The Role of Overseas Returnees in FDI Knowledge Spillovers: Evidence From Chinese High-tech Firms

Rui Guo

Submitted in fulfillment of the requirements of the

Degree of Doctor of Philosophy

School of Business and Management

Queen Mary University of London

Nov 2021

Statement of Originality

I, Rui Guo, confirm that the research included within this thesis is my own work or that where it has been carried out in collaboration with, or supported by others, that this is duly acknowledged below and my contribution indicated. Previously published material is also acknowledged below.

I attest that I have exercised reasonable care to ensure that the work is original, and does not to the best of my knowledge break any UK law, infringe any third party's copyright or other Intellectual Property Right, or contain any confidential material.

I accept that the College has the right to use plagiarism detection software to check the electronic version of the thesis.

I confirm that this thesis has not been previously submitted for the award of a degree by this or any other university.

Signature: Rui Guo

Date: 30/11/2021

Abstract

In the emerging country context, FDI has been acknowledged as a key external knowledge source to improve local firm performance. Recently, returnees, as another critical external knowledge source, have received increasing attention. Returnees are those who have studied and/or worked abroad and then returned to their homeland. They can bring multi-cultural knowledge and superior skills after several years' experience abroad. However, limited literature has examined how the interplay between FDI and returnees influences local firm performance. Most studies, if any, only focus on the role of individual returnees in FDI knowledge externalities. In this Ph.D. thesis, I integrate these two streams of literature and hope to investigate both aggregated and contingent roles of returnees in FDI knowledge diffusion. Based on a unique panel dataset from the annual census filed by Chinese high-tech manufacturing and services firms in Zhongguancun Science Park (ZSP), which is equivalent to the "Silicon Valley", in Beijing from 2007 to 2013, I adopt the system-GMM model with Heckman corrections to test my hypotheses. My results suggest that FDI spillovers can improve local firms' productivity in ZSP. However, this effect is contingent on the returnees' repatriation process into local industries and on the returnees' local clustering structures. More specifically, I first confirm that a fast pace of returnees' repatriation facilitates FDI knowledge spillovers, while an irregular pace of repatriation hinders it. Second, a concentrated clustering of returnees promotes the FDI externalities, whereas a competitive structure attenuates it. Third, returnees clustered in related industries strengthen FDI spillovers, however, unrelated industrial clustering weakens it. Overall, this Ph.D. thesis not only calls for greater and more stable preferential policies to attract FDI and returnees to the local market but also suggests that policy-makers need to introduce returnees in a faster and rhythmic mode. And it is necessary to place more emphasis on managing the clustering structures of returnees to facilitate FDI knowledge spillovers.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

FDI: Foreign Direct Investment

MNEs: Multinational enterprises

ZSP: Zhongguancun Science Park

GMM: Generalized method of moments

OLS: Ordinary least square

WDI: World development indicator

TFP: Total factor productivity

RV: Related variety

UV: Unrelated variety

SOEs: State-owned enterprises

SIC code: Standard Industrial Classification code

VIF: Variance inflation factors

WRSA: Western Returned Scholars Association

QFII: Qualified Foreign Institutional Investor

BOTAP: Beijing implemented the Overseas Talent Aggregation Project

CSC: China Scholarship Council

Chapter 1 Introduction

1.1 Backgrounds and Motivations

As the largest developing country, China has accelerated its technological upgrading since the "reform and opening-up" in 1978. Constrained by relatively weak internal knowledge stocks, China has proactively sought external technological assistance and capital sources (Fu & Gong, 2011; Ning, Wang, & Li, 2016b). FDI has long been suggested as the main advanced technological source originating externally to the recipient countries, as its knowledge can spill to local firms and help them improve their technologies (Ning, Li, & Prevezer, 2016a; Zhang, Li, & Li, 2014). Many multinational enterprises (thereafter "MNEs") rapidly entered China and set up subsidiaries to expand their business. In 2019, the annual foreign capital in actual use had reached 141.23 billion US dollars in China, ranking 2rd in the world. However, the existing evidence of whether FDI knowledge spillovers can benefit local production efficiency remains inconclusive. Some scholars find positive FDI spillover effects on local firms' productivity, as foreign firms provide opportunities for local ones to observe and imitate the advanced technologies and managerial practice (Newman, Rand, Talbot, & Tarp, 2015; Tian, 2007, 2010; Wang & Wu, 2016; Zhang et al., 2014). In contrast, other studies hold the opposite opinion and argue that FDI can threaten indigenous technological upgrading by crowding out their market share (Buckley, Clegg, & Wang, 2010; Rojec & Knell, 2018).

One important reason for the mixed results of FDI spillovers is that the absorption of FDI advanced technology is not straightforward, given the culture, language and knowledge disparity between foreign and local firms. The emerging-market firms need to improve their capability to identify and assimilate FDI spillovers more effectively. Recently, local firms have realized the importance of returnees in enhancing the dissemination of foreign knowledge (Liu, Lu, & Choi, 2014). Returnees who received education or worked in developed countries and relocated to home countries have been theorized as a cohesive group with distinctive cross-cultural social capital that can help local absorborption of advanced foreign knowledge (Filatotchev, Liu, Lu, & Wright, 2011; Liu, Lu, Filatotchev, Buck, & Wright, 2010a). They also provide human resources with 'prior related knowledge' to decode ideas from the outside and improve local firms' capability to identify the advanced FDI technologies and overcome some of the technological and organizational barriers that prevent learning from FDI spillovers (Marcin, 2008; Zhang, Li, Li, & Zhou, 2010). Moreover, as the returnees have studied and/or worked outside their homeland for several years, they often understand across-cultural knowledge, possess high-level technological and managerial expertise, so that may close the knowledge disparity between the MNEs and local firms (Lin, Lu, Liu, & Zhang, 2016; Liu et al., 2014). The current literature also regards the returnees as a "brain gain" for emerging economies to improve their knowledge base, leapfrog some technological development stages and catch up with their developed counterparts (Dai & Liu, 2009; Filatotchev et al., 2011; Liu et al., 2014).

Since the turn of the 21st century, return talents have gained increasing popularity and significance in China when the leadership realized that "empowering the nation with talents" is key to "rejuvenating the nation with science, technology, and education". Chinese governments have put great efforts to attract highly skilled returnees back to the local labor market (Bai, Johanson, & Martín Martín, 2017; Yuping & Suyan, 2015). For instance, the central government has promoted many national policies like "Recruitment Program of Global Experts", the "Thousand Talents Program" and the "Ten Thousand Talent Program" to support returnees to contribute to the improvement of the academic and the business (see Tables 2-4 and 2-6 for the sample programs related to the talent attraction, retaining, and utilization). Besides, all the local governments in Chinese provinces issued preferential programs to compete in attracting returnees. For example, Beijing implemented the Overseas Talent Aggregation Project (BOTAP) in 2009 to introduce more return migrations into high-tech enterprises. Guangdong province also establishes the international youth innovation workshop to invite return talents to take part in the development of Guangdong-Hong Kong-Macau Greater Bay Area.

Under a series of supporting policies, an increasing number of returnees choose to come back to their home. According to the Chinese Ministry of Education, 5,194,900 Chinese students studied abroad between 1978 and 2017, of whom more than 3,132,000 had returned to China by the end of 2017. From 2007 to 2019, the number of returnee students increases from 44 thousand to 580.3 thousand, and the reflux rate experienced a great increase from 30.56% to 82.49%. Moreover, according to the survey of Wang (2012), the destinations of Chinese overseas students have been mostly developed economies with high-level science and technology, education, and income, like the UK, western Europe, and the US, etc., which to some extent provides a certain guarantee for the human capital level of the returnees. And after return, the returnees mainly work in high-tech industries, emerging service industries, technology-intensive industries located in the upstream and downstream of the value chain, or industries that have a significant role in promoting industrial development, which accounts for more than 70% of the returnees.

Meanwhile, a large number of returnees voluntarily form groups, like Wester Returned Scholars Association (Overseas-educated Scholars Association of China, thereafter "WRSA"), to promote the contact and exchange among members of the groups, and become a platform for domestic talents, return talents and overseas talents to exchange and communicate. They hold many summits, seminars, and exchanges, and act as bridges for the communication between domestic and foreign firms, promoting the cooperation between talents from MNEs and domestic firms, and strengthening the return of talents to serve the local technological upgrading (Bai, Holmström-Lind, & Johanson, 2018; Wang & Bao, 2015). Through such social networks, the returnees from different firms or industries can interact with each other and their inter-personal interactions can greatly influence their contributions to knowledge externalities and the local development.

Although the importance of returnees in knowledge dissemination has been stressed, we know relatively little about whether and how returnees at the aggregated level can influence FDI knowledge spillovers and local firm performance. Several studies have well acknowledged that returnees with cross-cultural knowledge and language advantages can help the local firm to absorb FDI externalities and improve their technology (Filatotchev et al., 2011; Liu et al., 2014). However, most of them only focus on the impact of individual returnees on knowledge diffusion, due to the lack of a comprehensive dataset to construct aggregated indicators (Liu, Wright, Filatotchev, Dai, & Lu, 2010b; Wang, Zweig, & Lin, 2011). Currently, China is deepening its open up to the outside world and expecting to improve its capability to learn from advanced external technology. Moreover, upon a background of many talents returning to China, it is also necessary to effectively restructure and manage the returnees to enhance their role in promoting knowledge externalities and local technological upgrading. In this thesis, I mainly focus on the dynamic and structural role of returnees in FDI knowledge spillovers to deepen our understanding of the relationship between FDI and returnees.

I contend that it is critical to consider the dynamic characteristics of returnees' repatriation at the aggregated level in FDI knowledge spillovers. Since returnees have been away from their homeland for several years, when they go back to their emerging market home countries, they usually experience a seemingly familiar, yet different, environment (Liu & Almor, 2016; Yuping & Suyan, 2015). Particularly in China, the swiftly changing economic environment imposes more difficulties on this issue. The returnees thus need some time to deal with the readjustment issues after their return before they can play a role in promoting local absorptive capability (Bai et al., 2018; Lee & Roberts, 2015; Lin, Zheng, Lu, Liu, & Wright, 2019; Qin, Wright, & Gao, 2017). In this case, the returnees' repatriation into local industries is not a static process and its dynamic characteristics might influence the contribution of returnees to the local knowledge base. Speed and irregularity are two representative time-based features that can be used to depict the returnee's repatriation, which has been widely used to indicate the dynamic entry process (Wang et al., 2012a, Vermeulen and Barkema, 2002). Nevertheless, the current literature has not examined this important topic.

Besides, the returnees in the labor markets do not work alone but rather interact with others (Li, 2020; Liu et al., 2010b; Qin & Estrin, 2015). They would agglomerate in different firms or industries and form certain specialized or diversified clustering structures. As individual returnees embody tacit knowledge, their different agglomeration would influence the scale and scope of their interactions within and across industries, which might bring knowledge externality and affect the local absorption of FDI advanced knowledge (Ma, Zhu, Meng, & Teng, 2018; Pruthi, 2014). It is thus also critical to apply the agglomeration perspective to analyse the structural impact of returnees.

More specifically, on the one hand, from the specialized agglomeration perspective, the returnees would either concentrate on certain industries to form a concentrated clustering structure or distribute in different firms to form a competitive clustering structure. These two types of agglomeration may have different impacts on FDI knowledge externalities. The concentrated clustering reflects the overall intensity of returnees within an industry (Ellison & Glaeser, 1999; Leppälä, 2020). The returnees' concentration in certain industries would magnify their interactive learning process and improve the entire industrial knowledge pool, which would promote the local technological upgrading and the absorption of FDI knowledge spillovers. In contrast, competitive clustering depicts the distribution of returnees over firms within certain industries (Drucker, 2011; Hoffmann, Lavie, Reuer, & Shipilov, 2018). As the resources are limited, the returnees' fierce competition within industries might influence their efforts to local firms to develop sufficient common knowledge bases and establish stable business relationships with foreign firms, which might affect the FDI spillovers process.

On the other hand, from the diversified agglomeration perspective, the returnees can also distribute in technologically related or unrelated industries, and their across-industry interaction would exert different impacts on the FDI knowledge externalities. The current literature emphasizes the externalities of inter-industry cognitive distance in FDI spillovers and classifies the diversified agglomeration into two specific dimensions, namely related and unrelated variety (Aarstad, Kvitastein, & Jakobsen, 2016; Frenken, Van Oort, & Verburg, 2007). In this case, when returnees are clustered into industries that share technologically related knowledge stocks (related variety), they can interact more frequently and effectively, so that facilitate technology transfer and dissemination. In contrast, the unrelated variety of returnees refers to a structure, in which the returnees are distributed in sectors sharing limited complementary competencies (Frenken et al., 2007; Fritsch & Kublina, 2018). The returnees clustered in unrelated sectors can lack technological relatedness and organizational proximity to warrant effective communication and coordination across foreign and local firm boundaries to disseminate FDI knowledge. The returnees' across-industry interaction thus would be restricted and would hamper the knowledge diffusion process.

So far, the prior scholars have investigated specialized and diversified agglomeration externalities in FDI technological spillovers (Ning et al., 2016a; Ning et al., 2016b; Wang, Ning, Li, & Prevezer, 2016a). However, the current evidence and arguments are mainly based on the overall employment structure, while often neglecting the clustering structure of returnees as a special labor force (Caragliu, de Dominicis, & de Groot, 2016; de Vor & de Groot, 2010). With the growing number of talents returning to their homeland, how their repatriation process and agglomeration can influence knowledge dissemination should be placed more emphasis. As argued above, the distinctive group structures formed by the returnees with multi-cultural knowledge and social networks should significantly influence local absorption and diffusion of FDI spillovers. To my knowledge, little is known about the externalities of returnees' clustering structures in host country FDI spillovers, and there is even less evidence regarding high-tech science parks in emerging economies. Therefore, I make the first attempt to apply the agglomeration perspective and examine the role of the specialized and diversified clustering structure of returnees in FDI knowledge externalities. Drawing upon the cluster approach, my findings can deepen our understanding of the structural and dynamic role of returnees in the emerging market firms' performance and add more empirical evidence to the cluster theory and FDI knowledge spillovers literature.

1.2 Statement of Purposes

In this Ph.D. thesis, the core research purpose is to investigate how the returnees at the aggregated level influence the FDI spillovers and the local firm performance. It aims to answer the following questions so that to expand the FDI and returnee literature on host country firms.

Research Question 1*: How does the returnees' repatriation process (include speed and irregularity) into local industries influence FDI knowledge spillovers and local firm productivity?*

Research Question 2*: How does returnees' specialized clustering agglomeration (include concentrated and competitive structures) influence FDI knowledge spillovers and local firm productivity?*

Research Question 3*: How does returnees' diversified clustering agglomeration (include related variety and unrelated variety structures) affect FDI knowledge spillovers and local firm productivity?*

More specifically, first, this thesis examines how the time-based characteristics of the returnees' repatriation process into local industries, namely speed, and irregularity, influence the local firm productivity and the FDI knowledge spillovers. The local and foreign firms are located in Zhongguancun Science Park in Beijing and can be distinguished based on their registration type in China's industrial and commercial system. Currently, it is still unclear how the returnees collectively and dynamically influence the absorption of FDI spillovers (Choudhury, 2015; Lin et al., 2016; Liu et al., 2014; Wang, 2015). I propose that the different paces of returnees' repatriation can play different roles in boosting local firms to learn from FDI advanced knowledge. It makes the first attempt to help us to better understand the dynamic and collective role of returnees in the FDI spillovers theoretical framework.

Second, I investigate the impact of different types of specialized agglomeration of returnees, including concentrated and competitive structures, on FDI knowledge spillovers. Due to the lack of detailed information on firms' and industrial labor force structure, the existing literature is not able to analyse the structural effect of returnees (Filatotchev et al., 2011; Fu, Hou, & Sanfilippo, 2017). As argued above, the returnees would cluster in certain industries and form a concentrated structure, or distribute in different firms and form a competitive structure. These different types of clustering structures would influence the returnees' within-industry interactions and further affect the knowledge dissemination (Mayr & Peri, 2008; Qin & Estrin, 2015; Zweig & Han, 2010). Upon a background of attracting return talents in China, it is critical to effectively promote the returnees' agglomeration and enhance knowledge diffusion. By applying the agglomeration perspective and examining the role of the specialized clustering structure of returnees in the knowledge spillovers process, I link the cluster theory with FDI and returnee literature.

Third, this thesis applies the concept of related variety and unrelated variety to analyse how the diversified agglomeration of returnees influences the FDI knowledge externalities. It links the notion of "interindustry cognitive distance" to FDI knowledge spillovers. I hope to demonstrate that returnees' clustering in related industries is likely to foster opportunities in inter-firm communications and interactions due to the interindustry cognitive proximity, which would enhance FDI technological spillovers. In contrast, an unrelated variety clustering structure of returnees hinders knowledge flows and transfers due to limited interindustry complementary and shared competencies. To my knowledge, this thesis provides the first empirical evidence of the externality of the diversified clustering structure of returnees and will help us to obtain a clearer understanding of the interplay between FDI spillovers and returnees.

1.3 Ph.D. Thesis Outlines

This Ph.D. thesis addresses how the time-based characteristics and clustering structures of returnees influence the FDI knowledge spillovers process and local firm performance, based on evidence from Zhongguancun Science Park firms in China. Figure 1-1 illustrates the overall research framework of this thesis.

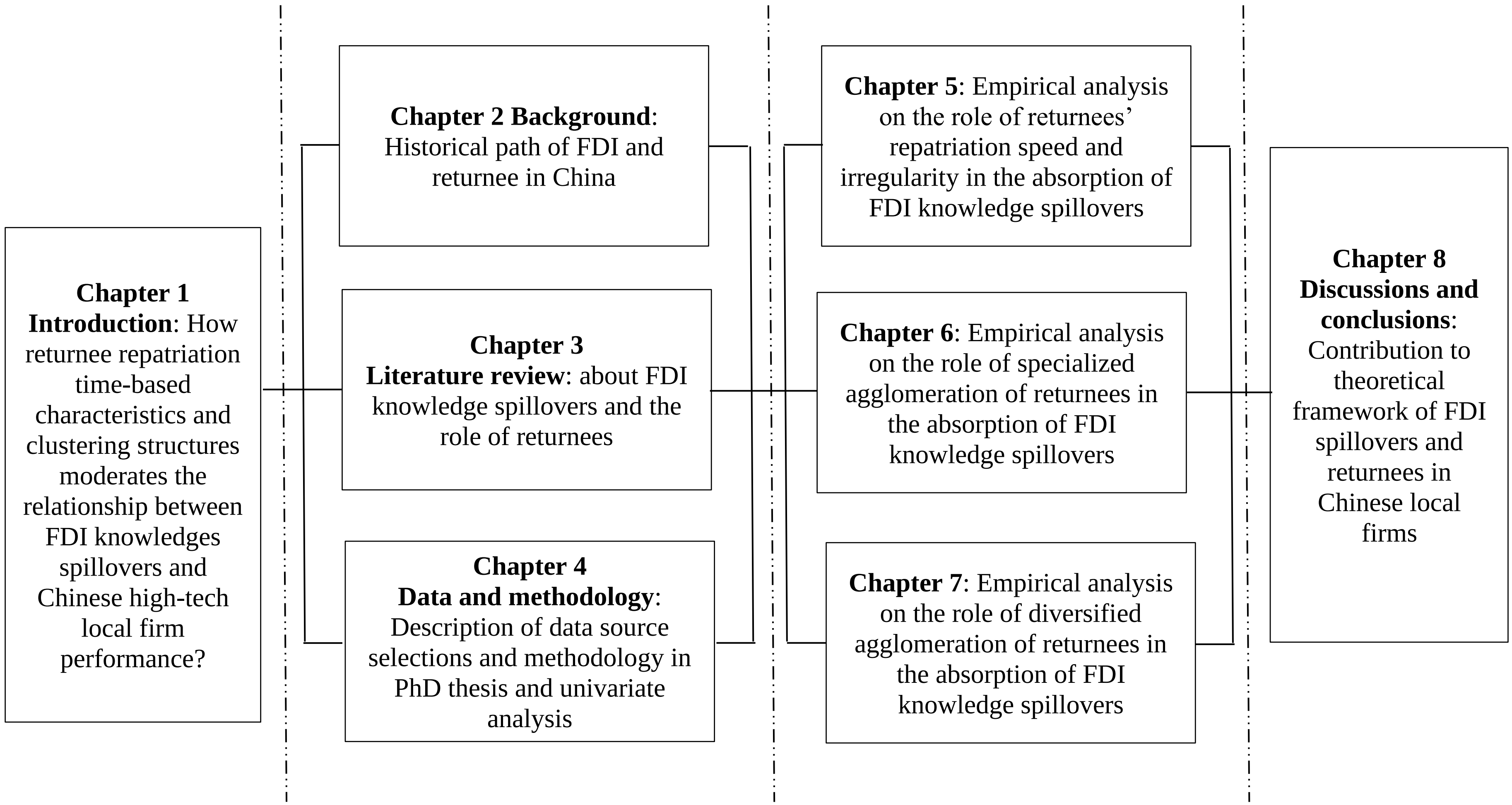

Figure 1-1 Overall Research Framework of the Ph.D. Thesis

This section introduces the framework of the Ph.D. thesis. The remainder of this thesis is organized as follows:

Chapter 2 expatiates the historical path of FDI in China's technological upgrading over three periods after China's "reform and opening up" policy: 1978-1991, 1992-2008, 2009-the present. Meanwhile, it also summarizes the key developmental path of returnees in China. The main objective of Chapter 2 is to provide an overview of the development of China's FDI and returnees and help us to better understand why it is important to investigate the interplay between FDI and returnees in China.

Chapter 3 is the literature review. It systematically discusses both theoretical and empirical findings regarding FDI spillovers, the returnees' repatriation process, and clustering structures in technological upgrading from previous studies and helps to provide a solid theoretical framework for the Ph.D. research. The first section in this chapter presents the theoretical rationales behind the FDI knowledge spillovers and empirical evidence in different country contexts. The second section emphasizes the impact of returnees on local firm performance and FDI knowledge spillovers. It first analyses the characteristics of returnees, which include an inexplicit knowledge structure in related fields and dual social networks in both their homeland and overseas. It then summarizes what the returnees can bring to the local firm's performance. In line with the rationale of FDI knowledge spillovers, it also discusses the contributions of returnees to local absorptive capacities and FDI externalities. Based on the analysis of previous literature, it concludes that the existing studies mainly examine the role of returnees from the individual level, while ignoring the collective perspective. Consequently, the third section, from a collective view, illustrates how the two specific time-based features of the returnees' repatriation process into local industries, namely speed, and irregularity, impact FDI spillovers. Moreover, from the specialized agglomeration perspective, the fourth section discusses the mechanism of concentrated and competitive clustering structures of returnees in improving local firm performance and facilitating the FDI knowledge diffusion process. Concentrated and competitive structures are found to affect knowledge dissemination in different ways. Finally, based on the diversified agglomeration view, the fifth section emphatically elaborates the mechanism of related variety and unrelated variety of returnees in FDI knowledge spillovers. Similar to the Concentrated and competitive structures, related variety and unrelated variety are also scarcely used to explain the collective role of returnees and this section makes the first attempt.

Chapter 4 introduces the data sources and methodology. It aims to construct appropriate datasets and research methodology for the empirical analysis. It first expatiates the information about the research context, Zhongguancun Science Park, in this thesis. It details the development and the main characteristics of ZSP regarding multinational enterprise and returning labor force. Then it introduces the annual census of ZSP high-tech firms, which is adopted in the Ph.D. thesis. In line with the specific research questions, it systematically expatiates on the dataset processing, the definitions of the variables, the estimation methods, and the univariate analysis in Chapters 5, 6, 7. Hence, it provides an empirical research context for the Ph.D. thesis.

Chapter 5 investigates how the time-based characteristics of the returnees' repatriation into local industries, namely speed, and irregularity, influence the local firm productivity and the FDI knowledge spillovers. Based on the panel data of Zhongguancun Science Park firms over the period 2007-2013, the estimation results demonstrate that FDI spillovers exert a significantly positive impact on Chinese high-tech firms' total factor productivity. Focusing on the time-based characteristics of returnees' repatriation, it also finds that a fast pace of returnees' repatriation improves the local firm productivity while an irregular pace of returnees' repatriation irregularity hampers it. Concerning the moderating role of returnees, the results confirm that the positive relationship between FDI in the industry and the productivity of local firms become stronger as the returnees' repatriation speed increases while weaker as the returnees' repatriation irregularity increases.

Chapter 6 investigates the impact of returnees' specialized agglomeration, including concentrated and competitive structures, on local firm productivity and FDI knowledge spillovers. In this chapter, I construct the industrial concentration and competition indexes of returnees based on the annual census of ZSP firms over the period 2007-2013 and employ the system generalized method of moments (GMM) model with Heckman corrections to test the hypotheses. The empirical results once again confirm the positive effects of foreign presence on local firm performance. I also find that both the returnees' concentrated and competitive clustering structures directly promote Chinese high-tech firms' productivity. Regarding their moderating role in FDI knowledge spillovers, this chapter finds that while returnees' concentrated clustering structure facilitates FDI spillovers, their competitive clustering structure hinders it.

Chapter 7 aims to investigate the impact of returnees' diversified agglomeration, including related variety and unrelated variety, on local firm productivity and FDI knowledge spillovers. Also based on the panel data of Zhongguancun Science Park firms over the period 2007-2013, this chapter shows a positive spillover effect of FDI on Chinese high-tech firms. Focusing on the diversified clustering structure, it confirms that both returnees related and unrelated variety can promote local firms' productivity, which improves our knowledge on returnees and adds more empirical evidence to the cluster theory. However, regarding their moderating role in FDI spillovers, only the related variety clustering structure of returnees facilitates FDI spillovers and their unrelated variety hampers the process.

Chapter 8 is the final chapter of the Ph.D. thesis, and its objective is to summarise the research. First, I conclude each of the preceding chapters and discuss the empirical findings, as well as propose some policy suggestions for central and local authorities to consider. Then, in the next section, the theoretical contributions are presented. Finally, I emphatically state the research limitations of the Ph.D. thesis and make several recommendations for future studies.

Chapter 2 Historical Path of FDI and Returnees in China

Before the literature review, this chapter is going to introduce the historical path of FDI and returnees in China. Nowadays, innovation has become a new engine for China's economic development. However, given the limited internal resources and knowledge base for conducting innovative activities, China has spent a lot on seeking and learning from external advanced technology. FDI and returnees are two of the important external knowledge sources. Since the reform and opening up, China has made great achievements in attracting foreign investment (Fu & Gong, 2011; Hu & Jefferson, 2002). Foreign businessmen have gradually expanded their investment areas and amounts in China, and investment methods have innovated a lot compared with the previous time (Howell, 2019; Xiao & Park, 2018). Therefore, how to effectively learn from advanced foreign technologies has become an important issue for China. Besides, the returnees have been argued as important knowledge brokers in disseminating foreign knowledge (Choudhury, 2015; Liu et al., 2010b). However, whether and how the interplay between FDI and returnees can influence local firm performance has not been fully understood. With the swift change of the situation of globalization, China is faced with an increasing number of highly skilled overseas talents returning to their homeland. Given such huge numbers of returnees, how to effectively structure and manage the returnees to promote knowledge dissemination is also a critical issue.

Since the reform and opening up, China has made great achievements in attracting foreign investment and returnees (Fu & Gong, 2011; Hu & Jefferson, 2002). The field of opening up has been continuously expanded and the level has been continuously improved. From the perspective of the change in foreign investment and returnees policy, China has experienced three major stages in attracting foreign investment and returnees after the “reform and opening up”, including the stage of exploration (1978-1991), the stage of all-round open up (1992-2008) and the stage of high-quality development (2009-current). In the following sections, I would detail the development path of FDI and returnees in China to help us understand why it is important to analyse the structural impact of returnees on FDI knowledge spillovers in China’s context.

2.1 The Stage of Exploration: 1978-1991

In this initial stage of “opening up and reform”, both FDI and returnee policy was at an exploration stage.

2.1.1 The Development of FDI During 1978-1991

Concerning the development of FDI, although the scale of attracting capital was not large, China’s FDI inflows as a proportion of GDP maintained an upward trend, and in 1988 it exceeded 1% for the first time (see Table 2-1). The overall attractiveness of inward FDI improved during this period. FDI inflows continued to increase and the rank of China in the world rose slightly, but the proportion of FDI in GDP stayed around 1%. Generally speaking, China’s utilization of foreign capital in this stage has three main characteristics:

First, the use of foreign capital was mainly based on external borrowing, while the proportion of foreign direct investment was less than half of the external borrowing. According to data from the National Bureau of Statistics, from 1979 to 1991, China's total external borrowing was US$52.56 billion, accounting for 65% of the actual use of foreign capital; foreign direct investment was US$25.06 billion, accounting for 31% of the total use of foreign capital (as shown in Figure 2-1). This shows that in the early days of reform and opening up, China used foreign capital mainly through external borrowing and that FDI accounted for a small proportion of China's actual use of foreign capital.

Second, capital from Hong Kong, Macao, and Taiwan (HMT) and overseas Chinese was the main target during this period, as it can take the language and ethnic advantages. At this stage, regardless of the number of enterprises or the amount of investment, the investment of firms from HMT and overseas Chinese in the mainland accounted for about 70% of the foreign direct investment used in the country.

Third, the entry mode of FDI was mainly based on the establishment of joint ventures and cooperative enterprises in eastern areas. At this stage, China's opening up was based on the sequence of "special economic zone-coastal open city-coastal economic open zone", forming a frontier zone for opening up. Matching with the open areas, the coastal areas absorbed more than 90% of foreign direct investment during this period.

Table 2-1 FDI Inflow in China During 1978-1991

Year	FDI inflow	Rank in the world	The proportion of FDI over GDP	Rank in the world	The trend of FDI inflow
1978	N/A	N/A	N/A	N/A	N/A
1979	0.0008	122	0	N/A	N/A
1980	0.057	57	0.03	N/A	+
1981	0.265	29	0.14	N/A	+
1982	0.43	19	0.21	116	+
1983	0.916	16	0.4	103	+
1984	1.419	8	0.55	77	+
1985	1.956	7	0.63	76	+
1986	2.244	10	0.75	63	+
1987	2.314	13	0.85	67	+
1988	3.194	12	1.02	56	+
1989	3.393	10	0.98	77	+
1990	3.487	12	0.97	75	+
1991	4.366	11	1.14	68	+

Note: (1) Unit: 1 billion USD; %. (2) Source: World Development Indicators (WDI).

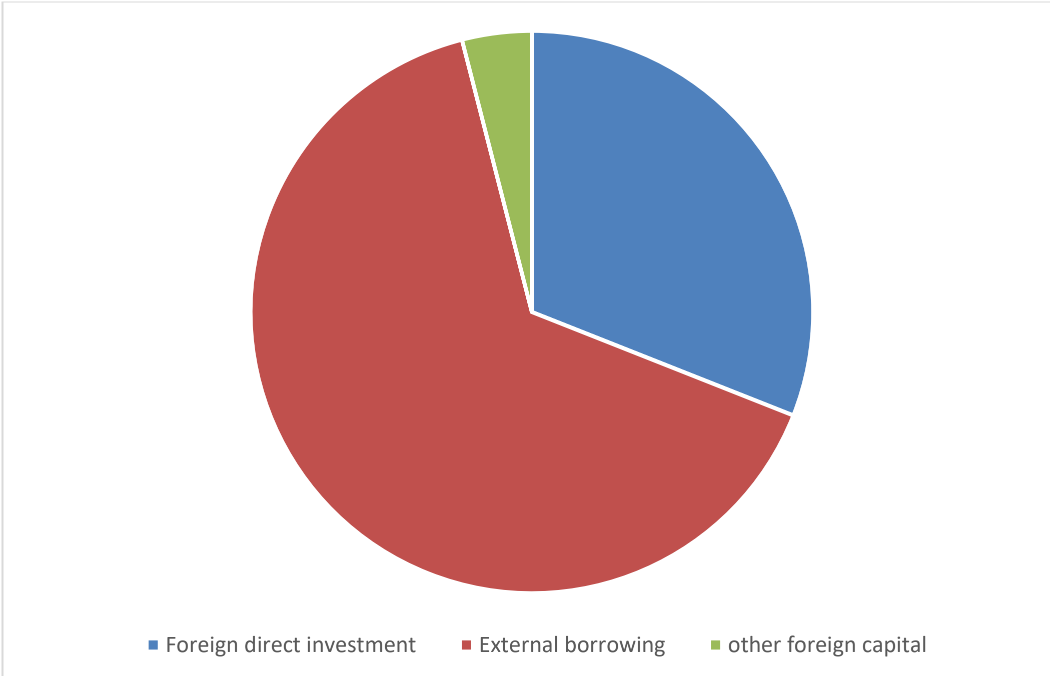

Figure 2-1 The Structure of Foreign Capital Utilized in China During 1978-1991

Data source: National Bureau of Statistics, sorted by the author

2.1.2 The Development of Returnees During 1978-1991

As for the returnee, in this stage, China began its exploration on how to promote the number of students studying abroad and attract them back after their education or work. More specifically, On June 23, 1978, when Comrade Deng Xiaoping listened to a report on the work of Tsinghua University by the Ministry of Education, he pointed out to support the increase in the number of overseas students, mainly in natural sciences. This marked the beginning of a period of exploration and development for overseas students. Later on July 11, 1978, the State Council approved the "Report on Increasing the Number of Overseas Students", which determined a plan to send 3,000 undergraduate students, graduate students, and postgraduates every year. On August 4, 1978, the "Notice on Additional Election of Overseas Students" issued by the Ministry of Education further clarified this goal and opened the prelude to China's large-scale dispatch of overseas students. According to statistics from the Ministry of Education, from 1978 to the end of 1989, China sent more than 96,000 people to study abroad, of which about 30,000 were sent by the central government, accounting for 31.2%.

Besides, to implement the policy of opening to the outside world, during this stage, China also decided to open channels for self-funded studying abroad. In 1981, the State Council approved the "Interim Regulations on Self-funded Overseas Students", which recognized that "self-funded overseas student is a channel for cultivating talents". From 1978 to the end of 1989, China sent a total of 22,000 self-financed overseas students, accounting for 23.6% of the total number of students studying abroad. And the proportion of self-funded overseas students has gradually reached 58.57% in 1990.

However, during this period, with the expansion of the scale of studying abroad, the phenomenon of overseas students not returning became more and more serious, due to the relatively lagging behind local economic development. Indeed, China had actively created conditions to attract overseas students back. For example, in 1983, China promulgated the "Interim Measures for the Distribution and Dispatch of Graduated International Students", which established a job distribution and dispatch system for all types of returnees based on the principle of consistent learning and recruitment. But in fact, the phenomenon of overseas students staying and not returning was still serious. From 1978 to June 1984, there were more than 26,000 publicly-sponsored overseas students and more than 7,000 self-funded overseas students. Nevertheless, the number of government-sponsored overseas students who returned to China was only around 8,000 and only a few hundred self-funded overseas students returned.

Moreover, the majors of returnees in this stage are mainly natural science and applied science. For example, from 1978 to 1981, the Minister of Education had sent 7,456 students abroad, out of which 81% majored in natural science-related subjects. This is because the aim of sending overseas students was to nature talents for the development of China’s science and technology in this stage.

2.2 The Stage of All-round Opening Up: 1992-2008

2.2.1 The Development of FDI During 1992-2008

After Deng Xiaoping’s southern speech in 1992 and with more than a decade of development, the confidence of foreign investors in China’s operating environment had improved significantly, and the proportion of FDI in the use of total foreign capital had rapidly increased. Unlike the previous stage, China’s utilization of FDI in this stage had another three main characteristics.

First, the scale of FDI had grown rapidly, and it had become China’s leading way of utilizing foreign capital. Since 1992, China had continuously become the developing country with the largest scale of attracting capital from foreign countries. The period from 1992 to 1997 was the first period of rapid development for China to attract FDI. The amount of FDI used increased rapidly from 11.008 billion USD in 1992 to 108.312 billion USD in 2008 (as shown in Table 2-2). The Asian financial crisis in 1998 caused a short-term negative impact on FDI inflows, and after 2000 it entered a rapid growth channel. Moreover, the contributions of FDI to China's Economy grew rapidly. As shown in Table 2-3, the share of foreign firm employment increased from 0.77% in 1992 to 2.98% in 2008. The share of export and tax from MNEs also reached a peak in 2008. Besides, because China's total capital expenditure grew faster than the FDI inflow, the proportion of foreign capital expenditure experienced a slight decrease from 1997 to 2008.

Table 2-2 FDI Inflow in China During 1992-2008

	FDI inflow	Rank in the world	The proportion of FDI over GDP	Rank in the world	The trend of FDI inflow
1992	11.008	5	2.58	37	+
1993	27.515	2	6.19	15	+
1994	33.767	2	5.98	13	+
1995	37.521	2	5.11	28	+
1996	41.726	2	4.83	31	+
1997	45.257	2	4.71	43	+
1998	45.463	3	4.42	55	+
1999	40.319	8	3.69	83	-
2000	40.715	8	3.36	100	+
2001	46.878	4	3.5	80	+
2002	52.743	3	3.59	77	+
2003	53.505	1	3.22	74	+
2004	60.63	3	3.1	91	+
2005	72.406	3	317	82	+
2006	72.715	3	2.64	105	+
2007	83.521	6	2.35	125	+
2008	108.312	2	2.36	131	+

Note: (1) Unit: 1 billion USD; %. (2) Source: World Development Indicators (WDI).

Table 2-3 The Contributions of FDI to China's Economy During 1992-2008 (%)

	Share of employment	Share of export	Share of tax	The proportion of capital expenditure
1992	0.77	/	3.96	7.51
1993	0.73	/	5.67	12.13
1994	1.05	/	8.29	17.08
1995	1.27	/	10.52	15.65
1996	1.38	/	11.56	15.14
1997	1.44	23.03	12.55	15.04
1998	1.36	24.99	13.84	13.25
1999	1.36	24.58	16.29	11.18
2000	1.43	25.18	18.74	10.24
2001	1.43	26.14	19.94	10.42
2002	1.55	27.38	20.59	10.04
2003	1.73	28.24	22.35	7.97
2004	2.06	29.33	23.16	7.12
2005	2.42	31.24	23.06	6.68
2006	2.69	32.02	23.7	5.27
2007	2.92	31.95	22.57	4.62
2008	2.94	30.84	33.1	4.35

Source: http://www.stats.gov.cn/ National Statistics Bureau of China

Second, the sources of FDI were diversified, and the proportion of FDI from Hong Kong, Macau, Taiwan, and Southeast Asia had declined. In addition to the rapid development in scale, the sources of China's FDI inflows had also undergone great changes from the previous stage. First of all, from the perspective of the source of FDI, in the previous stage, FDI mainly came from investors (mainly Chinese) in Hong Kong, Macau, Taiwan, and Southeast Asia, accounting for about 70% of the total FDI, while in this stage, it mainly came from the United States and Japan. The proportion of FDI in developed countries such as Europe and Europe had increased, and the relative importance had gradually increased. The proportion of foreign capital utilized from Hong Kong, Macao, Taiwan, and Southeast Asia reached the highest point of 81.98% in 1992, and then declined year by year. The share of European, American and Japanese investment in China increased relatively.

Third, compared with the previous stage, the proportion of wholly foreign-owned operations had increased significantly, and foreign mergers and acquisitions (M&A) of Chinese companies had begun to be active, although the proportion of M&A in the total amount of FDI is not high. In the initial period of opening to the outside world, China did not allow foreign investors to establish wholly-owned enterprises. Since the 1990s, foreign investors had increasingly adopted sole proprietorship. After 2000, the proportion of FDI by wholly foreign-owned enterprises had exceeded 50%. It reached about 80% and tended to be stable (as shown in Figure 2-2). At the same time, according to the United Nations Conference on Trade and Development's World Investment Report, the amount of foreign capital M&A of Chinese companies from 2000 to 2007 was around 5% of FDI.

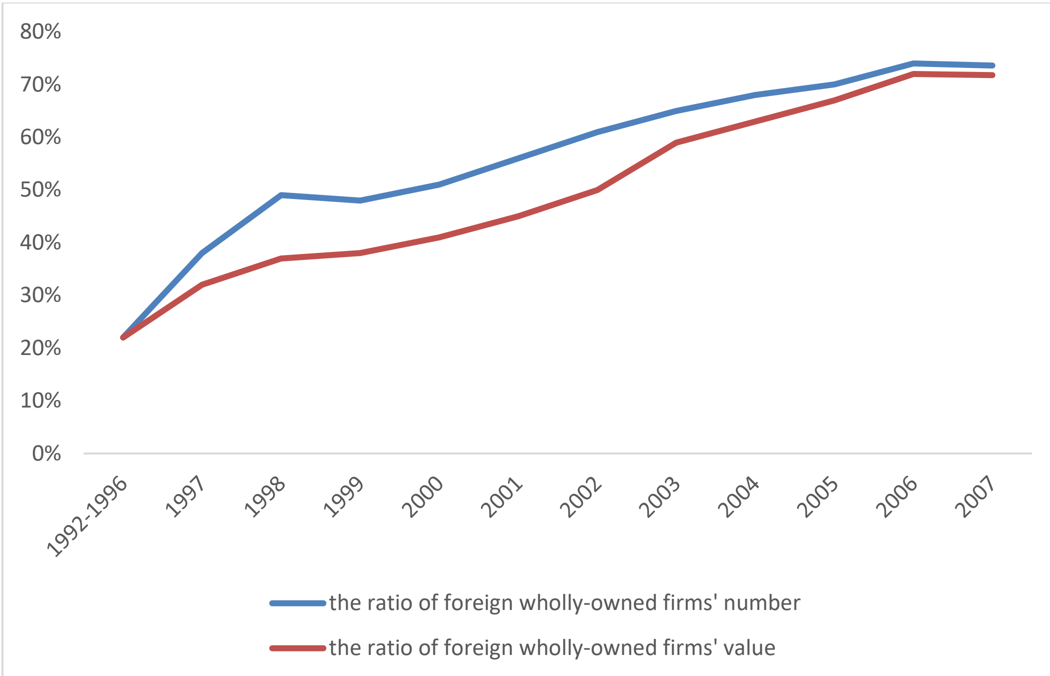

Figure 2-2 Wholly Foreign-owned Enterprises Accounted for the Proportion of Foreign Direct Investment Utilised During 1992-2007

Data source: National Bureau of Statistics, sorted by the author

2.2.2 The Development of Returnees During 1992-2008

As the reform and opening-up process was further accelerated, the returnee policy in this stage deepened the three main lines of "improving the selection and management system for government-sponsored overseas students, establishing a system to manage self-funded overseas students, and improving the service system for returning talents".

More specifically, in this stage, Chinese government-sponsored overseas students began to achieve standardized development. In February 1995, the State Education Commission put forward the “Proposal for Reforming the Management Measures for the Selection and Assignment of Overseas Students”, which determined the dispatch policy of both government-sponsored and self-funded overseas students. According to statistics from the Ministry of Education, from 1992 to 2000, the number of government-sponsored overseas students was between 1905 and 2888 each year, with little fluctuation; while from 2001 to 2006, the number exceeded 3,000. Later in 2007 and 2008, the number of government-sponsored students began to increase rapidly, with 8,853 and 11,400 overseas students respectively.

In addition, the policy on self-funded overseas students has matured, and the self-funded team has also grown rapidly. In 1993, the State Education Commission issued the “Supplementary Regulations on Self-funded Overseas Students for Persons with Undergraduate Degrees and Above”, which removed the restriction that undergraduate graduates can study abroad only after their graduation. Besides, to reward outstanding self-financed overseas students and encourage them to return to China, the China Scholarship Council (CSC) established the “National Scholarship for Outstanding Self-funded Overseas Students” in 2003. About 500 self-funded overseas students receive funding each year. Under such supports, a growing number of self-funded students studied or worked abroad. Taking the data of 1992, 2000, and 2008 as examples, the number of self-funded students studying abroad was 13,480, 32,293, and 262,461 respectively, accounting for 60.05%, 82.83%, and 92.20% of the total number of students studying abroad that year.

Besides, the service policy for returnees has also been further developed, “Support studying abroad and encourage returning” has become an important policy for China during this period.

China has successively issued a series of policies and plans (see Table 2-4 for sample programs related to talent attraction, retaining, and utilization), creating a new era in which a large number of outstanding talents return to serve the country. For example, in 1996, the Ministry of Education formally established the "Chunhui Plan". In 1998, the Ministry of Education and the Li Ka-Shing Foundation jointly raised funds to establish the Cheung Kong Scholars Award Program. In 2001, "Several Opinions on Encouraging Overseas Students to Serve the Country in Various Forms", and in 2002 the "Outline of the National Talent Team Construction Plan for 2002-2005" were promulgated, which clarified the government funding support, property rights protection and other preferential policies for returnees. Under the guidance of corresponding policies, the return rate of government-sponsored overseas students in the late 1990s reached 92.8%. Since 2000, the number of overseas students returning to China has continued to rise, from 9,121 in 2000 to 44,000 in 2007, and a sharp increase to 69,300 in 2008.

Moreover, compared with the previous stage, with the rapid expansion of the number of self-funded students, political factors are no longer the main driving factor for overseas students and the goal of returnees had become more diverse. For the government, the goal of government-sponsored overseas students is still to train high-level talents for national construction and technological upgrading, especially those in short supply and urgent need, during the transition and development stage of China. For universities, sending overseas students will help universities and institutions to enhance the level of internationalization, strengthen the development of emerging and urgently needed disciplines, and be more conducive to the construction of a high-level discipline echelon and the rapid growth of academic leaders. For individuals, studying abroad can make up for the shortage of high-quality educational resources in China, meet the demand of the masses for high-quality educational resources, and help them to improve their comprehensive ability and realize their value.

Table 2-4 Sample Programs Related to the Talent Attraction, Retaining, and Utilisation (1992-2008)

Program	Agency in charge	The target of the program	Year initiated
Hundred Talent Program	CAS	Scientists under 45 years old	1994
National Science Fund for Distinguished Young Scholars	NSFC	Academic leaders under 45 years old; frontier sciences and technology	1994
Chunhui Program	MOE	Chinese expatriates for short-term services	1996
Cheung Kong/Changjiang Scholar Program	MOE	Endowed professorships for under 45 years old; extended to 55 years old in social sciences and humanities	1998
111 Program	MOE and SAFEA	1000 foreign scholars from the top 100 universities and research institutions	2005
Thousand Talent Program	CLGCTW	1000 academics, corporate executives, and entrepreneurs under 55 years old to return from overseas	2008

Notes: MOE—Ministry of Education; NSFC—National Natural Science Foundation of China; SAFEA—State Administration of Foreign Expert Affairs; CLGCTW—Central Leading Group for the Coordination of Talent Work. Source: Author's research.

2.3 The Stage of High-quality Development: 2009-Current

2.3.1 The Development of FDI After 2009

During this stage, as China's economy is gradually entering the "new normal", the utilization of FDI also follows a high-quality and efficient-oriented mode. Generally, the global ranking of China's FDI inflows is relatively stable, and the total amount of FDI inflows has a relatively small change. China has become a major country in attracting investment in the world. However, the proportion and ranking of China's FDI inflows in GDP are not outstanding, indicating that the growth rate of FDI inflow is slower than China's economic development. This stage has four main characteristics.

First, although the growth of FDI flow has slowed down, the quality and efficiency of utilization of foreign capital have improved significantly (see Table 2-5). Although the growth of China's FDI flow has slowed since 2012, China is still one of the most attractive FDI investment destinations in the world. According to data from the Ministry of Commerce, in 2018, 60,533 foreign-invested firms were newly founded in China, a year-on-year increase of 69.8%, showing that foreign businessmen's confidence in China's investment remains strong. During 2018-2019, foreign-funded enterprises created nearly 1/2 of the national foreign trade volume, 1/4 of the profits of industrial enterprises (above designated size), and 1/5 of the tax revenue, with less than 3% of the country's total. The efficiency was significantly better than the national average.

Table 2-5 FDI Inflow in China During 2009-2017

	FDI inflow	Rank in the world	The proportion of FDI over GDP	Rank in the world	The trend of FDI Inflow
2009	95.0	2	1.86	134	-
2010	114.73	2	1.88	83	+
2011	123.98	2	1.64	98	+
2012	121.08	2	1.41	125	+
2013	123.91	2	1.29	108	+
2014	128.5	2	1.23	116	+
2015	135.61	4	1.23	144	+
2016	133.7	3	1.19	165	+
2017	144.0	2	1.18	178	+

Note: (1) Unit: 1 billion USD; %. (2) Source: World Development Indicators (WDI).

Second, the service industry replaces the manufacturing industry as the main area for attracting FDI. Since the service industry's use of foreign capital in 2010 surpassed that of the manufacturing industry for the first time, the service industry has become China's leading field in attracting FDI. The foreign capital used by the service industry in total FDI has increased from nearly one-half in 2010 to 67.9% in 2017. In terms of quality, at this stage, although the real estate industry has always occupied an important position in the use of foreign capital, the R&D service industry, and retail and wholesale industries have grown rapidly, becoming the fastest growing industries in the service industry.

Third, as for the entry mode, the proportion of M&A in foreign direct investment has increased significantly. Before 2014, the proportion of FDI realized through M&A has been low, while in 2015, foreign businessmen invested 17.77 billion U.S. dollars through M&A accounting for 14.1%

of China’s total foreign direct investment, an increase of 7 percentage points over the previous year, and maintaining the same proportion in 2016. According to public data from the Ministry of Commerce, in 2018, the amount of foreign M&A increased by 28.4% year-on-year, and the proportion of FDI in the whole year rose to 22.6%.

Fourth, the indirect use of foreign capital in the financial sector has accelerated. After 2008, the inflow of funds and the market value of holdings increased significantly. In 2012, the value of the Qualified Foreign Institutional Investor (QFII) stock market in circulation was 12.7 billion U.S. dollars at the exchange rate that year, which reached 11% of FDI that year. In 2014, this ratio reached 22%. According to data from the State Administration of Foreign Exchange, in 2018, QFII inflows amounted to 43.7 billion U.S. dollars, accounting for 1/3 of the FDI inflows that year. At the beginning of 2019, to satisfy foreign investors’ expanding investment demand in China’s capital market, the total amount of QFII expansion from 150 billion U.S. dollars to 300 billion U.S. dollars, showing China’s determination to continue to expand the utilization of FDI in the financial sector.

2.3.2 The Development of Returnees After 2009

In this stage, the Ministry of Education of China and the Ministry of Foreign Affairs of China issued the first comprehensive guide for the work of overseas students and returnees since the reform and opening up, namely “Opinions of the Ministry of Education and the Ministry of Foreign Affairs on Overseas Students” (referred to as the “20 Articles on Overseas Students”). Under such guidance, the development of returnees has entered a more formal and high-quality stage.

More specifically, first, the distribution of overseas students' majors is relatively stable. According to the survey conducted by (Wang, 2011), in 2010, "Business and Management", "Engineering science", "Social science" and "Engineering technology" were the four most popular majors for Chinese undergraduates to study abroad, accounting for 45.1%, 13.5%, 6.2%, and 6.0% respectively. Later in 2012, Chinese overseas students mainly majored in economics, finance, and management, accounting for 49% of the total in the survey Wang (2012), and 15.6% of the overseas students majored mainly in engineering, followed by those who majored in humanities and social sciences, natural sciences, medicine and other professions (including languages, law, arts, etc.). In 2016, although the proportion of undergraduates choosing "Business and Management" as their overseas study major has decreased, it is still the most popular major, accounting for 31.4%.

Second, in terms of the regions where Chinese students study abroad, most are western European countries, followed by North America and East Asia (Wang, 2012). As shown in Figure 2-3, in 2011, the UK had the largest number of overseas students, accounting for 21.1% of the total returnees, and the US was the second, accounting for 16.7%, followed by Australia, South Korea, France, Japan, Singapore, Canada, and Germany. As those countries are relatively developed economies with high-level science and technology, education, and income, which to some extent provides a certain guarantee for the human capital level of the returnees.

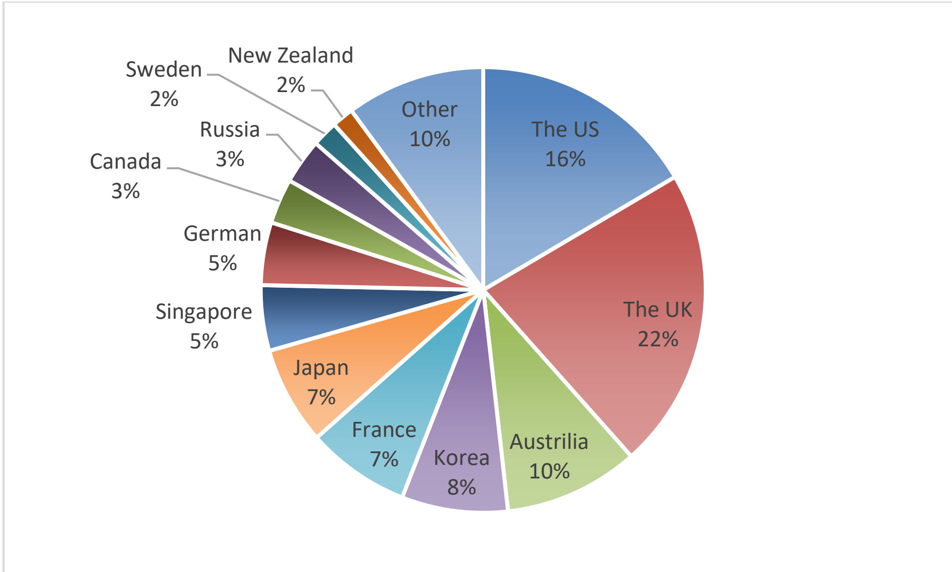

Figure 2-3 The Destinations of China's Overseas Students in 2011

Data source: (Wang, 2012), sorted by the author

Third, the human capital obtained by China's returnees is relatively high. According to the survey conducted by (Wang, 2012), 56.6% of returnees have obtained a master's degree, 18.7% have obtained a doctor's degree, and 0.1% have obtained a post-doctoral degree. In terms of the duration of studying abroad, the average duration is 3.59 years for those with a bachelor's degree, 2.82 years for those with a master's degree, and 7.38 years for those with a doctor's degree. From the perspective of overseas work experience, nearly 85% of Chinese returnees have overseas work experience (including internships). The average working time of all returnees is 2.05 years, and the average working time of those who have doctorate degrees is 3.75 years. Returnees not only have the experience of receiving higher education in economically and technologically developed countries, but also have a long time of experience of living and working abroad, so they have a relatively high level of human capital compared with the domestic students. The large-scale returnees have brought a lot of high-level human capital to China.

Given the importance of returnees in improving the local knowledge base, promoting technological upgrading, and accelerating the internationalization process, Chinese governments have made a greater emphasis to attract returnees back (Bai et al., 2017; Yuping & Suyan, 2015). The central government has promoted many national policies like "Recruitment Program of Global Experts", the "Thousand Talents Program" and the "Ten Thousand Talent Program" to support returnees to contribute to the improvement of the academic and the business (see Table 2-6 for the sample programs related to the talent attraction, retaining, and utilization from 2009 to 2018). For instance, In June 2010, the Central Committee of the Communist Party of China and the State Council issued the "Outline of the National Medium and Long-term Talent Development Plan (2010-2020)" to encourage more talents to return. Later in December 2010, the Central Talent Work Coordination Group approved the "Detailed Rules for the Introduction of Young Overseas High-level Talents" and decided to introduce about 400 outstanding overseas young talents every year starting in 2011. Besides, all the local governments in Chinese provinces issued preferential programs to compete in attracting returnees. For example, Beijing implemented the Overseas Talent Aggregation Project (BOTAP) in 2009 to introduce more return migrations into high-tech enterprises. Shanghai issued the Overseas High-level Talent Gathering Project to attract returnees. Guangdong province also establishes the international youth innovation workshop to invite return talents to take part in the development of Guangdong-Hong Kong-Macau Greater Bay Area.

Table 2-6 Sample Programs Related to the Talent Attraction, Retaining, and Utilisation (2009-2018)

Program	Agency in charge	The target of the program	Year initiated
Young Thousand Talent Program	CLGCTW	Academics under 40 years old with three-plus years of postdoctoral research	2010
Science Fund for Emerging Distinguished Young Scholars	NSFC	Researchers under 38 years old to work in academia	2011
Ten Thousand Talent Program	CLGCTW	To support high-end talent residing in China	2012
New Hundred Talent Program	CAS	Renewal of Hundred Talent Program	2014
Young Cheung Kong Scholar Program	MOE	Endowed professorships for young scholars at Chinese universities	2015

Notes: MOE—Ministry of Education; NSFC—National Natural Science Foundation of China; SAFEA—State Administration of Foreign Expert Affairs; CLGCTW—Central Leading Group for the Coordination of Talent Work. Source: Author's research.

Under these policies and the speeding-up development of the Chinese economy, a greater number of returnees choose to come back to their home. As shown in Figure 2-4, from 2009 to 2019, the number of returnee students increases from 108.3 thousand to 580.3 thousand. In the meantime, the number of students studying abroad also rise from 229.4 thousand to 608.4 thousand, and the reflux rate experienced a great increase from 47.23% to 82.49%. Moreover, a rough sum of the number of people attracted back through the various return programs suggests that, by 2018, the Chinese government had recruited back at least 16000 scientists and high-tech entrepreneurs (NBS). Others may have returned following less well-known but presumably more extensive provincial or institutional programs or on their own accord. The returnees with foreign experience have been found to greatly improve the quality of the local workforce and facilitate the adoption of strong corporate governance practices, internationalization, and knowledge diffusions (Dai & Liu, 2009; Fu et al., 2017; Wang, 2015).

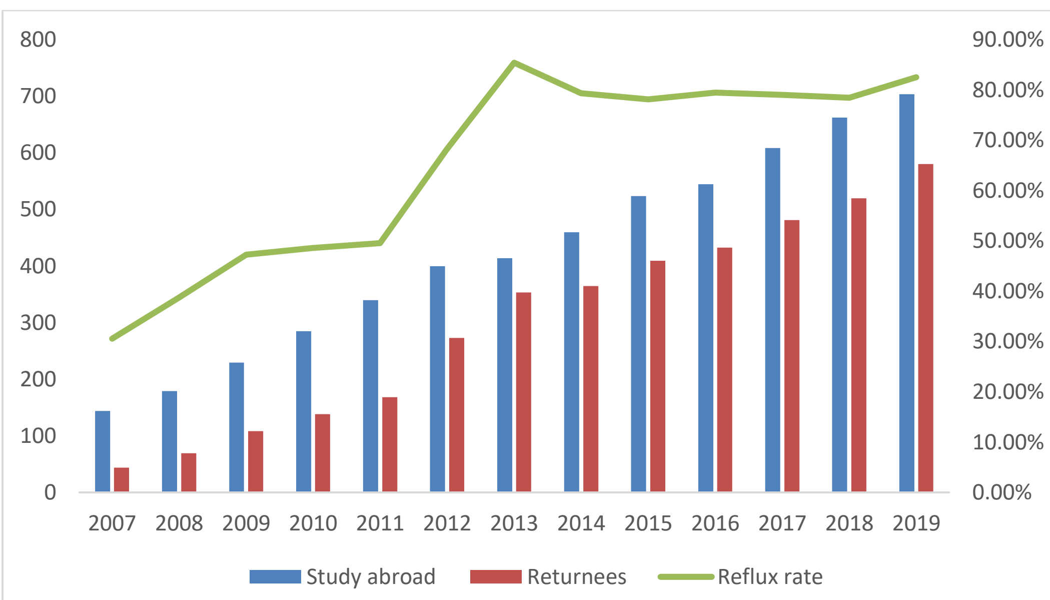

Figure 2-4 The Number of People Study Abroad and Return During 2009-2019

Source: Ministry of Education of the people's Republic of China

Besides, after return, many returnees start their businesses or work in different levels of governments, firms, universities, and research institutions. More specifically, first, in the survey of (Wang, 2012), more than 10% of returnees chose to start their own businesses. The proportion is much higher than that of local graduates in China. It also has been found that returnees have the following characteristics in entrepreneurship: First, entrepreneurship is concentrated in first-tier cities, and the urban market prospect is the most important factor for entrepreneurs. According to the survey, more than 40 percent choose to start their own businesses in Beijing (22 percent) and Shanghai (20 percent). 15.3 percent said they chose a city with good market prospects. Second, the entrepreneurial fields are concentrated in strategic emerging industries, with the new generation of information technology (33%), new bio-engineering/new medicine (19%) being the most active (see Figure 2-5).

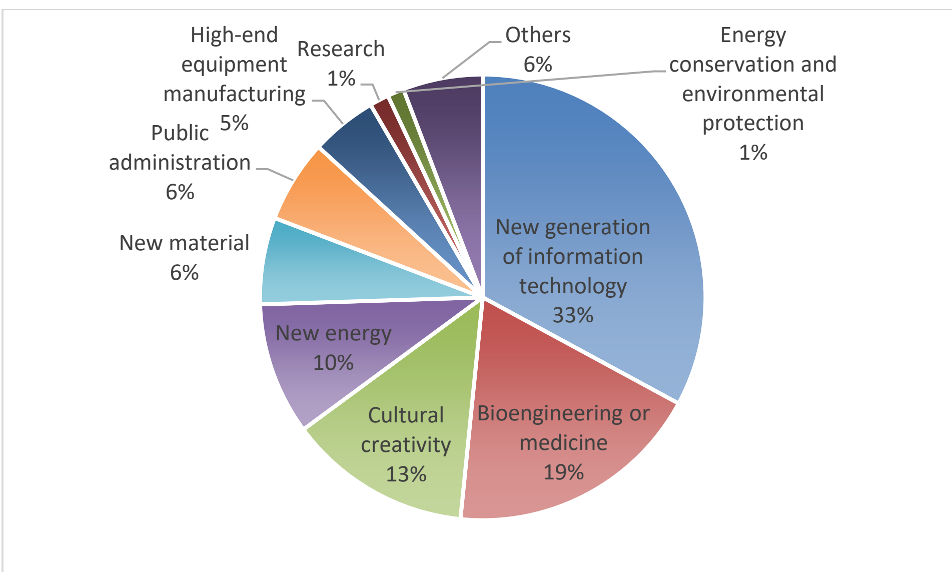

Figure 2-5 The Industrial Distribution of Returnees Entrepreneurs in 2011

Data source: (Wang, 2012), sorted by the author

Second, according to the survey of Wang (2012), the returnees mainly work in high-tech industries, emerging service industries, technology-intensive industries located in the upstream and downstream of the value chain, or industries that have a significant role in promoting industrial development, which account for more than 80% of the returnees. As shown in Figure 2-6, 48% of returnees chose to work in the financial and related services sector, followed by the education, scientific research industry (9%), and the new generation of electronic information technology, biological engineering, or medicine (9%), cultural creativity (7%), and the public administration (7%) and other industries. A large number of returning talents serve such industries, which is of great significance to China's industrial upgrading.

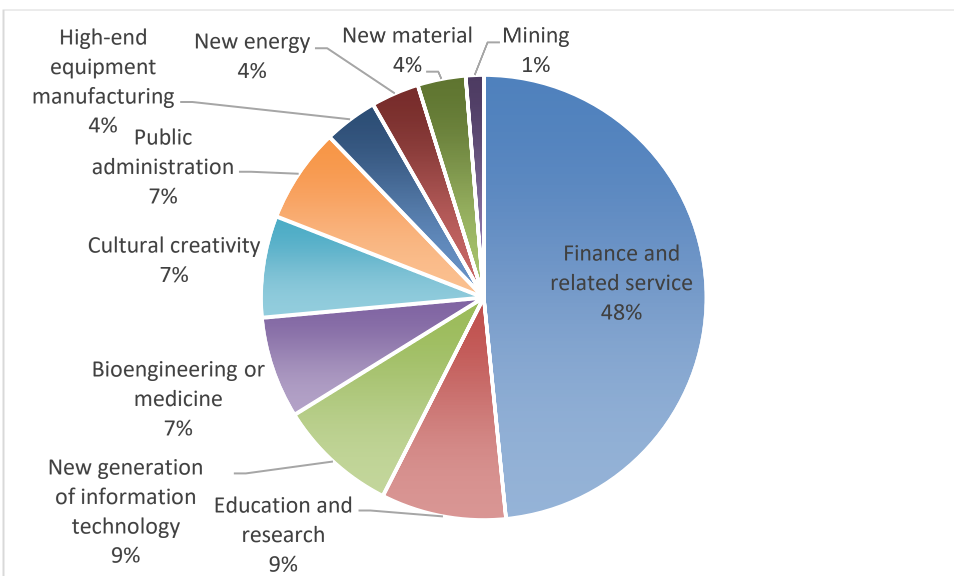

Figure 2-6 The Industrial Distribution of Returnees Employees in 2011

Data source: (Wang, 2012), sorted by the author

Meanwhile, a large number of returnees voluntarily form groups to promote the contact and exchange among members of the groups and become a platform for domestic talents, returned talents and overseas talents to exchange and communicate. For example, founded in October 1913 in Beijing, the Western Returned Scholars Association (WRSA) is an organization voluntarily formed by Chinese returnees. For over a century, the WRSA has united overseas students and applied advanced science, culture, and ideas to revitalize the country. In the early stage, there were Zhan Tianyou, Cai Yuanpei, etc. At present, its directors include Qian Yingyi, Li Kaifu, Zhang Chaoyang, and other excellent talents and entrepreneurs. The number of members in WRSA has reached 80,000 in 2016, and it has formed 15 national branches and established close relations with more than 100 groups of returnees and overseas students. The WRSA also holds many summits, seminars, and exchanges, and acts as a bridge for the communication between domestic and foreign talents, promoting the cooperation between talents from MNEs and domestic firms, and strengthening the return of talents to serve the local economic development. Such interactions between returnees significantly influence their role as knowledge brokers between foreign and domestic firms, which might affect the foreign knowledge dissemination to the local environment.

2.4 Concluding Remarks

This chapter has analysed the development path of FDI and returnees in China. Constrained by relatively weak internal knowledge stocks, China has proactively sought technological assistance and capital from overseas and accelerated the “catch-up” process. In the past 40 years of reform and opening up, as the degree of openness continues to deepen, China has had a close relationship with the development of the world economy through international investment. A large number of MNEs rapidly entered China and set up subsidiaries to expand their business in China. FDI, as a key external technological source, can facilitate the dissemination of advanced technology and managerial patterns to local actors, thus building up Chinese indigenous innovative capabilities (Fu & Gong, 2011; Fu, Pietrobelli, & Soete, 2011). Thanks to several FDI spillover channels, such as labor mobility, demonstration effects forward and backward linkages, China has rapidly promoted its local technological upgrading, and avoided less risky and costly in-house S&T activities. Nevertheless, due to the underdeveloped local absorptive capacity, China has also attracted many highly skilled talents to improve the local knowledge base and expect to facilitate foreign knowledge dissemination. The effect of FDI and returnees on the optimization of China's improvement of technology level, and the transformation of economic growth mode has been greatly emphasized (Chang & Xu, 2008; Fu & Gong, 2011; Hu & Jefferson, 2002; Tian, 2007). With the experience of studying, living, and working abroad, return talents have more overseas connections and more channels to contact and cooperate with MNEs than local Chinese groups. Upon a background of a growing number of talents are returning to China's labor market, it is necessary to effectively restructure and manage the returnees to promote their role in facilitating FDI knowledge spillovers and local development.

Chapter 3 Literature Review

The core research purpose of this Ph.D. thesis is to identify the time-based repatriation features and clustering structures of returnees in FDI knowledge dissemination and find out how they affect Chinese high-tech firms' performance. Previously, an increasing number of studies have shown that FDI spillovers are contingent upon a set of factors such as the host region's absorptive capability, industrial structures, and degree of openness (Crespo & Fontoura, 2007; Ning et al., 2016a; Ning et al., 2016b). Individual returnees can act as knowledge brokers and organizational spanners to facilitate the knowledge externalities. However, the collective impact of returnees in the knowledge dissemination process has not been fully understood. In the following sections, I would extensively review the current literature and present the theoretical framework of this Ph.D. thesis.

The Literature Review is structured as follows. The first section introduces the rationale of FDI knowledge spillovers. It explains how the foreign presence can influence the local firms' performance and discusses the related contingent factors. The second section reviews the existing literature on the relationship between returnees and FDI knowledge dissemination. It introduces the characteristics of returnees and how they affect the local firm performance and absorption of FDI advanced technology. In the third to fifth sections, I emphatically discussed three determinants in FDI spillovers, namely the returnees' expansion time-based characteristics, specialized and diversified clustering, which are normally neglected by most studies. This helps to build up the general theoretical grounding in this Ph.D. thesis. Overall, this chapter aims to systematically review the existing studies regarding the relationship between inward FDI and returnees and provide solid theoretical supports for the analysis in Chapters 5, 6, and 7.

3.1 FDI Knowledge Spillovers and Local Firm Performance

Based on the resource dependence theory, inward FDI is a key external knowledge resource for firms in the emerging market, and domestic firms can learn from FDI knowledge spillover (Buckley, Clegg, & Wang, 2002; Hu & Jefferson, 2002; Jeon, Park, & Ghauri, 2013; Jin, García, & Salomon, 2018; Ning et al., 2016b). The so-called “spillovers” suggest that the technological superiority and strong management practices of FDI can be disseminated to local firms with the help of geographical and cultural proximity, which may result in productivity increases among domestic firms (Buckley et al., 2010; Newman et al., 2015). As a result, local firms in the host country are devoted to seeking opportunities to establish a relationship with FDI and expect to improve their performance by assimilating the advanced technology (Fu & Gong, 2011; Fu et al., 2011).

Previous studies have identified some channels such as business linkage, employee turnover, demonstration effect, and competition effect, through which local firms can learn from FDI knowledge externalities (Zhang et al., 2014). More specifically, first, by establishing backward and forward business linkage, local firms can assimilate the advanced management practices and technologies from FDI (Tzeng, 2018b; Wang, Deng, Kafouros, & Chen, 2012). Second, when employees from a foreign firm find a new job in domestic firms, their experience and knowledge about foreign superior technology can diffuse to domestic firms and increase the firm productivity (Orlic, Hashi, & Hisarciklilar, 2018). Third, the demonstration effect means that domestic firms can observe and imitate the foreign firms' activities in their operations when extensively exposed to the FDI environment (Fu, 2012; Lu, Tao, & Zhu, 2017). The fourth channel is the competition effect, as the increased challenge from FDI may force domestic firms to improve their capability like innovative ability and managerial structures to deal with the competition, which may improve their productivity (Zhang et al., 2014).

However, existing empirical evidence of FDI knowledge spillover is still inconclusive and mixed. Some of the previous studies have argued that the improvement of local performance is positively correlated with FDI (Buckley et al., 2010; Newman et al., 2015; Orlic et al., 2018; Tzeng, 2018b). For example, Ford and Rork (2010) use the data on US states and find that FDI improves the local patent rates and thus promotes economic growth. Moreover, this knowledge can spill across state borders so that contributes to the neighboring states. Smith and Thomas (2017) analyse the regional innovation process in Russia and they confirm significant positive spillovers from FDI. They further show that the regional absorptive capacity can strengthen this effect. Wang and Wu (2016) study the regional production innovation in China and find that foreign-invested firms can promote indigenous innovation. Moreover, they highlight the importance of geographical proximity and vertical industrial linkages in the dissemination of FDI knowledge spillovers. Similarly, Corredoira and McDermott (2014) examine the survey data of the Argentine auto industry and also confirm that local suppliers benefit from the presence of MNE subsidiaries.

Nevertheless, other scholars suggested that the effect of FDI are not always positive and sometimes can be a threat to domestic firms (Martinez-Noya, Garcia-Canal, & Guillen, 2013). The most important argument for the negative impact of FDI is that, with advanced innovative capabilities and more export experience, FDI can produce “crowd-out effects” and/ or “market-stealing” effect so that is harmful to domestic firms’ performance (Hu & Jefferson, 2002; Lu et al., 2017). For example, Ben Hamida and Gugler (2009) analyse the innovation activity surveys of manufacturing firms in Switzerland and they find that not all firms can learn from the FDI knowledge spillover. Only those who invest a lot in human capital can absorb advanced technology. Similarly, Wang and Kafouros (2009) construct an industry-level dataset of Chinese firms and their findings also suggest that FDI does not always bring positive spillovers to local firms. They raise concerns about the moderating factors in facilitating FDI knowledge dissemination. García, Jin, and Salomon (2013) investigate the relationship between FDI and Spanish local firms at both the industry and firm level, and they also confirm a negative impact of FDI knowledge spillovers on the host country firms.

To explain the mixed results, a growing trend of studies argues that certain requirements need to be met for domestic firms to learn from FDI effectively (Blalock & Gertler, 2009; Orlic et al., 2018; Zhang et al., 2010). The local institutional development, geographical proximity, regional industrial structures, the key characteristics of the MNEs and local firms are extensively studied as important factors for the FDI spillovers process (Huang, Liu, & Xu, 2012; Javorcik & Spatareanu, 2011; Ning et al., 2016b; Zhang et al., 2010).

More specifically, first, the local institutional development is critical for FDI knowledge diffusion. A stronger institutional development in the host country is argued to enhance the positive impacts of FDI and reduce its negative ones, as it can facilitate efficient demonstration effect from FDI and provide sufficient protection for the private property of foreign firms. Wang, Gu, Tse, and Yim (2013) collect data for 287 Chinese cities throughout 1999–2005 and also find that the strong institutions in China reduce transaction costs and uncertainty and help local firms to improve their absorptive capability to learn from FDI advanced technology. Following this trend of research, Yi, Chen, Wang, and Kafouros (2015) also find stronger support for the positive moderating role of the regional institution in the productivity spillovers of FDI, by employing a firm-level dataset of Chinese manufacturing firms during the period 2005–2007. Similarly, Nuruzzaman, Singh, and Pattnaik (2019) use a dataset of the Middle East and North Africa (MENA) firms to investigate specific institutional factors and find a more significantly positive FDI spillovers when the region has a greater role of government, and these institutional factors can enhance the innovation spillovers in the regions. However, some scholars also hold the opposite view. For example, Xiao and Park (2018) find a negative moderating role of institutional development after extending the dataset from 1998 to 2007 and integrating the institutional factors with the ownership restructuring of foreign subsidiaries. One reason for the contrasting results is that, as argued by Xiao and Park (2018), under the developing institutional environment, the foreign entrants would take protective efforts to prevent the knowledge diffusion to local firms.

Second, the FDI knowledge spillovers are also contingent on geographical or spatial proximity. Proximity refers to ‘being close to something measured on certain dimensions. Previous literature has acknowledged that proximity is a principal determinant of innovation (Audretsch & Feldman, 1996; Capaldo & Petruzzelli, 2014; Oerlemans & Meeus, 2005). This is because proximity reduces uncertainty and enhances coordination, thereby affecting the inter-organizational relationship of firms adopting open strategies to share, transfer and create knowledge (Knoben & Oerlemans, 2006). Merlevede and Purice (2016) find larger and faster spillover effects on local firms who have a shorter distance from foreign firms. Mariotti, Mutinelli, Nicolini, and Piscitello (2015) also find positive impact of FDI on local firms in Italy. Using a database of foreign firms from 1999 to 2005, they do not demonstrate a positive moderating effect of co-location in the productivity spillovers but find that this effect is stronger for distantly located foreign affiliates, especially for knowledge-intensive service sectors, the logic of which mainly lies in that local firms are more likely to access to the information, and services in larger geographical areas. Similarly, Wang and Wu (2016) integrate both spillover and industrial cluster theories and analyse the FDI at a county-level in the context of China. Their findings further prove that FDI significantly facilitates local firms' production innovation, especially at lower proximity, and local firms' innovative activities can enhance this effect. Moreover, by employing a large firm-level for the 217 regions from eight CEECs countries, Stojčić and Orlić (2019) find more evidence of the spatial dependency of FDI spillovers for other transition economies, and their results further suggest a positive effect of FDI spillovers on downstream firms' productivity and this effect does not decay with the increase of distance.

Third, the local industrial structures also serve as a critical contingency for the FDI knowledge spillovers process. Industrial structure refers to the composition of industrial business activities, and it has long been suggested to exert externalities and facilitate FDI knowledge dissemination. For example, Ning et al. (2016b) use a unique dataset consisting of 30 regions over the period 1999–2008 and find that the local specialized agglomeration structures weaken the positive effects of FDI, however, the local diversified agglomeration strengthens the FDI knowledge spillovers. Moreover, by integrating spatial proximity and industrial structures, Ning et al. (2016a) empirically show that the positive spatial spillover effects of FDI on regional patent innovation are contingent upon specialized and diversified industrial structures of local cities. Specifically, specialized urban structures positively moderate the FDI spillovers process, because it provides highly specialized, requite knowledge bases for assimilating foreign technology and expedites the local spread of FDI spillovers, while diversified structure can restrict the spatial externalities of FDI since it brings various degrees of knowledge and mixed interactions with foreign firms. One critical contribution of their study is that they move beyond previously separate perspectives on the moderating role of geographical factors and industrial agglomeration in absorbing FDI knowledge spillovers.

Fourth, apart from the abovementioned environmental factors, some key characteristics of the MNEs are also examined in the FDI spillovers process. The most important two include the level of presence and dynamic attributes. On the one hand, the level of foreign presence refers to the number of foreign firms or the volume of foreign capital inflow in the local market. It is argued to affect the local productivity as it can bring a different level of business and technological activities (García et al., 2013; Ning et al., 2016b). Previous literature has provided evidence about its impact on FDI knowledge spillovers. For example, Wang and Kafouros (2009) construct an industry-level dataset for China and demonstrate that the impact of FDI is more likely contingent on the local opportunities and foreign presence. Altomonte and Pennings (2009) use a 10,650 firms' dataset during 1995-2001 and find that as the number of MNEs exceeds a certain threshold, the impact of FDI spillovers can be negative on local firms' TFP. They also find these effects vary between manufacturing and services.

On the other hand, the dynamic attributes are usually represented by the characteristics of the entry process of the foreign firm into the local markets. Many scholars investigate this aspect and suggest that the FDI knowledge spillovers take time to occur and local firms need time to absorb the advanced knowledge. In this case, the dynamic process of FDI also can influence the spillovers effect. For example, Wang et al. (2012) develop the constructs of pace and irregularity of foreign entry, which is the first one to depict the dynamic attribute of FDI presence in the last 10 years. They demonstrate that the pace and irregularity of foreign entry negatively moderate the spillover effect of FDI by arguing that domestic firms cannot benefit from the abrupt and discontinuous foreign entry with insufficient absorptive capacities. Besides, Zhang et al. (2014) focus on the dynamic characteristics of FDI entry in its spillover process and extend a range of moderating factors. They find that a higher speed of foreign firms' entry can lead to lower imitative barriers, so that contribute more to domestic firms' productivity. Going a step further, they employ the Annual Industrial Survey Database for Chinese firms and find this spillover effect can be stronger when the foreign firms have lower export intensity, lower intangible asset intensity, and more rhythmic entry pattern since these factors can significantly influence the information asymmetry and network between domestic and foreign firms. Similarly, Wang, Ning, and Zhang (2017b) combine the FDI entry process with the spatial models and suggest that the pace and rhythm of FDI entry not only influence the intra-regional spillovers but also affect the inter-regional knowledge dissemination.

Finally, previous literature finds that the direction and magnitude of FDI externalities can also be contingent on the local absorptive capacity, which is mostly reflected by local human capital, R&D investment, the technology gaps between local and foreign firms. Absorptive capacity reflects local firms' ability to understand and assimilate external knowledge (Castellani & Zanfei, 2003; Lund Vinding, 2006). Due to the tacit and contextual nature, knowledge absorption is built around interpersonal contacts for knowledge sharing, idea generation, and learning (Girma, 2005). Human capital and R&D investment are two of the most critical factors in forming firms' absorptive capacity: human capital provides human resources with 'prior related knowledge' to decode ideas from the outside and builds around interpersonal contacts for technology transferring (Lund Vinding, 2006); while R&D capital offers the necessary financial resources to ease the identification and assimilation of external foreign knowledge (Denicolai, Ramirez, & Tidd, 2016; Vancauteren, 2018). Besides, the technology gap stands for relative technology level compared with firms in the same industry (Hamida, 2013). It can influence the potential benefit of FDI knowledge spillovers to local firms and the difficulty of local capabilities to assimilate and absorb the advanced FDI technology.

The current literature has provided extensive empirical evidence on this contingency. As for human capital, Ben Hamida and Gugler (2009) examine the Swiss firms and confirm a positive impact of FDI knowledge. Their findings also suggest that firms with substantial investments in upgrading their human capital can benefit more from assimilating the FDI-advanced technology. Girma (2005) similarly claims that Chinese local firms would invest more into human capital due to the competition arising from the FDI presence. Concerning the R&D investment as a proxy for local absorptive capability, Liang (2017) demonstrates that the positive spillover of FDI on upstream sectors can be strengthened when local firms have in-house R&D. Marin and Sasidharan (2010) investigate around 3,000 Indian firms for the period 1994-2002 and also find a positive moderating effect of domestic firms' R&D activities. While for the technology gap, Zhang et al. (2010) analyse Chinese manufacturing firms and find that the positive FDI knowledge spillovers are stronger when the technology gap between FDI and the domestic firms is intermediate. Damijan, Rojec, Majcen, and Knell (2013) also suggest that positive horizontal spillovers seem more likely to be present in medium or high-productivity firms.

3.2 The Relationship Between Returnees and FDI Spillovers

3.2.1 Definition and Characteristics of Returnees

Since the onset of the 2008 Global Economic Crisis, developed countries have seen large numbers of highly educated and skilled immigrants (and their families, including children) who had left emerging economies like India, China, Russia, and Brazil returning to their home countries. This phenomenon is referred to as the "reverse brain drain." Returning migrants, who once went abroad in search of greater opportunities, are being lured back to their home countries by their high rates of economic growth. Some scholars argue that as the reverse migration trend intensifies, the "brain drain" is being transformed into a "talent flow" (Carr et al. 2005). Schler and Jackson (1987) put forward a theory of “brain circulation,” arguing that the reverse brain drain only implies a one-way movement of global talent. Brain circulation, by contrast, reflects the circular aspects of this movement, which benefit both the countries of origin and destination of migrating talent (Bai, Holmström Lind, & Johanson, 2016; Dai, Kong, & Liu, 2018; Farquharson & Pruthi, 2015).

According to the current scholars, the returnees are defined as those who returned to their motherland after several years of study or work abroad (Chen, 2008; Dai & Liu, 2009; Filatotchev et al., 2011). With training and learning experience in other countries, returnees often have cross-cultural knowledge and language capability, who have been broadly considered as transnational intermediaries, who can bridge foreign resources and the local development in their motherland (Filatotchev et al., 2011; Fu et al., 2017; Han, Jennings, Liu, & Jennings, 2019). Based on the existing studies, the returnees have several distinguished advantages and disadvantages over their native counterparts.

Concerning the advantages, returnees are typically equipped with inexplicit knowledge structures in related fields and dual social networks (Armanios, Eesley, Li, & Eisenhardt, 2017; Liu et al., 2010a). On the one hand, the abroad experience enables the returnees to get access to and further grasp the advanced technical knowledge (Liu et al., 2014). Particularly in technological fields, returnees have often acquired superior knowledge and skills through the scientific and technical training they received in developed countries. Moreover, their transnational experience can also ensure them to manage the advanced management concepts, corporate governance skills and have a deeper understanding of the overseas markets (Pruthi, 2014). Furthermore, when returnees study or work in developed countries, they have been extensively exposure the advanced technological and business context. This exposure enables the returnees to identify the technological and business practice gaps between the developed and their home countries after their return, which is important for the emerging markets to follow and catch up the economic and technological development process in developed countries (Hao, Yan, Guo, & Wang, 2017; Lee & Roberts, 2015; Lin et al., 2016). Returnees' exposure to the gaps makes them able to identify entrepreneurship and innovation opportunities (Wang, 2015). Thus, returnees can contribute to the performance of technology ventures by identifying and capitalizing upon brokerage opportunities.

On the other hand, with several years of working or learning experience abroad, the returnees can establish the overseas social network, which complements their original local social networks in their home country. Their foreign experience can enhance their social and human capital by providing enhanced reputations, and broad social and business networks (Dai et al., 2018). The current literature has conducted extensive survey studies and emphasized that the dual social network can be the main strength for returnees. For example, Han et al. (2019) focus on the return managers' international experience to investigate how their overseas network influence the local firms' corporate and social responsibility. Their findings suggest that returnees' international experience can both, directly and indirectly, improve the local firms' CSR performance. Moreover, Liu et al. (2014) analyse the returnees in Zhongguancun Science Park in China and they find that the returnees' dual social network can enhance the technical and marketing spillovers on local firms' innovation and financial performance. Overall, these cross-cultural ties, which are novel to the local market context, enable the returnees to identify more new venture creation opportunities, and allow them, in particular, to offset institutional and cultural barriers to dissemination knowledge.

However, returnees have distinct disadvantages as well, and the most important one is the lack of local embeddedness. Several scholars have pointed out that after several years away from their home country, many returnees lack a mature understanding of the local economic development, government practices, social norms, and major historical events (Lin, Lu, Li, & Liu, 2015; Lin et al., 2019; Lin, Chen, & Lin, 2018). Particularly in China, the swiftly changing economic environment imposes more difficulties on this issue. When returnees go back to their emerging market home countries, they usually experience a seemingly familiar, yet different, environment (Liu & Almor, 2016; Yuping & Suyan, 2015). As they are absent in the local development of economic, social, and cultural environment and the environment in the home country and developed countries are different, the returnees may not have comprehensive and well-established frameworks to characterize the institutional contexts in the emerging markets (Wang, 2020; Zheng, Lin, Lu, Liu, & Wright, 2016). Many of the returnees lack a mature, independent understanding of China's swiftly changing contemporary development, social system, regime, government policies, or major historical events. After years of living out of their home countries, they also have missed opportunities to build their local connections and may have lost old contacts (Qin & Estrin, 2015; Qin et al., 2017).

The current studies stress the importance of returnees' inadequacy in the local embeddedness. For example, using a survey about high-tech firms in Zhongguancun Science Park, Armanios et al. (2017) find that returnees lack sufficient local embeddedness and they need the local government to provide admission and funding support to do business in the ZSP. Lin et al. (2019) also focus on the Chinese returnees and suggest the return migrants' local context unknown can significantly affect their local entrepreneurship. This local embeddedness can also be influenced by the interactions of the returnees' ties in the different periods of pre-overseas, during overseas, and after the return. Wang (2020) analyses the returnees from the US to China and their findings indicate that returnees who have weak local social ties suffer a lot from the negative impact of local embeddedness. Thus, returnees' disadvantages in local embeddedness can adversely affect their contributions to local development.

3.2.2 The Impact of Returnees on Local Firm Performance

In the initial literature, some studies regard the phenomenon of returnees as a 'brain drain' in the source country, as numerous best talents leave the poor developing countries while do not come back (Bhagwati & Hamada, 1974). However, in recent years, the "brain drain" gradually gives way to "brain gain". This is because scholars have been examining a new channel of international knowledge spillover that considers the eventual return of overseas talent to their home countries bearing additional knowledge and skills that were learned abroad. Such returning talent provides new knowledge and positive spillover effects to local firms, thus shifting the 'brain drain' event to a 'brain circulation' or 'brain gain' event (Agrawal, Kapur, McHale, & Oettl, 2011; Giannetti, Liao, & Yu, 2015; Mayr & Peri, 2008).

(1) Returnees and Local Firm Innovation

Concerning the impact of returnees on local firm performance, the current literature has gradually recognized that the returnees can influence the local firms' innovative activities and consciousness, since they can add to the local human capital and bring knowledge heterogeneity (Jonkers & Cruz-Castro, 2013; Yuan & Wen, 2018). Most of the existing studies support that the returnees can promote the local firm innovation performance and the reasons are as follows.

Firstly, building upon a knowledge-based view, returnees themselves can add to the local human capital and the knowledge transfer through returned entrepreneurs can promote the local firms' innovation performance. It has been widely acknowledged that human resource is a critical factor that can drive innovation, as the knowledge resides in the people and their interactions (Basile, Pittiglio, & Reganati, 2017; Burger & Meijers, 2016; de Groot, Poot, & Smit, 2016). After the scientific training and business practice, the returnees may have gained academic and management knowledge. The mobility of returnees can build the local knowledge base and promote the transfer of competence (Dustmann, Fadlon, & Weiss, 2011; Levin & Barnard, 2013). Filatotchev et al. (2011) have confirmed that the returnees can both improve local firms' innovation output and exert significant spillovers, so that promote other local firms' innovation. By analyzing the high-tech firms located in Zhongguancun Science Park in Beijing, their results suggest that returnees can act as special human capital as they have specific knowledge with varying degrees of transferability. Similarly, Liu, Wright, and Filatotchev (2013) also find a positive relationship between returnees and firm innovation performance, and their arguments indicate that local firms benefit from the returnees' entrepreneur experiential and vicarious learning capabilities.

Secondly, from a knowledge heterogeneity perspective, the returnees can bring heterogeneity to local firms' knowledge base, which enables local firms to access a broader range of knowledge, perspectives, and experiences, and interactions across individuals will augment the firm's capability to make novel linkages and associations (Mohammadi, Broström, & Franzoni, 2017; Østergaard, Timmermans, & Kristinsson, 2011). As confirmed by previous literature, employees' educational background is beneficial for firms' knowledge search and the ability to capitalize on external knowledge flows. The diversity in employees' educational level, such as in the composition of bachelors, masters, and doctors can influence the information, knowledge, and skills that employees contribute to the firm. Using firm-level data of Danish companies, Bogers, Foss, and Lyngsie (2018) confirm that the knowledge embedded in diverse employees may also enable firms to establish different social networks and professional communities. Lin (2014) examines Taiwanese industrial data and also proves that the heterogeneity in the employees' educational background brings to a local firm with adequate skills and information, which can help local industries find more exploratory ideas. This type of diversity facilitates local firms to search for broader relationships with foreign firms and cope with the complex cognitive tasks that are required to bring different knowledge domains together.

Thirdly, the returnees can promote the local innovation consciousness so that further enhance the innovation achievements in local firms. Li, Zhang, Li, Zhou, and Zhang (2012) argue that the returnees' exposure to both the developed countries and their home countries make them realize the technology gaps between different country contexts, which further enable them to identify innovation opportunities easier compared with their local peers. Yuan and Wen (2018) also suggest that highly skilled talents with foreign experience are scarce resources, who can receive the attention from employers, employees, and foreign investors. In this case, the returnees may increase a firm's willingness to invest in innovative activities, so that promote the local firm performance. Moreover, Dai et al. (2018) further indicate that returnees can provide managerial experience and dual social and business networks, which are important for improving the local firms' innovation efficiency. Combining with the three above arguments, the returnees are believed to improve the local firms' innovation.

(2) Returnees and Local Firm Entrepreneurship

The second impact of returnees is that they can bring entrepreneurship to local firms, however, the current researchers have not reached a consensus on whether returnees can promote the local entrepreneur's performance. Some scholars suggest a positive effect of returnees on local entrepreneurship and their main argument lies in returnees' cross-border networks. For example, Wang (2020) analyses a large sample of returnees from the US and their results suggest that the cross-border ties of returnees are novel to the local market context. This linkage enhances the returnees' ability to identify new venture opportunities in their home counties and increases the likelihood of the returnees to create ventures. Similarly, Kenney, Breznitz, and Murphree (2013) analyse the returnees in China and India and find that returnee entrepreneurship plays an important role in the second development phase of the start-ups in the ICT industries.

Nevertheless, other scholars hold an opposite opinion and indicate that returnees might perform worse than the local entrepreneurs. For instance, Li et al. (2012) focus on the certified firms in Zhongguancun Science Park in Beijing and confirm that returnees are not always present a higher performance on entrepreneurship but rather have a significantly negative relationship with venture employment size and sales. Similarly, Sun (2013) makes a comparison between returnee venture capitalists and local entrepreneurs and finds that returnees are less productive, especially in providing value-added services and making promising projects. Moreover, based on a sample of technological ventures in China, Qin et al. (2017) also find that returnees are slower in establishing new ventures in the home country than their local counterparts. The reason for the mixed findings is more likely due to the net effect of the returnees' advantages of higher education and overseas experience and disadvantages in the lack of both local connections and local knowledge.

(3) Returnees and Local Firm Internationalization

A third aspect that can be brought by returnees to local firms is that they can improve the firms' internationalization process. As suggested by the traditional Uppsala internationalization model, internationalization is an innovative act that exposes a firm to the environment of international markets (Cui, Li, Meyer, & Li, 2015). By participating the internationalization, firms can gain more overseas markets and promote their new product, however, they can be faced with extensive competition. International knowledge and R&D capability have been widely recognized as essential factors that can facilitate firms' internationalization process (Hsu, Lien, & Chen, 2013). Returnees have acquired certain international experience and R&D

capabilities, which permits them to constitute local firms' sources of international knowledge, enlarge the access to the international market and help to promptly react to opportunities (Bai et al., 2018; Bai et al., 2017; Cui et al., 2015).

In specific, firstly, returnee entrepreneurs tend to apply the experience gained while living abroad in starting ventures that may target markets outside of their home country (Cui et al., 2015). The returnee entrepreneurs can transfer part of their experience to other managers/employees in the firm, which may enable them to implement an internationalization strategy where mistakes could be avoided and where the returnee entrepreneurs' experience may serve as a springboard that gives firms a learning advantage (Chen & Tan, 2016). For example, by employing a sample of Chinese firms that are managed or owned by returnees, Li (2020) confirms that the dual network of returnee entrepreneurs helps them to promote their firms' internationalization performance. Bai et al. (2018) also provide evidence on the positive impact of the returnees' overseas social network on their firms' internationalization. Wentrup, Nakamura, and Ström (2020) analyse Moroccan digital enterprises and find that the inflow of returnee entrepreneurs would promote the international ambitions of local firms and further close their gaps with the global market. Moreover, Brzozowski, Cucculelli, and Surdej (2019) investigate the returnee entrepreneurs in the Italian ICT industry, and they confirm that return migrations might focus more on the transnational market and facilitate firms' internationalization. Similarly, Bai et al. (2016) analyse a sample of China's international joint ventures and find that when returnee managers have higher international networking capability, their firms would have better international business.

Secondly, the technological knowledge acquired by returnees from operating in international high-technology markets can help improve their firms' internationalization (Filatotchev, Liu, Buck, & Wright, 2009). Integrating the high-technology international markets requires knowledge on both selling and developing new products. Returnee entrepreneurs with advanced technological knowledge are capable of engaging in product development and producing new products with the potential to compete in the international markets (Dai & Liu, 2009). This argument is strongly supported by the study conducted by many studies. For example, Filatotchev et al. (2009) analyse a dataset of small and medium enterprises located in Zhongguancun Science Park in Beijing, and they find that the returnees with solid technical knowledge and international experience can significantly promote the technological upgrading in the SMEs' production development, which further improves the SMEs' export orientation and performance. Schotter and Abdelzaher (2013) also confirm that Muslim return migrations who live in the west can promote the internationalization processes of firms from the Organization of Islamic Conference countries. In addition to technological knowledge, Liu and Almor (2016) suggest that returnees also have specific knowledge about how to interact with customers and authorities, which influences the development of new products. Similarly, using an event-historical dataset of Chinese electronic manufacturing firms, Cui et al. (2015) also confirm that returnee managers with cross-culture knowledge are positively associated with emerging economy firms' likelihood of conducting international business, especially foreign direct investment.

3.2.3 The Impact of Returnees on FDI Knowledge Spillovers: An Absorptive Capacity Perspective

As suggested in the previous section, local firms in emerging markets can benefit from FDI spillovers since it often represents a critical external knowledge resource (Ning & Wang, 2018). Previous studies have identified several channels, such as business networks, financial linkage, employee turnover, demonstration effect, and competition effect, through which local firms can gain advanced knowledge from foreign firms (Li, Sutherland, & Ning, 2017; Zhang et al., 2014). Nevertheless, the existing empirical evidence of FDI knowledge spillovers remains inconclusive. One of the reasons, as some scholars have argued, is because that the heterogeneity of local absorptive capacity is problematic in developing countries, given their insufficient knowledge base (Fu & Gong, 2011; Girma, 2005). It is widely acknowledged that acquiring external knowledge from FDI spillover is not straightforward, and domestic firms need sufficient absorptive capacities to benefit from FDI (Kang & Lee, 2017).

Based on the absorptive capacity theory, absorptive capacity reflects local firms' or regions' ability to understand and assimilate external knowledge (Castellani & Zanfei, 2003; Lund Vinding, 2006). Human capital is one of the critical factors in forming local absorptive capacity, as it provides human resources with 'prior related knowledge' to decode ideas from the outside and builds around interpersonal contacts for technology transferring (Lund Vinding, 2006). The previous literature has acknowledged that, by increasing human capital, local firms can improve their capability to identify the advanced FDI technologies and overcome some of the technological and organizational barriers that prevent learning from FDI spillovers

(Marcin, 2008; Zhang et al., 2010). Extensive empirical evidence has been conducted on this contingency. For instance, Ben Hamida and Gugler (2009) examine the Swiss firms and suggest that firms with substantial investments in upgrading their human capital can benefit more from assimilating the FDI advanced technology. Liang (2017) find that a large quantity of local firms' in-house R&D human capital facilitates the learning from MNEs.

In this thesis, I mainly focus on a specific type of human capital, returnees, as a new factor of absorptive capacity. Since the returnees often understand multiple cultures, possess technological and managerial expertise, they represent a critical type of human capital that can act as a 'bridge' between the MNEs and local firms (Lin et al., 2016; Liu et al., 2014). Therefore, returnees can add to local human capital and absorptive capacity and are vital for domestic firms to learn more from FDI knowledge spillovers. It is necessary to find out the specific effect of returnees and better exploit it. Specifically, there are two main reasons for how returnees can improve local absorptive capacity for FDI spillovers from the knowledge base and knowledge brokerage perspective.

First, returnees can collectively improve the technological base of local industries and promote local absorptive capacities (Dai & Liu, 2009; Filatotchev et al., 2011). Given the advanced skills and confidence with world-class technologies, the presence of returnees presence can not only contribute to the firm and industry's talent pool, but also stimulate the local elites to improve, and thus promote the local knowledge base (Lin et al., 2015; Wang, 2015). In addition, in China, highly skilled returnees are scarce resources at the firm level. Therefore, the returnees may receive attention from employers, employees, and foreign investors

(Viederyte, 2016; Yuan & Wen, 2018). As a result, it may stimulate local firms to invest more in innovative activities. Meanwhile, when learning from FDI, given the same amount of investment, returnee with advanced knowledge might be better in choosing projects (Yuan & Wen, 2018), which may increase the chance of project success, improve firm capabilities, and ultimately benefit the firm from absorbing the FDI knowledge spillover more effectively.

Second, the returnees can serve as knowledge brokers between FDI and domestic firms (Lin et al., 2016; Xiao & Tsui, 2007). With a long time of training abroad, the returnees are usually equipped with superior technical and entrepreneurial skills and professional international networks (Kenney et al., 2013). After their return, their knowledge of both their home and host countries enables them to identify cross-border differences and knowledge gaps between foreign and domestic firms (Bai et al., 2017). In this case, the returnees can act as knowledge brokers in transferring technological and business knowledge from FDI (Obukhova, 2012). Wang (2015) also argues that these returnee knowledge brokers can understand the resources and preferences of both foreign and local firms so that help identify the institutional and cultural differences. Moreover, the dual networks of returnees enable local firms to collect information, identify opportunities and establish new contacts with multinational enterprises (Tzeng, 2018b). Thus, the returnees may improve local absorptive capacities to learn more from FDI knowledge spillovers and further promote local firm performance.

Although important, the moderating role of returnees in FDI knowledge spillovers has not been fully researched in the context of China as well as other emerging markets (Filatotchev et al., 2011; Wei, Liu, Lu, & Yang, 2017). Very limited literature has examined how the interplay between FDI and returnees influences local firm performance. Most of them, if any, only focus on the impact of individual returnees on foreign knowledge diffusion, due to the lack of a comprehensive dataset to construct aggregated indicators (Liu et al., 2010b; Wang et al., 2011). In this thesis, based on an extensive firm-level dataset in ZSP, I make the first attempt to integrate these two streams of literature and hope to investigate the contingent role of returnees at the collective level in FDI knowledge diffusion. More specifically, based on the absorptive capacity theory and from a dynamic perspective, I would first review how returnees' repatriation into local industries influences FDI knowledge spillovers in section 3.3. Then, combined with the cluster theory, I would illustrate how different clustering structures of returnees can affect local absorptive capacities and FDI knowledge dissemination in sections 3.4 and 3.5. Figure 3-1 presents an overview of the theoretical framework in this thesis.

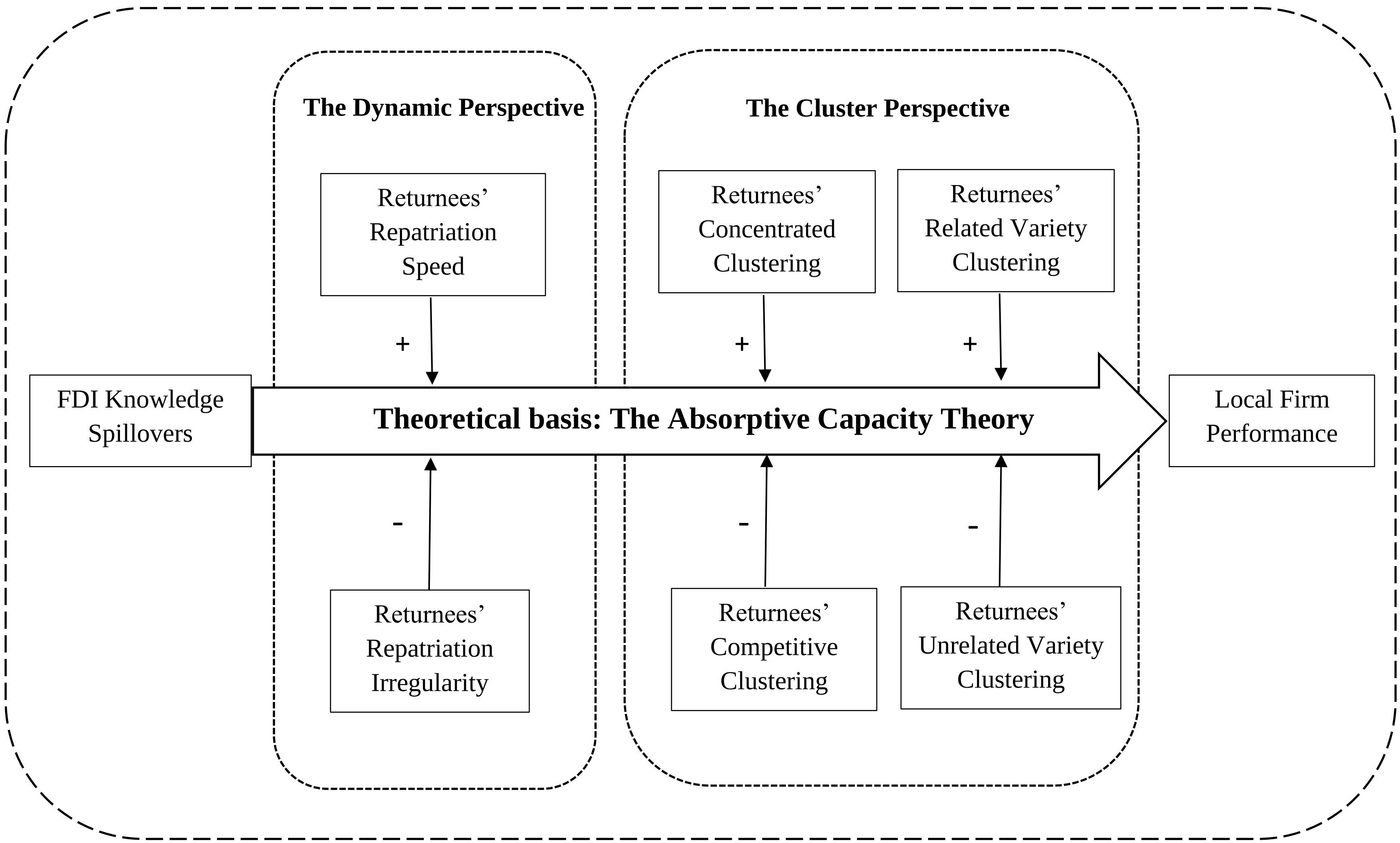

Figure 3-1 An Overview of the Theoretical Framework

3.3 Returnees' Repatriation into Local Industries and FDI Spillovers

3.3.1 Speed and Irregularity: Two Dynamic Characteristics of Repatriation Process

"Time" has long been considered a key issue in international business, as it affects a wide range of both MNEs' and local firms' activities (Vermeulen & Barkema, 2002; Wang et al., 2012). Previous literature argues that learning is a process that takes time to occur, as firms need time to identify, assimilate and imitate foreign technology (Zhang et al., 2014). Based on this dynamic perspective, many studies suggest that the entry of returnees is also a process-dependent approach (Cui et al., 2015; Qin & Estrin, 2015). After several years away from their homeland, the returnees need time to readjust to the local environment and their role in improving the local knowledge base and establishing networks also require a period of time (Lin et al., 2019; Zheng et al., 2016). Therefore, considering the time-based attributes of returnee repatriation is very important to find out their functions in the absorption of FDI knowledge spillovers. However, previous research mainly considered the static characteristics of returnees, and little is known about their dynamic attributes over time.

I contend that the learning process from FDI spillovers is dependent on the returnees' repatriation mode. Speed and irregularity are two of the most important dynamic attributes of returnees over time. Speed measures how rapidly returnee's repatriation into the industry at a point in time (Hao, Wen, & Welch, 2016). As the knowledge resides in the individual returnees, when the highly skilled talents speed up their repatriation into the industry, they may transfer more new knowledge to the local industry so that can accelerate the improvement of firm absorptive capacities as well as innovation capabilities (Hao et al., 2016; Wright, Tartari, Huang, Di Lorenzo, & Bercovitz, 2018). Irregularity is another time-related attribute, which indicates the rhythm or progress of returnees' entry. The irregularity of returnees' repatriation into local industries also affects knowledge dissemination. The core argument is that the returnees' readjustment to the local context is more likely to emerge when the returnees' repatriation process is predictable and continuous. the rhythm of MNEs' foreign expansion also affects technology transfers and dissemination. In other words, returnees can contribute more to the local knowledge base when they enter the local industries through a stable, constant, and rhythmic process (Wang et al., 2012).

I follow the work of Vermeulen and Barkema (2002) and use Figure 3-1 to explain the returnees' repatriation speed and irregularity intuitively. Considering the returnees' repatriation paths into Industry 1 and Industry 2, speed and irregularity are two independent dimensions of their repatriation process. For example, the returnees have the same repatriation speed in industry 1 and industry 2, but their irregularity is entirely different. Assuming the time span in Figure 1 is one year, the annual increased number of returnees in Industry 1 is constant. It is considered that the returnees will establish entry into Industry 1 in a rhythmic and regular pattern, and their total number will increase sequentially. On the contrary, In Industry 2, the returnees only enter it in two separate years, and the number of returnees on the first occasion is larger than on the second. Therefore, although the total number of returnees for both industries is the same, the returnees' repatriation in Industry 2 is much more irregular and unpredictable.

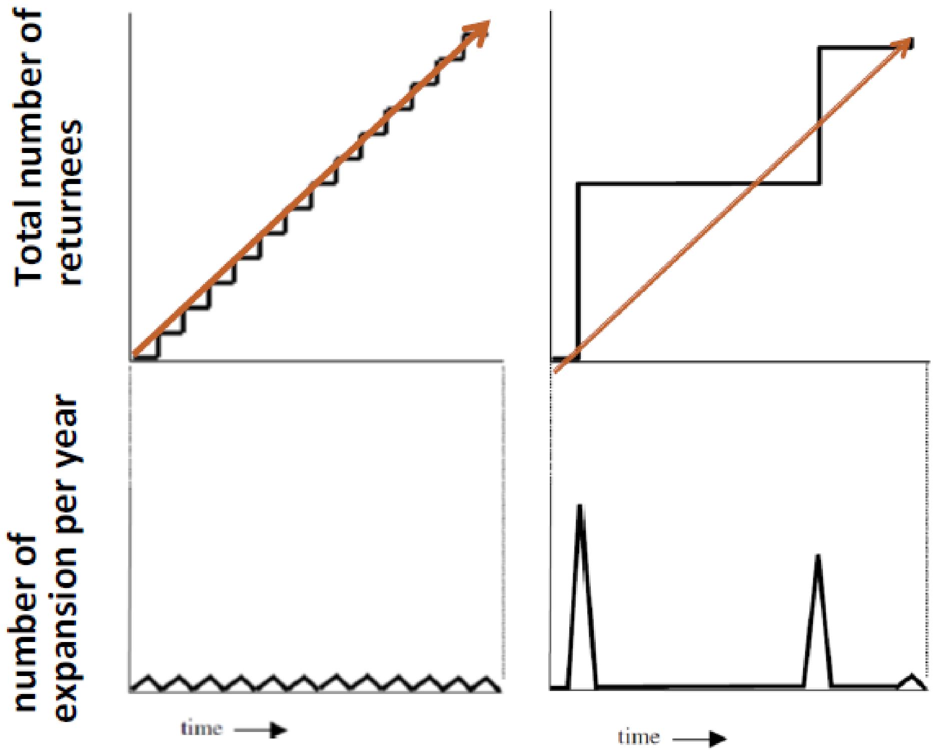

Figure 3-2 A Comparison Between Rhythmic and Irregular Returnees' Repatriation Patterns

In previous literature, these two types of dynamic attributes are initially used in explaining a firm's entry strategy into a target market. For instance, Vermeulen and Barkema (2002) denote that the rhythm describes the changing number of subsidiaries in one individual MNE over a time period, measured by the kurtosis of the first derivative of the number of subsidiaries. Later, many scholars expand these concepts to the foreign firms' entry process at the collective level and explore how the time-based characteristics of MNEs activities influence the knowledge externality. For example, using a panel dataset from Chinese manufacturing industries over the period 1998-2006, Wang et al. (2012) demonstrated that the pace of foreign entry negatively moderates the relationship between foreign presence and local firms' total factor productivity. Moreover, such negative effects are more evident for domestic firms operating in low-tech sectors, as FDI spillovers to host region industries are also accompanied by crowding-out effects (Spencer, 2008). MNEs that employ state-of-the-art technology disseminate great pressures to local firms in emerging economies, and these quickly spread over a compressed time. On the contrary, using a panel dataset on Chinese cities from 2004-2011, Wang et al. (2017b) demonstrated that rapid foreign expansions exert a positive moderating effect on intercity FDI spillovers, and an irregular foreign expansion would hamper the knowledge exchange process. Based on this line of research, I make the first attempt to apply the two critical dynamic attributes to analyse how the returnees' repatriation influence the local firm performance and FDI knowledge spillovers.

3.3.2 Returnees' Repatriation Speed and FDI Spillovers

As argued above, the returnees can play a key role in helping absorb FDI knowledge spillover and the time-based attributes of returnee repatriation deserve more attention. These highly skilled individuals can increase a firm's availability of valuable prior related knowledge for learning FDI advanced technology (Liu et al., 2014; Lund Vinding, 2006). The more returnees in local industries at a particular time, the narrower the technological gaps with foreign firms, leading to a more significant improvement of local absorptive capacities. To step further, there are good reasons to believe that a rapid speed of returnee repatriation into local industries may positively facilitate FDI knowledge dissemination.

First, when the returnees speed up their entry into the industry, they may transfer more new knowledge to the local industry so that can accelerate the improvement of firm absorptive capacities as well as innovation capabilities (Kang & Lee, 2017; Lichtenthaler & Lichtenthaler, 2009). Previous studies demonstrate that the innovation speed positively moderates knowledge spillovers, and domestic firms may obtain competitive advantages through the fast commercialization of technology (Markman, Gianiodis, et al. 2005). In certain high-tech sectors, new knowledge is regarded as the key to competitive advantages, therefore, domestic firms prefer to explore a rapid returnee entry to improve their knowledge base in a more effective way (Kang & Lee, 2017). Consequently, domestic firms need to adjust mechanisms in highly competitive labor markets and make full use of a rapid returnee entry.

Second, returnees often have an incentive to enter early to enjoy the first-mover advantages in the labor market (Qin et al., 2017). With a long time of training abroad, the returnees are usually equipped with superior technical and entrepreneurial skills and professional international networks (Kenney et al., 2013). When returning to their home country, their knowledge of both their home and host countries enables them to identify cross-border differences and knowledge gaps between foreign and local firms (Bai et al., 2017). These incentives will also push them to interact or ally with foreign companies, establish stronger business linkages, acquire more information advantages, and thus give local firms more opportunities to learn from foreign knowledge spillovers (Bai et al., 2018; Zheng et al., 2016). Meanwhile, when learning from FDI, given the same amount of investment, returnee with advanced knowledge might be better in choosing projects (Yuan & Wen, 2018), which may increase the chance of project success, improve firm capabilities, and ultimately benefit the firm from absorbing the FDI knowledge spillover more effectively.

3.3.3 Returnees' Repatriation Irregularity and FDI Spillovers

Contrary to repatriation speed, the fundamental mechanism of how the returnees' repatriation irregularity moderates the FDI spillovers is more likely to be negative. The reasons are twofold. First, the returnees need time to readjust and play a role in enhancing local absorptive capacities. Apart from skilled expertise, the returnees have been isolated from their home countries for years and may face readjustment difficulties when returning to their home countries (Lin et al., 2019). Also, according to Armanios et al. (2017), the low context relevance of the returnees may make it difficult for them to apply capabilities effectively. Therefore, from the local embeddedness view, a stable environment is necessary for returnees to readjust to local cultural and institutional settings (Qin et al., 2017). When the returnees enter into the local industries irregularly, this process is unpredictable and discontinuous and may cause an unstable working environment. Only a rhythmic and progressive expansion process by the returnees entering into the industry can help them build robust and stable social networks, accelerate their readjustment to the local context, thereby allowing knowledge exchange to take place through business interactions with foreign knowledge (Farquharson & Pruthi, 2015; Ma et al., 2018).

Second, an irregularity of returnee entry may cause fluctuating competition, which might not benefit the returnees' contributions to local absorptive capacity. An abrupt and discontinuous change in the number of returnees entry into an industry is often accompanied by a sudden rise or fall of labor competition (Hao et al., 2016). In such an unstable business environment, it is also difficult for returnees to interact with local workers and improve the knowledge base (Choudhury, 2015; Qin, 2015). Moreover, if competition fluctuates dramatically, it may also increase the risk and complexity of the returnees working with foreign firms. Consequently, the contributions of returnees to local absorptive capacity can be constrained if they are unable to readjust to local settings because of irregular repatriation. Only a rhythmic and progressive repatriation process can reduce the potential uncertainty, establish robust and stable local networks (Lin et al., 2016; Lin et al., 2019), thereby helping returnees realize their functions in building up the local absorptive capacity. Based on the above reasoning, I contend that a rhythmic path of returnees' repatriation is required to help local firms benefit more from the FDI knowledge spillovers.

3.4 Specialized Agglomeration of Returnees and FDI Spillovers

In the previous part, it is argued that the transmission of FDI knowledge spillovers is contingent on certain factors. Among the factors, it has been widely recognized that industrial agglomeration affects local absorptive capacities and the knowledge diffusion of local productivity (Henderson, 1997; Paci & Usai, 1999). Firms usually prefer to be geographically agglomerated in clusters and benefit from the spatial technological spillovers (Basile et al., 2017; Burger & Meijers, 2016; Diodato, Neffke, & O'Clery, 2018; Jia, Li, Tallman, & Zheng, 2017). In the literature of cluster theory, two types of industrial agglomeration are widely considered to play an important role in facilitating the knowledge externality, including specialized industrial agglomeration (specialization), which operates mainly within specific industries, and diversified industrial agglomeration (diversification) which works across industries (Beaudry & Schiffauerova, 2009; Capozza, Salomone, & Somma, 2018; de Groot et al., 2016). More specifically, on the one hand, the concept of specialization is developed by Marshall Marshall (1890), Arrow (1962), and Romer (1986) and further formalized by Glaeser et al (1992). They argue that the specialized industrial structure facilitates the within-industry transmission of knowledge, as the geographical proximity favors the information exchange and face-to-face interactions, reduces the transportation costs for the innovation resources, and provides a more efficient labor market. In contrast, Jacobs (1969) proposes a concept of industrial diversification and believes that it is the diversity of local industries that serve as the engine for innovation. They suggest that the variety of industrial activities provide a higher potential for knowledge interaction and economic dynamism.

Despite the volume of research on specialized industrial agglomeration, relatively less apply these two perspectives to analyse the collective role of returnees in the local firm performance and FDI knowledge diffusion process. Indeed, the cluster theory holds a view that the sectors are not working alone but rather exert knowledge interactions and externality that can contribute to the local firm performance and the absorption of external knowledge sources (Capozza et al., 2018; Faggio, Silva, & Strange, 2020). Similarly, returnees, as a very important and special labor force for emerging markets, are also not working alone (Hao et al., 2016; Wang, 2011). With the help of geographical proximity, returnees can agglomerate in certain industries and regions, so that form different types of clustering structures. Their communications within and across industries can magnify or restrict their collectively interactive learning process, so that influence their contributions to local absorptive capacities. Although the current literature has extensively emphasized the critical role of returnees at the individual level in promoting the local firm performance and bridging the foreign and domestic, their collective role has not received enough attention. I, therefore, make the first attempt to apply the industrial agglomeration perspective to explain the collective impact of returnees on local absorptive capacities and FDI knowledge spillovers. In section 3.4, I would review the relevant literature on the industrial specialization debate and discuss how the specialized industrial structures of returnees affect the FDI knowledge spillovers process. Then in section 3.5, I would introduce how to apply the diversified industrial structures view to analyse the structural impact of returnees on local firm performance and the FDI externalities.

3.4.1 Concentrated and Competitive Structures: Two Dimensions of Specialized Agglomeration

The specialized agglomeration depicts the intra-industry knowledge externality and mainly includes two types of structures, namely concentrated and competitive structures (Bucci & Ushchev, 2020; Gabe & Abel, 2012). On the one hand, in existing literature, a concentrated industrial structure reflects the overall agglomeration of certain industries and is also known as the Marshall–Arrow–Romer (MAR) specialization (Barrios, Bertinelli, & Strobl, 2006; Ellison & Glaeser, 1999; Feldman & Audretsch, 1999; Gabe & Abel, 2012). This model contends that the concentration of an industry in a region promotes knowledge spillovers between firms and facilitates innovation in that particular industry within that region, as the similar knowledge base facilitates the exchange of knowledge, processes of business interaction, and inter-firm labor mobility (Holmes & Stevens, 2002; Martin, Mayer, & Mayneris, 2011). Such interactions can thus positively influence firm productivity and growth. On the other hand, Porter (1998) proposes an industrial competition perspective, and their arguments about the intra-industry knowledge diffusion suggest that it is strong industrial competition in the same market, rather than a local monopoly, provide significant incentives to innovate and further promote local firm performance.

3.4.2 Concentrated Industrial Structure and Local Performance

The existing researchers have not reached a consensus or found conclusive empirical results on the role of concentrated industrial structure and competitive industrial structure on local performance. As for the concentrated industrial structure, a majority of scholars consider it can promote local productivity and innovation. The core argument is that the geographically concentrated firms in the same industry enable them to learn from one other, to exchange ideas, to employ imitation business interactions, as well as to access external knowledge and resources (Saxenian, 1994). These unintentional and uncompensated exchanges of knowledge can help to configure a firm’s specific capabilities and returns.

The existing studies have found much evidence for this impact. For example, Guevara-Rosero, Riou, and Autant-Bernard (2019) analyse the Economic Census of Ecuador and find that the industrial concentration indeed exerts a positive effect on the regional productivity and innovative performance in Ecuador. van der Panne (2004) research the context of Dutch and their results also show that the argument of MAR thesis on industrial concentration is correct, especially for R&D intensive and small firms. Ketelhöhn (2006) investigate the US semiconductor industry and find that the industrial specialization, as well as proximity between buyers and suppliers, is positively related to the local innovation output. Barrios et al. (2006) examine the Irish manufacturing industries and confirm a positive relationship between the local industrial concentration and firms' scale and productivity. Martin et al. (2011) search in the French context and their findings suggest that firms in French benefit a lot from the concentration of similar industries. Liang and Goetz (2018) investigate the data on the NAICS industries of the US and also find positive spillovers from the MAR industrial concentration, and the sectors with low technology intensities can get a higher benefit. Besides, in the context of Italy, Basile et al. (2017) also confirm a positive impact of industrial concentration on local firm performance, such as survival and productivity, particularly in services sectors. As for UK's situation, Faggio et al. (2020) estimate a model for manufacturing sectors and also confirm the importance of industrial concentration.

However, others hold an opposite opinion and find negative impacts of industrial concentration, as they think the highly specialized knowledge base might cause the firms into a "locked-in" situation. Firms might lose economic dynamism and only focus on a narrow range of technological activities, which restricts the local technological upgrading process. For instance, de Vor and de Groot (2010) investigate the municipality in Amsterdam and they suggest that the concentration of industries does not facilitate but rather restricts the local productivity growth. Viladecans-Marsal (2004) finds that only certain manufacturing industries can benefit from the industrial concentration in Spain. Camisón and Villar-López

(2012) also suggest that firms should not be expected to learn from the knowledge spillovers that arise from the co-location of similar industries. Moreover, in the study of Drucker (2011), the authors examine the data on US firms and confirm that the industrial concentration might cause a decline in regional employment. Similarly, Wang, Madsen, and Steiner (2017a) investigate the impact of industrial on local employment growth in Canada and finally find a negative relationship. Wójcik and MacDonald-Korth (2015) further indicate that the co-location of industries does not suffice to generate positive external returns for the local firms. In the context of China, Ning et al. (2016b) also confirm a lock-in effect of industrial concentration by using the comprehensive city-level dataset.

3.4.3 Competitive Industrial Structure and Local Performance

The traditional arguments on the mechanism of how industrial competition stimulates local performance mainly lie in two aspects – one is the rivalrous spirit and the other is resource relevance. On the one hand, the rivalrous spirit refers to that firms would compete with each other to keep their superiority (de Groot et al., 2016; Gnyawali & Ryan Charleton, 2018). Given the limited resources and markets, firms would consistently promote their technology and expect to keep ahead of their competitors (Porter, 2011). When firms are located close to other firms in the same industry, the geographical proximity would exert higher motivation for them to make improvements and thus simulate the local dynamism and growth. On the other hand, resource relevance indicates that a similar knowledge base between firms and their competitors would facilitate the immediate use by another competitor with little additional investment (Bucci & Ushchev, 2020; Gnyawali & Ryan Charleton, 2018). When technology is improved by one actor, other firms can quickly assimilate or even update the technology with the help of similar resources and knowledge base. Pushing by this competitive behavior, the local technological upgrading is thus enhanced.

Researches on industrial competition are not so large, and there exists inconclusive empirical evidence on its effect, given the disagreements from the MAR model and Poter's model. Some scholars agree with the MAR argument and find a positive relationship between industrial competition on regional or firms' development. For example, Drucker (2015) examines the US industries and their results suggest that a competitive industrial structure is important for regional economic development and employment growth. Gao (2004) also finds that the local competition can promote regional industrial productivity as well as innovation performance, based on the provincial-level data in the context of China. Similarly, Wang et al. (2017a) investigate the Canadian industrial structure and confirm that the local employment change benefits from the competition within the industries.

Nevertheless, other scholars find a negative impact of local industrial competition. Their core argument is that an environment with many rivalrous firms restricts the bargaining power of individual firms and expands the local pool of suppliers, restricting efficiency within local supplier industries and labor markets (Porter 1990; Helper 1991). For example, van der Panne (2004) analyse the Dutch firms and confirm a negative impact of local competition within an industry on firms' innovation performance. Moreover, larger firms might take the advantage of the competition over smaller firms as they have at their disposal substantial means to engage in R&D and exploit economies of scale and scope in the innovation process (Essletzbichler & Rigby, 2005; Gao, 2004).

3.4.4 Concentrated Clustering Structure of Returnees and FDI Spillovers

When applying the industrial specialization perspective to analyse the collective role of returnees, on the one hand, I posit that returnees' concentrated clustering would promote the local firms' productivity. This is because that a concentrated clustering structure of returnees can minimize transaction costs for returnees to establish communications as scale increases through efficient sharing of similar infrastructure, supplies, and markets (Ellison, Glaeser, & Kerr, 2010). Generally speaking, the highly skilled returnees is a special but relatively weak labor force in emerging markets (Hao et al., 2016; Li et al., 2012). Their concentration would magnify the interactive learning process and thus promote their sharing of ideas and information. Moreover, the presence of concentrated economic activity may increase the pool of available inputs in a location so that further local firm growth (Baptista & Swann, 1999).

On the other hand, a concentrated clustering structure of returnees would also enhance local absorptive capacities and facilitate the FDI knowledge spillovers process. Firstly, the returnees' concentration can provide a specialized knowledge base for the industries to learn from FDI advanced knowledge. As discussed in the previous section, returnees are equipped with cross-cultural and language competence (Filatotchev et al., 2011; Wang, 2015). Given the knowledge they bring to the local market, their concentration can collectively affect the local technological base, so that further help domestic firms to identify and assimilate the FDI spillovers. Moreover, the returnees within industries often share a similar cognitive structure and knowledge base, which facilitate their interactions (Ellison & Glaeser, 1999; Gabe & Abel, 2012). Those smoother communication and knowledge sharing between returnees at the intra-industry level would enhance the returnees' role in correcting the information transmission errors and when local firms are struggling to understand the FDI technology.

Secondly, a concentrated clustering structure of returnees can enlarge the returnees' role in bridging the business or technical networks between foreign and domestic firms. The frequent and repeated interactions are required for local firms to learn from FDI spillovers, however, this process calls for them to develop mutual trust (Levin & Barnard, 2013; Tian, 2007). As discussed before, the returnees' dual social capital acquired from the long experience abroad enables them can act as a bridge or knowledge brokerage between the MNEs and domestic firms (Liu et al., 2014; Wang, 2015). When returnees are co-located within certain industries, their concentration can enhance their ethnic ties and common language, so that helps them to play their role as a collective part to build up the trust among the knowledge actors beyond the organizational boundaries. In this case, a concentrated clustering structure of returnees can promote the information exchanges and form informal networks between foreign and domestic firms, thus contributing to the FDI knowledge spillovers process.

3.4.5 Competitive Clustering Structure of Returnees and FDI Spillovers

In contrast to the industrial concentration, a competitive clustering structure of returnees might cause different impacts on the local firm performance and FDI spillovers. On the one hand, following Porter's competition perspective, I contend that returnees' competitive clustering would promote local firm performance. Similar to the rivalrous spirit view, returnees are also faced with fierce competition from each other, due to the limited resources and increasingly tight labor market (Li et al., 2012; Liu & Almor, 2016). The competitive behavior between returnees can also simulate they make more contributions to the local firm performance. Moreover, as suggested by Qin and Estrin (2015), the peer effect of returnees might facilitate their access to information and resources, as the differences in social networks may account for varying access to information and resources. The status homophily between returnees enables them to make more associations with those with whom they share similar social status characteristics (Lerner and Malmendier, 2013). With similar resources and knowledge, returnees can effectively learn from the technological upgrading induced by their competitors.

On the other hand, however, the competitive clustering structure of returnees might restrict the development of local absorptive capacity and thus hamper the knowledge externality of FDI to local firm productivity. Firstly, a competitive clustering structure might restrict the returnees to local firms to develop sufficient common knowledge bases to absorb FDI spillovers. When returnees are distributed sparsely across firms within industries, it might diminish their collective contributions to the local knowledge pool, limit their joint local problem-solving efforts and restrict the support they received from the domestic firms (Gimeno, 2004; Plummer & Acs, 2014; Wang et al., 2017a). Those limitations would hamper the returnees to establish and maintain interactions with FDI so that they are not able to display their role in promoting the local absorptive capability and learning from the FDI knowledge spillovers.

Second, when returnees are distributed in many different firms, it is difficult for them to collectively establish stable business linkages between foreign and local firms. As suggested by previous literature, an environment with many rivalrous firms restricts the bargaining power of individual firms and expands the local pool of suppliers, increasing competition and efficiency within local supplier industries and labor markets (Drucker, 2011; Martin et al., 2011). The competitive behavior between returnees thus may constrain them to apply their capability effectively. In this case, the returnees in an industrial cannot help local firms form solid business networks with foreign firms, so that reduces the knowledge dissemination to the local environment.

3.5 Diversified Agglomeration of Returnees and FDI Spillovers

As discussed in section 3.4, previous literature has not applied the industrial agglomeration perspectives to analyse the collective role of returnees in the local technological upgrading and FDI knowledge spillovers. Moreover, the specialized clustering structure of returnees might influence the knowledge diffusion process. Besides the specialized structure, another type of agglomeration, a diversified clustering structure, might influence the FDI externality differently. This is because that the interaction between returnees might not be restricted within a specific industry, but rather across different industries. This cross-industry interaction would exert a distinct impact on the local absorptive capacity of external knowledge. In this section, I first review the relevant literature on the diversified structure and then apply this perspective to explain the collective role of returnees in the FDI knowledge spillovers.

3.5.1 Related and Unrelated Variety: Two Dimensions of Diversified Agglomeration

In the literature cluster theory, diversified industrial structure (diversification) is also a critical agglomeration and would influence the knowledge spillovers process (Cainelli & Iacobucci, 2016; Diodato et al., 2018; van der Panne, 2004; Wang, Pan, Li, & Ning, 2016b). The concept of diversification is firstly proposed by Jacobs (1969) and it portrays the interactions across different industries, which believes that it is the diversified composition of industries that serve as the engine for innovation and technological upgrading. Based on this view, the following scholars have done extensive researches on whether diversity can truly contribute the technological development, however, there are still no conclusive results. Some researchers further propose that knowledge transfers and dissemination across different industries can only exist when the industries share related competencies (Rawley, 2010; Zabala-Iturriagagoitia, Porto Gómez, & Aguirre Larracoechea, 2020). Previous literature has emphasized the importance of inter-industry cognitive distance in explaining the impact of a diversified industrial structure on effective interactions across industries and firms (Nooteboom, Van Haverbeke, Duysters, Gilsing, & van den Oord, 2007). Interpersonal interactions require a small cognitive distance, and when the cognitive distance is large, it might be difficult for local firms to identify, imitate, and communicate on the technologies diffused by other industries (Nooteboom et al., 2007). Therefore, Porter (2003) and Frenken et al. (2007) further move beyond the conventional concept of industrial diversification and divide it into the related variety and unrelated variety.

The related and unrelated variety stresses the importance of knowledge relatedness across industrial knowledge externality. In specific, the related variety is an industrial structure that reflects the geographical agglomeration of different industries with cognitive proximity and knowledge relatedness (Asheim, Boschma, & Cooke, 2011; Cainelli & Iacobucci, 2012; Frenken et al., 2007). By contrast, the unrelated variety represents the geographical agglomeration of a set of industries that share limited related resources and complementarities. The way that unrelated variety influences the local knowledge diffusion mainly lies that it can bring a "portfolio-effect" to the regional economic and technological development, by affecting the vulnerability of the local environment (Content, Frenken, & Jordaan, 2019; Frenken et al., 2007; Fritsch & Kublina, 2018). Compared with related variety, unrelated variety emphasizes more on the risk-spreading strategies to avoid specific-sector shocks and triggers technological breakthroughs (Castaldi, Frenken, & Los, 2015; Essletzbichler & Rigby, 2005).

3.5.2 Related Variety and Local Performance

In the line of research on related variety, there are mainly two reasons to believe that related variety exerts a positive effect on local technological performance. Firstly, a related variety of industrial structures facilitates worker mobility across industries as the knowledge bases are technologically related (Cainelli & Iacobucci, 2012; Content et al., 2019). It is widely acknowledged the labor mobility is an essential channel for knowledge spillovers since knowledge resides in persons and their turnover may bring new knowledge to other firms (Liu et al., 2010b; Mancusi, 2008; Oettl & Agrawal, 2008). The cognitive proximity between industries enables the worker to utilize their knowledge and experience easily in their new firms, thus fostering knowledge diffusion and promoting overall productivity.

Secondly, related variety facilitates the building up of inter-industry linkages and contributes to technological upgrading within a larger product scope. The supplier chains can disseminate new knowledge from technology-producing industries to technology-using ones (Hauknes & Knell, 2009). In the early studies, some scholars argued that technological innovation is often driven by frequent interactive activities across industries (Robertson & Langlois, 1995). Technologically related sectors are more likely to set up stable sectoral linkages such as joint R&D activities and supply-demand relationships and promote firms' technological capabilities in cities (Aarstad et al., 2016; Cainelli & Ganau, 2019). Therefore, the complementary and shared competencies of related variety facilitate interactive activities between firms in different industries and intensify technology transfers and diffusions.

Third, related variety can promote incremental technological upgrading in the local firms. This is because knowledge spillovers across a set of technologically related sectors often come from the recombination and recreation of pre-existing technology in newly created ways (Frenken & Boschma, 2007). When industries share close cognitive proximity (related variety), it helps to create a stable business environment and stimulate productivity and recombinant innovation in a more evolutionary and less risky way. Prior literature has also argued that decision-makers in companies are often constrained by limited cognitive capability, so external knowledge that is unrelated to their internal knowledge basis impedes the identification of sources for technological upgrading (Nooteboom, 2000; Nooteboom et al., 2007)

Scholars have made extensive researches on the role of related variety in a different context and most of them find a positive relationship between related variety and local performance. For example, using a Dutch city-level dataset, Frenken et al. (2007) find that related variety significantly promotes economic and employment growth in cities. Essletzbichler (2015) investigate the US regions and their results suggest that related variety significantly stimulates the emergence of new industries. Similarly, from the analysis on Italian provinces, Boschma and Iammarino (2009a) demonstrate that regions that are endowed with related variety exhibit better economic performance. Using both a patent and associated citation dataset for US states over the period 1977-1999, Castaldi et al. (2015) confirm that related variety enhances technological innovation, as it fosters opportunities to recombine knowledge in a new manner.

3.5.3 Unrelated Variety and Local Performance

As well as knowledge spillovers across technologically related industries (related variety), it is necessary to distinguish another type of industrial diversity, namely unrelated variety. Unrelated variety refers to industries that do not share complementary competencies and knowledge. It has no substantial input-output linkages to establish a complete supply chain, and each sector in unrelated variety is technologically isolated from the others (Boschma & Iammarino, 2009a). In contrast to the related variety, the unrelated variety mainly influence the local development via the portfolio effect, which may affect the stability of the economic environment (Castaldi et al., 2015; Frenken et al., 2007). The portfolio effect emphasizes the importance of maintaining product diversification to reduce potential risks and uncertainty, as a stable business environment can minimize fluctuations in demand and supply (Montgomery, 1994). A higher unrelated variety can protect the region from the economic shocks that might dampen the local technological upgrading since if the shocks hit specific industries, the region can still develop with other unrelated sectors (Castaldi et al., 2015; Tavassoli & Carbonara, 2014). For example, take a city that has an industrial structure consisting of 20 different sectors that are technologically unrelated. If sector-specific shocks occur (e.g. oil price fluctuations or a trade war), they are unlikely to hit all 20 sectors at the same time. In other words, unrelated variety spreads the risks across a set of unrelated sectors, enabling the creation of a relatively stable business environment. Based on empirical evidence from developed economies, unrelated variety often dampens unemployment growth because due to the portfolio strategy (Frenken et al., 2007). Fewer fluctuations in the employment marketplace are likely to facilitate long-term R&D collaborations and alliances, thereby contributing to overall urban technological upgrading in cities.

Moreover, it is acknowledged that technological breakthrough often builds upon knowledge (re)-combinations across unrelated knowledge. This is because unrelated variety builds up blocks of unrelated knowledge, and creates the cornerstone for technological breakthroughs (Castaldi et al., 2015). More specifically, the recombination and recreation of unrelated knowledge can lead to wholly new functionalities and applications, further expanding new technological trajectories in the future (Dosi, 1982). In other words, unrelated variety is likely to trigger breakthrough technological innovation in cities. Due to the large inter-industry cognitive distance, unrelated variety can help technological developments by reducing the risk of uncertainty in cities. As the unrelated variety provides abundant unrelated knowledge for inter-industrial interactions, it is also argued that the unrelated variety is more likely to promote the local firms to make more radical innovations (Aarstad et al., 2016). The current literature has provided specific evidence about this argument. For instance, using a dataset from the Netherlands for the period 1996-2002, Frenken et al. (2007) explored the role of unrelated variety in avoiding sector-specific shocks in cities. They confirmed the argument about regional shock resistance and stated that unrelated variety creates a stable business environment. Similarly, using a data sample of US state-level patents and associated citations from 1977-1999, Castaldi et al. (2015) demonstrated that radical innovation is more likely to stem from unrelated variety, as technologically unrelated knowledge can be recombined and used to create new functionalities (e.g. technological breakthroughs). This also reflects the fact that cities with a high level of unrelated variety intensity can trigger technological breakthroughs. Based on a sub-regional data sample (including densely populated urban areas) from the UK at the two-digit level for 23 industries, Bishop and Gripaios (2010) showed that industrial unrelated diversification significantly enhances environmental stability, thereby facilitating regional growth across sectors.

Nevertheless, other scholars hold an opposite opinion that the unrelated variety harms regional and firm productivity, given the large cognitive distance and minimal portfolio effect. For example, using an export and import statistical dataset from Italian provinces, Boschma and Iammarino (2009a) also found that the portfolio-protecting effects of unrelated variety are not evident. In other words, it is difficult for cities with a high level of unrelated variety to avoid sector-specific shocks in technological upgrading. Using the new industrial relatedness indexes proposed by the study of Porter (2003), their empirical results show that unrelated variety does not exert effects on regional value-added growth. Based on a patent-level dataset of 366 US cities from 1981-2010, Boschma, Heimeriks, and Balland (2014) found that a high level of relatedness greatly increases the probability of the entry of new technology, and that unrelated variety impedes technological upgrading in urban areas.

3.5.4 Related Variety Clustering Structure of Returnees and FDI Spillovers

As argued before, the current literature has extensively emphasized the critical role of returnees at the individual level in promoting the local firm performance, while there is less research on explaining the collective role of returnees from the perspective of industrial related variety and unrelated variety. Combining the above theoretical arguments on the role of returnees at the individual level with the cross-industry knowledge externality perspective, I contend that the returnees' related and unrelated variety clustering structure would also exert certain impacts on the local firm performance and FDI knowledge spillovers process.

Following the definition of the traditional related variety, returnees' related variety clustering structure refers to returnees are clustered in related industries. I posit that it would enhance the FDI knowledge spillovers process. Firstly, returnees in related sectors can ease FDI knowledge assimilation across related fields to increase local firms' productivity. Skill- and technology-related sectors often overlap with social networks (Neffke & Henning, 2013). Frequent interactions and mutual trust among knowledge actors and multiple domains beyond organizational boundaries are essential for sharing and learning contextual knowledge (Balland & Rigby, 2017; Szulanski & Jensen, 2006). Returnees' ethnic ties, common language, and culture make them boundary spanners that are more suited for bridging formal organizational and technological boundaries both within and across local firms and MNEs to overcome cross-domain information and cross-cultural social barriers (Mäkelä, Barner-Rasmussen, Ehrnrooth, & Koveshnikov, 2019). When returnees agglomerate in related sectors, their scope in spanning across multiple related and complementary technological fields expands with the degree of their variety. It creates more linkages for otherwise disconnected foreign and local firms and increases multidomain knowledge acquisition and learning opportunities for local firms to increase productivity.

Secondly, the clustering of returnees in related sectors can enlarge the scope of FDI spillovers through recontextualization to spur local technological upgrading. Returnees' home and host country embeddedness equip them with an understanding of cross-border institutional, cultural and social nuances, local market conditions, and the overall strategies of MNEs (Dougherty & Heller, 1994; Tzeng, 2018b). The clustering of returnees in related sectors at the aggregated level thus can form a broader related knowledge base to recontextualize and complement FDI technologies from various domains. It can intensify communication and reduce ambiguity for cross-fertilization of ideas. This lowers the cost of foreign knowledge spillovers and allows foreign knowledge components to be spread across several related technological domain activities locally. As returnees in related sectors conglomerate with shared competence and an increasing scale, domestic firms can consider a border set of multidomain technologies brought by FDI at a low cost. The higher the degree of related varieties of returnees clustering, the higher the probability that FDI externalities can be absorbed and learned by host country firms.

3.5.5 Unrelated Variety Clustering Structure of Returnees and FDI Spillovers

Based on the traditional definition, unrelated variety indicates that local interactions are diversified into very different types of industrial activities (Frenken et al., 2007; Fritsch & Kublina, 2018). When applying this definition to the structure of returnees, the returnees' unrelated variety thus depicts that the returnees are clustered in industries sharing limited competence. In contrast to related variety, skills and competencies in unrelated industries do not overlap (Boschma & Iammarino, 2009b).

In this thesis, I contend that the unrelated variety of returnees would negatively moderate the effect of FDI spillovers on local firm productivity. First, returnees clustered in unrelated sectors can lack technological relatedness and organizational proximity to warrant effective communication and coordination across foreign and local firm boundaries to improve local absorptive capacity and to disseminate FDI knowledge. It can be difficult for local firms without prior knowledge to understand the nature of new foreign knowledge even if they have been recontextualized by returnees from distant fields. Consequently, local firms find it more ambiguous to reconfigure foreign knowledge to increase productivity.

Second, a high unrelated variety of returnees clustering may limit the combinatory potential of FDI knowledge components for local firms to pursue more radical technological inventions. Knowledge combination with unrelated components often shows a high level of uncertainty, cognitive distance, knowledge tacitness, and lack of economic input-output linkages, all of which hamper the loci and local firms to achieve scale economies in knowledge reproduction and increase the cost of recombination. Moreover, unrelated industrial activities and human resources can be loosely embedded without substantial pecuniary linkage and demand in the regional context, and are more likely to disappear and exit in the region (Boschma, 2017; Grillitsch, Asheim, & Trippl, 2018). Unrelated variety of returnees do not facilitate local firms to absorb FDI spillovers.

3.6 Concluding Remarks

This chapter presents systematic literature reviews on FDI spillovers, returnees, and the returnees' repatriation process and clustering structures. Plenty of literature has investigated the impact of FDI spillovers on host country firms' performance, but the results of the empirical studies on FDI knowledge sharing and transfers are still mixed and inconclusive. One key reason for that is that the local absorptive capacity in host countries or regions differs greatly and local firms need to develop their capability to assimilate the advanced FDI technology. In the emerging market context, returnees have received increasing attention and the current literature has emphasized their role in improving local absorptive capacity and disseminating foreign knowledge. However, the majority of studies only focus on the impact of individual returnees but have neglected the externalities of their collective repatriation process and clustering structures in FDI spillovers. From the agglomeration and dynamic perspectives, this chapter establishes a systematic and solid theoretical foundation for the research for this Ph.D. thesis.

108

Chapter 4 Data and Methodology

In the last chapter, I systematically reviewed the theoretical frameworks regarding FDI spillovers, returnees, cluster theory and indicated the research gaps in the previous literature. To carry out an empirical analysis, it is necessary to select appropriate data sources and a methodology. This chapter aims to describe the data sources and processing methods used in this Ph.D. thesis. Generally, the prior literature on FDI spillovers has adopted various methodologies, including comparative analysis, evolutionary analysis, explanatory analysis, descriptive analysis, and case studies as well as questionnaire survey analysis. Therein, this Ph.D. thesis adopts both descriptive and econometric analysis in each empirical chapter.

The remainder of this chapter is organized as follows. Section 4.1 introduces the research context, Zhongguancun Science Park, in this Ph.D. thesis. Section 4.2 elaborates the key database source adopted in this thesis, namely The Annual Census of ZSP Firms. Section 4.3-4.5 emphatically expatiates on the data collection, the variable definitions, and the econometric configurations used in Chapters 5, 6, and 7, respectively, to provide a deeper understanding of the methodological framework for this Ph.D. research.

4.1 The Research Context: Zhongguancun Science Park

4.1.1 The Developmental Path of ZSP

Zhongguancun Science Park (ZSP for short) is China's first national independent innovation demonstration zone. It is a cluster dominated by industries such as electronic information, biomedicine, new materials, advanced manufacturing, new energy, and environmental protection (Tan, 2006). With the support of national policies, ZSP has achieved world-renowned achievements after years of development, demonstrating strong innovation capabilities and growth potential. After several years of strategic layout, ZSP has gathered a large number of innovative resources and innovative talents and established a system and mechanism for collaborative innovation. At the same time, it has attracted a large number of foreign-funded enterprises and highly skilled returnees, which is very suitable for the research theme of this thesis. Generally speaking, the development of ZSP mainly includes four periods:

(1) The period of the "Electronic Street": 1980-1988

On October 23, 1980, Chen Chunxian, a researcher at the Institute of Physics of the Chinese Academy of Sciences, who had visited Silicon Valley twice before, with the support of the Beijing Association for Science and Technology, established the Advanced Technology Development Service of the Beijing Plasma Society unit. Around 1984, the Zhongguancun area had a group of scientific and technological personnel to do business. They explored ways to transform scientific and technological achievements into productivity by establishing private scientific and technological enterprises.

(2) Period of "Beijing New Technology Industry Development Pilot Zone": 1988-1999

On May 10, 1988, the State Council formally approved the "Beijing New Technology Industry Development and Pilot Zone Interim Regulations" and stipulated that the area of about 100 square kilometers in the Haidian District of Beijing was designated as Beijing's new technology industry. On May 20, the Beijing Municipal Government issued the "Interim Regulations of Beijing Municipality for the Development and Pilot Zone of New Technology Industries," and as a result, the Beijing Municipality for New Technology Industry Development and Pilot Zone (The predecessor of Zhongguancun Science Park) was formally established. In April 1994, the National Science and Technology Commission approved Fengtai Park and Changping Park to be included in the experimental zone policy area. In January 1999, with the approval of the National Science and Technology Commission, the experimental area was adjusted again, and the Electronic City and Yizhuang were included in the policy area of the experimental area.

(3) Period of "Zhongguancun Science Park": 1999-2009

On June 5, 1999, the State Council issued the "Reply on Relevant Issues Concerning the Construction of Zhongguancun Science and Technology Park" and constructed Zhongguancun Science and Technology Park. Later, on January 17, 2006, with the approval of the State Council, the National Development and Reform Commission adjusted the area of Zhongguancun Science Park and the total area is 23,252.29 hectares with a spatial pattern of "One District and Ten sub-Parks".

(4) Period of "Zhongguancun National Independent Innovation Demonstration Zone": 2009-current

On March 13, 2009, the State Council's released the "Approval to Support the Zhongguancun Science Park to Build a National Independent Innovation Demonstration Zone", which clarifies the new positioning of the Zhongguancun Science Park as a national independent innovation demonstration zone, and the goals are to become a technological innovation with global influence center. Later on October 13, 2012, the State Council approved the adjustment of the space scale and layout of the Zhongguancun National Independent Innovation Demonstration Zone, increasing from one district with ten sub-parks to one district with sixteen sub-parks, including Dongcheng Park, Xicheng Park, Chaoyang Park, Haidian Park, Fengtai Park, Shijingshan Park, Mentougou Park, Fangshan Park, Tongzhou Park, Shunyi Park, Daxing-Yi Manor, Changping Park, Pinggu Park, Huairou Park, Miyun Park, and Yanqing Park.

4.1.2 The Key Characteristics of ZSP

With 40 years of development, until now, the ZSP has long been known as China's largest intellectual cluster. It has three main characteristics:

Firstly, ZSP has a dense concentration of research and education establishments. Among the establishments are over a dozen best Chinese universities and more than two dozen leading research institutes affiliated with the Chinese Academy of Sciences (CAS). The central government initiates projects to directly support certain scientific research and development initiatives such as "Program 863", which was aimed at narrowing the gap between China and the rest of the industrial world in terms of high-tech development (Tan, 2006). Such initiatives were subsequently complemented by the more aggressive "Torch Program", which contributed to a boom of technology start-ups (Filatotchev et al., 2011). The restructuring of research institutions/universities and the new programs and projects have formed a favorable environment for Chinese high-tech development and their innovative potential.

With the help of many supporting policies and unique networks, ZSP develops greatly and has been the region with the most intensive science and education intelligence and talent resources in China (Dong, Hu, Yin, & Kuo, 2019). There are a growing number of science and business institutions in ZSP. Now it has more than 40 institutions of higher universities represented by Peking University and Tsinghua University, and 206 national (municipal) research institutes represented by the Chinese Academy of Sciences and the Chinese Academy of Engineering[1]. Besides, 112 national-level laboratories, 38 national engineering research centers, and more than 20,000 high-tech firms were established in ZSP[2].

With highly innovative capability, the total revenue of ZSP experiences a rapid improvement, which increases from 903.57 billion RMB to 5302.58 billion RMB from 2007 to 2017 (see Figure 4-1). The total number of the patent application and the granted patent in ZSP also increase from 12.97 thousand to 86.42 thousand, and 6.10 thousand to 46.05 thousand respectively (see Figure 4-2). Moreover, the expenditures for scientific and technological activities have grown rapidly, which expenditures reached 78.1 billion yuan in 2019, an increase of 26% over the previous year.

[1] Source: Beijing Statistical Yearbook 2018

[2] Ibid.

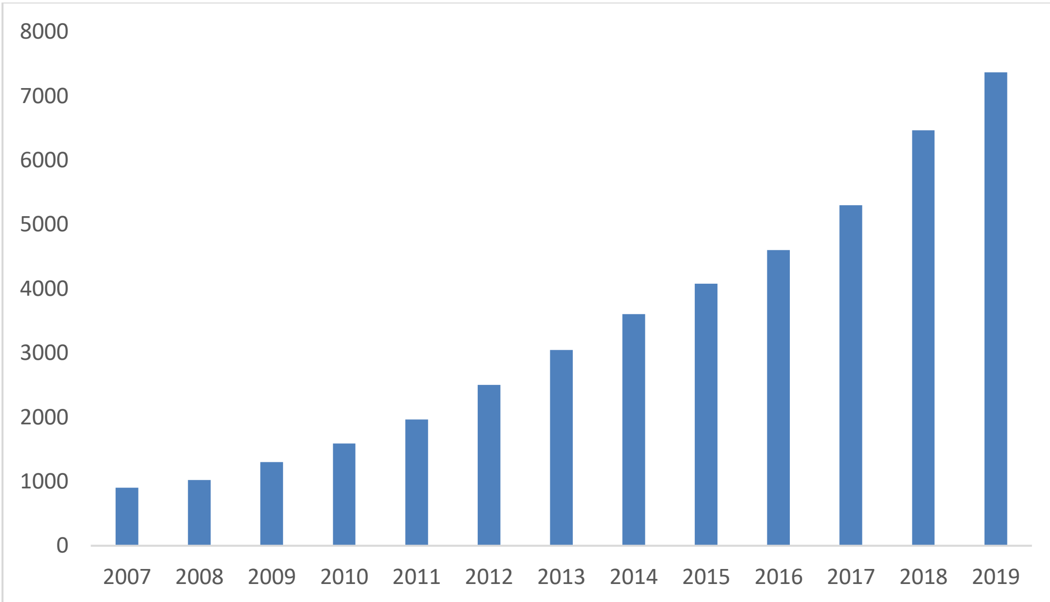

Figure 4-1 Total Revenue in ZSP During 2007-2019 (Billion RMB)

Source: Beijing Statistical Yearbook

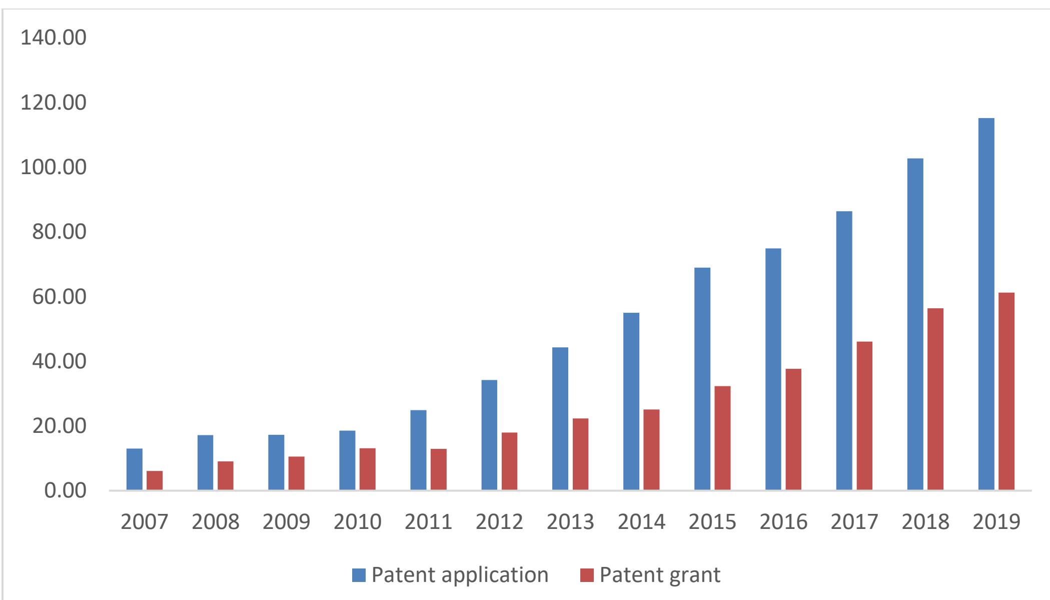

Figure 4-2 The Number of Patent Application and Grant in ZSP During 2007-2019 (thousand)

Source: Beijing Statistical Yearbook

Second, another unique characteristic in ZSP has been that entrepreneurs have combined their informal interpersonal networks with inter-organizational ties to exchange information (Wang, Duan et al 2015). The information exchange in ZSP has mainly been achieved through price-listing periodicals by certain information networks, which issues weekly periodicals that list prices of different types of products available within the ZSP region, and through a few non-profit organizations, such as the CEO Club or the Beijing High-tech Firms Industrial Alliance (Wang, Duan et al 2015). For example, the industrial alliance developed quickly, the number of which increased from 49 to 156 during 2008-2013 (see Figure 4-3). Such information exchange is mainly supported by membership dues and advertising revenue (Etzkowitz & Zhou, 2018; Filatotchev et al., 2011). These networks exist in different periods help solve many specific problems, such as adapting to the changing policy in economic reform or seeking credit guarantees by other firms (Dong et al., 2019).

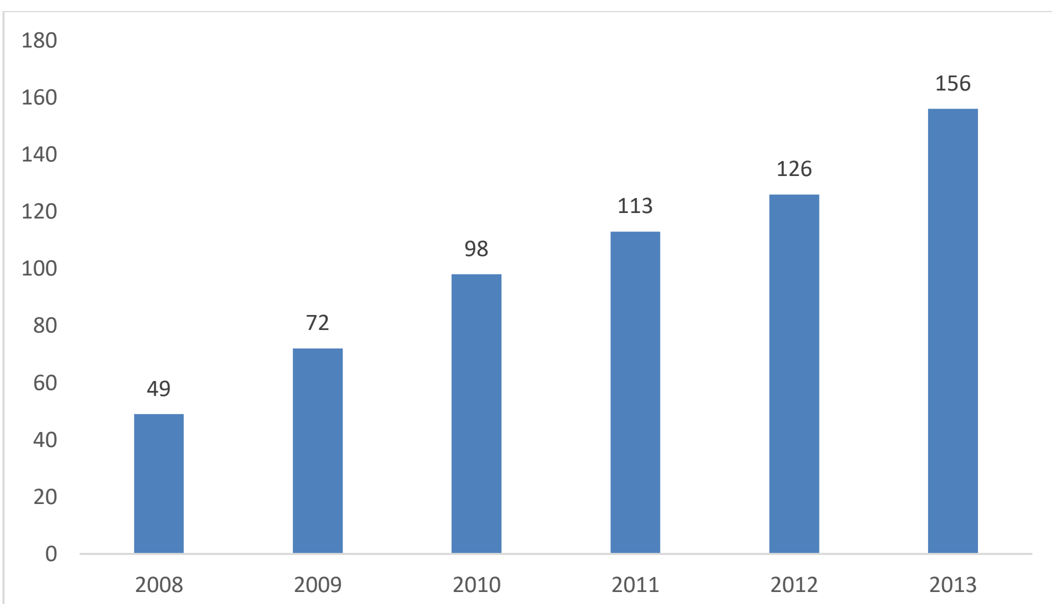

Figure 4-3 The Number of Industry Alliance in ZSP During 2008-2013

Source: Beijing Statistical Yearbook

Third, after thirty years of development, ZSP has become the most innovative cluster in China. It contains “one district and sixteen sub-parks” and the sub-parks display distinct characteristics, which are suitable to study the differences of various regions. As shown in Table 4-1, among the sixteen sub-parks, Haidian takes the leading place and its area, the number of investment enterprises, revenue, profit and FDI inflow are the largest. Besides, the sub-parks are geographically close to each other, which reduces the cost for inter-personal interactions and knowledge exchanges. Moreover, ZSP has also formed as a high-tech industrial cluster represented by electronic information, biomedicine, energy and environmental protection, new materials, advanced manufacturing, and aerospace, with R&D investment and service. As of 2019, ZSP has undertaken more than 1,300 major special projects, accounting for about 40% of the country’s major special projects (*ibid*). Venture capital accounts for one-third of the country, and energy consumption per 10,000 yuan of industrial added value accounts for one-tenth of the country. At the same time, as many as 4,000 new technology-based enterprises are established every year, and the modern service industry accounts for 2/3 of the total income, which has become the leading industry in ZSP (*ibid*). Generally speaking, the ZSP as the most innovative cluster is gaining momentum.

Table 4-1 The Key Indicators of Sub-parks of ZSP in 2019

Sub-parks	Area	Investment enterprise	Revenue	Profit	FDI Inflow
Haidian	17430.6	29985	2745.9	145.5	158.9
Fentai	818	12506	627.3	38.71	3.9
Changping	5140	4813	457	25.81	13.03
Chaoyang	2610	2212	688.9	42.47	19.82
Daxing	2678	1189	723.5	57.42	42.1
Xicheng	1000	842	337.1	31.29	20.2
Dongcheng	603	2630	303.6	24.62	0.32
Shijingshan	1334	3163	261.3	30.97	3.9
Tongzhou	3434	526	94.8	4.8	2.4
Pinggu	1124	245	17.1	0.26	0.5
Mentougou	189	278	36.5	1.17	1.49
Fangshan	1572	340	50.4	1.33	0.2
Shunyi	1208	577	196.1	12.34	32.81
Miyun	1000	159	40.6	-2.24	0.9
Huairou	711	180	57.4	3.38	0.1
Yanqing	491	62	14.5	0.26	0.1
Total	41854	59645	6642.2	418.26	294.8

Note: (1) Area is measured in Hectares; (2) Investment enterprise is measured in 1 firm; (3) Revenue, profit and FDI inflow are measured in 1 billion Chinese Yuan.

4.1.3 The Development of FDI and Returnees in ZSP

As I am devoted to finding the relationship between FDI and returnees, I would also introduce the development of FDI and returnees in the ZSP. On the one hand, as one of the largest clusters of high-tech firms in China, ZSP consists of both domestic and foreign-invested firms. It provides the same location for different types of firms to interact and collaborate (Tan, 2006). Among the high-tech firms in ZSP, many received foreign capital from developed markets and a growing number of firms are owned by foreign entities. The total value of FDI inflow in ZSP increases from 6.73 billion to 29.48 billion dollars from 2007 to 2019 (see Figure 4-4).

On the other hand, ZSP is also an important destination for overseas high-level returnees. ZSP establishes 34 pioneer parks for overseas students, gives firms 1 million RMB of free funding, supports firms to independently or jointly undertake major national projects, and set up preferential channels for services in areas such as talent registration, children's enrollment and social insurance (Wang, Duan et al 2015). As a result, the human resources of highly skilled returnees are highly intensive in the ZSP. From 2007 to 2019, returnees in ZSP display a great increase from 9,527 to 47,452 (see Figure 4-5). Among the returnees, those with a doctor's degree grew from 1,550 to 3,385, and those with a master's degree increased from 4300 to 34,009.

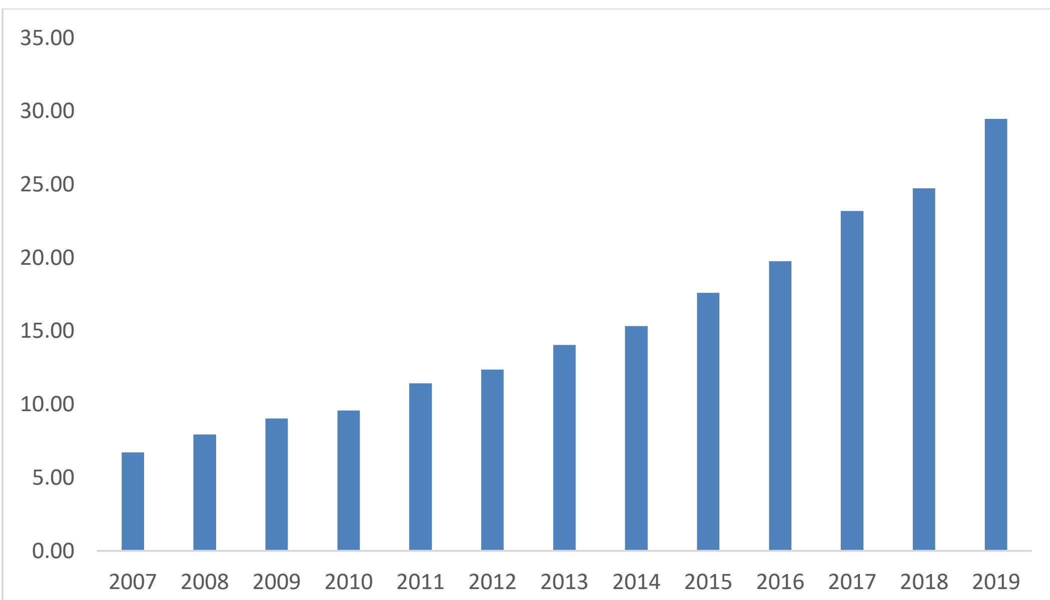

Figure 4-4 The Amount of FDI Inflow into ZSP During 2007-2019 (Billion $)

Source: Beijing Statistical Yearbook

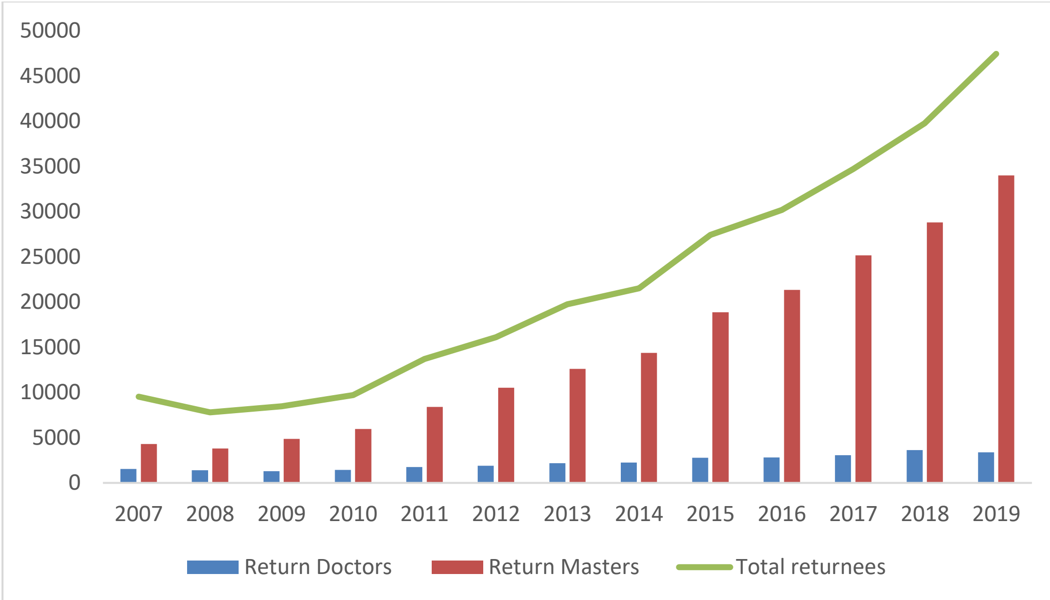

Figure 4-5 The Number of Returnees in ZSP During 2007-2019

Source: Beijing Statistical Yearbook

To summarize, as shown above, FDI is a significant capital source and returnees play an important part in ZSP's labor force. Both of the MNEs and returnees have contributed a lot to ZSP's development. The geographical proximity in ZSP not only facilitates the returnees to establish business linkages between foreign and local firms but also provides opportunities for the returnees to closely interact with each other and collectively improve the local knowledge base. ZSP thus is highly suitable for studying the interplay between returnees and FDI. Moreover, firms in ZSP were required to report their full information from 2007, including their financial characteristics, managerial structures, and labor structures. I, therefore, have a very comprehensive dataset to conduct my research (Guan & Liu, 2016; Zhang, Zheng, & Ning, 2018). With this dataset concerning high-tech firms in the ZSP, I am devoted to figuring out the structural role of returnees in the process of FDI knowledge spillovers.

4.2 Data Source Selection and Collection- The Annual Census of ZSP Firms

To answer the core research question of this Ph.D. thesis, “How do the returnees at the aggregated level moderate the relationship between inward FDI and local firm performance?”, it was necessary to collect firm-level data. ZSP is an ideal context for studying the interplay between returnees and FDI, because FDI is a significant external knowledge source for ZSP’s development, and returnees also play an important part in its labor force.

My data was compiled from the annual census filed by firms under the request of the ZSP Administrative Committee from 2007 to 2013. The high-tech firms were required to take part in the census survey providing detailed information, mainly in 4 aspects. The first is the basic information of the legal entity of enterprises. The second is concerning production management and financial statuses, such as information about the firm’s capital input, asset, ownership structure, the total products, and sales, etc. The third is about the enterprise technology activities and related information, which includes R&D investment, technological programs, patents, trademarks, scientific publications, and so on. And the fourth is related to human resources and labor structures. From this database, I can know exactly the capital structures of the high-tech firms, which is essential to discern the foreign capital versus domestic capital. Moreover, the production and financial status are useful for our evaluation of firm performance. Last but not least, the labor structure contains information about the number of returnees recruited by the firms.

From this database, I can know exactly the capital structures of the high-tech firms, which is essential to discern the foreign capital versus domestic capital. Moreover, the production and financial status are useful for my evaluation of firm performance. Last, the labor structure contains information about the number of returnees recruited by the firms. This database also classifies firms into 4-digit, 3-digit as well as 2-digit ISIC, and includes firms with firms that have more than ten employees. Therefore, this dataset allows us to construct more detailed firm-level and industry-level variables regarding FDI and returnee labor structures. It is frequently used to explore the relevant topics of international business and strategic management such as the studies of Zhang et al. (2018) and Guan and Yam (2015).

4.3 Returnees' Repatriation into Local Industries and FDI Spillovers

4.3.1 Dataset Collection and Processing of Chapter 5

The annual census filed by firms under the request of the ZSP Administrative Committee from 2007 to 2013 is used to test my hypotheses. The high-tech firms were required to take part in the census survey by providing detailed information, including legal entity of enterprises, production management and financial status, the enterprise technology activities, and the labor structures. From this database, I construct more detailed firm-level and industry-level variables regarding FDI and returnee labor force.

In this chapter, I focus on the collective rather than individual effects of returnees on local firms' productivity and FDI knowledge spillovers process. For the period the data is available to us, I initially obtained 12,821 firms with 56,905 firm-year observations, out of which 1,288 are foreign firms with 6,114 firm-year observations. I then required firms to have at least three years' financial information to calculate my measurements of variables. After excluding foreign firms and observations with missing values, I obtained a final unbalanced sample of 45,544 firms' years' observations for 7,920 unique local firms and with more than 50,000 returnee employees from 2007 to 2013.

4.3.2 Variable Definitions of Chapter 5

4.2.2.1 Dependent Variable

To investigate the spillover effect of FDI on local firm performance, I choose ***TFP*** at the firm level as the dependent variable. TFP is a productive efficiency index, which measures the level of efficiency and intensity of the inputs utilized in production (Fu & Gong, 2011; Haskel, Pereira, & Slaughter, 2007). Previous literature argues that the firm performance is enhanced more through TFP than via other factors like capital accumulation or labor productivity, and the TFP can reflect more gains from FDI on firms' adoption of foreign knowledge (Alfaro, Kalemli-Ozcan, & Sayek, 2009; Haskel et al., 2007; Klenow & Rodriguez-Clare, 2005). As a result, it is extensively used to proxy the productive evolution in local firms.

The existing studies have used a range of ways to measure TFP, such as semi-parametric analysis like Olley and Pakes (OP) method, Levinsohn and Petrin (LP) method and Ackerberg, Caves, and Frazer (ACF) model (Ackerberg, Caves, & Frazer, 2015; Levinsohn & Petrin, 2003;

Olley & Pakes, 1996). The estimation of TFP often starts with a Cobb–Douglas production function:

$$Y_{it} = A(t)F(L, K, a, u) \tag{1}$$

Where $A(t)$ is the TFP, indicating the cumulated technical changes over time. For estimation purposes, converting the function above into logarithm form gives:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_a a_{it} + u_{it} \tag{2}$$

Where y_{it} is log output for firm i in period t; l_{it}, k_{it} are the log values of labor and capital inputs; a_{it} is the age of the firm; u_{it} contains information on a firm's TFP $(A(t))$ in logarithmic form, which is assumed to follow a first-order Markov process. This function can be used to control for the simultaneity problems in estimating productivity at the firm level and can be estimated by OLS. However, using a simple linear estimation method to estimate equation (2) will produce inconsistent results because of simultaneity bias. In the actual production process, a part of the efficiency of enterprises can be observed in the current period and decision-makers might adjust the input of production factors according to this information. In this case, if the error term represents TFP, one part of it (the observed part) will affect the choice of factor input, which will lead to the error of OLS estimation.

Olley and Pakes (1996) first proposed the two-step consistent estimation method, whose core idea is to take the company's investment level as a proxy variable of productivity. The method assumes that firms make investment decisions based on the current state of productivity, so the current investment of firms is taken as the proxy variable of unobservable productivity impact, thus solving the problem of simultaneity bias and being an appropriate method to estimate firm-level productivity. The coefficient estimates for variable inputs (labor and capital etc.) will be consistent and the error term is no longer correlated with the inputs. Once Equation (2) is estimated, all the coefficients in the production function will be successfully estimated. Using this result, we can fit the log of residuals (u_{it}) in the production function, which is also the log of *TFP*.

In this thesis, I mainly follow the method of Olley and Pakes (1996) to calculate the TFP. This is not only because that the OP method considers more about firm-level investment behavior (Wei et al., 2017; Yasar, Raciborski, & Poi, 2008), but also the data of intermediate input is unavailable at the science park level, which is required in the LP method (Levinsohn & Petrin, 2003). As in the Stata command, I use the clustered bootstrap, treating all observations for a single firm as one cluster and obtaining consistent results for local firm TFP. Besides, corresponding with previous studies like Wei et al. (2017), output required in Stata command of OP estimation (namely: opreg) is measured by total sales adjusted by the ex-factory price index of industrial output, labor is the number of employees and capital is total capital.

4.3.2.2 Explanatory variables

*Foreign Direct Investment (**FDI**).* Previous literature uses many methods to capture the FDI knowledge spillover, such as the share of foreign firms' employees, sales or total assets in a given industry and the number of foreign-invested firms in the industry (Buckley et al., 2010; Ning et al., 2016b; Orlic et al., 2018). In my Ph.D. thesis, I mainly follow Buckley et al. (2002) and employ the share of a foreign firm asset in the total assets in the four-digit level industry to capture the FDI knowledge spillover, as it reflects the theoretical justification that foreign assets increase the potential for knowledge spillovers and technological transfer to influence domestic innovation performance (Belderbos, Lokshin, & Sadowski, 2015; Smith, 2014). Alternative measurements for FDI presence such as the total value of foreign capital or the total number of MNE firms are considered for robustness tests.

*Returnee repatriation Speed (**Speed**)*. Speed is a time-based attribute of the returnee's repatriation. It measures how rapidly returnee's repatriation into the industry at a point in time. I construct the speed variable based on the prior study of Vermeulen and Barkema (2002) and Wang et al. (2017b):

$$Speed_{j,t} = \frac{Returnee_{j,t} - Returnee_{j,t-1}}{Returnee_{j,t-1}} \times 100\% \tag{3}$$

In which $Returnee_{j,t}$ denotes the number of returnees of four-digit level industry j in year t. Different values for adjacent years indicate an increasing or decreasing number of returnees in a given industry. A large ($Speed_{jt}$) value indicates a faster pace of returnees' repatriation into a four-digit level industry.

*Returnee repatriation Irregularity (**Irregularity**)*. Irregularity is another time-related attribute, which indicates the rhythm or progress of returnees' repatriation in an industry. I employ the kurtosis of returnee's repatriation to represent irregularity based on previous literature (Vermeulen & Barkema, 2002).

$$Irregularity_j = \left\{\frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum_{t=2007}^{2013} \left(\frac{x_{jt} - \bar{x}_j}{s_j}\right)^4\right\} - \frac{3(n-1)^2}{(n-2)(n-3)} \quad (4)$$

In which *n* is the number of observations in the four-digit level industry *j* and *s* is the standard deviation of the returnees' change in the industry in year *t*. x_{jt} is the number of returnees in year *t* and industry *j*, and $\bar{x}$ is the average number of returnees in industry *j*. More stable and regular returnees' repatriation leads to a relatively flat distribution (Vermeulen & Barkema, 2002), while a high value of $Irregualrity_j$ indicates either long-term inactivity or large peaks over a period of returnees' repatriation in a certain industry.

4.3.2.3 Control variables

A set of control variables is used to take other factors that might affect TFP into account (also see Table 4-2 for variable definitions).

Firm age: in my Ph.D. thesis, I measure it as the number of years since a firm was founded. Firm age has been argued to have a significant impact on firms' performance as it can influence firms' experience and capability to utilize their resources (Su & Liu, 2016).

Firm size: I mainly use firms' total assets to proxy firm size, based on previous literature like García et al. (2013). Firm size can also affect productivity efficiency as it reflects a firm's operational and management capabilities and may influence the resources available for firms' innovative activity (Jeon et al., 2013).

State-ownership: state-ownership is captured by a dummy variable, which equals 1 when a firm is registered as a state-owned or collective-owned company. In China's context, state-ownership has been widely considered as an important factor that influences firms' TFP, as it affects the resources that firms can obtain from the government (Fu et al., 2011).

Profitability: since profitable ability can influence the investment of the firm in innovative activity and further impact firms' TFP, I, therefore, include this control variable and calculate it as the return on assets (the ratio of profit in total assets) in my Ph.D. thesis, based on previous literature like Sánchez-Sellero, Rosell-Martínez, and García-Vázquez (2014) and Orlic et al. (2018).

R&D intensity: research and development investment (R&D) intensity is measured by firms' total amount of inner R&D investment per employee (Sánchez-Sellero et al., 2014). R&D intensity represents a firm's technological input and has been widely recognized as a critical factor that can influence a firm's TFP (Sánchez-Sellero et al., 2014; Wang & Kafouros, 2009).

Knowledge stock: knowledge stock is proxied by the total number of patent applications of a firm in the last three years. I include it to control for a firm's experience and capabilities in innovative activities, which might also influence its production efficiency (Ito, Yashiro, Xu, Chen, & Wakasugi, 2012; Jin et al., 2018).

Table 4-2 Variable Definitions of Chapter 5

Variables	Definition
TFP	Natural log of the Total Factor Productivity of firm *i* in year *t*
FDI	Natural log of the amount of FDI into an industry at the four-digit level in year *t*
Speed	The change rate of the number of returnees into an industry at the four-digit level in year *t*
Irregularity	The kurtosis of the number of returnees into an industry at the four-digit level in year *t*
Firm age	Natural log of the age of firm *i* in year *t*
Firm size	Natural log of the total assets of firm *i* in year *t*
SOE	A dummy variable that equals 1 if firm i is state-owned; otherwise is 0
Profitability	Natural log of the return on assets of firm *i* in year *t*
R&D intensity	Natural log of R&D investment per employee of firm *i* in year *t*
Knowledge stock	Natural log of the number of patents in the past three years of firm *i* in year *t*

4.3.3 Estimation Methods of Chapter 5

Previous literature has widely suggested that there might exist selection bias concerning issues about returnees. For example, some scholars argue that the recruitment of returnees might not be random as firms with more competitive capability and generous financial support would be more affordable for those highly skilled talents (Liu et al., 2010a; Roberts & Beamish, 2017). This means that the returnees might be self-selected in different local firms. In this case, the improvement of a firm's performance might not be because of the entry of returnees, but that a firm with higher performance would become more attractive for returnees. Therefore, one needs to solve such selection bias when examining the impact of returnees on local firm performance. The Heckman two-stage model has been widely used when potential selection problems exist (Certo, Busenbark, Woo, & Semadeni, 2016; Heckman, 1979; Lennox, Francis, & Wang, 2012). In Chapter 5, therefore, I use the Heckman two-stage models to address such selection issues and estimate the agglomeration impact of returnees in the local firm performance and FDI spillover process.

In the first stage, I estimated a Probit model of a firm's propensity of recruiting returnees. It aims to find out whether the returnees would be self-selected into local firms. This regression is later used in the second stage to correct for the likelihood of inclusion. Following previous literature, I consider several factors that might affect the entry (or the recruitment) of returnees, which include firm age, size, profitability, state-ownership, R&D intensity, and firm average wage (Kenney et al., 2013; Lin et al., 2016). I also include one additional predictor, the industrial average wage in the first stage, as the exclusive restriction to check the appropriateness of the Heckman two-stage estimation. As suggested by previous literature, the industrial average wage would indirectly influence a firm's propensity to recruit returnees as it reflects the prospect of the industry and may affect the attractive for returnees, however, it does not influence a firm's recruitment strategy (Kenney et al., 2013; Wang, 2020). In this case, it can serve as a proper exclusive restriction. Then, based on the Probit estimation, I can calculate an inverse Mill's ratio (IMR). The IMR represents the selection hazard of a firm's recruitment activity of returnees (Certo et al., 2016; Heckman, 1979). Evaluating the statistical significance of IMR proxies the presence of a meaningful selection effect in the second stage model. Therefore, I include the IMR in the second stage to check the existence of the selection effect. More specifically, if IMR is significant in the second stage, then it suggests that there indeed exists selection issues and it is proper to use the Heckman two-stage models.

In the second stage, to test my hypotheses, I mainly employ the commonly used system generalized method of moments (GMM) estimation methodology, which is regarded as an appropriate model for dealing with unobserved heterogeneity and endogeneity for dynamic panel datasets. As suggested by previous literate such as Comin (2017) and Lagos (2006), a firm's production efficiency might be influenced by its previous status and it may experience economic shocks every year. Therefore, it is recommended to consider a dynamic panel structure to study the dynamic trend of dependent variables and the short-term or long-term effects of independent variables on dependent variables. Typically, the main characteristic of the dynamic panel model is that the lag term of the dependent variable is controlled for the trends of the dependent variable:

$$y_{i,t} = \alpha y_{i,t-1} + \beta x_{i,t} + \delta_i + \varepsilon_{i,t} \tag{5}$$

Where $x_{i,t}$ represents control variable, δ_i represents fixed effect, and $\varepsilon_{i,t}$ represents the residual term. The traditional approach to estimating dynamic panel data models is to remove the unobserved effect by first-differencing and then use instrumental variables (IVs) methods for estimating the differenced equation. However, as the lag term of the dependent variable is added, the common fixed-effect estimation method with IVs will lead to the inconsistency of parameter estimation, so other estimation methods are needed. The "Generalized Method of Moments" was introduced by L. Hansen in 1982 (Hansen, 1982) to deal with such dynamic panel models. Many standard estimators, including IV and OLS, can be seen as special cases of GMM estimators, as they are mostly first-order moment estimations (Baum, Schaffer, & Stillman, 2003; Windmeijer, 2005). With the development of GMM, there are two widely used dynamic panel estimation methods, namely difference GMM estimation, and System GMM estimation. The method adopted by Difference GMM is to remove the fixed effect at first because the fixed effect is related to the lag term of y:

$$\Delta y_{i,t} = \alpha \Delta y_{i,t-1} + \beta \Delta x_{i,t} + \Delta \varepsilon_{i,t} \tag{6}$$

However $\Delta y_{i,t-1}$ is still related to $\Delta \varepsilon_{i,t}$ and a common way to solve this issue is to use IVs. The Difference GMM mainly choose $\Delta y_{i,t-2}$ and its lag variables as the instrument variables to solve such endogeneity. One problem of the instrumental variables selected by Difference GMM is that they are likely to be weak instrumental variables, because their correlation might be relatively small, which will lead to large variance and insignificant results.

System-GMM method has been considered as a more suitable model than the Differenced GMM since it chooses more proper instrument variables. It combines the first-differenced model with its corresponding model in levels and uses lagged differences of the endogenous variables as instruments (Roodman, 2009; Su & Liu, 2016). It also provides extensive tests to ensure the effectiveness of those instrument variables and to eliminate the overidentification effect (Roodman, 2009). Moreover, the system-GMM method also helps to more fully exploit the available moment conditions in a finite sample. Therefore, I mainly report the estimates based on the system-GMM methods. The system-GMM estimate the following equation:

$$
\begin{aligned}
TFP_{i,t} = \alpha_i + \gamma TFP_{i,t-1} + \beta_1 FDI_{ij,t} + \beta_2 Speed_{i,t} + \beta_3 FDI_{ij,t} \times Speed_{i,t} \\
+ \beta_4 Irregularity_i + \beta_5 FDI_{ij,t} \times Irregularity_i + \beta_6 X_{ij,t} + \beta_7 IMR + \delta_i \\
+ \varepsilon_{i,t} \ (7)
\end{aligned}
$$

Where $TFP_{i,t-1}$ is the lag level of the dependent variable. The reason for including it in the system-GMM estimation is that the lag level of the dependent variable tends to be correlated with the dependent variable, but not correlate with the residuals, so it serves as a proper instrument variable in the system-GMM estimation (Roodman, 2009). The IMR obtained from the first stage is also included in the system-GMM estimation to control for the selective bias. Such inclusion of IMR as a control variable has also been widely used in previous literature like Flores-Lagunes and Schnier (2012) and Semykina and Wooldridge (2013). Contrastingly, the exclusive restriction in the first stage of Heckman estimation is not included as a control variable in the second stage to avoid potential multicollinearity with IMR.

In the formal estimation, I use the first differences of the second and third lags and lag level of dependent and explanatory variables as instruments. Moreover, following the direction of Windmeijer (2005), I conducted several tests to check the effectiveness of the instrument variables. I first use the two-step covariance matrix was used to estimate the finite samples. Then I inspect the Arellano–Bond (AR) tests to check the validity of the instrument variables. Arellano and Bond develop a test for a phenomenon that would render some lags invalid as instruments, namely, autocorrelation in the idiosyncratic disturbance term, $\varepsilon_{i,t}$ (Roodman, 2009; Windmeijer, 2005). The AR test is applied to the residuals in differences. Because $\Delta\varepsilon_{i,t}$ is mathematically related to $\Delta\varepsilon_{i,t-1}$ via the shared $\varepsilon_{i,t-1}$ term, negative first-order serial correlation (AR (2) test) is expected in differences and evidence of it is uninformative, which means that the result of the AR (1) test is fundamentally significant. Thus to check for first-order serial correlation in levels, we look for second-order correlation (AR (2) test) in differences, on the idea that this will detect the correlation between the $\varepsilon_{i,t-1}$ in $\Delta\varepsilon_{i,t-1}$ and the $\varepsilon_{i,t-2}$ in $\Delta\varepsilon_{i,t-2}$. In this case, the system-GMM model need to pass the AR (2) test to ensure the effectiveness of the instrumental variables (Roodman, 2009).

Finally, I employ the Hansen's J test to check their overall validity in the system-GMM analysis (Roodman, 2009). The purpose of the test is to identify whether instrumental variables are completely exogenous and the null hypothesis is that instrumental variables are all valid instrumental variables. The main logic of this test is that the parameters estimated from different instrumental variables should not be very different. In the case that all of the instrumental variables are valid, the test result should obey the positive distribution with a mean value of 0, which means that the value of the Hansen-J test should be insignificant.

4.3.4 Univariate Analysis of Chapter 5

Tables 4.3-4.9 illustrate the summary statistics of the variables adopted in the regressions each year, with the variation tendency in both the dependent and independent variables over the 8 years. Focusing on the dependent variable, namely total factor productivity, the mean value increased from 2.992 to 3.244 over the period 2007-2013, indicating that firms in ZSP continuously promoted their production efficiency. Meanwhile, the mean value of FDI keeps around 0.180 from 2007 to 2013. Given that the average level of firm assets in ZSP grows to increase rapidly from 77.580 million RMB to 217.900 million Chinese Yuan during the observation period, the value of FDI indicates that the level of foreign firm assets at the utilization indeed maintained steady growth. In other words, this visually reflects that foreign presence might contribute to local firms' technological upgrading. Regarding the returnees' repatriation speed, the mean value fluctuated a lot. It reached a peak at 1.116 in 2012, while in other years, it kept at around 0.5. Regarding the returnees' repatriation irregularity, over the period 2004-2011, the summary statistics decreased slightly from 14.950 to 10.310.

In terms of the control variables, the Age mean value increased relatively stable over the period 2007-2013, indicating that firms in ZSP might not experience a severe exit rate. By contrast, firm assets exhibited a more evidently increasing mean value during the same period, from 77.580 million Chinese Yuan to 217.9 million Chinese Yuan. Focusing on ROA, the mean value increased steadily during the 8 years, reaching a peak of 0.037 in 2011, and then slightly decreased to 0.027 in 2013. The mean value of SOE remained stable at a relatively low level around 0.05. The R&D intensity mean values maintained steady growth, increased from 0.039 to 0.056 in 2013. The firms' knowledge stock experienced explicit growth, which increased from 0.461 to 2.111. This indicator shows that the firms in ZSP improve their technology considerably from 2007 to 2013.

Table 4-3 Summary Statistics of Variables in 2007 (Chapter 5)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	7,164	2.992	1.189	0.865	6.852	0.640	3.291
FDI	7,164	0.180	0.156	0.000	0.997	0.910	4.484
Speed	7,164	0.000	0.000	0.000	0.000		
Irregularity	7,164	14.950	19.850	0.000	55.620	0.813	1.954
Age	7,164	5.930	7.717	0.000	107.000	8.790	109.9
Size	7,164	77.580	598.900	0.000	22000	17.60	421.1
SOE	7,164	0.054	0.226	0.000	1.000	3.958	16.66
ROA	7,164	0.024	0.254	-1.534	0.493	-3.049	18.03
R&D intensity	7,164	0.039	0.385	0.000	23.380	45.18	2404
Knowledge stock	7,164	0.461	4.232	0.000	206.000	28.60	1105

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

Table 4-4 Summary Statistics of Variables in 2008 (Chapter 5)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	7,589	2.940	1.236	0.865	6.852	0.662	3.244
FDI	7,589	0.181	0.167	0.000	0.994	0.763	3.357
Speed	7,589	1.219	4.614	-0.980	20.900	3.420	14.12
Irregularity	7,589	12.720	17.820	0.000	55.620	1.030	2.426
Age	7,589	6.746	7.954	0.000	108.000	8.713	106.5
Size	7,589	79.220	662.100	0.000	20000.000	19.44	466.5
SOE	7,589	0.052	0.223	0.000	1.000	4.015	17.12
ROA	7,589	0.018	0.251	-1.534	0.493	-3.574	20.13
R&D intensity	7,589	0.049	0.131	0.000	8.365	48.01	2778
Knowledge stock	7,589	0.743	12.040	0.000	896.000	58.11	4100

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

Table 4-5 Summary Statistics of Variables in 2009 (Chapter 5)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	7,569	2.908	1.303	0.865	6.852	0.622	3.059
FDI	7,569	0.185	0.175	0.000	0.997	0.588	2.629
Speed	7,569	0.233	1.791	-0.980	20.900	9.415	101.7
Irregularity	7,569	12.650	17.800	0.000	55.620	1.044	2.461
Age	7,569	7.680	8.045	0.000	109.000	8.543	102.8
Size	7,569	94.710	851.400	-30.000	41000.000	25.70	935.0
SOE	7,569	0.052	0.222	0.000	1.000	4.039	17.31
ROA	7,569	0.034	0.249	-1.534	0.493	-3.502	20.74
R&D intensity	7,569	0.053	0.128	0.000	7.469	41.36	2026
Knowledge stock	7,569	1.224	19.060	0.000	1399.000	56.12	3894

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

Table 4-6 Summary Statistics of Variables in 2010 (Chapter 5)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	6,778	2.974	1.364	0.865	6.852	0.579	2.857
FDI	6,778	0.179	0.160	0.000	0.998	0.793	3.835
Speed	6,778	0.240	1.558	-0.980	20.900	11.71	150.4
Irregularity	6,778	12.760	17.860	0.000	55.620	1.030	2.428
Age	6,778	8.738	7.858	1.000	110.000	8.336	101.6
Size	6,778	122.800	906.600	0.000	30000.000	16.83	374.2
SOE	6,778	0.051	0.220	0.000	1.000	4.087	17.70
ROA	6,778	0.029	0.244	-1.534	0.493	-3.773	22.63
R&D intensity	6,778	0.049	0.053	0.000	2.868	27.88	1287
Knowledge stock	6,778	1.832	27.280	0.000	1888.000	53.05	3453

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

Table 4-7 Summary Statistics of Variables in 2011 (Chapter 5)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	6,298	3.047	1.418	0.865	6.852	0.573	2.750
FDI	6,298	0.178	0.159	0.000	0.998	0.855	4.020
Speed	6,298	0.401	1.562	-0.980	20.900	9.837	119.6
Irregularity	6,298	12.480	17.720	0.000	55.620	1.063	2.499
Age	6,298	9.871	8.081	1.000	111.000	8.195	97.17
Size	6,298	173.100	1415.000	0.000	57000.000	21.41	633.3
SOE	6,298	0.052	0.222	0.000	1.000	4.046	17.37
ROA	6,298	0.037	0.236	-1.534	0.493	-3.748	23.02
R&D intensity	6,298	0.049	0.060	0.000	2.920	28.75	1195
Knowledge stock	6,298	2.502	30.940	0.000	1750.000	38.64	1877

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

Table 4-8 Summary Statistics of Variables in 2012 (Chapter 5)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	5,705	3.153	1.452	0.865	6.852	0.499	2.610
FDI	5,705	0.171	0.172	0.000	0.999	1.049	4.256
Speed	5,705	1.116	3.999	-0.980	20.900	4.489	21.95
Irregularity	5,705	10.155	14.812	0.000	33.109	0.872	1.807
Age	5,705	10.920	8.055	2.000	112.000	8.067	95.37
Size	5,705	219.200	1703.000	0.000	65000.000	20.85	597.2
SOE	5,705	0.051	0.221	0.000	1.000	4.065	17.53
ROA	5,705	0.033	0.227	-1.534	0.493	-3.755	23.81
R&D intensity	5,705	0.050	0.109	0.000	6.752	47.27	2721
Knowledge stock	5,705	3.301	35.560	0.000	1437.000	29.15	1006

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

Table 4-9 Summary Statistics of Variables in 2013 (Chapter 5)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	4,441	3.244	1.330	0.865	6.852	0.490	2.754
FDI	4,441	0.174	0.167	0.000	0.999	1.042	4.810
Speed	4,441	0.347	2.761	-0.980	20.900	6.517	46.59
Irregularity	4,441	10.310	14.961	0.000	33.109	0.842	1.746
Age	4,441	11.700	7.393	3.000	113.000	8.325	107.4
Size	4,441	217.900	1849.000	0.000	60000.000	19.75	500.4
SOE	4,441	0.044	0.204	0.000	1.000	4.478	21.06
ROA	4,441	0.027	0.203	-1.534	0.493	-3.989	27.50
R&D intensity	4,441	0.056	0.096	0.000	5.971	54.49	3339
Knowledge stock	4,441	2.111	21.120	0.000	1019.000	32.62	1371

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

4.4 Specialized Clustering Structure of Returnees and FDI Spillovers

4.4.1 Dataset Collection and Processing of Chapter 6

Similar to Chapter 5, in Chapter 6, I also use the annual census filed by firms under the request of the ZSP Administrative Committee from 2007 to 2013 to test my hypotheses. From this database, I construct more detailed firm-level and industry-level variables regarding FDI and returnee labor force. For the period the data is available, I initially obtained 12,821 firms with 56,905 firm-year observations, out of which 1,288 are foreign firms with 6,114 firm-year observations. I then required firms to have at least three years' financial information to calculate my measurements of variables. After excluding foreign firms and observations with missing values, I obtained a final unbalanced sample of 45,544 firms' years' observations for 7,920 unique local firms and with more than 50,000 returnee employees from 2007 to 2013.

4.4.2 Variable Definitions of Chapter 6

4.4.2.1 Dependent Variable

Similar to Chapter 5, I employ a firm's *total factor productivity* (***TFP***) to capture the effect of FDI spillovers on the local firms' performance. TFP measures the level of efficiency and intensity of the inputs utilized in production, which has been extensively used to reflect technological upgrading and productive evolution (Wang et al., 2017b; Wei et al., 2017). The estimation of TFP often starts with a Cobb–Douglas production function:

$$Y_{it} = A(t)F(L, K, a, u) \tag{8}$$

Where $A(t)$ is the TFP, indicating the cumulated technical changes over time. For estimation purposes, converting the function above into logarithm form gives:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_a a_{it} + u_{it} \tag{9}$$

Where y_{it} is log output for firm *i* in period *t*; l_{it}, k_{it} are the log values of labor and capital inputs; a_{it} is the age of the firm; u_{it} contains information on a firm's *TFP* $(A(t))$ in logarithmic form, which is assumed to follow a first-order Markov process. Similar to Chapter 5, I employ the method of Olley and Pakes (1996) to calculate the firm-level TFP. The coefficient estimates for variable inputs (labor and capital etc.) will be consistent and the error term is no longer correlated with the inputs. Once Equation (9) is estimated, all the coefficients in the production function will be successfully estimated. Using this result, we can fit the log of residuals (u_{it}) in the production function, which is also the log of *TFP*. As in Stata command (opreg), I use the clustered bootstrap, treating all observations for a single firm as one cluster and obtaining consistent results for firm TFP. I proxy "output" by firms' total sales, indicate "labor" by the number of employees, and measure "capital" by total capital.

4.4.2.2 Explanatory variables

*Foreign Direct Investment (**FDI**).* Similar to Chapter 5, this chapter also follows Buckley et al. (2002) and employs the share of a foreign firm asset in the total assets in the four-digit level industry to capture the FDI knowledge spillover, as it reflects the theoretical justification that foreign assets increase the potential for knowledge spillovers and technological transfer to influence domestic innovation performance (Belderbos, Lokshin, & Sadowski, 2015; Smith, 2014). Alternative measurements for FDI presence such as the total value of foreign capital or the total number of MNE firms are considered for robustness tests.

*Concentrated clustering structure of returnees (**Concentration**)*: The industrial concentration of returnees is calculated by the relative specialization index, which reflects the Marshall–Arrow–Romer (MAR) type of industrial specialization. It measures the share of a sub-park's employment devoted to the given industry. To control for the size of the sectors at the sub-park level and to identify to what extent a sub-park is concentrated in a given industry compared with the ZSP, it is normalized to the share of ZSP's total returnee employment allocated to this sector. The industrial concentration index of returnees is thus as follows:

$$concentration_{ijt} = \left[\frac{R_{ijt}}{\sum_i R_{ijt}}\right] \Big/ \left[\frac{\sum_j R_{ijt}}{\sum_i \sum_j R_{ijt}}\right] \tag{10}$$

R_{ijt} represent the number of returnees in an industry *i* and sub-park *j* in year *t*.

*Competitive clustering structure of returnees (C**ompetition**)*: Following Porter (1990), the returnees' industrial competition is characterized as the returnees' size distribution of firms within industry s in sub-parks c. After a normalization at the ZSP level, I have:

$$competition_{ijt} = (S_{ijt}/R_{ijt}) \Big/ \left(\sum_i \sum_j S_{ijt} \Big/ \sum_i \sum_j R_{ijt} \right) \tag{11}$$

where S_{ijt} is the number of firms in an industry i and sub-park j in year t. Low values are indicative of fewer but larger firms that recruit more highly skilled returnees.

4.4.2.3 Control variables

Similar to the control variables in Chapter 5, I also include a set of variables that might affect TFP (also see Table 4-10 for variable definitions).

Firm age: in my Ph.D. thesis, I measure it as the number of years since a firm was founded. Firm age has been argued to have a significant impact on firms' performance as it can influence firms' experience and capability to utilize their resources (Su & Liu, 2016).

Firm size: I mainly use firms' total assets to proxy firm size, based on previous literature like (Buckley et al., 2002) and (García et al., 2013). Firm size can also affect productivity efficiency as it reflects a firm's operational and management capabilities and may influence the resources available for firms' innovative activity (Jeon et al., 2013).

State-ownership: state-ownership is captured by a dummy variable, which equals 1 when a firm is registered as a state-owned or collective-owned company. In China's context, state-ownership has been widely considered as an important factor that influences firms' TFP, as it affects the resources that firms can obtain from the government (Fu et al., 2011).

Profitability: since profitable ability can influence the investment of the firm in innovative activity and further impact firms' TFP, I, therefore, include this control variable and calculate it as the return on assets (the ratio of profit in total assets) in my Ph.D. thesis, based on previous literature like (Sánchez-Sellero et al., 2014) and (Orlic et al., 2018).

R&D intensity: research and development investment (R&D) intensity is measured by firms' total amount of inner R&D investment per employee (Sánchez-Sellero et al., 2014). R&D intensity represents a firm's technological input and has been widely recognized as a critical factor that can influence a firm's TFP (Wang & Kafouros, 2009) and (Sánchez-Sellero et al., 2014).

Knowledge stock: knowledge stock is proxied by the total number of patent applications of a firm in the last three years. I include it to control for a firm's experience and capabilities in innovative activities, which might also influence its production efficiency (Ito et al., 2012; Jin et al., 2018).

Table 4-10 Variable Definitions of Chapter 6

Variables	Definition
TFP	Natural log of the Total Factor Productivity of firm *i* in year *t*
FDI	Natural log of the amount of FDI into an industry at the four-digit level in year *t*
Concentration	The concentrated clustering index of returnees at the four-digit level in year *t*
Competition	The competitive clustering index of returnees at the four-digit level in year *t*
Speed	The change rate of the number of returnees into an industry at the four-digit level in year *t*
Irregularity	The kurtosis of the number of returnees into an industry at the four-digit level in year *t*
Firm age	Natural log of the age of firm *i* in year *t*
Firm size	Natural log of the total assets of firm *i* in year *t*
SOE	A dummy variable that equals 1 if firm i is state-owned; otherwise is 0
Profitability	Natural log of the return on assets of firm *i* in year *t*
R&D intensity	Natural log of R&D investment per employee of firm *i* in year *t*
Knowledge stock	Natural log of the number of patents in the past three years of firm *i* in year *t*

4.4.3 Estimation Methods of Chapter 6

The current research argues that the employment of highly skilled returnees might not be random as they would choose to join firms with competitive capability and generous financial support. In this case, there might exist selection bias if I directly estimate the collective role of returnees on local firm productivity. Similar to Chapter 5, I also use the hackman two-stage models in Chapter 6 to estimate the agglomeration impact of returnees in the local technological upgrading and FDI spillover process. In the first stage, I estimated a probit model of a firm's propensity of recruiting returnees. I consider several factors that might affect the entry (or the recruitment) of returnees, which include firm age, size, profitability, state-ownership, R&D intensity and firm average wage (Kenney et al., 2013; Lin et al., 2016). I also include one additional predictor, the industrial average wage in the first stage, as the exclusive restriction to check the appropriateness of the Heckman two-stage estimation. I then calculated an inverse Mill's ratio (IMR) from the first stage and then include it as a control variable in the second stage of the Heckman correction models.

To test my hypotheses, I mainly employ the commonly used system generalized method of moments (GMM) estimation methodology. System-GMM is considered as a suitable method to deal with unobserved heterogeneity and endogeneity and cases where variables are not strictly exogenous since it combines the first-differenced model with its corresponding model in levels and uses lagged differences of the endogenous variables as instruments (Ning & Wang, 2018). The equation:

$$TFP_{i,t} = \alpha_i + \gamma TFP_{i,t-1} + \beta_1 FDI_{ij,t} + \beta_2 Concentration_{i,t} + \beta_3 FDI_{ij,t} \times Concentration_{i,t} + \beta_4 Competition_i + \beta_5 FDI_{ij,t} \times Competition_i + \beta_6 X_{ij,t} + \beta_7 IMR + \delta_i \varepsilon_{i,t} \qquad (12)$$

I use the first differences of the second and third lags and lag level of dependent and explanatory variables as instruments and Hansen's J test to check their overall validity in the system-GMM analysis. The Arellano–Bond (AR) test is also employed to detect the existence of the first or second-order serial correlation. Finally, according to the suggestion of Windmeijer (2005), the two-step covariance matrix was used to estimate the finite samples.

4.4.4 Univariate Analysis of Chapter 6

Tables 4.11-4.17 illustrate the summary statistics of the variables adopted in the regressions each year, with the variation tendency in both the dependent and independent variables over the 8 years. Firstly, the mean value of the dependent variable, TFP, increased from 2.992 to 3.244 over the period 2007-2013, indicating that firms in ZSP continuously promoted their production efficiency. Secondly, the mean value of FDI keeps around 0.180 from 2007 to 2013. Given that the average level of firm assets in ZSP grows to increase rapidly from 77.580 million RMB to 217.900 million RMB during the observation period, the value of FDI indicates that the level of foreign firm assets at the utilization indeed maintained steady growth. In other words, this visually reflects that foreign presence might contribute to local firms' technological upgrading. Thirdly, regarding the returnees' concentrated clustering structure, its mean value maintained a steady growth. It reached a peak at 1.326 in 2008 and then decreased gradually to 1.213 in 2013. Fourthly, the competitive clustering structure of returnees also had slight changes. It increased from 1.175 in 2008 to 2.365 in 2012 and then decreased to 1.866 in 2013.

As for the control variables, the Age mean value increased relatively stable over the period 2007-2013, indicating that firms in ZSP might not experience a severe exit rate. By contrast, firm assets exhibited a more evidently increasing mean value during the same period, from 77.580 million Chinese Yuan to 217.9 million Chinese Yuan. Focusing on ROA, the mean value increased steadily during the 8 years, reaching a peak of 0.037 in 2011, and then slightly decreased to 0.027 in 2013. The mean value of SOE remained stable at a relatively low level around 0.05. The R&D intensity mean values maintained steady growth, increased from 0.039 to 0.056 in 2013. The firms' knowledge stock experienced explicit growth, which increased from 0.461 to 2.111. This indicator shows that the firms in ZSP improve their technology considerably from 2007 to 2013. Regarding the returnees' repatriation speed, the mean value fluctuated a lot. It reached a peak at 1.116 in 2012, while in other years, it kept at around 0.5. Concerning the returnees' repatriation irregularity, over the period 2004-2011, the summary statistics decreased slightly from 14.950 to 10.310.

Table 4-11 Summary Statistics of Variables in 2007 (Chapter 6)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	7,164	2.992	1.189	0.865	6.852	0.640	3.291
FDI	7,164	0.180	0.156	0.000	0.997	0.910	4.484
Concentration	7,164	1.175	10.120	0.000	584.500	54.24	3092
Competition	7,164	1.343	1.481	0.000	12.420	4.295	28.23
Speed	7,164	0.000	0.000	0.000	0.000	N/A	N/A
Irregularity	7,164	14.950	19.850	0.000	55.620	0.813	1.954
Age	7,164	5.930	7.717	0.000	107.000	8.790	109.9
Size	7,164	77.580	598.900	0.000	22000	17.60	421.1
SOE	7,164	0.054	0.226	0.000	1.000	3.958	16.66
ROA	7,164	0.024	0.254	-1.534	0.493	-3.049	18.03
R&D intensity	7,164	0.039	0.385	0.000	23.380	45.18	2404
Knowledge stock	7,164	0.461	4.232	0.000	206.000	28.60	1105

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

Table 4-12 Summary Statistics of Variables in 2008 (Chapter 6)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	7,589	2.940	1.236	0.865	6.852	0.662	3.244
FDI	7,589	0.191	0.167	0.000	0.994	0.763	3.357
Concentration	7,589	1.326	18.160	0.000	1447.000	69.39	5346
Competition	7,589	1.627	1.825	0.000	10.510	2.443	9.987
Speed	7,589	1.219	4.614	-0.980	20.900	3.420	14.12
Irregularity	7,589	12.720	17.820	0.000	55.620	1.030	2.426
Age	7,589	6.746	7.954	0.000	108.000	8.713	106.5
Size	7,589	79.220	662.100	0.000	20000.000	19.44	466.5
SOE	7,589	0.052	0.223	0.000	1.000	4.015	17.12
ROA	7,589	0.018	0.251	-1.534	0.493	-3.574	20.13
R&D intensity	7,589	0.049	0.131	0.000	8.365	48.01	2778
Knowledge stock	7,589	0.743	12.040	0.000	896.000	58.11	4100

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

Table 4-13 Summary Statistics of Variables in 2009 (Chapter 6)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	7,569	2.908	1.303	0.865	6.852	0.622	3.059
FDI	7,569	0.195	0.175	0.000	0.997	0.588	2.629
Concentration	7,569	1.045	4.950	0.000	254.000	45.90	2214
Competition	7,569	1.746	1.988	0.000	11.040	2.263	8.798
Speed	7,569	0.233	1.791	-0.980	20.900	9.415	101.7
Irregularity	7,569	12.650	17.800	0.000	55.620	1.044	2.461
Age	7,569	7.680	8.045	0.000	109.000	8.543	102.8
Size	7,569	94.710	851.400	-30.000	41000.000	25.70	935.0
SOE	7,569	0.052	0.222	0.000	1.000	4.039	17.31
ROA	7,569	0.034	0.249	-1.534	0.493	-3.502	20.74
R&D intensity	7,569	0.053	0.128	0.000	7.469	41.36	2026
Knowledge stock	7,569	1.224	19.060	0.000	1399.000	56.12	3894

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

Table 4-14 Summary Statistics of Variables in 2010 (Chapter 6)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	6,778	2.974	1.364	0.865	6.852	0.579	2.857
FDI	6,778	0.179	0.160	0.000	0.998	0.793	3.835
Concentration	6,778	1.013	3.567	0.000	252.300	55.73	3709
Competition	6,778	2.097	2.407	0.000	10.130	1.934	5.796
Speed	6,778	0.240	1.558	-0.980	20.900	11.71	150.4
Irregularity	6,778	12.760	17.860	0.000	55.620	1.030	2.428
Age	6,778	8.738	7.858	1.000	110.000	8.336	101.6
Size	6,778	122.800	906.600	0.000	30000.000	16.83	374.2
SOE	6,778	0.051	0.220	0.000	1.000	4.087	17.70
ROA	6,778	0.029	0.244	-1.534	0.493	-3.773	22.63
R&D intensity	6,778	0.049	0.053	0.000	2.868	27.88	1287
Knowledge stock	6,778	1.832	27.280	0.000	1888.000	53.05	3453

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

Table 4-15 Summary Statistics of Variables in 2011 (Chapter 6)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	6,298	3.047	1.418	0.865	6.852	0.573	2.750
FDI	6,298	0.178	0.159	0.000	0.998	0.855	4.020
Concentration	6,298	1.115	4.826	0.000	176.800	27.83	850.3
Competition	6,298	2.121	2.418	0.000	14.790	2.653	12.02
Speed	6,298	0.401	1.562	-0.980	20.900	9.837	119.6
Irregularity	6,298	12.480	17.720	0.000	55.620	1.063	2.499
Age	6,298	9.871	8.081	1.000	111.000	8.195	97.17
Size	6,298	173.100	1415.000	0.000	57000.000	21.41	633.3
SOE	6,298	0.052	0.222	0.000	1.000	4.046	17.37
ROA	6,298	0.037	0.236	-1.534	0.493	-3.748	23.02
R&D intensity	6,298	0.049	0.060	0.000	2.920	28.75	1195
Knowledge stock	6,298	2.502	30.940	0.000	1750.000	38.64	1877

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

Table 4-16 Summary Statistics of Variables in 2012 (Chapter 6)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	5,705	3.153	1.452	0.865	6.852	0.499	2.610
FDI	5,705	0.171	0.172	0.000	0.999	1.049	4.256
Concentration	5,705	1.203	8.199	0.000	386.300	40.35	1785
Competition	5,705	2.365	3.362	0.000	28.580	4.220	27.21
Speed	5,705	1.116	3.999	-0.980	20.900	4.489	21.95
Irregularity	5,705	10.155	14.812	0.000	33.109	0.872	1.807
Age	5,705	10.920	8.055	2.000	112.000	8.067	95.37
Size	5,705	219.200	1703.000	0.000	65000.000	20.85	597.2
SOE	5,705	0.051	0.221	0.000	1.000	4.065	17.53
ROA	5,705	0.033	0.227	-1.534	0.493	-3.755	23.81
R&D intensity	5,705	0.050	0.109	0.000	6.752	47.27	2721
Knowledge stock	5,705	3.301	35.560	0.000	1437.000	29.15	1006

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

Table 4-17 Summary Statistics of Variables in 2013 (Chapter 6)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	4,441	3.244	1.330	0.865	6.852	0.490	2.754
FDI	4,441	0.174	0.167	0.000	0.999	1.042	4.810
Concentration	4,441	1.213	10.800	0.000	689.700	59.02	3729
Competition	4,441	1.866	2.070	0.000	13.090	1.988	7.299
Speed	4,441	0.347	2.761	-0.980	20.900	6.517	46.59
Irregularity	4,441	10.310	14.961	0.000	33.109	0.842	1.746
Age	4,441	11.700	7.393	3.000	113.000	8.325	107.4
Size	4,441	217.900	1849.000	0.000	60000.000	19.75	500.4
SOE	4,441	0.044	0.204	0.000	1.000	4.478	21.06
ROA	4,441	0.027	0.203	-1.534	0.493	-3.989	27.50
R&D intensity	4,441	0.056	0.096	0.000	5.971	54.49	3339
Knowledge stock	4,441	2.111	21.120	0.000	1019.000	32.62	1371

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

4.5 Diversified Clustering Structure of Returnees and FDI Spillovers

4.5.1 Dataset Collection and Processing of Chapter 7

The annual census filed by firms under the request of the ZSP Administrative Committee from 2007 to 2013 is used to test my hypotheses. The high-tech firms were required to take part in the census survey by providing detailed information, including legal entity of enterprises, production management and financial status, the enterprise technology activities, and the labor structures. From this database, I construct more detailed firm-level and industry-level variables regarding FDI and returnee labor force. For the period the data is available to us, I initially obtained 12,821 firms with 56,905 firm-year observations, out of which 1,288 are foreign firms with 6,114 firm-year observations. I then required firms to have at least three years' financial information to calculate my measurements of variables. After excluding foreign firms and observations with missing values, I obtained a final unbalanced sample of 45,544 firms' years' observations for 7,920 unique local firms and with more than 50,000 returnee employees from 2007 to 2013.

4.5.2 Variable Definitions of Chapter 7

4.5.2.1 Dependent variable

Similar to Chapter 5, I employ a firm's *total factor productivity* (***TFP***) to capture the effect of FDI spillovers on the local firms' performance. TFP measures the level of efficiency and intensity of the inputs utilized in production, which has been extensively used to reflect technological upgrading and productive evolution (Wang et al., 2017b; Wei et al., 2017). The estimation of TFP often starts with a Cobb–Douglas production function:

$$Y_{it} = A(t)F(L, K, a, u) \tag{13}$$

Where $A(t)$ is the TFP, indicating the cumulated technical changes over time. For estimation purposes, converting the function above into logarithm form gives:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_a a_{it} + u_{it} \tag{14}$$

Where y_{it} is log output for firm i in period t; l_{it}, k_{it} are the log values of labor and capital inputs; a_{it} is the age of the firm; u_{it} contains information on a firm's TFP $(A(t))$ in logarithmic form, which are assumed to follow a first-order Markov process. I employ the method of Olley and Pakes (1996) to calculate the firm-level TFP. Olley and Pakes (1996) first proposed the two-step consistent estimation method, whose core idea is to take the company's investment level as a proxy variable of productivity. The method assumes that firms make investment decisions based on the current state of productivity, so the current investment of firms is taken as the proxy variable of unobservable productivity impact, thus solving the problem of simultaneity bias and being an appropriate method to estimate firm-level productivity. The coefficient estimates for variable inputs (labor and capital etc.) will be consistent and the error term is no longer correlated with the inputs. Once Equation (14) is estimated, all the coefficients in the production function will be successfully estimated. Using this result, we can fit the log of residuals (u_{it}) in the production function, which is also the log of *TFP*. As in Stata command (opreg), I use the clustered bootstrap, treating all observations for a single firm as one cluster and obtaining consistent results for domestic firms TFP. I proxy "output" by firms' total sales, indicate "labor" by the number of employees, and measure "capital" by total capital.

4.5.2.2 Explanatory variables

*Foreign Direct Investment (**FDI**)*. Similar to Chapter 5, this chapter also follows Buckley et al. (2002) and employs the share of a foreign firm asset in the total assets in the four-digit level industry to capture the FDI knowledge spillover, as it reflects the theoretical justification that foreign assets increase the potential for knowledge spillovers and technological transfer to influence domestic innovation performance (Belderbos, Lokshin, & Sadowski, 2015; Smith, 2014). Alternative measurements for FDI presence such as the total value of foreign capital or the total number of MNE firms are considered for robustness tests.

*Related variety clustering structure of returnees (**Related variety**)*. I measure the returnee clustering structure based on the unrelated and related variety index developed by Frenken et al. (2007). Following Frenken et al. (2007), in this paper, related variety and unrelated variety are measured by sectoral decomposition (using entropy measurement), where employment in detailed four-digit industries is considered to be functionally related to their two-digit aggregates, while two-digit sectors themselves are mutually unrelated. The entropy of the two-digit industrial distribution of returnees indicates the unrelated variety of returnee agglomeration, while the weighted sum of the entropy index at the four-digit level within each two-digit industry class denotes the related variety of returnee clustering. Formally, let all four-digit sectors *m* fall exclusively under a two-digit industry S_g, where g= 1, . . ., n. I derive the two-digit shares P_g of returnees, by summing the four-digit shares p_m of returnees of each sixteen ZSP sub-parks belonging to a two-digit industry:

$$P_g = \sum_{m \in S_g} p_m \tag{15}$$

Related variety (RV) of returnee clustering, as the weighted sum of the entropy of returnee distribution of the four-digit industries within each two-digit industry, is given by:

$$RV = \sum_{g}^{G} P_g \, H_g \tag{16}$$

Where:

$$H_g = \sum_{m \in S_g} \frac{P_m}{P_g} log_2 \left(\frac{1}{p_m / P_g} \right) \tag{17}$$

*Unelated variety clustering structure of returnees (**Unrelated variety**)*. The entropy of returnee clustering at the two-digit level, or the unrelated variety (UV) of returnee clustering, is given by

$$UV = \sum_{g=1}^{G} P_g \log_2 \left(\frac{1}{P_g}\right) \tag{18}$$

I replicate the above procedure to calculate the aggregate RV and UV of each sub-park. I then normalize the above returnee RV and UV through dividing them by the aggregate RV and UV of their corresponding sub-parks to take into account the size differences and control for potential changes of local industrial structure.

4.5.2.3 Control variables

I control for a set of variables that might affect TFP (see Table 4-18 for variable definitions).

Firm age: in my Ph.D. thesis, I measure it as the number of years since a firm was founded. Firm age has been argued to have a significant impact on firms' performance as it can influence firms' experience and capability to utilize their resources (Su & Liu, 2016).

Firm size: I mainly use firms' total assets to proxy firm size, based on previous literature like Buckley et al. (2002) and García et al. (2013). Firm size can also affect productivity efficiency as it reflects a firm's operational and management capabilities and may influence the resources available for firms' innovative activity (Jeon et al., 2013).

State-ownership: state-ownership is captured by a dummy variable, which equals 1 when a firm is registered as a state-owned or collective-owned company. In China's context, state-ownership affects the resources that firms can obtain from the government (Fu et al., 2011).

Profitability: since profitable ability can influence the investment of the firm in innovative activity and further impact firms' TFP, I, therefore, include this control variable and calculate it as the return on assets (the ratio of profit in total assets) in my Ph.D. thesis, based on previous literature like Sánchez-Sellero et al. (2014) and Orlic et al. (2018).

R&D intensity: research and development investment (R&D) intensity is measured by firms' total amount of inner R&D investment per employee (Sánchez-Sellero et al., 2014). R&D intensity represents a firm's technological input and has been widely recognized as a critical factor that can influence a firm's TFP (Sánchez-Sellero et al., 2014).

Knowledge stock: knowledge stock is proxied by the total number of patent applications of a firm in the last three years. I include it to control for a firm's experience and capabilities in innovative activities, which might also influence its production efficiency (Ito et al., 2012; Jin et al., 2018).

Table 4-18 Variable Definitions of Chapter 7

Variables	Definition
TFP	Natural log of the Total Factor Productivity of firm *i* in year *t*
FDI	Natural log of the amount of FDI into an industry at the four-digit level in year *t*
Related variety	The related variety clustering index of returnees at the four-digit level in year *t*
Unrelated variety	The unrelated variety clustering index of returnees at the four-digit level in year *t*
Concentration	The concentrated clustering index of returnees at the four-digit level in year *t*
Competition	The competitive clustering index of returnees at the four-digit level in year *t*
Speed	The change rate of the number of returnees into an industry at the four-digit level in year *t*
Irregularity	The kurtosis of the number of returnees into an industry at the four-digit level in year *t*
Firm age	Natural log of the age of firm *i* in year *t*
Firm size	Natural log of the total assets of firm *i* in year *t*
SOE	A dummy variable that equals to 1 if firm i is state-owned; otherwise is 0
Profitability	Natural log of the return on assets of firm *i* in year *t*
R&D intensity	Natural log of R&D investment per employee of firm *i* in year *t*
Knowledge stock	Natural log of the number of patents in the past three years of firm *i* in year *t*

4.5.3 Estimation Methods of Chapter 7

Similar to Chapter 5, Chapter 7 also use the hackman two-stage models to address the potential selection bias and to estimate the agglomeration impact of returnees in the local technological upgrading and FDI spillover process. In the first stage, I estimated a Probit model of a firm's propensity of recruiting returnees. I consider several factors that might affect the entry (or the recruitment) of returnees, which include firm age, size, profitability, state-ownership, R&D intensity and firm average level (Kenney et al., 2013; Lin et al., 2016). I also include one additional predictor, the industrial average wage in the first stage, as the exclusive restriction to check the appropriateness of the Heckman two-stage estimation. I then calculated an inverse Mill's ratio (IMR) from the first stage and then include it as a control variable in the second stage of the Heckman correction models.

In the second stage, I mainly employ the commonly used system generalized method of moments (GMM) estimation methodology to test the hypothesis. System-GMM is considered as a suitable method to deal with unobserved heterogeneity and endogeneity and cases where variables are not strictly exogenous since it combines the first-differenced model with its corresponding model in levels and uses lagged differences of the endogenous variables as instruments (Ning & Wang, 2018). The equation:

$$TFP_{i,t} = \alpha_i + \gamma TFP_{i,t-1} + \beta_1 FDI_{ij,t} + \beta_2 Related\ variety_{i,t} + \beta_3 FDI_{ij,t} \times Related\ variety_{i,t} + \beta_4 Unrelated\ variety_i + \beta_5 FDI_{ij,t} \times Unrelated\ variety_i + \beta_6 X_{ij,t} + \beta_7 IMR + \delta_i \varepsilon_{i,t} \tag{19}$$

I use the first differences of the second and third lags and lag level of dependent and explanatory variables as instruments and Hansen's J test to check their overall validity in the system-GMM analysis. The Arellano–Bond (AR) test is also employed to detect the existence of the first or second-order serial correlation. Finally, according to the suggestion of Windmeijer (2005), the two-step covariance matrix was used to estimate the finite samples.

4.5.4 Univariate Analysis of Chapter 7

Tables 4.19-4.25 illustrate the summary statistics of the variables adopted in the regressions each year, with the variation tendency in both the dependent and independent variables over the 8 years. Firstly, the mean value of the dependent variable, TFP, increased from 2.992 to 3.244 over the period 2007-2013, indicating that firms in ZSP continuously promoted their production efficiency. Secondly, the mean value of FDI keeps around 0.180 from 2007 to 2013. Given that the average level of firms assets in ZSP grows to increase rapidly from 77.580 million RMB to 217.900 million RMB during the observation period, the value of FDI indicates that the level of foreign firm assets at the utilization indeed maintained steady growth. In other words, this visually reflects that foreign presence might contribute to local firms' technological upgrading. Thirdly, regarding the returnees' related variety clustering structure, its mean value increased greatly from 0.061 in 2008 to 0.302 in 2013. Fourthly, the unrelated variety clustering structure of returnees had slight changes. It increased from 2.029 in 2008 to 2.105 in 2012 and then decreased to 1.925 in 2013.

Concerning the control variables, the Age mean value increased relatively stable over the period 2007-2013, indicating that firms in ZSP might not experience a severe exit rate. By contrast, firm assets exhibited a more evidently increasing mean value during the same period, from 77.580 million Chinese Yuan to 217.9 million Chinese Yuan. Focusing on ROA, the mean value increased steadily during the 8 years, reaching a peak of 0.037 in 2011, and then slightly decreased to 0.027 in 2013. The mean value of SOE remained stable at a relatively low level around 0.05. The R&D intensity mean value maintained steady growth, increased from 0.039 to 0.056 in 2013. The firms' knowledge stock experienced explicit growth, which increased from 0.461 to 2.111. This indicator shows that the firms in ZSP improve their technology considerably from 2007 to 2013. Regarding the returnees' repatriation speed, the mean value fluctuated a lot. It reached a peak at 1.116 in 2012, while in other years, it kept at around 0.5. About the returnees' repatriation irregularity, over the period 2004-2011, the summary statistics decreased slightly from 14.950 to 10.310. In terms of the returnees' concentrated clustering structure, its mean value maintained a steady growth. It reached a peak at 1.326 in 2008 and then decreased gradually to 1.213 in 2013. The competitive clustering structure of returnees also had slight changes. It increased from 1.175 in 2008 to 2.365 in 2012 and then decreased to 1.866 in 2013.

Table 4-19 Summary Statistics of Variables in 2007 (Chapter 7)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	7,164	2.992	1.189	0.865	6.852	0.640	3.291
FDI	7,164	0.180	0.156	0.000	0.997	0.910	4.484
Related variety	7,164	0.061	0.026	-0.330	0.000	-7.688	76.46
Unrelated variety	7,164	2.029	0.243	0.000	2.076	-5.919	39.93
Concentration	7,164	1.175	10.120	0.000	584.500	54.24	3092
Competition	7,164	1.343	1.481	0.000	12.420	4.295	28.23
Speed	7,164	0.000	0.000	0.000	0.000		
Irregularity	7,164	14.950	19.850	0.000	55.620	0.813	1.954
Age	7,164	5.930	7.717	0.000	107.000	8.790	109.9
Size	7,164	77.580	598.900	0.000	22000	17.60	421.1
SOE	7,164	0.054	0.226	0.000	1.000	3.958	16.66
ROA	7,164	0.024	0.254	-1.534	0.493	-3.049	18.03
R&D intensity	7,164	0.039	0.385	0.000	23.380	45.18	2404
Knowledge stock	7,164	0.461	4.232	0.000	206.000	28.60	1105

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

Table 4-20 Summary Statistics of Variables in 2008 (Chapter 7)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	7,589	2.940	1.236	0.865	6.852	0.662	3.244
FDI	7,589	0.191	0.167	0.000	0.994	0.763	3.357
Related variety	7,589	0.134	0.045	-0.366	0.141	-9.030	95.49
Unrelated variety	7,589	2.056	0.261	0.000	2.105	-5.787	37.58
Concentration	7,589	1.326	18.160	0.000	1447.000	69.39	5346
Competition	7,589	1.627	1.825	0.000	10.510	2.443	9.987
Speed	7,589	1.219	4.614	-0.980	20.900	3.420	14.12
Irregularity	7,589	12.720	17.820	0.000	55.620	1.030	2.426
Age	7,589	6.746	7.954	0.000	108.000	8.713	106.5
Size	7,589	79.220	662.100	0.000	20000.000	19.44	466.5
SOE	7,589	0.052	0.223	0.000	1.000	4.015	17.12
ROA	7,589	0.018	0.251	-1.534	0.493	-3.574	20.13
R&D intensity	7,589	0.049	0.131	0.000	8.365	48.01	2778
Knowledge stock	7,589	0.743	12.040	0.000	896.000	58.11	4100

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

Table 4-21 Summary Statistics of Variables in 2009 (Chapter 7)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	7,569	2.908	1.303	0.865	6.852	0.622	3.059
FDI	7,569	0.195	0.175	0.000	0.997	0.588	2.629
Related variety	7,569	0.060	0.047	-0.343	0.347	-5.581	54.84
Unrelated variety	7,569	2.093	0.277	0.000	2.149	-5.531	34.83
Concentration	7,569	1.045	4.950	0.000	254.000	45.90	2214
Competition	7,569	1.746	1.988	0.000	11.040	2.263	8.798
Speed	7,569	0.233	1.791	-0.980	20.900	9.415	101.7
Irregularity	7,569	12.650	17.800	0.000	55.620	1.044	2.461
Age	7,569	7.680	8.045	0.000	109.000	8.543	102.8
Size	7,569	94.710	851.400	-30.000	41000.000	25.70	935.0
SOE	7,569	0.052	0.222	0.000	1.000	4.039	17.31
ROA	7,569	0.034	0.249	-1.534	0.493	-3.502	20.74
R&D intensity	7,569	0.053	0.128	0.000	7.469	41.36	2026
Knowledge stock	7,569	1.224	19.060	0.000	1399.000	56.12	3894

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

Table 4-22 Summary Statistics of Variables in 2010 (Chapter 7)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	6,778	2.974	1.364	0.865	6.852	0.579	2.857
FDI	6,778	0.179	0.160	0.000	0.998	0.793	3.835
Related variety	6,778	0.097	0.031	-0.125	0.261	-3.068	29.11
Unrelated variety	6,778	2.231	0.300	0.000	2.291	-5.401	33.03
Concentration	6,778	1.013	3.567	0.000	252.300	55.73	3709
Competition	6,778	2.097	2.407	0.000	10.130	1.934	5.796
Speed	6,778	0.240	1.558	-0.980	20.900	11.71	150.4
Irregularity	6,778	12.760	17.860	0.000	55.620	1.030	2.428
Age	6,778	8.738	7.858	1.000	110.000	8.336	101.6
Size	6,778	122.800	906.600	0.000	30000.000	16.83	374.2
SOE	6,778	0.051	0.220	0.000	1.000	4.087	17.70
ROA	6,778	0.029	0.244	-1.534	0.493	-3.773	22.63
R&D intensity	6,778	0.049	0.053	0.000	2.868	27.88	1287
Knowledge stock	6,778	1.832	27.280	0.000	1888.000	53.05	3453

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

Table 4-23 Summary Statistics of Variables in 2011 (Chapter 7)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	6,298	3.047	1.418	0.865	6.852	0.573	2.750
FDI	6,298	0.178	0.159	0.000	0.998	0.855	4.020
Related variety	6,298	0.324	0.073	-0.224	0.339	-5.070	29.39
Unrelated variety	6,298	2.108	0.282	0.000	2.164	-5.241	30.34
Concentration	6,298	1.115	4.826	0.000	176.800	27.83	850.3
Competition	6,298	2.121	2.418	0.000	14.790	2.653	12.02
Speed	6,298	0.401	1.562	-0.980	20.900	9.837	119.6
Irregularity	6,298	12.480	17.720	0.000	55.620	1.063	2.499
Age	6,298	9.871	8.081	1.000	111.000	8.195	97.17
Size	6,298	173.100	1415.000	0.000	57000.000	21.41	633.3
SOE	6,298	0.052	0.222	0.000	1.000	4.046	17.37
ROA	6,298	0.037	0.236	-1.534	0.493	-3.748	23.02
R&D intensity	6,298	0.049	0.060	0.000	2.920	28.75	1195
Knowledge stock	6,298	2.502	30.940	0.000	1750.000	38.64	1877

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

Table 4-24 Summary Statistics of Variables in 2012 (Chapter 7)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	5,705	3.153	1.452	0.865	6.852	0.499	2.610
FDI	5,705	0.171	0.172	0.000	0.999	1.049	4.256
Related variety	5,705	0.253	0.062	-0.158	0.619	0.609	31.46
Unrelated variety	5,705	2.105	0.293	0.000	2.165	-4.924	26.23
Concentration	5,705	1.203	8.199	0.000	386.300	40.35	1785
Competition	5,705	2.365	3.362	0.000	28.580	4.220	27.21
Speed	5,705	1.116	3.999	-0.980	20.900	4.489	21.95
Irregularity	5,705	10.155	14.812	0.000	33.109	0.872	1.807
Age	5,705	10.920	8.055	2.000	112.000	8.067	95.37
Size	5,705	219.200	1703.000	0.000	65000.000	20.85	597.2
SOE	5,705	0.051	0.221	0.000	1.000	4.065	17.53
ROA	5,705	0.033	0.227	-1.534	0.493	-3.755	23.81
R&D intensity	5,705	0.050	0.109	0.000	6.752	47.27	2721
Knowledge stock	5,705	3.301	35.560	0.000	1437.000	29.15	1006

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

Table 4-25 Summary Statistics of Variables in 2013 (Chapter 7)

Variable	Obs	Mean	Std.Dev.	Min	Max	Skew	Kurtosis
TFP	4,441	3.244	1.330	0.865	6.852	0.490	2.754
FDI	4,441	0.174	0.167	0.000	0.999	1.042	4.810
Related variety	4,441	0.302	0.061	-0.146	0.313	-5.791	35.63
Unrelated variety	4,441	1.925	0.243	0.000	1.917	-5.212	31.11
Concentration	4,441	1.213	10.800	0.000	689.700	59.02	3729
Competition	4,441	1.866	2.070	0.000	13.090	1.988	7.299
Speed	4,441	0.347	2.761	-0.980	20.900	6.517	46.59
Irregularity	4,441	10.310	14.961	0.000	33.109	0.842	1.746
Age	4,441	11.700	7.393	3.000	113.000	8.325	107.4
Size	4,441	217.900	1849.000	0.000	60000.000	19.75	500.4
SOE	4,441	0.044	0.204	0.000	1.000	4.478	21.06
ROA	4,441	0.027	0.203	-1.534	0.493	-3.989	27.50
R&D intensity	4,441	0.056	0.096	0.000	5.971	54.49	3339
Knowledge stock	4,441	2.111	21.120	0.000	1019.000	32.62	1371

Note: (1) Firm size is measured in 1 million Chinese Yuan; (2) Source: the Annual Census of ZSP firms

4.6 Concluding Remarks

In this chapter, I have systematically introduced the datasets and methodology adopted in this Ph.D. thesis to conduct the econometric analysis. First, I introduced the research context, Zhongguancun Science Park, in this Ph.D. thesis. Second, I presented the main database, namely The Annual Census of Zhongguancun Science Park Firms. According to the specific research question in this thesis, I expatiated on the statistical compositions, definitions, and sources of the database. Third, I discussed the research design and methodology selection, namely system-GMM models with Heckman corrections, for this Ph.D. thesis. Fourth, I illustrated the procedures used to collect and process the datasets from the selected databases in each empirical chapter. After that, I defined both the dependent and independent variables adopted in the empirical chapters, as well as the econometric configurations. Finally, to provide more detailed characteristics of the datasets, I implemented a univariate analysis. This provides an overview of the indicators' sequential variations, corresponding to the econometric analysis in the following three empirical chapters, using the specific identified methods and datasets.

Chapter 5 How Does FDI Knowledge Spillovers Improve Local Firms Productivity? The Role of Returnees' Repatriation Process Into Local Industries

5.1 Introduction

In the literature review chapter, we know that it was well acknowledged that FDI is a critical external knowledge source for emerging market firms to improve their technology, and returnees with cross-cultural knowledge and language advantages can help the local absorption of FDI knowledge spillovers. Nevertheless, we still know limited about the collective and dynamic role of returnees, especially the time-based characteristics of their industrial repatriation process, including repatriation speed and irregularity, in the local firm performance and FDI knowledge diffusion. Moreover, there is relatively less empirical evidence in the emerging markets context. Therefore, in this chapter, I would like to investigate the first research question: "*How do the time-based characteristics of the returnees' repatriation into local industries, namely speed and irregularity, influence the local firm productivity and the FDI knowledge spillovers*?"

Firms in China have put great efforts to learn from advanced foreign technology and expect to catch up with the economic development. Currently, FDI knowledge spillovers provide Chinese firms opportunities of bridging their technological gap with developed countries (Ito et al., 2012). However, given the knowledge disparity between foreign and local knowledge bases, local firms are unable to absorb advanced technology effectively (Fu & Gong, 2011). Therefore, local firms need to improve their absorptive capacity and exploit FDI spillovers more effectively. In recent years, emerging markets have gradually realized the importance of returnees and are eager to hire them (Liu et al., 2014). As the returnees have studied and/or worked outside the Chinese mainland for several years, they often possess a global perspective, understand multiple cultures, and are equipped with advanced technological skills, hence their functions in the improvement of local absorptive capacity might enhance the local absorption of FDI knowledge spillovers (Lin et al., 2015).

The previous literature has already acknowledged the role of individual returnees in FDI knowledge diffusion. For example, Wang (2015) and Tzeng (2018b) argue that returnees' dual social network and technological capability in both countries enable them to act as knowledge brokers between foreign and local firms and help them establish new contacts. However, it is still unclear what is the collective and dynamic role of returnees in absorbing FDI spillovers as previous literature only considers the individual returnees in a small sample of firms (Fu et al., 2017; Liu et al., 2010a). Indeed, on the one hand, the returnees do not work alone but rather interact with others, which would collectively influence the local industrial knowledge base. The industrial interactions between returnees might also bring knowledge externality and help improve the local firms' productivity. On the other hand, the returnees' repatriation is not a static process. From a dynamic perspective, returnees' might need some time to deal with the readjustment issues after they return to their homeland before they play a role in promoting the local absorptive capability (Bai et al., 2018; Lee & Roberts, 2015; Lin et al., 2019; Qin et al., 2017). The time-based characteristics of the returnees' repatriation process therefore should be considered in the process of absorbing FDI knowledge diffusion. Nevertheless, the current literature has not examined this important topic. The existing inconclusive evidence may be inadequate to instruct an effective way to fully exploit the function of returnees and enhance the local firm productivity upgrading.

To this end, this chapter is devoted to filling up the gap by investigating the collective role of returnees in promoting the local firm productivity and facilitating the FDI knowledge spillovers from a dynamic industrial repatriation perspective. I propose that the time-based characteristics of returnees' repatriation, into local industries including speed and irregularity, can play different roles in boosting local firms to learn from FDI knowledge spillover.

More specifically, on the one hand, the speed of returnees' repatriation refers to how quickly the returnees enter the local industrial labor market. Since the returnees are often skilled adequacy and may serve as the knowledge brokerage between local firms and FDI (Lin et al., 2016), the quicker they join in domestic industry, the more improvements on local firms' knowledge base and they can help establish more linkages between local and foreign firms, then it may enable local firms to benefit more from FDI advanced knowledge. On the other hand, the irregularity of returnees' repatriation refers to the rhythm or progress of the returnees' entry into local industries. An irregularity of the returnees' repatriation, such as an abrupt and discontinuous change of the returnees in an industry, is often accompanied by a sudden rise in labor competition (Hao et al., 2016; Hao et al., 2017). It has been widely acknowledged that the returnees are usually local context unknown and suffering from insufficient local embeddedness after studying or working abroad for many years, and they need regular time to establish local relationships and readjust to the local environment (Lin et al., 2019). Therefore, the unstable environment might restrict the returnees to act as knowledge brokers between local and foreign firms, which may constrain the returnee's role in helping to absorb FDI knowledge spillover (Qin & Estrin, 2015; Wang et al., 2017b). By highlighting the importance of the time-based attributes of returnees' repatriation in improving firm performance, I aim to help local firms choose a better strategy to attract highly skilled returnees and to exploit FDI knowledge spillovers more effectively.

Generally, this chapter mainly contributes to the current knowledge in two ways. Firstly, it enriches the small but growing literature on the economic effects of the returnees. Although the returnees are important, current literature does not place much emphasis on their collective role in the local firms' performance, let alone considering the returnees' industrial repatriation with a dynamic perspective (Bai et al., 2017; Chen, 2008; Tzeng, 2018b). This chapter makes the first attempt to explain the collective impact of returnees by distinguishing the two critical characteristics of their repatriation process into local industries, namely speed and irregularity. The findings suggest that only when returnees enter the local industries at a quick but rhythmic mode, can they help improve the local firm productivity. Secondly, it moves beyond existing FDI spillover studies and sheds new light on a special factor that helps local firms absorb FDI knowledge diffusions. In the existing studies, little is known about the collective role of returnees in the absorption of FDI advanced knowledge (Choudhury, 2015; Filatotchev et al., 2011; Fu et al., 2017; Lin et al., 2016). In this chapter, I confirm that returnees can collectively play an important role in facilitating FDI knowledge spillovers to local firms. My results indicate that the returnees' repatriation speed promotes the positive impact of FDI spillovers on local firm productivity, however, their repatriation irregularity weakens the FDI spillovers. All the findings advance the research on knowledge flows by placing more emphasis on returnees as a unique labor force that influences FDI knowledge spillovers.

My research context is Zhongguancun Science Park (ZSP) in China as the MNEs and returnee workers have played important role in the growth in ZSP (*Zhongguancun Report 2019*). First, in my data, the average share of MNEs sales at the two-digit industry level was 18.64%. 130 out of the Fortune 500 companies have set up R&D centers here, such as Microsoft, IBM, Bell, Oracle, and Intel, some of which have been there since the early 1990s (ibid). This again provides us with a long period of observation for analyzing the interaction and impact of FDI on local firm performance. Second, ZSP is a top destination for educated returnees to locate. Since the late 1990s, central and local governments have launched many policies to attract returnees such as the "Thousand talents program," "Beijing Haigui Program," and "ZSP Clustering Program of Global Talents." These policies typically provide direct funding to facilitate returnees' early-stage technology ventures, acquisition of apparatus, or exemption from taxes on their businesses or personal incomes (ibid). Third, the ZSP comprises 16 sub-parks and the returnees are clustered in several industries and sub-park, which allows me to distinguish the returnees' industrial concentration and competition in the dataset and examine their impacts on local firms' productivity and FDI knowledge spillovers.

The organization of this chapter is as follows. The second section presents the literature review and hypotheses development, summarizing previous studies on the relationship between inward FDI and local firm productivity as well as returnees. The third section describes the sample data used in the statistical analysis. The fourth section presents both descriptive and econometric analysis. Finally, the conclusions and discussions are presented in the fifth section.

5.2 Theoretical Framework and Hypotheses Development

5.2.1 FDI Knowledge Spillovers and Local Firm Performance

Based on the resource dependence theory, inward FDI has long been considered as a key external knowledge resource for firms in an emerging market, and local firms can learn from FDI knowledge spillover (Buckley et al., 2002; Hu & Jefferson, 2002; Jin et al., 2018; Ning et al., 2016b). The so-called "spillovers" suggests that the technological superiority and strong management practices of FDI can be transferred to local firms in emerging markets with the help of geographical and cultural proximity, which may result in productivity increases among local firms (Buckley et al., 2010; Newman et al., 2015). As a result, local firms in the host country are devoted to seeking opportunities to establish a relationship with FDI and expect to improve their productivity by observing and imitating the successful technologies (Fu & Gong, 2011; Fu et al., 2011).

Previous studies have identified some channels such as business linkage, employee turnover, demonstration effect, and competition effect, through which local firms can learn from FDI knowledge spillover (Zhang et al., 2014). To be specific, first, by establishing backward and forward business linkage, domestic suppliers and distributors can assimilate the advanced management practices and technologies from FDI (Tzeng, 2018b; Wang et al., 2012). Second, when employees from a foreign firm find a new job in local firms, their experience and knowledge about foreign superior technology can diffuse to local firms and increase the firm productivity (Orlic et al., 2018). Third, the demonstration effect means that local firms can observe and imitate the foreign firms' activities in their operations when extensively exposed to the FDI environment (Fu, 2012; Lu et al., 2017). The fourth channel is the competition effect, however, this channel may lead to two different outcomes. One outcome is that the increased challenge from FDI may force local firms to improve their capability like innovative ability and managerial structures to deal with the competition, which may improve their productivity (Zhang et al., 2014). On the contrary, when foreign firms exploit much superior technologies and management practices, which can significantly decrease their cost and attract demand away from their domestic competitors. In this case, with advanced innovative capabilities and more export experience, the severe competition effect of FDI can produce “crowd-out effects” and/ or “market-stealing” effect and can be harmful to local firms’ performance (Hu & Jefferson, 2002; Lu et al., 2017).

Based on the contrasting theories, therefore, it is not surprising that the existing empirical evidence of FDI knowledge spillover is still inconclusive and mixed. Some of the previous studies have argued that the improvement of local firm performance is positively correlated with FDI, via channels like demonstration effect, business linkages, and worker mobility (Buckley et al., 2010; Newman et al., 2015; Orlic et al., 2018; Tzeng, 2018b). In contrast, other scholars suggested that the effect of FDI are not always positive (Martinez-Noya et al., 2013). The main arguments lie in that with advanced innovative capabilities and more export experience, FDI can produce “crowd-out effects” and/ or “market-stealing” effects which is harmful to domestic firms’ performance (Hu & Jefferson, 2002; Lu et al., 2017).

To explain the mixed results, a growing trend of studies argue that certain requirement needs to be met for a local firm to learn from FDI more effectively (Blalock & Gertler, 2009; Orlic et al., 2018; Zhang et al., 2010). Geographical proximity, industrial structures, the key characteristics of foreign firms, and local absorptive capacity are extensively studied (Huang et al., 2012; Javorcik & Spatareanu, 2011; Ning et al., 2016b; Zhang et al., 2010). For example, proximity theory argues that the FDI knowledge diffusion weakens as the distance between foreign and local firms increase (Jude, 2016; Ning et al., 2016a). Moreover, the industrial structure is regarded to play an important role in moderating FDI spillovers. A common argument is that industrial diversity strengthens knowledge spillovers, but specialization reduces the positive effects of inward FDI (Ning et al., 2016b). Besides, many studies also research on how the attributes of FDI, such as foreign firms' country origins (Javorcik & Spatareanu, 2011; Zhang et al., 2010), entry processes like expansion pace and rhythm (Wang et al., 2017b; Zhang et al., 2014), and asset composition (Blalock & Gertler, 2009; Rojec & Knell, 2018), may affect spillover effects and have led to diverse results.

Local absorptive capacity is another important cornerstone for local firms to learn foreign knowledge (Huang, Lin, Wu, & Yu, 2015; Sánchez-Sellero et al., 2014). Absorptive capacity refers to the ability of firms to assimilate and exploit external knowledge and it can be developed by investing in research and development (R&D) and human capital (Castellani & Zanfei, 2003; Wang et al., 2012). In the emerging market context, returnees are an important and special labor force that can contribute to the local human capital. Since the returnees have studied and/or worked in foreign countries, they often understand multiple cultures, possess technological and managerial expertise, and may act as a 'bridge' between the MNEs and local firms (Lin et al., 2016; Liu et al., 2014). Therefore, returnees are vital for local firms to learn more from FDI knowledge spillovers and it is necessary to find out the specific effect of returnees and better exploit it.

Previous literature has acknowledged that returnees can facilitate FDI knowledge spillovers as they can improve the local knowledge base and serve as knowledge brokers between FDI and local firms (Lin et al., 2016; Xiao & Tsui, 2007). With a long time of training abroad, the returnees are usually equipped with superior technical and entrepreneurial skills and professional international networks (Kenney et al., 2013). When returning to their home country, their knowledge of both their home and host countries enables them to identify cross-border differences and knowledge gaps between foreign and local firms (Bai et al., 2017). In this case, the returnees can act as knowledge brokers in transferring technological and business knowledge from FDI (Obukhova, 2012b). Thus, the returnees may facilitate FDI knowledge diffusion and exert an increase in the firm productivity.

Nevertheless, I have very limited evidence about the dynamic attributes of returnees in the process of FDI knowledge spillovers. Previous literature argues that learning is a process that takes time to occur, as firms need time to identify, assimilate and imitate foreign technology (Zhang et al., 2014). Based on this dynamic perspective, the returnees' role in improving the local knowledge base and establishing networks requires a period of time, so many studies suggest that the entry of returnees is a process-dependent approach (Cui et al., 2015; Qin & Estrin, 2015). Moreover, from a local embeddedness view, a stable environment is necessary for returnees to readjust to local cultural and institutional settings (Qin et al., 2017). Therefore, in the following part, I would illustrate how the time-based attributes of returnee's industrial repatriation influence the local firm productivity as well as the process of FDI knowledge spillovers.

5.2.2 Returnee's' Repatriation Speed, Irregularity and FDI Spillovers

I believe that the improvement of local technology upgrading and learning process from FDI knowledge spillovers is dependent on the returnees' repatriation mode. Speed and irregularity are two of the most important dynamic attributes of returnees' collective repatriation over time. Speed measures how rapidly returnee's repatriation into the industry at a point in time (Hao et al., 2016). Since it may take returnees some time to accumulate experiences and communicate with local elites, so when the returnees speed up their entry into the industry, they may transfer more new knowledge to the local industry so that can accelerate the improvement of firm absorptive capacities as well as innovation capabilities (Hao et al., 2016; Wright et al., 2018). Irregularity is another time-related attribute, which indicates the rhythm or progress of returnees' entry. As argued above, returnees are often local context unknown, only a progressive process and stable environment can facilitate their readjustment to local settings (Wang et al., 2017b; Zhang et al., 2014). Therefore, these two time-related attributes of returnee entry can play a contrasting role in absorbing FDI knowledge spillover.

5.2.2.1 The Impact of Returnees' Repatriation Speed

(1) Returnees' Repatriation Speed and Local Firm Performance

As defined before, the returnees' repatriation speed refers to how rapidly the returnees enter an industry, and a higher repatriation speed reflects that local industries recruit more returnees at a particular point in time. Improving returnees' industrial repatriation speed can benefit local firms' productivity in several ways.

Firstly, fast repatriation of returnees brings more knowledge flow into local firms at a quicker speed. Due to their acquired skills and confidence with world-class technologies, the returnees can not only contribute to the firm and industry's talent pool, but also stimulate the local elites to improve, and thus promote the local knowledge base (Lin et al., 2015; Wang, 2015). The inflow of these highly skilled returnees with various educational backgrounds enables a firm to access a broader range of knowledge and experiences (Qin et al., 2017). In addition, in China, highly skilled returnees are scarce resources at the firm level. Therefore, the returnees may become superstars in the industry or even the capital market, and they will receive the attention from employers, employees, and foreign investors (namely, the eyeball effect (Viederyte, 2016; Yuan & Wen, 2018). As a result, it may increase a firm's willingness to invest more in technological upgrading and further improve the firm's production efficiency.

Secondly, fast repatriation incentivizes returnees to play their part more actively. Since time is a scarce resource, returnees are often eager to enter early and expect to enjoy the first-mover advantages in the labor market (Li et al., 2012; Lin et al., 2016). When returnees enter local industries in a rapid mode, they are more able to capture the window of opportunity and obtain an upper hand in the competition, which can accelerate them to realize their functions in improving the local knowledge base and absorptive capacity (Li et al., 2012; Qin et al., 2017). Moreover, education facilitates the evolution of technologies, and technological progress is an increasing function of the level of human capital (Checchi, De Simone, & Faini, 2007; Vancauteren, 2018). As significant knowledge conveyors, a growing number of returnees can add more to local firms' knowledge pool and human capital. Consequently, an increasing repatriation speed of returnees can improve local firms' performance.

(2) Returnees' Repatriation Speed and FDI Knowledge Spillovers

Besides, a higher speed of returnee repatriation can also support local firms to learn more from FDI spillovers. These highly skilled individuals can increase a firm's availability of valuable prior related knowledge for learning FDI advanced technology (Liu et al., 2014; Lund Vinding, 2006). The more returnees in local firms at a particular time, the narrower the technological gaps with foreign firms, leading to a more significant improvement of a local firm's absorptive capacities. Moreover, the incentives to enjoy the first-mover advantage encourages returnees to establish stronger business links and have more interactions with foreign firms (Bai et al., 2018). The development of such closer links may expedite the improvement of a firm's absorptive capacity because these relationships may 'thicken' the knowledge flow from foreign firms, thus increasing the efficiency of the transfer of FDI knowledge (Lund Vinding, 2006).

More specifically, firstly, returnees often have an incentive to enter early to enjoy the first-mover advantages in the labor market (Qin et al., 2017). With a long time of training abroad, the returnees are usually equipped with superior technical and entrepreneurial skills and professional international networks (Kenney et al., 2013). When returning to their home country, their knowledge of both their home and host countries enables them to identify cross-border differences and knowledge gaps between foreign and local firms (Bai et al., 2017). These incentives will also push them to interact or ally with foreign companies, establish stronger business linkages, acquire more information advantages, and thus give local firms more opportunities to learn from foreign knowledge spillovers (Bai et al., 2018; Zheng et al., 2016). Meanwhile, when learning from FDI, given the same amount of investment, returnee with advanced knowledge might be better in choosing projects (Yuan & Wen, 2018), which may increase the chance of project success, improve firm capabilities, and ultimately benefit the firm from absorbing the FDI knowledge spillover more effectively.

Secondly, when the returnees speed up their repatriation into the industry, they may transfer more new knowledge to the local industry so that can accelerate the improvement of firm absorptive capacities as well as innovation capabilities (Kang & Lee, 2017; Lichtenthaler & Lichtenthaler, 2009). Previous studies demonstrate that the innovation speed positively moderates knowledge spillovers, and local firms may obtain competitive advantages through the fast commercialization of technology (Markman, Gianiodis, et al. 2005). In certain high-tech sectors, new knowledge is regarded as the key to competitive advantages, therefore, local firms prefer to explore a rapid returnee entry to improve their knowledge base in a more effective way (Kang & Lee, 2017). Consequently, local firms need to adjust mechanisms in highly competitive labor markets and make full use of a rapid returnee entry.

Hypothesis 1a: A higher speed of returnees' repatriation promotes the local firms' productivity.

Hypothesis 1b: The speed of returnees' repatriation positively moderates the relationship between FDI and local firm productivity.

5.2.2.2 The Impact of Returnees' Repatriation Irregularity

(1) Returnees' Repatriation Irregularity and Local Firm Performance

As defined earlier, returnees' industrial repatriation irregularity is another time-related feature of the returnees, which indicates the rhythm of the returnees' entry into an industry. A higher irregularity suggests either long-term inactivity or large peaks over a period of returnees' repatriation in a certain industry. Contrary to returnees' industrial repatriation speed, the impacts of returnees' repatriation irregularity on local firm productivity are more likely to be negative. The reasons mainly include two aspects.

First, an irregular repatriation process might bring an unstable working environment and is difficult for the returnees to get adapt to the local context. Apart from skilled expertise, the returnees have been isolated from their home countries for years and may face readjustment difficulties when returning to their home countries (Lin et al., 2019). The contributions of the returnees' social network and technological capability to the local firm performance as well as knowledge exchange are contingent on their sufficient local knowledge, as they need to identify what are the most suitable technology and business management methods for the local market (Li et al., 2012; Qin et al., 2017). Therefore, the returnees need to readjust and play a role. However, an irregular repatriation process makes it impossible for returnees to anticipate the next stage of the firms and industrial development. Returnees who enter at different periods have difficulties establishing contact and helping each other and have potential uncertainties when playing their role in the improvement of the local knowledge base. Only a rhythmic and progressive expansion process by the returnees entering into the industry can accelerate their readjustment to the local context, thereby allowing them to help improve the local firm performance (Farquharson & Pruthi, 2015; Ma et al., 2018).

Second, irregular returnees' repatriation may cause fluctuating competition. An abrupt and discontinuous change in the number of returnees entry into an industry is often accompanied by a sudden rise or fall of labor competition (Hao et al., 2016). In such an unstable business environment, it is also difficult for returnees to interact with local workers and improve the knowledge base (Choudhury, 2015; Qin, 2015). Moreover, if competition fluctuates dramatically, it may also increase the risk and complexity of the returnees working with foreign firms. Consequently, the contributions of returnees to the knowledge base can be constrained. A rhythmic and progressive repatriation process is required to establish robust and stable local networks (Lin et al., 2016; Lin et al., 2019), thereby helping returnees realize their functions in building up the local technological capability and improving local firm performance.

(2) Returnees' Repatriation Irregularity and FDI Knowledge Spillovers

Similarly, the fundamental mechanism of returnees' repatriation irregularity on the moderation of FDI knowledge spillovers is also likely to be negative. Firstly, irregular repatriation might not help the returnees promote the local absorptive capacity as it restricts their readjustment process. As indicated by Armanios et al. (2017), the low context relevance of the returnees may make it difficult for them to apply capabilities effectively. The returnees thus require a stable and robust environment to help them readapt to the local context so that they can contribute to the local absorptive capacity. Moreover, under irregular repatriation, local workers are not able to seize the opportunity to establish solid networks with returnees. It is not beneficial for the improvement of the local knowledge base and capabilities to learn from advanced foreign technology.

Secondly, the knowledge exchange requires stable interpersonal interaction and business network, however, the returnees' irregular repatriation makes it difficult for them to establish solid linkages between local and foreign firms. As argued above, the irregular repatriation might cause fierce labor competition between the returnees and the local workers cannot anticipate establishing networks with the returnees. Given the unstable social environment, returnees are unable to play their role as the knowledge brokers between foreign and local firms, so that cannot help identify the cross-organizational technological barriers. Based on the above reasoning, I argue that a rhythmic returnees' industrial repatriation is required to help local firms benefit more from the FDI knowledge spillovers and upgrade their technology. Since most of the previous studies use the kurtosis as the measurement of rhythm, which is the indication of irregularity, so following this tradition I propose:

Hypothesis 2a: A higher irregularity of returnees' repatriation hampers the local firms' productivity.

Hypothesis 2b: The irregularity of returnees' repatriation negatively moderates the relationship between FDI and local firm productivity.

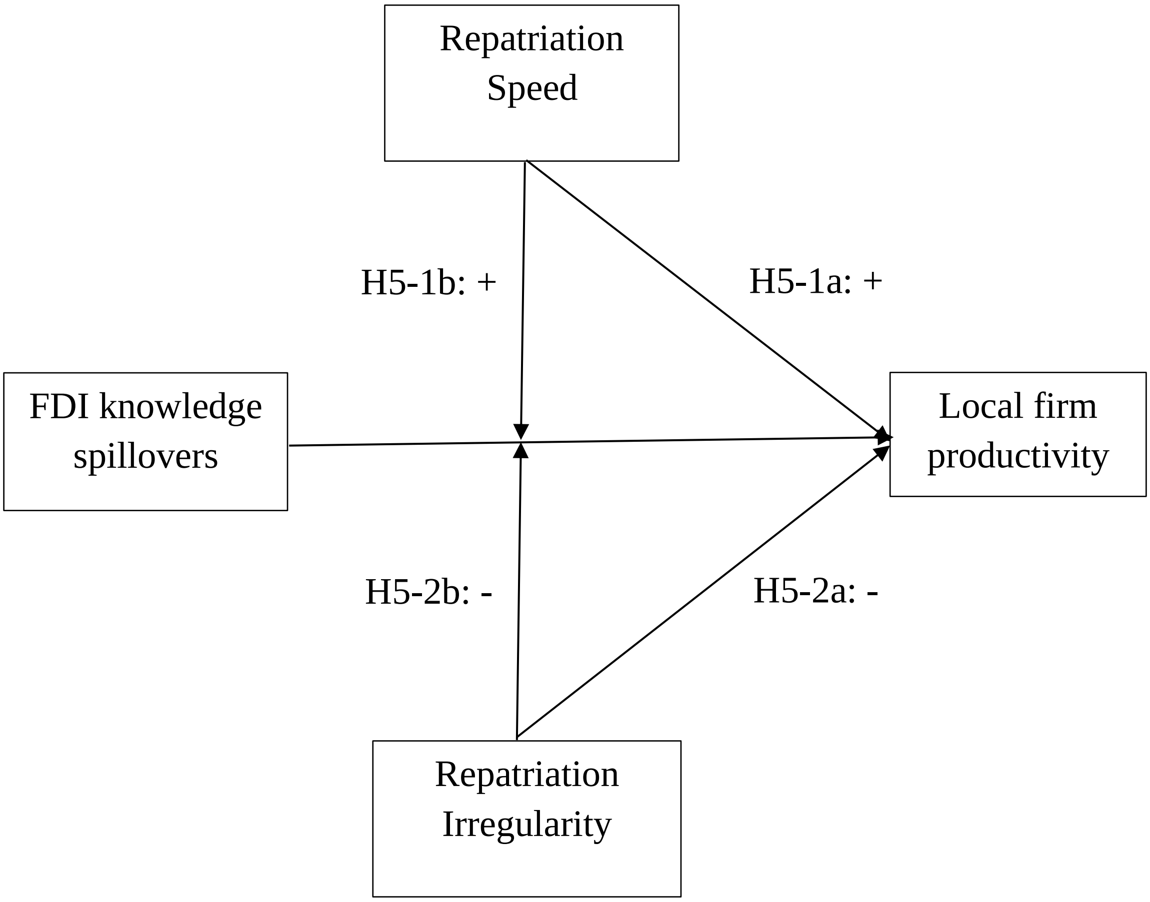

Figure 5-1 The Theoretical Framework of Chapter 5

5.3 Data and Methodology

5.3.1 Data

I employ a unique dataset associated with Chinese high-tech manufacturing companies in Beijing's Zhongguancun science park (ZSP). The dataset was collected by the ZSP regulatory body's statistical yearbook over a period from 2007 to 2013 (Zhang et al., 2018). The high-tech firms were required to take part in the census survey with providing detailed information about their legal entity, production management, and financial status, technology activities, and labor structures. This database also classifies firms into 4-digit, 3-digit as well as 2-digit ISIC, and includes firms with firms that have more than ten employees. Therefore, this dataset allows us to construct more detailed firm-level time-varying variables regarding FDI and returnee labor force. The survey is a statistical census of ZSP firms of the comprehensive information in which is of great significance to our in-depth research on FDI, returnee, and firm performance. The original dataset contains 12,821 high-tech firms of 56,905 observations. To test my hypotheses, I make some data cleaning procedures. First, I have dropped firms that have incomplete records or with less than 3-year observations. Second, since our study is focusing on the FDI spillover effect on local firms, so I drop foreign firms based on their registration type in the final estimation. The final data sample, therefore, covers 7,920 local firms for the period 2007-2013, which comprise 45,544 firm-year observations. Regarding the estimation methods, I mainly employ the system-GMM panel estimation with Heckman correction as presented in Chapter 4. Moreover, to diagnose the existence of the dynamic issues, I also present the results of the pooled ordinary least square (OLS) models with robust standard errors as a comparison.

5.3.2 Methodology

As suggested in Chapter 4, I mainly use the system-GMM estimation with Heckman corrections to test my hypothesis. Firstly, there might exist selection bias concerning issues about returnees as the recruitment of returnees might not be random as firms with more competitive capability and generous financial support would be more affordable for those highly skilled talents (Liu et al., 2010a; Roberts & Beamish, 2017). This means that the returnees might be self-selected in different local firms. In this case, the improvement of a firm's performance might not be because of the entry of returnees, but that a firm with higher performance would become more attractive for returnees. Therefore, we need to solve such selection bias when examining the impact of returnees on local firm performance. The Heckman two-stage model has been widely used when potential selection problems exist (Certo et al., 2016; Heckman, 1979). In the first stage, I estimated a Probit model of a firm's propensity of recruiting returnees. It aims to find out whether the returnees would be self-selected into local firms. Following previous literature, such as in Kenney et al. (2013) and Lin et al. (2016), I consider several factors that might affect the entry (or the recruitment) of returnees, which include firm age, size, profitability, state-ownership, R&D intensity, and firm average wage. I also include one additional predictor, the industrial average wage in the first stage, as the exclusive restriction to check the appropriateness of the Heckman two-stage estimation. Then, based on the Probit estimation, I can calculate an inverse Mill's ratio (IMR).

The IMR represents the selection hazard of a firm's recruitment activity of returnees (Certo et al., 2016; Heckman, 1979). Evaluating the statistical significance of IMR proxies the presence of a meaningful selection effect in the second stage model. Therefore, I include the IMR in the second stage (the system-GMM estimation) to check the existence of the selection effect.

Secondly, a firm's production efficiency might be influenced by its previous status and it may experience economic shocks every year (Comin, 2017; Lagos, 2006), which requires to consider a dynamic panel structure to study the dynamic trend of dependent variables and the short-term or long-term effects of independent variables on dependent variables. Typically, the main characteristic of the dynamic panel model is that the lag term of the dependent variable is controlled for the trends of the dependent variable. However, as the lag term of the dependent variable is added, the common fixed-effect estimation method with IVs will lead to the inconsistency of parameter estimation, so other estimation methods are needed. System-GMM method has been considered as a more suitable model to deal with the dynamic panels since it chooses more proper instrument variables. It combines the first-differenced model with its corresponding model in levels and uses lagged differences of the endogenous variables as instruments (Roodman, 2009; Su & Liu, 2016). It also provides extensive tests to ensure the effectiveness of those instrument variables and to eliminate the overidentification effect (Roodman, 2009). Moreover, the system-GMM method also helps to more fully exploit the available moment conditions in a finite sample. Therefore, in the second stage, I mainly use the system-GMM methods and include the IMR to control for the potential selection bias to test my hypothesis.

In the formal estimation, I use the first differences of the second and third lags and lag level of dependent and explanatory variables as instruments. Moreover, following the direction of (Windmeijer 2005), I conducted several tests to check the effectiveness of the instrument variables. I first use the two-step covariance matrix was used to estimate the finite samples. Then I inspect the Arellano–Bond (AR) tests to check the validity of the instrument variables. Arellano and Bond develop a test for a phenomenon that would render some lags invalid as instruments, namely, autocorrelation in the idiosyncratic disturbance term, $\varepsilon_{i,t}$ (Roodman, 2009; Windmeijer, 2005). The AR test is applied to the residuals in differences. Because $\Delta\varepsilon_{i,t}$ is mathematically related to $\Delta\varepsilon_{i,t-1}$ via the shared $\varepsilon_{i,t-1}$ term, negative first-order serial correlation (AR (2) test) is expected in differences and evidence of it is uninformative, which means that the result of the AR (1) test is fundamentally significant. Thus to check for first-order serial correlation in levels, we look for second-order correlation (AR (2) test) in differences, on the idea that this will detect the correlation between the $\varepsilon_{i,t-1}$ in $\Delta\varepsilon_{i,t-1}$ and the $\varepsilon_{i,t-2}$ in $\Delta\varepsilon_{i,t-2}$. In this case, the system-GMM model need to pass the AR (2) test to ensure the effectiveness of the instrumental variables (Roodman, 2009).

Finally, I employ the Hansen's J test to check their overall validity in the system-GMM analysis (Roodman, 2009). The purpose of the test is to identify whether instrumental variables are completely exogenous and the null hypothesis is that instrumental variables are all valid instrumental variables. The main logic of this test is that the parameters estimated from different instrumental variables should not be very different. In the case that all of the instrumental variables are valid, the test result should obey the positive distribution with a mean value of 0, which means that the value of the Hansen-J test should be insignificant.

5.4 Empirical Results

5.4.1 Descriptive Analysis

Table 5-1 presents the descriptive statistics and correlation matrix of each variable used in Chapter 5. As shown, the mean level of TFP is 3.019 and the FDI is 0.182, which means that on average the share of foreign firms' total assets over the four-digit industrial total asset is 18.2 percent. Moreover, the average age of firms is 8.120 and the average size is 74.281 million Chinese RMB. As for the time-based characteristics of returnees' repatriation, the mean level of speed is 0.506 and the average irregularity is 229. On the other hand, the correlation coefficients between the dependent variable and independent variables are relatively high, which indicates that the choice of variables is good. Moreover, the positive correlation (0.038) between TFP and FDI preliminarily indicates that there might exist a positive relationship between FDI knowledge spillovers and local firms' productivity. I further tested the potential multicollinearity by not only examining the value of the correlation coefficient between independent variables but also calculating the variance inflation factor (VIF). All values are within the acceptable range and the average VIF is 2.16.

Table 5-1 Correlation Matrix of Variables in Chapter 5

Variable	Mean	Std.Dev.	1	2	3	4	5	6	7	8	9	10
TFP	2.869	1.231	1.000									
FDI	0.183	0.165	0.038	1.000								
Firm age	7.999	4.836	0.233	-0.103	1.000							
Firm size	46.182	205.095	0.401	0.088	0.186	1.000						
State-ownership	0.051	0.220	-0.003	0.070	0.238	0.068	1.000					
Profitability	-0.008	0.139	0.239	-0.028	0.113	0.090	0.036	1.000				
R&D intensity	0.010	0.028	0.223	0.013	-0.077	0.092	0.013	0.095	1.000			
Knowledge stock	0.556	2.457	0.374	0.067	0.127	0.284	0.015	0.100	0.191	1.000		
Speed	0.503	2.804	-0.007	0.069	0.015	-0.006	0.007	-0.008	-0.006	0.017	1.000	
Irregularity	216	798	0.042	0.220	0.143	0.003	-0.026	0.002	-0.112	0.026	0.156	1.000

Note: All absolute correlation coefficients greater than 0.006 are significant at the 5% level.

5.4.2 Econometric Results

Table 5-2 presents the results of the Heckman first-stage regression. I first employ the Probit model to estimate the propensity of local firms to recruit returnees and then obtain the inverse mill ratio (IMR), which can be used in the Heckman second stage estimation to control for the potential selection bias problems. It can be seen that firm age is significantly negatively associated with the firms' propensity to recruit returnees. In contrast, firm size, profitability, R&D intensity, knowledge stock and firm average wage all positively influence whether local firms recruit returnees. The coefficient of the industrial average wage is significantly positive, which indicates a proper inclusion of the exclusion restriction. After the Probit estimation, I can calculate the IMR for each observation and then include it in the section stage system-GMM estimation.

Table 5-3 displays the main regression results. Apart from the system-GMM estimations (Model 2, 4, 6, 8, 10), I also present the ordinary least squares regression results (Models 1, 3, 5, 7, 9) as a comparison. I first only incorporate the independent and control variables (Models 1 and 2). Then, I incorporate the interaction between FDI and returnees' repatriation speed and irregularity in models 3-10. Models 10 is my full model, which is used to interpret my main findings.

As shown in Table 5-3, the coefficients of the variables are not consistent across the pooled OLS models, which suggests that the OLS might suffer from the potential endogeneity and it is necessary to deal with the issues using system-GMM estimation. For our control variables, firm age is significantly and negatively related to local firms' TFP. The coefficients of firm size and profitability are significantly positive. State ownership is insignificantly correlated with the dependent variable. R&D intensity and knowledge stock are positive and significant at the 1% level throughout all the system GMM models for local firm TFP.

Concerning the system-GMM results, to begin with, I first inspect the consistency, which requires valid instruments and the absence of a second-order serial correlation, of the System-GMM estimators. When I include only the independent and control variables in the full sample and matched sample, and the significant Hansen J-statistic of system-GMM is most likely a result of omission effects. Apart from this, Hansen J-statistics across all our models support the view that the instrumental variables are uncorrelated to residuals. Moreover, the Arellano–Bond (AR) tests in all models indicate that the first-order AR (1) and not the second-order AR (2) error terms are serially corrected. This finding also supports the use of system GMM for our estimation in our models.

For our key explanatory variable, as expected and shown in table 5-3, the effects of FDI are positive and significant throughout OLS and system-GMM estimations. For example, in model 10, the coefficient of FDI is significantly positive ($\beta = 0.104$, $p < 0.01$). This demonstrates that FDI spillovers can indeed take place in local firms and improve their firm performance.

Hypothesis 1a proposes that returnees' repatriation speed would strengthen the local firms' performance. As indicated before, a fast pace of returnees' repatriation brings more knowledge flow into local firms at a quicker speed and fast repatriation incentivizes returnees to play their part more actively. Moreover, the inflow of these highly skilled returnees with various educational backgrounds enables a firm to access a broader range of knowledge and experiences, which may stimulate the development of the technological process (Qin et al., 2017). In model 10, the system-GMM results reveal that the primary effect of speed is positively and significantly related to the local firms' productivity ($\beta = 0.051$, $p < 0.05$), which means that a higher speed in returnees' industrial repatriation speed would improve the local firms' total factor productivity. The results thus confirm my hypothesis 1a.

Hypothesis 1b suggests that the positive relationship between FDI and local firms' productivity becomes stronger as the returnees' repatriation speed increases. As shown before, when the returnees speed up their entry into the industry, they may transfer more new knowledge to the local industry so that can accelerate the improvement of firm absorptive capacities and establish stronger business linkages with foreign companies, which may give local firms more opportunities to learn from foreign knowledge spillovers. It can be seen that, in Model 10, the interaction term *FDI*Speed* in system-GMM estimation is positive and significant ($\beta = 0.417$, $p < 0.01$), showing a positive moderating effect of returnee repatriation speed on the relationship between FDI and local firms' total factor productivity. The results thus support my hypothesis 1b.

By contrast, hypothesis 2a proposes that the returnees' repatriation irregularity would hamper the improvement of local firms' productivity. As indicated before, In model 10, the system-GMM results reveal that the primary effect of irregularity is negatively and significantly related to the local firms' productivity ($\beta = -0.019$, $p < 0.01$), which means that irregular repatriation of returnees' into local industries would negatively impact the local firms' total factor productivity. The results thus confirm my hypothesis 2a.

Hypothesis 2b suggests that the positive relationship between FDI and local firms' productivity becomes weaker as the returnees' repatriation irregularity increases. As argued before, the returnees need time to readjustment and play a role, as they have been isolated from their home countries for years. Only a rhythmic and progressive repatriation process can reduce the potential uncertainty, establish robust and stable local networks (Lin et al., 2016; Lin et al., 2019), thereby helping returnees realize their functions in building up the local absorptive capacity to improve the FDI knowledge spillovers. It can be seen that, in Model 10, the interaction term *FDI*Irregularity* in system-GMM estimation is negative and significant ($\beta = -0.033$, $p < 0.01$), showing a negative moderating effect of returnee entry irregularity on the relationship between FDI and local firms' total factor productivity. The results thus support my hypothesis 2b.

Table 5-2 The Propensity of Firms to Recruit Returnees: the First-Stage Heckman Probit Model

VARIABLES	Returnee dummy (0=No, 1=Yes)		
	Estimate	S.E	P-value
Firm age	-0.119***	(0.018)	[0.000]
Firm size	0.153***	(0.006)	[0.000]
Profitability	-0.255***	(0.036)	[0.000]
State-ownership	-0.003	(0.043)	[0.946]
R&D Intensity	0.062***	(0.006)	[0.000]
Knowledge stock	0.200***	(0.014)	[0.000]
Firm average wage	0.072***	(0.008)	[0.000]
Industrial average wage	0.120***	(0.018)	[0.000]
Constant	-1.622***	(0.296)	[0.000]
Year dummies	Included		
Industry dummies	Included		
Region dummies	Included		
LR Chi^2	3069.40		
Pseudo R^2	0.169		
Log-likelihood	-12623.451		
Observations	40,566		

Notes: (1) Robust standard errors are reported in the parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 5-3 The Impact of FDI and Returnees' Repatriation on Local Firm TFP: OLS and system-GMM Models

VARIABLES	(1) OLS TFP	(2) GMM TFP	(3) OLS TFP	(4) GMM TFP	(5) OLS TFP	(6) GMM TFP	(7) OLS TFP	(8) GMM TFP	(9) OLS TFP	(10) GMM TFP
Firm age	0.001	-0.407***	-0.017*	-0.400***	-0.018*	-0.380***	-0.019*	-0.395***	-0.019*	-0.366***
	(0.011)	(0.053)	(0.010)	(0.053)	(0.010)	(0.059)	(0.010)	(0.053)	(0.010)	(0.056)
Firm size	0.428***	0.126***	0.437***	0.126***	0.437***	0.122***	0.436***	0.126***	0.436***	0.123***
	(0.003)	(0.011)	(0.003)	(0.011)	(0.003)	(0.011)	(0.003)	(0.011)	(0.003)	(0.011)
State-ownership	-0.073***	-0.141	-0.083***	-0.165	-0.082***	-0.108	-0.077***	-0.187	-0.079***	-0.095
	(0.024)	(0.289)	(0.024)	(0.287)	(0.024)	(0.290)	(0.024)	(0.276)	(0.024)	(0.287)
Profitability	0.038*	0.035	0.041*	0.036	0.040*	0.041	0.037*	0.028	0.037*	0.037
	(0.022)	(0.027)	(0.022)	(0.027)	(0.022)	(0.028)	(0.022)	(0.027)	(0.022)	(0.028)
R&D intensity	0.711***	0.083**	0.726***	0.081**	0.727***	0.077**	0.730***	0.084**	0.728***	0.078**
	(0.036)	(0.032)	(0.036)	(0.032)	(0.036)	(0.033)	(0.036)	(0.033)	(0.036)	(0.033)
Knowledge stock	0.285***	0.031***	0.308***	0.032***	0.308***	0.035***	0.306***	0.035***	0.306***	0.035***
	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)	(0.011)	(0.009)	(0.010)	(0.009)	(0.011)
IMR	0.026***	0.020***	0.019***	0.018***	0.018***	0.021***	0.014***	0.022***	0.012***	0.023***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.002)	(0.004)	(0.005)	(0.004)	(0.005)
L.TFP		0.861***		0.864***		0.873***		0.871***		0.874***
		(0.015)		(0.015)		(0.015)		(0.014)		(0.014)
FDI			0.318***	0.108***	0.319***	0.105***	0.387***	0.107***	0.347***	0.104***
			(0.031)	(0.024)	(0.031)	(0.025)	(0.063)	(0.022)	(0.065)	(0.028)
Speed					0.037***	0.054***			0.035***	0.051***
					(0.008)	(0.019)			(0.008)	(0.019)
FDI* Speed					0.044***	0.335***			0.136***	0.417***

					(0.013)	(0.083)			(0.032)	(0.071)
Irregularity							-0.017***	-0.014***	-0.017***	-0.019***
							(0.001)	(0.004)	(0.002)	(0.005)
FDI* Irregularity							-0.076***	-0.032**	-0.073***	-0.033**
							(0.005)	(0.016)	(0.006)	(0.016)
Constant	0.095	0.012	0.085	0.070	0.083	0.023	0.096**	0.080	0.099**	0.096
	(0.122)	(0.199)	(0.048)	(0.190)	(0.048)	(0.344)	(0.047)	(0.190)	(0.050)	(0.258)
Year dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Industry dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Region dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
R-squared	0.577	N/A	0.568	N/A	0.595	N/A	0.589	N/A	0.597	N/A
AR(1)	N/A	0.000	N/A	0.000	N/A	0.000	N/A	0.000	N/A	0.000
AR(2)	N/A	0.331	N/A	0.346	N/A	0.299	N/A	0.374	N/A	0.363
Hansen	N/A	0.194	N/A	0.188	N/A	0.179	N/A	0.243	N/A	0.182
Observations	36,844	36,844	36,844	36,844	36,844	36,844	36,844	36,844	36,844	36,844

Notes: (1) Robust standard errors are reported in the parentheses. (2) The system-GMM estimations are clustered at the industry level (3) *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

5.4.3 Robustness Tests

I further conduct several robustness tests to check the extent to which my results are affected by alternative specifications. First, I use alternative measurements of FDI, which include the share of foreign firm R&D investment over the total industrial R&D investment and the share of foreign firms in an industry in different sub-parks. Both of the FDI measurement is at the four-digit industry level. I present the results in Table 5-4. Models 1-4 are estimated with the share of FDI R&D as the independent variable, while Models 5-8 are the share of FDI firms. As shown in the full models 4 and 8, in both circumstances, the interactions between FDI and the moderating variables are significant and in line with my hypotheses. More specifically, regarding the moderating of Speed, the interaction term *FDI*Speed* in system-GMM estimation are positive and significant ($\beta = 0.069$, $p < 0.01$ in Model 4; $\beta = 0.019$, $p < 0.05$ in Model 8), which further confirms a positive moderating effect of returnee entry speed on the relationship between FDI and local firms' TFP. Besides, regarding the moderating of Irregularity, the interaction term *FDI*irregularity* in system-GMM estimation are negative and significant ($\beta = -0.032$, $p < 0.01$ in Model 4; $\beta = -0.008$, $p < 0.05$ in Model 8), which further confirms a negative moderating effect of returnee entry speed on the relationship between FDI and local firms' total factor productivity. Taking these robustness tests enables us to reduce the concerns about the misspecification of FDI.

Second, I consider the whole sample of ZSP firms, which means to include the foreign firms of ZSP in our estimation. I present the results in Table 5-5. As shown in the full model 5, the coefficient of FDI is significantly positive ($\beta = 0.140$, $p < 0.1$). Concerning the moderating role of returnees' repatriation speed, the interaction term *FDI*Speed* in system-GMM estimation is also positive and significant (β = 0.031, $p < 0.1$). In contrast, the interaction term *FDI*Irregularity* in system-GMM estimation is negative and significant (β = -0.008, $p < 0.1$). Compared with the baseline results in Table 5-3, the estimation results from the whole sample are most consistent, while with a relatively lower level of significance. Overall speaking, this robustness test still supports our main findings.

Third, I alternatively measure the returnees' repatriation speed and irregularity at the two-digit industry level. I present the OLS and system-GMM estimation results in Tables 5-6. I then add the moderating variable subsequently and the full model is Model 5 and 6. The OLS is a baseline. Concerning the role of speed, as shown in Model 6, the coefficient of Speed is positive and significant (β = 0.018, $p < 0.01$), which indicates that. Moreover, the interaction term *FDI*speed* in system-GMM estimation is negative and significant (β = 0.135, $p < 0.01$), which also confirms my hypothesis 2. As for the role of Irregularity, as shown in Model 6, the coefficient of Irregularity is negative and significant (β = -0.012, $p < 0.05$), which indicates that. Moreover, the interaction term *FDI*Irregularity* in system-GMM estimation is negative and significant (β =-0.069, $p < 0.05$), which also confirms my hypothesis 2.

Finally, I consider alternative measurements of the control variables. I measure firm size by the firm's total employment, firm R&D intensity by the firm's R&D investment per sale, and firm knowledge stock by the firm's total patent stock in the past five years. I present the OLS and system-GMM estimation results in Tables 5-7. As shown, using the alternative specification of control variables does not change my main findings. More specifically, Regarding the role of speed, as shown in Model 6, the coefficient of Speed is positive and significant ($\beta = 0.012$, $p < 0.05$), and the interaction term *FDI*speed* in system-GMM estimation are negative and significant ($\beta = 0.181$, $p < 0.01$), which also confirms my hypothesis 2. For the role of Irregularity, as shown in Model 6, the coefficient of Irregularity is positive and significant ($\beta = -0.027$, $p < 0.01$), and the interaction term *FDI*Irregularity* in system-GMM estimation are negative and significant ($\beta = -0.020$, $p < 0.01$), which also confirms my hypothesis 2.

Table 5-4 Robustness Test 1 The Impact of FDI and Returnees' Repatriation on Local Firm TFP: Alternative Measurement of FDI Presence

	FDI R&D share				Share of FDI firms			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM
VARIABLES	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP
Firm age	-0.395***	-0.487***	-0.412***	-0.466***	-0.399***	-0.418***	-0.419***	-0.397***
	(0.052)	(0.080)	(0.053)	(0.075)	(0.053)	(0.052)	(0.051)	(0.052)
Firm size	0.127***	0.121***	0.120***	0.120***	0.126***	0.122***	0.120***	0.123***
	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
State-ownership	-0.098	-0.089	-0.455	-0.312	-0.159	-0.129	-0.466	-0.376
	(0.285)	(0.279)	(0.315)	(0.307)	(0.291)	(0.279)	(0.315)	(0.298)
Profitability	0.037	0.043	0.034	0.035	0.040	0.038	0.032	0.034
	(0.027)	(0.029)	(0.028)	(0.030)	(0.027)	(0.027)	(0.027)	(0.027)
R&D intensity	0.081**	0.112***	0.075**	0.104**	0.043**	0.047***	0.043**	0.046**
	(0.032)	(0.042)	(0.033)	(0.043)	(0.012)	(0.013)	(0.012)	(0.013)
Knowledge stock	0.032***	0.034***	0.037***	0.036***	0.042***	0.045***	0.048***	0.044***
	(0.010)	(0.013)	(0.010)	(0.014)	(0.010)	(0.010)	(0.010)	(0.011)
IMR	0.038***	0.038***	0.041***	0.046***	0.067***	0.066***	0.065***	0.068***
	(0.011)	(0.014)	(0.011)	(0.014)	(0.021)	(0.021)	(0.021)	(0.021)
L.TFP	0.862***	0.857***	0.875***	0.868***	0.863***	0.865***	0.875***	0.877***
	(0.015)	(0.018)	(0.014)	(0.017)	(0.015)	(0.015)	(0.014)	(0.014)
FDI	0.112***	0.119***	0.129***	0.159**	0.046**	0.048*	0.045**	0.048***
	(0.033)	(0.038)	(0.043)	(0.069)	(0.023)	(0.026)	(0.020)	(0.018)
Speed		0.077***		0.053***		0.069***		0.049***
		(0.024)		(0.019)		(0.015)		(0.017)

FDI* Speed		0.042***		0.069***		0.013***		0.019**
		(0.013)		(0.013)		(0.002)		(0.010)
Irregularity			-0.013***	-0.012***			-0.011***	-0.009***
			(0.002)	(0.004)			(0.003)	(0.003)
FDI* Irregularity			-0.012**	-0.032**			-0.010***	-0.008**
			(0.006)	(0.014)			(0.003)	(0.004)
Constant	0.051	0.033	0.019	0.044	0.132	0.120	0.135	0.131
	(0.196)	(0.415)	(0.198)	(0.465)	(0.197)	(0.215)	(0.199)	(0.214)
Year dummies	Included	Included	Included	Included	Included	Included	Included	Included
Industry dummies	Included	Included	Included	Included	Included	Included	Included	Included
Region dummies	Included	Included	Included	Included	Included	Included	Included	Included
AR(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	0.259	0.293	0.274	0.297	0.434	0.415	0.399	0.409
Hansen	0.122	0.121	0.136	0.151	0.233	0.265	0.224	0.273
Observations	36,844	36,844	36,844	36,844	36,844	36,844	36,844	36,844

Notes: (1) Robust standard errors are reported in the parentheses. (2) The system-GMM estimations are clustered at the industry level (3) *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 5-5 Robustness Test 3 The Impact of FDI and Returnees' Repatriation on Local Firm TFP: The Estimation on the Whole Sample

	(1)	(2)	(3)	(4)	(5)
	GMM	GMM	GMM	GMM	GMM
VARIABLES	TFP	TFP	TFP	TFP	TFP
Firm age	-0.438***	-0.433***	-0.392***	-0.425***	-0.381***
	(0.051)	(0.050)	(0.057)	(0.051)	(0.053)
Firm size	0.134***	0.135***	0.129***	0.133***	0.130***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
State-ownership	-0.130	-0.135	-0.153	-0.155	-0.123
	(0.292)	(0.291)	(0.305)	(0.283)	(0.299)
Profitability	0.023	0.024	0.026	0.021	0.024
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
R&D intensity	0.050	0.048	0.042	0.049	0.045
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Knowledge stock	0.026***	0.027***	0.029***	0.029***	0.029***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
IMR	-0.031***	-0.030***	-0.037***	-0.034***	-0.032***
	(0.010)	(0.010)	(0.013)	(0.010)	(0.011)
L.TFP	0.860***	0.861***	0.872***	0.870***	0.876***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
FDI		0.155**	0.151**	0.127*	0.140*
		(0.070)	(0.069)	(0.070)	(0.077)
Speed			0.016***		0.016***
			(0.005)		(0.006)
FDI* Speed			0.039**		0.031*
			(0.017)		(0.017)
Irregularity				-0.013***	-0.014***
				(0.004)	(0.005)
FDI* Irregularity				-0.009	-0.008*
				(0.012)	(0.005)
Constant	0.053	0.050	0.020	0.049	0.053
	(0.211)	(0.216)	(0.238)	(0.217)	(0.275)
Year dummies	Included	Included	Included	Included	Included
Industry dummies	Included	Included	Included	Included	Included
Region dummies	Included	Included	Included	Included	Included
AR(1)	0.000	0.000	0.000	0.000	0.000
AR(2)	0.651	0.399	0.484	0.514	0.433
Hansen	0.192	0.263	0.177	0.169	0.210
Observations	40,566	40,566	40,566	40,566	40,566

Notes: (1) Robust standard errors are reported in the parentheses. (2) The system-GMM estimations are clustered at the industry level (3) *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 5-6 Robustness Test 2 The Impact of FDI and Returnees' Repatriation on Local Firm TFP: Alternative Measurement of Returnees' Repatriation Speed and Irregularity

VARIABLES	(1) OLS TFP	(2) GMM TFP	(3) OLS TFP	(4) GMM TFP	(5) OLS TFP	(6) GMM TFP
Firm age	-0.112***	-0.311***	0.108***	-0.338***	-0.108***	-0.328***
	(0.009)	(0.068)	(0.009)	(0.058)	(0.009)	(0.061)
Firm size	0.342***	0.110***	0.339***	0.108***	0.339***	0.111***
	(0.003)	(0.011)	(0.003)	(0.011)	(0.003)	(0.011)
State-ownership	-0.167***	-0.053	-0.178***	-0.114**	-0.178***	-0.168
	(0.021)	(0.339)	(0.021)	(0.050)	(0.021)	(0.332)
Profitability	0.114***	0.076***	0.118***	0.062**	0.118***	0.072**
	(0.020)	(0.028)	(0.020)	(0.028)	(0.020)	(0.029)
R&D intensity	0.063**	0.066**	0.064**	0.069**	0.059**	0.065**
	(0.031)	(0.033)	(0.032)	(0.034)	(0.030)	(0.032)
Knowledge stock	0.269***	0.243***	0.257***	0.253***	0.258***	0.252***
	(0.008)	(0.011)	(0.008)	(0.011)	(0.008)	(0.011)
IMR	1.051***	0.293***	1.058***	0.282***	1.059***	0.270***
	(0.011)	(0.016)	(0.011)	(0.016)	(0.011)	(0.016)
L.TFP		0.950***		0.959***		0.961***
		(0.016)		(0.017)		(0.016)
FDI	0.234***	-0.287***	0.325***	0.283***	0.279***	0.285***
	(0.028)	(0.078)	(0.084)	(0.077)	(0.085)	(0.076)
Speed	0.025***	0.020**			0.021***	0.018***
	(0.008)	(0.009)			(0.008)	(0.005)
FDI* Speed	0.098***	0.128***			0.129***	0.135***
	(0.036)	(0.045)			(0.031)	(0.047)
Irregularity			-0.030***	-0.003	-0.031***	-0.012**
			(0.002)	(0.013)	(0.002)	(0.006)
FDI* Irregularity			-0.045***	-0.057**	-0.050***	-0.069**
			(0.007)	(0.025)	(0.007)	(0.031)
Constant	1.633***	1.327***	1.009***	0.769***	1.013***	1.097***
	(0.038)	(0.465)	(0.044)	(0.247)	(0.044)	(0.301)
Year dummies	Included	Included	Included	Included	Included	Included
Industry dummies	Included	Included	Included	Included	Included	Included
Region dummies	Included	Included	Included	Included	Included	Included
R-squared	0.600		0.603		0.603	
AR(1)	N/A	0.000	N/A	0.000	N/A	0.000
AR(2)	N/A	0.335	N/A	0.298	N/A	0.341
Hansen	N/A	0.142	N/A	0.119	N/A	0.133
Observations	36,844	36,844	36,844	36,844	36,844	36,844

Notes: (1) Robust standard errors are reported in the parentheses. (2) The system-GMM estimations are clustered at the industry level (3) *** p < 0.001, ** p < 0.01, * p < 0.05.

Table 5-7 Robustness Test 4 The Impact of FDI and Returnees' Repatriation on Local Firm TFP: Alternative Measurement of Control Variables

VARIABLES	(1) OLS TFP	(2) GMM TFP	(3) OLS TFP	(4) GMM TFP	(5) OLS TFP	(6) GMM TFP
Firm age	-0.103***	-0.112***	-0.102***	-0.105***	-0.102***	-0.105***
	(0.005)	(0.010)	(0.005)	(0.006)	(0.005)	(0.007)
Firm size	0.927***	0.951***	0.926***	0.952***	0.930***	0.952***
	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
State-ownership	-0.061***	0.026	-0.063***	0.022*	-0.061***	0.009
	(0.012)	(0.018)	(0.012)	(0.011)	(0.012)	(0.018)
Profitability	0.202***	0.205***	0.203***	0.205***	0.204***	0.204***
	(0.011)	(0.013)	(0.011)	(0.103)	(0.011)	(0.004)
R&D intensity	0.101***	0.100***	0.102***	0.116***	0.101***	0.115***
	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)	(0.002)
Knowledge stock	0.062***	0.064***	0.061***	0.063***	0.062***	0.062***
	(0.004)	(0.002)	(0.004)	(0.001)	(0.005)	(0.001)
IMR	0.028***	0.029***	0.029***	0.030***	0.030***	0.031***
	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.008)
L.TFP		0.012***		0.013***		0.014***
		(0.003)		(0.002)		(0.002)
FDI	0.104***	0.117***	0.181***	0.149***	0.167***	0.142***
	(0.016)	(0.017)	(0.048)	(0.040)	(0.049)	(0.043)
Speed	0.012**	0.014**			0.016***	0.012**
	(0.005)	(0.007)			(0.004)	(0.006)
FDI* Speed	0.107***	0.141***			0.125***	0.181***
	(0.021)	(0.018)			(0.018)	(0.036)
Irregularity			-0.023***	-0.022***	-0.024***	-0.027***
			(0.001)	(0.002)	(0.001)	(0.002)
FDI* Irregularity			-0.017***	-0.016***	-0.017***	-0.020***
			(0.004)	(0.004)	(0.004)	(0.006)
Constant	0.474***	0.349***	0.518***	0.296***	0.516***	0.254***
	(0.020)	(0.113)	(0.024)	(0.077)	(0.024)	(0.088)
Year dummies	Included	Included	Included	Included	Included	Included
Industry dummies	Included	Included	Included	Included	Included	Included
Region dummies	Included	Included	Included	Included	Included	Included
R-squared	0.569		0.569		0.568	
AR(1)	N/A	0.000	N/A	0.000	N/A	0.000
AR(2)	N/A	0.336	N/A	0.376	N/A	0.397
Hansen	N/A	0.128	N/A	0.145	N/A	0.116
Observations	36,844	36,844	36,844	36,844	36,844	36,844

Notes: (1) Robust standard errors are reported in the parentheses. (2) The system-GMM estimations are clustered at the industry level (3) *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

5.5 Discussion and Conclusion

In this chapter, I mainly employ the system-GMM model with Heckman corrections to address endogenous regressors and potential selection bias regarding the recruitment of returnees to investigate the impact of FDI knowledge spillovers on local firm performance and the moderating role of returnees' repatriation process in this relationship. The dependent variable is local firm TFP. Based on the analysis of a unique and comprehensive dataset of high-tech firms in ZSP science park in Beijing for the period from 2007 to 2013, I made the first attempt to translate the returnees at the collective level into the moderating role in helping local firms absorb FDI knowledge spillover and improve firms' productivity. I thus provide a contingency view and new empirical evidence to reconcile the conflicting FDI spillover effects.

My results strongly confirm that FDI knowledge indeed exerts a positive spillover effect on the local firms' TFP. This is in line with the wider findings of the literature on positive FDI knowledge and technology spillovers (Liang, 2017; Meyer & Sinani, 2009; Orlic et al., 2018). Meanwhile, this chapter indicates that the time-based attributes of returnees' industrial repatriation, namely speed and irregularity, can play different moderating roles in the relationship between FDI spillovers and local firm performance. The results indicate that the returnees' repatriation speed strengthens the impact of FDI knowledge spillover, while their repatriation irregularity weakens the FDI spillovers. Therefore, this chapter contributes to previous literature by investigating the dynamic and collective attributes of returnees in the externalities of FDI knowledge and demonstrates their interactive effects which are never discussed before (Ma et al., 2018; Wei et al., 2017).

In policy terms, my findings yield several important implications for policymakers in improving firm performance. First, my empirical analysis indicates that advanced knowledge is often embedded in FDI flowing to recipient countries and FDI presents a great potential for knowledge spillovers (Jeon et al., 2013; Jin et al., 2018). As a result, policies continuously attract and promote FDI, especially in the emerging market context where local technological capabilities are weak, need to be put greater emphasis (Jeon et al., 2013; Wang et al., 2017b). Second, it confirms the positive effect of returnees in improving the local knowledge base and bridging local firms with FDI (Liu et al., 2014; Wang, 2015). Therefore, more efforts, such as offer favorable policies like registered residences, premier medical service, and social security, etc., are required to promote attracting highly-skilled returnees to the local labor market (Fu et al., 2017; Lin et al., 2019; Wang, 2015). Third, this chapter also provides suggestions for local policymakers on how to manage the hiring of the returnee labor force to maximize FDI spillovers. As argued in this chapter, a rapid repatriation of returnees would improve local firm performance as well as FDI knowledge spillovers. In current China, given that the economy has experienced a rapid economic development and social change in recent years, local policies change quickly and are less likely to be sustainable (Liu, Simon, Sun, & Cao, 2011; Zhang & Guan, 2021), which might not be helpful for returnees to enter local industries. Therefore, the local government in Beijing need provide stable preferential policies to help highly skilled returnees quickly enter into local industries and adapt to local context. Moreover, I also confirm that an irregularity repatriation of returnees might hamper local firm performance. Therefore, local government in Beijing need to avoid incoherent policies, for example, in one year they attract too much returnees while in the other year do not introduce the returnees, so that ensure a more rhythmic pace of returnees' repatriation. Such regular repatriation would facilitate the returnees' readjustment into local context and applying their capabilities to improve the local absorptive capacity, thereby disseminating more FDI spillovers.

This study has certain limitations, and future studies can further explore these issues and expand the literature. First, my study only focuses on FDI knowledge spillovers in China. It can be better to generalize our theoretical analysis to other emerging economies. Second, my firm-level dataset is just limited to one high-tech science park. Although ZSP is one of the most important science parks in China and can be a good representative (Tan, 2006; Trunina, Liu, & Chen, 2018), I still need additional evidence by combining other science parks or industrial clusters. Last but not least, I am also limited by the availability of the specific data of returnees that could help to specify their characteristics like their past study and/or work experience, and their explicit skills. Previous literature often uses individual surveys to collect the information (Dai & Liu, 2009; Farquharson & Pruthi, 2015; Qin et al., 2017), while my firm-level data is limited on the returnees' characteristics. It might be important to conduct a comprehensive survey about the returnees not only on the firm-level but on the individual level. This may help us to know more specific functions of returnees' characteristics in moderating FDI knowledge spillover.

Chapter 6 How Does FDI Knowledge Spillovers Improve Local Firms Productivity? The Role of Returnees' Specialized Agglomeration

6.1 Introduction

In Chapter 5, I confirmed the positive FDI knowledge spillovers on the Chinese local firms' productivity. I also examined the impact of returnees' industrial repatriation process on the FDI knowledge diffusion and demonstrated that a fast pace of returnees' repatriation improves the local absorption of FDI spillovers, while irregular repatriation hampers the process. However, as suggested in the literature review section, FDI spillovers are contingent not only on the dynamic characteristics of returnees' industrial repatriation but also on the agglomerated factors of returnees' clustering (Crespo & Fontoura, 2007; Ning et al., 2016a; Wang & Wu, 2016). One of the key types is the specialized agglomeration structures, which mainly include concentrated and competitive clustering structures, and it reflects the intra-industry distribution and interactions of returnees (Beaudry & Schiffauerova, 2009; Drucker, 2011; Guevara-Rosero et al., 2019). However, we know relatively little about its role in local firm performance and the FDI diffusion process. In this chapter, I mainly discuss the second research question of this Ph.D. thesis: "*What are the externalities of returnees' specialized agglomeration, including concentrated and competitive structures, in local firm productivity and FDI knowledge spillovers*?"

As argued before, the internal resource for emerging markets firms' technological upgrading might be limited and they must seek external knowledge sources (Buckley et al., 2002; Newman et al., 2015). Foreign direct investment (FDI) has been widely considered as an important external source as its knowledge can spill to local firms and help them improve their technologies and productivity (Buckley et al., 2002; Newman et al., 2015; Ning et al., 2016b). Given the knowledge disparity between foreign and local firms, however, it requires the specific absorptive capability to identify and assimilate the FDI advanced technology (Cohen & Levinthal, 1990; Girma, 2005). In the emerging markets, the returnees are the critical human capital that can close these knowledge disparities, as they are typically equipped with language advantages, multi-cultural knowledge, and advanced technological competence (Filatotchev et al., 2011; Liu et al., 2014; Wang, 2015). From an agglomeration economy view, the returnees in the labor markets do not work alone, but rather cluster in certain industries and form a specialized industrial structure, which would influence their interpersonal interactions and knowledge dissemination and further contribute to the local firms' productivity (de Vor & de Groot, 2010; Hervas-Oliver, Sempere-Ripoll, Rojas Alvarado, & Estelles-Miguel, 2018).

Moreover specifically, based on the cluster theory, the specialized clustering structures of returnees refers to the extent that returnees are clustered within a specific industry, and there are two dimensions in this type of agglomeration, namely concentrated and competitive structures (Bucci & Ushchev, 2020; van der Panne, 2004). These two types of agglomerations might affect the local firms' productivity and the local absorption of FDI spillovers differently. On the one hand, the concentrated clustering of returnees reflects the overall intensity of returnees within an industry (Ellison & Glaeser, 1999; Leppälä, 2020). It is acknowledged that the repatriation of returnees with multi-cultural knowledge and overseas networks is regarded as a "brain gain" for emerging economies to catch up with their developed counterparts and leapfrog some technological development stages (Dai & Liu, 2009; Filatotchev et al., 2011; Liu et al., 2014). Their concentration in certain industries would magnify this interactive learning process and improve the entire industrial knowledge base (Gabe & Abel, 2012; Holmes & Stevens, 2002). Moreover, the geographical proximity favors the returnees' within-industry knowledge exchange and idea sharing, which might contribute to the local technological upgrading and the absorption of FDI knowledge spillovers.

On the other hand, a competitive clustering structure depicts the distribution of returnees over firms within certain industries (Drucker, 2011; Hoffmann et al., 2018). As the resources in an industry are limited, the returnees' fierce competition within the industry might influence their contributions to local firms to develop sufficient common knowledge bases and establish stable business relationships with foreign firms, which might hamper the FDI spillovers process. Nevertheless, the current literature has not examined this topic. Upon a background of attracting return talents in emerging economies, how to effectively play the role of returnees is a critical issue. A clear understanding of the collective role of returnees is important for policymakers and firm managers to introduce these types of talents and learn from FDI technologies.

To this end, this paper examines how the specialized clustering structure of returnees influences the local firm performance and FDI spillovers in China. To the best of my knowledge, this chapter is the first to apply the specialized agglomeration perspective to analyse the collective role of returnees in the FDI diffusion process. It makes two contributions to the previous theoretical frameworks. First, prior scholars have mainly explored the specialized agglomeration based on the overall employment structure (Caragliu et al., 2016; de Vor & de Groot, 2010), but have often neglected returnees, which is a special labor force in the emerging markets. The agglomeration view has long provided arguments centered on which sectoral composition of local interpersonal interactions within industries can affect the local development (Feldman & Audretsch, 1999; Hervas-Oliver et al., 2018; Martin et al., 2011). Drawing upon the cluster approach, I make the first attempt to apply the agglomeration perspective to examine the role of the specialized agglomeration structure of returnees. I confirm that both concentrated and competitive clustering structures of returnees can promote local firms' productivity, which deepens our understanding of the collective role of returnees and adds more empirical evidence to the cluster theory.

Second, I bridge the cluster literature and FDI literature by examining the contingency effect of returnees at the aggregated level. Prior studies have demonstrated the impacts of specialized agglomeration on technology transfers and dissemination of FDI knowledge spillovers, however, they have largely ignored the specialized clustering structures of returnees in this relationship (Ning et al., 2016a; Ning et al., 2016b). I conjecture that different types of returnees' agglomeration should have different impacts on local firms' productivity and moderate FDI spillovers process. In this chapter, I mainly find that while a concentrated clustering structure of returnees facilitates FDI spillovers, their competitive clustering hinders it. In doing so, I provide a more integrated perspective and new evidence on the contingencies of FDI spillovers through exploring the attributes of the returnees' agglomeration to contribute to the FDI externalities literature.

My research context is Zhongguancun Science Park (ZSP) in China as the MNEs and returnee workers have played important role in the growth in ZSP (*Zhongguancun Report 2019*). It attracts many MNEs, such as Microsoft, IBM, Bell, Oracle, and Intel, to operate in the Science Park (ibid). Besides, with considerable supporting policies, ZSP attracts a great number of returnees to work in local firms or start technological and business ventures here (ibid). Moreover, the ZSP comprises 16 sub-parks and the returnees are clustered in several industries and sub-park, which allows me to measure the returnees' clustering structures in the dataset and examine their impacts on local firm productivity and FDI knowledge spillovers.

The remainder of this chapter is structured as follows. The second part includes the theoretical framework and develops the hypotheses on the relationship between the returnee's industrial concentration, competition, and local firms' productivity, as well as their role in the FDI knowledge spillovers process. The third section presents the sample and methodology. The fourth section reports the analysis of the econometric results. Finally, the conclusions, implications, and limitations are discussed in the fifth section.

6.2 Theoretical Framework and Hypotheses Development

6.2.1 FDI Knowledge Spillovers and Specialized Agglomeration

From the Literature Review in Chapter 3, based on the resource dependence theory, inward FDI represents a key external knowledge resource for firms in emerging markets (Orlic et al., 2018; Tian, 2007). Previous research has long argued that MNEs may bring intended or unintended diffusion to local firms since when they cannot fully appropriate their superior technologies, their surplus knowledge can spill across organizational boundaries the local firms they interact with (Inkpen, Minbaeva, & Tsang, 2019b; Liang, 2017; Newman et al., 2015). The so-called "spillovers" suggest that the technological superiority and strong management practices of FDI can be transferred to local firms with the help of geographical and cultural proximity, which may improve local productivity (Haskel et al., 2007; Zhang et al., 2010). As a result, domestic firms in the host country are seeking opportunities to establish a relationship with FDI and expecting to improve their technological upgrading by observing and assimilating the advanced knowledge (Fu & Gong, 2011; Girma, 2005).

However, whether FDI knowledge spillovers can benefit local production efficiency remains inconclusive. Some scholars find positive FDI spillover effects on local firms' productivity, as foreign firms provide opportunities for local ones to observe and imitate new technologies and management practice (Jude, 2016; Newman et al., 2015; Ning et al., 2016b; Tian, 2007, 2010; Wang & Wu, 2016; Zhang et al., 2014). Some channels theorized several broad underlying spillover mechanisms. These include 'demonstration effects' where local firms emulate foreign technologies and managerial practices through observation of MNEs' local operations; labor mobility enables local workers to gain knowledge and experience from MNEs and then migrate to domestic firms and apply their learning locally; competition induced by MNEs incentivizes domestic firms to learn, upgrade and adopt new knowledge or technologies to improve efficiency; finally, there is the pecuniary relationship established between foreign and local firms through the 'vertical or horizontal linkage' effect (Meyer & Sinani, 2009; Rojec & Knell, 2018; Zhang et al., 2014).

In contrast, other studies hold the opposite opinion and argue that FDI can threaten indigenous technological upgrading because the MNEs with advanced business acumen can outcompete local firms, whose market share would be crowded out (Buckley et al., 2010; Rojec & Knell, 2018). For example, Ben Hamida and Gugler (2009) demonstrate that FDI does not have significant direct spillover effects in Switzerland. Ashraf, Herzer, and Nunnenkamp (2016) indicate that FDI may not have a significant impact on local productivity. Utilizing data from 1799 Spanish manufacturing firms from 1990 to 2002, García et al. (2013) confirm that FDI inflows into Spain are negatively associated with the ex-post innovation of local firms. Similarly, Lu et al. (2017) examine China's context and also find that FDI harms the productivity of local firms in the same industry.

Based on mixed evidence of FDI impacts, many researchers begin to explore contingent factors that can affect the direction and magnitude of FDI knowledge spillovers (Javorcik & Spatareanu, 2011; Ning et al., 2016b; Zhang et al., 2010). Scholars have investigated that the FDI externalities can be contingent on the local absorptive capacity, the level of MNE presence and their entry process, the local institutional development, and a series of other factors (Ito et al., 2012; Javorcik & Spatareanu, 2011; Li et al., 2017; Tzeng, 2018a; Wang et al., 2017b; Zhang et al., 2014). Despite the volume of research, given that the knowledge transmission is tacit and requires interpersonal contacts, a growing literature begin to indicate that the major contingencies for FDI spillovers faced by firms are in their environment and suggest that the firms' agglomeration might influence the FDI spillovers, as the interpersonal interactions within and across industries might affect the knowledge diffusion process (Ning & Wang, 2018; Ning et al., 2016b).

Indeed, firms usually prefer to geographically agglomerate in clusters and benefit from the spatial technological spillovers (de Groot et al., 2016; Diodato et al., 2018). The cluster literature has emphasized that the intensity and scope of interpersonal interactions within the industry, i.e. specialized agglomeration, can not only exert knowledge externalities but affect local absorptive capability and should be considered a precondition for knowledge externalities to occur (Hervas-Oliver et al., 2018; Ketelhöhn, 2006; Mantegazzi, McCann, & Venhorst, 2020). Several research has established the linkage between local agglomeration and FDI knowledge diffusion. For example, Ning et al. (2016b) and Wang et al. (2016a) find that the regional specialized agglomeration would facilitate the FDI spillovers effect. Nevertheless, a series of research still argue that the specialized agglomeration needs to be further distinguished into dimensions, including concentrated and competitive structures, as these are two of specialization and exert different impact on local knowledge externalities (de Groot et al., 2016; Drucker, 2011).

More specifically, on the one hand, the concentrated structure refers to the overall intensity of activity within a specific industry. The concept of concentration originates from the Marshall–Arrow–Romer (MAR) type of externalities, which argues that the similar knowledge base within the industry facilitates the exchange of knowledge, processes of business interaction, and inter-firm labor mobility, so that finally promote the local innovation performance (Holmes & Stevens, 2002; Martin et al., 2011). Such interactions can thus positively influence firm productivity and facilitate their assimilation of foreign advanced knowledge. (Glaeser, Kallal, Scheinkman, & Shleifer, 1992) further suggest that "local monopoly is better for growth than the local competition because local monopoly allows externalities to be internalized by the innovator." The MAR model, therefore, perceives monopoly as better than competition as it protects ideas and allows the rents from innovation to be appropriated.

On the other hand, unlike concentration, Porter (1998) stresses that it is the local competition between firms within the same sector, rather than the simple concentration of industries, that fosters the rapid adoption of innovation and knowledge diffusion. A competitive agglomeration reflects firms' strength and competitive behaviors within a specific industry (Feldman & Audretsch, 1999; Porter, 2011). The traditional arguments on the mechanism of how the competitive agglomeration stimulates local firm performance and knowledge spillovers mainly lie in two aspects – one is the rivalrous spirit and the other is resource relevance. The rivalrous spirit emerges when firms are competing to improve or defend their superiority (de Groot et al., 2016; Gnyawali & Ryan Charleton, 2018). In contrast, resource relevance suggest that firms and their competitors are faced with the same opportunities and challenges (Bucci & Ushchev, 2020; Gnyawali & Ryan Charleton, 2018). When a firm makes an innovative activity, the pre-existing specialization of competitors' resources facilitates immediate use by another competitor with little additional investment, so that improves the overall productivity.

Although the previous studies have emphasized the importance of concentrated and competitive agglomeration, a potential research gap is that they mainly focus on the role of overall employment interactions within a particular industry in the FDI knowledge externalities, which might not explain the specific role of the special labor force, returnees, in emerging markets. As reviewed in Chapter 2.2, in the emerging markets context, the returnee is a critical type of human capital that can close the knowledge disparity between foreign and local firms (Bai et al., 2017; Li, 2020; Liu, Xia, Jiangyong, & Lin, 2019). As individual returnees embody tacit knowledge, their specialized agglomeration might also influence the scale and scope of their interactions within industries to generate knowledge externalities and affect the local absorption of FDI knowledge spillovers (Ma et al., 2018; Pruthi, 2014). However, limited attention has been placed on this topic. To address this research gap, I make the first attempt to incorporate the industrial specialized agglomeration perspective and examine the specialized agglomeration effect of returnees, including the concentrated and competitive clustering structures of returnees, on local technological upgrading and FDI spillovers process.

6.2.2 Returnees' Specialized Agglomeration, FDI Spillovers, and Local Firm Performance

As argued previously, the existing literature has broadly demonstrated that returnees can improve firms' innovation, productivity, and provide the prerequisites necessary for successful imitation from external knowledge. For example, Lin, Lu, Liu, and Choi (2014) examines Taiwanese industrial data and proves that the returnees can bring knowledge heterogeneity and adequate skills and information to local firms' knowledge base, which can help local industries to search for broader relationships with foreign firms and cope with the complex cognitive tasks that are required to bring different knowledge domains together. Li et al. (2012) argue that the returnees' exposure to both the developed countries and their home countries make them realize the technology gaps between different country context, which further enable them to identify innovation opportunities easier compared with their local peers. Tzeng (2018b) also show that the returnees can serve a boundary-spanning role and help understand existing knowledge resources, introduce foreign knowledge to colleagues, and integrate foreign knowledge with local firms.

Nevertheless, the current line of inquiry mainly emphasizes the role of individual returnees in FDI knowledge diffusion, the collective role of returnees has not been fully understood. As indicated in the previous section, industrial concentration and competition are two main specialized agglomerations and reflect the knowledge externality within industries (Bucci & Ushchev, 2020; de Groot et al., 2016). It can also be applied to analyse the collective role of returnees at the within-industry level. In the following section, therefore, I would borrow the agglomeration perspective to explain how the concentrated and competitive clustering structure of returnees influence the local firm productivity as well as the FDI knowledge spillovers process.

6.2.2.1 The Impact of Returnees' Concentrated Clustering Structure

(1) Returnees' Concentrated Clustering Structure and Local Firm Productivity

As indicated above, the concept of concentrated clustering structure is derived from the MAR view of industrial concentration, which is defined as the overall industrial activity intensity within a certain industry (Drucker, 2011; Ellison & Glaeser, 1999). It considers that the productive efficiency of a particular industry in a given region is mainly boosted by the possible interactions of firms within the industry in a region (Barrios et al., 2006; Faggio et al., 2020; Ketelhöhn, 2006). Following this line of research, the concentrated clustering structure of returnees in this chapter thus refers to the overall extent that returnees are concentrated in a certain industry. When a huge number of returnees are agglomerated in an industry, then the level of returnees' industrial concentration is high, otherwise is low.

I contend that the concentrated clustering structure of returnees might promote local firms' productivity for the following reasons. First, the industrial co-location can magnify the returnees' interactive learning process and sharing of ideas and information, so that promotes the knowledge externalities of returnees to the local firms (Ellison et al., 2010). As indicated in section 2.2, returnees themselves can add to the local human capital and the knowledge transfer through returned entrepreneurs can promote the local firms' innovation performance. It has been widely acknowledged that human resource is a critical factor that can drive innovation, as the knowledge resides in the people and their interactions (Hao et al., 2016; Li et al., 2012). The concentration of returnees in an industry in a region can promote their knowledge externalities to local firms and improve innovation in that particular industry, as the similar knowledge base facilitates the exchange of knowledge, processes of business interaction, and inter-firm labor mobility (Diodato et al., 2018). The concentrated clustering structure would also minimize transaction costs for the communications between returnees since the scale economy increases the efficient sharing via similar infrastructure, supplies, and markets and the spatial proximity facilitates industry knowledge transmission and technological appropriation.

Second, the concentrated clustering structure of returnees would promote the local innovation consciousness as well as innovation efficiency. As suggested by Yuan and Wen (2018), highly skilled returnees are scarce resources, who can become superstars in the local labor market and would place more emphasis on the importance of R&D to firm growth. Moreover, Dai et al. (2018) further indicate that returnees can provide managerial experience, enhanced reputations, access to financial institutions, and broad social and business networks. As a consequence, their concentration in certain industries will enhance the attention from employers, employees and foreign investors, which may not only stimulate local firms' willingness to invest in innovative activities but also improve the local innovation efficiency (Hao et al., 2017; Pruthi, 2014). The innovative externalities from returnees concentrated agglomeration would thus help improve the local firms' productivity.

(2) Returnees' Concentrated Clustering Structure and FDI Knowledge Spillovers

I conjecture that the concentrated clustering of returnees may enhance the knowledge spillovers FDI brings to the local firms. First, when returnees are concentrated in specific industries, it can provide a specialized knowledge base to facilitate the FDI externalities. As discussed in the previous section, it is widely acknowledged that acquiring external knowledge from FDI spillover is not straightforward, and domestic firms need sufficient absorptive capacities to benefit from FDI (Sánchez-Sellero et al., 2014). Given the advanced knowledge they bring home, returnees may collectively affect the technological base of local industries (Filatotchev et al., 2011; Lin et al., 2015; Lin et al., 2014). In this case, their industrial concentration can magnify the improvement of the local knowledge base, so that foster the local firms to develop similar technological activities and interpretative schemes when learning from FDI advanced knowledge.

Second, the concentrated clustering structure of returnees can lower the cost for local firms to get access to the FDI information. As suggested by Welch and Welch (2008), the efficiency of knowledge exchange can be promoted when the knowledge receivers and senders share a common ground and understand the context. After the training or education abroad for several years, the returnees typically have language advantages and cross-board knowledge, compared with their local counterparts (Kenney et al., 2013; Liu et al., 2010b). After returning, the returnees' knowledge of both their home and host countries enables them to identify cross-border differences and knowledge gaps with FDI (Liu et al., 2014; Wang, 2020). The returnees with share competence clustered in certain industries can thus make it easier for local firms the identify and establish interactions with the foreign firms, so that enable them to overcome the technology transfer barriers. The communication and knowledge sharing between returnees within industries would also help correct the information transmission errors and enhance the local firms' understanding of the foreign advanced technology (Bai et al., 2018; Bai et al., 2017; Tzeng, 2018b; Wang, 2015).

Third, when returnees are concentrated in certain industries, their specialized technological fields create more linkages between foreign and local firms. To learn from FDI knowledge spillovers, frequent and repeated interactions among knowledge actors beyond organizational boundaries are required (Balland & Rigby, 2017; Szulanski & Jensen, 2006). This process involves knowledge transmitters and recipients to develop mutual trust through socialization (Fu, Revilla Diez, & Schiller, 2013). With a long time of training abroad, the returnees are usually equipped with cross-cultural social capital and professional international networks, who can act as a 'bridge' between the MNEs and domestic firms and transfer technological and business knowledge from FDI (Kenney et al., 2013). In this case, the returnees can act as knowledge brokers in transferring technological and business knowledge from FDI. Returnees' ethnic ties and common identity in the concentrated industrial environment can further build up the trust between a foreign and local firm and form informal networks for information exchange (Filatotchev et al., 2011; Lin et al., 2019; Pruthi, 2014). Thus, the returnees' industrial concentration may facilitate the FDI knowledge diffusion process.

Combing the above analysis, I propose:

H1a: The concentrated clustering structure of returnees positively influences the local firms' productivity.

H1b: The concentrated clustering structure of returnees positively moderates the relationship between FDI knowledge spillovers and local firms' productivity.

6.2.2.2 The Role of Returnees' Competitive Clustering Structure

(1) Returnees' Competitive Clustering Structure and Local Firm Performance

The competitive clustering structure is another type of specialized industrial agglomeration, which depicts firms' strength within a specific industry (Guevara-Rosero et al., 2019; Porter, 2011). It considers that the improvement of the industry is mainly boosted by the rivalrous spirit and the resource relevance between firms within the industry (Gnyawali & Ryan Charleton, 2018; Greve, 2009; Porter, 1998). Based on this concept, the competitive clustering structure of returnees thus refers to the distribution of returnees over the firms in a certain industry. When returnees are agglomerated only in a small number of firms in an industry, then the level of returnees' industrial competition is low, otherwise is high.

Following the traditional arguments, I also expect that the competitive clustering structure of returnees might stimulate the local firms' productivity. On the one hand, from the rivalrous spirit view, in a higher industrial competition environment, the returnees in many different firms would still compete for scarce resources and improve their capability. Since the resources, markets, and technology are scarce, returnees are motivated to consistently improve in "an incessant race to get or to keep ahead of one another" (Porter, 2011). Moreover, as suggested by previous studies, returnees often have an incentive to enter the industry in a fast mode so that enjoy the first-mover advantages in the labour market (Qin et al., 2017). The rivalrous spirit between returnees would push them to interact or ally with foreign companies, establish stronger business linkages, acquire more information advantages, and thus bring more knowledge externalities to local firms (Liu et al., 2019; Zheng et al., 2016). It can thus accelerate local technological upgrading because upgrading at a more rapid pace than competitors help firms to achieve a competitive edge.

On the other hand, from the resource relevance perspective, returnees represent a key knowledge-based resource and their competitive clustering can provide the stronger capability for local firms to deal with the resource relevance issues (Lin et al., 2015; Wang, 2015). Resource relevance means that resources developed to pursue incompatible positions are likely of high relative value between competitors (Gnyawali & Park, 2009; Ingram & Qingyuan Yue, 2008). Since the returnees within industries often share a similar cognitive structure and knowledge base, their resource relevance would further lead their competitors to develop overlapping dominant logics and a deep understanding of each other's competitive behaviour and priorities. When opportunities arise, the returnees are more likely to learn from their competitors more quickly so that helps their firms to make more technological progress (Bucci & Ushchev, 2020).

(2) Returnees' Competitive Clustering Structure and FDI Knowledge Spillovers

Although the competitive clustering structure might improve the local firms' productivity, it may hamper the knowledge externality of FDI from the following three ways. First, a high level of competitive clustering of returnees might restrict their contributions to local firms to develop sufficient common knowledge bases, which is required for the absorption of FDI spillovers. As argued before, Joint local problem-solving efforts, support, and even knowledge of failure others experienced in similar situations are critical to reduce costs and risks and to facilitate the successful application and the spread of FDI knowledge (Bathelt, Malmberg, & Maskell, 2004). Since returnees have acquired skills and confidence with world-class technologies, their presence can not only contribute to the firm and industry's talent pool, but also stimulate the local elites to improve, and thus further promote the local knowledge base (Liu et al., 2014; Wang, 2015). However, a higher industrial competition might hamper the returnees' contribution to the local knowledge pool, limit their joint local problem-solving activities and restrict the support they received from the domestic firms (Agrawal et al., 2011; Greve, 2009). Those fierce competitions might not help the returnees to display their role in promote the local knowledge base and learn from the FDI knowledge spillovers.

Second, when returnees are clustered in many different firms within industries, it is difficult for them to collectively establish stable business linkage between foreign and local firms. As argued in the previous chapter, the returnees can serve as knowledge brokers between FDI and domestic firms (Lin et al., 2016; Xiao & Tsui, 2007). However, an environment with many rivalrous firms restricts the bargaining power of individual returnees in a specific firm (Drucker, 2011; Martin et al., 2011). Moreover, the competitive behavior among the returnees makes it difficult for them to help local firms to establish linkages with foreign firms. In this case, a competitive clustering structure of returnees might not benefit the FDI knowledge dissemination.

Third, a competitive clustering structure of returnees might not help them to readjust to the local environment, which also restricts their impact on the local absorptive capability. As indicated before, the returnees have been isolated from their home countries for years and may face readjustment difficulties when returning to their home countries (Lin et al., 2019;

Liu & Almor, 2016). Particularly in China, the swiftly changing economic environment imposes more difficulties on this issue. When returnees go back to their emerging market home countries, they usually experience a seemingly familiar, yet different, environment (Li et al., 2012). When the returnees are distributed into many different firms within an industry, this type of industrial structure might not benefit the returnees' interpersonal interactions, which is important for them to establish local cross-firm linkages and readapt the local business context. Without local embeddedness, the returnees are not able to effectively play their role in both the improvement of the local knowledge base and the establishment of business linkage between local and foreign firms (Lin et al., 2019; Qin et al., 2017). In this case, the local firms might have fewer opportunities and absorptive capabilities to learn from the advanced FDI knowledge spillovers.

Based on the above arguments, I propose:

H2a: The competitive clustering structure of returnees positively influences the local firms' productivity.

H2b: The competitive clustering structure of returnees negatively moderates the relationship between FDI knowledge spillovers and local firms' productivity.

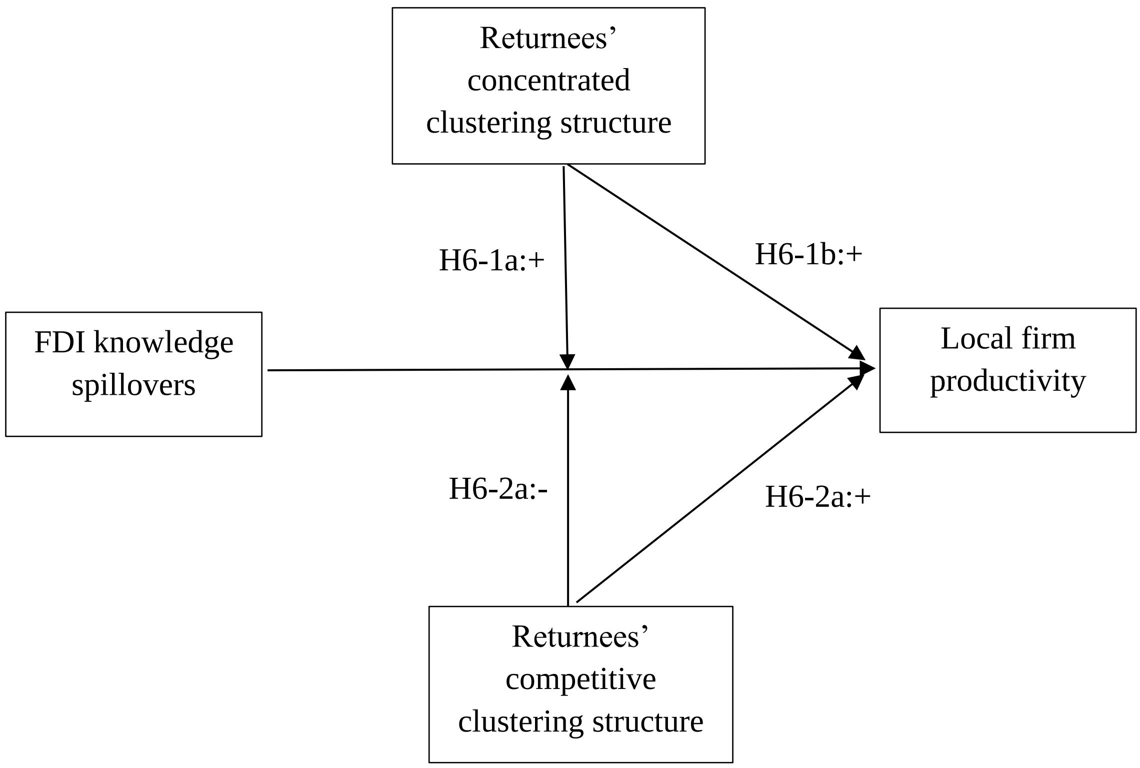

Figure 6-1 The Theoretical Framework of Chapter 6

6.3 Data and Methods

6.3.1 Data

Similar to Chapter 5, this chapter also employs a unique dataset associated with Chinese high-tech manufacturing companies in Beijing's Zhongguancun science park (ZSP). The dataset was collected by the ZSP regulatory body's statistical yearbook over a period from 2007 to 2013 (Zhang et al., 2018). The high-tech firms were required to take part in the census survey with providing detailed information about their legal entity, production management, and financial status, technology activities, and labor structures. This database also classifies firms into 4-digit, 3-digit as well as 2-digit ISIC, and includes firms with firms that have more than ten employees. Therefore, this dataset allows us to construct more detailed firm-level time-varying variables regarding FDI and returnee labor force. The original dataset contains 12,821 high-tech firms of 56,905 observations. To test my hypotheses, I make some data cleaning procedures. First, I have dropped firms that have incomplete records or with less than 3-year observations. Second, since this study is focusing on the FDI spillover effect on local firms, so I drop foreign firms based on their registration type in the final estimation. The final data sample, therefore, covers 7,920 local firms for the period 2007-2013, which comprise 45,544 firm-year observations for my pooled OLS with robust standard errors and system-GMM panel estimations.

6.3.2 Methodology

As suggested in Chapter 4 and similar to Chapter 5, I mainly use the system-GMM estimation with Heckman corrections to test my hypothesis. Firstly, there might exist selection bias concerning issues about returnees as the recruitment of returnees might not be random as firms with more competitive capability and generous financial support would be more affordable for those highly skilled talents (Liu et al., 2010a; Roberts & Beamish, 2017). This means that the returnees might be self-selected in different local firms. In this case, I use the Heckman two-stage model to deal with such potential selection problems (Certo et al., 2016; Heckman, 1979). In the first stage, I estimated a Probit model of a firm's propensity of recruiting returnees (Certo et al., 2016; Heckman, 1979). I mainly the industrial average wage has been included in the first stage as the exclusive restriction to check the appropriateness of the Heckman two-stage estimation. Previous literature suggests that the industrial average wage would influence a firm's propensity to recruit but not directly affect firm performance. In this case, it can serve as a proper exclusive restriction. Then, based on the Probit estimation, I can calculate an inverse Mill's ratio (IMR). The IMR represents the selection hazard of a firm's recruitment activity of returnees (Certo et al., 2016; Heckman, 1979). I include the IMR in the second stage to check the existence of the selection effect. More specifically, if IMR is significant in the second stage, then it suggests that there indeed exists selection issues and it is proper to use the Heckman two-stage models.

In the second stage, a firm's production efficiency might be influenced by its previous status and it may experience economic shocks every year (Comin, 2017; Lagos, 2006), which requires to consider a dynamic panel structure to study the dynamic trend of dependent variables and the short-term or long-term effects of independent variables on dependent variables. And I mainly use the system-GMM method and include the IMR to deal with the dynamic panels since it chooses more proper instrument variables (Roodman, 2009; Su & Liu, 2016). In the formal estimation, I use the first differences of the second and third lags and lag level of dependent and explanatory variables as instruments. Moreover, following the direction of Windmeijer (2005), I conducted the Arellano–Bond (AR) tests and the Hansen's J test to check their overall validity in the system-GMM analysis. A proper system-GMM estimation requires the result of the AR (1) test to be significant, and the result of the AR (2) test and the Hansen's J test to be insignificant.

6.4 Empirical Results

6.4.1 Descriptive Analysis

Table 6-1 presents the descriptive statistics and the correlation matrix of all my hypothesized and control variables. In the full sample, firms on average invest 0.011 million Yuan of R&D investment per employee, hold an asset of 74.281 million Yuan and possess 6.986 patents in the last five years. I also inspect the potential multicollinearity between variables by computing the Variance Inflation Factors (VIF). All values are within an acceptable range with a mean VIF value of 2.19. All correlation coefficients between my independent variables are below 0.374. These suggest that my estimations may not be biased with multicollinearity issues.

6.4.2 Econometric Results

Table 6-2 presents the coefficients and corresponding significance of the first-stage Heckman selection Probit model. It tests the propensity of firms to recruit returnees. I lagged all the explanatory variables to control for the potential time effect. As shown, firm size, profitability, R&D intensity, knowledge stock and firm average wage are all significantly positively related to a firm's propensity to recruit returnees, while firm age has a significantly negative impact and state-ownership has an insignificant effect. The coefficient of the industrial average wage is significantly positive, which indicates a proper inclusion of the exclusion restriction. The inverse Mills ratio was calculated to correct the possible selection bias in my second stage model.

Table 6-1 Summary Statistics and Correlation Matrix

Variable	Mean	Std.Dev.	1	2	3	4	5	6	7	8	9	10	11	12
TFP	3.019	1.327	1.000											
FDI	0.182	0.166	0.038	1.000										
Returnee concentration	1.153	10.000	0.017	0.013	1.000									
Returnee competition	1.856	2.272	-0.079	-0.219	-0.009	1.000								
Firm age	8.120	4.938	0.233	-0.103	-0.007	0.037	1.000							
Firm size	74.281	296.259	0.401	0.088	0.005	-0.061	0.186	1.000						
State-ownership	0.051	0.220	-0.003	0.070	-0.005	-0.011	0.238	0.068	1.000					
Profitability	-0.006	0.141	0.239	-0.028	0.002	-0.006	0.113	0.090	0.036	1.000				
R&D intensity	0.011	0.030	0.223	0.013	0.009	-0.079	-0.077	0.092	0.013	0.095	1.000			
Knowledge stock	0.793	3.164	0.374	0.067	0.012	-0.038	0.127	0.284	0.015	0.100	0.191	1.000		
Speed	0.506	2.779	-0.007	0.069	0.003	-0.057	0.015	-0.006	0.007	-0.008	-0.006	0.017	1.000	
Irregularity	229	821	0.042	0.220	-0.005	-0.105	0.143	0.003	-0.026	0.002	-0.112	0.026	0.156	1.000

Notes: (1) size 100 million, R&D million; (2) R&D intensity is measured by 1 million RMB per employee. (3) Firm size is the total assets of a firm and is measured by 1 million RMB. (4) All absolute correlation coefficients greater than 0.006 are significant at the 5% level.

Table 6-2 The Propensity of Firms to Recruit Returnees: the First-Stage Heckman Probit Model

VARIABLES	Returnee dummy (0=No, 1=Yes)		
	Estimate	S.E	P-value
Firm age	-0.119***	(0.018)	[0.000]
Firm size	0.153***	(0.006)	[0.000]
Profitability	-0.255***	(0.036)	[0.000]
State-ownership	-0.003	(0.043)	[0.946]
R&D Intensity	0.062***	(0.006)	[0.000]
Knowledge stock	0.200***	(0.014)	[0.000]
Firm average wage	0.072***	(0.008)	[0.000]
Industrial average wage	0.120***	(0.018)	[0.000]
Constant	-1.622***	(0.296)	[0.000]
Year dummies	Included		
Industry dummies	Included		
Region dummies	Included		
LR Chi^2	3069.40		
Pseudo R^2	0.169		
Log-likelihood	-12623.451		
Observations	40,566		

Notes: (1) Robust standard errors are reported in the parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 6-3 presents the results of the OLS estimations in Models 1, 3, 5, 7, 9 as a baseline comparison and the system-GMM estimations as to the main models in Models 2, 4, 6, 8, and 10. I first include my control variables and then add in my main explanatory variables subsequently with the full models 9 and 10. First of all, the insignificant Hansen J-statistics across all our system-GMM models support the view that the instrumental variables are uncorrelated to residuals. Moreover, the Arellano–Bond (AR) tests in all models indicate that the first-order AR (1) and not the second-order AR (2) error terms are serially corrected. Besides, the inconsistent results in the pooled OLS models further support the use of GMM for our estimation in our models. Secondly, the inverse Mill's ratio is significant across all models and indicates that the potential selection bias has been controlled for. Finally, as for the main explanatory variable, I can find that the coefficients of FDI are significantly positive across all models, which is in line with previous literature. Regarding the control variables, my results suggest that firm size, profitability, R&D intensity, and knowledge stock are significantly positively associated with local firms' productivity, while firm age has a significantly negative impact. Concerning state ownership, the coefficients are inconsistent or insignificant across the models. Moreover, the coefficients for the returnees' industrial repatriation speed are significantly positive, while for returnees' industrial repatriation irregularity are significantly negative, which are corresponds with the findings in the last chapter.

Hypothesis 1a proposed a positive externality from the concentrated clustering structure of returnees to local firm productivity, as the industrial co-location can magnify the returnees' interactive learning process and sharing of ideas and information, so that promotes the knowledge externalities of returnees to the local firms (Ellison, Glaeser, & Kerr, 2010). Moreover, the industrial concentration of returnees would promote the local innovation consciousness as well as innovation efficiency. In my full model 10, I find a positive and significant coefficient of the concentrated clustering of returnees ($\beta = 0.008$, $p < 0.05$). The coefficient indicates that a 1-unit increase of industrial concentration of returnees might lead to a 0.008 unit increase of local firms' TFP. These results are consistent across all models and suggest that the concentrated clustering structure positively stimulates the technological upgrading of local firms, supporting my hypothesis 1a.

Hypothesis 1b contends that the concentrated clustering structure of returnees facilitates the absorption of FDI knowledge spillovers. This is because that when returnees are concentrated in specific industries, it can provide a specialized knowledge base to facilitate the FDI externalities, and it can lower the cost for local firms to get access to the FDI information. Moreover, the returnees' specialized technological fields create more linkages between foreign and local firms. Their ethnic ties and common identity in the concentrated industrial environment can further build up the trust between a foreign and local firm and form informal networks for information exchange (Filatotchev et al., 2011; Lin et al., 2019; Pruthi, 2014). In my full model 10, the interaction term FDI*concentration is statistically significantly positive ($\beta = 0.251$, $p < 0.05$), which suggests that a higher level of returnees' concentrated clustering would promote the positive impact of FDI knowledge spillovers on local firms' productivity. This strongly supports Hypothesis 1b.

Hypothesis 2a proposed a positive externality from the competitive clustering structure of returnees. The arguments mainly include that in a higher industrial competition environment, the returnees in many different firms would still compete for scarce resources and improve their capability. Moreover, from the resource relevance perspective, returnees represent a key knowledge-based resource and their competition can provide the stronger capability for local firms to deal with the resource relevance issues (Lin et al., 2015; Wang, 2015). As shown in Table 6-3, In my full model 10, I find a positive and significant coefficient of the returnees' competitive clustering structure ($\beta = 0.024$, $p < 0.01$). These results are consistent across all models and suggest that a high returnees' competitive clustering structure negatively influences the technological upgrading of local firms, supporting my hypothesis 2a.

Hypothesis 2b contends that the competitive clustering structure of returnees hampers the absorption of FDI knowledge spillovers. As argued before, a high industrial competition of returnees might restrict their contributions to local firms to develop sufficient common knowledge bases and might not help returnees to readjust to the local environment, which is required for the absorption of FDI spillovers. Moreover, when returnees are clustered in many different firms within an industry, it is difficult for them to collectively establish stable business linkage between foreign and local firms. In my full model 10, the interaction term FDI*competition is significantly negative ($\beta = -0.282$, $p < 0.01$), which indicates that a higher level of returnees' competitive clustering structure would restrict the positive impact of FDI knowledge spillovers on local firms' productivity, which supports Hypothesis 2b.

Table 6-3 The Impact of FDI and Returnees' Specialized Clustering on Local Firm TFP: OLS and system-GMM Models

VARIABLES	(1) OLS TFP	(2) GMM TFP	(3) OLS TFP	(4) GMM TFP	(5) OLS TFP	(6) GMM TFP	(7) OLS TFP	(8) GMM TFP	(9) OLS TFP	(10) GMM TFP
Firm age	-0.003	-0.407***	0.017	-0.401***	-0.017	-0.400***	-0.015	-0.396***	-0.015	-0.394***
	(0.010)	(0.053)	(0.010)	(0.053)	(0.010)	(0.053)	(0.010)	(0.053)	(0.010)	(0.052)
Firm size	0.429***	0.126***	0.437***	0.126***	0.437***	0.126***	0.436***	0.125***	0.436***	0.125***
	(0.003)	(0.011)	(0.003)	(0.011)	(0.003)	(0.011)	(0.003)	(0.011)	(0.003)	(0.011)
State-ownership	-0.066	-0.129***	-0.083	-0.134***	-0.083	-0.167***	-0.088	-0.174***	-0.087	-0.173***
	(0.124)	(0.027)	(0.124)	(0.022)	(0.124)	(0.023)	(0.124)	(0.028)	(0.124)	(0.028)
Profitability	0.041*	0.085***	0.041*	0.086***	0.041*	0.085***	0.038*	0.083***	0.038*	0.084***
	(0.022)	(0.027)	(0.022)	(0.027)	(0.022)	(0.027)	(0.022)	(0.027)	(0.022)	(0.027)
R&D intensity	0.697***	0.082**	0.727***	0.083**	0.726***	0.081**	0.724***	0.083**	0.725***	0.083**
	(0.036)	(0.032)	(0.036)	(0.032)	(0.036)	(0.032)	(0.036)	(0.032)	(0.036)	(0.032)
Knowledge stock	0.286***	0.032***	0.307***	0.032***	0.307***	0.033***	0.305***	0.034***	0.305***	0.034***
	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)
Speed	0.013**	0.026***	0.011**	0.027**	0.011**	0.028***	0.012**	0.020**	0.013**	0.019**
	(0.006)	(0.010)	(0.006)	(0.012)	(0.006)	(0.009)	(0.006)	(0.009)	(0.006)	(0.009)
Irregularity	-0.013***	-0.010***	-0.011***	-0.010***	-0.011***	-0.010***	-0.011***	-0.010***	-0.012***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
IMR	0.020**	0.019**	0.019**	0.021**	0.019**	0.018*	0.031**	0.020**	0.031**	0.020**
	(0.011)	(0.010)	(0.009)	(0.011)	(0.009)	(0.011)	(0.014)	(0.010)	(0.014)	(0.010)
L.TFP		0.861***		0.864***		0.864***		0.863***		0.863***
		(0.015)		(0.015)		(0.015)		(0.015)		(0.015)
FDI			0.338***	0.254**	0.341***	0.284***	0.285***	0.454**	0.319***	0.416**
			(0.035)	(0.116)	(0.045)	(0.040)	(0.044)	(0.177)	(0.053)	(0.175)

Concentration					0.017**	0.010**			0.016**	0.008**
					(0.007)	(0.005)			(0.007)	(0.004)
FDI*Concentration					0.133***	0.242***			0.122***	0.251**
					(0.042)	(0.078)			(0.042)	(0.100)
Competition							0.017***	0.025***	0.017***	0.024***
							(0.003)	(0.009)	(0.003)	(0.009)
FDI*competition							-0.018	-0.293***	-0.017**	-0.282***
							(0.020)	(0.101)	(0.007)	(0.093)
Constant	0.666***	0.058***	0.470***	0.052***	0.572***	0.039**	0.547***	0.070***	0.547***	0.074***
	(0.122)	(0.018)	(0.050)	(0.018)	(0.050)	(0.019)	(0.050)	(0.025)	(0.050)	(0.025)
Year dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Industry dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Region dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
R-squared	0.687	N/A	0.687	N/A	0.675	N/A	0.687	N/A	0.675	N/A
AR(1)	N/A	0.000	N/A	0.000	N/A	0.000	N/A	0.000	N/A	0.000
AR(2)	N/A	0.322	N/A	0.308	N/A	0.273	N/A	0.399	N/A	0.352
Hansen	N/A	0.134	N/A	0.109	N/A	0.116	N/A	0.228	N/A	0.169
Observations	36,844	36,844	36,844	36,844	36,844	36,844	36,844	36,844	36,844	36,844

Notes: (1) Robust standard errors are reported in the parentheses. (2) The system-GMM estimations are clustered at the industry level (3) *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

6.4.3 Robustness Tests

I further conducted several robustness tests. First, similar to the robustness test in Chapter 5, I use alternative measurements of FDI, which include the share of foreign firm R&D investment over the total industrial R&D investment and the share of foreign firms over the total industrial firms. Both of the FDI measurement is at the four-digit industry level. I present the results in Table 6-4. Models 1-4 are estimated with the share of FDI R&D as the independent variable, while Models 5-8 are the share of FDI firms. As shown in the full models 4 and 8, in both circumstances, the interactions between FDI and the moderating variables are significant and in line with my hypotheses. More specifically, the interaction term *FDI*Concentration* in system-GMM estimation are positive and significant ($\beta = 0.159$, $p < 0.01$ in Model 4; $\beta = 0.081$, $p < 0.01$ in Model 8), which further confirms a positive moderating effect of returnees' concentration on the relationship between FDI and local firms' total factor productivity. Besides, interaction term *FDI*Competition* in system-GMM estimation are negative and significant ($\beta = -0.030$, $p < 0.01$ in Model 4; β = 0.-0.013, $p < 0.01$ in Model 8), which further confirms a negative moderating effect of returnees' competitive clustering structure on the relationship between FDI and local firms' total factor productivity. Taking these robustness tests enables us to reduce the concerns about the misspecification of FDI.

Second, I consider the whole sample of ZSP firms, which means to include the foreign firms of ZSP in our estimation. I present the results in Table 6-5. As shown in the full model 5, the coefficient of FDI is significantly positive (β = 0. 275 $p < 0.1$). Concerning the moderating role of returnees' repatriation speed, the interaction term *FDI*Concentration* in system-GMM estimation is also positive and significant ($\beta = 0.006$, $p < 0.05$). In contrast, the interaction term *FDI*Competition* in system-GMM estimation is negative and significant ($\beta =-0.191$, $p < 0.05$). Compared with the baseline results in Table 6-3, the estimation results from the whole sample are most consistent, while with a relatively lower level of significance. Overall speaking, this robustness test still supports our main findings.

Third, I consider alternative measurements of the control variables. I measure firm size by the firm's total employment, firm R&D intensity by the firm's R&D investment per sale, and firm knowledge stock by the firm's total patent stock in the past five years. I present the OLS and system-GMM estimation results in Table 6-6. As shown, using the alternative specification of control variables does not change my main findings. More specifically, as shown in Model 6, the coefficient of concentrated clustering structure of returnees is positive and significant ($\beta = 0.012$, $p < 0.01$), and the interaction term *FDI*Concentration* in system-GMM estimation are positive and significant ($\beta = 0.131$, $p < 0.01$), which also confirms my hypothesis 1a and 1b. Concerning the role of returnees' competitive clustering structure, as shown in Model 6, the coefficient of Competition is positive and significant ($\beta = 0.023$, $p < 0.05$), and the interaction term *FDI** Competition in system-GMM estimation is negative and significant ($\beta = -0.310$, $p < 0.01$), which also confirms my hypothesis 2a and 2b.

Table 6-4 Robustness Test 5 The Impact of FDI and Returnees' Specialized Clustering on Local Firm TFP: Alternative Measurements of FDI Presence

	FDI R&D share				FDI capital share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM
VARIABLES	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP
Firm age	-0.468***	-0.382***	-0.396***	-0.420***	-0.398***	-0.396***	-0.400***	-0.396***
	(0.063)	(0.053)	(0.052)	(0.076)	(0.053)	(0.053)	(0.053)	(0.053)
Firm size	0.120***	0.127***	0.125***	0.129***	0.126***	0.125***	0.125***	0.125***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
State-ownership	-0.006	-0.096	-0.154	-0.143	-0.118	-0.138	-0.167	-0.156
	(0.296)	(0.284)	(0.285)	(0.291)	(0.284)	(0.287)	(0.287)	(0.287)
Profitability	0.040	0.036	0.037	0.030	0.038	0.035	0.036	0.035
	(0.029)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
R&D intensity	0.103***	0.080**	0.081**	0.062	0.083**	0.082**	0.082**	0.082**
	(0.038)	(0.032)	(0.032)	(0.043)	(0.032)	(0.032)	(0.032)	(0.032)
Knowledge stock	0.047***	0.033***	0.032***	0.043**	0.033***	0.033***	0.033***	0.032***
	(0.013)	(0.010)	(0.010)	(0.021)	(0.010)	(0.010)	(0.010)	(0.010)
Speed	0.897***	0.021*	0.022*	0.026**	0.020**	0.027**	0.025**	0.024**
	(0.258)	(0.012)	(0.012)	(0.013)	(0.010)	(0.012)	(0.012)	(0.012)
Irregularity	-0.006***	-0.004***	-0.004***	-0.004***	-0.003***	-0.002**	-0.002**	-0.002**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
IMR	0.061***	0.067***	0.066***	0.062***	0.097***	0.099***	0.120***	0.120***
	(0.015)	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
L.TFP	0.845***	0.865***	0.864***	0.855***	0.863***	0.865***	0.865***	0.865***
	(0.017)	(0.015)	(0.014)	(0.016)	(0.015)	(0.014)	(0.014)	(0.014)

FDI	0.338**	0.325***	0.337***	0.397**	0.068***	0.052***	0.064***	0.044***
	(0.148)	(0.067)	(0.068)	(0.189)	(0.012)	(0.017)	(0.013)	(0.016)
Concentration		0.010**		0.019**		0.005**		0.006***
		(0.004)		(0.009)		(0.002)		(0.002)
FDI*Concentration		0.188***		0.159***		0.075***		0.081***
		(0.039)		(0.035)		(0.022)		(0.029)
Competition			0.004***	0.006***			0.008***	0.008***
			(0.001)	(0.001)			(0.002)	(0.002)
FDI*competition			-0.017***	-0.030***			-0.013***	-0.013***
			(0.003)	(0.006)			(0.003)	(0.003)
Constant	0.136	0.141	0.108	0.116	0.055	0.065	0.058	0.068
	(0.102)	(0.183)	(0.174)	(0.220)	(0.189)	(0.189)	(0.188)	(0.189)
Year dummies	Included	Included	Included	Included	Included	Included	Included	Included
Industry dummies	Included	Included	Included	Included	Included	Included	Included	Included
Region dummies	Included	Included	Included	Included	Included	Included	Included	Included
AR(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	0.336	0.301	0.298	0.284	0.318	0.377	0.356	0.412
Hansen	0.147	0.134	0.201	0.228	0.106	0.152	0.177	0.210
Observations	36,844	36,844	36,844	36,844	36,844	36,844	36,844	36,844

Notes: (1) Robust standard errors are reported in the parentheses. (2) The system-GMM estimations are clustered at the industry level (3) *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 6-5 Robustness Test 6 The Impact of FDI and Returnees' Specialized Clustering on Local Firm TFP: The Estimation on the Whole Sample

VARIABLES	(1) GMM TFP	(2) GMM TFP	(3) GMM TFP	(4) GMM TFP	(5) GMM TFP
Firm age	-0.439***	-0.434***	-0.435***	-0.425***	-0.425***
	(0.051)	(0.050)	(0.050)	(0.050)	(0.050)
Firm size	0.134***	0.134***	0.135***	0.134***	0.134***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
State-ownership	-0.117	-0.131	-0.119	-0.125	-0.123
	(0.289)	(0.284)	(0.287)	(0.284)	(0.284)
Profitability	0.024	0.024	0.024	0.024	0.024
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
R&D intensity	0.050	0.049	0.049	0.051*	0.051*
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Knowledge stock	0.027***	0.027***	0.027***	0.027***	0.027***
	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)
Speed	0.024*	0.023**	0.024**	0.023**	0.023**
	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)
Irregularity	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
IMR	-0.030***	-0.027***	-0.029***	-0.029***	-0.029***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
L.TFP	0.860***	0.862***	0.861***	0.862***	0.862***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
FDI		0.194*	0.153*	0.273*	0.275*
		(0.110)	(0.084)	(0.159)	(0.152)
Concentration			0.009*		0.008*
			(0.005)		(0.005)
FDI*Concentration			0.008**		0.006**
			(0.008)		(0.003)
Competition				0.017**	0.017**
				(0.009)	(0.009)
FDI*competition				-0.196**	-0.191**
				(0.094)	(0.089)
Constant	0.085	0.070	0.085	0.038	0.045
	(0.207)	(0.205)	(0.211)	(0.191)	(0.186)
Year dummies	Included	Included	Included	Included	Included
Industry dummies	Included	Included	Included	Included	Included
Region dummies	Included	Included	Included	Included	Included
AR(1)	0.000	0.000	0.000	0.000	0.000
AR(2)	0.489	0.324	0.471	0.422	0.365
Hansen	0.238	0.198	0.151	0.142	0.277
Observations	40,566	40,566	40,566	40,566	40,566

Notes: (1) Robust standard errors are reported in the parentheses. (2) The system-GMM estimations are clustered at the industry level (3) *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 6-6 Robustness Test 7 The Impact of FDI and Returnees' Specialized Clustering on Local Firm TFP: Alternative Measurements of Control Variables

VARIABLES	(1) OLS TFP	(2) GMM TFP	(3) OLS TFP	(4) GMM TFP	(5) OLS TFP	(6) GMM TFP
Firm age	-0.103***	-0.110***	-0.103***	-0.109***	-0.103***	-0.109***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
Firm size	0.926***	0.952***	0.926***	0.952***	0.926***	0.952***
	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
State-ownership	-0.062***	-0.022*	-0.063***	-0.022*	-0.061***	-0.022*
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Profitability	0.203***	0.205***	0.203***	0.205***	0.203***	0.206***
	(0.011)	(0.013)	(0.011)	(0.013)	(0.011)	(0.014)
R&D intensity	0.101***	0.100***	0.101***	0.100***	0.101***	0.100***
	(0.001)	(0.005)	(0.001)	(0.004)	(0.001)	(0.006)
Knowledge stock	0.062***	0.063***	0.061***	0.063***	0.062***	0.063***
	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)
Speed	0.011***	0.026	0.011***	0.025***	0.011	0.026***
	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.005)
Irregularity	-0.001*	-0.001*	-0.001*	-0.001*	-0.001*	-0.001*
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
IMR	0.030***	0.019***	0.029***	0.020***	0.028***	0.020***
	(0.007)	(0.001)	(0.007)	(0.001)	(0.007)	(0.001)
L.TFP		0.013***		0.013***		0.013***
		(0.002)		(0.002)		(0.002)
FDI	0.201***	0.216***	0.222***	0.220***	0.213***	0.228***
	(0.018)	(0.015)	(0.021)	(0.020)	(0.025)	(0.022)
Concentration	0.012***	0.011***			0.014***	0.012***
	(0.003)	(0.003)			(0.004)	(0.003)
FDI*Concentration	0.157**	0.124***			0.115***	0.131***
	(0.076)	(0.039)			(0.034)	(0.041)
Competition			0.007***	0.023**	0.008***	0.023**
			(0.001)	(0.011)	(0.001)	(0.010)
FDI*competition			-0.007	-0.309***	-0.009	-0.310***
			(0.010)	(0.008)	(0.008)	(0.008)
Constant	0.479***	0.282***	0.487***	0.285***	0.480***	0.284***
	(0.020)	(0.069)	(0.021)	(0.073)	(0.021)	(0.071)
Year dummies	Included	Included	Included	Included	Included	Included
Industry dummies	Included	Included	Included	Included	Included	Included
Region dummies	Included	Included	Included	Included	Included	Included
R-squared	0.542	N/A	0.543	N/A	0.543	N/A
AR(1)	N/A	0.000	N/A	0.000	N/A	0.000
AR(2)	N/A	0.349	N/A	0.384	N/A	0.410
Hansen	N/A	0.120	N/A	0.118	N/A	0.165
Observations	36,844	36,844	36,844	36,844	36,844	36,844

Notes: (1) Robust standard errors are reported in the parentheses. The system-GMM estimations are clustered at the industry level. *** p < 0.001, ** p < 0.01, * p < 0.05.

6.5 Discussion and Conclusion

This chapter explores how the specialized agglomeration of returnees, including the concentrated and competitive clustering structures of returnees, influences the FDI knowledge spillovers process and contributes to the local production efficiency. I construct the specialized agglomeration index of returnees based on the panel dataset of ZSP firms over the period 2007-2013 and employ the system generalized method of moments (GMM) model with Heckman corrections to obtain the empirical evidence. Previous studies have investigated the role of returnees in the FDI spillovers process and suggested that returnees with cross-cultural advantages can close the knowledge disparity between foreign and local firms, thereby facilitating the FDI externality (Wang, 2015; Wei et al., 2017). However, existing literature only considers the role of returnees from an individual level. As knowledge transmission requires frequent and effective interpersonal interaction, the clustering of returnees would also affect the local absorption of FDI spillovers and exert externality to local firms (Bai et al., 2018; Ning et al., 2016b). Nevertheless, limited research has examined the structural role of returnees.

Based on the analysis of a unique and comprehensive dataset of high-tech firms in ZSP science park in Beijing for the period from 2007 to 2013, I made the first attempt to translate the clustering structures of returnees into the moderating role in helping domestic firms absorb FDI knowledge spillover and improve firms' productivity. I employ the system GMM method with the Heckman corrections to address the potential selection bias and endogenous issues.

My empirical results first confirm a positive knowledge spillover effect of FDI, which is in line with the current literature that contends that the FDI knowledge spillovers would improve local productivity. Second, the results suggest that the concentrated clustering structure of returnees would not only directly improve local firms' productivity but also positively moderate the relationship between FDI spillovers and local productivity. Finally, my findings indicate that while the competitive clustering structure of returnees would positively affect local firms' productivity, it might exert a negative moderating effect on the FDI spillovers process.

The empirical results in this chapter will be helpful to policymakers in host regions and have several implications as follows. First, in line with previous literature, I confirm a positive FDI knowledge spillovers effect on local production efficiency. In emerging markets, keeping open and attracting foreign investment can still benefit local firm performance as their superior technology and management practice would spill to local firms and stimulate their technological improvement. Second, my research suggests that, in addition to attracting individual returnees to relocate by firms, one needs to consider their collective and catalytic role in local firms' innovation environment. On the one hand, returnees with several years' experience of working or studying in developed countries can be a very special labor force for emerging markets. On the other hand, I have provided a more holistic view of the returnee clustering effects in facilitating FDI spillovers. I show that returnees are an important bonding agent to recontextualize and disseminate FDI knowledge. A concentrated industrial structure of returnees enhances FDI spillovers effects on local productivity, while a competition structure damps the FDI spillovers effect on local productivity. My study thus helps policymakers and business leaders to refocus their innovation promotion efforts and consider different strategies and policies for maximizing FDI spillovers through returnees in the local technological environment.

This chapter still has some limitations that need to be further investigated in future research. First, the empirical context is China, which has demonstrated unprecedented rapid growth, industrial agglomeration, and a substantial inflow of FDI and returnees within a short period. The effects might be more pronounced than in other host countries. Future studies could explore my proposed mechanism in a cross-country setting to generalize my conclusions further. Secondly, I follow the knowledge externalities literature to estimate the spillover effects and do not consider the effects of firm-level individual returnee mobility, reverse knowledge spillovers, nor specific modes of knowledge transfers such as licensing or strategic alliances as I am limited by my data to do so. Finally, other factors might moderate the relationships I have identified here. Future studies can build on my study and explore potential contingencies such as the returnee clustering effect based on vertical and horizontal linkages, the nature of technologies or products such as the degree of their modularization or technology intensity.

Chapter 7 How Does FDI Knowledge Spillovers Improve Local Firms Productivity? The Role of Returnees' Diversified Agglomeration

7.1 Introduction

In the last chapter, I confirmed the positive impact of FDI spillovers on Chinese local firms' productivity. I also demonstrated that the specialized agglomeration, including concentration and competition, of returnees, can affect the FDI knowledge spillovers process. I confirmed that the returnees' concentrated clustering structure can not only improve the local firm productivity but also facilitate the local absorption of FDI knowledge diffusion. In contrast, returnees' competitive clustering can only promote the local productivity while is not beneficial for the FDI knowledge externalities. Nevertheless, as indicated before, FDI spillovers are dependent not only on the within industries interactions of returnees, but also on across-industries interactions (Crespo and Fontoura, 2007). Diversified structures are also the key type of agglomeration, which includes the related and unrelated variety and depicts the across-industries interactions. However, our understanding of their impacts on FDI spillovers remains limited. In this chapter, I discuss the third research question of this Ph.D. thesis: "*How does returnees' diversified agglomeration, including related and unrelated variety, affect FDI knowledge spillovers and local firm productivity?*"

As argued in Chapter 3, FDI has been widely considered as an essential external technological source for emerging markets (Ben Hamida & Gugler, 2009; Tian, 2007). Multinational enterprises (MNEs) bring not only advanced technology but also superior management paradigm, which can be assimilated and imitated by the local firms so that they might promote local firm performance (Haskel et al., 2007; Zhang et al., 2010). In current literature, many scholars in international business and economics have investigated the relationship between FDI knowledge spillovers and local firms' growth in productivity, innovation, and financial performance, as well as contingencies such as absorptive capabilities, industrial structure, and openness of regions that enable FDI knowledge spillovers (Crespo & Fontoura, 2007; Tian, 2010; Wang et al., 2017b). Yet, the empirical evidence is mixed and inconclusive. A growing strand of research further argues that it is still needed to clarify the contingent factors that can affect the direction and magnitude of FDI knowledge spillovers (Inkpen, Minbaeva, & Tsang, 2019a; Rojec & Knell, 2018).

The previous literature suggests that it is the interaction between individuals that can create and diffuse technological knowledge and human capital plays an important role in transferring FDI knowledge spillovers (Crespo & Fontoura, 2007; Girma, 2005). In the emerging market context, the returnees are a special labor force and have made great contributions to local firms, as seen in the rise of East Asian tigers and India (Wang, 2011). They have been theorized as a cohesive group with distinctive cross-cultural social capital that can absorb and convey advanced knowledge external and new to the region (Filatotchev et al., 2009; Useche, Miguelez, & Lissoni, 2019). With cross-culture knowledge and language advantages, many scholars have investigated and explained the returnees' impact on the local firm innovation performance, internationalization process, entrepreneurial venture formation, and the localization of their foreign knowledge as well as the closing of the knowledge disparity between local firms and MNEs (Filatotchev et al., 2011; Liu et al., 2014). Although extensive research has emphasized the role of individual returnees in FDI spillovers, little is known about how the agglomeration of returnees across industries affect the local firm performance and the FDI knowledge diffusion process. As indicated before, from an agglomeration economy view, the returnees in emerging markets also do not work alone, but rather interact with other returnees. Since knowledge transmission is built around interpersonal contacts for knowledge sharing, idea generation, and learning (Cohen & Levinthal, 1990; Tian, 2010), the returnees' distribution in different industries might form diversified industrial structures, which can also influence the idea creation, learning opportunities and local absorptive capabilities (Chesbrough, 2013; Enkel et al., 2009). Upon a background of attracting return talents in emerging economies, a clear understanding of the structural role of returnees is important for policymakers and firm managers to introduce these talents and learn from FDI technologies effectively.

Indeed, different types of diversified clustering structures of returnees might affect the local firms' productivity and the local absorption of FDI spillovers differently. This is because knowledge across technologically related sectors seems to be recombined and used in new ways. It is difficult for firms to fully recognize, assimilate and exploit technologies from other sectors that are unrelated to their internal knowledge basis (Castaldi et al., 2015, Nooteboom, 2000). Prior literature has coined the concept of "industrial related variety and unrelated variety" (related and unrelated variety thereafter), enabling the diversified agglomeration to be divided into two specific dimensions in a given area (Essletzbichler, 2005, Frenken et al., 2007, Boschma and Iammarino, 2009). Therein, related variety refers to industrial variety in terms of shared and complementary competencies. Unrelated variety refers to the degree of technological independence across different sectors (Castaldi et al., 2015, Dettmann et al., 2015). Although the current literature has emphasized the importance of returnees in knowledge dissemination, the diversified agglomeration effect of returnees on the extent of FDI knowledge diffusion has not been explained both theoretically and empirically.

To this end, this chapter borrows the concept of diversified agglomeration from the cluster theory to analyse the structural role of returnees in the local firm performance and FDI spillovers process in China. It mainly focuses on two types of returnees' diversified clustering structures, namely related and unrelated variety. More specifically, the related variety depicts the distribution of returnees in related industries, while the unrelated variety represents the distribution of returnees in industries that shares limited competence and resources (Bucci & Ushchev, 2020; Guevara-Rosero et al., 2019). I use a unique statistical census collected by the Zhongguancun Science Park (ZSP) Administrative Committee from 2007 to 2013 to test my hypotheses and employ the system generalized method of moments (GMM) model with Heckman corrections to address the potential endogeneity and selection bias issue in this research.

This chapter makes two major contributions. First, I contribute to the cluster literature by examining the externalities of returnees' diversified agglomeration structure. The agglomeration view has long provided arguments centered on which sectoral composition of local interpersonal interactions across industries can affect the local development (Feldman & Audretsch, 1999; Hervas-Oliver et al., 2018; Martin et al., 2011). Drawing upon the cluster approach, I confirm that both returnees' related and unrelated variety can promote local firms' productivity, which improves our knowledge on returnees and adds more empirical evidence to the cluster theory.

Second, I contribute to the FDI literature by examining the contingency effect of returnees at the aggregated level from a diversified agglomeration perspective, which bridges cluster theory and knowledge spillovers literature. It is widely acknowledged that, due to its tacit and contextual nature, knowledge transmission is built around interpersonal contacts for knowledge sharing, idea generation, and learning (Antonelli & Scellato, 2013; Fleming & Sorenson, 2001). The local interpersonal interactions across different industries may thus serve as a precondition for knowledge spillovers to occur (Castaldi et al., 2015; Frenken et al., 2007). I conjecture that different agglomeration types of returnees as distinctive groups should have different impacts on FDI spillovers and moderate their effect on local firms' productivity. In doing so, I provide a more integrated perspective and new evidence on the contingencies of FDI spillovers through exploring the attributes of the locality to contribute to the FDI externalities literature.

Similar to the previous chapter, the research context in this chapter also is Zhongguancun Science Park (ZSP) in China. The MNEs and returnees have played important role in the growth of ZSP. The comprehensive firm-level dataset of ZSP firms provides us with a long period of observation for analyzing the impact of FDI and returnees on local firm performance. Moreover, the ZSP comprises 16 sub-parks and the returnees are clustered in several industries and sub-park, which allows me to distinguish the returnees' related and unrelated variety in the dataset and examine their impacts on local firms' productivity and FDI knowledge spillovers.

The remaining is structured as follows. The second section reviews the literature and develops the hypotheses. The third section describes the data, variable measurements, and methodology. The fourth presents the analysis of the econometric results. Finally, the conclusions and limitations are shown in the fifth section.

7.2 Theoretical Framework and Hypotheses Development

7.2.1 FDI Knowledge Spillovers and Diversified Agglomeration

Based on the literature review in Chapter 3, it is acknowledged that MNEs may bring intended or unintended impact to local firms (Inkpen et al., 2019b; Newman et al., 2015). From the knowledge spillovers view, when MNEs cannot fully appropriate their superior technologies, their surplus knowledge can spill across organizational boundaries the local firms they interact with (Inkpen et al., 2019b; Liang, 2017). However, whether FDI knowledge spillovers can benefit local production efficiency remains inconclusive. Some scholars find positive FDI spillover effects on local firms' productivity, as foreign firms provide opportunities for local ones to observe and imitate new technologies and management practice (Jude, 2016; Newman et al., 2015; Ning et al., 2016b; Tian, 2007, 2010; Wang & Wu, 2016; Zhang et al., 2014).

Some channels theorized several broad underlying spillover mechanisms. These include 'demonstration effects' where local firms emulate foreign technologies and managerial practices through observation of MNEs' local operations; labor mobility enables local workers to gain knowledge and experience from MNEs and then migrate to domestic firms and apply their learning locally; competition induced by MNEs incentivizes domestic firms to learn, upgrade and adopt new knowledge or technologies to improve efficiency; finally, there is the pecuniary relationship established between foreign and local firms through the ‘vertical or horizontal linkage’ effect (Meyer & Sinani, 2009; Rojec & Knell, 2018; Zhang et al., 2014). In contrast, other studies argue that FDI can threaten indigenous technological upgrading because the MNEs with advanced business acumen can outcompete local firms, whose market share would be crowded out (Buckley et al., 2010; Rojec & Knell, 2018). For example, Ben Hamida and Gugler (2009) demonstrate that FDI does not have significant direct spillover effects in Switzerland. Ashraf et al. (2016) also indicate that FDI may not have a significant impact on total factor productivity (TFP) in both developing and developed countries.

Based on mixed evidence of FDI impacts, many researchers begin to explore contingent factors that can affect the direction and magnitude of FDI knowledge spillovers (Javorcik & Spatareanu, 2011; Ning et al., 2016b; Zhang et al., 2010). For instance, some scholars, like Girma (2005), Jin et al. (2018) and Sultana and Turkina (2020), confirm that the FDI externalities can be contingent on the local absorptive capacity to utilize newly acquired knowledge, reflected in the amount of local human capital, employment mobility, and R&D activities. Wang et al. (2012) and Wang et al. (2017b) also suggest that the level of MNE presence and their entry process might affect the FDI spillovers process. Wang et al. (2013) and Yi et al. (2015) indicate that the local institutional development is also a critical contingency factor for FDI knowledge diffusion. For example, local governments would establish science and technology innovation centers, just like Zhongguancun Science Park in Beijing, and Donghu Science Park in Wuhan, to attract foreign enterprises so that provides more opportunities for local firms to access advance technologies brought by FDI (Dong et al., 2019; Xie et al., 2018). Moreover, within the science centers, they can further establish business incubators and run summits or dialogues to strengthen the communication between foreign firms and local firms as well as public sectors so that promote the their cooperation and knowledge exchange (Tan, 2006; Trunina et al., 2018). Through such formal interfirm interactions, local firms can benefit more from FDI knowledge spillovers. Despite the volume of research, given that the knowledge transmission is tacit and requires direct, unintended, and repeated interpersonal contacts, a growing literature begin to indicate that the major contingencies for FDI spillovers faced by firms are in their environment and suggest that the interpersonal interactions within industries might affect the knowledge diffusion process (Ning & Wang, 2018; Ning et al., 2016b).

Indeed, the cluster literature has proposed that the intensity and scope of interpersonal interactions across different industries would affect local absorptive capability and knowledge diffusion (Hervas-Oliver et al., 2018; Ketelhöhn, 2006; Mantegazzi et al., 2020). Jacob (1969) contends that the most important sources of knowledge spillovers are external to the industry in which firms operate. The geographical agglomeration of firms belonging to different industries triggers the exchange of ideas, encourages knowledge spillovers, thus generating new knowledge that can be incorporated in the production of other industries. Therefore, from a Jacobian perspective, a more diversified industrial structure within a local area can influence knowledge dissemination. Frenken, Van Oort, and Verburg (2007) claim that the concept of Jacobian externalities encompasses two different economic effects at the same time, the complementary knowledge spillover effect and the portfolio effect. In this case, they decompose the diversified agglomeration into the related variety and the unrelated variety of the industrial structure and many following researchers suggest that the two dimensions of diversification might exert different impacts on local knowledge externalities.

7.2.2 Returnees' Diversified Agglomeration, FDI Spillovers, and Local Productivity

As discussed earlier, FDI externalities are often accompanied by contingencies. Following the work of Dess and Beard (1984), an extensive literature has indicated the major contingencies faced by firms is in their environment. Building upon the agglomeration literature, I explore the diversified clustering structural effect of returnees. Much of the clustering literature has elucidated whether the intensity and scope of interpersonal interactions in the same industry or different industries are more conducive to learning and innovation at the regional level (Boschma, 2017). Frenken et al. (2007) further suggest that diversified industrial composition can exhibit both knowledge spillovers and industry portfolio effects. The idea of technological relatedness for innovation has since been adopted to explain a range of phenomena related to knowledge spillovers such as the development of the regional technological system, research collaboration, and labor mobility (Boschma, 2017; Timmermans & Boschma, 2014). Recent literature proposes that the role of related and unrelated varieties reflects regional absorptive capability and should be considered a precondition for knowledge externalities to occur (Fritsch & Kublina, 2018).

In the emerging markets context, the returnee is a critical type of human capital that can close the knowledge disparity between foreign and local firms (Filatotchev et al., 2011; Lin et al., 2016). The unique characteristic of returnees is that they have been exposed to different institutional environments and knowledge contexts. Their language advantages, new technological capabilities, world-class business knowledge, and familiarity with both their home and host countries enable them to identify gaps and capitalize on cross-border differences or distances (Lin et al., 2016; Wang, 2015). Previous literature has broadly demonstrated that returnees can improve firms' innovation, productivity, and provide the prerequisites necessary for successful imitation from external knowledge (Liu et al., 2019; Pruthi, 2014).

While the current line of inquiry emphasizes the role of individual returnees in FDI knowledge diffusion, the role of returnee agglomeration has not been fully understood. As individual returnees embody tacit knowledge, their agglomeration might also enlarge the scale and scope of their interactions within industries to generate knowledge externalities (Ma et al., 2018; Pruthi, 2014). Their social networks should form a distinctive group structure that significantly influences local absorption and diffusion of FDI spillovers. Intense network density is likely to be associated with a higher innovative activity. I incorporate the work of Frenken et al. (2007) into our studies of returnees' industrial composition and split the diversity into related and unrelated structures to examine their effects on FDI spillovers.

7.2.2.1 The Impact of Returnees' Related Variety Clustering Structure

(1) Returnees' Related Variety Clustering Structure and Local Firm Productivity

The traditional related variety is defined as local interactions in industries that are related to each other in terms of the degree of shared or complementary competencies (Boschma, 2017). When applying this concept to depict the returnees' industrial related variety, it refers to an industrial structure that returnees are clustered in related industries. I contend that a related variety of returnees would directly improve the local firms' productivity.

First, variety in related activities conducted by returnees can stimulate productive interactions and cross-fertilisations within a region. The traditional arguments on agglomeration suggest that a related variety of industrial structures facilitate worker mobility across industries as the knowledge bases are technologically related. It is widely acknowledged that labor mobility is an essential channel for knowledge spillovers since knowledge resides in persons and their turnover may bring new knowledge to other firms (Fu, 2012; Lu et al., 2017). Regions with a variety of returnees associated with related education and/or related tasks may facilitate matching externalities in the labor market, as well as inter-firm knowledge transfers through returnees' mobility. Moreover, due to the geographical proximity and cognitive proximity of returnees from different industries, local firms may benefit from exposure to multiple ideas and experiences; this exposure allows them to think creatively and develop novel combinations of knowledge (Levinthal and March 1993; Levitt and March 1988).

Second, the related variety of returnees provides technological relatedness that helps local firms understand and absorb the new knowledge/technologies developed and transferred by the other (Asheim et al., 2011). The related variety approach argues that complementary firms/ sectors share similar technological capabilities and competencies (Boschma, 2015). It facilitates the building up of inter-industry linkages and contributes to technological upgrading within a larger product scope. the knowledge transfers and dissemination across different industries can only exist when the industries share related competencies (Frenken et al., 2007). Previous literature has emphasized the importance of cognitive distance in explaining the impact of a diversified industrial structure on effective interactions across industries and firms (Boschma & Iammarino, 2009a; Boschma, Minondo, & Navarro, 2012). Interpersonal interactions require a small cognitive distance, and when the cognitive distance is large, it might be difficult for local firms to identify, imitate, and communicate on the technologies diffused by other industries (Cainelli & Ganau, 2019; Content et al., 2019). Moreover, the supplier chains can disseminate new knowledge from technology-producing industries to technology-using ones (Hauknes and Knell, 2009). As the level of knowledge relatedness influences the opportunities for firms to innovate (Breschi et al. 2003), when returnees are clustered in related industries, this industrial structure is likely to have a positive effect on local firm productivity.

(2) Returnees' Related Variety Clustering Structure and FDI Knowledge Spillovers

Besides the positive direct impact of returnees' related variety on local firm productivity, I argue that a related variety of returnee agglomeration should be more conducive to FDI knowledge spillovers that increase local firms' productivity in three main ways.

First, the clustering of returnees in related sectors can enlarge the scope of FDI spillovers through recontextualization to spur local technological upgrading. Cohen and Levinthal (1990) underscore the importance of knowledge relatedness for absorptive capabilities and learning. Foreign knowledge may contain regulatory, cognitive, and normative elements distant from those of host countries. The knowledge that was developed elsewhere under a different socio-cultural environment thus requires recontextualization to be cognitively relevant to local firms (Buckley et al., 2002; Lin et al., 2016). Returnees' home and host country embeddedness equip them with an understanding of cross-border institutional, cultural and social nuances, local market conditions, and the overall strategies of MNEs. They can align foreign knowledge with local values and behavioral norms to establish its legitimacy and mitigate the liability of foreignness (Dougherty & Heller, 1994; Tzeng, 2018b). They are also in a brokerage position to access valuable information and select opportunities that are better suited for solving local problems (Lin et al., 2016; Wang, 2015). The clustering of returnees in related sectors at the aggregated level thus can form a broader related knowledge base to recontextualize and complement FDI technologies from various domains. It expands the scope and availability of recontextualized FDI knowledge spillovers to be considered by local firms.

Secondly, returnees in related clustering can serve as “boundary spanners” that ease FDI knowledge assimilation across related fields to increase local firms’ productivity. Skill- and technology-related sectors often overlap with social networks (Neffke & Henning, 2013). Frequent and repeated interactions among knowledge actors and multiple domains beyond organizational boundaries are essential for sharing and learning contextual knowledge (Balland & Rigby, 2017; Szulanski & Jensen, 2006). This process involves knowledge transmitters and recipients to develop mutual trust through socialization (Fu, Diez, & Schiller, 2013). Returnees’ ethnic ties, common language, and culture create a sense of social identity with their local counterparts, building up the trust to form informal networks for information exchange and interactive learning (Filatotchev et al., 2011; Lin et al., 2019). These make returnees boundary spanners that are more suited for bridging formal organizational and technological boundaries both within and across local firms and MNEs to overcome cross-domain information and cross-cultural social barriers (Mäkelä et al., 2019). When returnees agglomerate at the aggregated level in related sectors, their scope in spanning across multiple related and complementary technological fields expands with the degree of their variety. It creates more linkages for otherwise disconnected foreign and local firms and increases multidomain knowledge acquisition and learning opportunities for local firms to increase productivity.

Thirdly, the clustering of related returnees lowers the cost of absorbing FDI spillovers and experimenting with foreign knowledge components for local firms to increase productivity. Given the cognitive and technological proximity, related clustering of returnees can intensify communication and reduce ambiguity for cross-fertilization of ideas. Solutions or inventions developed in one industry can be incorporated by another in related variety structures (Buerger & Cantner, 2011). This lowers the cost of foreign knowledge spillovers and allows foreign knowledge components to be spread across several related technological domain activities locally. A related structure also enables local pooling of resources and capabilities that induces economies of scale in pecuniary production of discrete or complementary combinations, yielding synergies among industries' innovation activities (Ng, 2007). As returnees in related sectors conglomerate with shared competence and an increasing scale, domestic firms can consider a border set of multidomain technologies brought by FDI at a low cost. Moreover, the presence of returnees should also be particularly favorable for domestic firms to reduce costs through mitigating uncertainty, overcome technology transfer barriers, and correct information transmission errors associated with a disparity in resources, culture, and knowledge gaps with foreign firms (Bai et al., 2017; Lin et al., 2019; Tzeng, 2018b; Wang, 2015). The higher the degree of related varieties of returnees clustering, the higher the probability that FDI externalities can be absorbed and learned by host country firms. Taken together I posit:

Hypothesis 1a: The related variety structure of returnees can improve the local firm productivity.

Hypothesis 1b: the related variety structure of returnees positively moderates the relationship between FDI technological spillovers and the level of local firm productivity.

7.2.2.2 The Impact of Returnees' Unrelated Variety Clustering Structure

(1) Returnees' Unrelated Variety Clustering Structure and Local Firm Productivity

Unrelated variety indicates that local interactions are diversified into very different types of industrial activities (Frenken et al., 2007). Borrowing from this traditional definition, the returnees' industrial unrelated variety thus depicts that the returnees are clustered in unrelated industries. In contrast to related variety, skills and competencies in unrelated industries do not overlap (Boschma & Iammarino, 2009b). The previous literature on whether unrelated variety can promote local technological upgrading does not reach a consensus. Some previous studies contend that the existence of a diverse set of unrelated activities may not foster learning and innovation as the distance of cognitive proximity is high (Kemeny & Storper, 2015). However, others suggest that the unrelated variety brings a portfolio effect on regional development, and one of the advantages of this positioning would be that an economic downturn in one sector would not negatively affect the other sectors in a territory with a high degree of unrelated variety (Castaldi et al., 2015; Tavassoli & Carbonara, 2014). The unrelated variety would thus provide a stable environment for local firms to improve their productivity. In this study, I contend that the unrelated variety of returnees would exert a positive effect on local development based on the following two reasons.

First, based on the portfolio effect assumption, I argue that a higher unrelated variety of returnees can be conducive to the local technological upgrading by providing a stable environment for economic development. The portfolio effect perspective emphasizes the importance of unrelated variety on protecting the region from the economic shocks since if the shocks hit specific industries, the region can still develop with other unrelated sectors

(Aarstad et al., 2016; Zabala-Iturriagagoitia et al., 2020). Similarly, the unrelated variety of returnees can also contribute to regional and firm productivity, as their clustering in unrelated industries would also provide a more resilient agglomeration structure and enable stable economic growth.

Second, apart from the portfolio effect, I contend that an unrelated variety of returnees would bring more novel technological spillovers to local firms. Previous studies have found that unrelated variety comprises sectors with dissimilar knowledge anchored in different institutional domains, thereby making them arguably suited for cross-sector learning and knowledge exchange (Aarstad et al., 2016; Naldi, Criaco, & Patel, 2020). Moreover, the unrelated diversification of returnees is important to avoid regional lock-ins and ensure long-term competitive advantage (Boschma and Capone, 2015; Pinheiroi et al., 2018). In this case, returnees clustered in unrelated industries might provide abundant unrelated knowledge for inter-industrial interactions and contribute to the improvement of local firms' radical technological upgrading.

(2) Returnees' Unrelated Variety Clustering Structure and FDI Knowledge Spillovers

Although the unrelated clustering structure of returnees might directly stimulate local firm performance, I expect that it would negatively moderate the effect of FDI spillovers on local firm productivity. First, an unrelated variety of returnees might provide the region with the flexibility to re-orient toward accommodating the flow of FDI in technological fields different from host regions' technological trajectories. However, returnees clustered in unrelated sectors can lack technological relatedness and organizational proximity to warrant effective communication and coordination across foreign and local firm boundaries to disseminate FDI knowledge. The frequency and scope of their interactions are also limited given the lack of cognitive proximity and complementarities. It can be difficult for local firms without prior knowledge to understand the nature of new foreign knowledge even if they have been recontextualized by returnees from distant fields. Consequently, local firms find it more ambiguous to reconfigure foreign knowledge to increase productivity.

Second, a high unrelated variety of returnees clustering may limit the combinatory potential of FDI knowledge components for local firms to pursue more complex technological inventions. Although the unrelated variety of returnee structure might recontextualize a wider variety of distant FDI knowledge, recombinant innovation in unrelated sectors does not produce rapid economic benefits (Castaldi et al., 2015; Fleming & Sorenson, 2001). Knowledge combination with unrelated components often shows a high level of uncertainty, cognitive distance, knowledge tacitness, and lack of economic input-output linkages, all of which hamper the loci and local firms to achieve scale economies in knowledge reproduction and increase the cost of recombination. Moreover, unrelated industrial activities and human resources can be loosely embedded without substantial pecuniary linkage and demand in the regional context, and are more likely to disappear and exit in the region (Boschma, 2017; Grillitsch et al., 2018). Regions have been found to discourage knowledge creation that does not match its related and existing capabilities and technological areas (Fritsch & Kublina, 2018; Neffke, Henning, & Boschma, 2011). Unrelated variety of returnees do not facilitate local firms to absorb FDI spillovers. Hence, I propose:

Hypothesis 2a: The unrelated variety structure of returnees can improve the local firm productivity.

Hypothesis 2b: the unrelated variety structure of returnees negatively moderates the relationship between FDI technological spillovers and the level of local firm productivity.

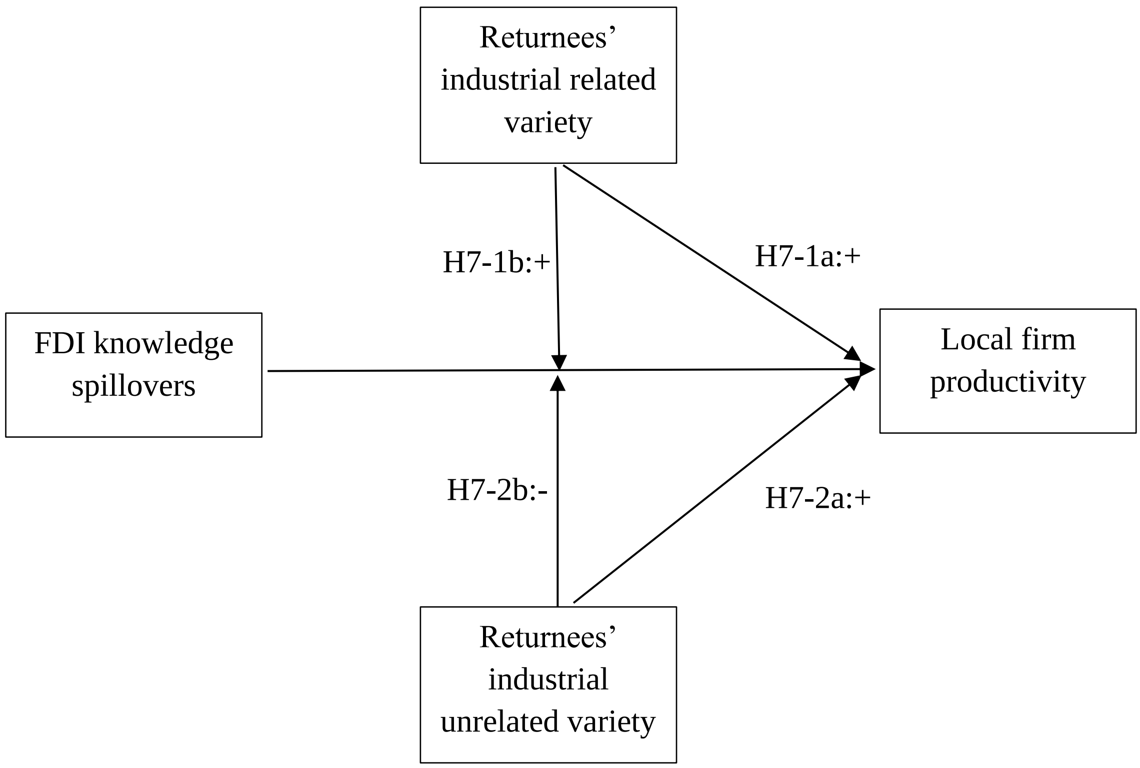

Figure 7-1 The Theoretical Framework of Chapter 7

7.3 Data and Methodology

7.3.1 Data

Our data was uniquely constructed through a combination of two sources. All annual financial and registration information was compiled from the annual census filed by firms under the request of the ZSP Administrative Committee. In this paper, I focus on the structural rather than individual effects of returnees. The number of returnee employees is obtained from the census, which does not contain personal information. For the period the data is available to us, I initially obtained 12,821 firms with 56,905 firm-year observations, out of which 1,288 are foreign firms with 6,114 firm-year observations. I then required firms to have at least three years' financial information during the observation period to calculate the variables. After excluding firms with missing values, I obtained a final unbalanced sample of 45,544 firms' years' observations for 7,920 unique local firms and with more than 50,000 returnee employees from 2007 to 2013.

7.3.2 Methodology

As suggested in Chapter 4 and similar to Chapter 5 and Chapter 6, I mainly use the system-GMM estimation with Heckman corrections to test my hypothesis. Firstly, there might exist selection bias concerning issues about returnees as the recruitment of returnees might not be random as firms with more competitive capability and generous financial support would be more affordable for those highly skilled talents (Liu et al., 2010a; Roberts & Beamish, 2017).

This means that the returnees might be self-selected in different local firms. In this case, I use the Heckman two-stage model to deal with such potential selection problems (Certo et al., 2016; Heckman, 1979). In the first stage, I estimated a Probit model of a firm's propensity of recruiting returnees (Certo et al., 2016; Heckman, 1979). I mainly the industrial average wage has been included in the first stage as the exclusive restriction to check the appropriateness of the Heckman two-stage estimation. Previous literature suggests that the industrial average wage would influence a firm's propensity to recruit but not directly affect focal firms' performance (Kenney et al., 2013; Wang, 2020). In this case, it can serve as a proper exclusive restriction. Then, based on the Probit estimation, I can calculate an inverse Mill's ratio (IMR). The IMR represents the selection hazard of a firm's recruitment activity of returnees (Certo et al., 2016; Heckman, 1979). I include the IMR in the second stage to check the existence of the selection effect. More specifically, if IMR is significant in the second stage, then it suggests that there indeed exists selection issues and it is proper to use the Heckman two-stage models.

In the second stage, a firm's production efficiency might be influenced by its previous status and it may experience economic shocks every year (Comin, 2017; Lagos, 2006), which requires to consider a dynamic panel structure to study the dynamic trend of dependent variables and the short-term or long-term effects of independent variables on dependent variables. And I mainly use the system-GMM method and include the IMR to deal with the dynamic panels since it chooses more proper instrument variables (Roodman, 2009; Su & Liu, 2016). In the formal estimation, I use the first differences of the second and third lags and lag level of dependent and explanatory variables as instruments. Moreover, following the direction of Windmeijer (2005), I conducted the Arellano–Bond (AR) tests and the Hansen's J test to check their overall validity in the system-GMM analysis. A proper system-GMM estimation requires the result of the AR (1) test to be significant, and the result of the AR (2) test and the Hansen's J test to be insignificant.

7.4 Empirical Results

7.4.1 Descriptive Analysis

Table 7-1 presents the descriptive statistics and correlation matrix of each variable in the full sample. Similar to Chapters 5 and 6, for the full sample, the mean level of TFP is 3.019 and the FDI is 0.182, which means that on average the share of foreign firms' total assets over the four-digit industrial total asset is 18.2 percent. Moreover, the average age of firms is 8.120 and the average size is 74.281 million Chinese RMB. As for returnees' diversified industrial agglomeration, the mean level of related variety is 0.506 and the average unrelated variety is 229. The correlation coefficients between the dependent variable and independent variables are relatively high, which indicates that the choice of variables is good. The same as indicated in Chapters 5 and 6, the positive correlation (0.038) between TFP and FDI preliminarily indicates that there might exist a positive relationship between FDI knowledge spillovers and local firms' productivity. I further tested the potential multicollinearity by not only examining the value of the correlation coefficient between independent variables but also calculating the variance inflation factor (VIF). All values are within the acceptable range and the average VIF is 2.21.

7.4.2 Econometric Results

Table 7-2 presents the results of the Heckman first-stage regression. I first employ the Probit model to estimate the propensity of local firms to recruit returnees and then obtain the inverse mill ratio (IMR), which can be used in the Heckman second stage estimation to control for the potential selection bias problems. It can be seen that firm age is significantly negatively associated with the firms' propensity to recruit returnees. In contrast, firm size, profitability, R&D intensity, knowledge stock and firm average wage all positively influence whether local firms recruit returnees. As for the exclusion restriction, the industrial average wage is positively related to the propensity of the recruitment activities. After the probit estimation, I can calculate the IMR for each observation and then include it in the section stage system-GMM estimation.

Table 7-1 Summary Statistics and Correlation Matrix

	Mean	Std.Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14
TFP	3.019	1.327	1.000													
FDI	0.182	0.166	0.038	1.000												
Returnee related variety	0.134	0.045	0.041	0.007	1.000											
Returnee unrelated variety	2.056	0.261	-0.043	0.079	0.124	1.000										
Firm age	8.120	4.938	0.233	-0.103	0.368	-0.002	1.000									
Firm size	74.281	296.259	0.401	0.088	0.057	0.003	0.186	1.000								
State-ownership	0.051	0.220	-0.003	0.070	-0.003	0.020	0.238	0.068	1.000							
Profitability	-0.006	0.141	0.239	-0.028	-0.004	-0.003	0.113	0.090	0.036	1.000						
R&D intensity	0.011	0.030	0.223	0.013	-0.264	-0.021	-0.077	0.092	0.013	0.095	1.000					
Knowledge stock	0.793	3.164	0.374	0.067	0.098	-0.015	0.127	0.284	0.015	0.100	0.191	1.000				
Speed	0.506	2.779	-0.007	0.069	0.069	0.012	0.015	-0.006	0.007	-0.008	-0.006	0.017	1.000			
Irregularity	229	821	0.042	0.220	0.280	-0.042	0.143	0.003	-0.026	0.000	-0.112	0.026	0.156	1.000		
Returnee concentration	1.153	10.000	0.017	0.013	-0.030	-0.122	-0.007	0.005	-0.005	0.002	0.009	0.012	0.003	-0.005	1.000	
Returnee competition	1.856	2.272	-0.079	-0.219	0.124	0.137	0.037	-0.061	-0.011	-0.006	-0.079	-0.038	-0.057	-0.105	-0.009	1.000

Notes: (1) size 100 million, R&D million; (2) R&D intensity is measured by 1 million RMB per employee. (3) Firm size is the total assets of a firm and is measured by 1 million RMB. (4) All absolute correlation coefficients greater than 0.006 are significant at the 5% level.

Table 7-2 The Propensity of Firms to Recruit Returnees: the First-Stage Heckman Probit Model

VARIABLES	Returnee dummy (0=No, 1=Yes)		
	Estimate	S.E	P-value
Firm age	-0.119***	(0.018)	[0.000]
Firm size	0.153***	(0.006)	[0.000]
Profitability	-0.255***	(0.036)	[0.000]
State-ownership	-0.003	(0.043)	[0.946]
R&D Intensity	0.062***	(0.006)	[0.000]
Knowledge stock	0.200***	(0.014)	[0.000]
Firm average wage	0.072***	(0.008)	[0.000]
Industrial average wage	0.120***	(0.018)	[0.000]
Constant	-1.622***	(0.296)	[0.000]
Year dummies	Included		
Industry dummies	Included		
Region dummies	Included		
LR Chi^2	3069.40		
Pseudo R^2	0.169		
Log-likelihood	-12623.451		
Observations	40,566		

Notes: (1) Robust standard errors are reported in the parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 7-3 reports the results of our baseline linear ordinary least squares (OLS) regressions in models 1, 3, 5, 7, and 9 and SGMM regressions in models 2, 4, 6, 8, and 10. I first only incorporate the independent and control variables (Models 1 and 2). Then, I incorporate the interaction between FDI and returnees' related variety and unrelated variety in models 3-10. Models 10 is my full model, which is used to interpret my main findings. Regarding the control variables, similar to previous chapters, my results suggest that firm size, profitability, R&D intensity, and knowledge stock are significantly positively associated with local firms' productivity, while firm age has a significantly negative impact. Concerning state ownership, the coefficients are inconsistent or insignificant across models. Moreover, the coefficients for the returnees' industrial repatriation speed are significantly positive, while for returnees' industrial repatriation irregularity are significantly negative, which are corresponds with the findings in the last chapter.

Concerning the system-GMM results, to begin with, I first inspect the consistency, which requires valid instruments and the absence of a second-order serial correlation, of the System-GMM estimators. When I include only the independent and control variables in the full sample and matched sample, and the significant Hansen J-statistic of system-GMM is most likely a result of omission effects. Apart from this, Hansen J-statistics across all our models support the view that the instrumental variables are uncorrelated to residuals. Moreover, the Arellano–Bond (AR) tests in all models indicate that the first-order AR (1) and not the second-order AR (2) error terms are serially corrected. This finding also supports the use of system GMM for our estimation in our models.

Hypothesis 1a proposes that returnees' related variety clustering structure would strengthen the local firms' performance. As indicated before, variety in related activities conducted by returnees can stimulate productive interactions and cross-fertilisations within a region. Moreover, the related variety of returnees provides technological relatedness that helps local firms understand and absorb the new knowledge/technologies developed and transferred by the other (Asheim et al., 2011). As the level of knowledge relatedness influences the opportunities for firms to innovate (Breschi et al. 2003), when returnees are clustered in related industries, this clustering structure is likely to have a positive effect on local firm productivity. As shown in Table, In model 10, the system-GMM results reveal that the primary effect of related variety is positively and significantly related to the local firms' productivity ($\beta = 0.393$, $p<0.01$), which means that a higher level of returnees' related variety clustering structure would improve the local firms' total factor productivity. The results thus confirm my hypothesis 1a.

Hypothesis 1b suggests that the positive relationship between FDI knowledge spillovers in an industry and local firms' productivity becomes stronger as the returnees' related variety clustering structure increases. As argued before, the clustering of returnees in related sectors can enlarge the scope of FDI spillovers through recontextualization and lowers the cost of absorbing FDI spillovers and experimenting with foreign knowledge components to spur local technological upgrading. Moreover, returnees in related clustering can serve as "boundary spanners" that ease FDI knowledge assimilation across related fields to increase local firms' productivity. It can be seen that in Table, in Model 10, the interaction term *FDI*Related Variety* in system-GMM estimation are positive and significant ($\beta = 0.261$, $p<0.01$), showing a positive moderating effect of returnees' related variety on the relationship between FDI and local firms' total factor productivity. The results thus support my hypothesis 1b.

By contrast, hypothesis 2a proposes that the returnees' unrelated variety clustering would promote local firms' productivity. I mainly contend that a higher unrelated variety of returnees can be conducive to the local technological upgrading by providing a stable environment for economic development. It can also bring more novel technological spillovers to local firms, so that avoid regional lock-ins and ensure long-term competitive advantage and improve radical production efficiency (Boschma, 2017). As shown in Table 7-3, In model 10, the system-GMM results reveal that the primary effect of unrelated variety is positively and significantly related to the local firms' productivity ($\beta = 0.261$, $p<0.05$), which means that the returnees' unrelated clustering would improve the local firms' total factor productivity. The results thus strongly confirm my hypothesis 2a.

Hypothesis 2b suggests a negative moderating role of returnees' unrelated variety in the FDI knowledge spillovers. As argued before, an unrelated variety of returnees may lack technological cognitive proximity so that limits the combinatory potential of FDI knowledge components for local firms to improve their performance. It can be seen that in Table 7-3, in Model 10, the interaction term *FDI*Unrelated variety* in system-GMM estimation are negative and significant for full and matched sample ($\beta = -0.385$, $p<0.01$), showing a negative moderating effect of returnees' unrelated clustering in the relationship between FDI and local firms' total factor productivity. The results thus support my hypothesis 2b.

Table 7-3 The Impact of FDI and Returnees' Diversified Clustering on Local Firm TFP: OLS and system-GMM Models

VARIABLES	(1) OLS TFP	(2) GMM TFP	(3) OLS TFP	(4) GMM TFP	(5) OLS TFP	(6) GMM TFP	(7) OLS TFP	(8) GMM TFP	(9) OLS TFP	(10) GMM TFP
Firm age	0.002	-0.355***	-0.004	-0.105*	-0.018*	-0.454***	-0.005	-0.320***	-0.005	-0.225***
	(0.010)	(0.034)	(0.010)	(0.055)	(0.010)	(0.048)	(0.010)	(0.038)	(0.010)	(0.026)
Firm size	0.426***	0.298***	0.429***	0.133**	0.435***	0.123***	0.428***	0.323***	0.428***	0.122***
	(0.003)	(0.040)	(0.003)	(0.055)	(0.003)	(0.011)	(0.003)	(0.051)	(0.003)	(0.011)
State-ownership	-0.072***	-0.109	-0.070***	-0.160	-0.083***	-0.317	-0.070***	-0.270	-0.070***	-0.159
	(0.024)	(0.283)	(0.024)	(0.216)	(0.024)	(0.271)	(0.024)	(0.224)	(0.024)	(0.293)
Profitability	0.132***	0.190***	0.135***	0.184***	0.133***	0.137***	0.135***	0.108**	0.135***	0.137***
	(0.022)	(0.039)	(0.022)	(0.137)	(0.022)	(0.027)	(0.022)	(0.046)	(0.022)	(0.028)
R&D intensity	0.706***	0.062**	0.701***	0.109	0.724***	0.074**	0.705***	0.068**	0.705***	0.068**
	(0.036)	(0.031)	(0.036)	(0.132)	(0.036)	(0.032)	(0.036)	(0.031)	(0.036)	(0.032)
Knowledge stock	0.284***	0.037***	0.286***	0.049**	0.305***	0.036***	0.287***	0.048***	0.287***	0.035***
	(0.009)	(0.010)	(0.009)	(0.025)	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)
Speed	0.042**	0.020**	0.046**	0.029***	0.064***	0.016**	0.046**	0.017**	0.046**	0.016**
	(0.019)	(0.010)	(0.019)	(0.010)	(0.019)	(0.008)	(0.019)	(0.08)	(0.019)	(0.008)
Irregularity	-0.007***	-0.005***	-0.007***	-0.004***	-0.006***	-0.004***	-0.007***	-0.002**	-0.007***	-0.004***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Concentration	0.012**	0.009**	0.013***	0.011**	0.010**	0.011**	0.014***	0.011**	0.014***	0.011**
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Competition	0.015***	0.013***	0.011***	0.011***	0.014***	0.013***	0.011***	0.010**	0.011***	0.013***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.005)	(0.003)	(0.002)
IMR	0.033**	0.024***	0.025*	0.027***	0.032***	0.029***	0.025**	0.034***	0.025*	0.029***
	(0.015)	(0.008)	(0.015)	(0.009)	(0.012)	(0.011)	(0.012)	(0.013)	(0.015)	(0.010)

L.TFP		0.760***		0.835***		0.864***		0.766***		0.885***
		(0.026)		(0.034)		(0.015)		(0.032)		(0.014)
FDI			0.252***	0.199***	0.133**	0.198***	0.182***	0.188***	0.162***	0.176***
			(0.035)	(0.067)	(0.053)	(0.063)	(0.042)	(0.043)	(0.033)	(0.036)
Related variety					0.559***	0.315**			0.322***	0.393***
					(0.099)	(0.149)			(0.123)	(0.052)
FDI* Related variety					0.409**	0.503*			0.281**	0.261**
					(0.218)	(0.293)			(0.132)	(0.128)
Unrelated variety							0.107***	0.207**	0.079***	0.111**
							(0.021)	(0.096)	(0.023)	(0.057)
FDI* Unrelated variety							-0.277**	-0.318**	-0.255***	-0.385***
							(0.089)	(0.163)	(0.069)	(0.127)
Constant	0.562***	1.176***	0.599***	1.031***	0.944***	1.073***	0.357***	1.244***	0.426***	1.282***
	(0.122)	(0.248)	(0.122)	(0.291)	(0.050)	(0.172)	(0.128)	(0.452)	(0.131)	(0.153)
Year dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Industry dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Region dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
R-squared	0.682	N/A	0.682	N/A	0.697	N/A	0.697	N/A	0.698	N/A
AR(1)	N/A	0.000	N/A	0.000	N/A	0.000	N/A	0.000	N/A	0.000
AR(2)	N/A	0.353	N/A	0.396	N/A	0.310	N/A	0.372	N/A	0.341
Hansen	N/A	0.144	N/A	0.172	N/A	0.158	N/A	0.253	N/A	0.220
Observations	36,844	36,844	36,844	36,844	36,844	36,844	36,844	36,844	36,844	36,844

Notes: (1) Robust standard errors are reported in the parentheses. (2) The system-GMM estimations are clustered at the industry level (3) *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

7.4.3 Robustness tests

I further conduct several robustness tests to check the extent to which my results are affected by alternative specifications. Similar to Chapter 5, I use alternative measurements of FDI, which include the share of foreign firm R&D investment over the total industrial R&D investment and the share of foreign firms over the total firms. Both of the FDI measurement is at the four-digit industry level. I present the results in Table 7-4. Models 1-4 are estimated with the share of FDI R&D as the independent variable, while Models 5-8 are the share of FDI capital. As shown in the full models 4 and 8, in both circumstances, the interactions between FDI and the moderating variables are significant and in line with my hypotheses. Taking these robustness tests enables us to reduce the concerns about the misspecification of FDI. Moreover, Second, I consider the whole sample of ZSP firms, which means to include the foreign firms of ZSP in our estimation. I present the results in Table 7-5. Compared with the baseline results in Table 7-3, the estimation results from the whole sample are most consistent, while with a relatively lower level of significance. Overall speaking, this robustness test still supports our main findings. Finally, I consider alternative measurements of the control variables. I measure firm size by the firm's total employment, firm R&D intensity by the firm's R&D investment per sale, and firm knowledge stock by the firm's total patent stock in the past five years. I present the OLS and system-GMM estimation results in Table 7-6. As shown, using the alternative specification of control variables does not change my main findings.

Table 7-4 Robustness Test 8 The Impact of FDI and Returnees' Diversified Clustering on Local Firm TFP: Alternative Measurements of FDI Presence

	FDI R&D share				FDI firm share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM
VARIABLES	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP
Firm age	-0.767***	-0.446***	-0.363***	-0.406***	-0.395***	-0.451***	-0.375***	-0.412***
	(0.089)	(0.048)	(0.053)	(0.048)	(0.053)	(0.048)	(0.053)	(0.048)
Firm size	0.178***	0.124***	0.123***	0.120***	0.126***	0.123***	0.122***	0.119***
	(0.021)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
State-ownership	-0.321	-0.257	-0.094	-0.189	-0.117	-0.378	-0.125	-0.275
	(0.829)	(0.262)	(0.285)	(0.255)	(0.284)	(0.300)	(0.292)	(0.288)
Profitability	0.042***	0.039**	0.034**	0.037**	0.068***	0.067***	0.066***	0.069***
	(0.015)	(0.017)	(0.017)	(0.017)	(0.027)	(0.027)	(0.027)	(0.027)
R&D intensity	0.064**	0.071**	0.077**	0.072**	0.083**	0.074**	0.078**	0.072**
	(0.033)	(0.032)	(0.033)	(0.032)	(0.032)	(0.032)	(0.033)	(0.032)
Knowledge stock	0.036***	0.037***	0.038***	0.040***	0.033***	0.036***	0.037***	0.040***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Speed	0.017**	0.022*	0.019**	0.019*	0.018*	0.017*	0.015**	0.017**
	(0.009)	(0.012)	(0.010)	(0.012)	(0.010)	(0.010)	(0.006)	(0.008)
Irregularity	-0.004**	-0.004***	-0.004***	-0.004***	0.005***	-0.005***	-0.005***	-0.006***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Concentration	0.010**	0.010**	0.009*	0.010**	0.011**	0.011**	0.009*	0.010**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Competition	0.005**	0.004**	0.003*	0.004**	0.004*	0.004**	0.003*	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

IMR	0.158***	0.119***	0.119***	0.120***	0.117***	0.119***	0.121***	0.120***
	(0.024)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
L.TFP	0.880***	0.866***	0.878***	0.878***	0.864***	0.864***	0.873***	0.876***
	(0.118)	(0.015)	(0.014)	(0.014)	(0.015)	(0.015)	(0.014)	(0.015)
FDI	0.162**	0.113**	0.264**	0.245**	0.068***	0.054***	0.066***	0.063***
	(0.087)	(0.052)	(0.125)	(0.107)	(0.015)	(0.015)	(0.018)	(0.016)
Related variety		0.227**		0.182**		0.140***		0.134***
		(0.109)		(0.089)		(0.018)		(0.015)
FDI* Related variety		0.142**		0.120***		0.081**		0.070**
		(0.060)		(0.033)		(0.040)		(0.030)
Unrelated variety			0.051***	0.064***			0.050***	0.058***
			(0.011)	(0.014)			(0.012)	(0.015)
FDI* Unrelated variety			-0.117***	-0.083***			-0.068***	-0.098***
			(0.037)	(0.021)			(0.021)	(0.023)
Constant	0.124	0.116	0.136	0.089	0.096	0.125	0.098	0.138
	(0.084)	(0.177)	(0.224)	(0.194)	(0.190)	(0.178)	(0.220)	(0.196)
Year dummies	Included	Included	Included	Included	Included	Included	Included	Included
Industry dummies	Included	Included	Included	Included	Included	Included	Included	Included
Region dummies	Included	Included	Included	Included	Included	Included	Included	Included
AR(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	0.362	0.431	0.355	0.387	0.415	0.447	0.486	0.411
Hansen	0.105	0.128	0.122	0.173	0.200	0.195	0.184	0.118
Observations	36,844	36,844	36,844	36,844	36,844	36,844	36,844	36,844

Notes: (1) Robust standard errors are reported in the parentheses. (2) The system-GMM estimations are clustered at the industry level (3) *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 7-5 Robustness Test 9 The Impact of FDI and Returnees' Diversified Clustering on Local Firm TFP: The Estimation on the Whole Sample

VARIABLES	(1) GMM TFP	(2) GMM TFP	(3) GMM TFP	(4) GMM TFP	(5) GMM TFP
Firm age	-0.367***	-0.042	-0.487***	-0.325***	-0.259***
	(0.032)	(0.054)	(0.046)	(0.036)	(0.025)
Firm size	0.278***	0.148***	0.129***	0.284***	0.128***
	(0.040)	(0.045)	(0.011)	(0.050)	(0.011)
State-ownership	-0.105	0.115	-0.108	-0.146	-0.123
	(0.286)	(0.231)	(0.283)	(0.277)	(0.292)
Profitability	-0.067**	0.485***	0.026	-0.070*	0.028
	(0.033)	(0.110)	(0.023)	(0.038)	(0.023)
R&D intensity	0.033	0.161	0.042	0.034	0.034
	(0.029)	(0.118)	(0.030)	(0.030)	(0.030)
Knowledge stock	-0.030***	0.024	-0.031***	-0.040***	-0.029***
	(0.009)	(0.024)	(0.009)	(0.009)	(0.009)
Speed	0.033***	0.038***	0.023***	0.017**	0.013***
	(0.011)	(0.011)	(0.001)	(0.007)	(0.001)
Irregularity	-0.004***	-0.005***	-0.004***	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Concentration	0.015***	0.014***	0.016***	0.013***	0.007*
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
Competition	0.012***	0.013***	0.013***	0.019**	0.012**
	(0.002)	(0.003)	(0.002)	(0.008)	(0.006)
IMR	-0.215***	-0.210***	-0.230***	-0.229***	-0.211***
	(0.008)	(0.009)	(0.010)	(0.013)	(0.010)
L.TFP	0.779***	0.892***	0.862***	0.795***	0.885***
	(0.025)	(0.032)	(0.014)	(0.030)	(0.014)
FDI		0.175***	0.098*	0.145**	0.123**
		(0.058)	(0.057)	(0.066)	(0.056)
Related variety			0.064*		0.078*
			(0.38)		(0.043)
FDI* Related variety			0.337**		0.202*
			(0.143)		(0.111)
Unrelated variety				0.022**	0.031*
				(0.010)	(0.018)
FDI* Unrelated variety				-0.075**	-0.066*
				(0.039)	(0.037)
Constant	0.043	0.033	0.047	0.050	0.033
	(0.254)	(0.298)	(0.196)	(0.445)	(0.153)
Year dummies	Included	Included	Included	Included	Included

Industry dummies	Included	Included	Included	Included	Included
Region dummies	Included	Included	Included	Included	Included
AR(1)	0.000	0.000	0.000	0.000	0.000
AR(2)	0.441	0.374	0.514	0.488	0.512
Hansen	0.119	0.243	0.156	0.162	0.299
Observations	40,566	40,566	40,566	40,566	40,566

Notes: (1) Robust standard errors are reported in the parentheses. (2) The system-GMM estimations are clustered at the industry level (3) *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 7-6 Robustness Test 10 The Impact of FDI and Returnees' Diversified Clustering on Local Firm TFP: Alternative Measurements of Control Variables

VARIABLES	(1) OLS TFP	(2) GMM TFP	(3) OLS TFP	(4) GMM TFP	(5) OLS TFP	(6) GMM TFP
Firm age	-0.053***	-0.106***	-0.053***	-0.106***	-0.053***	-0.102***
	(0.005)	(0.026)	(0.005)	(0.026)	(0.005)	(0.026)
Firm size	0.926***	0.952***	0.926***	0.952***	0.930***	0.952***
	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
State-ownership	-0.061***	-0.034*	-0.062***	-0.021*	-0.059***	-0.035*
	(0.012)	(0.020)	(0.012)	(0.012)	(0.012)	(0.021)
Profitability	0.203***	0.305***	0.203***	0.432***	0.205***	0.405***
	(0.011)	(0.033)	(0.011)	(0.041)	(0.011)	(0.026)
R&D intensity	0.101***	0.125***	0.101***	0.089***	0.101***	0.092***
	(0.001)	(0.005)	(0.001)	(0.002)	(0.001)	(0.002)
Knowledge stock	0.062***	0.043***	0.062***	0.043***	0.064***	0.051***
	(0.004)	(0.001)	(0.004)	(0.001)	(0.005)	(0.001)
Speed	0.011***	0.020***	0.011***	0.016***	0.011***	0.019***
	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)	(0.006)
Irregularity	-0.006***	-0.017***	-0.005***	-0.012***	-0.006***	-0.011**
	(0.001)	(0.005)	(0.001)	(0.004)	(0.001)	(0.005)
Concentration	0.011***	0.019***	0.011***	0.016***	0.011***	0.016***
	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)
Competition	0.005**	0.009***	0.005**	0.009***	0.005**	0.009***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
IMR	0.030***	0.040***	0.030***	0.042***	0.030***	0.044***
	(0.007)	(0.011)	(0.007)	(0.011)	(0.007)	(0.011)
L.TFP		0.613***		0.613***		0.612***
		(0.022)		(0.022)		(0.022)
FDI	0.115***	0.111***	0.103*	0.132*	0.103**	0.125***
	(0.021)	(0.011)	(0.055)	(0.073)	(0.050)	(0.047)
Related variety	0.145***	0.218***			0.260***	0.324***
	(0.056)	(0.024)			(0.060)	(0.024)
FDI* Related variety	0.169	0.177***			0.270**	0.288**
	(0.117)	(0.040)			(0.129)	(0.143)
Unrelated variety			0.028***	0.043***	0.024**	0.033***
			(0.010)	(0.012)	(0.012)	(0.009)
FDI* Unrelated variety			-0.112*	-0.121*	-0.205*	-0.309**

			(0.061)	(0.065)	(0.112)	(0.156)
Constant	0.474***	0.277***	0.543***	0.377***	0.530***	0.351***
	(0.021)	(0.064)	(0.029)	(0.076)	(0.030)	(0.068)
Year dummies	Included	Included	Included	Included	Included	Included
Industry dummies	Included	Included	Included	Included	Included	Included
Region dummies	Included	Included	Included	Included	Included	Included
R-squared	0.869	N/A	0.869	N/A	0.868	N/A
AR(1)	N/A	0.000	N/A	0.000	N/A	0.000
AR(2)	N/A	0.275	N/A	0.342	N/A	0.352
Hansen	N/A	0.188	N/A	0.146	N/A	0.103
Observations	36,844	36,844	36,844	36,844	36,844	36,844

Notes: (1) Robust standard errors are reported in the parentheses. (2) The system-GMM estimations are clustered at the industry level (3) *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

7.5 Discussion and Conclusion

This chapter investigates how the diversified agglomeration of returnees, including the related and unrelated clustering structures of returnees, influences the FDI knowledge spillovers process and contributes to the local production efficiency. Based on the analysis of a unique and comprehensive dataset of high-tech firms in ZSP science park in Beijing for the period from 2007 to 2013, I made the first attempt to translate the clustering structures of returnees into the moderating role in helping domestic firms absorb FDI knowledge spillover and improve firms' productivity. My empirical results suggest that the related variety clustering structure of returnees would not only directly improve local firms' productivity but also positively moderate the relationship between FDI spillovers and local productivity. Moreover, my findings indicate that while the unrelated variety clustering structure of returnees would positively affect local firm performance, however, it might exert a negative moderating effect on the FDI spillovers process.

My contribution is that I advanced the FDI spillovers literature by unraveling both aggregate and contingency effects of returnee interactions in explaining their catalytic and collective role in FDI knowledge diffusion. FDI spillovers as an unintended knowledge transfer source indeed depend on interpersonal interactions and the extent to which recipient firms are embedded in their environment (Inkpen et al., 2019a; Ning et al., 2016b). While prior studies have examined mainly the role of individual returnees such as knowledge broker, spanner, or labor mobility effects on local innovation (Lin et al., 2016; Liu et al., 2010a; Wang, 2015), the aggregated interconnectedness among returnees from diverse industries has not been explained both theoretically and empirically. Drawing upon the agglomeration literature, I explore the aggregated clustering effect of returnees and further divide the structure into related and unrelated varieties. Due to overlapping between skill- and technology-related sectors and social networks (Neffke & Henning, 2013), I consider the social interaction aspect of returnees in its aggregated form to understand the technological environmental impact on local innovation.

I conjectured and empirically tested the moderating effects of different returnee clustering types on FDI technological spillovers, as well as conceptualizing the underlying mechanism between returnees clustering, local productivity, and FDI spillovers. My findings advance our understanding that returnees clustering has an impact on local technological upgrading. Their different dimensions have created different interactive environments in disseminating FDI spillovers. Firms can benefit from their innovation-enhancing effect due to the technological and social proximity formed under these structures (Balland & Rigby, 2017; Boschma, 2017). Although both clustering types create an environment for recontextualizing FDI externalities, only related variety clustering exhibits positive effects when FDI presents. The related returnee clustering promotes local productivity as the flow of complementary and multi-domain knowledge flourishes, while unrelated clustering tends to dampen it due to a lack of cognitive proximity. This provides an additional explanation for the mixed effect of FDI spillovers as well as underscoring the need for a theoretical understanding of the context of knowledge diffusion in firms' innovation through the lens of returnees' clustering structure. I disentangle the role of different returnee clusterings and provide a detailed account of how they affect FDI externalities for host country firms to improve their productivity.

My study helps policymakers and business leaders to refocus their innovation promotion efforts and consider different strategies and policies for maximizing FDI spillovers through returnees in the local technological environment. In emerging markets, keeping open and attracting foreign investment can still benefit local firms as their superior technology and management practice would spill to local firms and stimulate their technological improvement. Moreover, my research suggests that, in addition to attracting individual returnees to relocate by firms, one needs to consider their collective and catalytic role in local firms' innovation environment. I show that returnees are an important bonding agent to recontextualize and disseminate FDI knowledge. A related variety clustering structure of returnees enhances FDI spillovers effects on local productivity, while an unrelated variety structure damps the FDI spillovers. My study thus helps policymakers and business leaders to refocus their innovation promotion efforts and consider different strategies and policies for maximizing FDI spillovers through returnees in the local technological environment.

This chapter also has certain limitations. First, the empirical context is China, which has demonstrated unprecedented rapid growth, industrial agglomeration, and a substantial inflow of FDI within a short period. The effects might be more pronounced than in other host countries. Future studies could explore our proposed mechanism in a cross-country setting to generalize our conclusions further. Secondly, I follow the knowledge externalities literature to estimate the spillover effects and do not consider the effects of firm-level individual returnee mobility, reverse knowledge spillovers, nor specific modes of knowledge transfers such as licensing or strategic alliances as I am limited by our data to do so. Thirdly, other factors might moderate the relationships I have identified here. Future studies can build on our study and explore potential contingencies such as the returnee clustering effect based on vertical and horizontal linkages, the nature of technologies or products such as the degree of their modularization or technology intensity. I provide a useful contextual perspective on FDI externalities and the development of host country firms' performance.

Chapter 8 Discussions and Conclusions

This Ph.D. thesis aims to advance our understanding of the relationship between inward FDI and Chinese high-tech firm productivity by considering the contingency role of returnees at the aggregated level. My findings help us to explain how Chinese local firms exploit the advanced FDI and highly-skilled returnees to accelerate their technological upgrading. In the emerging country context, FDI is a critical external technological source originating externally to the recipient countries, as its advanced knowledge can spill to local firms and help them improve their technologies (Crespo & Fontoura, 2007; Ning et al., 2016). In recent years, returnees, as another important knowledge source that can bring external knowledge to emerging markets, have also received increasing attention. Although FDI and returnees are essential, many studies examine them separately and limited literature has examined the interplay between them in facilitating local firm performance. How to effectively utilize the two resources and promote local productivity is a critical issue. In this Ph.D. thesis, I integrate these two streams of literature into a theoretical framework, and I hope to investigate the contingent role of returnees at the aggregated level in FDI knowledge diffusion. It contributes to the understanding of FDI and returnees literature from a contingency perspective.

The current studies have extensively examined the role of FDI in China's development and argued that the presence of foreign firms may bring intended or unintended diffusion to local firms (Inkpen et al., 2019b; Liang, 2017; Newman et al., 2015). However, given the knowledge disparity between foreign and local firms, the emerging market context needs to improve their absorptive capacity to learn from FDI spillovers more effectively. Emerging markets have gradually realized the importance of returnees in the improvement of local absorptive capacity (Liu et al., 2014). This is because that the returnees, who have studied and/or worked outside the Chinese mainland for several years, often understand multiple cultures, possess technological and managerial expertise, so that they can close the knowledge disparity between the MNEs and local firms (Lin et al., 2016; Liu et al., 2014).

However, the current literature only considers the role of individual returnees in the FDI knowledge dissemination, limited attention has been placed on their structural effect, and does not consider the dynamic process of returnees' repatriation. Indeed, learning is process-dependent and needs time to occur. The returnees also need time to deal with the readjustment issues after they return to their homeland before they play a role in promoting the local absorptive capability (Li et al., 2012; Lin et al., 2019). The time-based characteristics of the returnees' industrial repatriation therefore should be considered in the process of absorbing FDI knowledge diffusion. In this thesis, I argue that the extent of FDI spillovers depends upon the returnees' dynamic repatriation into local industries.

Moreover, as individual returnees embody tacit knowledge, their agglomeration might also enlarge the scale and scope of their interactions to generate knowledge externalities (Ma et al., 2018; Pruthi, 2014). From an agglomeration economy view, the returnees in the labor markets do not work alone, but rather aggregate in certain industries and form specific clustering structures, which would influence their interpersonal interactions and knowledge dissemination and further contribute to the local firms' productivity. The returnees' specialized concentration in a certain industry would magnify this interactive learning process and improve the entire industrial knowledge base, however, the returnees' fierce competition within the industry might influence their role in helping local firms to establish stable business relationships with foreign firms (Bai et al., 2018; Zheng et al., 2016). Besides, based on the interindustry cognitive distance perspective, the diversified clustering of returnees in related or unrelated sectors would also impact their contributions to the local absorptive capacity. It is necessary to move beyond the conventional concept of industrial agglomeration and differentiate the impact of specialized and diversified clustering structures of returnees on the local firm performance and FDI diffusion. Hence, this Ph.D. thesis hopes to provide a better understanding of the interplay between FDI spillovers and returnees in promoting local firm performance based on evidence from China.

8.1 Findings Regarding the Role of Returnees' Process in FDI Knowledge Spillovers

In Chapter 5, I found that FDI knowledge indeed exerts a positive spillover effect on the Chinese high-tech firms' TFP over the period 2005-2013 in Zhongguancun Science Park. The findings confirm the existence of positive FDI spillover effects in host country firms, which is in line with the wider findings of the literature on positive FDI knowledge and technology spillovers (Liang, 2017; Meyer & Sinani, 2009; Orlic et al., 2018). Local firms can identify, imitate, and assimilate the advanced FDI knowledge and then promote their performance.

Besides, I found strong evidence that the extent of FDI spillovers is contingent on the returnees' repatriation process into local industries. The time-based attributes of returnees' repatriation, namely speed and irregularity, can also play different moderating roles in the relationship between FDI spillovers and local firm performance. Industries with a fast pace of returnees' repatriation can benefit more from the FDI technology transfer and dissemination, as when the returnees speed up their entry into the industry, they may transfer more new knowledge and accelerate the improvement of local absorptive capacities. By contrast, an irregular pace of returnees' repatriation into the local industries often leads to an unstable working environment and competition effects, which restricts their role in absorbing the FDI advanced technology. The findings are in line with the existing arguments regarding the individual role of returnees in facilitating the FDI knowledge externalities (Choudhury, 2015; Liu et al., 2014; Liu et al., 2010b). My findings explain the mechanism through which the returnees' repatriation process affects FDI spillovers: a regular and quick returnees' repatriation allows Chinese local firms to benefit more from knowledge spillovers from MNEs.

Moreover, I confirm the direct impact of returnees' repatriation into local industries on the local firms' performance. More specifically, a fast pace of returnees' repatriation brings more knowledge flow into local firms at a quicker speed, so that promotes the local firm productivity. In contrast, an irregular pace of returnees' repatriation might restrict the local technological upgrading, as the irregularity would restrict the returnees' readjustment process so that constrain their contributions to the local firm performance. My results, therefore, contribute to the understanding of the relationship between the returnees as an important external knowledge source and local productivity, based on evidence from Chinese high-tech firms.

8.2 Findings Regarding the Role of Returnees' Specialized Agglomeration in FDI Spillovers

In Chapter 6, I further confirm the positive FDI knowledge spillover effect on the Chinese high-tech firms over the period 2005-2013. Moreover, I explored the impact of the returnees' specialized clustering structures, namely concentrated and competitive structures, on local firm productivity and FDI knowledge spillovers. I found both the concentrated and competitive structure of returnees can directly promote technological upgrading in Chinese high-tech firms. The main arguments lie in that industrial co-location can magnify the returnees' interactive learning process and sharing of ideas and information, so that promotes the knowledge externalities of returnees to the local firms (de Vor & de Groot, 2010; Viladecans-Marsal, 2004). Moreover, in a highly competitive industrial environment, the returnees in many different firms would compete for scarce resources and improve their capability so that contribute more to local firms (Bucci & Ushchev, 2020; Plummer & Acs, 2014). My findings thus advance our understandings of the collective impact of returnees on local technological upgrading.

More importantly, I found that only the concentrated clustering structure of returnees enhances FDI spillovers to local firms; the competitive clustering structure does not. When returnees are concentrated in specific industries, it can provide a specialized knowledge base and can create more linkages between foreign and local firms to facilitate the FDI externalities. However, a competitive clustering structure of returnees might be difficult for the returnees to collectively establish stable business linkage across the organizational boundary, which restricts the local absorptive capacity. My findings, therefore, complement the conventional arguments about the role of individual returnees in promoting knowledge dissemination. Although the individual returnees can act as knowledge brokers or organizational spanners to help local firms learn from FDI advanced technology, their interactions within industries can strengthen or weaken their role in knowledge externalities.

8.3 Findings Regarding the Role of Returnees' Diversified Agglomeration in FDI Spillovers

In Chapter 7, I also found a positive FDI knowledge spillover effect on the Chinese high-tech firms. Besides, I investigated the role of the returnees' diversified clustering structures, namely related variety and unrelated variety, on local firm productivity and FDI knowledge spillovers. I found the both of the related and unrelated variety clustering structures of returnees directly promote local firms' productivity during the period of 2005-20013 in Zhongguancun Science Park. My findings correspond with the existing debates about the impact of industrial diversification on regional technological development. The traditional arguments on agglomeration suggest that technological relatedness can help local firms understand the new knowledge/technologies developed and transferred by the other (Boschma & Iammarino, 2009b; Frenken et al., 2007). Moreover, the unrelated variety can provide portfolio effect and ensure a stable environment for technological upgrading (Cainelli & Iacobucci, 2012; Castaldi et al., 2015). I make the first attempt to apply the traditional "industrial diversification" perspective to analyse the collective role of returnees and therefore deepen our understanding of the relationship between clustering structures of returnees and local firm performance, based on evidence from Chinese high-tech firms.

More importantly, I found that the FDI spillovers are contingent on the diversified structures of the returnee. However, only the concentrated clustering structure of returnees enhances local firms; the competitive clustering structure does not. This is because when returnees are clustered in related industries, the interindustry cognitive proximity enables them to intensify their communication and interactions, which would enlarge the scope of FDI knowledge spillovers and ease the FDI knowledge assimilation across related fields to increase local firms' productivity. In contrast, when returnees are clustered in unrelated industries, the lack of technological relatedness and organizational proximity may not permit the returnees to have effective communication and coordination across foreign and local firm boundaries to disseminate FDI knowledge. My findings, therefore, complement the impact of individual returnees on the FDI knowledge spillovers and confirm that their interactions across industries would also influence their role in knowledge externalities.

8.4 Theoretical Contributions to the Literature

As reviewed in Chapter 2, this thesis is built upon FDI knowledge spillovers theory and the cluster theory to investigate how returnees can influence local firm performance and the absorption of FDI knowledge spillovers. The leading theory is the FDI knowledge spillovers theory and I hope to add to this theory by identifying a new channel, i.e., returnees at the aggregated level, for the dissemination of FDI knowledge spillovers. And the cluster theory is applied to explain the structural role of returnees in the FDI knowledge spillovers process. I hope to fill some of the research gaps indicated in the chapter of Literature Review, and provide some insightful empirical evidence.

First, the most important contribution of this thesis is that, it adds to FDI knowledge spillovers literature by investigating the contingent role of returnees at the aggregated level as a new factor of absorptive capacity. Building upon the perspective of knowledge spillovers, FDI has been considered as a key external source of advanced knowledge and technologies for emerging economies (Crespo & Fontoura, 2007; Ning et al., 2016). When MNEs cannot fully internalize the value of their superior technologies and skills, their knowledge can leak across the organizational boundary and emerging market firms can absorb that spilled knowledge to improve their technological capabilities (Inkpen et al., 2019). However, as the culture, language, political background are different between foreign and local firms, the knowledge absorption is not so straightforward (Rojec & Knell, 2018). Local firms need to develop their absorptive capabilities before they can learn from FDI advanced technologies (Girma, 2005; Tian, 2007). The previous literature has already acknowledged the role of individual returnees, such as knowledge brokers and organizational spanners, in foreign knowledge diffusion (Liu et al., 2014; Liu et al., 2010b; Wang, 2015). However, limited attention has been placed on their structural effect and does not consider the dynamic perspective. One possible reason is that the current research lacks detailed firm-level or industry-level data of labor structure, and not all emerging markets have experienced an increasing number of returnees, which restricts the previous research to analyse the impact of returnees from a collective perspective (Filatotchev et al., 2011; Tzeng, 2018b). Thanks to the detailed ZSP data, I can construct variables about the structure of returnees at the aggregated level and analyse the collective role of returnees in FDI knowledge dissemination. Moreover, as the context is ZSP, which is the most innovative cluster in China, my findings might provide some basis for other high-tech industrial clusters to better exploit their resources on FDI and returnees.

Second, it links the FDI knowledge spillover literature to returnees' repatriation process from a process-dependent perspective and expands the existing theoretical frameworks of contingent factors in FDI spillovers. The existing studies have suggested that the returnees' repatriation is not a static process and mainly focused on how the individual returnees enter into the local labor market and play a role (Lin et al., 2019; Liu et al., 2010b; Qin et al., 2017). However, they seldom discuss the benefits and disadvantages of the time-based characteristics of returnees' repatriation into local industries that affect knowledge transfers and dissemination. This thesis moves beyond the individual level of returnees to an aggregated industry level with a process-dependent perspective and makes the first attempt to explain how FDI knowledge spillovers are contingent on the time-based characteristics of returnees' repatriation process.

Third, it extends the FDI knowledge spillovers literature by applying the cluster theory to examine the underlying mechanism about how returnees' agglomeration influences local absorptive capacities and FDI knowledge dissemination. The cluster theory was first proposed by Alfred Marshall in 1890 and it suggested that greater economic activity would occur when many firms cluster in one area (Baptista & Swann, 1999; Porter, 1998). The later researchers have enriched the cluster theory and have recognized that more detailed classifications are needed for local clustering structures. Therefore, they further propose the concepts of industrial specialization, competition, and diversification, etc. (Feldman & Audretsch, 1999; Frenken et al., 2007). Drawing upon the cluster theory, I make the first attempt to disentangle the returnee agglomeration into specialized and diversified clustering structures and provide a detailed account of how they affect FDI externalities for host country firms to improve their productivity. The returnees' clustering structures would influence their interpersonal interactions and their different dimensions have created different interactive environments in disseminating FDI spillovers (de Vor & de Groot, 2010; Hervas-Oliver et al., 2018). It has also shown that the specialized and diversified agglomerations are preconditions for knowledge spillovers to occur, and they would exert distinct impacts on the knowledge dissemination process (Ning et al., 2016a; Ning et al., 2016b; Wang et al., 2016a). This Ph.D. thesis takes a further step towards showing that FDI spillovers are enhanced by concentrated and related variety clustering structures of returnees, but are diminished by competitive and unrelated variety clustering structures. This provides an additional explanation for the mixed effect of FDI spillovers as well as underscoring the need for a theoretical understanding of the context of knowledge diffusion in firms' innovation through the lens of returnees' clustering.

Fourth, it also enriches the small but growing literature on returnees. While prior studies have examined mainly the role of individual returnees such as knowledge broker, spanner, or labor mobility effects on local innovation (Lin et al., 2016; Liu et al., 2010a; Wang, 2015), the aggregated interconnectedness among returnees from diverse industries has not been explained both theoretically and empirically. I am the first to consider the social interaction aspect of returnees in its aggregated form to understand their technological environmental impact on local innovation. Firms can benefit from the innovation-enhancing effect of returnees at the aggregated level, due to the technological and social proximity formed under these agglomeration structures (Balland & Rigby, 2017; Boschma, 2017). This Ph.D. thesis shows that both the concentrated and competitive clustering structure of returnees can directly improve local firms' productivity since the co-location can magnify the returnees' interactive learning process and rivalry spirit so that stimulate their contributions to local firms. Moreover, the related returnee clustering promotes local productivity as the flow of complementary and multi-domain knowledge flourishes, while unrelated clustering tends to dampen it due to a lack of cognitive proximity. With such findings, this Ph.D. thesis advances our understandings of how to effectively restructure the returnees, who are a special labor force in emerging markets, to help improve local firm performance.

8.5 Practical Implications

In policy terms, my findings yield several important implications for policymakers in improving firm performance. First, advanced knowledge is often embedded in FDI flowing to recipient countries and FDI presents a great potential for knowledge spillovers (Jeon et al., 2013; Jin et al., 2018). My empirical analysis indicates that FDI is an important external knowledge source and can significantly promote local firm performance. In emerging markets, keeping open and introducing foreign investment can still benefit local firm performance as their superior technology and management practice would spill to local firms and stimulate their technological improvement (Tian, 2007; Zhang et al., 2014). For example, local authorities are urged to remove foreign entry barriers and set preferential policies such as tax relief or subsidies to attract MNEs, to improve the foreign presence in local areas. Moreover, Beijing governments also need to promote opportunities for local firms to interact with the MNEs, to help domestic firms proactively interact and collaborate with foreign investors. For instance, as my research context is Zhongguancun Science Park, which is the largest "special technological zones" in Beijing, China, my findings suggest that it can be helpful for the governments to establish science or technological parks to encourage FDI activities in the local area (Majocchi & Presutti, 2009). The science parks would facilitate the worker mobility from foreign to local firms because of the geographical proximity, and help local firms to establish forward and backward linkages due to the industrial agglomerations (Jeon et al., 2013; Wang et al., 2017b). In this case, other economies may also establish more science parks or business incubators to help indigenous firms to benefit more from the proactive interactions with MNEs and absorb more advanced technology.

Second, my results also provide suggestions for local policymakers on how to manage the hiring of the returnee labor force to maximize FDI spillovers. Returnees are often equipped with high skills and diverse cultural backgrounds, so they can not only serve as a knowledge brokerage between foreign and local firms but also help local firms absorb FDI spillover (Fu et al., 2017; Tzeng, 2018b). Although returnees are critical in improving the local absorptive capability, they might possess less local embeddedness. They need to readjust to the local environment before they can contribute to the local knowledge base, and a stable labor market can be helpful for their readjustment and play a key role (Kenney et al., 2013; Li et al., 2012). My results have demonstrated that returnees are very important factors for firms in emerging markets like China to learn from foreign advanced knowledge. Moreover, based on my analysis, the time-based characteristics of returnees' repatriation need further emphasis when analyzing their collective impact on local firm performance. A fast and irregular pace of the repatriation process can be helpful for the returnees to establish local business and social linkages. In current China, given that the economy has experienced a rapid economic development and social change in recent years, local policies change quickly and are less likely to be sustainable (Liu et al., 2011; Zhang & Guan, 2021), which might not be helpful for returnees to enter local industries. Therefore, the Beijing government should introduce stable and long-term local policies help highly skilled returnees quickly enter into local industries and adapt to local context. Besides, local government in Beijing need to avoid incoherent policies, for example, in one year they attract too much returnees while in the other year do not introduce the returnees, so that ensure a more rhythmic pace of returnees' repatriation. Such regular repatriation would facilitate the returnees' readjustment into local context and applying their capabilities to improve the local absorptive capacity, thereby disseminating more FDI spillovers.

Third, my research suggests that, in addition to attracting individual returnees to relocate by firms, Beijing government needs to consider their collective and catalytic role in local firms' innovation environment. I confirm that both the concentrated structure and competitive structure of returnees can promote local productivity. In this case, it is important for host region policymakers to pay more attention to the industrial restructuring of returnees. Moreover, I have provided a more holistic view of the returnee clustering effects in facilitating FDI spillovers. I show that returnees are an important bonding agent to recontextualize and disseminate FDI knowledge. A concentrated industrial structure of returnees enhances FDI spillovers effects on local productivity, while a competitive structure damps the FDI spillovers. Given that the competitive structure of returnees would directly improve the local firm productivity, it is important for host region policymakers to pay more attention to the industrial restructuring of returnees. For example, for regions without a high level of foreign-invested firms, it might be helpful to concentrate the returnees in certain industries but establish a competitive environment to benefit more from the returnees' knowledge externality. In contrast, if the target of a local authority is to benefit more from learning the MNEs' advanced technology, it can be beneficial to concentrate the strength of returnees and avoid the sparse distribution of returnees, so that build up higher absorptive capacity for FDI spillovers. My study thus helps policymakers and business leaders to refocus their innovation promotion efforts and consider different strategies and policies for maximizing FDI spillovers through returnees in the local technological environment.

Fourth, I have provided a more holistic view of the returnee diversified clustering effects in facilitating FDI spillovers. I show that a related variety of returnee structures enhances FDI spillovers effects on local firm productivity. Additionally, unrelated variety weakens the FDI spillovers effect on local firm performance, potentially limiting recombination potential of FDI knowledge components introduced from technological trajectories different from the local firms and region. As a result, policymakers in Beijing need to pay more attention to the industrial restructuring of returnees. Moreover, the findings can be extended to other similar settings. For example, if the target of a local authority is to benefit more from FDI knowledge spillovers, it can be beneficial to develop a more related industrial structure for returnees, so that build up higher local absorptive capacity. Overall speaking, my study helps policymakers and business leaders to refocus their innovation promotion efforts and consider different strategies and policies for maximizing FDI spillovers through returnees in the local technological environment.

8.6 Limitations and Recommendations for Future Research

This Ph.D. thesis has some limitations and shortcomings, and further studies need to be undertaken.

First, to measure the effect of FDI knowledge spillovers, this Ph.D. thesis only takes total factor productivity (TFP) as the dependent variable. Although it is widely acknowledged that TFP can represent some impact of FDI advanced technology, it can only reflect how efficiently the input is utilized in production (Boscá et al., 2004, Fu and Gong, 2011). It cannot explain whether the technological progression is successfully transformed to final outputs. The existing literature has suggested some other measurements to investigate the impact of FDI on local firms, like patent applications and new products as alternative measurements of innovation (Ning et al., 2016b; Wang et al., 2017b). However, due to the limitations on the dataset, I did not use patents or new products to capture the impact of FDI knowledge spillovers. Indeed, using different measurements of technological upgrading could provide more convincing evidence to explain FDI spillovers in Chinese high-tech firms. Therefore, in future studies, it might be helpful to adopt other measurements of local firm performance to see whether the findings of this thesis can be replicated.

Second, this Ph.D. thesis has not considered the composition of FDI when analyzing the impact of FDI knowledge spillovers. Indeed, as suggested by previous literature, the origins of foreign capital might have different impacts on local firm performance or host regions' technological upgrading. For example, Buckley et al. (2010) show that the activities conducted by MNEs from the developed countries might bring more knowledge spillovers than the MNEs from emerging economies, due to the technological gap. Contrastingly, Wei et al. (2017) indicate that FDI from firms from Hong Kong, Macau, and Taiwan (HMT) would diffuse more knowledge because of the ethnic similarity. Zhang et al. (2010) further suggest that a higher level of diversity of FDI origins would have a more positive impact on local firm performance. The existing studies have not reached a consensus on this topic. However, the ZSP firm-level dataset cannot provide detailed statistics on FDI types and origins, so it is highly recommended to expand future research by differentiating FDI in terms of home regional origins and investment fields.

Third, this Ph.D. thesis does not consider the local business environment to investigate FDI spillovers. The previous literature has acknowledged that the business linkage is a channel of FDI knowledge spillovers and FDI can generate different vertical and horizontal linkage effects on local firm performance (Javorcik & Spatareanu, 2011; Jeon et al., 2013). The business linkages might also influence the externalities of returnees' agglomeration. However, I could not consider both forward and backward linkages based on ZSP firm-level dataset, because it does not provide ZSP level input-output (I-O) table information to measure the linkage between different industries. In other words, it is difficult to specify knowledge transfers and sharing through interindustry trade. Moreover, due to data unavailability, I am also not able to distinguish the specific institutional platforms in the local business environment, for example, the incubators, the returnees' associations, etc. Hence, in future studies, it might be better to take further steps to consider forward and backward linkages and conduct more detailed surveys to examine what specific local institutional environment can affect FDI knowledge spillovers and the impact of returnees.

Fourth, I am also limited by the availability of the specific data of returnees that could help to specify their characteristics like their past study and/or work experience, and their explicit skills. Previous literature often uses individual surveys to collect the information (Qin, Wright, and Gao 2017, Dai and Liu 2009, Farquharson and Pruthi 2015), while our firm-level data is limited on the returnees' characteristics. It might be important to conduct a comprehensive survey about the returnees not only on the firm level but on the individual level. This may help us to know more specific functions of returnees' characteristics in moderating FDI knowledge spillover.

Fifth, I follow the knowledge externalities literature to estimate the spillover effects and do not consider the effects of firm-level individual returnee mobility, reverse knowledge spillovers, nor specific modes of knowledge transfers such as licensing or strategic alliances as I am limited by my data to do so. Moreover, we are also not able to distinguish the specific impact of returnees on local workers or salaries due to data unavailability. Furthermore, this chapter is limited to the assumption of personal interaction mainly in physical form. In the wake of the Covid-19 pandemic, new ways of non-physical or geographically bounded personal interactions such as online communication may become predominant. Forman and van Zeebroeck (2019) suggest that digital technologies can facilitate knowledge flows between geographic locations with shared common knowledge. It may mean that the extent and pattern of personal contacts vary significantly across industries. Nevertheless, returnees might keep providing further linkages for these locations.

Last but not least, the evidence in this Ph.D. is limited to one high-tech science park. ZSP is only one of the most important science parks in China (Tan 2006, Trunina, Liu, and Chen 2018). Its supporting policies for MNEs and return talents, institutional stability, the level of protection of property rights, and contract enforcement are very different from other science parks, for example, Donghu Science Park in Wuhan China or International Tech Park Bangalore in India (Etzkowitz & Zhou, 2018; Hobbs, Link, & Scott, 2017). Given the huge differences, the lessons from ZSP might not able to be directly applied to other science parks or industrial clusters. However, due to data limitations, I can not make a detailed comparison among them. In the future study, I would like to collect more comprehensive datasets about FDI, firm performance, and returnees in other industrial clusters or regions so that generalize my findings.

Bibliography

Aarstad, J., Kvitastein, O. A., & Jakobsen, S.-E. 2016. Related and unrelated variety as regional drivers of enterprise productivity and innovation: A multilevel study. ***Research Policy***, 45(4): 844-856.

Ackerberg, D. A., Caves, K., & Frazer, G. 2015. Identification properties of recent production function estimators. ***Econometrica***, 83(6): 2411-2451.

Agrawal, A., Kapur, D., McHale, J., & Oettl, A. 2011. Brain drain or brain bank? The impact of skilled emigration on poor-country innovation. ***Journal of Urban Economics***, 69(1): 43-55.

Alfaro, L., Kalemli‐Ozcan, S., & Sayek, S. 2009. FDI, productivity and financial development. ***World Economy***, 32(1): 111-135.

Altomonte, C., & Pennings, E. 2009. Domestic plant productivity and incremental spillovers from foreign direct investment. ***Journal of International Business Studies***, 40(7): 1131-1148.

Antonelli, C., & Scellato, G. 2013. Complexity and technological change: knowledge interactions and firm level total factor productivity. ***Journal of Evolutionary Economics***, 23(1): 77-96.

Armanios, D. E., Eesley, C. E., Li, J., & Eisenhardt, K. M. 2017. How entrepreneurs leverage institutional intermediaries in emerging economies to acquire public resources. ***Strategic Management Journal***, 38(7): 1373-1390.

Asheim, B. T., Boschma, R., & Cooke, P. 2011. Constructing Regional Advantage: Platform Policies Based on Related Variety and Differentiated Knowledge Bases. ***Regional Studies***, 45(7): 893-904.

Ashraf, A., Herzer, D., & Nunnenkamp, P. 2016. The effects of Greenfield FDI and cross‐border M&As on total factor productivity. ***The world economy***, 39(11): 1728-1755.

Audretsch, D. B., & Feldman, M. P. 1996. R&D spillovers and the geography of innovation and production. ***The American economic review***: 630-640.

Bai, W., Holmström-Lind, C., & Johanson, M. 2018. Leveraging networks, capabilities and opportunities for international success: A study on returnee entrepreneurial ventures. ***Scandinavian Journal of Management***, 34(1): 51-62.

Bai, W., Holmström Lind, C., & Johanson, M. 2016. The performance of international returnee ventures: the role of networking capability and the usefulness of international business knowledge. ***Entrepreneurship & Regional Development***, 28(9/10): 657-680.

Bai, W., Johanson, M., & Martín Martín, O. 2017. Knowledge and internationalization of returnee entrepreneurial firms. ***International Business Review***, 26(4): 652-665.

Balland, P.-A., & Rigby, D. 2017. The Geography of Complex Knowledge. ***Economic Geography***, 93(1): 1-23.

Baptista, R., & Swann, G. M. P. 1999. A comparison of clustering dynamics in the US and UK computer industries. ***Journal of evolutionary economics***, 9(3): 373-399.

Barrios, S., Bertinelli, L., & Strobl, E. 2006. GEOGRAPHIC CONCENTRATION AND ESTABLISHMENT SCALE: AN EXTENSION USING PANEL DATA*. ***Journal of Regional Science***, 46(4): 733-746.

Basile, R., Pittiglio, R., & Reganati, F. 2017. Do agglomeration externalities affect firm survival? ***Regional Studies***, 51(4): 548-562.
Bathelt, H., Malmberg, A., & Maskell, P. 2004. Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation. ***Progress in Human Geography***, 28(1): 31-56.
Baum, C. F., Schaffer, M. E., & Stillman, S. 2003. Instrumental variables and GMM: Estimation and testing. ***The Stata Journal***, 3(1): 1-31.
Beaudry, C., & Schiffauerova, A. 2009. Who's right, Marshall or Jacobs? The localization versus urbanization debate. ***Research Policy***, 38(2): 318-337.
Ben Hamida, L., & Gugler, P. 2009. Are there demonstration-related spillovers from FDI?: Evidence from Switzerland. ***International Business Review***, 18(5): 494-508.
Bishop, P., & Gripaios, P. 2010. Spatial Externalities, Relatedness and Sector Employment Growth in Great Britain. ***Regional Studies***, 44(4): 443-454.
Blalock, G., & Gertler, P. J. 2009. How firm capabilities affect who benefits from foreign technology. ***Journal of Development Economics***, 90(2): 192-199.
Bogers, M., Foss, N. J., & Lyngsie, J. 2018. The "human side" of open innovation: The role of employee diversity in firm-level openness. ***Research Policy***, 47(1): 218-231.
Boschma, R. 2017. Relatedness as driver of regional diversification: A research agenda. ***Regional Studies***, 51(3): 351-364.
Boschma, R., Heimeriks, G., & Balland, P.-A. 2014. Scientific knowledge dynamics and relatedness in biotech cities. ***Research Policy***, 43(1): 107-114.
Boschma, R., & Iammarino, S. 2009a. Related Variety, Trade Linkages, and Regional Growth in Italy. ***Economic Geography***, 85(3): 289-311.
Boschma, R., & Iammarino, S. J. 2009b. Related variety, trade linkages, and regional growth in Italy. ***Economic geography***, 85(3): 289-311.
Boschma, R., Minondo, A., & Navarro, M. 2012. Related variety and regional growth in Spain. ***Papers in Regional Science***, 91(2): 241-256.
Brzozowski, J., Cucculelli, M., & Surdej, A. 2019. Exploring transnational entrepreneurship. Immigrant entrepreneurs and foreign-born returnees in the Italian ICT sector. ***Journal of Small Business & Entrepreneurship***, 31(5): 413-431.
Bucci, A., & Ushchev, P. 2020. Specialization versus competition: an anatomy of increasing returns to scale. ***Journal of Economic Geography***.
Buckley, P. J., Clegg, J., & Wang, C. 2002. The Impact of Inward FDI on the Performance of Chinese Manufacturing Firms. ***Journal of International Business Studies***, 33(4): 637-655.
Buckley, P. J., Clegg, J., & Wang, C. 2010. Is the Relationship between Inward FDI and Spillover Effects Linear? An Empirical Examination of the Case of China. In P. J. Buckley (Ed.), ***Foreign Direct Investment, China and the World Economy***: 192-215. London: Palgrave Macmillan UK.
Buerger, M., & Cantner, U. 2011. The regional dimension of sectoral innovativeness: An empirical investigation of two specialized suppliers and two science‐based industries*. ***Papers in Regional Science***, 90(2): 373-393.
Burger, M. J., & Meijers, E. J. 2016. Agglomerations and the rise of urban network externalities. ***Papers in Regional Science***, 95(1): 5-15.

Cainelli, G., & Ganau, R. 2019. Related variety and firm heterogeneity. What really matters for short-run firm growth? ***Entrepreneurship & Regional Development***, 31(9-10): 768-784.
Cainelli, G., & Iacobucci, D. 2012. Agglomeration, Related Variety, and Vertical Integration. ***Economic Geography***, 88(3): 255-277.
Cainelli, G., & Iacobucci, D. 2016. Local variety and firm diversification: an evolutionary economic geography perspective. ***Journal of Economic Geography***, 16(5): 1079-1100.
Camisón, C., & Villar-López, A. 2012. On How Firms Located in an Industrial District Profit from Knowledge Spillovers: Adoption of an Organic Structure and Innovation Capabilities. ***British Journal of Management***, 23(3): 361-382.
Capaldo, A., & Petruzzelli, A. M. 2014. Partner Geographic and Organizational Proximity and the Innovative Performance of Knowledge - Creating Alliances. ***European Management Review***, 11(1): 63-84.
Capozza, C., Salomone, S., & Somma, E. 2018. Local industrial structure, agglomeration economies and the creation of innovative start-ups: evidence from the Italian case. ***Entrepreneurship & Regional Development***, 30(7-8): 749-775.
Caragliu, A., de Dominicis, L., & de Groot, H. L. F. 2016. Both Marshall and Jacobs were Right! ***Economic Geography***, 92(1): 87-111.
Castaldi, C., Frenken, K., & Los, B. 2015. Related Variety, Unrelated Variety and Technological Breakthroughs: An analysis of US State-Level Patenting. ***Regional Studies***, 49(5): 767-781.
Castellani, D., & Zanfei, A. 2003. Technology gaps, absorptive capacity and the impact of inward investments on productivity of European firms. ***Economics of Innovation and New Technology***, 12(6): 555-576.
Certo, S. T., Busenbark, J. R., Woo, H. s., & Semadeni, M. 2016. Sample selection bias and Heckman models in strategic management research. ***Strategic Management Journal***, 37(13): 2639-2657.
Chang, S. J., & Xu, D. 2008. Spillovers and competition among foreign and local firms in China. ***Strategic Management Journal***, 29(5): 495-518.
Checchi, D., De Simone, G., & Faini, R. 2007. Skilled migration, FDI and human capital investment: IZA Discussion Papers.
Chen, P.-L., & Tan, D. 2016. Foreign knowledge acquisition through inter-firm collaboration and recruitment: Implications for domestic growth of emerging market firms. ***International Business Review***, 25(1): 221-232.
Chen, Y.-C. 2008. The Limits of Brain Circulation: Chinese Returnees and Technological Development in Beijing. ***Pacific Affairs***, 81(2): 195-215.
Choudhury, P. 2015. Return migration and geography of innovation in MNEs: a natural experiment of knowledge production by local workers reporting to return migrants. ***Journal of Economic Geography***, 16(3): 585-610.
Cohen, W. M., & Levinthal, D. A. 1990. Absorptive capacity: A new perspective on learning and innovation. ***Administrative science quarterly***: 128-152.
Comin, D. 2017. Total Factor Productivity, ***The New Palgrave Dictionary of Economics***: 1-4. London: Palgrave Macmillan UK.

Content, J., Frenken, K., & Jordaan, J. A. 2019. Does related variety foster regional entrepreneurship? Evidence from European regions. ***Regional Studies***, 53(11): 1531-1543.

Corredoira, R. A., & McDermott, G. A. 2014. Adaptation, bridging and firm upgrading: How non-market institutions and MNCs facilitate knowledge recombination in emerging markets. ***Journal of International Business Studies***, 45(6): 699-722.

Crespo, N., & Fontoura, M. P. 2007. Determinant Factors of FDI Spillovers – What Do We Really Know? ***World Development***, 35(3): 410-425.

Cui, L., Li, Y., Meyer, K., & Li, Z. 2015. Leadership Experience Meets Ownership Structure: Returnee Managers and Internationalization of Emerging Economy Firms. ***Management International Review (MIR)***, 55(3): 355-387.

Dai, O., & Liu, X. 2009. Returnee entrepreneurs and firm performance in Chinese high-technology industries. ***International Business Review***, 18(4): 373-386.

Dai, Y., Kong, D., & Liu, S. 2018. Returnee Talent and Corporate Investment: Evidence from China. ***European Accounting Review***, 27(2): 313-337.

Damijan, J. P., Rojec, M., Majcen, B., & Knell, M. 2013. Impact of firm heterogeneity on direct and spillover effects of FDI: Micro-evidence from ten transition countries. ***Journal of Comparative Economics***, 41(3): 895-922.

de Groot, H. L. F., Poot, J., & Smit, M. J. 2016. WHICH AGGLOMERATION EXTERNALITIES MATTER MOST AND WHY? ***Journal of Economic Surveys***, 30(4): 756-782.

de Vor, F., & de Groot, H. L. F. 2010. Agglomeration externalities and localized employment growth: the performance of industrial sites in Amsterdam. ***The Annals of Regional Science***, 44(3): 409-431.

Denicolai, S., Ramirez, M., & Tidd, J. 2016. Overcoming the false dichotomy between internal R&D and external knowledge acquisition: Absorptive capacity dynamics over time. ***Technological Forecasting and Social Change***, 104: 57-65.

Dess, G. G., & Beard, D. W. 1984. Dimensions of organizational task environments. ***Administrative Science Quarterly***, 29(1): 52-73.

Diodato, D., Neffke, F., & O'Clery, N. 2018. Why do industries coagglomerate? How Marshallian externalities differ by industry and have evolved over time. ***Journal of Urban Economics***, 106: 1-26.

Dong, X., Hu, Y., Yin, W., & Kuo, E. 2019. The History of Zhongguancun. In X. Dong, Y. Hu, W. Yin, & E. Kuo (Eds.), ***Zhongguancun Model: Driving the Dual Engines of Science & Technology and Capital***: 1-16. Singapore: Springer Singapore.

Dougherty, D., & Heller, T. 1994. The illegitimacy of successful product innovation in established firms. ***Organization Science***, 5(2): 200-218.

Drucker, J. 2011. Regional Industrial Structure Concentration in the United States: Trends and Implications. ***Economic Geography***, 87(4): 421-452.

Drucker, J. 2015. An Evaluation of Competitive Industrial Structure and Regional Manufacturing Employment Change. ***Regional Studies***, 49(9): 1481-1496.

Dustmann, C., Fadlon, I., & Weiss, Y. 2011. Return migration, human capital accumulation and the brain drain. ***Journal of Development Economics***, 95(1): 58-67.

Ellison, G., & Glaeser, E. L. 1999. The Geographic Concentration of Industry: Does Natural Advantage Explain Agglomeration? ***American Economic Review***, 89(2): 311-316.

Ellison, G., Glaeser, E. L., & Kerr, W. R. 2010. What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns. ***American Economic Review***, 100(3): 1195-1213.

Essletzbichler, J. 2015. Relatedness, industrial branching and technological cohesion in US metropolitan areas. ***Regional Studies***, 49(5): 752-766.

Essletzbichler, J., & Rigby, D. 2005. Competition, variety and the geography of technology evolution. ***Tijdschrift voor economische en sociale geografie***, 96(1): 48-62.

Etzkowitz, H., & Zhou, C. 2018. Innovation incommensurability and the science park. ***R&D Management***, 48(1): 73-87.

Faggio, G., Silva, O., & Strange, W. C. 2020. Tales of the city: what do agglomeration cases tell us about agglomeration in general? ***Journal of Economic Geography***, 20(5): 1117-1143.

Farquharson, M., & Pruthi, S. 2015. Returnee Entrepreneurs: Bridging Network Gaps in China after Absence. ***South Asian Journal of Management***, 22(2): 9-35.

Feldman, M. P., & Audretsch, D. B. 1999. Innovation in cities:: Science-based diversity, specialization and localized competition. ***European Economic Review***, 43(2): 409-429.

Filatotchev, I., Liu, X., Buck, T., & Wright, M. 2009. The export orientation and export performance of high-technology SMEs in emerging markets: The effects of knowledge transfer by returnee entrepreneurs. ***Journal of International Business Studies***, 40(6): 1005-1021.

Filatotchev, I., Liu, X., Lu, J., & Wright, M. 2011. Knowledge spillovers through human mobility across national borders: Evidence from Zhongguancun Science Park in China. ***Research Policy***, 40(3): 453-462.

Fleming, L., & Sorenson, O. 2001. Technology as a complex adaptive system: evidence from patent data. ***Research Policy***, 30(7): 1019-1039.

Flores‐Lagunes, A., & Schnier, K. E. 2012. Estimation of sample selection models with spatial dependence. ***Journal of applied econometrics***, 27(2): 173-204.

Ford, T. C., & Rork, J. C. 2010. Why buy what you can get for free? The effect of foreign direct investment on state patent rates. ***Journal of Urban Economics***, 68(1): 72-81.

Forman, C., & van Zeebroeck, N. 2019. Digital technology adoption and knowledge flows within firms: Can the Internet overcome geographic and technological distance? ***Research policy***, 48(8): 103697.

Frenken, K., & Boschma, R. A. 2007. A theoretical framework for evolutionary economic geography: industrial dynamics and urban growth as a branching process. ***Journal of economic geography***, 7(5): 635-649.

Frenken, K., Van Oort, F., & Verburg, T. 2007. Related variety, unrelated variety and regional economic growth. ***Regional studies***, 41(5): 685-697.

Fritsch, M., & Kublina, S. 2018. Related variety, unrelated variety and regional growth: the role of absorptive capacity and entrepreneurship. ***Regional Studies***, 52(10): 1360-1371.

Fu, W., Diez, J. R., & Schiller, D. 2013. Interactive learning, informal networks and innovation: Evidence from electronics firm survey in the Pearl River Delta, China. ***Research Policy***, 42(3): 635-646.

Fu, W., Revilla Diez, J., & Schiller, D. 2013. Interactive learning, informal networks and innovation: Evidence from electronics firm survey in the Pearl River Delta, China. ***Research Policy***, 42(3): 635-646.

Fu, X. 2012. Foreign Direct Investment and Managerial Knowledge Spillovers through the Diffusion of Management Practices. ***Journal of Management Studies***, 49(5): 970-999.

Fu, X., & Gong, Y. 2011. Indigenous and Foreign Innovation Efforts and Drivers of Technological Upgrading: Evidence from China. ***World Development***, 39(7): 1213-1225.

Fu, X., Hou, J., & Sanfilippo, M. 2017. Highly skilled returnees and the internationalization of EMNEs: Firm level evidence from China. ***International Business Review***, 26(3): 579-591.

Fu, X., Pietrobelli, C., & Soete, L. 2011. The Role of Foreign Technology and Indigenous Innovation in the Emerging Economies: Technological Change and Catching-up. ***World Development***, 39(7): 1204-1212.

Gabe, T. M., & Abel, J. R. 2012. Specialized knowledge and the geographic concentration of occupations. ***Journal of Economic Geography***, 12(2): 435-453.

Gao, T. 2004. Regional industrial growth: evidence from Chinese industries. ***Regional Science and Urban Economics***, 34(1): 101-124.

García, F., Jin, B., & Salomon, R. 2013. Does inward foreign direct investment improve the innovative performance of local firms? ***Research Policy***, 42(1): 231-244.

Giannetti, M., Liao, G., & Yu, X. 2015. The brain gain of corporate boards: Evidence from China. ***The Journal of Finance***, 70(4): 1629-1682.

Gimeno, J. 2004. Competition within and Between Networks: The Contingent Effect of Competitive Embeddedness on Alliance Formation. ***Academy of Management Journal***, 47(6): 820-842.

Girma, S. 2005. Absorptive Capacity and Productivity Spillovers from FDI: A Threshold Regression Analysis*. ***Oxford Bulletin of Economics and Statistics***, 67(3): 281-306.

Glaeser, E. L., Kallal, H. D., Scheinkman, J. A., & Shleifer, A. 1992. Growth in cities. ***Journal of political economy***, 100(6): 1126-1152.

Gnyawali, D. R., & Park, B. j. 2009. Co - opetition and technological innovation in small and medium - sized enterprises: A multilevel conceptual model. ***Journal of small business management***, 47(3): 308-330.

Gnyawali, D. R., & Ryan Charleton, T. 2018. Nuances in the Interplay of Competition and Cooperation: Towards a Theory of Coopetition. ***Journal of Management***, 44(7): 2511-2534.

Greve, H. R. 2009. Bigger and safer: the diffusion of competitive advantage. ***Strategic Management Journal***, 30(1): 1-23.

Grillitsch, M., Asheim, B., & Trippl, M. 2018. Unrelated knowledge combinations: the unexplored potential for regional industrial path development. ***Cambridge Journal of Regions, Economy and Society***, 11(2): 257-274.

Guan, J., & Liu, N. 2016. Exploitative and exploratory innovations in knowledge network and collaboration network: A patent analysis in the technological field of nano-energy. ***Research Policy***, 45(1): 97-112.

Guan, J., & Yam, R. C. 2015. Effects of government financial incentives on firms' innovation performance in China: Evidences from Beijing in the 1990s. ***Research Policy***, 44(1): 273-282.

Guevara-Rosero, G. C., Riou, S., & Autant-Bernard, C. 2019. Agglomeration externalities in Ecuador: do urbanization and tertiarization matter? ***Regional Studies***, 53(5): 706-719.

Hamida, L. B. 2013. Are there regional spillovers from FDI in the Swiss manufacturing industry? ***International Business Review***, 22(4): 754-769.

Han, Q., Jennings, J. E., Liu, R., & Jennings, P. D. 2019. Going home and helping out? Returnees as propagators of CSR in an emerging economy. ***Journal of International Business Studies***, 50(6): 857-872.

Hansen, L. P. 1982. Large sample properties of generalized method of moments estimators. ***Econometrica: Journal of the econometric society***: 1029-1054.

Hao, J., Wen, W., & Welch, A. 2016. When sojourners return: Employment opportunities and challenges facing high-skilled Chinese returnees. ***Asian and Pacific Migration Journal***, 25(1): 22-40.

Hao, X., Yan, K., Guo, S., & Wang, M. 2017. Chinese returnees' motivation, post-return status and impact of return: A systematic review. ***Asian and Pacific Migration Journal***, 26(1): 143-157.

Haskel, J. E., Pereira, S. C., & Slaughter, M. J. 2007. Does Inward Foreign Direct Investment Boost the Productivity of Domestic Firms? ***The Review of Economics and Statistics***, 89(3): 482-496.

Hauknes, J., & Knell, M. 2009. Embodied knowledge and sectoral linkages: An input–output approach to the interaction of high-and low-tech industries. ***Research Policy***, 38(3): 459-469.

Heckman, J. J. 1979. Sample selection bias as a specification error. ***Econometrica: Journal of the econometric society***: 153-161.

Henderson, V. 1997. Externalities and industrial development. ***Journal of urban economics***, 42(3): 449-470.

Hervas-Oliver, J.-L., Sempere-Ripoll, F., Rojas Alvarado, R., & Estelles-Miguel, S. 2018. Agglomerations and firm performance: who benefits and how much? ***Regional Studies***, 52(3): 338-349.

Hobbs, K. G., Link, A. N., & Scott, J. T. 2017. Science and technology parks: an annotated and analytical literature review. ***The Journal of Technology Transfer***, 42(4): 957-976.

Hoffmann, W., Lavie, D., Reuer, J. J., & Shipilov, A. 2018. The interplay of competition and cooperation. ***Strategic Management Journal***, 39(12): 3033-3052.

Holmes, T. J., & Stevens, J. J. 2002. Geographic Concentration and Establishment Scale. ***The Review of Economics and Statistics***, 84(4): 682-690.

Howell, A. 2019. Industry relatedness, FDI liberalization and the indigenous innovation process in China. ***Regional Studies***: 1-15.

Hsu, C.-W., Lien, Y.-C., & Chen, H. 2013. International ambidexterity and firm performance in small emerging economies. ***Journal of World Business***, 48(1): 58-67.

Hu, A. G. Z., & Jefferson, G. H. 2002. FDI Impact and Spillover: Evidence from China's Electronic and Textile Industries. ***The World Economy***, 25(8): 1063-1076.

Huang, K.-F., Lin, K.-H., Wu, L.-Y., & Yu, P.-H. 2015. Absorptive capacity and autonomous R&D climate roles in firm innovation. ***Journal of Business Research***, 68(1): 87-94.

Huang, L., Liu, X., & Xu, L. 2012. Regional innovation and spillover effects of foreign direct investment in China: A threshold approach. ***Regional Studies***, 46(5): 583-596.

Ingram, P., & Qingyuan Yue, L. 2008. 6 structure, affect and identity as bases of organizational competition and cooperation. ***The Academy of Management Annals***, 2(1): 275-303.

Inkpen, A., Minbaeva, D., & Tsang, E. W. 2019a. Unintentional, unavoidable, and beneficial knowledge leakage from the multinational enterprise. ***Journal of International Business Studies***, 50(2): 250-260.

Inkpen, A., Minbaeva, D., & Tsang, E. W. K. 2019b. Unintentional, unavoidable, and beneficial knowledge leakage from the multinational enterprise. ***Journal of International Business Studies***, 50(2): 250-260.

Ito, B., Yashiro, N., Xu, Z., Chen, X., & Wakasugi, R. 2012. How do Chinese industries benefit from FDI spillovers? ***China Economic Review***, 23(2): 342-356.

Jacobs, J. 1969. Strategies for helping cities. ***The American Economic Review***, 59(4): 652-656.

Javorcik, B. S., & Spatareanu, M. 2011. Does it matter where you come from? Vertical spillovers from foreign direct investment and the origin of investors. ***Journal of Development Economics***, 96(1): 126-138.

Jeon, Y., Park, B. I., & Ghauri, P. N. 2013. Foreign direct investment spillover effects in China: Are they different across industries with different technological levels? ***China Economic Review***, 26: 105-117.

Jia, L., Li, S., Tallman, S., & Zheng, Y. 2017. Catch-up via agglomeration: A study of township clusters. ***Global Strategy Journal***, 7(2): 193-211.

Jin, B., García, F., & Salomon, R. 2018. Inward foreign direct investment and local firm innovation: The moderating role of technological capabilities. ***Journal of International Business Studies***.

Jonkers, K., & Cruz-Castro, L. 2013. Research upon return: The effect of international mobility on scientific ties, production and impact. ***Research Policy***, 42(8): 1366-1377.

Jude, C. 2016. Technology spillovers from FDI. Evidence on the intensity of different spillover channels. ***The World Economy***, 39(12): 1947-1973.

Kang, M., & Lee, M.-J. 2017. Absorptive capacity, knowledge sharing, and innovative behaviour of R&D employees. ***Technology Analysis & Strategic Management***, 29(2): 219-232.

Kemeny, T., & Storper, M. 2015. Is specialization good for regional economic development? ***Regional Studies***, 49(6): 1003-1018.

Kenney, M., Breznitz, D., & Murphree, M. 2013. Coming back home after the sun rises: Returnee entrepreneurs and growth of high tech industries. ***Research Policy***, 42(2): 391-407.

Ketelhöhn, N. W. 2006. The role of clusters as sources of dynamic externalities in the US semiconductor industry. ***Journal of Economic Geography***, 6(5): 679-699.

Klenow, P. J., & Rodriguez-Clare, A. 2005. Externalities and growth. ***Handbook of economic growth***, 1: 817-861.

Knoben, J., & Oerlemans, L. A. 2006. Proximity and inter‐organizational collaboration: A literature review. ***International Journal of Management Reviews***, 8(2): 71-89.

Lagos, R. 2006. A model of TFP. ***The Review of Economic Studies***, 73(4): 983-1007.

Lee, J.-H., & Roberts, M. J. D. 2015. International returnees as outside directors: A catalyst for strategic adaptation under institutional pressure. ***International Business Review***, 24(4): 594-604.

Lennox, C. S., Francis, J. R., & Wang, Z. 2012. Selection models in accounting research. ***The accounting review***, 87(2): 589-616.

Leppälä, S. 2020. Innovation, R&D Spillovers, and the Variety and Concentration of the Local Industry Structure*. ***The Scandinavian Journal of Economics***, 122(3): 1231-1255.

Levin, D. Z., & Barnard, H. 2013. Connections to distant knowledge: Interpersonal ties between more- and less-developed countries. ***Journal of International Business Studies***, 44(7): 676-698.

Levinsohn, J., & Petrin, A. 2003. Estimating Production Functions Using Inputs to Control for Unobservables. ***The Review of Economic Studies***, 70(2): 317-341.

Li, H. 2020. Role of overseas ethnic and non-ethnic ties and firm activity in the home country in the internationalization of returnee entrepreneurial firms. ***Journal of International Management***, 26(1): 100706.

Li, H., Zhang, Y., Li, Y., Zhou, L.-A., & Zhang, W. 2012. Returnees Versus Locals: Who Perform Better in China's Technology Entrepreneurship? ***Strategic Entrepreneurship Journal***, 6(3): 257-272.

Li, J., Sutherland, D., & Ning, L. 2017. Inward FDI spillovers and innovation capabilities in Chinese business: exploring the moderating role of local industrial externalities. ***Technology Analysis & Strategic Management***, 29(8): 932-945.

Liang, F. H. 2017. Does foreign direct investment improve the productivity of domestic firms? Technology spillovers, industry linkages, and firm capabilities. ***Research Policy***, 46(1): 138-159.

Liang, J., & Goetz, S. J. 2018. Technology intensity and agglomeration economies. ***Research Policy***, 47(10): 1990-1995.

Lichtenthaler, U., & Lichtenthaler, E. 2009. A Capability-Based Framework for Open Innovation: Complementing Absorptive Capacity. ***Journal of Management Studies***, 46(8): 1315-1338.

Lin, D., Lu, J., Li, P. P., & Liu, X. 2015. Balancing Formality and Informality in Business Exchanges as a Duality: A Comparative Case Study of Returnee and Local Entrepreneurs in China. ***Management and Organization Review***, 11(2): 315-342.

Lin, D., Lu, J., Liu, X., & Choi, S.-J. 2014. Returnee CEO and innovation in Chinese high-tech SMEs. ***International Journal of Technology Management***, 65(1-4): 151-171.

Lin, D., Lu, J., Liu, X., & Zhang, X. 2016. International knowledge brokerage and returnees' entrepreneurial decisions. ***Journal of International Business Studies***, 47(3): 295-318.

Lin, D., Zheng, W., Lu, J., Liu, X., & Wright, M. 2019. Forgotten or not? Home country embeddedness and returnee entrepreneurship. ***Journal of World Business***, 54(1): 1-13.

Lin, J.-Y. 2014. Effects on diversity of R&D sources and human capital on industrial performance. ***Technological Forecasting and Social Change***, 85: 168-184.

Lin, Y.-H., Chen, C.-J., & Lin, B.-W. 2018. The dual-edged role of returnee board members in new venture performance. ***Journal of Business Research***, 90: 347-358.

Liu, F.-c., Simon, D. F., Sun, Y.-t., & Cao, C. 2011. China's innovation policies: Evolution, institutional structure, and trajectory. ***Research Policy***, 40(7): 917-931.

Liu, X., Lu, J., & Choi, S.-j. 2014. Bridging knowledge gaps: returnees and reverse knowledge spillovers from Chinese local firms to foreign firms. ***Management International Review***, 54(2): 253-276.

Liu, X., Lu, J., Filatotchev, I., Buck, T., & Wright, M. 2010a. Returnee entrepreneurs, knowledge spillovers and innovation in high-tech firms in emerging economies. ***Journal of International Business Studies***, 41(7): 1183-1197.

Liu, X., Wright, M., & Filatotchev, I. 2013. Learning, firm age and performance: An investigation of returnee entrepreneurs in Chinese high-tech industries. ***International Small Business Journal***, 33(5): 467-487.

Liu, X., Wright, M., Filatotchev, I., Dai, O., & Lu, J. 2010b. Human mobility and international knowledge spillovers: evidence from high-tech small and medium enterprises in an emerging market. ***Strategic Entrepreneurship Journal***, 4(4): 340-355.

Liu, X., Xia, T., Jiangyong, L., & Lin, D. 2019. Under what institutional conditions does overseas business knowledge contribute to firm performance? ***International Business Review***, 28(3): 588-602.

Liu, Y., & Almor, T. 2016. How culture influences the way entrepreneurs deal with uncertainty in inter-organizational relationships: The case of returnee versus local entrepreneurs in China. ***International Business Review***, 25(1, Part A): 4-14.

Lu, Y., Tao, Z., & Zhu, L. 2017. Identifying FDI spillovers. ***Journal of International Economics***, 107: 75-90.

Lund Vinding, A. 2006. Absorptive capacity and innovative performance: A human capital approach. ***Economics of innovation and New Technology***, 15(4-5): 507-517.

Ma, Z., Zhu, J., Meng, Y., & Teng, Y. 2018. The impact of overseas human capital and social ties on Chinese returnee entrepreneurs' venture performance. ***International Journal of Entrepreneurial Behavior & Research***, 25(1): 67-83.

Majocchi, A., & Presutti, M. 2009. Industrial clusters, entrepreneurial culture and the social environment: The effects on FDI distribution. ***International Business Review***, 18(1): 76-88.

Mäkelä, K., Barner-Rasmussen, W., Ehrnrooth, M., & Koveshnikov, A. 2019. Potential and recognized boundary spanners in multinational corporations. ***Journal of World Business***, 54(4): 335-349.

Mancusi, M. L. 2008. International spillovers and absorptive capacity: A cross-country cross-sector analysis based on patents and citations. ***Journal of International Economics***, 76(2): 155-165.

Mantegazzi, D., McCann, P., & Venhorst, V. 2020. The impact of language borders on the spatial decay of agglomeration and competition spillovers. ***Journal of Regional Science***, 60(3): 558-577.

Marcin, K. 2008. How does FDI inflow affect productivity of domestic firms? The role of horizontal and vertical spillovers, absorptive capacity and competition. ***The Journal of International Trade & Economic Development***, 17(1): 155-173.

Marin, A., & Sasidharan, S. 2010. Heterogeneous MNC subsidiaries and technological spillovers: Explaining positive and negative effects in India. ***Research Policy***, 39(9): 1227-1241.

Mariotti, S., Mutinelli, M., Nicolini, M., & Piscitello, L. 2015. Productivity Spillovers from Foreign Multinational Enterprises to Domestic Manufacturing Firms: To What Extent Does Spatial Proximity Matter? ***Regional Studies***, 49(10): 1639-1653.

Martin, P., Mayer, T., & Mayneris, F. 2011. Spatial concentration and plant-level productivity in France. ***Journal of Urban Economics***, 69(2): 182-195.

Martinez-Noya, A., Garcia-Canal, E., & Guillen, M. F. 2013. R&D Outsourcing and the Effectiveness of Intangible Investments: Is Proprietary Core Knowledge Walking out of the Door? ***Journal of Management Studies***, 50(1): 67-91.

Mayr, K., & Peri, G. 2008. Return migration as a channel of brain gain: National Bureau of Economic Research.

Merlevede, B., & Purice, V. 2016. Distance, time since foreign entry, and productivity spillovers from foreign direct investment. ***Papers in Regional Science***, 95(4): 775-800.

Meyer, K. E., & Sinani, E. 2009. When and where does foreign direct investment generate positive spillovers? A meta-analysis. ***Journal of International Business Studies***, 40(7): 1075-1094.

Mohammadi, A., Broström, A., & Franzoni, C. 2017. Workforce Composition and Innovation: How Diversity in Employees' Ethnic and Educational Backgrounds Facilitates Firm-Level Innovativeness. ***Journal of Product Innovation Management***, 34(4): 406-426.

Naldi, L., Criaco, G., & Patel, P. C. 2020. Related and unrelated industry variety and the internationalization of start-ups. ***Research Policy***, 49(10): 104050.

Neffke, F., & Henning, M. 2013. Skill relatedness and firm diversification. ***Strategic Management Journal***, 34(3): 297-316.

Neffke, F., Henning, M., & Boschma, R. 2011. How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. ***Economic geography***, 87(3): 237-265.

Newman, C., Rand, J., Talbot, T., & Tarp, F. 2015. Technology transfers, foreign investment and productivity spillovers. ***European Economic Review***, 76: 168-187.

Ng, D. W. 2007. A modern resource based approach to unrelated diversification. ***Journal of Management Studies***, 44(8): 1481-1502.

Ning, L., Li, J., & Prevezer, M. 2016a. Foreign Direct Investment Spillovers and the Geography of Innovation in Chinese Regions: The Role of Regional Industrial Specialization and Diversity AU - Wang, Yuandi. ***Regional Studies***, 50(5): 805-822.

Ning, L., & Wang, F. 2018. Does FDI Bring Environmental Knowledge Spillovers to Developing Countries? The Role of the Local Industrial Structure. ***Environmental and Resource Economics***, 71(2): 381-405.

Ning, L., Wang, F., & Li, J. 2016b. Urban innovation, regional externalities of foreign direct investment and industrial agglomeration: Evidence from Chinese cities. ***Research Policy***, 45(4): 830-843.

Nooteboom, B. 2000. Learning by interaction: absorptive capacity, cognitive distance and governance. ***Journal of management and governance***, 4(1): 69-92.

Nooteboom, B., Van Haverbeke, W., Duysters, G., Gilsing, V., & van den Oord, A. 2007. Optimal cognitive distance and absorptive capacity. ***Research Policy***, 36(7): 1016-1034.

Nuruzzaman, N., Singh, D., & Pattnaik, C. 2019. Competing to be innovative: Foreign competition and imitative innovation of emerging economy firms. ***International Business Review***, 28(5): 101490.

Obukhova, E. 2012. The Role of Returnee-Entrepreneurs in Cluster Emergence: The Case of Shanghai's Semiconductor-Design Industry. ***Available at SSRN 2066864***.

Oerlemans, L., & Meeus, M. 2005. Do organizational and spatial proximity impact on firm performance? ***Regional studies***, 39(1): 89-104.

Oettl, A., & Agrawal, A. 2008. International labor mobility and knowledge flow externalities. ***Journal of International Business Studies***, 39(8): 1242-1260.

Olley, G. S., & Pakes, A. 1996. The Dynamics of Productivity in the Telecommunications Equipment Industry. ***Econometrica***, 64(6): 1263-1297.

Orlic, E., Hashi, I., & Hisarciklilar, M. 2018. Cross sectoral FDI spillovers and their impact on manufacturing productivity. ***International Business Review***, 27(4): 777-796.

Østergaard, C. R., Timmermans, B., & Kristinsson, K. 2011. Does a different view create something new? The effect of employee diversity on innovation. ***Research Policy***, 40(3): 500-509.

Paci, R., & Usai, S. 1999. Externalities, knowledge spillovers and the spatial distribution of innovation. ***GeoJournal***, 49(4): 381-390.

Plummer, L. A., & Acs, Z. J. 2014. Localized competition in the knowledge spillover theory of entrepreneurship. ***Journal of Business Venturing***, 29(1): 121-136.

Porter, M. E. 1998. ***Clusters and the new economics of competition***: Harvard Business Review Boston.

Porter, M. E. 2003. The competitive advantage of regions. ***Regional studies***, 6(7): 549-578.

Porter, M. E. 2011. ***Competitive advantage of nations: creating and sustaining superior performance***: simon and schuster.

Pruthi, S. 2014. Social ties and venture creation by returnee entrepreneurs. ***International Business Review***, 23(6): 1139-1152.

Qin, F. 2015. Global talent, local careers: Circular migration of top Indian engineers and professionals. ***Research Policy***, 44(2): 405-420.

Qin, F., & Estrin, S. 2015. Does Social Influence Span Time and Space? Evidence from Indian Returnee Entrepreneurs. ***Strategic Entrepreneurship Journal***, 9(3): 226-242.

Qin, F., Wright, M., & Gao, J. 2017. Are 'sea turtles' slower? Returnee entrepreneurs, venture resources and speed of entrepreneurial entry. ***Journal of Business Venturing***, 32(6): 694-706.

Rawley, E. 2010. Diversification, coordination costs, and organizational rigidity: evidence from microdata. ***Strategic Management Journal***, 31(8): 873-891.

Roberts, M. J. D., & Beamish, P. W. 2017. The Scaffolding Activities of International Returnee Executives: A Learning Based Perspective of Global Boundary Spanning. ***Journal of Management Studies***, 54(4): 511-539.

Robertson, P. L., & Langlois, R. N. 1995. Innovation, networks, and vertical integration. ***Research policy***, 24(4): 543-562.

Rojec, M., & Knell, M. 2018. WHY IS THERE A LACK OF EVIDENCE ON KNOWLEDGE SPILLOVERS FROM FOREIGN DIRECT INVESTMENT? ***Journal of Economic Surveys***, 32(3): 579-612.

Roodman, D. 2009. How to do xtabond2: An introduction to difference and system GMM in Stata. ***The stata journal***, 9(1): 86-136.

Sánchez-Sellero, P., Rosell-Martínez, J., & García-Vázquez, J. M. 2014. Absorptive capacity from foreign direct investment in Spanish manufacturing firms. ***International Business Review***, 23(2): 429-439.

Schotter, A., & Abdelzaher, D. 2013. The Boundary Spanning Effects of the Muslim Diaspora on the Internationalization Processes of Firms from Organization of Islamic Conference Countries. ***Journal of International Management***, 19(1): 82-98.

Semykina, A., & Wooldridge, J. M. 2013. Estimation of dynamic panel data models with sample selection. ***Journal of Applied Econometrics***, 28(1): 47-61.

Smith, N., & Thomas, E. 2017. Regional conditions and innovation in Russia: the impact of foreign direct investment and absorptive capacity. ***Regional Studies***, 51(9): 1412-1428.

Spencer, J. W. 2008. The Impact of Multinational Enterprise Strategy on Indigenous Enterprises: Horizontal Spillovers and Crowding out in Developing Countries. ***The Academy of Management Review***, 33(2): 341-361.

Stojčić, N., & Orlić, E. 2019. Spatial dependence, foreign investment and productivity spillovers in new EU member states. ***Regional Studies***: 1-12.

Su, Y., & Liu, Z. 2016. The impact of foreign direct investment and human capital on economic growth: Evidence from Chinese cities. ***China Economic Review***, 37: 97-109.

Sultana, N., & Turkina, E. 2020. Foreign direct investment, technological advancement, and absorptive capacity: A network analysis. ***International Business Review***, 29(2): 101668.

Sun, W. 2013. The productivity of return migrants: the case of China's "Sea Turtles". ***IZA Journal of Migration***, 2(1): 5.

Szulanski, G., & Jensen, R. J. 2006. Presumptive adaptation and the effectiveness of knowledge transfer. ***Strategic Management Journal***, 27(10): 937-957.

Tan, J. 2006. Growth of industry clusters and innovation: Lessons from Beijing Zhongguancun Science Park. ***Journal of Business Venturing***, 21(6): 827-850.

Tavassoli, S., & Carbonara, N. 2014. The role of knowledge variety and intensity for regional innovation. ***Small Business Economics***, 43(2): 493-509.

Tian, X. 2007. Accounting for sources of FDI technology spillovers: evidence from China. ***Journal of International Business Studies***, 38(1): 147-159.

Tian, X. 2010. Managing FDI technology spillovers: A challenge to TNCs in emerging markets. ***Journal of World Business***, 45(3): 276-284.

Timmermans, B., & Boschma, R. 2014. The effect of intra-and inter-regional labour mobility on plant performance in Denmark: the significance of related labour inflows. ***Journal of Economic Geography***, 14(2): 289-311.

Trunina, A., Liu, X., & Chen, J. 2018. Small and medium technology enterprises in Zhongguancun and Silicon Valley: Regional innovation system approach. ***Journal of Science and Technology Policy Management***, 10(1): 35-57.

Tzeng, C.-H. 2018a. How Domestic Firms Absorb Spillovers: A Routine-Based Model of Absorptive Capacity View. ***Management and Organization Review***, 14(3): 543-576.

Tzeng, C.-H. 2018b. How foreign knowledge spillovers by returnee managers occur at domestic firms: An institutional theory perspective. ***International Business Review***, 27(3): 625-641.

Useche, D., Miguelez, E., & Lissoni, F. 2019. Highly skilled and well connected: Migrant inventors in cross-border M&As. ***Journal of International Business Studies***: 1-27.

van der Panne, G. 2004. Agglomeration externalities: Marshall versus Jacobs. ***Journal of Evolutionary Economics***, 14(5): 593-604.

Vancauteren, M. 2018. The effects of human capital, R&D and firm's innovation on patents: a panel study on Dutch food firms. ***The Journal of Technology Transfer***, 43(4): 901-922.

Vermeulen, F., & Barkema, H. 2002. Pace, rhythm, and scope: process dependence in building a profitable multinational corporation. ***Strategic Management Journal***, 23(7): 637-653.

Viederyte, R. 2016. How Corporate Decisions Force Innovations: Factors and Choices to Act. ***Procedia Economics and Finance***, 39: 357-364.

Viladecans-Marsal, E. 2004. Agglomeration economies and industrial location: city-level evidence. ***Journal of Economic Geography***, 4(5): 565-582.

Wang, C., Deng, Z., Kafouros, M. I., & Chen, Y. 2012. Reconceptualizing the spillover effects of foreign direct investment: A process-dependent approach. ***International Business Review***, 21(3): 452-464.

Wang, C., & Kafouros, M. I. 2009. What factors determine innovation performance in emerging economies? Evidence from China. ***International Business Review***, 18(6): 606-616.

Wang, C., Madsen, J. B., & Steiner, B. 2017a. Industry diversity, competition and firm relatedness: the impact on employment before and after the 2008 global financial crisis. ***Regional Studies***, 51(12): 1801-1814.

Wang, C. C., & Wu, A. 2016. Geographical FDI knowledge spillover and innovation of indigenous firms in China. ***International Business Review***, 25(4): 895-906.

Wang, D. 2015. Activating Cross-border Brokerage: Interorganizational Knowledge Transfer through Skilled Return Migration. ***Administrative Science Quarterly***, 60(1): 133-176.

Wang, D. J. 2020. When do return migrants become entrepreneurs? The role of global social networks and institutional distance. ***Strategic Entrepreneurship Journal***, 14(2): 125-148.

Wang, D. T., Gu, F. F., Tse, D. K., & Yim, C. K. 2013. When does FDI matter? The roles of local institutions and ethnic origins of FDI. ***International Business Review***, 22(2): 450-465.

Wang, F., Ning, L., & Zhang, J. 2017b. FDI pace, rhythm and host region technological upgrading: Intra- and interregional evidence from Chinese cities. ***China Economic Review***, 46: S65-S76.

Wang, H. 2011. Chinese Returnees, a Globalization Force in Changing Modern China. ***Available at SSRN 1976774***.

Wang, H. 2012. ***Globalizing China: the influence, strategies and successes of Chinese returnee entrepreneurs***: Emerald Group Publishing.

Wang, H., & Bao, Y. 2015. ***Reverse migration in contemporary China: Returnees, entrepreneurship and the Chinese economy***: Springer.

Wang, H., Zweig, D., & Lin, X. 2011. Returnee Entrepreneurs: impact on China's globalization process. ***Journal of Contemporary China***, 20(70): 413-431.

Wang, Y., Ning, L., Li, J., & Prevezer, M. 2016a. Foreign Direct Investment Spillovers and the Geography of Innovation in Chinese Regions: The Role of Regional Industrial Specialization and Diversity. ***Regional Studies***, 50(5): 805-822.

Wang, Y., Pan, X., Li, J., & Ning, L. 2016b. Does technological diversification matter for regional innovation capability? Evidence from China. ***Technology Analysis & Strategic Management***, 28(3): 323-334.

Wei, Y., Liu, X., Lu, J., & Yang, J. 2017. Chinese migrants and their impact on homeland development. ***The World Economy***, 40(11): 2354-2377.

Welch, D. E., & Welch, L. S. 2008. The importance of language in international knowledge transfer. ***Management International Review***, 48(3): 339-360.

Wentrup, R., Nakamura, H. R., & Ström, P. 2020. Closing the digital entrepreneurship gap the case of returnee entrepreneurs in Morocco. ***Journal of Entrepreneurship and Innovation in Emerging Economies***, 6(1): 140-162.

Windmeijer, F. 2005. A finite sample correction for the variance of linear efficient two-step GMM estimators. ***Journal of Econometrics***, 126(1): 25-51.

Wójcik, D., & MacDonald-Korth, D. 2015. The British and the German financial sectors in the wake of the crisis: size, structure and spatial concentration. ***Journal of Economic Geography***, 15(5): 1033-1054.
Wright, M., Tartari, V., Huang, K. G., Di Lorenzo, F., & Bercovitz, J. 2018. Knowledge Worker Mobility in Context: Pushing the Boundaries of Theory and Methods. ***Journal of Management Studies***, 55(1): 1-26.
Xiao, S., & Park, B. I. 2018. Bring institutions into FDI spillover research: Exploring the impact of ownership restructuring and institutional development in emerging economies. ***International Business Review***, 27(1): 289-308.
Xiao, Z., & Tsui, A. S. 2007. When brokers may not work: The cultural contingency of social capital in Chinese high-tech firms. ***Administrative Science Quarterly***, 52(1): 1-31.
Xie, K., Song, Y., Zhang, W., Hao, J., Liu, Z., & Chen, Y. 2018. Technological entrepreneurship in science parks: A case study of Wuhan Donghu High-Tech Zone. ***Technological Forecasting and Social Change***, 135: 156-168.
Yasar, M., Raciborski, R., & Poi, B. 2008. Production function estimation in Stata using the Olley and Pakes method. ***The Stata Journal***, 8(2): 221-231.
Yi, J., Chen, Y., Wang, C., & Kafouros, M. 2015. Spillover Effects of Foreign Direct Investment: How do Region-Specific Institutions Matter? ***Management International Review***, 55(4): 539-561.
Yuan, R., & Wen, W. 2018. Managerial foreign experience and corporate innovation. ***Journal of Corporate Finance***, 48: 752-770.
Yuping, M. A., & Suyan, P. A. N. 2015. Chinese Returnees from Overseas Study: An Understanding of Brain Gain and Brain Circulation in the Age of Globalization. ***Frontiers of Education in China***, 10(2): 306-329.
Zabala-Iturriagagoitia, J. M., Porto Gómez, I., & Aguirre Larracoechea, U. 2020. Technological diversification: a matter of related or unrelated varieties? ***Technological Forecasting and Social Change***, 155: 119997.
Zhang, C., & Guan, J. 2021. Returnee policies in China: Does a strategy of alleviating the financing difficulty of returnee firms promote innovation? ***Technological Forecasting and Social Change***, 164: 120509.
Zhang, D., Zheng, W., & Ning, L. 2018. Does innovation facilitate firm survival? Evidence from Chinese high-tech firms. ***Economic Modelling***, 75: 458-468.
Zhang, Y., Li, H., Li, Y., & Zhou, L.-A. 2010. FDI spillovers in an emerging market: the role of foreign firms' country origin diversity and domestic firms' absorptive capacity. ***Strategic Management Journal***, 31(9): 969-989.
Zhang, Y. A., Li, Y., & Li, H. 2014. FDI spillovers over time in an emerging market: The roles of entry tenure and barriers to imitation. ***Academy of Management Journal***, 57(3): 698-722.
Zheng, W., Lin, D., Lu, J., Liu, X., & Wright, M. 2016. "Returnee social networks, resource acquisition and returnee entrepreneurship". ***Academy of Management Proceedings***, 2016(1): 11400.
Zweig, D., & Han, D. 2010. Sea turtles' or 'seaweed?'the employment of overseas returnees in China'. ***The internationalization of labour markets***: 89-104.