas.

## Chapter 1: CHINESE MNEs' DATABASE CONSTRUCTION

---

This chapter presents the construction of the database utilized in the two following chapters of this thesis to uncover the cross-border knowledge sourcing and internal knowledge integration of Chinese MNEs. Patent data are widely used in the innovation literature, mainly using large-scale sources such as *PatentsView*, *OECD Patent dataset*, or *WIPO Patentscope*. These databases provide rich information on various aspects. However, it is hard to acquire precise information on the internal knowledge linkages between inventors from overseas MNEs' research units based on these existing sources. For this reason, I decided to build my own patent dataset on the largest Chinese MNEs and their research units around the world to analyze these issues.

The main objective is to collect detailed information on Chinese MNEs' overseas research units, collect their patents and inventors, and further identify their knowledge linkages among these units with the home company, on the one hand, and external partners, on the other hand. This database also presents an overview of Chinese MNEs' overseas research units' innovation activities.

### 1.1 METHODOLOGY FOR THE DATABASE CONSTRUCTION

The construction of the database is carried out through the following steps:

1. Identification of leading Chinese MNEs that have established research units in foreign countries and their locations.
2. Extraction of these MNEs' patent applications.
3. Data processing and identification of the inventors and the patent applications related to these units.

In the first step, the leading Chinese MNEs with overseas research units are initially identified through the 2018 top 500 Chinese enterprises by Fortunechina.com and the 2019 OECD scoreboard of the top 2000 global corporate R&D investors<sup>1</sup>. In the first sample, 264 Chinese companies with subsidiaries in foreign countries are selected based on their basic online information. An extensive search is employed to gather further information to identify if these MNEs have established overseas research units via various sources, including their official websites, annual reports, news articles, and investment reports. Related information, including these units' locations, set-up date, and construction method, is also documented at this stage. Consequently, the sample has been restricted to 63 MNEs, which have established a total number of 173 research units across 27 countries.

The second step is the extraction of patents associated with these Chinese MNEs. Their patent applications, filed at various patent offices, are derived from the *Lens database*<sup>2</sup>. The period of study is 2000-2020, during which Chinese MNEs experienced a solid global expansion. Data have been collected over previous periods to build inventor networks prior to patenting. The *Lens database* is advantageous over alternative databases as it aggregates patent data from multiple sources, including data from most main patent offices worldwide. It also allows for the searching and extracting of patent applications based on the company level. Thus, it serves as an ideal data source for this research. It is common for MNEs to apply for patents of the same contents in different offices to protect their intellectual property better. However, in empirical analysis, this phenomenon leads to redundant issues. The extracted patent applications are consolidated at the family level to avoid redundancy.

The extracted patent applications are processed in the third step. First, inventor names need to be disambiguated. Previous research (Breschi et al., 2014; Yin et al., 2020) yields the importance of inventor name empirical research using patent data to increase accuracy. Some leading patent databases, especially *Patentsview* and *ICROIS-PASTAT*, also provide disambiguated inventor names. This thesis's second and third chapters calculate inventor and unit-related variables based on MNE-level networks. Thus, inventor name disambiguation is

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<sup>1</sup> the JRC/OECD COR&DIP© database, v.2. 2019

<sup>2</sup> Lens.org

also carried at the MNE level. Concretely, the inventor names of each MNE are disambiguated with the FuzzyWuzzy string matching package in Python, which uses Levenshtein distance to calculate the differences between sequences. Fuzzy matching has been proven to be a reliable method of name disambiguation (Tang & Walsh, 2010). Due to the difficulty in disambiguating the names of Chinese inventors, the string similarity ratio in disambiguation is set at 95% to identify the possible same inventors' names.

The geographical information of applicants and inventors is available based on patent application numbers extracted in the second step. Patentsview, OECD patent database, and Wanfang Patent Database (WFPD) are used to acquire geographical information as location data is not included in the dataset download function of Lens data. This information is compared with the location of units collected in the sample established during the first step. Inventors at locations identical to unit locations or nearby regions are selected. Their patent application and affiliation histories are further examined to exclude employees associated with collaborating entities. The co-inventor information is also documented in the database. The patent applications of inventors distinguished as employees working at overseas research units are consolidated at the unit level. Several Chinese MNEs and their overseas research units are omitted during this phase due to the following reasons: 1. units established in recent years may not have started patenting yet as there is a lag between innovation outcome and the patent filing process. In these cases, their innovation activities are not reflected in the database. 2. Patents are applied by the headquarters due to the policy of the MNEs; thus, in some cases, it is hard to distinguish the inventors of overseas research units. At this stage, a number of 100 overseas research units remain in the database.

The final database comprises 149,570 patent applications from 51 Chinese MNEs from 2005 to 2020. The database contains the following information: 1. Patent application number, 2. Patent application date, 3. Patent priority number and date, 4. Patent Title, 5. Applicants, 6. Inventors, 7. IPC<sup>3</sup> classifications, 8. The name of MNEs, 9. The research unit. The database is stored in Rdata format.

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<sup>3</sup> IPC – International Patent Classification

## 1.2 DESCRIPTION OF THE DATABASE

This section presents an overview of the database, including the geographical and industrial dispersion of the Chinese MNEs in the sample, the construction method of the units, the evolution of patent numbers, and the evolution of inventor numbers.

### 1.2.1 The geographical dispersion of the overseas research units and inventors of Chinese MNEs

The 100 overseas research units in the final dataset are distributed across 23 countries in various regions of the world as shown in Figure 1.1.

**Figure 1.1 Geographical distribution of Chinese MNEs' overseas research units**



The majority of Chinese MNEs tend to select developed countries as their preferred host locations for establishing research units (Table 1.1). Notably, North American and European countries emerge as the most popular destinations, with 31 units established in the United States and 20 units in Germany. Additionally, Japan stands out as an attractive option, hosting 11 research units due to its advanced technology industry and geographical proximity. Overseas research units in developed countries mainly aim at knowledge sourcing. However,

in recent years, Chinese MNEs have made significant technological advancements, leading to the expansion of their market share in developed countries. Consequently, a few research units have been established in developing countries such as India and Brazil. This selection can be attributed to the dual purpose of adapting products to local markets and benefiting from a local talent pool with relatively lower labor costs. The geographical distribution of units present in the database is coherent with Wang et al. (2018)'s description.

**Table 1.1 Geographical distribution of research units and Inventors**

<b>Country</b>	<b>Unit</b>	<b>Inventors</b>
Austria	1	371
Australia	2	81
Brazil	2	73
Canada	2	498
Switzerland	1	554
Czech	1	768
Germany	20	3238
Egypt	1	14
Finland	1	10
France	1	917
United Kingdom	5	1127
Hungary	1	33
India	5	501
Italy	4	563
Japan	11	3986
Korea	1	503
Netherland	2	345
New Zealand	2	105
Poland	1	60
Russia	1	30
Sweden	1	346
Singapore	3	156
United States	31	5790

The distribution of inventors in overseas research units follows a similar pattern to the distribution of research units among various countries, with the United States, Japan, and Germany hosting the largest numbers of inventors affiliated to Chinese MNEs' overseas research units. Notably, despite Japan having fewer research units than Germany, it hosts a higher number of inventors. This discrepancy may stem from various factors, including cultural and geographical proximity, as mentioned above. It might also be attributed to the fact that Japan is among the initial countries hosting Chinese MNEs' overseas units. Consequently, the

cumulative inventor count in Japan might reflect the relatively longer duration over which these units have been established.

**Table 1.2 Firm level # of Inventors and R&D units across Economic activities (ISIC Rev.4 sections)**

<b>Industry</b>	<b>Sectors (Aggregated)</b>	<b># units</b>	<b>#Inventors</b>	<b># firms</b>
F	Construction	1	23	1
J	Information and communication	13	4494	6
C	Manufacturing	84	15473	42
B	Mining and quarrying	1	63	1
E	Water supply; sewerage, waste management and remediation activities	1	16	1

<b>Industry</b>	<b>Sectors</b>	<b># units</b>	<b>#Inventors</b>	<b># firms</b>
F	Construction of buildings	1	23	1
J	Computer programming, consultancy and related activities	2	255	2
J	Information and communication	1	63	1
J	Information service activities	1	32	1
J	Telecommunications	8	4064	1
C	Manufacture of chemicals and chemical products	11	1067	8
C	Manufacture of computer, electronic and optical products	10	2412	3
C	Manufacture of electrical equipment	14	2582	6
C	Manufacture of fabricated metal products, except machinery and equipment	2	29	2
C	Manufacture of food products	3	93	2
C	Manufacture of machinery and equipment	12	1053	5
C	Manufacture of motor vehicles, trailers and semi-trailers	19	4943	9
C	Manufacture of other transport equipment	7	2753	2
C	Manufacture of pharmaceuticals, medicinal chemical and botanical products	5	460	4
C	Manufacture of textiles	1	105	1
C	Other manufacturing	1	56	1
B	Extraction of crude petroleum and natural gas	1	63	1
E	Water collection, treatment and supply	1	16	1

### 1.2.2 The Industrial dispersion of the overseas research units and inventors of Chinese MNEs

Table 1.2 presents the distribution of Chinese MNEs across various industries based on the International Standard Industrial Classification sections, as sourced from the CSMAR database<sup>4</sup>. The table shows the number of research units and the number of inventors at the firm level. Further subdivisions have been employed to provide more precise information. Chinese MNEs that establish overseas research units operate across a broad spectrum of industries, with a notable concentration in the information and communication sector. This

<sup>4</sup> China Stock Market & Accounting Research Database

intensity can be attributed to the knowledge-intensive nature of this industry, prompting Chinese MNEs to set up research units in developed countries. This strategy allows them to engage in knowledge-sourcing activities, thereby shortening the technical distance between themselves and established players in the respective industries. Table 1.7 provides a detailed table of each MNE's industry and patents.

### **1.2.3 Characteristics of Chinese MNEs' overseas research units**

According to Anderson and Sutherland (2015), establishing research units in foreign countries can be accomplished through two primary methods: self-built and mergers and acquisitions (M&A). In this thesis, collaboration is identified as an additional significant strategy.

1. *Self-built* refers to cases when MNEs choose to construct a research unit in foreign countries on their own, which is also known as the "Greenfield" model.
2. *Mergers and acquisitions* refers to cases when MNEs acquire foreign subsidiaries and use them as overseas research units.
3. *Collaborations* refers to cases when MNEs collaborate with a local institution to set up research units in foreign countries.

Concerning Chinese MNEs in the database, self-built research units emerge as the most popular approach, representing 61% of the samples in the dataset. Furthermore, 29% of the MNEs acquire existing companies or divisions as their overseas research units (Figure 1.2.) Compared to self-built units, these research units are relatively more independent. Some of them even have no co-patenting relationship with other units within the MNEs in China. Collaboration is the least preferred method among the Chinese MNEs present in the database. This phenomenon can be explained by the greater control that MNEs possess over self-built units. At the same time, collaboration faces a higher risk of knowledge leakage and requires higher integration costs (Frishammar et al., 2015).

**Figure 1.2 The percentage of Chinese MNEs' overseas research units according to construction**

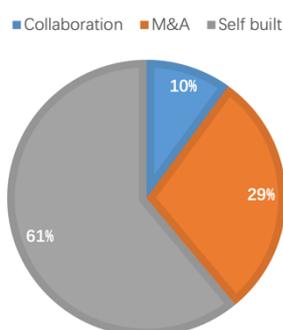


Table 1.3 gives further information regarding the distribution of research units across industries and regions. The self-built solution emerges as the predominant choice across all regions. M&A methods appear less adopted in the United States (US) compared to other regions. Furthermore, the prevalence of the collaboration method in the US and European Union (EU) regions may be attributed to a more comprehensive legal framework related to the protection of intellectual property. Table 1.6 in the appendix presents in more detail for each MNE, the research units in the database, their characteristics (self-built, M&A or Collaboration) as well as their precise location.

**Table 1.3 Industrial distribution of Chinese MNEs' overseas research units**

Industries	US			EU			Asia			Others		
	SB	MA	C	SB	MA	C	SB	MA	C	SB	MA	C
Construction	0	0	0	0	0	1	0	0	0	0	0	0
Information and communication	4	0	0	2	0	3	3	1	0	0	0	0
Manufacturing	16	6	4	20	12	2	10	6	0	4	4	0
Mining and quarrying	1	0	0	0	0	0	0	0	0	0	0	0
Water supply; sewerage, waste management and remediation activities	0	0	0	1	0	0	0	0	0	0	0	0
# of units	21	6	4	23	12	6	13	7	0	4	4	0

Note: SB : self-built; MA : Merger and Acquisition ; C : collaborations  
% in the table

**1.3 DESCRIPTIVE STATISTICS AT THE MNE AND RESEARCH UNIT-LEVEL**

Table 1.4 describes observations at the MNE level. Among the 51 Chinese MNEs included in the database, which have established overseas research units, patent activity exhibits considerable variation. The number of patent applications filed by these MNEs ranges from a minimum of 79 applications to a maximum of 47,512 applications, with an average of 2,950.5. The dispersion in the data is notable, as evidenced by the standard deviation of 7,092.06. The number of inventors associated with these patent applications shows a mean value of approximately 2,193.51, with a standard deviation of 4,043.56, indicating significant diversity in inventor involvement across the observed MNEs. Respectively, the minimum and maximum inventor counts are 86 and 25,368. The number of R&D units spans from a minimum of 1 to a maximum of 8, with an average of 1.96 and a standard deviation of 1.63. The variable Inventor productivity is calculated as # of patent applications/# of inventors. The average productivity is approximately 1.24, with a standard deviation of 0.76. The productivity values range from a minimum of 0.32 to a maximum of 3.47, which exhibits a relatively smaller variation compared to the variables above.

**Table 1.4 Descriptive statistics of MNE-level data**

	Mean	SD	Min	Max
# of patent applications	2 950.54	7 092.06	79	47 512
# of inventors	2 193.51	4 043.56	86	25 368
# of overseas Research units	1.96	1.63	1	8
Inventor productivity	1.24	0.76	0.325	3.478
51 MNEs				

Table 1.5 presents descriptive statistics for overseas research units. Among the 100 observations included in the database, the number of patent applications exhibits a considerable variation, ranging from a minimum of 12 applications to a maximum of 3,348, with an average of approximately 671. The standard deviation of 794 indicates a wide dispersion in the number of patent applications. Similarly, the number of inventors reveals notable variation, with the average number of inventors being approximately 200. The standard deviation of 239 suggests some diversity in inventor involvement across the observed applications, with a range from 9 to 1027 inventors. Additionally, inventor productivity displays an average value of approximately 3.51, indicating a relatively higher

level of productivity than the overall situation of Chinese MNEs in the database. However, the standard deviation of 2.51 highlights considerable variation in unit-level productivity, which ranges from a minimum of 1.15 to a maximum of 21.17.

**Table 1.5 Descriptive statistics of unit-level data**

	count	Mean	SD	Min	Max
# of patent applications	100	671	794	12	3348
# of inventors	100	200	239	9	1027
Inventor productivity	100	3.51	2.51	1.15	21.17
Observations	100				

**Figure 1.3 The evolution of overseas research units’ patent applications number**

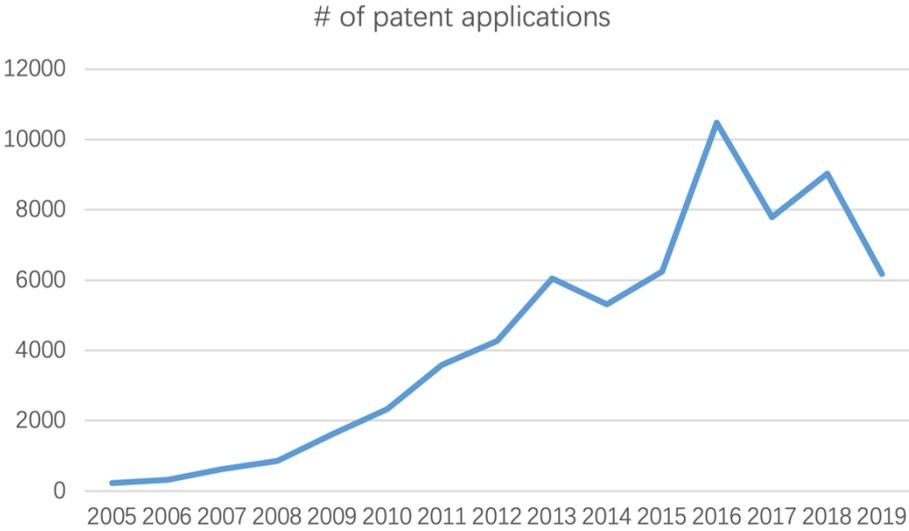


Figure 1.3 presents the evolution of the number of patent applications by Chinese MNEs’ overseas research units in the database from 2005 to 2019. The number of patent applications started at a relatively modest level in 2005, with 230 applications. It experienced continuous growth until 2016, except for a slight decrease in 2014 compared to the previous year. In 2016, the number of applications reached a remarkable peak of 10,482. The year 2019 witnessed a significant downfall in the number of patent applications due to the trade war. As shown in the previous section, over one-third of the overseas research units in the database are located

in the US. The innovation activities of these units, especially the ones in the ICT industry, experienced difficulties in the political turmoil.

#### **1.4 CONTRIBUTIONS AND LIMITATIONS OF THE DATABASE**

This chapter serves as a comprehensive overview of the database construction methods tailored to encapsulate patent data from diverse Chinese MNEs. It also lays the foundation for the following chapters by providing a detailed insight into the database's structure. As mentioned in the introduction, the thesis aims to delve deeper into the mechanisms of knowledge acquisition and creation within EM MNEs. Hence, it is necessary to explore the connections between the internal network of these MNEs' inventors and their external collaborators. Existing databases have limitations in providing insights into the internal configurations of MNEs. Consequently, the initial and pivotal step of this thesis involves the creation of a novel database specifically designed to look into these relationships.

The primary contribution of this database lies in its ability to distinguish inventors operating within the overseas research units of Chinese MNEs. As expressed in chapters two and three, this differentiation is important in distinguishing the boundaries existing between various units within the MNEs. In contrast to prior studies, which mostly focus on distinguishing MNE inventors and their external partners, this thesis introduces an approach that categorizes inventors into three groups: MNEs' inventors in the home country, MNEs' inventors in overseas environments, and their external partners. This classification facilitates a more comprehensive understanding of the dynamics within Chinese MNEs as it enables further empirical analysis not only on these overseas inventors' own innovation performance but also their moderating role in transmitting knowledge back to home company. Meanwhile, it also helps to understand how inventors in home companies benefit from external knowledge and absorb it for new recombination.

However, while this database provides valuable insights, it is not without limitations. It faces certain shortcomings. First, the capture of external relations is not exhaustive. The

identification of external partners relies primarily on co-inventor relations in the Lens database. Consequently, informal connections among inventors are somewhat overlooked. Second, the depiction of MNEs' internal structure within the home company is obscured. Although extensive efforts have been undertaken to differentiate various units of the MNEs located in China, the internal boundaries remain somewhat ambiguous. This ambiguity stems from the challenging task of distinguishing relations between the headquarters and other divisions due to the patent application policies of certain MNEs.

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## 1.6 APPENDIX CHAPTER 1

**Table 1.6 Location of overseas R&D Unit**

<b>MNE</b>	<b>Name</b>	<b>Model</b>	<b>Country</b>	<b>Region</b>
Angel	ANGEL_A2	Self_built	EG	Bani sweif
Angel	ANGEL_A1	Self_built	RU	Lipetsk Oblast
BGI	BGI_A1	Self built	US	Mount view
BYD	BYD_A1	Self Built	US	Los angeles
BYD	BYD_A2	Self built	NL	Rotterdam
BeiqiFoton	BEIQI_A1	Self built	DE	Sttugart
BeiqiFoton	BEIQI_A2	Self built	JP	Yokohama
Bright	BRIGHT_A1	M&A	NZ	Dunsandel
CNPC	CNPC_A1	Self built	US	Houston
CRRC	CRRC_A5	Collaboration	CH	Winterthur
CRRC	CRRC_A4	Collaboration	CZ	Prague
CRRC	CRRC_A6	Selfbuilt	AT	Kottingbrunn
CRRC	CRRC_A2	Self built	US	New Jersey
CRRC	CRRC_A1	Collaboration	GB	Lincoln
CRRC	CRRC_A3	Self built	DE	Dresden
Changan	CHANGAN_A5	Self built	IT	Turin
Changan	CHANGAN_A3	Collaboration	JP	Yokohama
Changan	CHANGAN_A2	Collaboration	US	Los anglese
Changan	CHANGAN_A1	Self built	US	Detroit
Changan	CHANGAN_A4	Collaboration	GB	Birmingham
Changjiang	CHANGJIANG_A1	Self bilt	SG	Singapore
Dunan	DUNAN_A1	Selfbuilt	US	San jose
GCL	GCL_A1	Self built	US	San francisco
Genscript	GENSCRIPT_A1	Self built	US	New Jersey
Goodix	GOODIX_A1	Self bilt	US	St diego
Greatwall	GREATWALL_A1	Self built	JP	Yokohama
Haier	HAIER_A5	Self built	IN	Bangalore
Haier	HAIER_A1	Self built	DE	Nuremberg
Haier	HAIER_A3	M&A	JP	Osaka
Haier	HAIER_A2	Self built	US	Indiana
Haier	HAIER_A6	Self built	KR	Souel
Haier	HAIER_A4	M&A	NZ	Orkland
Hikvision	HIKVISION_A1	Self built	CA	Montreal
Hisense	HISENSE_A3	Self built	US	Atlanta
Hisense	HISENSE_A1	Self built	DE	Duesseldorf
Hisense	HISENSE_A4	M&A	CA	Toronto
Hisense	HISENSE_A2	Self built	JP	Tokyo
Hongfa	HONGFA_A1	self built	US	El paso
Huagong	HUAGONG_A1	M&A	AU	Sunshine West
Huagong	HUAGONG_A2	Self built	DE	Offenbach
Huarui	HUARUI_A1	M&A	DE	Dochum
JAC	JAC_A1	Self built	JP	Yokohama
JAC	JAC_A2	self built	IT	Turin
Joyson	JOYSON_A2	M&A	DE	Dresden
Joyson	JOYSON_A3	M&A	US	Aluburn Hills
Joyson	JOYSON_A1	M&A	JP	Tokyo
Kangde	KANGDE_A1	Collaboration	DE	Munich
Kelun	KELUN_A1	Self built	US	New Jersey
Kingenta	KINGENTA_A1	Self built	US	Washington

Kingfa	KINGFA_A3	M&A	IN	Shinde
Kingfa	KINGFA_A1	Self built	DE	Wiesbaden
Kingfa	KINGFA_A2	Self built	US	Canton
Lenovo	LENOVO_A1	M&A	JP	Kanagawa
Lenovo	LENOVO_A5	Self built	US	Morrisville
Lenovo	LENOVO_A3	Self built	IN	Bengaluru
Lenovo	LENOVO_A4	Self built	DE	Stuttgart
Lenovo	LENOVO_A2	Self built	BR	Sao Paulo
Lepu	LEPU_A1	Self built	NL	Heerenveen
Linglong	LINGLONG_A1	Self built	US	Medina
Lingyi	LINGYI_A1	M&A	FI	Salo
Liugong	LIUGONG_A4	Selfbuilt	IN	Indore
Liugong	LIUGONG_A3	Collaboration	PL	Warsaw
Liugong	LIUGONG_A2	Self built	UK	Portsmouth
Liugong	LIUGONG_A1	M&A	US	Huston
Longsheng	LONGSHENG_A1	M&A	DE	Raunheim
Luthai	LUTHAI_A1	Self bilt	IT	Milan
Luxi	LUXI_A1	self built	DE	Frankfurt
Luxshare	LUXSHARE_A1	Self built	US	San jose
Luye	LUYE_A1	Self built	DE	Miesbach
Luye	LUYE_A2	Self built	US	Princeton
Origin	ORIGIN_A1	Selfbuilt	AU	Nambour
Sanhua	SANHUA_A1	Self built	JP	Saitama
Sanhua	SANHUA_A2	M&A	DE	Neukirch
Sanhua	SANHUA_A3	Self built	US	San Jose
Sumec	SUMEC_A1	Self buily	DE	Willich
Suning	SUNING_A1	Self built	US	San jose
Tencent	TENCENT_A1	Self built	US	Seattle
Wanhua	WANHUA_A1	Self built	US	Covent
Wanhua	WANHUA_A2	M&A	HU	Kazincbarcika
XCMG	XCMG_A2	Self built	US	Nevada
XCMG	XCMG_A1	M&A	DE	Duesseldorf
XCMG	XCMG_A3	Self built	BR	Pouso Alegre
Yuhong	YUHONG_A1	Collabotation	US	Bethlehem
ZTE	ZTE_A2	Self built	JP	Tokyo
ZTE	ZTE_6	Self built	SE	Kista
ZTE	ZTE_A7	Self built	DE	Dusseldorf
ZTE	ZTE_A4	Collaboration	GB	London
ZTE	ZTE_A3	Self built	IN	Bangalore
ZTE	ZTE_A5	Self built	FR	Poitier
ZTE	ZTE_A8	Self built	US	Dallas
ZTE	ZTE_A1	Collaboration	IT	LAquila
Zhongding	ZHONGDING_A1	M&A	US	Southfield
Zhongding	ZHONGDING_A4	M&A	DE	Heilbronn
Zhongding	ZHONGDING_A3	M&A	DE	Kassel
Zhongding	ZHONGDING_A2	M&A	DE	Kirchheim
Zhongwang	ZHONGWANG_A1	M&A	US	Kentucky
Zotye	ZOTYE_A1	Self built	JP	Yokohama
Huaxiang	HUAXIANG_A1	M&A	GB	Nottingham
Keda	KEDA_A1	Self bilt	SG	Singapore
Zhonghuan	ZHONGHUAN_A1	Self bilt	SG	Singapore

**Table 1.7 Patenting activity of EM MNEs and industry characteristics**

<b>MNE</b>	<b># patents</b>	<b>Industry ISIC</b>	<b>Code</b>	<b>Industry Division</b>	<b>Code</b>
Angel	249	Manufacturing	C	Manufacture of food products	C10
BeiqiFoton	7145	Manufacturing	C	Manufacture of motor vehicles, trailers and semi-trailers	C29
BGI	1041	Manufacturing	C	Manufacture of pharmaceuticals, medicinal chemical and botanical products	C21
Bright	911	Manufacturing	C	Manufacture of food products	C10
BYD	10076	Manufacturing	C	Manufacture of motor vehicles, trailers and semi-trailers	C29
Changan	6455	Manufacturing	C	Manufacture of motor vehicles, trailers and semi-trailers	C29
Changjiang	1336	Information and communication	J	Manufacture of electrical equipment	C27
CNPC	2367	Mining and quarrying	B	Extraction of crude petroleum and natural gas	B06
CRRC	6277	Manufacturing	C	Manufacture of other transport equipment	C30
Dunan	117	Manufacturing	C	Manufacture of other transport equipment	C30
GCL	482	Manufacturing	C	Manufacture of chemicals and chemical products	C20
Genscript	83	Manufacturing	C	Manufacture of pharmaceuticals, medicinal chemical and botanical products	C21
Goodix	986	Information and communication	J	Information and communication	J63
Greatwall	7076	Manufacturing	C	Manufacture of motor vehicles, trailers and semi-trailers	C29
Haier	7410	Manufacturing	C	Manufacture of electrical equipment	C27
Hikvision	4715	Manufacturing	C	Manufacture of computer, electronic and optical products	C26
Hisense	4152	Manufacturing	C	Manufacture of computer, electronic and optical products	C26
Hongfa	982	Manufacturing	C	Manufacture of electrical equipment	C27
Huagong	307	Manufacturing	C	Manufacture of electrical equipment	C27
Huarui	906	Manufacturing	C	Manufacture of machinery and equipment	C28
Huaxiang	272	Manufacturing	C	Manufacture of motor vehicles, trailers and semi-trailers	C29
JAC	770	Manufacturing	C	Manufacture of motor vehicles, trailers and semi-trailers	C29
Joyson	623	Manufacturing	C	Manufacture of electrical equipment	C27
Kangde	951	Construction	F	Construction of buildings	F41
Keda	556	Information and communication	J	Information service activities	J63
Kelun	960	Manufacturing	C	Manufacture of pharmaceuticals, medicinal chemical and botanical products	C21
Kingenta	283	Manufacturing	C	Manufacture of chemicals and chemical products	C20
Kingfa	1782	Manufacturing	C	Manufacture of chemicals and chemical products	C20
Lenovo	21353	Manufacturing	C	Manufacture of computer, electronic and optical products	C26
Lepu	339	Manufacturing	C	Other manufacturing	C32
Linglong	345	Manufacturing	C	Manufacture of motor vehicles, trailers and semi-trailers	C29
Lingyi	79	Manufacturing	C	Manufacture of fabricated metal products, except machinery and equipment	C25
Liugong	1865	Manufacturing	C	Manufacture of machinery and equipment	C28

Longsheng	753	Manufacturing	C	Manufacture of chemicals and chemical products	C20
Luthai	422	Manufacturing	C	Manufacture of textiles	C13
Luxi	345	Manufacturing	C	Manufacture of chemicals and chemical products	C20
Luxshare	404	Manufacturing	C	Manufacture of electrical equipment	C27
Luye	209	Manufacturing	C	Manufacture of pharmaceuticals, medicinal chemical and botanical products	C21
Origin	138	Water suppl, sewerage, waste management	E	Water collection, treatment and supply	E36
Sanhua	625	Manufacturing	C	Manufacture of machinery and equipment	C28
Sumec	217	Manufacturing	C	Manufacture of machinery and equipment	C28
Suning	957	Information and communication	J	Computer programming, consultancy and related activities	J62
Tencent	2166	Information and communication	J	Computer programming, consultancy and related activities	J62
Wanhua	875	Manufacturing	C	Manufacture of chemicals and chemical products	C20
XCMG	3258	Manufacturing	C	Manufacture of machinery and equipment	C28
Yuhong	625	Manufacturing	C	Manufacture of chemicals and chemical products	C20
Zhongding	779	Manufacturing	C	Manufacture of motor vehicles, trailers and semi-trailers	C29
Zhongwang	134	Manufacturing	C	Manufacture of fabricated metal products, except machinery and equipment	C25
Zotye	542	Manufacturing	C	Manufacture of motor vehicles, trailers and semi-trailers	C29
ZTE	47512	Information and communication	J	Telecommunications	J61

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## Chapter 2: MNEs' OVERSEAS INNOVATION PERFORMANCE: THE ROLE OF DUAL EMBEDDEDNESS<sup>5</sup>

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### 2.1 INTRODUCTION

In today's rapidly evolving landscape of innovation and technology, the globalization of R&D has emerged as an important trend. MNEs are increasingly expanding their R&D activities beyond borders, driven by the compelling need to tap into global knowledge and talent pools. R&D globalization enhances their innovation capabilities and ensures their competitive edge in a highly dynamic market (Ernst & Kim, 2002). It is particularly noteworthy for MNEs from emerging markets. These companies often rely on knowledge acquisition from developed nations as a strategic tool for bridging the gap with established industrial incumbents (Verbeke, 2009). This knowledge transfer plays a pivotal role in accelerating their technological progress and innovation capabilities. Overseas R&D units set up by these MNEs serve as bridgeheads in sourcing knowledge from foreign countries (Wang et al., 2018).

However, knowledge sourcing in foreign environments faces challenges. These difficulties include profound cultural differences, which can impede effective communication and collaboration, as well as coordination problems among geographically dispersed R&D locations (Westney, 2001) and the barriers set up by local incumbents (Cantwell & Mudambi, 2011). To overcome these complex obstacles and make the most of the newly acquired knowledge, MNEs must configure **their internal and external networks**. Scholars have termed this configuration as "dual embeddedness" (Figueiredo, 2011), highlighting the need for MNEs to establish **connections within their organizations and with external partners to optimize their innovation**. While the dual embeddedness of MNEs has frequently been explored at the company level and mainly based on case studies, there remains a need for further research based on large datasets of MNEs and exploiting micro data on individual inventors as they

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<sup>5</sup> The first draft of this work has been presented at *18th Conference of the International Joseph Schumpeter Society*, July 8-10, 2021, Rome.

serve as the central components of overseas R&D units and function as the fundamental entities in R&D activities (Blomkvist et al. ,2014).

Thus, the aim of this chapter is to better understand **the mechanisms behind the innovation process of MNEs' overseas research units through the lens of their inventors** by investigating 1) the respective impact of their embeddedness in external and internal co-inventor networks and 2) their interplay on innovation. The innovation performance is assessed in two ways: the productivity of inventors and the degree of novelty of the patents they invent, as an indicator of exploration of new technologies. Corresponding to these assessments, the analysis is carried out at the inventor level. The contribution is theoretical as well as empirical. From a theoretical point of view, it applies network theory to the literature on MNEs' R&D globalization. Network analysis serves as an appropriate way to capture the detail of overseas research units' activities and better understand the interplay between external knowledge sourcing and internal embeddedness quantitatively. Embeddedness is assessed through structural and relational indicators. Structural factors are measured through degree centrality and ego betweenness centrality. They provide a direct view of inventors' position in the external and internal environment, while relational factors measured through tie strength describe the role of reciprocal exchanges with partners.

From an empirical point of view, it exploits an original dataset based on patent data. It enables the construction of a detailed network of inventors in overseas research units set up by Chinese MNEs worldwide and within their corporations. As most of the existing literature focuses on the relation between dual embeddedness and innovation at a company level, this chapter contributes to the understanding of the micro-foundations of innovation activity in foreign environments. The whole network of these inventors and their collaborators is constructed using co-inventor relationships in patent applications to calculate variables concerning external and internal embeddedness.

The findings are twofold. First, the productivity and novelty of technologies produced within overseas research units are explained by intra-firm relationships. These results confirm the results of previous literature, such as the positive impact of internal relational embeddedness on innovation output and the inverted U-shaped relationship between external structural

embeddedness and the level of innovation. Second, external partnerships have rather a negative impact, except for novelty, where external structural embeddedness as inverted U-shaped. Third, the reverse effects of dual embeddedness as the interaction of dual embeddedness have a competing impact on the exploration of new technology.

The chapter is organized as follows. The next section presents a review of the literature and the hypothesis to be tested. Section 3 describes the data, variables, and empirical methodology employed in the empirical analysis. The results are presented in Section 4, and the final section concludes and discusses the study's implications and limitations.

## **2.2 THEORETICAL BACKGROUND AND HYPOTHESES**

### **2.2.1 R&D globalization**

Innovation can be regarded as a problem-solving process in which solutions to problems are discovered through knowledge search (Choi et al., 2018). Accumulation of knowledge enhances companies' ability to develop new ideas and convert their knowledge base into further innovations (Cohen & Levinthal, 1990). Nevertheless, a large proportion of knowledge is locally embedded (Asheim, 1999). Overseas knowledge-seeking is identified as a general motivation for R&D globalization (Kuemmerle, 1997; Cantwell & Mudambi, 2005; Shu & Steinwender, 2018). MNEs tend to acquire foreign knowledge that does not exist in their home country's knowledge base by tapping into the local knowledge pool (Kuemmerle, 1999). Meyer et al. (2009) emphasize that the institutional framework of the host country alters MNEs' R&D globalization patterns. Unit size (Kuemmerle, 1998), geographical distance (Shimizutani & Todo, 2008; Nepelski & De Prato, 2015), and cultural proximity also serve as crucial determinants of R&D globalization (Shimizutani & Todo, 2008). According to Singh (2007), MNEs' knowledge-seeking activities stimulate the productivity growth of home countries.

In recent years, MNEs from emerging markets (EM) such as China, India, Brazil, Russia, and Vietnam evolved in the trend of R&D globalization. These new players gradually aroused the

interest of researchers. Cross-border knowledge sourcing activities are especially important for these MNEs, as knowledge acquired from developed countries helps them to shorten the distance from industrial incumbents (Verbeke, 2009). Some determinants of EM MNEs' R&D globalization differ from MNEs of developed countries. For example, cultural proximity and geographical distance are not significant determinants for EM MNEs' decisions regarding R&D globalization (Wang et al., 2018).

**MNEs set up overseas research units to take advantage of specific knowledge in different locations** (Meyer et al., 2009). Concerning this knowledge seeking purpose, Kuemmerle (1999) suggests that overseas subsidiaries are more likely to be involved in capability-augmenting (explorative) R&D activities in host countries with a relatively higher knowledge level. Explorative units take advantage of the resources in host countries (Meyer et al., 2009) to augment parent companies' technological competencies (Cantwell & Mudambi, 2005). They engage in basic or applied research and obtain knowledge from host countries to enlarge the existing knowledge base (Shimizutani & Todo, 2008). They are usually vertically integrated with less control from headquarters (Davis et al., 2000). MNEs favor acquisition as a rapid way of setting up explorative R&D units (Anderson & Sutherland, 2015).

Frost (2001) confirms that patterns of R&D globalization are closely related to the age of overseas units. Older units are more likely to conduct explorative activities in host countries because knowledge exchange between partners largely depends on reciprocal trust, which requires time-consuming interactions. Meanwhile, according to Nepelski and DePrato (2015), the knowledge level of host countries does not seem to significantly impact MNEs' choice of setting up explorative units in the case of China, as Chinese MNEs also emerge in the South-south technology transfer network.

Cantwell and Mudambi (2011) reveal that it is difficult for MNEs to build local network connections in foreign environments when there exist powerful established domestic incumbents, which create a barrier to knowledge sourcing. Thus, it is common for these "Latecomers" from emerging markets to use acquisitions as springboards to shorten the distance with industry incumbents. The self-built or so-called "Greenfield" model is another choice for EM MNEs, not only to acquire foreign strategic assets but also to adapt their specific

advantages to local markets (Anderson & Sutherland, 2015). Besides these two entry modes, collaboration with local research institutes and companies is also utilized, as shown in the description of the database presented in Chapter 1.

### 2.2.2 Dual embeddedness of overseas inventors

The process of recombination, in which firms integrate new knowledge with existing ones in original ways, is an important source of innovation (Davis & Eisenhardt, 2011). Adapting this concept to the case of MNEs, the outcomes of their innovation activities often depend on the integration of novel knowledge sourced in foreign environments outside MNEs as well as the utilization of knowledge inside MNEs. The overseas research units and the inventors within them are embedded in the organization's internal and external networks for knowledge sourcing and integration. Several studies explore both internal and external aspects of MNEs' knowledge sourcing and integration from a social network perspective and describe the involvement of MNEs in both two aspects as “**dual embeddedness**” (Figueiredo, 2011; Athreye et al., 2016; Ferraris et al., 2020).

But as Blomkvist et al. (2014) suggest, the variation of innovation contributions made by individual inventors of MNEs' foreign units remains largely unexplored. Castellani et al. (2022) also note the fact that the current understanding of the role of individual-level factors in intra-firm knowledge transfer and integration is limited. This is the same case for dual embeddedness literature. Both internal and external embeddedness at the organizational level have been proven to have a profound impact on innovation, respectively. Meanwhile, the impact of inventor-level dual embeddedness on their innovation performance has rarely aroused the attention of researchers.

As described in social learning theory, knowledge is largely created through interactions between individuals (Noorderhaven & Harzing, 2009). Furthermore, Inkpen and Tsang (2005) distinguish several types of internal and external networks, such as intra-corporate networks, strategic alliances, trade associations and industrial districts. They emphasize the importance of individuals' roles in the knowledge transfer process through these networks as well as the fact that the individual and organizational level factors are intertwined. Thus, it is necessary

to explore the micro-foundations of individual-level dual embeddedness and its impact on innovation.

### *2.2.2.1 The concept of embeddedness*

The term “embeddedness” was first coined by Karl Polanyi to describe the phenomenon that economic activities are tightly related to non-economic institutions such as political, cultural, and religious institutions (Beckert, 2009). Granovetter (1985) introduces the concept of “embeddedness” in a new economic sociology context. According to his definition, **embeddedness refers to the fact that economic actions and outcomes are affected by actors' interpersonal relations and the structure of the network of these relations.** He uses embeddedness in social networks as an explanation of most market orders and disorders. Previous researchers have identified different dimensions of embeddedness: structural, relational, cultural, political, and cognitive (Zukin & DiMaggio, 1990).

Economic and management literature emphasizes the distinction between structural and relational embeddedness. The **structural dimension of embeddedness** is generated by complex network structures composed of multiple dyadic or triadic relationships (Uzzi, 1996). Nahapiet and Ghoshal (1998) describe structural embeddedness as “**the impersonal configuration of linkages between people or units**” and concerns the social system's properties and the whole network of relations. It includes network features such as connectivity, centrality, density, and hierarchy (Moran, 2005; Yan et al., 2019). The **relational dimension of embeddedness** denotes relationships people have developed through a history of interactions with each other (Nahapiet & Ghoshal, 1998; Kim, 2014). Contrary to the structural dimension, relational embeddedness concerns the **content and quality of ties** or what happens within (namely, dyads or dyadic relationships) relationships. Interpersonal trust and trustworthiness, overlapping identities, and feelings of closeness are regarded as crucial factors of relational embeddedness (Moran, 2005).

Following a description of the concept of embeddedness and its different dimensions, the ensuing discussion will explore the influence of dual embeddedness on innovation activities.

### 2.2.2.2 *External embeddedness and knowledge sourcing*

External embeddedness denotes the position of overseas research units and the inventors within them **in the network of external partners** and their relationship with them. Embedded in an external local environment enables inventors to have better and more frequent interaction with local peers to source the specific knowledge in this environment and gain an understanding of the potential usage of the knowledge acquired (Hohberger & Wilden, 2022).

Previous organizational-level studies confirm the role of **structural external embeddedness**; overseas research units externally embedded in their local network may occupy positions that enable them to access external partners' knowledge base (Figueiredo, 2011) and approach local players for critical information to develop a new learning process (Kim, 2014). The central position also guarantees tighter linkages with possible consumers who may trigger new innovative ideas (Mazzola & Kamuriwo, 2015). Van der Wouden and Rigby (2019) suggest that individuals embedded in knowledge-specialized cities with higher inventor density are likely to have a higher innovation outcome measured by the number of patents.

On the other hand, external relationships suppose high resources and coordination costs that are even higher when collaborations occur abroad due to distances in language and culture (Boschma, 2005). Collaboration may increase the breadth of knowledge sourcing, which increases the opportunities for exploration, but as the process of innovation and knowledge integration may be longer, it may as well have a negative impact on innovation level and exploration, at least in the short run.

**External relational embeddedness** helps to reduce partners' opportunistic behavior and lower the risk of knowledge leakages. Ebers and Maurer (2014) mention that relational embeddedness related to trust and reciprocity motivates partners to invest their energy and efforts in the knowledge exchange process, which facilitates innovation outcomes. In Inkpen and Tsang's (2005) discussion on external networks, individual-level relational trust is highlighted as a crucial factor in the process of knowledge exchange.

Nevertheless, **external over-embeddedness** may undermine actors' efforts in pursuing innovation development. When reaching a certain threshold, repetitive interactions with partners limit the search scope of external knowledge and decrease the new knowledge a unit may acquire (Haans et al., 2016). Furthermore, overwhelmed external knowledge sometimes leads to technical isolation (Monteiro et al., 2008), which leads to insufficient exploitation of internal resources. These disadvantages eventually diminish the possibility of innovation. As mentioned in section 2.1, one of the main purposes of the overseas research units is the exploration of new knowledge in foreign countries. It is likely that inventors in these units engage in the explorative activities. Thus, besides the overall level of innovation, it is also meaningful to test the impact of external embeddedness on the inventors' exploration of new knowledge. Thus, the first hypothesis is as follows:

***H1: External embeddedness has an inverted U-shape impact on MNEs' overseas inventors' innovation productivity and exploration of new knowledge.***

#### *2.2.2.3 Internal embeddedness and knowledge integration*

Internal embeddedness denotes the overseas research units and inventors' position inside the home company's own network, relationship with headquarters and other corporate units.

Ciabuschi et al. (2017) confirm that highly internally embedded research units may occupy essential strategic positions in the network and can gain more access to knowledge flows that positively affect the innovation outcome. This can be explained by literature evidence concerning the **structural dimension of embeddedness**. Actors with a central position in the whole network structure can acquire three essential benefits that positively impact innovation: knowledge gathering, knowledge accumulation, and scale (Ahuja, 2000). Birkinshaw and Hood (1998) suggest that intra-corporate competition within organizations requires subsidiaries to compete for necessary resources for development. Thus, units with forth mentioned position are more likely to win out in this sort of intra-MNE competition. Paruchuri and Awate (2016) conducts an individual-level empirical study and confirms that inventors' network reach in the internal network increases the depth and reach of local knowledge search, which may positively influence the innovation outcome.

Inventors can gain access to internal knowledge through their personal ties. The relation dimension of embeddedness plays an essential role in this sort of informal knowledge exchange. The ties between individuals enhance the knowledge exchange initiated at the organizational level (Inkpen and Tsang, 2005). From a **relational point of view**, high internal embeddedness suggests the existence of strong relational ties between the inventors and their colleagues inside the MNE. These strong ties facilitate the exchange of high-quality information and tacit knowledge (Uzzi, 1996) with internal partners. Relational embeddedness inside organizations can also increase knowledge-absorptive ability (Maurer, 2014), which facilitates the integration of the new knowledge sourced externally for the creation of innovation.

Consequently, high internal embeddedness is essential for inventors to benefit from knowledge flows from various parts of the MNE and absorb them effectively through solid ties in the network, leading to better exploration of new knowledge and innovation productivity. Thus, the second hypothesis is:

***H2: Internal embeddedness has a positive effect on MNEs' overseas inventors' innovation productivity and exploration of new knowledge.***

The interplay between the internal and external embeddedness of MNEs in foreign environments is still under debate. Internal embeddedness particularly increases the absorptive capacity of externally acquired knowledge by enhancing the information exchange between various units (Gölgeci et al., 2019). It thus helps moderate the technological isolation that may occur in the external knowledge-sourcing process. Ferraris et al.'s (2018) study on internal and external embeddedness from a relational aspect also confirms this view. However, on the other hand, it is evident that both aspects require high coordination costs; thus, as Yamin and Andersson (2011) propose, the internal and external embeddedness possibly have a competing effect on their product development activities. The investment in one aspect may limit the development in the other. The third hypothesis tests whether the interplay of dual embeddedness has a negative effect on individual-level innovation.

***H3: Interaction between external and internal embeddedness has a negative impact on MNEs' overseas inventors' innovation productivity and exploration of new knowledge.***

## **2.3 METHOD**

### **2.3.1 Data**

The innovation process of overseas research units is investigated through the lens of their inventors. As the first step of this study, an original dataset of Chinese MNEs' patent application information is constructed. After examining the ranking of the 2018 top 500 Chinese enterprises by Fortunechina.com and the 2019 OECD scoreboard of the top 2000 global corporate R&D investors<sup>6</sup>, Chinese MNEs with overseas R&D units are identified via various sources (annual reports, news, investment reports, etc.). At this stage, a total of 173 units set up by 63 enterprises in 27 countries worldwide are recorded. Their patent applications at various patent offices are extracted from the Lens database<sup>7</sup>. Finally, the database comprises 10,564 patent applications from 100 units of 51 MNEs that are consolidated at the patent family level to avoid redundant issues. The analysis period is 2010-2019, during which Chinese MNEs experienced a solid global expansion. Based on patent application information, an inventor list is made for each overseas research unit, including their patent application details, co-inventor names, and available location information. Inventor names are disambiguated and attributed to their proper units<sup>8</sup>. A more detailed description of the database and the process of construction is provided in Chapter 1.

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<sup>6</sup> the JRC/OECD COR&DIP© database, v.2. 2019

<sup>7</sup> Lens.org

<sup>8</sup> Inventor names are disambiguated with the Fuzzywuzzy string matching package in Python, which uses Levenshtein Distance to calculate the differences between sequences.

### 2.3.2 Network construction

In the database, three groups of inventors are distinguished: 1. Inventors located in Chinese MNEs' overseas research units; 2. Inventors located in Chinese MNEs' headquarters or divisions within China; 3. Inventors from MNEs' external partners. Making use of this setting, the overall network of each MNE is built and two subsamples are extracted. The internal network focuses MNE's inventors whether they are in China or in overseas research units. The external network focuses on MNE's inventors and their external partnerships. Once these networks are built, the analysis focuses exclusively on inventors within overseas research units and extracts their ego-network to characterize their position and relationships within the MNE (internal) and outside the MNE (external). The construction of networks and variables is realized using Igraph package in R program. The internal and external networks enable the calculation of various network variables, which is mentioned in the following section.

### 2.3.3 Variables

The aim of this chapter is to study the innovation process of MNEs' overseas research units by exploring how their inventors' source and produce new knowledge through their embeddedness in coinventor collaborations within their home companies and with external partners.

#### 2.3.3.1 Dependent variables

Two dependent variables are considered to characterize innovation performance at the inventor level within research units. First, *inventor productivity* is the yearly number of patent applications of an inventor. This variable highlights her innovative activity. Second, *inventor technological novelty* computes for each inventor and year the number of new 4-digit IPC classes that are new to the firm technological portfolio. It measures inventors' exploration of new knowledge.

### 2.3.3.2 Independent variables

The position of inventors within networks is assessed through **structural and relational embeddedness**.

*Structural embeddedness* refers to the configuration of linkages between people or units (Nahapiet & Ghoshal, 1998) generated by complex network structures (Uzzi, 1996). Here, structural embeddedness is proxied by two indicators, namely, standardized ego betweenness centrality and degree centrality. *Betweenness centrality* “calculates how many times an actor sits on the geodesic (i.e. the shortest path) linking two other actors together” (Prell, 2012 P.114). Here, I focus on the ego network betweenness at the inventor level instead of the whole company network. *Degree centrality* is also used as an alternative measure of structural embeddedness measured at the inventor level. Degree centrality is simply the number of direct co-inventors. Both variables are computed for both internal and external networks. This means that I consider the ego subnetwork of the inventor and her relationships with inventors outside the unit but within the firm (internal ties) and the ego subnetwork of the inventor and its relationship with inventors outside the unit and outside the firm (external ties).

*Relational embeddedness* can be regarded as relationships developed through a history of interactions with each other (Nahapiet & Ghoshal, 1998) and concerns the content and quality of ties (Moran, 2005). Thus, relational embeddedness is measured as  $RE = \sum_{k=1}^n \delta_{ki} / n$  where  $n$  is the number of unique co-inventors of inventor  $i$  and  $\delta_{ki}$  is the total number of patents co-invented by inventor  $k$  and  $i$  during the five prior years before the focal year  $t$ . This indicator measures the inventors' propensity to co-invent patents with their co-inventors (Yan et al. 2019). It is again computed based on the internal network, that is, the relationship of research unit inventors and firm inventors, and the external network, that is, the relationship of research unit inventors with extra-firm inventors.

An additional variable *Inventor external ties* (0/1) is introduced to test the general impact of external ties, not considering its characteristics in terms of structural or relational embeddedness. It takes value 1 if the inventor has at least one external co-inventor over the past five years and zero otherwise.

**Table 2.1 Description of variables**

<b>Dependent variables</b>	
Inventor productivity (# of patents)	Number of patents per year and per unit inventor. It is a proxy for inventor productivity
New technologies (4-digit IPC codes)	Number of new technologies introduced in the MNE's technology patent portfolio by the unit inventor
<b>Variables of interest</b>	
Inventor external ties (0/1)	Takes value 1 if the unit inventor has external ties, that is, direct collaborations with inventors outside the home company during the 5 years before the invention (= 5 previous years)
<b>Structural embeddedness</b>	
Internal Degree centrality	Degree centrality (= number of direct co-inventors) of the unit inventor with inventors located in the home company during the 5 previous years
External Degree centrality	Degree centrality (= number of direct co-inventors) of the unit inventor with inventors located outside the home company during the 5 previous years
Internal ego betweenness	Standardized internal ego betweenness during the 5 previous years – it is the ego betweenness centrality of the unit inventor with inventors within the home company standardized by the number of inventors in his ego network (Everett and Borgatti, 2005). It is an indicator of inventor centrality as it lies on many geodesics. Standardized Betweenness centrality = $2 * \text{Betweenness centrality} / [(n-1)(n-2)]$ , n is the size of the ego-network
Internal ego betweenness	Standardized external ego betweenness during the 5 previous years – it is the ego betweenness centrality of the unit inventor with inventors outside the home company standardized by the number of inventors in his ego network
<b>Relational embeddedness</b>	
Internal Relational embeddedness	Internal relational embeddedness is calculated as the total number of patents co-inventors by inventors l and co-inventor k during the five-previous years and divided by the total number of coinventors $RE_i = \sum_{k=1}^n \delta_{ik} / n$
External Relational embeddedness	External relational embeddedness
<b>Control variables</b>	
Inventor experience	The number of patents invented by the inventor during the 5 previous years
Research unit # of inventors	The number of inventors within the unit
Company # of patents (MNE)	The size of the home company patent portfolio
Company # of inventors (MNE)	The number of inventors in the home company
# of research units (MNE)	The MNE's number of units all over the world

### 2.3.3.3 Control variables

Several control variables are introduced to control for the level and characteristics of the inventive activity at the inventor, research unit, and firm level. At the inventor level, the first control variable is *Inventor experience*, which refers to the inventor's number of past patent applications over the five prior years. *No external network* is also introduced to account for the fact that variables characterizing the external network of the inventor take a value 0 when the inventor has no external co-inventors. In this case, it takes values 1 and 0 otherwise.

At the research unit level, the inventive activity is controlled by *Research unit # of inventors*, which is the number of inventors within the unit in which the inventor is involved. At the MNE level, three controls are introduced. *Company # of patents* refers to the number of patent applications of the given MNE for the past five years. *Company # of inventors* represents the number of inventors of the given MNE in the past five years. *Company # of units* is also included to control the MNE's openness and the geographical dispersion within the firm.

For regressions, the natural log is used for continuous variables to reduce dispersion except betweenness centrality, which is between 0 and 1.

### 2.3.4 Model

The analysis of the relationship between innovation and dual embeddedness uses fixed effects to control for unobserved heterogeneity, which may affect the empirical results. I regress inventors' performance on indicators of internal and external embeddedness as well as several control variables at the inventor, firm, and research unit levels.

At the inventor level, the estimated model is:

$$\ln y_{itTcF} = \alpha \ln IE_{it} + \beta \ln EE_{it} + \gamma \ln IE_{it} \times \ln EE_{it} + \theta \text{Controls}_{itcF} + \delta_i + \delta_t + \delta_T + \varepsilon_{itTcF}$$

IE is internal embeddedness; EE is external embeddedness.

$i$  is the inventor,  $t$  stands for year,  $T$  is the technology,  $c$  is the research unit and  $F$  is the firm.  $\delta_i, \delta_t, \delta_T$  represent respectively a set of fixed effects at the inventor, year, and technology level. Errors are clustered at the inventor and research unit level to control mainly for correlations in performance within research units.

### 2.3.5 Descriptive statistics

Table 2.2 details the distribution of inventors, research units, and MNE firms in the final sample across industries. This final sample focuses on inventors within research units that have at least two patents over the period [t-5;t] in order to be able to build network variables over [t-5; t-1] and relate it to their patenting activity in year  $t$ . Most MNEs in the sample

concentrate on two industries: Manufacturing and information and communication. Industries are further broken down into disaggregated sectors. The number of inventors and overseas research units from MNEs specializing in the manufacturing of electrical equipment, as well as the production of motor vehicles, trailers, and semi-trailers, outpaces that of other sectors. Table 2.9 in the appendix describes research units through time. Most MNEs have a few units, and the time gives additional information on units, the first year and last year, and the number of years for which application data are available.

As the aim is to study the impact of internal versus external embeddedness, this chapter will focus analysis only on manufacturing MNEs that have both internal and external ties compared to the other industries in which they are nearly absent.

**Table 2.2 Inventors, R&D units and firms across Economic activities (ISIC Rev.4 sections)**

<b>Industry</b>	<b>Sectors (Agregated)</b>	<b># inventors</b>	<b># units</b>	<b># firms</b>
F	Construction	3	1	1
J	Information and communication	222	12	6
C	Manufacturing	721	69	38
B	Mining and quarrying	4	1	1
E	Water supply; sewerage, waste management and remediation activities	2	1	1

<b>Industry</b>	<b>Sectors</b>	<b># inventors</b>	<b># units</b>	<b># firms</b>
F	Construction of buildings	3	1	1
J	Computer programming, consultancy and related activities	18	2	2
J	Information and communication	32	1	1
J	Information service activities	4	1	1
J	Telecommunications	164	7	1
C	Manufacture of chemicals and chemical products	73	7	6
C	Manufacture of computer, electronic and optical products	111	9	3
C	Manufacture of electrical equipment	300	11	6
C	Manufacture of fabricated metal products, except machinery and equipment	1	1	1
C	Manufacture of food products	8	3	2
C	Manufacture of machinery and equipment	65	12	5
C	Manufacture of motor vehicles, trailers and semi-trailers	214	14	8
C	Manufacture of other transport equipment	96	7	2
C	Manufacture of pharmaceuticals, medicinal chemical and botanical products	57	4	4
C	Manufacture of textiles	5	1	1
C	Other manufacturing	9	1	1
B	Extraction of crude petroleum and natural gas	4	1	1
E	Water collection, treatment and supply	2	1	1

Table 2.3 provides descriptive statistics for the main variables of interest for internal and external embeddedness and the size of the ego network of inventors in overseas research units. The table shows a highly skewed distribution for the external ego network size as well

as associated external structural variables. This means that most inventors have no extra-firm relationships, and only a small portion, which represents 25% of the observations, have extra-firm networks and some of them have rather large external ego network sizes. The rest of the table shows the same distribution for information and communication as well as manufacturing industries. The result highlights that the skewness of external networks is even larger for Information and Communication, where very few of the inventors have extra-firm ties in contrast with manufacturing, for which the distribution is nevertheless very skewed.

<b>Table 2.3 Descriptive statistics for the main variable of interest</b>								
<b>Variables</b>	<b>Mean</b>	<b>P25</b>	<b>Median</b>	<b>P75</b>	<b>P95</b>	<b>P99</b>	<b>Min</b>	<b>Max</b>
<b>Whole sample – 6 521 observations</b>								
Internal ego network size	145.52	21.00	66.00	193.00	558.50	966.00	2.00	2253.00
External ego network size	3.02	0.00	0.00	0.00	13.00	89.00	0.00	158.00
Internal Degree centrality	19.28	5.00	11.00	24.00	59.00	120.00	1.00	590.00
External Degree centrality	0.86	0.00	0.00	0.00	6.00	22.00	0.00	72.00
Internal ego betweenness	0.20	0.00	0.10	0.37	0.67	0.79	0.00	1.00
External ego betweenness	0.01	0.00	0.00	0.00	0.00	0.38	0.00	0.75
Internal Relational embeddedness	1.09	0.77	0.99	1.29	1.92	2.51	0.00	3.36
External Relational embeddedness	0.08	0.00	0.00	0.00	0.69	1.83	0.00	2.53
<b>Information and communication – 1 352 observations</b>								
Internal ego network size	176.66	25.00	109.00	268.00	582.00	677.00	2.00	802.00
External ego network size	0.06	0.00	0.00	0.00	0.00	0.00	0.00	27.00
Internal Degree centrality	20.95	6.00	13.00	31.00	62.00	85.00	1.00	96.00
External Degree centrality	0.04	0.00	0.00	0.00	0.00	0.00	0.00	9.00
Internal ego betweenness	0.35	0.02	0.37	0.59	0.77	0.83	0.00	1.00
External ego betweenness	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03
Internal Relational embeddedness	1.03	0.73	0.88	1.10	1.95	2.76	0.69	3.36
External Relational embeddedness	0.01	0.00	0.00	0.00	0.00	0.00	0.00	1.39
<b>Manufacturing – 5 134 observations</b>								
Internal ego network size	138.14	21.00	60.00	165.00	556.00	1005.00	2.00	2253.00
External ego network size	3.90	0.00	0.00	0.00	23.00	99.00	0.00	158.00
Internal Degree centrality	18.97	5.00	11.00	22.00	59.00	131.00	1.00	590.00
External Degree centrality	1.09	0.00	0.00	0.00	8.00	23.00	0.00	72.00
Internal ego betweenness	0.17	0.00	0.07	0.29	0.60	0.75	0.00	1.00
External ego betweenness	0.01	0.00	0.00	0.00	0.01	0.41	0.00	0.75
Internal Relational embeddedness	1.11	0.79	1.03	1.32	1.92	2.46	0.00	2.91
External Relational embeddedness	0.10	0.00	0.00	0.00	1.01	1.90	0.00	2.53

Table 2.4 presents descriptive statistics for the inventors of the 69 units and 38 firms in the manufacturing sector. The final sample includes 4,873 observations. The inventor's productivity stands at 4.54, with a relatively high standard deviation of 7.48, indicating considerable variation in patent output across inventors. The introduction of new technologies has a mean value of 0.40 and a standard deviation of 0.98, signifying variations

in the adoption of new knowledge. When examining the presence of inventor external ties (0/1), it is evident that, on average, a relatively low percentage of inventors have external collaborations. This variable has a mean of 0.08 and a standard deviation of 0.27. The internal and external structural embeddedness of inventors measured by degree centrality has a mean of 19.63 and 1.12, with a high variation among inventors. Internal structural embeddedness measured by ego betweenness has a mean of 0.17, whereas the external aspect has a much lower mean of 0.01. In terms of relational embeddedness, internal relational embeddedness has a mean of 1.13, and external relational embeddedness has a lower mean of 0.11, once again indicating differences in inventors' internal and external collaborations. The control variables, including inventor experience, unit and company characteristics, and geographic presence of units, also exhibit variability across the inventors and MNEs.

**Table 2.4 Descriptive statistics – Manufacturing industry**

	Mean	S.D	Min	Max
<b>Dependent variables</b>				
Inventor productivity (# of patents)	4.54	7.48	1.00	158.00
New technologies (4-digit IPC codes)	0.40	0.98	0.00	9.00
<b>Variables of interest</b>				
Inventor external ties (0/1)	0.08	0.27	0.00	1.00
<b>Structural embeddedness</b>				
Internal Degree centrality	19.63	32.39	1.00	590.00
External Degree centrality	1.12	4.68	0.00	72.00
Internal ego betweenness	0.17	0.21	0.00	1.00
External ego betweenness	0.01	0.07	0.00	0.75
<b>Relational embeddedness</b>				
Internal Relational embeddedness	1.13	0.40	0.41	2.91
External Relational embeddedness	0.11	0.39	0.00	2.53
<b>Control variables</b>				
Inventor experience	1.11	1.09	0.00	5.43
Unit # of inventors	4.02	1.19	0.69	5.59
Company # of patents (MNE)	6.77	1.66	0.00	9.37
Company # of inventors (MNE)	6.77	1.28	1.61	8.61
# of research units (MNE)	3.91	1.17	1.10	5.58
Observations	4873			

## 2.4 RESULTS

Table 2.5. provides a regression of internal and external embeddedness on inventor productivity measured by the number of patents. Here, the structural aspect of embeddedness is measured by the degree centrality. It appears that research units mainly benefit from the relationship of their inventors with their home company counterparts. Regarding their external ties, the coefficient is negative and highly significant, meaning that extra-firm ties reduce inventor productivity.

**Table 2.5 Impact of dual embeddedness on inventor productivity**

	# patents				
	(1)	(2)	(3)	(4)	(5)
Inventor external ties (0/1)	-0.222*** [0.073]	-0.199*** [0.070]			
Internal Degree centrality	-0.089 [0.126]	0.309*** [0.042]	0.308*** [0.042]	0.318*** [0.043]	0.306*** [0.043]
Internal Degree centrality square	0.080*** [0.024]				
Internal Relational embeddedness	1.222*** [0.204]	1.175*** [0.203]	1.243*** [0.202]	0.908*** [0.065]	1.242*** [0.199]
Internal Relational embeddedness square	-0.121+ [0.068]	-0.107 [0.065]	-0.125+ [0.066]		-0.118+ [0.065]
External Degree centrality			0.534 [0.459]	-0.019 [0.097]	-0.140 [0.085]
External Degree centrality square			-0.116 [0.099]		
External Relational embeddedness			-1.619*** [0.473]	-1.551*** [0.478]	-1.512*** [0.458]
External Relational embeddedness square			0.470*** [0.161]	0.436** [0.166]	0.477** [0.182]
Internal Degree centrality # External Degree centrality					0.024 [0.026]
Internal Relational embeddedness # External Relational embeddedness					-0.090 [0.104]
Inventor experience	-0.140*** [0.033]	-0.128*** [0.033]	-0.125*** [0.032]	-0.128*** [0.032]	-0.129*** [0.033]
unit # of inventors	0.042 [0.061]	0.022 [0.062]	0.017 [0.061]	0.017 [0.062]	0.022 [0.061]
Company # of patents	-0.046** [0.018]	-0.032+ [0.017]	-0.025 [0.017]	-0.025 [0.017]	-0.028+ [0.017]
Company # of inventors	0.029 [0.021]	0.029 [0.020]	0.028 [0.020]	0.028 [0.020]	0.028 [0.020]
Company # of units	0.070 [0.054]	0.079 [0.054]	0.077 [0.053]	0.077 [0.054]	0.075 [0.053]
No external network			-0.406 [0.598]	-0.990*** [0.290]	-1.135*** [0.291]
Constant	-0.316 [0.274]	-0.769*** [0.250]	-0.424 [0.638]	0.333 [0.397]	0.313 [0.377]
Observations		4873	4873	4873	4873
R-Squared	.69	.68	.69	.69	.69

Structural embeddedness is measured by degree centrality  
711 individual inventors, 69 units and 38 firms  
Inventor, priority year and technology fixed effects – Standard errors are clustered by inventor and unit level.  
+ 0.10 \*\* 0.05 \*\*\* 0.01

This may be explained by the fact that collaborations outside the firm imply a lot of coordination efforts, and maybe also the collaboration implies high learning efforts that reduce the invention at the research unit level. Moreover, if inventors are involved in projects with their home company counterparts, they may have more difficulties devoting time and effort to external collaborations. The corollary is that external degree centrality is not significant. Thus, there is no non-linear impact of structural embeddedness.

Figure 2.1. illustrates the fact that external ties have a negative impact on patenting. The inverted U-shaped hides here the fact that the upward slope only concerns a very marginal share of inventors. Within the firm, co-inventor ties explain patenting at the unit level, and the fact of having external ties leads to a lower level of patenting.

**Figure 2.1. Impact of internal and external embeddedness (Table 2.5.)**

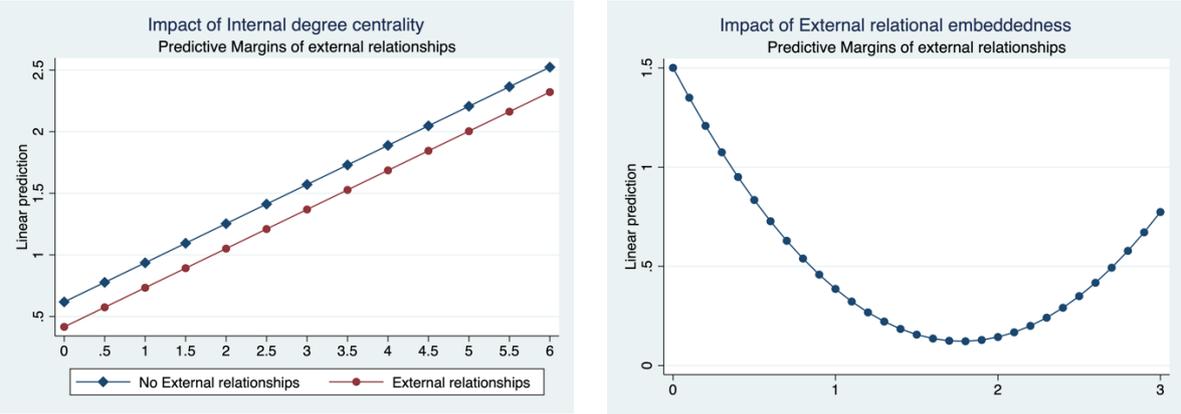


Table 2.6 also tests the impact of dual embeddedness on inventor productivity, but this time standardized inventor ego network betweenness is used for the measurement of structural embeddedness. Results confirm those obtained in Table 2.5. Internal structural embeddedness has a positive and highly significant impact on inventor productivity, while external structural embeddedness remains non-significant. This is probably due to the same reasons explained above. Thus, there is no non-linear impact of external structural embeddedness as well.

**Table 2.6 Impact of dual embeddedness on inventor productivity**

	# patents				
	(1)	(2)	(3)	(4)	(5)
Inventor external ties (0/1)	-0.164**	-0.163**			
	[0.078]	[0.079]			
Internal ego betweenness	0.909***	0.559***	0.545***	0.548***	0.547***
	[0.273]	[0.100]	[0.100]	[0.101]	[0.106]
Internal ego betweenness square	-0.570				
	[0.473]				
Internal Relational embeddedness	1.731***	1.758***	1.827***	1.828***	1.817***
	[0.227]	[0.227]	[0.224]	[0.225]	[0.226]
Internal Relational embeddedness square	-0.262***	-0.270***	-0.286***	-0.288***	-0.280***
	[0.072]	[0.073]	[0.073]	[0.073]	[0.074]
External ego betweenness			1.104	0.154	0.110
			[1.130]	[0.357]	[0.562]
External ego betweenness square			-1.903		
			[2.335]		
External Relational embeddedness			-1.883***	-1.819***	-1.830***
			[0.439]	[0.465]	[0.458]
External Relational embeddedness square			0.555***	0.544***	0.626***
			[0.160]	[0.164]	[0.177]
Internal ego betweenness # External ego betweenness					0.123
					[1.481]
Internal Relational embeddedness # External Relational embeddedness					-0.102
					[0.122]
Inventor experience	-0.065**	-0.062**	-0.061**	-0.062**	-0.062**
	[0.027]	[0.026]	[0.026]	[0.026]	[0.026]
unit # of inventors	-0.024	-0.022	-0.024	-0.024	-0.022
	[0.052]	[0.051]	[0.051]	[0.051]	[0.051]
Company # of patents	-0.024	-0.027	-0.022	-0.021	-0.023
	[0.017]	[0.018]	[0.017]	[0.017]	[0.017]
Company # of inventors	0.032	0.031	0.030	0.030	0.030
	[0.020]	[0.020]	[0.021]	[0.021]	[0.021]
Company # of units	0.142***	0.149***	0.146***	0.146***	0.144***
	[0.044]	[0.043]	[0.042]	[0.042]	[0.042]
No external network			-1.130***	-1.101***	-1.143***
			[0.297]	[0.312]	[0.311]
Constant	-0.713***	-0.732***	0.344	0.310	0.361
	[0.230]	[0.230]	[0.352]	[0.368]	[0.375]
Observations		4873	4873	4873	4873
R-Squared	.67	.67	.67	.67	.67

Structural embeddedness is measured by ego betweenness centrality

711 individual inventors, 69 units and 38 firms

Inventor, priority year and technology fixed effects – Standard errors are clustered by inventor and unit level.

+ 0.10 \*\* 0.05 \*\*\* 0.01

**Figure 2.2 Impact of internal and external embeddedness (Table 2.6)**

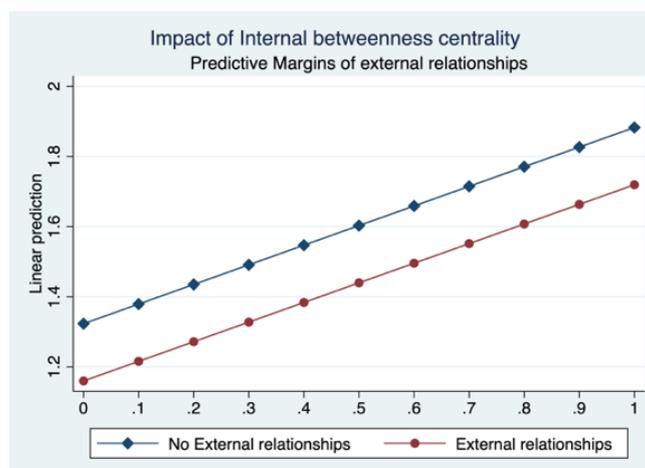


Figure 2.2 illustrates that it is the co-inventor ties that explain patenting at the inventor level. Inventors with a central position measured by ego betweenness centrality are more productive. However, as stated before, having external ties reduces inventor productivity.

Table 2.7 studies the impact of dual embeddedness on the exploration of new knowledge. The dependent variable is the number of new technologies, that is, 4-digit IPC codes, introduced by research unit inventors in the MNE's patent portfolio. External ties still have a negative impact for the same reasons as those explained previously. That is inventors have a hard time relying on their external ties to produce novel technologies.

This time, internal structural embeddedness measured by degree centrality has a nonlinear form, suggesting that only those inventors with many direct co-inventors can produce novel technologies. And in a way this result is confirmed in Table 2.8, as inventors with external ego network betweenness seem to have an advantage in producing new technologies. The interplay between internal structural embeddedness and external collaboration is further tested. For inventors with external ties, the internal embeddedness measured by degree centrality has an inverted relation with the exploration of new technology, which is illustrated in Figure 2.3. Internal relational embeddedness is proven to have an inverted U-shaped relation with the exploration of new technology as well.

It is interesting to notice that among the control variables, the size of the research units and MNEs in terms of the number of inventors are positively related to inventors' exploration of new technology, which suggests that inventors are more likely to obtain more internal collaborators who are crucial to the exchange of new knowledge within larger R&D units and MNEs. However, these factors do not contribute to the inventor's overall productivity of innovation as they are not significant in the regressions.

**Table 2.7 Impact of dual embeddedness on the number of inventor new technologies**

	# Exploratory				
	(1)	(2)	(3)	(4)	(5)
Inventor external ties (0/1)	-0.096+ [0.049]				
Internal Degree centrality	-0.188*** [0.057]	-0.202*** [0.061]	-0.195*** [0.058]	-0.208*** [0.062]	-0.256*** [0.067]
Internal Degree centrality square	0.045*** [0.011]	0.048*** [0.012]	0.047*** [0.011]	0.049*** [0.012]	0.057*** [0.013]
Internal Relational embeddedness	0.514*** [0.180]	0.536*** [0.188]	0.521*** [0.179]	0.519*** [0.179]	0.556*** [0.184]
Internal Relational embeddedness square	-0.135** [0.063]	-0.141** [0.067]	-0.135** [0.063]	-0.136** [0.063]	-0.148** [0.064]
External Degree centrality		0.180 [0.200]	-0.012 [0.050]	0.051 [0.067]	
External Degree centrality square		-0.051 [0.051]			
External Relational embeddedness		-0.273 [0.334]	-0.065 [0.104]	-0.006 [0.191]	
External Relational embeddedness square		0.070 [0.123]			
Internal Degree centrality # External Degree centrality				-0.026 [0.019]	
Internal Relational embeddedness # External Relational embeddedness				-0.007 [0.076]	
Inventor external ties (0/1)					-1.147*** [0.276]
Inventor external ties (0/1) # Internal Degree centrality					0.789*** [0.166]
Inventor external ties (0/1) # Internal Degree centrality square centrality					-0.132*** [0.025]
Inventor experience	-0.052*** [0.015]	-0.052*** [0.015]	-0.052*** [0.015]	-0.050*** [0.015]	-0.048*** [0.014]
unit # of inventors	0.060+ [0.030]	0.057+ [0.031]	0.059+ [0.030]	0.055+ [0.030]	0.054+ [0.031]
Company # of patents	-0.163*** [0.013]	-0.160*** [0.013]	-0.162*** [0.013]	-0.159*** [0.012]	-0.159*** [0.011]
Company # of inventors	0.038*** [0.011]	0.037*** [0.010]	0.037*** [0.010]	0.037*** [0.011]	0.036*** [0.011]
Company # of units	0.015 [0.026]	0.016 [0.026]	0.015 [0.026]	0.016 [0.026]	0.019 [0.027]
Constant	0.589*** [0.136]	0.581*** [0.136]	0.589*** [0.134]	0.589*** [0.134]	0.633*** [0.124]
Observations	4873	4873	4873	4873	4873
R-Squared	.64	.64	.64	.64	.65

Structural embeddedness is measured by degree centrality

711 individual inventors, 69 units and 38 firms

Inventor, priority year and technology fixed effects – Standard errors are clustered by inventor and unit level.

+ 0.10 \*\* 0.05 \*\*\* 0.01

**Figure 2.3 Impact of internal structural embeddedness (Table 2.7)**

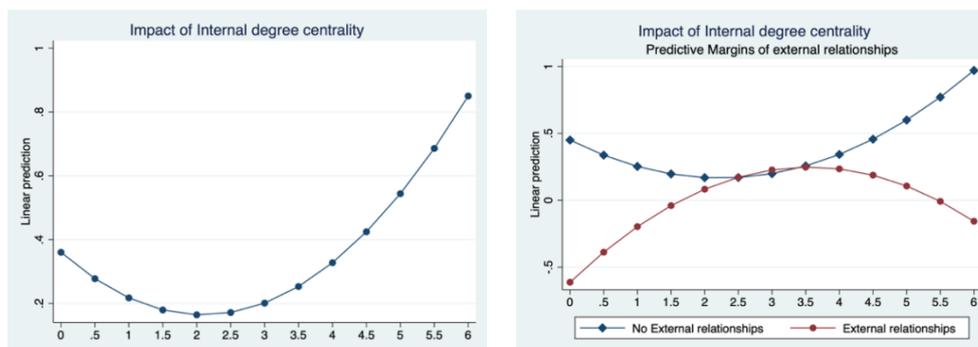


Figure 2.3 illustrates the impact of internal structural embeddedness measured by degree centrality on the exploration of new technologies moderated by whether inventors have external ties or not. The relationship has a u-shaped for inventors who have no external ties but appears to exhibit an inverted U-shape for inventors with external ties. This graph reveals the interplay between inventors' internal and external networks. It confirms the substitution effect of internal and external embeddedness on the exploration of new technologies from the structural aspect.

In Table 2.8, inventors with external ties are still disadvantaged, however, the variable is only moderately significant. Inventors standing in between intra-firm inventors have no benefit in producing novel technologies. This is rather surprising. The variable is positive but not significant. One possible explanation is that only the most inventive inventors and occupying gatekeeping positions can produce novel technologies, as will be seen in the next chapter. In contrast, inventors with high external ego network betweenness seem to have an advantage in producing new technologies. But this is only the case for a minority of inventors as we know that only a small portion of these inventors have extra-firm networks. Thus, it is not the number of external co-inventors (degree) that matters but the fact that they occupy some specific position in the extra-firm network that are able to gain an advantage and produce novel technologies. The result for internal relational embeddedness remains the same as in Table 2.7.

Figure 2.4 illustrates the impact of the inventor external structural embeddedness measured by standardized ego betweenness centrality on the exploration of new technology. The relation exhibits an inverted U-shape, which confirms the fact that though embeddedness in the external network positively contributes to the exploration of new technologies, external over-embeddedness may lead to technological isolation and hinder the application of new technologies.

**Table 2.8 Impact of dual embeddedness on the number of inventor new technologies**

	# Exploratory				
	(1)	(2)	(3)	(4)	(5)
Inventor external ties (0/1)	-0.080+	-0.079+			
	[0.047]	[0.047]			
Internal ego betweenness	0.111	0.075	0.068	0.068	0.073
	[0.132]	[0.055]	[0.054]	[0.054]	[0.057]
Internal ego betweenness square	-0.059				
	[0.203]				
Internal Relational embeddedness	0.551***	0.554***	0.554***	0.554***	0.555***
	[0.190]	[0.190]	[0.188]	[0.188]	[0.190]
Internal Relational embeddedness square	-0.144**	-0.145**	-0.141**	-0.141**	-0.142**
	[0.064]	[0.064]	[0.064]	[0.063]	[0.065]
External ego betweenness			1.544**	1.542**	1.585**
			[0.721]	[0.705]	[0.779]
External ego betweenness square			-2.887**	-2.894**	-2.744***
			[1.115]	[1.149]	[1.012]
External Relational embeddedness			-0.131	-0.117***	-0.125
			[0.134]	[0.036]	[0.118]
External Relational embeddedness square			0.008		
			[0.074]		
Internal ego betweenness # External ego betweenness					-0.454
					[0.915]
Internal Relational embeddedness # External Relational embeddedness					-0.001
					[0.072]
Inventor experience	-0.039***	-0.039***	-0.038**	-0.037**	-0.037**
	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]
unit # of inventors	0.043	0.043	0.042	0.042	0.041
	[0.030]	[0.030]	[0.030]	[0.030]	[0.029]
Company # of patents	-0.154***	-0.155***	-0.154***	-0.154***	-0.154***
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]
Company # of inventors	0.038***	0.038***	0.037***	0.037***	0.037***
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Company # of units	0.027	0.028	0.027	0.027	0.028
	[0.026]	[0.026]	[0.026]	[0.026]	[0.026]
Constant	0.341**	0.339**	0.341**	0.340**	0.338**
	[0.135]	[0.134]	[0.130]	[0.134]	[0.135]
Observations		4873	4873	4873	4873
R-Squared	.64	.64	.64	.64	.64

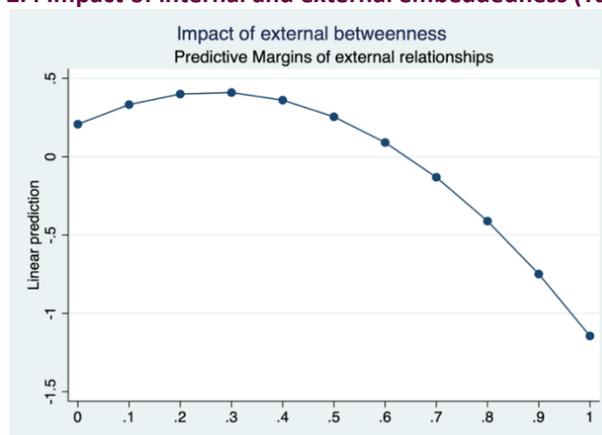
Structural embeddedness is measured by ego betweenness centrality

711 individual inventors, 69 units and 38 firms

Inventor, priority year and technology fixed effects – Standard errors are clustered by inventor and unit level.

+ 0.10 \*\* 0.05 \*\*\* 0.01

**Figure 2.4 Impact of internal and external embeddedness (Table 2.8)**



The turning point is 0.26 and concerns the top 1 % of inventors.

## 2.5 CONCLUSIONS

An escalating trend in the globalization of R&D has gained significant attention over recent decades. This phenomenon has been particularly observed among MNEs from emerging markets, with their substantial involvement in this trajectory since the beginning of the new millennium. The establishment of overseas R&D units serves as a pivotal strategic choice to fulfill the goals of R&D globalization, especially the sourcing of foreign-specific knowledge. To comprehensively evaluate the innovation performance of these MNEs, it is necessary to examine the inventor-level factors linked to their innovation processes in foreign contexts. In this regard, both internal and external embeddedness emerge as crucial determinants that exert profound influences on innovation outcomes. However, the precise mechanisms underlying these influences require further exploration. Consequently, this paper breaks down the concept of internal and external embeddedness into structural and relational aspects and further explores their relative functions in inventor-level innovation.

The contributions of this chapter can be summarized as follows. Empirically speaking, it explores an original database of patent information on inventors from Chinese MNEs' overseas R&D units. As presented in Chapter 1, this database draws a broader picture of these units' geographical and industrial distribution, providing a better understanding of the strategic choice of MNEs when entering foreign host countries. Based on this database, a collaboration network is built for these overseas inventors using the co-patenting information. This network enables empirical analysis of dual embeddedness and innovation performance.

From a theoretical perspective, this paper not only confirms several findings in the existing literature but also enriches the comprehension of the micro-foundations of the impact of dual embeddedness. The empirical findings reveal the multifaceted impact of internal and external embeddedness. Specifically, the study demonstrates that internal structural embeddedness is positively associated with inventor productivity, whereas internal relational embeddedness exhibits an inverted U-shaped relationship. The influence of external structural embeddedness on productivity is statistically insignificant, while external relational

embeddedness follows a U-shaped pattern. Regarding the exploration of new technologies, it is noteworthy that internal structural embeddedness has an adverse effect. Meanwhile, internal relational embeddedness maintains its impact. External structural embeddedness shows an inverted U-shaped relationship when measured by ego betweenness centrality, whereas external relational embeddedness does not yield statistically significant results. However, as inventors with external ties remain a minority in the sample, the results related to external embeddedness should be interpreted with caution.

The findings of this study hold several practical implications, shedding light on the dynamics and interactions of inventor-level dual embeddedness, which can offer guidance to EM MNEs seeking to operate overseas R&D units for innovation activities. The results underscore the nuanced roles of dual embeddedness in shaping both inventor innovation productivity and the exploration of new technologies, indicating the need for tailored strategies to align with the objectives of inventors. When optimizing productivity is the primary goal, inventors should strive to maintain a central position within the internal network to maximize their innovative output. However, it is advisable to avoid over exchange with specific partners as knowledge redundancy may occur. While external knowledge sourcing is generally perceived as a booster for innovation, it's crucial to recognize that forging stable collaborations with external partners in a foreign environment demands considerable resources and time, which potentially hinders productivity.

Conversely, if the objective is to explore new technologies, the approach diverges. Overemphasis on establishing more internal relations may trap the inventor within the existing technological trajectory of the firm, hindering the pursuit of novel technologies. Instead, it is crucial for inventors to occupy distinctive positions within the internal network. It is also the case for external knowledge sourcing. A position with high betweenness centrality contributes to acquiring new knowledge, but excessive focus on external networks may result in technological isolation, which may harness the adoption of new technologies for recombination with existing knowledge. The interaction between internal and external embeddedness from a structural aspect also suggests that it should maintain an equilibrium between partners from both networks.

This chapter has several limitations. The main limitation comes from the fact that most MNEs have invested in overseas research units only recently. For this reason, most MNEs have only a few units with a limited patenting activity and only over a short period of time. On average, research units were created after 2009, and 25 % of units have less than six years of patenting data, and 50 % have less than 8 years with lags. With limited observations per research units, there is a strong density of ties for inventors in research units and probably insufficient variations to be able to capture all subtleties of the relationships studied. Second, this limitation in data is ever more accurate when it comes to studying the impact of external relationships. The number of units with external ties is rather limited, and it is the same for the number of patents. Therefore, results are most of the time not significant, and it is difficult to really assess whether it is representative of the real tendency or the outcome of a shortage of observations. This is the reason why the final sample focuses on the manufacturing sector. Finally, the shortage of observations and variations did not enable to consider whether dual embeddedness vary across different types of research units, namely whether units are self-built, mergers and acquisitions, or collaborations. Nor was it possible to consider whether results vary across sectors within manufacturing and across industries.

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**Table 2.9 Appendix 1. Research units years of patenting**

Name	Firm	First year	Last year	# of years
ANGEL_A1	Angel	2011	2020	4
ANGEL_A2	Angel	2008	2015	2
BEIQI_A1	BeiqiFoton	2008	2020	13
BEIQI_A2	BeiqiFoton	2009	2020	12
BGI_A1	BGI	2013	2018	6
BGI_B1	BGI	2008	2020	13
BRIGHT_A1	Bright	2007	2019	10
BYD_A1	BYD	2012	2019	8
BYD_A2	BYD	2013	2019	7
CHANGAN_A1	Changan	2009	2020	8
CHANGAN_A2	Changan	2012	2019	8
CHANGAN_A3	Changan	2009	2020	8
CHANGAN_A4	Changan	2015	2019	4
CHANGAN_A5	Changan	2013	2019	6
CHANGJIANG_A1	Changjiang	2009	2020	9
CNPC_A1	CNPC	2012	2020	9
CRRC_A1	CRRC	2014	2019	6
CRRC_A2	CRRC	2014	2020	7
CRRC_A3	CRRC	2014	2016	3
CRRC_A4	CRRC	2015	2020	6
CRRC_A5	CRRC	2014	2019	6
CRRC_A6	CRRC	2015	2019	5
DUNAN_A1	Dunan	2008	2014	5
DUNAN_B1	Dunan	2004	2012	5
DUNAN_B2	Dunan	2007	2014	7
GCL_A1	GCL	2015	2017	3
GENSCRIPT_A1	Genscript	2008	2019	11
GOODIX_A1	Goodix	2017	2019	3
GREATWALL_A1	Greatwall	2008	2014	7
GREATWALL_B1	Greatwall	2007	2020	14
HAIER_A1	Haier	2007	2019	8
HAIER_A2	Haier	1997	2020	15
HAIER_A3	Haier	2010	2016	7
HAIER_A4	Haier	1999	2018	18
HAIER_A5	Haier	2008	2019	12
HAIER_A6	Haier	1997	2019	23
HIKVISION_A1	Hikvision	2015	2020	6
HISENSE_A1	Hisense	2013	2020	8
HISENSE_A2	Hisense	2012	2020	9
HISENSE_A3	Hisense	2011	2018	8
HISENSE_A4	Hisense	2013	2018	6
HONGFA_A1	Hongfa	2002	2020	14
HUAGONG_A1	Huagong	2017	2020	4
HUAGONG_A2	Huagong	2017	2020	4
HUARUI_A1	Huarui	2006	2018	12
HUAXIANG_A1	huaxiang	2011	2019	6
JAC_A1	JAC	2016	2017	2
JAC_A2	JAC	2016	2017	2
JOYSON_A1	Joyson	2010	2020	11
JOYSON_A2	Joyson	2008	2020	12
JOYSON_A3	Joyson	2005	2020	13
KANGDE_A1	Kangde	2013	2018	4
KEDA_A1	keda	2007	2019	10
KINGENTA_A1	Kingenta	2008	2019	11
KINGFA_A1	Kingfa	2008	2019	8
KINGFA_A2	Kingfa	2017	2019	3
KINGFA_A3	Kingfa	2012	2020	9
LENOVO_A1	Lenovo	2000	2020	21
LENOVO_A2	Lenovo	2014	2019	5
LENOVO_A3	Lenovo	2003	2019	11
LENOVO_A4	Lenovo	2011	2019	9
LENOVO_A5	Lenovo	2005	2019	15
LEPU_A1	Lepu	2013	2020	8
LINGLONG_A1	Linglong	2015	2020	6
LINGYI_A1	Lingyi	2017	2019	3

LIUGONG_A1	Liugong	2014	2018	5
LIUGONG_A2	Liugong	2015	2018	4
LIUGONG_A3	Liugong	2014	2020	7
LIUGONG_A4	Liugong	2013	2019	7
LONGSHENG_A1	Longsheng	2009	2019	10
LUTHAI_A1	Luthai	2008	2020	10
LUXI_A1	Luxi	2011	2020	10
LUXSHARE_A1	Luxshare	2012	2020	7
LUYE_A1	Luye	2003	2015	10
LUYE_A2	Luye	2012	2020	8
ORIGIN_A1	Origin	2018	2020	3
SANHUA_A1	Sanhua	2017	2019	3
SANHUA_A2	Sanhua	2010	2018	8
SANHUA_A3	Sanhua	2016	2019	4
SUMEC_A1	Sumec	2016	2020	5
SUNING_A1	Suning	2014	2020	7
TENCENT_A1	Tencent	2008	2020	5
WANHUA_A1	Wanhua	2012	2017	6
WANHUA_A2	Wanhua	1986	2014	16
XCMG_A1	XCMG	2012	2019	8
XCMG_A2	XCMG	2014	2019	6
XCMG_A3	XCMG	2017	2019	3
YUHONG_A1	Yuhong	2009	2019	8
ZHONGDING_A1	Zhongding	2003	2019	10
ZHONGDING_A2	Zhongding	2015	2019	3
ZHONGDING_A3	Zhongding	1987	2018	23
ZHONGDING_A4	Zhongding	1978	2018	36
ZOTYE_A1	Zotye	2012	2019	6
ZTE_A1	ZTE	2003	2017	15
ZTE_A2	ZTE	2005	2017	12
ZTE_A3	ZTE	2009	2018	9
ZTE_A4	ZTE	2007	2018	11
ZTE_A5	ZTE	2005	2017	13
ZTE_A6	ZTE	2009	2017	7
ZTE_A7	ZTE	2002	2017	16
ZTE_A8	ZTE	2004	2016	13

### Summary statistics

	Mean	SD	Min	Max
First year	2009	6.5	1978	2018
Last year	2018	1.65	2012	2020
# of years	8.63	5.15	2	36

### Distribution of the number of units and the number of years for which apply for patents

# of year	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	18	21	23	36
# of research units	3	9	8	6	13	9	14	6	7	5	5	4	1	3	2	1	1	2	1



## Chapter 3: THE ROLE OF INTRA-FIRM NETWORKS AND GATEKEEPERS FOR TECHNOLOGICAL CATH-UP<sup>9</sup>

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### 3.1 INTRODUCTION

The ability of emerging markets multinational corporations (EM MNE) to leverage reverse knowledge across dispersed foreign subsidiaries has become essential for achieving knowledge absorption and technological catch-up. Knowledge absorption and integration from geographically dispersed subsidiaries remain a challenge (Hennart, 2012; Alnuaimi et al., 2012; Chen et al., 2019). Different from the traditional phenomenon of knowledge flowing from the parent company to foreign subsidiaries (Meyer et al., 2008), overseas research units of EM MNEs usually transfer knowledge from host countries back home (Wang et al., 2018). Knowledge acquired from developed countries is crucial to the challenge of catching-up for EM MNEs and helps to shorten the distance between EM MNEs and incumbents (Verbeke, 2009). However, knowledge sourcing *per se* does not guarantee success in innovation outcomes, EM MNEs must combine external knowledge with their own knowledge base to produce recombinant creations (Anand et al., 2021). Difficulties are often observed in this integration process (Amighini et al., 2015) due to the lack of knowledge absorptive capacity. High transaction cost caused by geographical distance and cultural differences in various foreign sites remains an obstacle to EM MNEs' knowledge integration (Alnuaimi et al., 2012). Singh (2008) underlines the fact that dispersion of R&D activities may even have a negative effect on the value of innovations if a company does not have enough ability to integrate cross-regional knowledge, namely absorptive capacity. Cohen and Levinthal (1990) define absorptive capacity as "a company's ability to recognize the value of new external knowledge, assimilate it, and apply it to commercial ends" (p.128). Various studies have confirmed the positive relationship between knowledge absorptive capacity and innovation outcome (Binder, 2020).

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<sup>9</sup> This work has been co-authored with Anne Plunket and a first draft has been presented at the 6<sup>th</sup> Geography of Innovation Conference, Milan 4-6 July 2022

In the specific case of EM MNEs, Mathews (2002; 2006) proposes a “Linkage-Leverage-Learning” framework, which provides an ideal company-level theoretical background to analyze the mechanism of knowledge absorptive capacity. Linkages refer to connections with incumbent knowledge owners in foreign countries and correspond to the strategy of external knowledge sourcing. Leverage refers to EM MNEs’ capacity to secure resources from external linkages (Chen et al., 2019), including transferring knowledge from overseas research units back to their home companies. The final learning stage describes applications of knowledge in the company’s own innovation outcomes.

Among the learning and absorption mechanisms, increasing attention has been devoted to cross-country collaborations and intra-firm networks and the interactions between inventors as integration mechanisms (Singh, 2008; Ebers and Maurer, 2014; Giuliani et al., 2016; Alnuaimi et al., 2012). Though previous researchers have shed light on EM MNEs’ knowledge absorptive capacity at the company level, only a few (Alnuaimi et al., 2012) break down into inventor level to explore the role of key individual players in the mechanism. Especially the role of these individuals in the process of reverse transfer of knowledge between overseas research units and home companies requires further exploration. Thus, in this chapter, we investigate the structure of intra-firm networks and the role of specific inventors, namely gatekeepers, as knowledge integration mechanisms in EM MNEs’ knowledge integration process, to fill this gap. Adapting its original definition (Giuliani and Bell, 2005; Grigoriou and Rothaermel, 2013; Le Gallo and Plunket, 2020) to the case of EM MNEs, gatekeepers are interfaces between intra- and extra-unit knowledge sources that serve as global pipelines of knowledge transfer and combine external search (linkage stage) with assimilation efforts (leverage stage).

The chapter is organized as follows. The next section discusses the theoretical backgrounds related to the hypotheses. Section 3 describes the data, variables, and the empirical methodology employed in the analysis. The results are presented in Section 4, and the final section concludes.

## 3.2 THEORETICAL BACKGROUND AND HYPOTHESES

### 3.2.1 Knowledge sourcing and foreign research units

Innovation has long been regarded as a process of recombination, in which firms integrate new knowledge with existing ones in original ways (Davis & Eisenhardt, 2011). The novelty of innovation is tightly related to external knowledge sourcing, which enlarges the breadth of a firm's knowledge base that can serve as input for recombination (Dahlander et al., 2016).

#### 3.2.1.1 *Technological catch-up and EM MNEs*

As Awate et al. (2015) state, the catch-up strategy is the main motivation for EM MNEs' R&D internationalization. It exists in both mature traditional industries and emerging knowledge-intensive industries. Knowledge acquired from developed countries is crucial to the challenge of catch-up for EM MNEs and helps to shorten the distance between EM MNEs and industrial incumbents (Verbeke, 2009). Previous researchers (Awate et al., 2015; Zhang & Zhou, 2016) demonstrate how various EM MNEs import foreign advanced technologies, adapt them to local market conditions, and gradually enter overseas markets to compete with industrial leaders. Giuliani et al. (2015) provide empirical evidence which confirms that EM MNEs benefit from cross-border co-inventions with developed countries. These collaborations lead to higher innovation quality and quantity and contribute to the catch-up strategy. Meanwhile, Zhao et al. (2021) provide an overview of R&D internationalization in various developing Asian countries. Their study shows that knowledge transfer between these countries is also growing. Based on cases of Chinese MNEs, Ebersberger and Mengis (2021) demonstrate a two-phase catch-up scenario: lower level of learning (e.g. cross-border ownership of advanced knowledge) help more in innovation during the early phase, while higher levels of learning (e.g. co-invention) is preferred in the later phase. The speed of technological catch-up is negatively related to geographic distance, which means it is harder for firms far away from industrial leaders to shorten the technological gap (Griffith et al., 2009).

To fulfill the goal of technological catch-up, various MNEs from emerging markets chose to set up overseas research units, both through the self-built model and acquisitions, to source

knowledge from foreign environments (Wang et al., 2018). These units enable both lower and higher levels of learning. Different from the traditional phenomenon of knowledge flowing from the parent company to foreign subsidiaries (Yang et al., 2008), overseas research units of EM MNEs usually transfer knowledge from host countries back home (Wang et al., 2018). The reverse knowledge transfer is closely related to the innovativeness of MNEs' subsidiaries, but this relation is not always positive. The effect of subsidiary innovativeness on reverse knowledge transfers has been proved to be an inverted U-shape (Mudambi et al., 2014). Najafi-Tavani et al.'s (2015) survey-based study reveals that the autonomy of subsidiaries engaging in reverse knowledge transfer increases within MNEs, especially when they have a high internal embeddedness. Nair et al. (2018) point out the fact that EM MNEs are more likely to engage with reverse knowledge transfer when dealing with tacit knowledge which facilitates their catch-up strategy. Compared to organizational-level studies on reverse knowledge transfer, relatively fewer researchers focus on the function of individuals in this process. Liu and Meyer (2020) highlight the importance of personal ability and team collaboration in the reverse knowledge transfer process, especially the role of the specific boundary spanners. Our study deepens the understanding of individual-level activities in reverse knowledge transfer.

#### *3.2.1.2 Potential gains from geographically distant sources and related difficulties*

Accumulation of knowledge enhances companies' abilities to develop new ideas and convert this knowledge base into further innovations (Cohen and Levinthal, 1990), which is crucial for EM MNEs during their technological catch-up. However, a large proportion of knowledge is locally embedded (Asheim, 1999). As mentioned above, EM MNEs set up overseas research units. One of the main functions of these units is to take advantage of specific knowledge and enjoy knowledge spillovers in different locations (Meyer et al., 2009). Although Shaver and Flyer (2000) indicate that collocation with other firms may cause knowledge outflow, this disadvantage is mainly the concern of local leading firms, while EM MNEs tend to benefit more than lose from proximate competitors.

As knowledge sourcing per se does not guarantee success in innovation outcomes, EM MNEs must combine knowledge sourced externally with their own knowledge base to produce

recombinant creations (Anand et al., 2021). Difficulties are often observed in this integration process (Amighini et al., 2015) due to the lack of absorptive capacity. The probability of recombination might be limited when firms are not familiar with distant knowledge and increase difficulties in internalizing and leveraging it, thus reducing the value of innovations (Capaldo et al., 2017). Singh (2008) underlines the fact that dispersion of R&D activities may even have a negative effect on the value of innovations if a company does not have enough ability to integrate cross-regional knowledge. High transaction cost remains an obstacle to EM MNEs' knowledge integration. The transaction cost is caused by geographical distance and cultural differences in various foreign sites (Alnuaimi et al., 2012). At the unit level, there also exists a sort of indirect cost, which includes the loss of opportunities to develop units' own learning capabilities (Andersson et al., 2015). Thus, well-fabricated knowledge absorption mechanisms become essential to cope with these difficulties.

### **3.2.2 Knowledge absorption mechanisms**

Cohen and Levinthal (1990) defined absorptive capacity as a company's ability to "recognize the value of new external knowledge, assimilate it and apply it to commercial ends". High absorptive capacity is identified as an essential element while maintaining wide access to external knowledge (Giuliani and Bell, 2005), which plays an essential role in the knowledge integration mechanism. Various literatures have confirmed the positive relationship between knowledge absorptive capacity and innovation outcome (Binder, 2020).

In the context of EM MNEs, Mathews (2002; 2006) advanced the "Linkage-Leverage-Learning" framework, offering a comprehensive firm-level theoretical perspective for examining the dynamics of knowledge absorptive capacity. Within this framework, "Linkages" denote associations with established knowledge holders abroad, aligning with the strategy of external knowledge acquisition. "Leverage" signifies the ability of EM MNEs to harness resources from these external associations, encompassing the transfer of knowledge from international research facilities to their respective parent entities. Lastly, "Learning" pertains to the utilization of this knowledge in the pursuit of the firm's own innovative endeavors.

Among the learning and absorption mechanisms, increasing attention has been devoted to cross-country collaborations and intra-firm networks and the interactions between inventors as integration mechanisms (Singh, 2008; Ebers and Maurer, 2014; Giuliani et al., 2015; Alnuaimi et al., 2012). This issue is discussed in the next subsection.

### *3.2.2.1 Internal network*

As stated above, knowledge sourcing in a foreign environment does not guarantee success in innovation outcomes. MNEs encounter various obstacles in integrating this knowledge into their knowledge base, such as geographical distance and cultural differences in various foreign sites (Alnuaimi et al., 2012). Singh et al. (2010) denote the fact that less connected members in the internal network have difficulties in accessing new information, and their efficiency will be diminished. Internal linkages among inventors and different units have long been identified as an important factor that affects the absorption of new knowledge. Frost and Zhou (2005) especially point out that internal linkages help to transfer locally sourced knowledge back to the parent company. Internal linkages also have a significant positive influence on firms' ability to organize innovation activities between locations with increased geographic distance (Lahiri, 2010).

As Frost and Zhou (2005) point out, internal linkages in the networks largely facilitate the reverse transfer of local knowledge back to the parent firm. Besides their positive role in knowledge internalization, Alcácer and Zhao (2012) also notice the function of internal ties in preventing knowledge expropriation by nearby competitors. Singh (2008) emphasizes the role of internal inventors with cross-regional linkages. Castellani and Scalera's (2022) recent study reconfirms Singh's (2008) finding that the mobility of inventors between locations within MNEs' internal networks is positively related to the cross-border knowledge integration process. As for the effects of internal network structure, Moreira and Laursen (2018) find empirical evidence that supports the fact that internal network diversity and density enhance firms' absorptive capacity of external knowledge, especially those distant from their existing knowledge base. However, the role of the internal network is not always positive.

Besides the positive impacts mentioned above, Grigoriou and Rothaermel (2017) observe that when a company possesses an internal network with high knowledge recombination ability, external knowledge sourcing is likely to be less effective. This phenomenon can be explained by the fact that internal and external knowledge-sourcing processing is substituted as external knowledge-sourcing efforts increase the burden of coordination costs. It should be noted that their findings are based on data from technological incumbents. Thus, the situation for EM MNEs seeking catch-up may differ.

We want first to identify if new knowledge sourced abroad by inventors in EM MNEs' overseas research units is successfully transmitted back to home companies through intra-firm networks with connected inventors and facilitates the further development of patents with new combinations. Hereby, we give out the first hypothesis:

***Hypothesis 1: Home companies with more direct connections with overseas research units are more likely to increase patent novelty.***

#### *3.2.2.2 Gatekeepers and technological proximity*

Firms occupying brokerage positions have higher possibilities to develop new combinations (Burt 1992). By bridging a structural hole between two disconnected actors, brokers may gain opportunities, including timely information, access to resources, and establish new, non-redundant ties (Burt 1992). Balachandran and Hernandez (2018) further distinguish three types of triads while studying brokerage and innovation. They suggest domestic, foreign, and mixed triads all enhance innovation performances: domestic ones mainly improve innovation volumes, and foreign ones improve innovation radicalness, while mixed triads are less efficient compared to the other two types. This also reflects the difficulty of knowledge recombination between actors facing geographical and technological distances. Lee (2010) points out that actors with high performance are more likely to seize brokerage opportunities. Adapting its original definition (Giuliani and Bell, 2005; Grigoriou and Rothaermel, 2013; Le Gallo and Plunket, 2020) to the case of EM MNEs, gatekeepers are defined in this chapter as interfaces between intra- and extra-unit knowledge sources that serve as global pipelines of knowledge transfer. The inventors help to source external knowledge and enhance the inventive

performance of teams (Le Gallo and Plunket, 2020). According to Ter wal et al. (2017), gatekeepers combine external search (linkage stage) with assimilation efforts (leverage stage).

In detail, the positive functions of gatekeepers come in two folds. First, by being located in overseas target regions, they benefit from geographic and social proximities with local firms to source new external knowledge (Broekel & Mueller, 2018). Second, they help to overcome the technological distance between overseas units and the home company. As Cassi and Plunket (2014) indicate, knowledge sharing is easier among actors with similar knowledge bases. On the contrary, a large technological distance is proved to be a barrier in the knowledge absorption process and thus diminishes the innovation performance (Gilsing et al., 2008). Gatekeepers can reduce such technological distance (Giuliani, 2011) by bridging various teams. Though previous researchers have shed light on EM MNEs' knowledge absorptive capacity at the company level, only a few (Alnuaimi et al., 2012) break down into inventor level to explore the role of key individual players in the mechanism. The role of gatekeepers in the reverse transfer of knowledge between overseas research units and home companies requires further exploration.

Cohen and Levinthal (1990) highlight combining knowledge as a central issue of innovation. In the case of EM MNEs, when new knowledge is transmitted back to home companies, it will not flow through the organization and generate new innovations automatically. Instead, it needs to be further combined with the knowledge that already exists in the organization to promote the innovation capacity of the whole company (Awate et al., 2015). Burt (2015) confirms that those who connect across structural holes are more likely to make use of segregated knowledge dispersed in different divisions of the organizations for new combinations. Grigoriou and Rothaermel (2013) also discuss the positive role of relational stars in the innovation process. According to Balachandran and Hernandez's (2018) research, foreign triads that span the boundary of a company correspond to the enhancement of innovation's radicalness, while domestic ones increase the volume of innovation. This implies that internal inventors with brokerage positions in the knowledge integration mechanism facilitate the combination of newly sourced external knowledge with existing ones. Eisenman and Paruchuri (2019) focus on knowledge integration after the merger of two firms and

confirm that inventors with high levels of brokerage are more likely to produce more knowledge recombination utilizing the new knowledge acquired.

Lissoni (2010) also builds on the work by Gould and Fernandez (1989) to distinguish different types of academic inventors with brokerage positions: *coordinators* are regarded as the ones with brokerage position between two other inventors from the same group; *brokers* are defined as the ones with brokerage position between two other inventors from another group; while *gatekeepers* are the ones who make use of the brokerage position to transfer knowledge from inventors outside his group to inventors within his group. So, gatekeepers act as a specific type of inventor with brokerage position and serves as an interface between different groups. They facilitate knowledge diffusion through their connections and offer greater potential for novel combinations and breakthrough inventions (Le Gallo & Plunket, 2020). Morrison (2008) also points out their function of interpreting external knowledge, which can transcode complex knowledge for diffusion with internal members. According to Allen's (1977) descriptions, gatekeepers have a central position in a network and are exposed to external information. To be more precise, in this paper, we define a gatekeeper as a broker who is highly embedded in the home company and related to overseas research unit's inventors. We assume that they are key actors in the EM MNEs' cross-border knowledge integration process with the ability of knowledge mediation and enhancing the capacity of knowledge transfer. Thus, the second hypothesis concerns the role of gatekeepers in EM MNEs' knowledge integration mechanism:

***Hypothesis 2: Gatekeepers within home companies are more likely to increase patent novelty.***

### **3.3 DATA AND VARIABLES**

#### **3.3.1 Data and network construction**

This research is based on an original self-built dataset which includes patent applications of Chinese MNEs with overseas research units in different countries. As described in Chapter 1, the list of Chinese MNEs is extracted from the top 500 Chinese enterprises 2018 by

Fortunechina.com and the 2019 OECD scoreboard of the top 2000 global corporate R&D investor<sup>10</sup>. An extensive search has enabled us to identify their overseas research units. Then, the patent applications from various patent offices (USPTO, EPO, CNIPA, etc.) has been extracted using the LENS database. Patent data have been further consolidated at the family level and inventor names have been disambiguated. Inventors have been attributed to the overseas R&D units on the one hand and to the home company on the other hand based on their location information. The final dataset contains 154,098 patent applications from 51 Chinese MNEs.

Based on these data, we investigate the mechanisms through which MNEs benefit from their relationships with their research units abroad to produce new knowledge. As knowledge is difficult to move across countries and continents, we investigate specific *mechanisms that facilitate knowledge integration from the home company in China*. More precisely, we investigate whether inventors from the home company having gatekeeping positions between abroad subsidiaries and their home company affect the degree of novelty of patents they contribute to inventions. To estimate the impact of the inventor position on patent novelty, we first construct the intra-firm co-inventor network. We define inventors as nodes in the intra-firm network (Paruchuri and Awate, 2017) and consider that there are ties between inventors if they appear on the same patent document. The intra-firm network is built for each year  $t$ , based on co-invention ties formed during the five previous years and excluding older ties (Breschi and Lissoni, 2009). The final data are restricted to inventors with at least one prior patent and who have at least two patents assigned to the same firm. This network is used to determine the extent of intra-firm network reach and gatekeeping positions. Network analysis is built using the Igraph R Package<sup>11</sup> (Csardi & Nepusz, 2006). Because of these restrictions of the initial sample, the final dataset includes 85 239 patents over the period applied by 51 firms.

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<sup>10</sup> the JRC/OECD COR&DIP© database, v.2. 2019

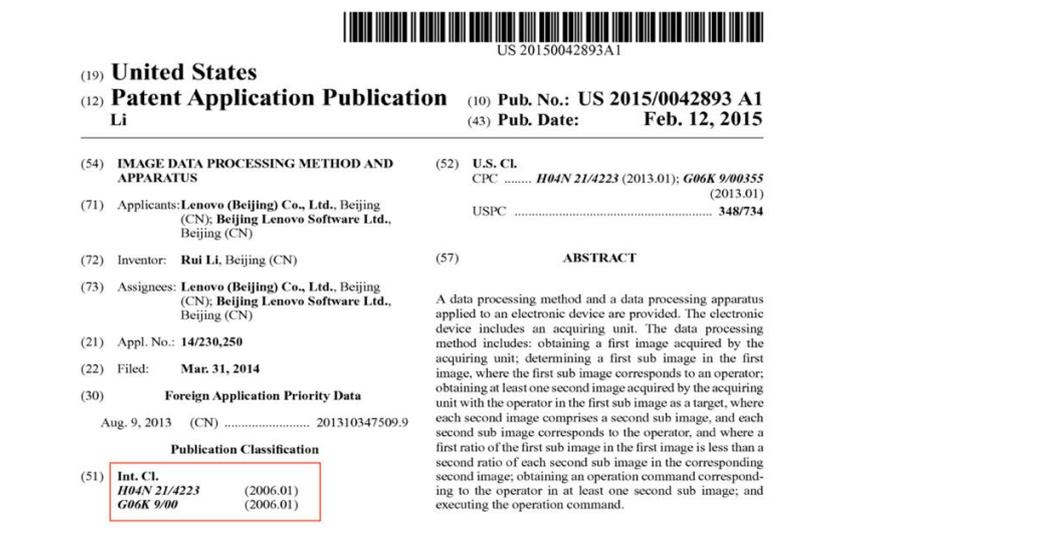
<sup>11</sup> Csardi, G., & Nepusz, T. (2006). The Igraph software package for complex network research. In *InterJournal: Vol. Complex Systems* (p. 1695). <https://igraph.org>

### 3.3.2 Variables

#### 3.3.2.1 Dependent variable

The aim of this chapter is to study whether EM MNEs benefit from their units abroad to renew their knowledge base and produce novelty. Said differently, do inventors become more creative when they are in a relationship with inventors located abroad?

Figure 3.1 Example of the patent document<sup>12</sup>



If exposed to knowledge coming from abroad, they may increase the novelty of their inventive output. Following previous literature, we built our analysis on the concept of recombinant search and measure novelty as a new combination of technological components (Fleming et al., 2007; Arts and Fleming, 2018). But unlike previous studies, we restrict the analysis to combinations that are new to the firm. **Patent novelty** is computed as the **number of new combinations**, that is, the number of pairwise subclass (4-digit IPC) combinations of a patent that appear for the first time in the company's patent portfolio. Figure 3.1. give an example of a USPTO patent document applied by Lenovo. The IPC code is highlighted by the red square.

<sup>12</sup> <https://www.lens.org/lens/patent/059-910-884-915-701/frontpage?l=en>

The 4-digit IPC codes in the example are H04N and G06K. If they are combined for the first time in a patent within the company, it is considered as a new combination.

### 3.3.2.2 *Independent variables*

All independent variables are calculated at the **patent level**. The main variables of interest rely on the position of inventors within MNEs and their relationship with unit inventors. The idea is to test various variables that consider the inventor's position within the home company and with unit inventors. Three sets of variables are distinguished.

First, we compute **the number of gatekeepers** within patent teams. An inventor with a gatekeeping position captures the fact that highly central inventors within the home company (excluding unit inventors) who are also directly connected to unit inventors are more likely to source knowledge from foreign subsidiaries and produce novel technologies. Gatekeepers are computed in two ways following the literature:

1. an inventor is a **gatekeeper (internal distance)** if she has a direct link to an inventor in a unit and has a distance-weighted reachability over the average within the home company. The distance-weighted reachability is computed as the sum of the inverse geodesic distance  $d_{ij}$  between the given inventor  $i$  and all the other inventors  $j$  within the home company divided by the number of inventors reached. It captures the number of inventors that can be reached by a given individual as well as the path length needed to reach them (Borgatti, 2006; Le Gallo and Plunket, 2020).

2. an inventor is a **gatekeeper (betweenness centrality)** if the inventor has a direct link to an inventor in a unit and a betweenness centrality over the average within the home company, excluding unit inventors.

In the regression, we consider the number of gatekeepers as well as the dummy variable, taking value 1 if there is at least one gatekeeper in the team.

Second, we compute **the network proximity to the units**, which is the sum of team inventors' inverse geodesic distance from home company to unit inventors.

Third, we compute **the number of direct collaborations with units**, that is, the number of unit inventors to which the team has a direct tie.

### 3.3.2.3 Control variables

For each patent, we compute several control variables characterizing the inventor team's inventive capacity.

**Technological diversity** captures the fact that greater diversity in the inventor team's knowledge base provides more opportunities to combine new technologies and produce novelty. It is as the Blau index of subclasses in the inventors' technological portfolio, averaged over the patent team (Cerere & Ozman, 2014). **Technological distance** is the technological distance between the home company inventor and inventors within units. This value is averaged over the team of inventors. It is computed as Jaffe's index (Jaffe, 1989), which is a proximity measure ranging between 0 and 1, depending on the degree of overlap between the inventors' prior patent IPC codes. The variables is calculated as:

$$(P_i, P_j) = \frac{\sum p_{ik}p_{jk}}{\sqrt{(\sum_k p_{ik}^2)(\sum_k p_{jk}^2)}}$$

The patent portfolio vector P specifies for each inventor the share of his patents in every one of n relevant patent subclasses, while  $p_{ik}$  represent the share inventor i has in class k (Jaffe, 1989).

**Inventor experience** is the average number of prior patents for all inventors in the patent team. The number of patents for each inventor is computed over the past five years. The **team size** is the number of inventors involved in the team that produced the patent. **The number of patent subclasses** is the number of IPC subclasses characterizing the patent. It controls the fact that more complex patents within more subclasses have a higher probability of producing new combinations. It also enables the control of patents with only one subclass for which it is difficult to decide the character of novelty. Prior knowledge helps inventors better interpret information and guide creative search, but it may also constrain search (Arts and Fleming, 2018). The **number of new subclasses** controls for the fact that the introduction of a new

subclass (see previous chapter) within the portfolio creates, by definition, a new combination when it is combined with any other subclass. The *firm stock* is controlled through the number of patents assigned to the firm over the prior five years.

All continuous variables are introduced in logs within regression.

**Table 3.1 Description of variables**

<b>Dependent variables</b>	
Patent novelty	The number of new combinations, that is, the number of pairwise subclass combinations of a patent that appear for the first time in the company's patent portfolio (in logs)
<b>Variables of interest</b>	
<b>Gatekeeper variables</b>	
Number of Gatekeepers (inventor distance)	The number of inventors with a gatekeeper position within the team in logs. A gatekeeper is a home company inventor that has a direct link to inventors within units and over the average reachability within the home company.
Number of gatekeepers (betweenness centrality)	The number of inventors with a gatekeeper position within the team in logs. A gatekeeper is a home company inventor that has a direct link to inventors within units and over the average betweenness centrality within the home company.
Gatekeepers (internal distance)	Takes value 1 if there is at least one inventor with a gatekeeper position within the team (based on internal distance)
Gatekeepers (betweenness centrality)	Takes value 1 if there is at least one inventor with a gatekeeper position within the team (based on betweenness centrality)
<b>Network variables</b>	
Network proximity to the units	the sum of team inventors' inverse geodesic distance from home company to unit inventors (in logs)
Number of direct collaborations with units	the number of unit inventors to which the team has a direct tie (in logs)
<b>Control variables</b>	
Technological diversity	The Blau index of subclasses in the inventors' technological portfolio, averaged over the patent team (in logs)
Technological distance	Technological distance between the home company inventor and inventors within units. This value is averaged over the team base on the Jaffe index.
Inventor experience	the average number of prior patents over all inventors in the patent team (in logs)
Number of patent subclasses	The number of subclasses in the patent (in logs)
Number of new subclasses	The number of new subclasses at the firm level appearing for the first time in this patent (in logs)
Firm patent stock	The number of patents assigned to the firm over the prior five years (in logs)
Team size	The number of inventors involved in the team that produced the patent (in logs)

### 3.3.3 Descriptive statistics

The final sample is composed of 85,239 observations for 51 MNEs among which three firms have no linkages with their units. Table 3.2. provides descriptive statistics for the variables used in the regressions. Notably, the mean patent novelty equals 0.10 with a standard deviation of 0.54. The mean value is rather low and illustrates the fact that only 7% of patents introduce novel combinations. Regarding gatekeepers, two definitions are adopted. 25% of

patents include gatekeepers (defined in terms of internal distance) and 19% for gatekeepers measured by betweenness centrality. The number of gatekeepers in the inventor teams demonstrates a relatively large variation. Inventor technological diversity exhibits an average of 0.53 with a moderate standard deviation, ranging from 0 to 1. Meanwhile, the average size of the inventor team is 2.55 with a standard deviation of 1.72, spanning from 1 to 9. Inventor experience shows an average of 15.12 in terms of past patenting activity, which also varies largely depending on different individuals. Firm stock shows an average of 6884.69, with a wide standard deviation of 7842.19, indicating the huge difference between the knowledge stock of MNEs in the samples. The number of IPC subclasses has an average of 1.27, with some variability and a standard deviation of 0.63. Number of new IPC subclasses exhibits a mean of 0.04, with a standard deviation of 0.24, which also suggests that most patents do not include external new knowledge.

**Table 3.2 Descriptive statistics**

	Mean	SD	Min	Max
Patent novelty	0.10	0.54	0	18
Number of Gatekeeper (internal distance)	0.36	0.72	0	8
Gatekeepers (internal distance)	0.25	0.43	0	1
Number of Gatekeepers (betweenness centrality)	0.23	0.53	0	5
Gatekeeper (betweenness centrality)	0.19	0.39	0	1
Inventor technological diversity	0.53	0.28	0	0.99
Team size	2.55	1.72	1	9
Inventor experience	15.12	21.47	1	168
Firm patent stock	6884.69	7842.19	6	24725
Number of IPC subclasses	1.27	0.63	0	8
Number of new IPC subclasses	0.04	0.24	0	5
Number of direct collaborations with the unit	1.49	3.87	0	71
Number of units	3.44	2.42	0	7
Brokerage	1.6	0.24	0.87	2
Network Proximity to the unit	1.90	1.95	0	16.16
Technological distance	0.56	0.32	0	1
Observations	85239			

The number of direct collaborations with the units has an average of 1.491, but a substantial standard deviation of 3.873. The number of units shows an average of 3.445, with a moderate standard deviation of 2.423, revealing the geographical dispersion of the MNEs in the sample. Brokerage has an average of 1.69 and low variability with a standard deviation of 0.247. Finally, Network Proximity to the unit" has an average of 1.901, with a moderate standard

deviation of 1.959, indicating the difference of social distance between various inventors in home companies and overseas units.

**Table 3.3 Patents and firms across Economic activities (ISIC Rev.4 sections)**

<b>Industry</b>	<b>Sectors (Agregated)</b>	<b># Patents</b>	<b># firms</b>
F	Construction	686	1
J	Information and communication	21002	6
C	Manufacturing	61893	41
B	Mining and quarrying	1619	1
E	Water supply; sewerage, waste management and remediation activities	39	1
<b>Industry</b>	<b>Sectors (Disagregated)</b>	<b># Patents</b>	<b># firms</b>
F	Construction of buildings	686	1
J	Computer programming, consultancy and related activities	1034	2
J	Information and communication	403	1
J	Information service activities	323	1
J	Manufacture of electrical equipment	300	6
J	Telecommunications	18555	1
C	Manufacture of chemicals and chemical products	4004	8
C	Manufacture of computer, electronic and optical products	16944	3
C	Manufacture of electrical equipment	5904	6
C	Manufacture of fabricated metal products, except machinery and equipment	81	2
C	Manufacture of food products	971	2
C	Manufacture of machinery and equipment	4201	5
C	Manufacture of motor vehicles, trailers and semi-trailers	24209	8
C	Manufacture of other transport equipment	4033	2
C	Manufacture of pharmaceuticals, medicinal chemical and botanical products	1440	4
C	Manufacture of textiles	350	1
C	Other manufacturing	443	1
B	Extraction of crude petroleum and natural gas	1619	1
E	Water collection, treatment and supply	39	1

Table 3.3. provides a distribution of the number of patents and the number of MNE firms in the sample and across industries. Firms are concentrated within Manufacturing and Information and communication, which is coherent with the description in the first chapter. Otherwise, the number of firms is rather dispersed across manufacturing with a concentration of patents Telecommunications, Computer electronic and optical products, and Motor vehicles trailers and semi-trailers.

Table 3.4 presents the results of a T-test on the equality of means comparing between patents with gatekeepers in the inventor team and patents without gatekeepers. The upper part shows the T-test for gatekeepers in terms of internal distance. The analysis reveals several statistically significant differences that shed light on the characteristics and behaviors of these

two groups. Teams with gatekeepers are found to have significantly lower technological distance, indicating higher technological proximity to unit inventors. They also exhibit greater inventor technological diversity, suggesting a broader range of knowledge breath within their teams. Additionally, teams with gatekeepers have a larger size and boast substantially more inventor experience, emphasizing their potential for creating new recombination. Teams with gatekeepers also engage in significantly more direct collaborations with the units and are more closely related to the units, as indicated by the network proximity. Furthermore, teams with gatekeepers have a significantly higher degree of brokerage in the network, underlining their pivotal position in bridging different actors in the network.

**Table 3.4 T-test of gatekeepers**

<b>T-test for Gatekeepers (internal distance)</b>				
	<b>Gatekeeper mean</b>	<b>Other mean</b>	<b>Difference Mean</b>	<b>S.E</b>
Technological distance	0.524	0.584	0.059***	0.003
Inventor technological diversity	0.584	0.524	-0.060***	0.002
Team size	3.385	2.269	-1.116***	0.013
Inventor experience	20.314	13.326	-6.987***	0.167
Number of direct collaborations with the unit	3.244	0.885	-2.359***	0.029
Brokerage	1.779	1.659	-0.120***	0.002
Network Proximity to the unit	3.741	1.265	-2.475***	0.013
Observations	21,892	63,347	85,239	

<b>T-test of gatekeeper (betweenness centrality)</b>				
	<b>Gatekeeper mean</b>	<b>Other mean</b>	<b>Difference Mean</b>	<b>SE</b>
Technological distance	0.526	0.579	0.053***	0.003
Inventor technological diversity	0.604	0.524	-0.080***	0.002
Team size	3.429	2.349	-1.080***	0.015
Inventor experience	21.981	13.505	-8.476***	0.185
Number of direct collaborations with the unit	2.783	1.186	-1.597***	0.033
Brokerage	1.802	1.664	-0.138***	0.002
Network Proximity to the unit	3.68	1.482	-2.198***	0.015
Observations	16,251	68,988	85,239	

The lower part of the table shows the results of the T-test when gatekeepers are measured by betweenness centrality. The number of patents with this type of gatekeeper in the teams is lower than the number of patents with the previous category of gatekeeper. But the overall characteristics are similar to those in the upper part of the table.

## 3.4 ESTIMATION STRATEGY AND RESULTS

### 3.4.1 Estimation strategy

The empirical analysis aims at understanding how home company inventors' position within the home company and towards research unit inventors facilitates knowledge integration and the production of patent novelty, measured by, the number of new combinations controlling for the inventor-team and invention characteristics.

The first strategy is to test a linear model using OLS estimations with firm ( $i$ ) and year ( $t$ ) fixed effects to control for invariant company-specific factors that may affect the empirical results.

$$\text{Novelty}_{it} = \alpha \text{Inventor network position}_{it} + \beta \text{Controls}_{it} + \delta_i + \delta_t + \varepsilon_{it}$$

Inventor network position may here be the number of gatekeepers within the team, the proximity, or the number of direct ties to unit inventors. Results are reported in table 3.7.

Because our data only record the patenting activity of inventor teams after collaboration, we cannot determine whether collaborations were formed to exploit an opportunity already identified or whether the gatekeeping and intermediation roles caused an increase in novelty as hypothesized. Said differently, there may be endogeneity between network structure and performance. The ideal situation would be to have a measure that enables to control for the intent to use the co-inventor network to produce new technological combinations. As this is not possible and to estimate the impact of external knowledge sourcing on the home companies' patent novelty, we use a two-stage least square model (2SLS) with a robust variance estimator to control for the effects of correlation between errors due to endogeneity between the network position of inventors and their innovative performance of their inventions. To remove endogeneity, we instrument the network variables (# of gatekeepers, proximity to the unit and # of direct ties) to remove endogeneity and omitted variable bias.

An effective instrumental variable needs to correlate with cohesion but not with the outcome measure to remove any variation that is correlated with an omitted variable. The

instrumentation strategy follows Zaheer and Soda (2009) and uses past network positions as instruments. As we used many instrumental variables, we also checked for the presence of over-identification of our model with a Sargan test, which provides a measure of instrument relevance. The inability to reject the null hypothesis indicates that the model is not over-identified and is accepted for the two-stage procedure. Instrumental variables used in the first stage are *inventor brokerage*, *betweenness centrality*, and *degree*. Each of these variables is the mean value for each inventor within the team. Following Lee (2010), the brokerage is computed as  $2 - \text{network constraint } (C_i)$  so that higher values indicate higher constraints (Burst, 1992; Lee, 2010)  $C_i = \sum_j (P_{ij} + \sum_{q \neq i \neq j} P_{iq} P_{qj})^2$ .  $C_i$  is the network constraint of inventor  $i$  and  $P_{ij}$  is the proportion of direct connections between two inventors  $i$  and  $j$  and  $\sum_{q \neq i \neq j} P_{iq} P_{qj}$  is the sum of indirect connections between inventors  $i$  and  $j$  that are both connected to inventor  $q$ . Lower values on this measure imply that the inventors occupy less constrained positions and consequently higher brokerage positions.

### 3.4.2 OLS estimation results

Table 3.5 reports estimates testing the impact of home company inventors' position within the home company and towards unit inventors on patent novelty using OLS estimations with firm and time-fixed effects.

Models 1 and 2 test the impact of having gatekeepers within the team upon the novelty of patents. The results, concerning both types of gatekeepers, are significant and exhibit a slightly positive correlation. Models 3 and 4 test the impact of the number of gatekeepers and enable to test a nonlinear specification by introducing their quadratic form. The outcomes obtained are significant and indicate an inverted U-shaped relationship between the number of gatekeepers and the novelty of patents. This phenomenon can be explained by the fact that though increasing gatekeepers can introduce new technology into the companies' knowledge base at the beginning stage of the knowledge integration process, when the knowledge breadth increases to a certain extent, the benefit will eventually diminish. Model 5 tests the impact of the number of direct collaborations with the units on the innovativeness of patents. And surprisingly, this result does not yield any significant outcomes unlike Network proximity

to the unit which has a positive and significant impact. This result could suggest that it is not the fact of having direct ties with inventors within units that matters but rather the position of inventors that are connected to them.

**Table 3.5 Estimation results – OLS estimation with fixed effects**  
**Dependent variable: Patent novelty (log of number of new combinations)**

	(1)	(2)	(3)	(4)	(5)	(6)
Gatekeepers (internal distance)	0.006*** [0.002]					
Gatekeepers (betweenness centrality)		0.005*** [0.002]				
# of Gatekeepers (internal distance)			0.019*** [0.005]			
# of Gatekeepers (internal distance) square			-0.014*** [0.004]			
# of Gatekeeper (betweenness centrality)				0.029*** [0.007]		
# of Gatekeeper (betweenness centrality) square				-0.027*** [0.007]		
# of direct collaborations with the unit					0.003 [0.002]	
# of direct collaborations with the unit square					-0.001 [0.001]	
Network Proximity to the unit						0.010*** [0.004]
Technological distance	0.021*** [0.003]	0.020*** [0.003]	0.020*** [0.003]	0.020*** [0.003]	0.020*** [0.003]	0.022+ [0.012]
Technological diversity	-0.057*** [0.012]	-0.057*** [0.012]	-0.058*** [0.012]	-0.058*** [0.012]	-0.058*** [0.012]	-0.059** [0.023]
Technological diversity square	0.083*** [0.019]	0.083*** [0.019]	0.085*** [0.019]	0.085*** [0.019]	0.085*** [0.019]	0.086** [0.036]
Team size	-0.020*** [0.002]	-0.020*** [0.002]	-0.019*** [0.002]	-0.019*** [0.002]	-0.019*** [0.002]	-0.028*** [0.010]
Inventor experience	0.003*** [0.001]	0.003*** [0.001]	0.003*** [0.001]	0.003*** [0.001]	0.004*** [0.001]	0.002 [0.002]
Firm patent stock	-0.007*** [0.002]	-0.007*** [0.002]	-0.007*** [0.002]	-0.007*** [0.002]	-0.007*** [0.002]	-0.008** [0.003]
Number of IPC subclasses	0.428*** [0.006]	0.428*** [0.006]	0.428*** [0.006]	0.428*** [0.006]	0.428*** [0.006]	0.428*** [0.067]
Number of New IPC subclasses	0.547*** [0.011]	0.548*** [0.011]	0.548*** [0.011]	0.548*** [0.011]	0.547*** [0.011]	0.547*** [0.052]
Constant	-0.228*** [0.014]	-0.228*** [0.014]	-0.229*** [0.014]	-0.228*** [0.014]	-0.228*** [0.014]	-0.222*** [0.057]
Observations	85239	85239	85239	85239	85239	85239
R-Squared	.39	.39	.39	.39	.39	.39
Patent level analysis - Year and firm fixed effects + 0.10 ** 0.05 *** 0.01						

The control variables are also very interesting to consider. Technological distance to unit inventors has a positive impact meaning that home company inventors benefit from a knowledge base that does not overlap with their own. Technological diversity within team

members affects the degree of novelty. The quadratic form indicates that novelty benefits from a certain diversity. Team size has a negative impact, whereas inventor experience favors the number of novel combinations.

**Table 3.5 Estimation results – OLS estimation with fixed effects (Continue)**

	(7)	(8)
Network Proximity to the unit	0.005 [0.007]	-0.000 [0.007]
Technological distance x Network Proximity to the unit	0.010 [0.010]	
# of unit locations		-0.022*** [0.007]
Network Proximity to the unit x # of unit locations		0.007+ [0.004]
Technological distance	0.014 [0.009]	
Technological diversity	-0.061** [0.023]	-0.067*** [0.023]
Technological diversity square	0.086** [0.036]	0.101*** [0.037]
Team size	-0.028*** [0.010]	-0.026*** [0.009]
Inventor experience	0.003 [0.002]	-0.000 [0.002]
Firm patent stock	-0.008** [0.003]	-0.008** [0.003]
Number of IPC subclasses	0.428*** [0.067]	0.429*** [0.067]
Number of New IPC subclasses	0.547*** [0.052]	0.548*** [0.051]
Constant	-0.216*** [0.056]	-0.173*** [0.049]
Observations	85239	85239
R-Squared	.39	.39
Patent level analysis - Year and firm fixed effects + 0.10 ** 0.05 *** 0.01		

The second part of the table 3.5. shows models 7 and 8, which test two interactions to verify the moderating effect of technological distance. In Model 8, the interaction between the number of unit locations and network proximity is examined. It is found to be significant and positively correlated with the novelty of the patents. This finding suggests that home companies' proximity to units enhances their absorptive capacities, enabling better absorption of external knowledge sourced from diverse locales.

### 3.4.1 Instrumental variable estimations

These estimations use the two-step GMM approach with robust standard errors using the `ivreghdfe` routine (Correia, 2017) in Stata based on Baum et al. (2003) `ivreg2` routine. Table 3.7 reports all the estimates of the GMM estimation, showing for each regression the second stage, which is the estimation of patent novelty and the first stage, which is the estimation of the instrumental variable(s). Year and fixed effects are also introduced in the regressions. Our instruments Brokerage, Betweenness and Degree centrality are significant across all the first-stage regressions. The end of the table gives a summary of tests on instruments as well as identification. These consist of the Hansen J test on the validity of instruments, and the test of underidentification based on the Kleibergen and Paap rk statistic. The Hansen J does not enable to reject the null hypothesis, which indicates that our instruments can be considered as appropriate.

The first stage regressions indicate that technological distance, firm patent stock, and the number of IPC subclasses have a negative impact. Interestingly, technological diversity has a U-shape relation with the presence of gatekeepers. The positive coefficient of unit locations suggests that gatekeepers are more likely to appear in teams with collaborations from various locations. Inventor experience has different impacts considering the measurement of gatekeepers. For gatekeepers, in terms of internal distance, it has a negative impact.

**Table 3.6 Estimation results – 2-Step GMM estimation - Dependent variable : Patent novelty (log of number of new combinations)**

	(1) Novelty	1 <sup>st</sup> stage Gatekeepers (int dist)	(2) Novelty	1 <sup>st</sup> stage Gatekeepers (betw)	(3) Novelty	1 <sup>st</sup> stage # of Gatekeeper (int dist)	(4) Novelty	(1 <sup>st</sup> stage # of Gatekeeper (betw)
Gatekeepers (int dist)	0.11*** [0.01]							
Gatekeepers (betw)			0.10*** [0.01]					
# of Gatekeeper (int dist)					0.26*** [0.05]			
# of Gatekeeper (int dist) # # of Gatekeeper (int dist)					-0.14** [0.06]			
# of Gatekeeper (betw)							0.91*** [0.11]	
# of Gatekeeper (betw) # # of Gatekeeper (betw)							-0.93*** [0.13]	
Brokerage		0.28*** [0.01]		0.19*** [0.01]		0.29*** [0.01]		-3.98*** [0.10]
Betweenness		0.01*** [0.00]		0.02*** [0.00]		0.00*** [0.00]		
Inventor collaborations (degree)		0.06*** [0.00]				0.06*** [0.00]		0.07*** [0.00]
Brokerage # Brokerage								2.34*** [0.06]
Technological distance	0.04*** [0.00]	-0.13*** [0.01]	0.03*** [0.00]	-0.06*** [0.00]	0.04*** [0.00]	-0.12*** [0.00]	0.03*** [0.00]	-0.04*** [0.00]
Technological diversity	-0.05*** [0.01]	-0.13*** [0.02]	-0.05*** [0.01]	-0.26*** [0.02]	-0.05*** [0.01]	-0.17*** [0.02]	-0.10*** [0.02]	-0.03** [0.02]
Technological diversity square	0.06*** [0.02]	0.24*** [0.04]	0.06*** [0.02]	0.44*** [0.03]	0.07*** [0.02]	0.31*** [0.03]	0.14*** [0.02]	0.15*** [0.03]
Team size	-0.05*** [0.00]	0.21*** [0.00]	-0.04*** [0.00]	0.16*** [0.00]	-0.05*** [0.01]	0.25*** [0.00]	-0.01*** [0.00]	0.17*** [0.00]
Inventor experience	-0.00*** [0.00]	-0.02*** [0.00]	-0.00*** [0.00]	0.02*** [0.00]	-0.00*** [0.00]	-0.02*** [0.00]	-0.01*** [0.00]	-0.01*** [0.00]
Firm patent stock	-0.01*** [0.00]	-0.01*** [0.00]	-0.01*** [0.00]	-0.02*** [0.00]	-0.01*** [0.00]	-0.01*** [0.00]	-0.01*** [0.00]	-0.01*** [0.00]
Number of IPC subclasses	0.43*** [0.01]	-0.02*** [0.01]	0.43*** [0.01]	-0.01** [0.01]	0.43*** [0.01]	-0.02*** [0.00]	0.43*** [0.01]	-0.01** [0.00]
Number of New IPC subclasses	0.55*** [0.01]	-0.01 [0.01]	0.55*** [0.01]	-0.01+ [0.01]	0.55*** [0.01]	-0.00 [0.01]	0.55*** [0.01]	-0.01 [0.01]
# of center locations	-0.03*** [0.00]	0.18*** [0.01]	-0.02*** [0.00]	0.12*** [0.01]	-0.03*** [0.00]	0.17*** [0.01]	-0.02*** [0.00]	0.10*** [0.01]
Observations	85239	85239	85239	85239	85239	85239	85239	85239
R-Squared	.33		.35		.33		.23	
Underidentification Kleibergen-Paap	2470		3428		1117		846	
P value (df)	0 (3)		0 (2)		0 (2)		0 (2)	
Overidentification Hansen J	0.60		0.62		0.45		1.4	
P value (df)	0.74 (2)		0.43 (1)		0.5 (1)		0.24 (1)	

**Table 3.6 (Continue)**

	(5)	1 <sup>st</sup> stage	(6)	1 <sup>st</sup> stage
	Novelty	# of direct collaborations with the unit	Novelty	# of direct collaborations with the unit
# of direct collaborations with the unit	0.12*** [0.01]		-0.04*** [0.01]	
# of direct collaborations with the unit square	-0.04*** [0.00]			
Tech. distance x # of direct collaborations with the unit			0.19*** [0.02]	
Brokerage		0.40*** [0.02]		0.40*** [0.02]
Betweenness		-0.03*** [0.00]		-0.03*** [0.00]
Degree		0.23*** [0.00]		0.23*** [0.00]
Technological distance	0.03*** [0.00]	-0.41*** [0.01]	-0.03*** [0.01]	-0.41*** [0.01]
Technological diversity	-0.07*** [0.01]	-0.46*** [0.03]	-0.04*** [0.01]	-0.46*** [0.03]
Technological diversity square	0.09*** [0.02]	0.55*** [0.05]	0.02 [0.02]	0.55*** [0.05]
Team size	-0.03*** [0.00]	0.49*** [0.01]	-0.05*** [0.00]	0.49*** [0.01]
Inventor experience	-0.01*** [0.00]	0.18*** [0.00]	-0.00 [0.00]	0.18*** [0.00]
Firm patent stock	-0.00** [0.00]	-0.07*** [0.00]	-0.01*** [0.00]	-0.07*** [0.00]
Number of IPC subclasses	0.43*** [0.01]	0.04*** [0.01]	0.43*** [0.01]	0.04*** [0.01]
Number of New IPC subclasses	0.55*** [0.01]	0.04*** [0.01]	0.55*** [0.01]	0.04*** [0.01]
# of unit locations	-0.03*** [0.00]	0.19*** [0.01]	-0.02*** [0.00]	0.19*** [0.01]
Observations	85239	85239	85239	85239
R-Squared	.35		.33	
Underidentification Kleibergen-Paap	3295		1973	
P value (df)	0 (2)		0 (2)	
Overidentification Hansen J	1.9		.001	
P value (df)	.17 (1)		.97 (1)	

**Table 3.6 (Continue)**

	(7)	1 <sup>st</sup> stage	1 <sup>st</sup> stage	(8)	1 <sup>st</sup> stage	1 <sup>st</sup> stage
	New combinations	Network Proximity to the unit	# of unit locations	New combinations	Network Proximity to the unit	Tech. distance
Network Proximity to the unit	0.19*** [0.04]			-0.01 [0.02]		
Network Proximity to the unit # # of unit locations	-0.08*** [0.02]					
Network Proximity to the unit # Tech. distance				0.08*** [0.03]		
Brokerage		3.03*** [0.18]	1.03*** [0.10]		2.28*** [0.18]	1.87*** [0.13]
Betweenness		0.02*** [0.00]	0.00*** [0.00]		0.02*** [0.00]	-0.00*** [0.00]
Degree		0.17*** [0.00]	-0.01*** [0.00]		0.18*** [0.00]	-0.04*** [0.00]
Brokerage square		-1.70*** [0.10]	-0.58*** [0.06]		-1.28*** [0.10]	-1.07*** [0.07]
Technological distance	0.05*** [0.01]	-0.18*** [0.00]	-0.07*** [0.00]	-0.18*** [0.06]		
Technological diversity	-0.04*** [0.02]	-0.10*** [0.02]	-0.04*** [0.01]	-0.11*** [0.02]	-0.04+ [0.02]	-0.27*** [0.02]
Technological diversity square	0.04+ [0.02]	0.13*** [0.03]	0.04+ [0.02]	0.18*** [0.03]	0.21*** [0.03]	0.41*** [0.02]
Team size	-0.09*** [0.01]	0.75*** [0.00]	-0.01*** [0.00]	-0.06*** [0.01]	0.74*** [0.00]	0.04*** [0.00]
Inventor experience	0.00 [0.00]	-0.01*** [0.00]	-0.01*** [0.00]	-0.01*** [0.00]	0.03*** [0.00]	-0.09*** [0.00]
Firm patent stock	-0.01 [0.00]	0.05*** [0.00]	-0.04*** [0.00]	-0.03*** [0.00]	0.06*** [0.00]	-0.01*** [0.00]
Number of IPC subclasses	0.43*** [0.01]	-0.01** [0.00]	0.00 [0.00]	0.49*** [0.01]	-0.00 [0.00]	-0.01** [0.00]
Number of New IPC subclasses	0.53*** [0.01]	0.04*** [0.01]	0.06*** [0.01]		-0.09*** [0.00]	0.09*** [0.00]
# of unit locations	0.27** [0.13]			-0.02*** [0.00]	0.31*** [0.01]	-0.08*** [0.00]
Observations	85239	85239	85239	85239	85239	85239
R-Squared	.31			.23		
Underidentification Kleibergen-Paap	66			187		
P value (df)	0 (2)			0 (3)		
Overidentification Hansen J	1.6			.96		
P value	.21 (1)			.62 (2)		

Compared to the OLS regressions, results are confirmed regarding the impact of gatekeepers on patent novelty, as shown in Models 1 to 4, however, it should be noticed the outcomes of other models are different, which confirms the existence of an endogeneity issue in the previous fixed effect models. Having gatekeepers in the team has a positive effect on the number of new combinations introduced (models 1 and 2), and the number of gatekeepers has an inverted U-shape, that is, when the number of gatekeepers increases, the new combinations increases up to a point, and then it decreases, presumably attributable to escalating coordination costs, as manifested in Models 2 and 3. The results validate the hypothesis related to gatekeepers.

Model 5 suggests a comparable inverted U-shaped relation between the number of direct links and the novelty of patents, a relation that was insignificant in preceding fixed-effect regression models. The influence of this variable is comparatively weaker than that of the gatekeepers. Model 6 unveils the beneficial role of more direct collaborations with units in moderating the obstacles encountered during the knowledge absorption process caused by technological distance. Thus, the network-level hypothesis is also validated.

An interesting issue is whether network proximity between the units and the home company facilitates the integration of distant knowledge, that is, knowledge that differs from the home company. Model 6 and 8 indicates that this is the case, as the interaction between technological distance and the number of direct ties on the one hand (Model 7), and network proximity on the other hand have a positive impact (Model 8). In contrast, the interaction between network proximity and the number of units has a positive impact, which leads to the conclusion that coordination costs between geographically dispersed units are high and are not compensated by network proximity.

### **3.5 CONCLUSIONS**

This chapter intends to uncover the mechanism of the reverse knowledge process behind EM MNEs' technological catch-up efforts. In detail, we explore the function of intra-firm networks and gatekeepers in this process, especially their impact on the companies' knowledge

absorptive capacity, which is one of the most important components of the reverse knowledge process.

Making use of a database of Chinese MNEs' patents from various overseas research units and the home company as well, we can construct the intra-firm network based on co-inventor relationships. Then, various network variables and the features of gatekeepers are calculated. On the other hand, the novelty of patents from home companies is calculated as the dependent variable to represent the outcome of reverse knowledge transfer and technology outcome. We further make regressions to uncover the impact of intra-firm networks and gatekeepers on the novelty of patents produced by home companies.

The results of regressions provide notable insights into the role of gatekeepers and the intra-firm network. The inclusion of gatekeepers in the team of home companies substantially augments new combinations, though this relationship manifests an inverted U-shape. This suggests that while gatekeepers initially enhance innovation, an increase in their number eventually leads to a decline, which can be explained by elevated coordination costs.

From the aspect of the whole intra-firm network, we find that the number of inventors with direct links and the novelty of patents exhibits another inverted U-shaped relation, but with a lesser impact compared to that of the gatekeepers. Direct collaborations with units have been identified as a moderator assisting in easing the difficulties encountered during the knowledge absorption process due to technological distance.

Furthermore, the results illuminate the significant role of network proximity in facilitating the absorption of diverse, externally sourced knowledge, especially those far from the existing knowledge base of the home company. Our results also highlight another advantage provided by network proximity, which is the enhancement of the absorptive capacity of knowledge sourced by geographically diverse units.

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**Table 3.7 Correlation table**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Patent novelty	1.00															
Number of Gatekeeper (internal distance)	0.00	1.00														
Gatekeepers (internal distance)	0.00	0.94*	1.00													
Gatekeepers (betweenness centrality)	0.00	0.82*	0.78*	1.00												
Number of Gatekeeper (betweenness centrality)	0.00	0.79*	0.81*	0.96*	1.00											
Inventor technological diversity	0.06*	0.11*	0.11*	0.12*	0.12*	1.00										
Team size	0.04*	0.34*	0.29*	0.28*	0.26*	0.12*	1.00									
Inventor experience	-0.04*	0.21*	0.23*	0.25*	0.26*	0.33*	0.27*	1.00								
Firm stock	-0.13*	-0.03*	-0.01*	-0.03*	-0.02*	-0.04*	-0.24*	0.05*	1.00							
Number of IPC subclasses	0.50*	0.02*	0.01*	0.00	0.00	0.12*	0.11*	0.00	-0.03*	1.00						
Number of new IPC subclasses	0.43*	-0.02*	-0.02*	-0.01*	-0.02*	0.03*	0.01*	-0.04*	-0.20*	0.17*	1.00					
Number of direct collaborations with the unit	-0.01*	0.56*	0.54*	0.41*	0.40*	0.13*	0.42*	0.45*	0.04*	0.03*	-0.02*	1.00				
Number of units	-0.10*	-0.06*	-0.04*	-0.07*	-0.05*	-0.08*	-0.26*	0.03*	0.70*	-0.04*	-0.12*	0.04*	1.00			
Brokerage	-0.01*	0.21*	0.21*	0.22*	0.22*	0.24*	0.22*	0.49*	0.04*	-0.01*	-0.03*	0.31*	-0.01*	1.00		
Network Proximity to the unit	-0.02*	0.59*	0.57*	0.47*	0.47*	0.18*	0.63*	0.44*	0.16*	0.05*	-0.06*	0.73*	0.14*	0.32*	1.00	
Technological distance	0.12*	-0.07*	-0.08*	-0.06*	-0.06*	0.02*	0.05*	-0.36*	-0.23*	0.04*	0.09*	-0.22*	-0.26*	-0.19*	-0.19*	1.00

\*p<0.05

## Chapter 4: IN SEARCH OF GOLDEN FLEECE: THE KNOWLEDGE DYNAMICS OF CHINESE MNEs' INVENTORS IN FOREIGN ENVIRONMENTS

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### 4.1 INTRODUCTION

MNEs are progressively accessing various locations across the globe to acquire specialized knowledge. Knowledge obtained from specific foreign countries is integrated with the existing knowledge base of the MNE to create new innovations (Marino et al., 2020). As highlighted in preceding chapters, EM MNEs exhibit a particular need for specialized foreign knowledge. This necessity arises from the aim to bridge the technological gap with established incumbents in developed countries (Verbeke, 2009). Despite numerous studies dedicated to exploring the knowledge sourcing mechanisms of MNEs in foreign environments, the dynamics of knowledge among overseas inventors working for these firms remain unclear. Thus, the objective of this chapter is to contribute to the existing literature by examining the knowledge dynamics of Chinese MNEs' overseas inventors in their mechanisms of interacting with knowledge in foreign environments.

This chapter builds on previous literature, such as Tubiana et al. (2022), who study how inventor productivity is affected by knowledge sourcing at multiple levels through their interactions within co-inventor networks, their location in metropolitan areas, and at the firm level. This study adopts their methodology and includes two crucial indicators, namely knowledge proximity and knowledge diversity in the inventors' local co-invention network, to better comprehend the knowledge dynamics of these inventors within the local environment. This chapter explores US patent data from the USPTO *Patentsview.org* database to empirically investigate Chinese MNEs' overseas inventors' inventive productivity over the period 2000 – 2022.

The findings indicate that the knowledge stocks at the firm and inventor network levels positively influence the innovation performance of Chinese MNEs' overseas inventors in foreign environments. However, the impact of metropolitan-level knowledge stock appears to be insignificant. When exploring the knowledge characteristics within the inventors' local

collaboration networks, it becomes evident that both knowledge proximity and diversity significantly contribute to their innovation performance.

The chapter follows this structure: The next section reviews the theoretical underpinnings pertinent to formulating the hypotheses. Section 3 presents the data, variables, and empirical methodology used for analysis. The findings are exhibited in Section 4, while the last section concludes, highlighting this study's implications and limitations.

## **4.2 THEORETICAL BACKGROUND AND HYPOTHESIS**

### **4.2.1 Knowledge sourcing at the metropolitan level**

Metropolitan areas have long been regarded as an important source of innovation. Tracing back to Jacob (1969)'s work, cities are places for vigorous knowledge recombination, which she qualified as "adding new work to old work" (p.50). On the one hand, the concentration of innovation in cities can be explained by the fact that transaction costs associated with technology transfers are lower when they are located within the same urban areas (Cappellin, 1988). On the other hand, this can also be explained by the fact that inventors tend to benefit from knowledge spillovers, which facilitate the exchange of ideas that is crucial for innovation (Carlino, 2001). Knowledge spillovers have been studied by Audretsch and Feldman (1996), who have emphasized the role of geographical concentration as a key factor.

A large local knowledge stock favors regional innovation as it provides the increased absorptive capacity of external knowledge (Miguelez & Moreno, 2015). Boschma et al. (2015) suggest that the entry of a new technology largely depends on its relatedness with the local knowledge base. Quatraro (2008) affirms the favorable influence of regional knowledge stock on productivity and underscores the significance of the characteristics of the knowledge base, noting that knowledge homogeneity demonstrates a positive impact, whereas diversity yields a contrasting effect.

The interaction with a regional knowledge base holds significant importance for firm performance, particularly in cases where their knowledge portfolios are coherent (Tsvetkova et al., 2020). Ott and Rondé (2019) decompose the role of regional knowledge base within innovation ecosystems, revealing that local firms derive benefits from the local stock of knowledge, thereby enhancing their innovation capacity. Simultaneously, these firms also contribute to bolstering the overall innovation potential of the region. Singh's (2008) analysis of a firm's cross-regional knowledge integration highlights that the local knowledge stock in which they are located enhances the value of their innovation output.

Several researchers have directed their attention toward exploring the connection between regional knowledge bases and individual innovation performance. Tubiana et al. (2022) confirm the importance of regional-level knowledge stock on inventor-level innovation productivity, which surpasses the impact of firm-level and inventor network-level knowledge stocks. Van der Wouden and Rigby (2019)'s study demonstrates how regional-level knowledge stocks affect the pattern of local inventors' knowledge production. They find that metropolitan areas with a more specialized knowledge base are more likely to provide a denser inventor network and thus positively affect inventors' patent productivity. As a consequence, the first hypothesis is as follows:

***Hypothesis 1. The metropolitan areas' knowledge stocks have a positive impact on the inventive productivity of overseas Chinese MNEs' inventors.***

#### **4.2.2 The role of the firm's knowledge stock**

The Knowledge-Based View (KBV) has emerged as a pivotal theory for examining a firm's long-term competitive edge and overall performance (Eisenhardt & Santos, 2000). According to Grant (1996), knowledge is identified as the most strategically significant resource for a firm's development. This perspective denotes that a firm's ability to manage, access, and leverage knowledge effectively is crucial for maintaining a competitive edge in a dynamic innovation landscape.

The firm's knowledge stock plays a central role in this setting, as discussed by Antonelli and Colombelli (2015). They provide empirical evidence suggesting that a firm's internal knowledge base contributes to its capacity for generating new technology and decreasing the expenses associated with knowledge production. Criscuolo et al. (2010) further confirm that MNEs tend to have a better innovation performance due to their globalized knowledge stock. Buckley et al. (2014) suggest that the impact of knowledge sourcing from various external locations on innovation performance is anticipated to be more significant for MNEs with a limited internal knowledge stock compared to those with a more extensive one. In addition, Rupiatta and Backes-Gellner (2019) investigate manufacturing operations in highly dynamic environments and show that the effect of knowledge stock on innovation performance is enhanced by the flow of knowledge among inventors.

Nevertheless, the impact of firm-level knowledge stocks on innovation output remains controversial, mainly regarding its effect on the absorptive capacity of external knowledge. Xie et al. (2011) argue that the network structure and knowledge stock of a firm positively impact absorptive capacity, which, in turn, influences innovation performance. In Tallman et al. (2004)'s conceptual model, though firm-specific knowledge stock contributes to the establishment of competitive advantage, it can also become an obstacle when absorbing external knowledge. Roper and Hewitt-Dundas (2015)'s research also suggests that the existing knowledge base may hinder new innovation output because path dependencies can have a negative impact.

Though in Tubiana et al. (2022)'s multi-level analysis, the knowledge stock of firms positively enhances the innovation productivity of their inventors, given the contradictory findings in prior literature concerning the influence of firm-level knowledge stock on innovation performance, the second hypothesis is divided into two aspects:

***Hypothesis 2a: The firm-level knowledge stock has a positive impact on the inventive productivity of overseas Chinese MNEs' inventors.***

***Hypothesis 2b: The firm-level knowledge stock has a negative impact on the inventive productivity of overseas Chinese MNEs' inventors.***

### 4.2.3 Co-inventors' network-level knowledge stock

Inventors engage in a dynamic process of knowledge sourcing by interacting and collaborating within their knowledge network of collaborators. This interactive engagement involves sharing, exchanging, and developing ideas, insights, and expertise, fostering a collective environment for knowledge creation and innovation (Uzzi & Spiro, 2005). According to Wuchty et al. (2007), contemporary knowledge production and innovation increasingly stem from collaborative teamwork. This implies the significance of a collective knowledge base within co-inventor networks.

Hereby, in this study the knowledge stock of the inventor network is also considered as an important factor in the knowledge dynamics. Thus, the following hypothesis is:

***Hypothesis 3: The co-inventor network-level knowledge stock has a positive impact on the inventive productivity of overseas Chinese MNEs' inventors.***

While emphasizing the role of local innovation environments for Chinese MNEs' overseas inventors, the specific issue of its underlying knowledge dynamic should be investigated. The characteristics of their local collaborations in terms of knowledge proximity and knowledge diversities may further explain how inventors source knowledge through their network relationships. A number of authors have shown that technological proximity significantly contributes to the establishment of collaborations (Boschma, 2005; Cassi and Plunket, 2014). This holds particular importance for overseas inventors within Chinese MNEs, given the inherent challenges these firms face when trying to establish connections within local knowledge networks, largely due to barriers imposed by local incumbents (Cantwell & Mudambi, 2011). Additionally, technological proximity aids in the entry of MNEs' inventors, especially considering the aforementioned prevalence of regional knowledge homogeneity. Cantner et al. (2010) confirm that the homogeneity of the regional knowledge pool serves as a booster of knowledge flows as it provides incentives for interaction between inventors. These collaborations facilitate the knowledge exchange between MNE inventors and local actors, which enables the former to tap into the local knowledge base and achieve higher innovation performance.

Knowledge diversity has been regarded as another important source of innovation as it expands the potential number and variety of knowledge combinations (Phelps, 2010). This positive effect is also confirmed by Jansen et al. (2006), which is especially the case for generating explorative innovation. Wen et al. (2021) concentrate on diversity within a firm's internal network, differentiating knowledge diversity into related and unrelated categories. Their findings suggest that diversity in related knowledge is advantageous for exploitative innovation, whereas diversity in unrelated knowledge is beneficial for explorative innovation. Gkypali et al. (2017) examine the influence of knowledge diversity on firm innovation, noting that the positive effects of knowledge diversity occur only upon the situation when outcomes outweigh the various costs associated with external knowledge sourcing and internal absorption of such knowledge.

Presented below are the following hypotheses concerning the knowledge proximity and diversity in Chinese MNEs' oversea inventors' local co-invention network:

***Hypothesis 4a: Knowledge diversity within the local co-inventors' network has a positive impact on the inventive productivity of overseas Chinese MNEs' inventors.***

***Hypothesis 4b: Knowledge proximity within the local co-inventors' network has a positive impact on the inventive productivity of overseas Chinese MNEs' inventors.***

## **4.3 METHODS**

### **4.3.1 Database construction**

As this chapter focuses on exploring the external knowledge sourcing of diverse overseas inventors affiliated with Chinese MNEs, the original database used for Chapter 2 and 3, which is constructed on the basis of MNEs, lacks sufficient regional-level knowledge information. To ensure a more comprehensive understanding of the external knowledge environment of these inventors, a broader database is preferred to gather additional insights. As highlighted in Chapter 1, the United States stands as the primary host country for Chinese MNEs' overseas

researchers. Consequently, the scope of this chapter is specifically directed toward Chinese MNEs' overseas inventors operating in the United States. To facilitate this analysis, USPTO patent application data sourced from the *PatentsView database*<sup>13</sup> has been employed. The PatentsView provides disambiguated data at both the inventor and assignee levels, thereby facilitating the analysis of relationships between inventors.

The database has been built following a number of steps:

1. the patentsView has been searched for all Chinese assignees and their inventors located in the United States.
2. the database has been limited to the 198 largest metropolitan areas in which inventors working for Chinese firms are located. More precisely data have been collected at the Core Based Statistical Area (CBSA) level which refers to both metropolitan statistical areas and micropolitan areas.
  - a. All the patents of these CBSA areas have been extracted with their inventors and assignees in order to compute CBSA-level stocks and all firms' (CBSA) local knowledge stock.
  - b. The whole *patentsview* database has been checked to extract all the patents and all the co-inventors of the inventors working in the above-mentioned CBSA to be able to build their co-inventor networks and past patenting.
3. The final sample used for regressions focuses on all inventors in the 198 CBSA areas and having at least two patents in order to compute their previous co-inventor network.
4. The Chinese firms have been checked manually to ensure that they are indeed Chinese firms and not multinational companies with subsidiaries with a location in China. The final sample includes 573 firms in 124 locations on which the regressions will focus.

The final sample used for regressions includes 124 CBSA areas, 14 199 firms, 42 173 inventors, and 573 Chinese assignees with 1 912 inventors over the years 2000-2022. Table 4.6 in the

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<sup>13</sup> <https://patentsview.org/>

Appendix provides a detailed description of the number of firms, MNEs and their inventors across the 124 Metropolitan areas (CBSA).

### 4.3.2 Variables

#### 4.3.2.1 Dependent variable

The objective of this chapter is to investigate the influence of external knowledge dynamics of different levels on the innovation performance of Chinese MNEs' overseas inventors. The innovation performance is assessed through **inventors' productivity** measured by the *annual count of their patents*.

#### 4.3.2.2 Variables of interest

Three variables are computed to explore the impact of external knowledge sourcing dynamics. The **metropolitan area knowledge stock** is computed following the permanent inventory method. It is the yearly accumulation of patents discounted at the traditional 15% depreciation rate (Hall et al. 2010). The **firm knowledge stock** is computed as the yearly accumulation of patents for each assignee and metropolitan area level and discounted at 15% following the permanent inventory method. The **co-inventor network** is simply the number of direct co-inventors over the five years prior to patenting.

**Chinese firm** takes value 1 if the inventor patents for a Chinese MNE and 0 otherwise. **Technological proximity** is computed as the Jaffe index (Jaffe, 1989), that is, the uncentered correlation between two vectors representing the focal inventor's technological portfolio and its co-inventors' technological portfolio. The index ranges from zero to one, depending on the degree of technological overlap between the inventor and its co-inventors prior patent IPC codes. It measures whether inventors co-invent with inventors that work in similar technologies. **Technological proximity with local co-inventors** is the same index but computed only between the focal inventor and its co-inventors within the metropolitan area. **Local technological diversity (HH)** is the technological diversity of co-inventors within the metropolitan area. It is computed as the inverse of the Herfindhal-Hirschman index based on all metropolitan co-inventors' patents and their 4-digit IPC codes. It measures whether co-

inventors within the metropolitan area have diversified knowledge bases, which increases the sources of knowledge variety.

**Table 4.1 Description of variables**

<b>Dependent variable</b>	
Inventor productivity (# of patents)	Number of patents per year per inventor. It is a proxy for inventor productivity
<b>Variables of interest</b>	
Network stock	The number of direct co-inventors over the five years prior to patenting
Firm stock	Yearly accumulation of patents for each assignee and metropolitan area level and discounted at 15% following the permanent inventory method
Metropolitan area stock	Yearly accumulation of patents discounted at 15% depreciation rate following the permanent inventory method
Chinese Firm	Takes value 1 if the inventor patents for a Chinese MNEs and 0 otherwise
Technological proximity	Uncentered correlation between the technologies (4-digit IPC codes) of the inventor and its co-inventors
Technological proximity with local co-inv	Uncentered correlation between the technologies (4-digit IPC codes) of the inventor and its co-inventors of the same metropolitan area
Local Technology diversity	Dispersion of IPC codes of co-inventors of the same metropolitan area
<b>Control variables</b>	
Inventor technology diversity	Dispersion of IPC codes within the inventor prior patents
# of assignees co-patenting	The average number of assignees appearing on the patent applications of the focal inventor

#### 4.3.2.1 Control variables

**Inventor technological diversity** measures if the inventors' patents over the past five years are distributed over a large variety of 4-digit IPC codes. It measures the variety of his technological knowledge base. The **# of assignees co-patenting** is the average number of assignees appearing on the patent applications of the focal inventor.

#### 4.3.2.2 Estimated model

A regression with fixed effects (FE) is used for the estimation.

$$\ln y_{it} = \beta_1 \ln MS_{it} + \beta_2 \ln FS_{it} + \beta_3 \ln NS_{it} + \beta_4 \ln NP_{it} + \beta_5 \ln ND_{it} + \theta \text{Controls}_{it} + \delta_i + \delta_t + \delta_r + \delta_T + \delta_{rT} + \delta_{tT} + \varepsilon_{i,t,r,T}$$

The inventor innovation performance measured by productivity ( $y$ ) is regressed on the metropolitan area knowledge stock (MS), firm-level knowledge stock (FS), and co-inventor network (NS), Knowledge proximity in local co-inventor network (NP), Knowledge diversity in local co-inventor network (ND) and the control variables. Multiple fixed effects are implemented to control for heterogeneity issues, as  $i$  stands for inventor,  $t$  stand for time,  $r$  stands for metropolitan area and  $T$  stands for technology. Interactions between fixed effects are also considered, as  $\delta_{rT}$  controls for variation of technology through time and  $\delta_{iT}$  represents the metropolitan-specific knowledge effect.

#### 4.3.2.3 Descriptive statistics

Table 4.2 shows the descriptive statistics for the whole sample. For the dependent variable, Inventor Productivity, measured by the number of patents, has an average of 4.38 and displays considerable variability with a standard deviation of 9.57 and a broad range from 1 to 1071 patents. It suggests large variation in the productivity of inventors in the sample. Metropolitan area stock shows a significant mean of 49309.59, alongside a large standard deviation, indicating substantial dispersion in knowledge stock across areas. Firm Stock and Network Knowledge Stock also present notable variations with respective means of 548.86 and 11.45. The knowledge proximity of the local co-inventor group has a mean value of 0.82, while the variation is relatively lower. The observations for this dataset is a total of 284,942.

	Mean	S.D	Min	Max
Inventor productivity (# of patents)	4.38	9.57	1.00	1071.00
Inventor technology diversity	4.99	3.95	1.00	60.59
Network stock	11.45	18.89	0.00	814.00
Firm stock	548.86	1341.81	1.14	10512.06
Metropolitan area stock	49309.59	40861.39	10.50	143540.20
# of assignees co-patenting	1.12	0.38	1.00	10.00
Chinese Firm	0.01	0.12	0.00	1.00
Technological proximity	0.82	0.33	0.00	1.00
Technological proximity with local co-inv	0.79	0.33	0.00	1.00
Local Technology diversity	17.07	21.35	0.00	200.37
Observations	284942			

**Table 4.3 Descriptive statistics – Chinese MNEs**

	Mean	S.D	Min	Max
Inventor productivity (# of patents)	7.89	17.18	1.00	331.00
Inventor technology diversity	5.26	4.64	1.00	50.51
Network stock	22.06	40.04	0.00	761.00
Firm stock	52.16	94.95	1.60	852.50
Metropolitan area stock	57471.98	45870.93	33.92	143540.20
# of assignees co-patenting	1.33	0.57	1.00	6.00
Chinese Firm	1.00	0.00	1.00	1.00
Technological proximity	0.89	0.27	0.00	1.00
Technological proximity with local co-inv	0.85	0.27	0.00	1.00
Local Technology diversity (HH)	23.58	28.18	0.00	186.35
Observations	4204			

**Table 4.4 T-test of Chinese MNEs versus Other firms**

	Chinese	Other	Difference	
	Mean	Mean	Coefficient	SD
Number of patents	7.894	4.326	-3.568***	0.148
Inventor technology diversity	5.263	4.989	-0.274***	0.061
Network stock	22.055	11.293	-10.762***	0.293
Firm stock	52.159	556.297	504.138***	20.828
Metropolitan area stock	57471.978	49187.360	-8284.618***	634.717
# of assignees co-patenting	1.326	1.115	-0.211***	0.006
Chinese Firm	1.000	0.000	-1.000	0.000
Technological proximity	0.888	0.822	-0.066***	0.005
Technological proximity with local co-inv	0.854	0.793	-0.061***	0.005
Local Technology diversity (HH)	23.584	16.969	-6.615***	0.332
Observations	4204	280738	284942	

Table 4.3 presents descriptive statistics focusing specifically on the subset of Chinese MNEs' overseas inventors located in the US. These inventors are more productive than the overall mean, and they are located in larger metropolitan areas than the average inventor. They also work for companies that co-patent more than the average inventor. They are embedded in local networks for which inventors have more diversified knowledge bases.

These differences are confirmed by Table 4.4, which provides T-tests between inventors working for Chinese multinationals and those working for non-Chinese firms. The comparison highlights several distinctions. Notably, the productivity of overseas inventors affiliated with Chinese MNEs appears to be higher than that of other inventors of the whole sample. This suggests that these overseas inventors, working for Chinese MNEs, are more productive in innovation activities compared to others. Moreover, these overseas inventors have more co-inventors than their peers and work in more inventive metropolitan areas. However, at firm-level, the knowledge stock of Chinese MNEs seems to be smaller than that of other firms. The

knowledge proximity with the local co-invention network of these overseas inventors is slightly higher, while the knowledge is more diverse in their local collaboration network, and the patents, they filed tend to have more assignees.

Table 4.7 provides details on the distribution of the number of yearly observations per inventors working for Chinese MNEs, and Table 4.8 gives the correlation table.

#### **4.4 ESTIMATION RESULTS**

Table 4.5 presents the results of the regressions that investigate the correlation between the knowledge dynamics at the metropolitan, firm, and inventor-network levels and the innovation performance of Chinese MNEs' overseas inventors. In a general context, as reflected by Model (1), the knowledge stock at all three levels significantly and positively influences the innovation performance of inventors located in the United States. In Model (2), the inclusion of the binary variable Chinese firm, representing inventors working for Chinese MNEs, reveals that inventors employed by these specific MNEs exhibit higher productivity levels compared to other inventors located in the US and working for other firms.

However, when the analysis specifically focuses on inventors working for Chinese MNEs in Model (3), the knowledge stock at the firm and inventor network levels continues to display a positive impact on innovation performance, but surprisingly, the metropolitan level no longer appears to have a statistically significant impact. This suggests that while inventors manage to benefit from the metropolitan area's innovative activity, those working for Chinese firms have a harder time benefiting from this environment. This result may reflect the difficulties for these firms to tap into local knowledge reservoirs and benefit from knowledge spillovers either because they have only been located there recently or for cultural reasons.

**Table 4.5 Multi-level knowledge stocks impact on inventor productivity**

	(1)	(2)	(3)	(4)	(5)	(6)
Network stock	0.095*** [0.007]	0.094*** [0.007]	0.094*** [0.006]	0.106*** [0.008]	0.106*** [0.008]	0.105*** [0.008]
Firm stock	0.018*** [0.004]	0.019*** [0.004]	0.019*** [0.004]	0.019*** [0.004]	0.019*** [0.004]	0.019*** [0.004]
Metropolitan area stock	0.175*** [0.049]	0.172*** [0.049]	0.172*** [0.049]	0.172*** [0.049]	0.172*** [0.049]	0.171*** [0.050]
Chinese Firm		0.195*** [0.024]	-0.196+ [0.113]	0.106*** [0.035]	0.102*** [0.038]	0.077*** [0.027]
Chinese Firm x Network stock			0.057*** [0.017]			
Chinese Firm x Firm stock			0.097*** [0.023]			
Chinese Firm x Metropolitan area stock			-0.005 [0.014]			
Technological proximity				-0.052*** [0.009]		-0.057*** [0.009]
Chinese Firm x Technological proximity				0.097*** [0.026]		
Technological proximity with local co-inv					-0.052*** [0.008]	
Chinese Firm x Technological proximity with local co-inv					0.106*** [0.029]	
Local Technology diversity (HH)						0.003** [0.002]
Chinese Firm x Local Technology diversity (HH)						0.044*** [0.009]
Inventor technology diversity	0.054*** [0.009]	0.055*** [0.009]	0.054*** [0.009]	0.055*** [0.009]	0.054*** [0.009]	0.054*** [0.009]
# of assignees co-patenting	0.638*** [0.017]	0.629*** [0.015]	0.631*** [0.015]	0.628*** [0.015]	0.628*** [0.015]	0.628*** [0.015]
Constant	-1.253** [0.498]	-1.231** [0.498]	-1.223** [0.495]	-1.213** [0.498]	-1.213** [0.498]	-1.199** [0.499]
Observations	284942	284942	284942	284942	284942	284942
<b>Fixed effects</b>						
Inventor	Yes	Yes	Yes	Yes	Yes	Yes
Region stock	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Technology	Yes	Yes	Yes	Yes	Yes	Yes
Year x Technology	Yes	Yes	Yes	Yes	Yes	Yes
Region x Technology	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors are clustered by region and firm level.

+ 0.10 \*\* 0.05 \*\*\* 0.01

In Models (4) to (6), the analysis further explores the influence of knowledge characteristics within inventors' collaboration networks. Model (4) particularly examines the inventors' technological proximity with their co-inventors disregarding their location. Chinese firms seem to benefit from technological proximity while other inventors have lower productivity when they work with inventors having similar knowledge bases. This suggests that Chinese firms through their inventors, try to increase their degree of specialization by collaborating with

inventors who have similar competences. An additional issue is whether it matters that these co-inventors are located within the metropolitan area. Models (5) and (6) explore, respectively, the impact of technological proximity and technological diversity of co-inventors located within the same metropolitan area. Results show that inventors working for Chinese firms benefit from both types of networks. That is, they benefit from their local network technological proximity and from the fact that these inventors have a certain technological diversity within similar domains.

In sum, their innovation performance seems more reliant on engagement with a local knowledge network possessing specific characteristics. As Chinese MNEs aim to access localized advanced knowledge for technological catch-up with developed country incumbents, the importance of knowledge proximity with local collaborators becomes apparent. This significance could be attributed to the likelihood that inventors with a coherent technological background are more inclined to exchange knowledge with local inventors, potentially contributing to their innovation performance. For other inventors not working for Chinese firms, given that many of these firms are local, there exists a probability that they are already well-acquainted with the local knowledge context. Therefore, knowledge proximity might limit the scope of their research. In this context, the diversity of knowledge among co-inventors assumes greater significance. The positive impact of knowledge diversity within the co-inventor network on overseas Chinese inventors situated in the US underscores the significance of a varied source of knowledge. While technological proximity holds importance, a diverse range of knowledge sources appears to offer considerable benefits in enhancing the innovation performance of these inventors.

## **4.5 CONCLUSIONS**

This chapter is dedicated to unraveling the mechanisms of how knowledge dynamics at different levels, particularly within local settings, contribute to the innovation performances of MNEs' overseas inventors. Taking inspiration from Tubiana et al.'s (2022) research, this chapter employs an approach focusing on three levels: metropolitan, firm, and inventor

networks. Using USPTO patent data, the study primarily focuses on Chinese MNEs' overseas inventors located in the United States. The descriptive statistics of these two groups provide a general scenario of knowledge exchange between the two countries.

The findings contribute to the existing literature by shedding light on the intricate relationships between knowledge dynamics at various levels and the innovation performance of Chinese MNEs' overseas inventors. For these inventors, while knowledge stock at the firm and inventor-network levels positively impacts innovation performance, the significance of metropolitan-level knowledge stock diminishes, implying obstacles in accessing and benefiting from local knowledge reservoirs. The analysis further digs into the knowledge characteristics within inventors' local collaboration networks. The positive impact of technological proximity and knowledge diversity is confirmed. These findings suggest that the access to a location with an extensive knowledge base itself is insufficient for the specific group of inventors affiliated with Chinese MNEs. Facing the barriers set up by existing powerful established domestic incumbents (Cantwell & Mudambi, 2011) together with the difficulties caused by geographical and cultural distances, knowledge proximity serves as an important factor for these inventors' knowledge searching endeavor, which eventually enhances their innovation performance.

The empirical findings offer practical insights for EM MNEs seeking to catch-up through their overseas inventors. The mere selection of a metropolitan area abundant in knowledge does not ensure the innovation performance. The alignment of inventors with similar knowledge backgrounds becomes crucial for optimal knowledge assimilation and application. Additionally, the reservoir of knowledge within MNEs and inventor networks is essential as well. They serve as moderators in absorbing external knowledge acquired from diverse environments, enabling its transformation into innovation.

This study has a number of limitations. First, the sample is only centered in the United States. It would have been interesting to add European countries as a benchmark. Second, the size of the sample of Chinese firms and inventors is rather small, respectively, Third, it would have been interesting to add inventors working from other emerging market such as India. It would have been interesting to consider whether inventors coming from other countries rely on the same knowledge dynamics. The sample of inventors would have been larger enabling to

explore other issues and in particular the type of collaborations between MNEs and other organizations, that is local firms, universities, or start-ups. Fourth, the sample of Chinese firms and moreover inventors remains small and the number of yearly observations are also small (see Table 4.7). This bears a number of constraints on the regressions that limit variations through time and the possibility to further explore the knowledge dynamic. Finally, the limitation lies in the incomplete resolution of endogeneity issues, despite the inclusion of various fixed effects in the regression analysis.

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## 4.7 CHAPTER 4 APPENDIX

**Table 4.6 Metropolitan area # of firms, Chinese MNEs, # inventors and # Inventors working for MNEs**

<b>cbsacode</b>	<b>Metropolitan statistical areas</b>	<b># inventors</b>	<b># inventors CN MNEs</b>	<b># firms</b>	<b># of CN MNEs</b>
10420	Akron, OH	637	14	161	4
10580	Albany-Schenectady-Troy, NY	6033	4	485	4
10740	Albuquerque, NM	437	2	105	2
10900	Allentown-Bethlehem-Easton, PA-NJ	1126	6	264	6
11180	Ames, IA	169	1	54	1
11460	Ann Arbor, MI	2160	12	353	8
12060	Atlanta-Sandy Springs-Roswell, GA	2700	11	583	9
12260	Augusta-Richmond County, GA-SC	46	1	18	1
12420	Austin-Round Rock, TX	4250	15	544	10
12580	Baltimore-Columbia-Towson, MD	1158	1	333	1
12780	Bartlesville, OK	297	3	17	1
13020	Bay City, MI	37	1	12	1
13180	Beaver Dam, WI	5	1	2	1
13460	Bend-Redmond, OR	25	1	18	1
13820	Birmingham-Hoover, AL	184	1	60	1
14010	Bloomington, IL	61	1	24	1
14020	Bloomington, IN	218	2	47	2
14260	Boise City, ID	1663	3	64	2
14460	Boston-Cambridge-Newton, MA-NH	18261	49	2851	34
14500	Boulder, CO	1462	3	277	2
14860	Bridgeport-Stamford-Norwalk, CT	1619	3	270	3
15380	Buffalo-Cheektowaga-Niagara Falls, NY	546	3	98	4
15500	Burlington, NC	28	1	14	1
15540	Burlington-South Burlington, VT	934	1	87	2
15940	Canton-Massillon, OH	122	2	35	2
16580	Champaign-Urbana, IL	497	2	119	2
16740	Charlotte-Concord-Gastonia, NC-SC	522	8	180	6
16980	Chicago-Naperville-Elgin, IL-IN-WI	7534	60	1060	27
17060	Chillicothe, OH	8	1	4	1
17140	Cincinnati, OH-KY-IN	1641	5	218	4
17200	Claremont-Lebanon, NH-VT	185	1	78	1
17460	Cleveland-Elyria, OH	1157	12	315	4
17780	College Station-Bryan, TX	216	2	76	1
18140	Columbus, OH	1001	9	221	7
18180	Concord, NH	64	2	33	2
18700	Corvallis, OR	433	1	45	3
19100	Dallas-Fort Worth-Arlington, TX	4296	67	696	14
19380	Dayton, OH	296	8	84	4
19500	Decatur, IL	16	1	6	1
19660	Deltona-Daytona Beach-Ormond Beach, FL	32	1	20	1
19740	Denver-Aurora-Lakewood, CO	1199	13	302	8
19780	Des Moines-West Des Moines, IA	798	3	62	2
19820	Detroit-Warren-Dearborn, MI	6261	34	444	15
20500	Durham-Chapel Hill, NC	1749	31	389	14
23060	Fort Wayne, IN	63	1	31	2
23540	Gainesville, FL	555	4	115	3
24340	Grand Rapids-Wyoming, MI	149	2	47	1
24660	Greensboro-High Point, NC	186	3	65	4
24860	Greenville-Anderson-Mauldin, SC	535	4	90	3
25540	Hartford-West Hartford-East Hartford, CT	1271	3	260	4
26420	Houston-The Woodlands-Sugar Land, TX	6255	73	812	19
26900	Indianapolis-Carmel-Anderson, IN	1741	28	307	7

27060	Ithaca, NY	423	6	92	5
27740	Johnson City, TN	133	1	17	1
28020	Kalamazoo-Portage, MI	133	1	49	1
28140	Kansas City, MO-KS	221	3	96	2
28500	Kerrville, TX	2	1	1	1
28740	Kingston, NY	118	1	33	1
28940	Knoxville, TN	402	1	86	1
29460	Lakeland-Winter Haven, FL	58	1	28	1
29540	Lancaster, PA	323	2	63	2
29820	Las Vegas-Henderson-Paradise, NV	272	3	101	3
30140	Lebanon, PA	60	1	18	1
30460	Lexington-Fayette, KY	269	5	137	3
31080	Los Angeles-Long Beach-Anaheim, CA	11022	104	2031	63
31140	Louisville/Jefferson County, KY-IN	234	5	82	3
31180	Lubbock, TX	52	1	14	1
31540	Madison, WI	1011	2	219	3
31700	Manchester-Nashua, NH	348	2	133	2
31820	Manitowoc, WI	28	1	8	1
32740	Meadville, PA	12	1	6	3
32900	Merced, CA	61	1	45	1
33100	Miami-Fort Lauderdale-West Palm Beach, FL	824	1	274	1
33220	Midland, MI	800	2	72	1
33340	Milwaukee-Waukesha-West Allis, WI	932	2	175	2
33460	Minneapolis-St. Paul-Bloomington, MN-WI	8349	11	619	8
34820	Myrtle Beach-Conway-North Myrtle Beach, SC-NC	17	1	9	1
34980	Nashville-Davidson--Murfreesboro--Franklin, TN	288	1	104	1
35300	New Haven-Milford, CT	1637	4	313	4
35620	New York-Newark-Jersey City, NY-NJ-PA	25291	185	2604	88
35660	Niles-Benton Harbor, MI	84	1	5	1
35980	Norwich-New London, CT	448	1	74	1
36100	Ocala, FL	10	1	5	1
36260	Ogden-Clearfield, UT	222	1	60	2
36740	Orlando-Kissimmee-Sanford, FL	407	4	129	1
37100	Oxnard-Thousand Oaks-Ventura, CA	1570	16	228	9
37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	8302	23	1315	19
38060	Phoenix-Mesa-Scottsdale, AZ	2950	10	496	10
38300	Pittsburgh, PA	2217	5	402	5
38340	Pittsfield, MA	35	1	17	1
38900	Portland-Vancouver-Hillsboro, OR-WA	4065	26	414	10
38940	Port St. Lucie, FL	13	2	7	1
39300	Providence-Warwick, RI-MA	601	3	211	2
39580	Raleigh, NC	2990	53	512	11
39740	Reading, PA	204	4	43	3
39900	Reno, NV	438	2	61	3
40140	Riverside-San Bernardino-Ontario, CA	900	6	332	5
40340	Rochester, MN	438	1	41	1
40380	Rochester, NY	2009	5	226	5
40860	Rutland, VT	59	1	31	1
40900	Sacramento--Roseville--Arden-Arcade, CA	1119	9	274	7
41180	St. Louis, MO-IL	2009	12	323	10
41620	Salt Lake City, UT	704	1	218	1
41700	San Antonio-New Braunfels, TX	260	2	85	3
41740	San Diego-Carlsbad, CA	17382	125	2104	56
41860	San Francisco-Oakland-Hayward, CA	29761	216	4352	94
41940	San Jose-Sunnyvale-Santa Clara, CA	44969	493	4488	122
42100	Santa Cruz-Watsonville, CA	632	3	181	3
42200	Santa Maria-Santa Barbara, CA	765	1	199	1
42220	Santa Rosa, CA	397	3	130	3
42540	Scranton--Wilkes-Barre--Hazleton, PA	15	1	12	1
42660	Seattle-Tacoma-Bellevue, WA	12895	73	988	26

43320	Show Low, AZ	2	1	2	1
44300	State College, PA	401	2	107	2
44700	Stockton-Lodi, CA	181	3	71	3
45300	Tampa-St. Petersburg-Clearwater, FL	394	3	149	3
45780	Toledo, OH	141	2	30	2
45940	Trenton, NJ	2328	16	457	15
46060	Tucson, AZ	716	14	144	5
46520	Urban Honolulu, HI	79	1	32	1
47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	3932	36	1053	28
48580	Whitewater-Elkhorn, WI	13	1	7	1
49180	Winston-Salem, NC	183	1	54	1
49340	Worcester, MA-CT	1544	7	403	6

**Table 4.7 Distribution of inventors working for CN MNEs**

# of years per inventor	# of inventors	%
2	246	12.87
3	219	11.45
4	185	9.68
5	170	8.89
6	129	6.75
7	123	6.43
8	133	6.96
9	112	5.86
10	81	4.24
11	87	4.55
12	68	3.56
13	55	2.88
14	73	3.82
15	60	3.14
16	39	2.04
17	44	2.30
18	30	1.57
19	18	0.94
20	20	1.05
21	17	0.89
22	2	0.10
23	1	0.05

The table shows the number of observations for each inventor working for CN MNEs and used for the regressions

**Table 4.8 Correlation table**

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Number of patents	1.00									
Technology diversity (HH)	0.18*	1.00								
Network stock	0.32*	0.28*	1.00							
Firm stock	0.14*	-0.02*	0.20*	1.00						
Metropolitan area stock	0.04*	0.02*	0.14*	0.18*	1.00					
# of assignees co-patenting	0.15*	0.15*	0.13*	-0.12*	-0.01*	1.00				
Chinese Firm	0.05*	0.00*	0.07*	-0.07*	0.02*	0.07*	1.00			
Technological proximity	0.11*	0.09*	0.62*	0.15*	0.09*	0.04*	0.02*	1.00		
Technological proximity with local co-inv	0.09*	0.05*	0.60*	0.15*	0.08*	0.03*	0.02*	0.99*	1.00	
Local Technology diversity (HH)	0.21*	0.33*	0.60*	0.27*	0.18*	0.06*	0.03*	0.65*	0.62*	1.00

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\*  $p < 0.05$

## CONCLUDING REMARKS

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This thesis delves into the knowledge dynamics of Emerging Market Multinational Enterprises (EM MNEs) by examining the cases of inventors affiliated to Chinese MNEs. It explores how EM MNEs utilize inventor networks to source knowledge from foreign environments, absorb this knowledge, and eventually leverage it to drive new innovations. The four chapters of this thesis offer insights into several specific aspects related to the main subject, including the embeddedness of these overseas inventors in internal and external networks, the significance of home company gatekeepers in reverse knowledge transfer, and an exploration into the knowledge sources of these inventors operating overseas. The study narrows its scope to concentrate on inventor-level activities based on patent data. This approach complements the existing body of company-level studies on the innovation processes of EM MNEs by providing micro-foundation evidence.

The practical implications derived from the results can also serve as references for managers of EM MNEs and policymakers. For EM MNEs managers, the findings of this thesis serve as a valuable resource for decision-making regarding the deployment and operation of inventors and research units in foreign environments. From the perspective of policy makers in EM countries, the results affirm the advantages of conducting overseas R&D for fostering innovation and aids in strategic decisions on allocating incentives to encourage MNEs in pursuing knowledge acquisition abroad.

The scope of future research presents multiple avenues to expand upon the findings within this thesis. While this study mainly focuses on the contributions of overseas inventors to Chinese MNEs, enriching the sample with inventors from other EM countries would significantly diversify and enhance its breadth. An exploration into the distinctions among various groups of external collaborators, including universities, research institutions, suppliers, and other entities, also appears as a promising direction for future study. Moreover, an area worth exploring involves investigating other pipelines of external knowledge for EM MNEs. Beyond the knowledge derived from overseas units and inventors, it is plausible that the home company also establishes direct connections with foreign inventors. Therefore, an interesting

direction for further study would involve comparing the efficacy of knowledge acquisition through various pipelines.