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### **Returnee Over Time and FDI Knowledge Spillover: How Does FDI Affect Firm Productivity in Emerging Markets**

**ABSTRACT**: This paper investigates the moderating effect of returnee's time-based features, which include entry speed and irregularity, in helping domestic firms absorbing Foreign Direct Investment (FDI) knowledge spillovers. Using an unparalleled dataset containing comprehensive information about 14065 Chinese high-tech firms located in Zhongguancun (ZGC) science park in Beijing during 2007 to 2013, we find that the positive relationship between FDI in the industry and the total factor productivity of domestic firms becomes stronger as the returnee entry speed increases while weaker as the returnee entry irregularity increases. Our research highlights that the time-based features of returnee should be carefully considered for domestic firms as special channels to absorb foreign knowledge and they may contribute to the inconclusiveness of FDI spillover effects. Therefore, the findings have important implications for policy-makers and practitioners.

Keywords: FDI, Returnee, Firm productivity, China

#### 1. INTRODUCTION

Foreign direct investment (FDI) has been widely acknowledged as an important external knowledge source (Ning et al., 2016b). Firms, especially in emerging markets like China, have put great efforts to learn from FDI when they lack advanced technology and business expertise (Zhang et al., 2014). Previous studies also argued that establishing business linkages with foreign firms and hiring skilled employees are efficient channels to absorb FDI knowledge spillovers (Blomström and Kokko, 1998). In recent years, China have witnessed a growing number of people, who have studied and/or worked outside Chinese mainland for at least two years, returning to their home and having become a significant skilled labor force in Chinese market. For example, in China, there were 608,400 students going abroad and 489,900 returning in 2017, with a reflux ratio of 79.04% compared to that of 29.5% in 2005<sup>1</sup>. As the returnees often possess a global perspective, understand multiple cultures, and are equipped with advanced skills, domestic firms are eager to hire them and expect they can act as a 'bridge' with the foreign firms, so that help absorbing FDI knowledge spillovers as the individual-level channel (Liu et al., 2014).

However, to the best of our knowledge, we have very limited research on this topic and most studies, which examine how the entry of returnee affect domestic firm performance and absorb FDI, have produced inconsistent findings. Some studies have found returnee has positive effects in improving firm performance and helping learn from foreign firms. For example, Wei et al. (2017) show that returnees play an important role in enhancing the exports of domestic firms, and Liu et al. (2014) also argue that returnees can help bridge knowledge gaps between domestic firms and foreign firms. On the contrary, some scholars have demonstrated that returnees have no effect or even perform worse than

<sup>&</sup>lt;sup>1</sup> Data source: Ministry of Education of the People's Republic of China. http://www.moe.edu.cn/jyb\_xwfb/gzdt\_gzdt/s5987/201803/t20180329\_331771.html. Accessed 14 Feb 2019.

domestic elites. For instance, Qin et al. (2017) suggest that returnees from abroad are slower in new venture entry in the home country, compared with homegrown entrepreneurs. Similarly, Fu et al. (2017) find that not all returnees contribute equally to firms' performance, and only those individuals in the most strategic functions, such as management and sales promote the level of firm internationalization.

To reconcile the mixed findings, we argue that the time-based features of returnee entry should be considered in the process. Specifically, we think the returnee entry speed and irregularity can play different roles in boosting domestic firms to absorb FDI knowledge spillover. As the returnees are often skill adequacy and may serve as the knowledge brokerage (Lin et al., 2016), the quicker they join in domestic market, the more improvements on domestic firms' knowledge base and absorptive capability, thus may help domestic firms benefit more from FDI knowledge. On the contrary, as the returnees have stayed abroad for a long time, they are usually context unknown and suffering from insufficient local embeddedness, so they need regular time to establish local relationship and readjust to the local environment (Lin et al., 2019). As a result, an irregularity of the returnee entry, such as an abrupt and discontinuous change of the returnee entry into an industry, is often accompanied by a sudden rise of competition (Wang et al., 2017). And the unstable environment makes the interaction between returnees and local environment very difficult, which may constrain the returnee's role in helping absorbing FDI knowledge spillover. By highlighting the importance of the time-based features of returnees' role in improving firm performance, we are hopefully to help domestic firms choose a better strategy to attract highly skilled returnees and to exploit FDI knowledge spillovers more effectively.

Our study is therefore to examine the role of the returnee entry speed and irregularity in moderating the relationship between FDI knowledge spillovers and local firm performance. We employ a unique dataset containing comprehensive information about 14065 Chinese high-tech firms located in Zhongguancun (ZGC) science park in Beijing during 2007 to 2013. Based on this unparalleled dataset, our study makes several contributions to the inconclusive literature. First, we move beyond existing FDI spillover studies and shed new light on a special channel of FDI knowledge diffusions. Based on knowledge base theory and local embeddedness perspectives, this study helps to provide new insights into the role of individuals with special characteristics in promoting knowledge spillovers. More specifically, we go a step further to investigate whether returnees help to improve local knowledge base and absorptive capabilities in learn from FDI advanced knowledge. The findings help advance research on knowledge flows by placing more emphasis on returnees as a special channel of FDI knowledge spillovers.

Second, our study enriches the small but growing literature on the economic effects of the returnees. Although the returnees are important, little empirical evidence is available (Lin et al., 2016), especially about the moderating role of their foreign experience in the relationship between FDI and firm performance. To the best of our knowledge, our study is the first attempt to explain the process by which the returnees are translated into a moderating role in helping domestic firms improving their performance. We find that the returnee entry speed positively moderate FDI knowledge spillover, while the irregularity of returnee entry cannot help absorbing FDI knowledge spillover. Moreover, using different subsample analysis, we also find that the roles of returnee entry speed and irregularity in moderating FDI knowledge spillover are robust, which further backs our findings.

The remainder of this paper is as follows. In Section 2, we examine the literature and develop our hypothesis. In Section 3, we introduce our data and model specification. In Section 4, we analyze our main results. We conclude in Section 5.

#### 2. THEORY AND HYPOTHESIS DEVELOPMENT

#### 2.1 FDI Knowledge Spillover and Firm Productivity

Inward FDI has long been seen as a key source of external knowledge for emerging market firms (Ning et al., 2016a). Due to relatively weak technology and business capabilities, domestic firms in the host country of FDI are seeking opportunities to establish relationship with foreign firms and expect to improve their productivity by observing and imitating the successful technologies (Fu et al., 2011). Previous studies have identified some channels such as business linkage, employee turnover, demonstration effect and competition effect, through which domestic firms can learn from FDI knowledge spillover (Spencer, 2008).These channels can also be direct, such as "forward and backward linkages", in which domestic firms can form partnership or supply-and-demand relationship with multinational enterprises, so that acquire foreign firms' advanced knowledge (Wang et al., 2012).

However, the existing empirical evidence of FDI knowledge spillover are still inconclusive. Some of the previous studies have argued that the improvement of local firm performance is positively correlated with FDI, as interactions between local and foreign firms intensify the knowledge flow and technology transfer (Wang et al., 2012). On the contrary, some scholars suggested that the effect of FDI are not always positive and sometimes can be a threat to domestic firms (Martinez-Noya et al., 2013). With advanced innovative capabilities and more export experience, foreign firms can produce "crowd-out effects" and/ or "market-stealing" effect and can be harmful to domestic firms' performance (Hu and Jefferson, 2002).

To explain the mixed results, some scholars suggest that domestic firms need build up their absorptive capabilities to recognize, assimilate and exploit FDI spillover (Castellani and Zanfei, 2003). Lack of absorptive capabilities is one of the main constraints that limit the positive externalities of inward FDI. Therefore, domestic firms are seeking to improve their knowledge base and absorptive capabilities and expect learning more from foreign knowledge spillovers. Since most of the previous studies have investigated the effect FDI spillovers on domestic firms' productivity (e.g., (Buckley et al., 2010)). Following this tradition, we propose:

Hypothesis 1. The entry of FDI in an industry has a positive relationship with the productivity of an individual domestic firm in the same industry.

#### 2.2 Returnee Entry Speed and FDI Spillover

Entry Speed is a time-based characteristic of the returnees, which measures how rapidly the returnees' entry into an industry at a particular point of time. To see the relationship between returnee entry speed and FDI spillover, we begin with analyzing the role of returnee in absorbing FDI knowledge.

As discussed above, it is acknowledged that acquiring external knowledge from FDI spillover is not straightforward, and domestic firms need sufficient absorptive capabilities to benefit from FDI. Some studies of knowledge exchange also suggested that knowledge receivers and senders need to share a common ground and understand the context to improve the efficiency (e.g., (Welch and Welch, 2008). As 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 domestic firms (Lin et al., 2016). Through returnees, domestic firms can improve their knowledge base and absorptive capabilities so that benefit more from FDI knowledge spillovers. There are two main reasons for this based on the knowledge brokerage and knowledge base theory.

First, the returnees can serve as knowledge brokers between foreign firms and domestic firms. Knowledge brokerage is derived from the theory of structural holes, which states that certain firms or individuals play a key role in bridging knowledge gaps and generating access among previously unconnected knowledge resources (Lin et al., 2016). With a long time 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 with both their home and host countries enables them to identify cross-border differences and knowledge gaps (Bai et al., 2017). In this case, the returnees are able to act as knowledge brokers in transferring technological and business knowledge from foreign to the domestic firms. Wang (2015) also argued that, these returnee knowledge brokers have experience and expertise about the specific domains in both countries and thus have advantages in understanding the resources and preferences being played against one another by actors from the foreign and domestic firms. Moreover, domestic firms can collect and evaluate information and knowledge possessed by these returnees, establish new contacts through returnees' networks and identify opportunities with multinational enterprises (Tzeng, 2018). Thus, the returnees may facilitate FDI knowledge diffusion and exert an increase in the firm productivity.

Second, the returnees can improve local knowledge base and promote firm absorptive capabilities. Given the advanced knowledge they bring home, returnees may collectively affect the technological base of local industry (Liu et al., 2014). Returnees represent a key source of knowledge-based resources due to their acquired skills and confidence with world-class technologies, and therefore their 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. In addition, in an emerging market like China, highly skilled returnees are scarce resources at the firm level. Therefore, the returnees may become super stars 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)). As a result, it may increase a firm's willingness to invest more. Furthermore, when learning from foreign firms, given the same amount of investment, returnee with advanced knowledge might be better in choosing projects (Yuan and Wen, 2018), which increases the chance of project success, improves firm capabilities, and ultimately benefits the firm from absorbing the FDI knowledge spillover more efficiently.

As argued above, the returnees can play a key role in help absorbing FDI knowledge spillover. And to step further, there are good reasons to believe that a rapid speed of returnee entry into an industry may enhance its positive moderating effect. First, returnees often have an incentive to enter early in order to enjoy the first mover advantages in the labor market. These incentives will also push the them to interact or ally with foreign companies, establish stronger business linkages, acquire more information advantages, and thus give domestic firms more opportunities to learn from foreign firms. Second, when the returnees speed up their entry into the industry, they may transfer more new knowledge to the local industry and can accelerate the improvement of firm absorptive capabilities. Therefore, we propose:

Hypothesis 2. The positive relationship between the entry of FDI in an industry and the total factor productivity of domestic firms becomes stronger as the returnee entry speed increases.

#### 2.3 Returnee Entry Irregularity and FDI Spillover

Entry irregularity is another time-related feature of the returnees. It indicates the degree of irregularity of the returnees' entry into an industry. Contrary to returnee entry

speed, the fundamental mechanism of how returnee irregularity moderates the FDI spillovers is more likely to be negative. The reasons are twofold.

First, the returnees need time to readjustment and play a role. Previous studies have argued that, 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, 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.

Second, an irregularity of returnee entry may cause fluctuating competition. An abrupt and discontinuous change in the number of returnee entry into an industry is often accompanied by a sudden rise or fall of labor competition. In such an unstable business environment, it is also difficult for returnees to interact with local workers, transfer foreign advanced technology and improve the knowledge base. Moreover, competition fluctuate dramatically may also increase the risk and complexity of the returnees working with foreign firms.

Based on the above reasoning, we argue that a rhythmic and progressive of returnee entry is required to help local firm benefiting more from the FDI. Since most of previous studies use the kurtosis of as the measurement of rhythm, which is the indication of irregularity, so following this tradition we propose:

Hypothesis 3. The positive relationship between the entry of FDI in an industry and the total factor productivity of domestic firms becomes weaker as the returnee entry irregularity increases.

#### 3. DATA AND METHODOLOGY

#### 3.1 Data Source and Sample

We used a unique data set associated with Chinese high-tech manufacturing companies in Beijing's Zhongguancun (ZGC) science and technology park. The data set, which contains detailed information on firms' products, innovations and labor force, was collected by the ZGC regulatory body's statistical yearbook of ZGC over a period from 2007 to 2013 of 76,000 observations (Zhang et al., 2018). The survey is a statistical census of ZGC firms (of more than ten employees), the comprehensive information in which is of great significance to our in-depth research on FDI, returnee and firm performance. We have dropped observation of firms that have incomplete records and negative sales due to data unavailability. And to control for the potential bias when using 3-year lag as instruments in system-GMM analysis, firms who age under 3-years have been deleted. Moreover, since our study is focusing on the FDI spillover effect on domestic firms, so we drop foreign firms based on their registration type in the final estimation. Our resulting dataset therefore includes 9531 domestic firms, which comprise 35279 firms' year level observations.

#### 3.2 Variables

#### 3.2.1 Dependent variable

*Total Factor Productivity (TFP).* To investigate the spillover effect of FDI on local firm performance, we estimate TFP at the firm level. TFP is determined by the inputs during the production process, and it has been widely used to reflect firm performance (Fu and Gong, 2011). Previous studies have used a range of alternative ways to measure TFP, such as semi-parametric analysis like Olley and Pakes (OP) method and Levinsohn and Petrin

(LP) method. In this paper, we mainly employ the method of Olley and Pakes (1996) because of the data unavailability of intermediate input at the science park level, which is required in the LP method (Levinsohn and Petrin, 2003). More specifically, corresponding with previous studies (e.g. (Wei et al., 2017)), output is measured by sales adjusted by exfactory price index of industrial output, labor is the number of employees and capital is total assets in the OP estimation.

#### 3.2.2 Independent 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. In our study, we mainly follow Buckley et al. (2002) and employ the share of foreign capital in the total capital in the two-digit level industry to capture the FDI knowledge spillover. In fact, using the alternative measurements like the number of foreign invested firms and the total foreign capital yield similar results, and we would display other measurements as the robustness checks.

#### 3.2.3 Moderating variables

*Returnee Entry Speed.* Speed is a time-based characteristic of the returnee's entry. It measures how rapidly returnee's entry into the industry at a point of time. It can be measured by the change rate of returnees entering into the industry as follows:

$$Pace_{j,t} = \frac{Returnee_{j,t} - Returnee_{j,t-1}}{Returnee_{j,t-1}} \times 100\%$$

In which  $Returnee_{j,t}$  denotes the number of returnees of two-digit industry *j* in year *t*. A large  $Pace_{jt}$  value indicates a high speed of returnees' entry.

*Returnee Entry Irregularity.* Irregularity is another time-related attribute, which indicates the rhythm or progress of returnee's entry in the two-digit industry, which can be measured by the kurtosis of returnees' entry (Vermeulen and Barkema, 2002).

$$Irregularity_{j} = \left\{ \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum_{t=2007}^{2013} \left(\frac{x_{jt} - \overline{x_{j}}}{s_{j}}\right)^{4} \right\} - \frac{3(n-1)^{2}}{(n-2)(n-3)}$$

In which *n* is the number of observations in the two-digit industry *j* and *s* is the standard deviation of the returnees' change in the industry in year *t*.  $x_t$  is the number of returnees in year *t*, and  $\bar{x}$  is the average number of returnees in industry *j*. A relatively flat distribution shows a constant returnee entry pattern and a low-value kurtosis, while a high value of *Irregualrity*<sub>*j*,*t*</sub> indicates the irregularity of the returnee entry pattern.

#### 3.2.4 Control variables

A set of control variables is used to take other factors that might affect TFP into account. First, firm age may have a significant impact on firms' performance. Second, the total number of employees is used to measure firm size, since the size of a firm may directly affect its performance. Additionally, research and development investment (R&D) has been argued to play a role in firm performance, so we control it and measure it by firms' total amount of inner R&D investment. Lastly, we include the firm's sale, which is the most widely used indicator of a firm's operational and management capabilities.

Table 1 reports the variables used in the statistical analysis. The dependent variable is the natural log of firm TFP between 2007 and 2013. All the independent and control variables are entered in natural log form, while the moderating variables are in nun form.

#### 3.3 Model Specification

To analyse the impact of industrial agglomeration and the spatial externalities of FDI on the intensity and spatiality of pollution, there is a need for dynamic specification. It is necessary to capture the effect of learning by doing or technology adoption from FDI that may have a cumulative effect. A lagged dependent variable is therefore included. We regard firms' TFP as a function of the FDI, returnee entry speed and irregularity, as well as the basic characteristics of firms, which is expressed in the form below:

$$\begin{split} lnTFP_{i,j,t} &= \alpha + \gamma lnTFP_{i,j,t-1} + \beta_1 lnFDI_{j,t} + \beta_2 Speed_{j,t} + \beta_3 Irregularity_{j,t} \\ &+ \beta_4 (lnFDI_{j,t} * Speed_{j,t}) + \beta_5 (lnFDI_{j,t} * Irregularity_{j,t}) \\ &+ \beta_6 lnX_{i,j,t} + \varepsilon_{i,j,t} \end{split}$$

In which  $TFP_{i,j,t-1}$  is our time-lagged dependent variable  $\gamma$  is its estimated coefficient.  $FDI_{j,t}$  is the share of foreign capital in two-digit industry j in year t, which means to capture the FDI spillover effect.  $Speed_{j,t}$  refers to returnee entry speed and  $Irregularity_{j,t}$  denotes the returnee entry irregularity into inustry j in year t. We also include the interaction terms between FDI, Speed and Irregularity.  $X_{i,j,t}$  contains a set of control variables, including firm's age, size, R&D and sale, and  $\varepsilon_{i,j,t}$  is the disturbance term.

In order to solve the potential simultaneity bias, we employ the commonly used dynamic generalized method of moments (GMM) estimation methodology, which uses the lag level or lag difference of endogenous variables as the instruments. Difference-GMM and system-GMM are two widely used dynamic GMM estimators. Since the former only uses lagged levels of the endogenous variables as instruments in a first-differenced fixedeffects model, while the latter combines the first-differenced model with its corresponding model in levels and uses lagged differences of the endogenous variables as instruments, so system-GMM is asymptotically more efficient than difference-GMM (Su and Liu, 2016). System-GMM is considered as a suitable method to deal with unobserved heterogeneity and endogeneity, as well as cases where variables are not strictly exogenous (Ning and Wang, 2018). Therefore, we mainly report the estimation results based on the system-GMM method, while the difference-GMM method is for the purpose of robustness check, and the results are consistent. We 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. At the same time, 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. RESULTS

#### 4.1 Empirical Results

#### 4.1.2 Statistical description

Table 2 shows the summary statistics and correlation matrix of each variable. The correlation coefficients between dependent variable and independent variable are relatively high, which indicates that the choice of variables is good. We 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 2.36. The correlations between FDI, speed and firm's TFP are negative. These pairwise correlations must be carefully interpreted because they show only contemporaneous effects and do not take into account the moderating effects that we include in our econometric analysis.

4.1.3 Baseline estimation and system-GMM results

We employ the ordinary least squares (OLS) regression as our baseline estimation. The baseline results and system-GMM estimation results are reported in Tables 3, and the main effects of variables are consistent in the two estimations.

We first inspect the consistency, which requires valid instruments and the absence of a second-order serial correlation, of the System-GMM estimators. In column (2), we include only the independent and control variables, and the significant Hansen J-statistic of system-GMM is most likely a result of omission effects. However, when taking returnee entry speed or irregularity into consideration, the insignificant values of the Hansen Jstatistics 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 further supports the use of GMM for our estimation in our models.

For our key explanatory variable, as expected and shown in table3, the effects of FDI are positive in OLS and system-GMM estimations. Especially when we take returnee entry speed or irregularity into account in column (3), (4), (5) and (6), the effect of FDI are all significant at 1% level. This demonstrates that FDI spillovers can indeed take place in domestic firms and improve their firm performance, which supports our hypothesis 1.

Regarding returnee entry speed, our system-GMM results reveal that the primary effect of speed is negatively and significantly related to the firm performance, ( $\beta$  = -0.005 and P < 0.01), which means that the benefits of a rapid speed in returnee entry speed in improving local absorptive capability might not be fully realized within the industry. The interaction term *FDI\*Speed* in system-GMM estimation is positive and significant ( $\beta$  = 0.146 and P < 0.01), showing the positive moderating effect of returnee entry speed on the relationship between FDI and domestic firms' TFP. This finding indicates that the

relationship between FDI and firm performance is positively moderated by the returnees' entry speed in the industry, which supports our hypothesis 2.

By contrast, in system-GMM model we find the main effect of returnee entry irregularity is insignificantly correlated with firm performance ( $\beta$ =0.011 and p > 0.05), while the interaction term *FDI\*Irregularity* is negative and significant at 1% level ( $\beta$ =-0.290 and p < 0.01). These results reflect the irregularity of returnee entry may constrain their abilities in establish stable networks and readjustment to the local environment. As a result, the greater level of returnee entry irregularity restrains higher level of FDI knowledge spillovers in improving local firm performance, which supports our hypothesis 3.

For our control variables, age and size are significantly and negatively related to domestic firms TFP. R&D is positively correlated with the dependent variable but is only significant throughout the OLS model while not significant in the system-GMM. Sale is positive and significant at the 1% level throughout all models for local firm TFP.

#### 4.2 Subsample analysis

To further back our findings, we spilt our dataset into different subsamples according to previous inconclusive results. On the one hand, previous literature has argued that ownership structures can give diverse advantages for returnees to establish business and public linkages, and the results are mixed. For example, Cui et al. (2015) demonstrate that the positive effect of return managers' international experience can be strengthened by private ownership but weakened by local-state ownership, since they have more rights to build their network in private firms. One the contrary, Lin et al. (2014) find that the returnee managers have a positive impact on firms' innovation performance when they work in publicly owned firms, where they have more opportunities to network with government agencies. On the other hand, some studies also suggested that the absorptive capabilities of domestic firms can be differ as their technology gap with foreign firm varies (Castellani and Zanfei, 2003). When the technology gap is large, which means domestic firms might have insufficient absorptive capabilities, then the effect of skilled returnees on improving knowledge base can be weaker. However, when the technology gap is small, domestic firms may be able to absorb foreign technology efficiently and benefit more with the help of skilled returnees. As a result, to reconcile the mixed role of returnees that subjects to the firms' ownership structures and their technology gap with foreign firms, we divide the firms into subsamples and try to find a consistent moderating role of returnee by taking the time-based features in consideration.

First, we split our target firms into subsamples of state-owned-enterprises (SOE) and private-owned-enterprises (POE) according to their registration type and also employ the system-GMM method. The estimate results are reported in Table 4. The coefficient of FDI are positive and remain significant which is consistent with the above analysis. As for returnee entry speed, no matter in SOE or POE sample, the interaction term *FDI\*Speed* are positive and significant at 1% level ( $\beta$  = 0.556 and  $\beta$  = 0.715 respectively). For returnee entry irregularity, the interaction term *FDI\*Irregularity* are negative and significant ( $\beta$  = -0.150, p<0.01 and  $\beta$  = -0.436, p<0.05 respectively). The coefficients for other control variables are largely remain unaffected. The results indicate that when we consider the time-based features in analyzing the role of returnees in concerning different ownership structure, the moderating effect of returnees' entry not differ in SOE and POE, which further support our full sample empirical results.

Second, we rank our sample firms by their technology gap with foreign firms, which is measured by the ratio of domestic firms TFP to the median level of foreign firm TFP in the same two-digit industry. We then implement the system-GMM regressions separately for the domestic firms ranked in the bottom quarter and those ranked in the top quarter, for sharper contrast. The results are reported in table 5. The coefficients for FDI in the two subsamples differ to some extent, while for other moderating and control variables largely remain unaffected. In the bottom quarter, which means there is large technology gap between local and foreign firms, FDI is insignificant. This suggests that when the technology gap is large, domestic firms may not be able to recognize or imitate advanced foreign technology. By contrast, in the top quarter, FDI is positive and significant, which is correspond with previous analysis. With respect to returnee entry speed, both in bottom quarter and top quarter, the interaction term *FDI\*Speed* are positive and significant at 5% level ( $\beta = 0.674$  and  $\beta = 1.006$  respectively). And for returnee entry irregularity, the interaction term FDI\*Irregularity are negative and significant at 1% level in both subsamples ( $\beta$  = -0.034 and  $\beta$  = -1.363 respectively). The coefficients for other control variables largely remain unaffected. This subsample analysis indicates no matter when the technology gap is large or small, the returnees can play an important role in improving domestic firms' absorptive capabilities and help learn from FDI spillover. Moreover, when we consider the time-based features, the moderating effect of returnees' entry not differ in the two subsamples, which also support our full sample empirical findings.

We further conduct several robustness tests to check the extent to which our results are affected by alternative specifications. First, we use alternative measurement of FDI, which include the number of foreign firms and the aggregate foreign capital in the twodigit level industry. Our main results remain materially unchanged. Second, we adopt the differenced GMM method in our model to treat with the endogeneity problem and the results remain unaffected. Finally, we use alternative measurement of control variables in the estimation and find that our main results remain robust. For brevity, the results are not reported and are available upon request.

#### 5. DISCUSSION AND CONCLUSION

#### 5.1 Conclusions

Although there is a growing body of literature that is devoted to studying FDI productivity and knowledge spillovers, the returnee as the individual level channel of FDI diffusion also deserves attention because it helps promoting local knowledge base and absorptive capabilities. This paper investigates the important time-based features of returnees in moderating the relationship between FDI and local firm performance. We also consider different cases and employ the system-GMM method to address endogenous regressors. Based on the analysis of a unique and comprehensive dataset of high-tech firms in ZGC science park in Beijing for the period from 2007 to 2013, we made what is, to the best of our knowledge, the first attempt to translate the returnees into the moderating role in helping domestic firms absorbing FDI knowledge spillover and improve firms' productivity. We thus provide a contingency view and new empirical evidence to reconcile the conflicting FDI spillover effects.

Our empirical results indicate the returnee entry speed and irregularity can play a moderating role in the relationship between FDI spillovers and local firm performance. Ceteris paribus, FDI brings positive spillover effects in promoting local firm productivity. Our results are broadly in support of the individual role of returnees in bridging between foreign and domestic firms. This is in line with the wider findings of literature on positive FDI knowledge and technology spillovers (e.g. (Meyer and Sinani, 2009). Our research highlights that the time-based features of returnee, such as entry speed and irregularity, should be carefully considered as special channels to absorb foreign knowledge and they may contribute to the inconclusiveness of FDI spillover effects.

#### 5.2 Practical implications

In policy terms, our findings yield several important implications for policy makers and local firm managers in improving firm performance especially those in emerging markets. First, technology is often embedded in FDI flowing to recipient countries. FDI thus presents a great potential for knowledge spillovers. Our empirical analysis indicates that FDI is an important external knowledge source and can significantly promote local firm performance. 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. Moreover, our study helps policy makers better understand the necessity of absorbing FDI advanced knowledge for domestic firms in the host country, and under what conditions they are more or less to improve local imitation.

Second, our results also provide suggestions for local firm managers on how to manage the hiring of returnee labor force in order to maximize FDI spillovers. Our results have demonstrated that returnees are very important factors for firms in emerging markets like China to learn from foreign advanced knowledge. Returnees are often equipped with high skills and diversity culture background, so they can not only serve as a knowledge brokerage between foreign and domestic firms, but also help domestic firms absorb FDI spillover. More importantly, as returnees have stayed abroad for a long time, a stable labor market can be helpful for them to readjust to local environment and play a key role. Based on our analysis, therefore, introducing more highly skilled returnees at a more rhythmic pace enables domestic firms to improve their knowledge base and absorptive capabilities, which can help in a better observation, understanding and networking with foreign firms, and thus, may benefit more from FDI spillovers.

#### 5.3 Limitations and future research

This study has certain limitations, and future studies can further explore these issues and expand the literature. First, our study mainly focuses on FDI knowledge spillovers in China; the question of whether our findings are generalizable to other emerging markets remains unanswered. The Chinese context has received a huge amount of FDI and has experienced a growing number of returnees in a very short period of time. Emerging markets, however, are difference along many dimensions, including the maturity of economic growth, institutional stability, and the level of protection of property rights and contract enforcement. Our results therefore might be particularly pronounced compared to other countries. Replicating this study in other emerging economy context would be a promising step in promoting the theoretical analysis presented in this paper.

Second, our research is limited by the availability of data from high-tech companies in the empirical context we chose. Our study can only access the firm-level data, especially for the returnee data, only in one high-tech science park, even if ZGC is the one of the most important science parks in China and can be a good representative. In future study, it would be much more pronouncing to collect comprehensive dataset in a broad level, like city- or regional- level firm data, to generalize this contingency view. Third, we are also limited by the availability of the specific data of returnee that could help specifying their characteristics like their past study and/or work experience, and their explicit skills. Previous literature often uses individual surveys to collect the information, however, our firm-level data is limited on the returnees' personal characteristics. Last but not least, a more complicated framework is needed to understand more detailed returnee entry and FDI diffusion mechanisms, such as the threshold effect of returnee in promoting FDI spillover, or levels of industrialization that can potentially facilitate more FDI. In conclusion, although we are limited by our data in achieving these, our research, based on the analysis in the ZGC science park context, provides a contingency view of channels at the individual level, including the moderating role of returnees' time-based features in absorbing FDI knowledge spillovers. We thus inform the inconclusive debate and provide practical ways forward for firms to benefit from such spillovers.

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#### Table 1 Variables and definitions

Variable	Definitions					
TFP	Natural log of the Total Factor Productivity of firm $i$ in year $t$					
EDI	Natural log of the share of foreign capital in the total capital of two-digit					
FDI	industry <i>j</i> in year <i>t</i>					
Speed	The change rate of returnees' entry into the two-digit industry $j$ in year $t$					
Irregularity	The kurtosis of returnees' entry into the two-digit industry <i>j</i> during 2007-2013					
Age	Natural log of firm <i>i</i> 's age					
Size	Natural log of firm <i>i</i> 's total number of employees					
R&D	Natural log of firm <i>i</i> 's inner R&D investment					
Sale	Natural log of firm <i>i</i> 's total sales					

## Table 2 Summary statistics

Variable	Mean	Std.Dev.	correlation							
TFP	15.06	110.5	1							
FDI	0.092	0.063	-0.001	1						
Speed	13.02	38.52	-0.013**	-0.217***	1					
Irregularity	0.169	20.90	-0.008	0.060***	-0.028***	1				
Age	9.589	4.892	0.016***	-0.043***	-0.059***	0.013**	1			
Employee	68.38	290.2	-0.012**	0.012**	-0.015***	0.038***	0.177***	1		
R&D	1484	16034	0.005	-0.004	-0.018***	0.001	0.099***	0.277***	1	
Sale	23992	178071	0.070***	-0.007	-0.018***	-0.008	0.111***	0.370***	0.419***	1

$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$			5				
$\begin{array}{c c c c c c c c c c c c c c c c c c c $		(1)	(2)	(3)	(4)	(5)	(6)
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		OLS	sys-GMM	OLS	sys-GMM	OLS	sys-GMM
(0.001)   (0.002)   (0.001)   (0.005)   (0.01)   (0.002)     InFDI   0.010   0.085   0.118***   0.402***   0.389***   2.239***     InAge   -0.205***   -0.128***   -0.201***   -0.215***   -0.204***   -0.008**     InAge   -0.205***   -0.128***   -0.215***   -0.215***   -0.204***   -0.008**     (0.005)   (0.014)   (0.005)   (0.018)   (0.005)   (0.013)     InSize   -1.247***   -1.446***   -1.247***   -1.145***   -1.246***   -1.142***     (0.002)   (0.016)   (0.002)   (0.008)   (0.002)   (0.007)     InR&D   -0.009***   0.004***   -0.008***   0.001   -0.009***   0.907     InSale   0.977***   0.995***   0.997***   0.999***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0	VARIABLES	lnTFP	InTFP	lnTFP	InTFP	lnTFP	lnTFP
(0.001)   (0.002)   (0.001)   (0.005)   (0.01)   (0.002)     InFDI   0.010   0.085   0.118***   0.402***   0.389***   2.239***     InAge   -0.205***   -0.128***   -0.201***   -0.215***   -0.204***   -0.008**     InAge   -0.205***   -0.128***   -0.215***   -0.215***   -0.204***   -0.008**     (0.005)   (0.014)   (0.005)   (0.018)   (0.005)   (0.013)     InSize   -1.247***   -1.446***   -1.247***   -1.145***   -1.246***   -1.142***     (0.002)   (0.016)   (0.002)   (0.008)   (0.002)   (0.007)     InR&D   -0.009***   0.004***   -0.008***   0.001   -0.009***   0.907     InSale   0.977***   0.995***   0.997***   0.999***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0.997***   0							
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	L.InTFP	0.022***	0.004**	0.023***	0.025***	0.022***	0.006***
(0.040)   (0.070)   (0.042)   (0.101)   (0.101)   (0.764)     InAge   -0.205***   -0.128****   -0.201***   -0.215***   -0.204***   -0.008**     InSize   -1.247***   -1.446***   -1.247***   -1.145***   -1.246***   -1.142***     (0.002)   (0.016)   (0.002)   (0.008)   (0.002)   (0.007)     InR&D   -0.009***   0.004***   -0.008***   0.001   -0.009***   0.001     InSize   -0.009***   0.001   (0.001)   (0.001)   0.001   0.000     InR&D   -0.099***   0.995***   0.977***   0.999***   0.977***   0.997***     (0.001)   (0.001)   (0.001)   (0.001)   (0.001)   (0.001)   (0.001)     InFDI*Speed   -   -   -0.003   0.146**   -   -   -   0.011   (0.012)   (0.012)   (0.014)   (0.011)   -   -   -   -   -   -   -   -   -   -   -		(0.001)	(0.002)	(0.001)	(0.005)	(0.001)	(0.002)
InAge -0.205*** -0.128*** -0.201*** -0.215*** -0.204*** -0.008**   InSize -1.247*** -1.446*** -1.247*** -1.145*** -1.246*** -1.142****   InSize -1.247*** -1.446*** -1.247*** -1.145*** -1.246*** -1.142****   InSize -0.009*** 0.0016 (0.002) (0.008) (0.002) (0.007)   InR&D -0.009*** 0.004*** -0.008*** 0.001 -0.009*** 0.000   InSale 0.977*** 0.995*** 0.977*** 0.999*** 0.977*** 0.997***   InFDI*Speed - - 0.001 (0.001) (0.001) (0.001) (0.001)   InFDI*Speed - - - 0.006*** 0.011 (0.012) (0.010)   InFDI*Irregularity - <td>lnFDI</td> <td>0.010</td> <td>0.085</td> <td>0.118***</td> <td>0.402***</td> <td>0.389***</td> <td>2.239***</td>	lnFDI	0.010	0.085	0.118***	0.402***	0.389***	2.239***
$0$ $(0.005)$ $(0.014)$ $(0.005)$ $(0.018)$ $(0.005)$ $(0.013)$ InSize $-1.247^{***}$ $-1.446^{***}$ $-1.247^{***}$ $-1.145^{***}$ $-1.246^{***}$ $-1.142^{***}$ $(0.002)$ $(0.016)$ $(0.002)$ $(0.008)$ $(0.002)$ $(0.007)$ InR&D $-0.09^{***}$ $0.004^{***}$ $-0.008^{***}$ $0.001$ $-0.009^{***}$ $0.000$ $(0.001)$ $(0.001)$ $(0.001)$ $(0.001)$ $(0.001)$ $(0.001)$ $(0.001)$ InSale $0.977^{***}$ $0.995^{***}$ $0.977^{***}$ $0.997^{***}$ $0.997^{***}$ $(0.001)$ $(0.001)$ $(0.001)$ $(0.001)$ $(0.001)$ $(0.001)$ Speed $\cdot$ $0.001^{***}$ $-0.003$ $0.146^{**}$ $inFDI*Speed$ $\cdot$ $-0.003$ $0.146^{**}$ $-0.056^{***}$ $0.011$ $(0.012)$ $(0.012)$ $(0.012)$ $(0.010)$ $(0.010)$ $(0.010)$ InFDI*Iregularity $-1.366^{***}$ $-1.045^{***}$ $-1.332^{***}$ $-1.731^{**}$ $-1.345^{***}$ $-2.242^{**}$ $(0.012)$ $(0.012)$ $(0.012)$ $(0.047)$ $(0.047)$ $(0.016)$ $(0.086)$ InFDI*Iregularity $-1.306^{***}$ $-1.045^{***}$ $-1.332^{***}$ $-1.731^{**}$ $-1.345^{***}$ $-2.242^{**}$ $(0.012)$ $(0.012)$ $(0.047)$ $(0.012)$ $(0.047)$ $(0.016)$ $(0.086)$ InFDI*Iregularity $-1.045^{***}$ $-1.332^{***}$ $-1.731^{**}$ $-1.345^{***}$ $-2.242^{***}$ <		(0.040)	(0.070)	(0.042)	(0.101)	(0.101)	(0.764)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	lnAge	-0.205***	-0.128***	-0.201***	-0.215***	-0.204***	-0.008**
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.005)	(0.014)	(0.005)	(0.018)	(0.005)	(0.013)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	lnSize	-1.247***	-1.446***	-1.247***	-1.145***	-1.246***	-1.142***
InSale (0.001) (0.011) (0.011) (0.012)		(0.002)	(0.016)	(0.002)	(0.008)	(0.002)	(0.007)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	lnR&D	-0.009***	0.004***	-0.008***	0.001	-0.009***	0.000
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	lnSale	0.977***	0.995***	0.977***	0.999***	0.977***	0.997***
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Speed			0.001***	-0.005*		
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	-			(0.000)	(0.003)		
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	InFDI*Speed				0.146**		
Irregularity $0.006^{***}$ $0.011$ InFDI*Irregularity $0.006^{***}$ $0.010$ InFDI*Irregularity $-0.056^{***}$ $-0.290^{***}$ Constant $-1.306^{***}$ $-1.045^{***}$ $-1.332^{***}$ $-1.731^{***}$ $-0.290^{***}$ Constant $-1.306^{***}$ $-1.045^{***}$ $-1.332^{***}$ $-1.731^{***}$ $-1.345^{***}$ $-2.242^{***}$ AR (1) $0.0012$ $0.012$ $(0.047)$ $(0.047)$ $(0.047)$ $(0.016)$ $(0.086)$ AR (2) $0.013$ $0.499$ $0.133$ $0.136$ Hansen $0.000$ $0.759$ $0.136$ Observations $35,279$ $35,279$ $35,279$ $35,279$	•			(0.003)	(0.059)		
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Irregularity			· · ·	· · · ·	0.006***	0.011
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$						(0.002)	(0.010)
Constant $-1.306^{***}$ (0.012) $-1.045^{***}$ (0.047) $-1.332^{***}$ (0.012) $-1.731^{***}$ (0.047) $(0.101)$ $-1.345^{***}$ (0.016) $-2.242^{***}$ (0.086)AR (1)0.0000.0012)0.0000.000AR (2)0.0130.4990.133Hansen0.0000.7590.136Observations35,27935,27935,27935,279	InFDI*Irregularity						
Constant $-1.306^{***}$ (0.012) $-1.045^{***}$ (0.047) $-1.332^{***}$ (0.012) $-1.345^{***}$ (0.047) $-2.242^{***}$ (0.086)AR (1)0.0000.012)0.0000.000AR (2)0.0130.4990.133Hansen0.0000.7590.136Observations35,27935,27935,27935,279	0 ,					(0.014)	(0.101)
(0.012)(0.047)(0.012)(0.047)(0.016)(0.086)AR (1)0.0000.0000.0000.000AR (2)0.0130.4990.133Hansen0.0000.7590.136Observations35,27935,27935,27935,279	Constant	-1.306***	-1.045***	-1.332***	-1.731***	. ,	. ,
AR (1)0.0000.0000.000AR (2)0.0130.4990.133Hansen0.0000.7590.136Observations35,27935,27935,27935,279		(0.012)	(0.047)	(0.012)	(0.047)	(0.016)	(0.086)
AR (2)0.0130.4990.133Hansen0.0000.7590.136Observations35,27935,27935,27935,279		· · /	· · · ·	· · ·	· · · ·	<b>、</b>	
Hansen0.0000.7590.136Observations35,27935,27935,27935,27935,279	AR (1)		0.000		0.000		0.000
Observations 35,279 35,279 35,279 35,279 35,279 35,279	AR (2)		0.013		0.499		0.133
	Hansen		0.000		0.759		0.136
	Observations	35,279	35,279	35,279	35,279	35,279	35,279
R-squared 0.989 0.989 0.989	R-squared	0.989		0.989		0.989	
Number of id   9,531   9,531   9,531   9,531   9,531   9,531	Number of id	9,531	9,531	9,531	9,531	9,531	9,531

Table 3 OLS and system-GMM estimation results

	(1)	(2)	(3)	(4)
	SOE		PG	DE
VARIABLES	lnTFP	lnTFP	lnTFP	lnTFP
L.InTFP	0.011*	0.005**	0.021***	0.015**
	(0.006)	(0.002)	(0.007)	(0.007)
lnFDI	0.966***	1.332***	0.671***	3.236**
	(0.217)	(0.414)	(0.176)	(1.444)
lnAge	-0.128***	-0.027	-0.140***	0.005
	(0.024)	(0.023)	(0.031)	(0.021)
lnSize	-1.116***	-1.154***	-1.140***	-1.160***
	(0.019)	(0.011)	(0.023)	(0.010)
lnR&D	0.004	0.000	0.002	0.000
	(0.005)	(0.001)	(0.004)	(0.001)
lnSale	0.988***	0.997***	0.994***	0.998***
	(0.005)	(0.001)	(0.004)	(0.002)
Speed	-0.023***		-0.030***	
	(0.007)		(0.008)	
InFDI*Speed	0.556***		0.715***	
	(0.153)		(0.178)	
Irregularity		-0.000		0.027
		(0.005)		(0.019)
InFDI*Irregularity		-0.150***		-0.436**
		(0.052)		(0.189)
Constant	-2.141***	-2.160***	-1.887***	-2.221***
	(0.076)	(0.077)	(0.100)	(0.153)
. –				
AR (1)	0.000	0.000	0.000	0.000
AR (2)	0.689	0.735	0.524	0.139
Hansen	0.991	0.263	0.995	0.371
Observations	13,279	13,279	20,539	20,539
Number of id	3,903	3,903	6,080	6,080

Table 4 System-GMM estimation results for the subsample of SOE and POE

	qu	artile		
	(1)	(2)	(3)	(4)
	Bottom Quartile		Top Q	uartile
VARIABLES	lnTFP	lnTFP	lnTFP	lnTFP
L.InTFP	0.014**	0.012***	0.034**	0.050***
	(-0.004)	(-0.003)	(-0.016)	(-0.01)
lnFDI	0.401	-0.024	1.211**	1.047***
	(-0.310)	(-0.072)	(-0.477)	(-0.349)
lnAge	-0.216***	-0.009	-0.235**	0.184***
	(-0.074)	(-0.016)	(-0.106)	(-0.064)
InSize	-1.068***	-1.118***	-1.206***	-1.202***
	(-0.036)	(-0.012)	(-0.043)	(-0.017)
lnR&D	0.001	0.030***	0.003	0.003
	(-0.004)	(-0.008)	(-0.011)	(-0.002)
InSale	0.994***	1.003***	0.991***	1.002***
	(-0.007)	(-0.001)	(-0.010)	(-0.004)
Speed	-0.030**		-0.045**	
	(-0.013)		(-0.020)	
InFDI*Speed	0.674**		1.066**	
	(-0.307)		(-0.434)	
Irregularity		-0.011***		0.100**
		(-0.003)		(-0.043)
InFDI*Irregularity		-0.034***		-1.363***
		(-0.013)		(-0.451)
Constant	-2.147***	-2.293***	-1.661***	-3.178***
	(-0.132)	(-0.053)	(-0.248)	(-0.409)
AR (1)	0.027	0.000	0.011	0.000
AR (2)	0.192	0.984	0.364	0.148
Hansen-J	0.635	0.393	0.148	0.291
Observations	8,716	8,640	8,681	8,614
Number of id	3,341	3,341	3,654	3,654

Table 5 System-GMM estimation results for the subsample of bottom and top