



# How do human capital and R&D structure facilitate FDI knowledge spillovers to local firm innovation? a panel threshold approach

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## Abstract

This paper examines how local firms' structure of human capital and R&D strategies influence their absorption of FDI knowledge spillovers. Using a unique dataset of Chinese firms in Beijing Zhongguancun Science Park from 2009 to 2015, our panel endogenous threshold models confirm two thresholds for human capital diversity and one threshold for R&D diversity in facilitating FDI spillovers. When human capital diversity is below its second threshold, FDI presence positively influences local firms' innovation performance; while above the second threshold, the FDI turns to an insignificant impact. Besides, when R&D diversity is below its single threshold, FDI spillovers are positively associated with local firms' innovation; otherwise, the effect of FDI is insignificantly negative. Our findings highlight the importance of human capital and R&D structures in local firms' absorptive capacity. Local organizations need to keep diversifying their human capital and R&D strategies to learn from FDI knowledge but avoid allocating their efforts evenly upon sub-categories within the two resources.

**Keywords** Foreign direct investment · Innovation · Human capital · R&D diversity

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## 1 Introduction

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 et al., 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 (Ning et al., 2016a; Zhang et al., 2014). In 2019, the annual foreign capital in actual use had reached 141.23 billion US dollars in China, ranking 2nd in the world. However, the existing evidence of whether FDI knowledge spillovers can benefit local production efficiency remains inconclusive. While some scholars find positive FDI spillovers effects, via channels like demonstration effect, employee turnover and business linkages (Newman et al., 2015; Tian, 2007, 2010; Wang & Wu, 2016; Zhang et al., 2014), others argue that FDI can threaten indigenous technological upgrading by out-competing and crowding out local firms (Buckley et al., 2010; Rojec & Knell, 2018).

One important reason for the mixed results is that the absorption of FDI knowledge spillovers requires certain absorptive capacities, given the knowledge disparity between foreign and local firms. Human capital and R&D investment are two critical factors in forming firms’ absorptive capacity: human capital provide 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 imitation and assimilation of external foreign knowledge (Denicolai et al., 2016; Vancauteran, 2018). In this regard, emerging market firms have put great efforts into the two aspects to build up their abilities to assimilate FDI advanced knowledge. For example, Chinese firms have been increasingly introducing more human capital, such as highly skilled returnees and local elites, and expect them to close the local knowledge disparities with foreign firms and help identify more opportunities to learn from FDI technology (Bai et al., 2018; Li, 2020). Moreover, they also apply for many R&D grants and supports to improve their technological input and innovative capabilities (Ning et al., 2017).

However, the current literature analyzing firms’ absorptive capacity mainly focuses on the volume or stock of human capital and R&D investment in learning FDI knowledge. For example, Bournakis et al. (2019) and Smith and Thomas (2017) confirm that a higher level of human capital can help local regions to absorb FDI spillovers. (Liang, 2017) find that a large quantity of local firms’ in-house R&D capital facilitates the learning from MNEs. Nevertheless, we know relatively little about how the structures of human capital and R&D strategies can influence the FDI knowledge spillovers (Castellani & Zanfei, 2003; Murovec & Prodan, 2009). Indeed, the heterogeneity of these knowledge sources is important for organizations (Lin, 2014; Parrotta et al., 2014). More specifically, concerning human capital, as returnees and local elites have different educational backgrounds and social networks, they may have distinct effects on local absorptive capacity. Returnees possess more cross-cultural knowledge and overseas social network, which can act actively in bridging foreign and local firms, while local laborers have deeper local embeddedness, which can help identify the most suitable foreign technology for local markets (Armanios et al., 2017; Liu et al., 2010). Besides, there also exist competitions between the returnees and local elites (Li et al., 2012; Liu & Almor, 2016). Considering their complementary and competing relationship, a diverse composition of returnees and local laborers would exert contrasting impacts on the local absorption of FDI technology. Similarly, different types

of firms' R&D, such as private business R&D, government R&D, and outsourcing R&D, also impact differently on local absorptive capacities, because they have distinct objectives and might affect local firms' resources redeployment (Cuervo-Cazurra et al., 2018; Lin, 2014). Given that the time and resources of local firms are limited, it is critical to examine the structure of R&D strategies and find how to enhance the local absorptive capacity more effectively.

In this paper, therefore, we aim to fill these gaps by investigating how the structures of a firm's human capital and R&D strategies influence its absorption of FDI knowledge spillovers. We employ a unique dataset of Chinese firms in Beijing Zhongguancun science park (ZSP) from 2009 to 2015 and the panel endogenous threshold model to test our arguments. We examine mainly a firm's human capital structure by focusing on its employees' diversity of returnees and local workers at different educational levels. Meanwhile, we consider the structure of a firm's R&D strategies by differentiating its three types of R&D, including private business R&D, government R&D, and outsourcing R&D. Given that these knowledge resources have different characteristics, the complementary but competitive relationship between the sub-categories within the two resources calls for local organizations to establish appropriate human capital structures and R&D strategies to absorb the FDI spillovers effectively.

This paper makes two main contributions. First, we add new evidence to a firm's absorptive capacities when learning from FDI advanced technology. Unlike previous literature that mainly focuses on the stock of human capital and R&D investment (Girma, 2005; Sultana & Turkina, 2020), we dig into their structures and highlight the importance of human capital and R&D strategies diversity in the local absorption of FDI spillovers. Second, we innovatively examine a threshold moderating effect of a firm's human capital composition and R&D strategies. Based on our empirical results from the panel endogenous threshold model, we confirm that moderate levels of human capital and R&D diversity are more beneficial to firms' absorptive capacity, while local firms need to avoid a too high level of diversity. Our results might also reconcile the mixed findings on the effects of FDI, as different levels of diverse structure of local firms' human capital and R&D strategies would lead to distinct absorption of FDI spillovers. Accordingly, local organizations need to keep diversifying their human capital and R&D strategies to learn from FDI knowledge but avoid allocating their efforts evenly upon sub-categories within the two resources.

The organization of this paper is as follows. Section 2 reviews the literature and presents the development of the hypotheses. Section 3 shows the data and methodology. Section 4 reports the results, and Sect. 5 presents the conclusions and further discussions.

## 2 Literature review and hypothesis development

### 2.1 The threshold effect of human capital diversity on firms' absorption of FDI spillovers

The stock of human capital is an essential factor for a firm's ability to decode and assimilate FDI advanced technology (Lund Vinding, 2006; Rojec & Knell, 2018). Previous studies have widely acknowledged the importance of employees' educational background in forming a firm's human capital and its ability to utilize external knowledge (Bogers et al., 2018; Lund Vinding, 2006). For example, Mohammadi et al. (2017) investigate the employer-employee-innovation data of Swedish firms and confirm that the employees' educational

background is beneficial for firms' external knowledge search. Østergaard et al. (2011) also point out that the educational level diversity in employees' composition of bachelors, masters and doctors can influence the information, knowledge, and skills that employees contribute to the firm. However, relatively little research has examined the role of diverse compositions of employees in the FDI knowledge spillovers. In this research, we make the first attempt to investigate how this type of human capital diversity influences the local absorption of FDI advanced technology. We distinguish a firm human capital into returnees and local workers with difference educational levels according to their educational background. Returnees refer to people who have studied away from the Chinese mainland for several years and then return to their homeland (Wang, 2015, Wei et al., 2017), while local workers are people who do not have overseas educational experience.

We contend that a mix of returnees and local workers can improve local firms' absorptive capacity because they have distinct but complementary impacts on the absorption of FDI spillovers. On the one hand, returnees have been theorized to belong to a cohesive group that is typically equipped with language advantages and sufficient technological knowledge after study or work abroad for several years (Lin et al., 2016; Wang, 2015). The FDI absorption process needs interpersonal interaction, and a similar knowledge background between senders and receivers can improve the efficiency of knowledge transfer (Lund Vinding, 2006). Given the knowledge disparity between foreign and local firms, returnees with distinctive cross-cultural social capital and advanced technological competence can help identify the knowledge gaps between foreign and local firms, which may facilitate localizing foreign knowledge (Liu et al., 2014; Wang, 2015). Wei et al. (2017) also confirm that returnees are often with both the FDI host- and home-country cultural embeddedness, which can contribute to the understanding of cross-border institutional nuances, local market conditions as well as the overall strategies of MNEs. The returnees are thus favorable for local firms to break foreign technology transfer barriers and localize FDI knowledge spillovers.

On the other hand, local workers can also contribute to firms' absorptive capacities. As suggested by Armanios et al. (2017), compared with returnees, local labor forces possess more local context knowledge and business ties but a less cross-cultural experience. Their local contextual tacit knowledge enables them to identify what foreign advanced technologies are more helpful to the local market. Moreover, local employees are often equipped with basic technical skills after domestic education and training, permitting them to conduct fundamental technological activities. Through their daily tasks, they will add to firms' knowledge stock, and their interactions would also stimulate relationships with other individuals outside the firm (Armanios et al., 2017; Bogers et al., 2018). Given the tacitness of foreign technology, the local workers' interactions within the firm or with the external environment can ease the assimilation and imitation of FDI spillovers.

Considering the different impacts of returnees and the local labor force, the benefit of mixing them can improve local firms' absorptive capacity for FDI spillovers. The underlying theoretical argument is that the diverse educational backgrounds enable local firms to have more access to a broader range of knowledge, perspectives, and experiences, and interactions across individuals will augment the firm's capability to make novel linkages and associations with foreign firms (Mohammadi et al., 2017; Østergaard et al., 2011). The returnees' overseas experience can improve local workers' cross-cultural knowledge, while the local workers can instead help returnees to enhance their local embeddedness. The mix of them can thus strengthen their contributions to the local knowledge base and facilitate local firms to search for broader opportunities to learn from FDI. Consequently, local firms' human capital diversity can facilitate the absorption of FDI spillovers.

However, a too high level of human capital diversity might not maintain positive effects in a firm's absorption of FDI knowledge inflows. Returnees and local workers have different educational backgrounds and may hold diverse social identities (Armanios et al. (2017) Li et al. (2012)). The heterogeneity of belief structures, priorities and ideas resulting from a higher level of diversity could increase the communication cost for firms' internal cooperation and lead to lower cohesion and slower decision making (Lin, 2014). The different knowledge bases and groups between returnees and local workers may also result in competitive behavior and conflicts, such as the competition in wages and opportunities (Ahuja & Novelli, 2016; Roberson et al., 2017). As the absorption of FDI spillovers requires sufficient and effective interpersonal interactions, the competition and distrust issues between returnees and local workers brought by a higher level of diversity may restrict them to apply their abilities to learn from FDI spillovers.

Taken together, we hypothesize that the FDI knowledge spillovers is contingent on a threshold effect of the firm's human capital diversity. And we propose:

**Hypothesis 1.** Human capital diversity exhibits a threshold moderating effect on the relationship between FDI spillovers and local firms' innovation performance.

## 2.2 The threshold effect of R&D diversity on firms' absorption of FDI spillovers

R&D investment reflects local organizations' efforts to discover new products, services, or operational procedures (Cohen & Levinthal, 1990; Griffith et al., 2003). A firm's R&D portfolio is composed of its private business R&D, government R&D, and outsourcing R&D (Cuervo-Cazurra et al., 2018). We focus on the diversity of a firm's R&D sources since all of the three types of R&D have different impacts on the improvement of local firms' absorptive capacities for FDI spillovers.

Firstly, a firm's private business R&D is a planned and managed function designed to extend the firm-specific knowledge base systematically (Girma, 2005). Through intensive and continuing experiments and training experience in the research and development activities, local organizations can accumulate their technological competencies (Griffith et al., 2003; Lin, 2014). This accumulation can gradually narrow the knowledge gap between the receiving and transferring organizations, so that provide necessary prerequisites for external knowledge exploitation. Lin (2014) also suggests that when the complication of learning is growing, to achieve more effective learning, more prior knowledge needs to be accumulated via private business R&D. The private R&D is thus considered as a necessary factor to build up local firms' required knowledge infrastructure to identify, assimilate, and utilize FDI knowledge.

Secondly, regarding government R&D, previous literature highlights that it is mostly with public missions and often seeks a one-time technological breakthrough (Foray et al., 2012). It provides direct financial injection to firm-funded projects, which lowers firms' R&D cost and provides fundamental information about a given technology's performance so that can help establish a bridge between local firms and external knowledge sources (Foray et al., 2012; Radas et al., 2015). Ahn et al. (2020) find that government R&D can stimulate a firm's innovation collaboration and enhance its absorptive capability via integrating and digesting the transferred external knowledge smoothly. Besides, Kleer (2010) suggests that the government R&D can provide a "signaling effect" for local firms to attract business linkages from foreign firms so that

it increases the opportunities for firms to access external knowledge. In this case, government R&D can also facilitate the absorption of FDI knowledge spillovers.

Thirdly, R&D outsourcing, also known as external R&D, refers to contractually paid R&D performed by an outside independent firm or research institution (Grimpe & Kaiser, 2010). Many studies, such as Murovec and Prodan (2009) and Denicolai et al. (2016), have argued the importance of external R&D in stimulating local firms' absorptive capacity. From a resource-based perspective, R&D outsourcing provides local firms with opportunities to establish cross-organizational networks. It can be subsequently developed with firms' existing resources so that it complements local firms' knowledge base and fosters creative capabilities (Grimpe & Kaiser, 2010; Medda, 2020). Meanwhile, as argued by Cuervo-Cazurra et al. (2018), local organizations can gain experience in dealing with external networks via cooperation with their outside R&D contractors. These cooperative activities allow firms to access different knowledge domains, which contributes to the firm's ability to establish and exploit the business linkages with foreign firms. Consequently, R&D outsourcing is also a critical approach to enhance the local firm's knowledge pool and absorb FDI spillovers.

Given the distinct impacts of these three types of R&D strategies, a proper mix of them might facilitate the local absorption of FDI knowledge spillovers. Most previous literature has examined the effect of each type of R&D strategy on firms' performance, however, relatively little research has examined their structure in the improvement of local absorptive capacity. Based on the knowledge heterogeneity perspective, we argue that local firms with various R&D strategies can have more access to different knowledge domains, bring multiple technological opportunities and complementary resources (Grimpe & Kaiser, 2010). Such a broader knowledge base would make local firms more capable of decoding external foreign knowledge and then making more novel linkages and associations with foreign firms. The collaboration between different types of R&D teams provides a firm with fresh knowledge about new markets and recent technology, thus allowing them to assimilate more from the FDI spillovers.

However, similar to human capital diversity, the positive impact of R&D diversity on local absorptive capacity also has a limit, because increasing the complexity of R&D strategy may increase intra-organizational management costs, given that these three types of R&D strategy have distinct objectives (Lin, 2014; Roberson et al., 2017). For example, Zuniga-Vicente et al. (2014) review the literature on government R&D and find that it may affect the firm's resource allocations and might crowd out the positive impact of local firms' private internal R&D. Gkypali et al. (2017) also maintain that dealing with external relationships with R&D outsourcing contractors or local government requires profound management attention, calling for stricter resource redeployment. Moreover, faced with competition from other types of R&D, the focal firms' private R&D might be crowded out, which restricts them to build up indigenous technological capabilities. Therefore, when a local firm maintains a too diversified R&D strategy, such resource and management cost may constrain them to establish solid relationship with foreign firms and to improve their absorptive capacity, so that benefit less from FDI knowledge spillovers.

In sum, we hypothesize that the FDI knowledge spillovers is contingent on a threshold effect of its R&D diversity. And we propose:

**Hypothesis 2.** R&D diversity exhibits a threshold moderating effect on the relationship between FDI spillovers and local firms' innovation performance.

### 3 Data and methodology

#### 3.1 Data

We employ a unique dataset associated with Chinese firms in Beijing's Zhongguancun science park (ZSP) to examine the abovementioned hypotheses. As China's first science and technology-based cluster, ZSP has been designated by the State Council as a leading pilot demonstration zone. Some of the well-known Chinese companies such as Baidu and Sohu all originated from the ZSP (*Zhongguancun Index 2019*). ZSP provides an ideal context for our research. First, MNEs have played a critical role in the development of ZSP. One hundred thirty out of the Fortune 500 companies have set up R&D centers here, such as Microsoft, IBM and Intel (*ibid*). In our dataset, until 2015, the average MNEs' employment share over the total employment in ZSP had reached 25.15%. Moreover, ZSP firms are actively engaged in innovative activities like inventing new products and upgrading their technological productivity, which enables us to analyze the impact of FDI on local firms' innovation performance. Second, ZSP firms have attracted many types of skilled returnees and local elites and have superior opportunities to apply for government R&D subsidies and make R&D contracts with other organizations (*ibid*). This allows us to construct detailed firm-level time-varying variables regarding firms' structures of human capital and R&D strategies and investigate their impact on the FDI spillovers process.

Our dataset is an annual census survey collected by the ZSP Administrative Committee. All the firms in ZSP are required to take part in the survey by providing detailed information on financial status, R&D activities, and labor structures. It is also frequently used to explore the relevant topics of economics, business and organizational management, such as in Zhang et al. (2018) and Guan and Liu (2016). The original dataset comprises 24,272 ZSP firms and 110,182 firm-year observations from 2009 to 2015. We first calculate our independent variable, four-digit industrial level FDI presence, based on the original full sample to ensure a comprehensive assessment for FDI spillovers. Second, since the panel endogenous threshold model requires a strongly balanced panel (Caner & Hansen, 2004; Hansen, 1999), we then only keep local firms with seven-year financial data in our final estimation. After excluding observations with missing values, we finally obtain a balanced sample of 41,559 firm-year observations for 5,937 unique local firms in ZSP to compute our measurements and test our hypotheses.

#### 3.2 Variables

##### 3.2.1 Dependent variable

Traditional empirical studies have tried to capture the magnitude of spillovers based on the analysis of domestic productivity (Altomonte & Pennings, 2009; Girma, 2005; Haskel et al., 2007; Liang, 2017; Liu et al., 2000; Zhang et al., 2010). More recently, some scholars have developed alternative empirical frameworks using new product sales (Nuruz-zaman et al., 2019; Wang & Wu, 2016; Wang et al., 2012; Xia & Liu, 2017) and local patent applications or citations (Ford & Rork, 2010; García et al., 2013; Jin et al., 2018; Ning et al., 2016b), as measures of the spillover impact of FDI. In this research, we mainly employ a firm's *new product sale* and *total factor productivity* (TFP) to comprehensively measure the effect of FDI spillovers on the firm's innovation performance.

More specifically, on the one hand, in China's context, the new product is defined as products that have a significant improvement in the quality and/or function of the existing product (Xia & Liu, 2017). These may result from the adoption of new structures, designs, or manufacturing techniques. This measure has some advantages to reflect the FDI knowledge spillovers. Firstly, an innovation that is facilitated by international knowledge spillovers can be more directly assessed by focusing on firms' efforts to launch new products (Salomon & Shaver, 2005). Secondly, compared with the patent as the indicator, new product sale also reflects certain un-patented innovation but have been employed in the production process (Liu & Buck, 2007). Based on previous literature, we mainly measure firms' new product sales in their logarithm form.

On the other hand, we also follow the traditional line of research and use firms' TFP to capture FDI spillover effects. 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., 2017; Wei et al., 2017). As FDI can bring new technology, product and management practice, their advanced knowledge can help improve local production efficiency (Chung et al., 2003; Girma, 2005). We employ the method of Olley and Pakes (1996) to calculate the firm-level TFP. For estimation purposes, we specify a Cobb–Douglas production format:

$$y_{it} = \beta_0 + \beta_1 l_{it} + \beta_k k_{it} + u_{it} \quad (1)$$

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;  $u_{it}$  is the productivity component, which is assumed to follow a first-order Markov process. As in Stata command (opreg), we use the clustered bootstrap, treating all observations for a single firm as one cluster and obtain consistent results for domestic firms TFP. We proxy "output" by firms' total sales, indicate "labor" by the number of employees and measure "capital" by total assets.

### 3.2.2 Independent variables

We measure mainly the extent of *FDI* presence by employing MNEs' employees' share of the total employees at the four-digit industry level, following previous studies like Buckley et al. (2002) and Tian (2007). In our context, it reflects the theoretical justification that knowledge is embedded in individuals whose interactions enable knowledge diffusion and innovation.

### 3.2.3 Diversity measures

Researchers commonly measure heterogeneity/diversity using a Shannon entropy index, which has theoretical foundations in information theory and represents the evenness of categories in a group. It can also provide a more accurate gauge of diversity when constituent groups are of different sizes (Taagepera & Lee Ray, 1977). A larger Shannon entropy index indicates a higher level of diversity and also means that the elements are spread evenly across the sub-categories. It has been widely used to measure the diversified structure of R&D strategy and workforce, for example in (Lin, 2014) and (Bae & Han, 2020). In our study, we first divide local firms' human capital and R&D into their corresponding sub-categories and then construct the Shannon entropy index.

**Human capital diversity.** We measure a local firm's human capital diversity by dividing its employees according to their overseas and local educational backgrounds and



educational level into five categories. Specifically, the categories include (1) returnees with a master's degree, (2) returnees with a doctor's degree, (3) local workers with a master's degree, (4) local workers with a doctor's degree, and (5) local workers with a bachelor's degree or below. Due to data unavailability, we are unable to distinguish returnees with a bachelor's degree or below. We then employ the Shannon index to measure human capital diversity:

$$HCdiversity = \sum_i P_i \ln\left(\frac{1}{P_i}\right); i = 1, 2 \dots 5 \quad (2)$$

where  $P_i$  denotes the proportion of type  $i$  of employees and  $\ln(1/P_i)$  is the weight of this type. The minimum value of 0 occurs when the employee within the firm belongs to the same category (for example, all employees are returnee masters or all employees are local doctors). As employees spread more evenly and cross more groups, the entropy index becomes larger. When the five categories have the same number of employees, the value of diversity reaches its maximum level.

**R&D diversity.** We mainly distinguish R&D into three types according to firms' R&D portfolio, including the firm's private business R&D, government R&D, and outsourcing R&D. Following the study of (Lin, 2014), we also use the Shannon entropy index to measure the firm's R&D diversity, which is calculated as

$$R\&Ddiversity = \sum_j P_j \ln\left(\frac{1}{P_j}\right); j = 1, 2, 3 \quad (3)$$

where  $P_j$  denotes the proportion of type  $j$  of R&D investment and  $\ln(1/P_j)$  is the weight of this type. When R&D strategies within the firm spread more evenly and crosses more categories, the entropy index becomes larger. When the three categories have the same amount of investment, the value of diversity reaches its maximum level.

**Control variables.** We include a range of factors that might influence a domestic firm's innovation performance. We first control for firm *size*, measured by total assets, and firm *age*, calculated as the number of years since a firm was founded, to control for the scale effect on firms' innovative activities (Zhang et al., 2014). We then control for a firm's technology inputs, namely *R&D intensity*, measured as the total R&D investment scaled by the firm's total employees. This variable also captures the impact of the volume of local firms' human capital and R&D investment. Thirdly, since the profitable ability can influence the investment of the firm in new product innovation, so we include it and measure it with a firm's profits over total assets (*ROA*). Fourthly, we include *industrial competition* measured by the Herfindahl index to capture the degree of local competition (Xia & Liu, 2017). Finally, to control for the potential time trend and industrial specific characteristics, we also include year dummy and industry dummy in the regressions. We expect that firms with higher R&D intensity and more profitable ability to have higher innovation performance.

### 3.3 Econometric specification

In previous literature, there are two common methods to test threshold effects. One is the exogenous grouping model, dividing the sample into two or more subsamples based on a break-point value selected from the observations and comparing the regression results (Girma, 2005). The other is to establish a model containing a square interaction term between two explanatory variables (Buckley et al., 2010; Caner & Hansen, 2004). However, according to

Girma (2005), both methods have disadvantages. The exogenous grouping model might cause the sample to be divided in a rather ad hoc fashion, as the decision concerning the appropriate thresholds is made somewhat arbitrarily. Moreover, the second approach cannot evaluate the exact threshold value, and it can mostly estimate one threshold. We thus mainly rely on the panel endogenous threshold model that extends from Hansen’s endogenous threshold approach (Caner & Hansen, 2004; Hansen, 1999) to test our hypothesis. The model has certain advantages compared with the traditional estimation methods and has been proved to be an effective method when possible asymmetric effects are present (Girma, 2005). Firstly, it is designed to split the sample into more than two regimes based on the identification of threshold levels, allowing us to explore the mixed moderating effects of firms’ human capital and R&D diversity (Caner & Hansen, 2004). Secondly, compared with studies adopting dummy variables or arbitrary approaches to split samples that may suffer from selection bias, the threshold parameters are not imposed but estimated (Caner & Hansen, 2004; Hansen, 1999). Thirdly, this method not only estimates the threshold values but also conducts statistical significance tests for the threshold values detected (Girma, 2005). The model has also been widely used in economic studies like Girma (2005) and Huang et al. (2012).

To illustrate the threshold model, we first introduce a zero-threshold model and then extend it to single- and double-threshold models. The zero-threshold model with FDI as an explanatory variable to assess the contribution of FDI spillovers towards local firms’ innovation performance is expressed as follows:

$$Y_{it} = \mu_i + \gamma X_{it-1} + \beta_1 FDI_{it-1} + \delta_2 DIV_{it-1} + \varepsilon_{i,t} \tag{4}$$

where  $i$  denotes the firm and  $t$  the year.  $Y_{it}$  represents the dependent variables and  $FDI_{it-1}$  is the share of MNEs’ employment.  $DIV_{it-1}$  contains local firms’ human capital diversity and R&D strategies diversity.  $X_{it-1}$  includes all the control variables. We lag all explanatory variables by one year to capture the delay in the new product innovation process and TFP upgrading and mitigate potential endogeneity.

Since the level of local firms’ human capital and R&D diversity is likely to have a non-linear moderation effect, we then extend to the single-threshold model (Caner & Hansen, 2004; Hansen, 1999):

$$Y_{it} = \mu_i + \gamma X_{it-1} + \beta_1 FDI_{it-1} \times I(DIV_{it-1} \leq \theta) + \beta_2 FDI_{it-1} \times I(DIV_{it-1} > \theta) + \varepsilon_{it} \tag{5}$$

where the  $DIV_{it-1}$  is the threshold variable, and  $\theta$  is the corresponding threshold value to be estimated.  $I(\cdot)$  is an indicator function.  $\beta_1$  and  $\beta_2$  are the coefficients of the impact of FDI on the two sides of the threshold value  $\theta$ .

Define

$$\beta = \begin{bmatrix} \gamma \\ \beta_1 \\ \beta_2 \end{bmatrix}, Z_{it}(\theta) = \begin{bmatrix} z_{1it-1} \\ z_{2it-1} \\ z_{3it-1} \end{bmatrix}$$

where

$$z_{1it-1} = X_{it-1}$$

$$z_{2it-1} = FDI_{it-1} \times I(DIV_{it-1} \leq \theta)$$

$$z_{3it-1} = FDI_{it-1} \times I(DIV_{it-1} > \theta)$$

Then the matrix form of Eq. (5) is:

$$Y_{it} = \mu_i + \beta' Z_{it-1}(\theta) + \varepsilon_{it} \tag{6}$$

We next subtract the group average for each observation to remove the individual effects  $\mu_i$  and obtain the following transformed equation:

$$Y_{it}^* = \beta' Z_{it-1}^* + \varepsilon_{it}^* \tag{7}$$

where  $Y_{it}^*$  and  $Z_{it-1}^*(\theta)$  are within-group deviations. Given a threshold value  $\theta$ , the ordinary least-squares estimator of  $\beta$  can be derived from Eq. (6) as follows:

$$\hat{\beta}(\theta) = \left( Z_{it-1}^*(\theta)' Z_{it-1}^*(\theta) \right)^{-1} Z_{it-1}^*(\theta)' Y_{it}^* \tag{8}$$

After  $\beta$  is estimated, we can obtain the corresponding sum of squared residuals  $S_n(\theta)$ .  $\theta$  is defined by the minimum of the resulting concentrated sum of squared errors function  $S_n(\theta)$ , that is:

$$\hat{\theta} = \text{argmin} S_n(\theta) \tag{9}$$

We employ the grid search method proposed in Hansen (1999) to minimize the squared residuals. After we obtain threshold value  $\theta$ , we can then estimate the coefficients  $\hat{\beta}(\theta)$ .

We conduct two tests to check the validity of the threshold models: one is the significant level of the threshold effects and the other is the equality between the estimates of the threshold values and the actual values. The null hypothesis of the first test is:

$$H_0 : \theta_1 = \theta_2$$

And the test statistic is:

$$F_1 = \frac{s_0 - s_1(\hat{\theta})}{\hat{\sigma}^2(\hat{\theta})} \tag{10}$$

where  $S_0$  represents the SSR after the threshold estimation under the null hypothesis; and  $\hat{\sigma}^2(\hat{\theta})$  is the VAR after the threshold estimation under the alternative hypothesis. We follow Hansen (1999) suggestion and employ the bootstrap procedure to simulate the distribution of  $F_1$  obtain the corresponding p-values.

For the second test, the null hypothesis is:

$$H_0 : \hat{\theta} = \theta_0$$

and its corresponding statistic is the likelihood ratio test statistic:

$$LR_1(\theta) = \frac{s_1 - s_1(\hat{\theta})}{\hat{\sigma}^2(\hat{\theta})} \tag{11}$$

Hansen (1999) also provide a simple equation for calculating the area of rejection, that is, when:

$$LR_1(\theta) > -2\ln(1 - \sqrt{1 - \alpha})$$

the null hypothesis is rejected, where  $\alpha$  is the level of significance. And as calculated by (Hansen, 1999), when the level of significance is 5%, the corresponding  $LR_1$  test value equals to 7.35.

Based the above illustration on the single-threshold model, we can then extend the estimations for a double-threshold model. We test the double threshold effect by:

$$Y_{it} = \mu_i + \gamma X_{it-1} + \beta_1 FDI_{it-1} \times I(DIV_{it-1} \leq \theta_1) + \beta_1 FDI_{it-1} \times I(\theta_1 < DIV_{it-1} \leq \theta_2) + \beta_2 FDI_{it-1} \times I(DIV_{it-1} > \theta_2) + \varepsilon_{it} \tag{12}$$

The second threshold value  $\theta_2$  is obtained by the grid search method and the minimization of  $S_2(\theta_2)$  after the single-threshold  $\theta_1$  is confirmed (Caner & Hansen, 2004; Hansen, 1999). The tests for the double-threshold model are similar as above, so we do not present them here.

## 4 Results

### 4.1 Descriptive analysis

Table 1 presents the descriptive statistics and correlation coefficients. As shown, the firm-level new product sales in our sample are 12.780 million RMB on average, and the average firm’s TFP is 5.080. The average share of foreign firm employees in total two-digit industrial employment is 0.272. The mean level of human capital and R&D diversity are 0.266 and 0.067, respectively. We also report the pairwise correlation matrix in Table 2. The correlation coefficients are relatively high, and the positive correlation between FDI and the dependent variables supports the intuition that the industry level FDI may exert positive knowledge spillovers to local firms. Additionally, the multicollinearity between the variables is not an actionable concern since the mean of variance inflation factors (VIF) is equal to 1.13.

**Table 1** Descriptive statistics

Variable	Obs	Mean	SD	Min	Max
New product sales	41,559	12.780	46.020	0.000	279.200
TFP	41,559	5.080	3.306	1.361	19.390
FDI	41,559	0.272	0.134	0.000	0.985
Human capital diversity	41,559	0.266	0.276	0.000	1.410
R&D diversity	41,559	0.067	0.185	0.000	1.096
Size	41,559	182.100	531.800	0.024	3200.000
Age	41,559	10.420	5.339	2.000	33.000
R&D intensity	41,559	0.041	0.066	0.000	0.395
ROA	41,559	0.027	0.122	-0.503	0.435
Industrial competition	41,559	0.043	0.095	0.004	0.690

Notes (1) New product sales, R&D intensity, and firm size are measured in 1 million Chinese Yuan

**Table 2** Correlation matrix

Variables	1	2	3	4	5	6	7	8	9	10
New product sales	1.000									
TFP	0.428	1.000								
FDI	0.041	0.007	1.000							
Human capital diversity	0.091	0.156	-0.028	1.000						
R&D diversity	0.173	0.228	0.004	0.214	1.000					
Firm size	0.318	0.599	-0.060	0.214	0.166	1.000				
Firm age	0.132	0.264	-0.042	0.038	0.075	0.238	1.000			
R&D intensity	0.187	0.142	0.025	0.269	0.212	0.152	0.016	1.000		
ROA	0.148	0.223	0.016	0.075	0.084	0.121	0.061	0.102	1.000	
Industrial competition	-0.017	0.059	-0.282	-0.005	-0.006	0.117	0.031	-0.062	0.002	1.000

*Note* All absolute correlation coefficients greater than 0.005 are significant at 5% level

## 4.2 Panel endogenous threshold estimations

We first test the existence and the number of the thresholds between FDI spillovers and local firms' innovation by using human capital diversity and R&D diversity as the threshold variables. Subsequently, we determine the threshold values and their corresponding confidence intervals. Finally, we calculate the coefficients for the threshold parameters. We use 1000 replications for the bootstrap tests.

Table 3 shows the tests of the threshold effects. As shown, when "new product sales" is the dependent variable and human capital diversity is the threshold variable, both the single and double thresholds of F-statistics are significant at the 1% level, while the triple threshold of the F-statistic is insignificant. The tests strongly reject the linear structure of the model and suggest that there exist double thresholds for human capital diversity. As for the diversity of R&D strategy, we observe that only the single threshold of F-statistics is significant at the 1% level, while the double and triple thresholds are insignificant. The results confirm a non-linear role of R&D diversity and indicate a single threshold model. We can also observe similar test results for TFP as the dependent variable, which means double thresholds for human capital diversity and a single threshold for R&D diversity.

We then examine the double-threshold model for human capital diversity and the single-threshold model for R&D diversity. Table 4 reports the estimated threshold values. First, when "new product sales" is the dependent variable and human capital diversity is the threshold variable, we find the corresponding first threshold value is 0.067 and the second threshold value is 0.593. Both of the threshold values fall within their corresponding 95% confidence interval. Concerning R&D diversity as the threshold variable, we observe the threshold value is 0.304 and significant at 5% level. Second, when TFP is the dependent variable, the estimated significant first and second threshold values of human capital diversity are 0.324 and 0.557, while the single threshold value of R&D diversity is 0.114.

We also construct the 5% critical value and plot the LR statistics in Fig. 1 to further confirm the threshold effect above. Figure 1a-d are plotted based on Models 1–4 in Table 5 subsequently. Figure 1a and b take new product sales as the dependent variables, while Fig. 1c and d take TFP. The dashed line represents the 5% critical value (equals to 7.35). In Fig. 1a and c, for human capital diversity as the threshold variable, the minimum likelihood ratio is reached at our estimated threshold 0.067 (0.324) and 0.593 (0.557) and all pass the 5% critical value, which confirms the existence of the double threshold values. In Fig. 1b and d, concerning R&D diversity as the threshold variable, we only observe a minimum likelihood ratio at the estimated value of 0.304 (0.114) and pass the 5% critical value, while the second threshold value does not pass. The confidence intervals confirm a correct identification of the single threshold model for R&D diversity as the threshold variable.

After we obtain the threshold values, we then calculate the parameters of the panel endogenous threshold models and test our hypotheses. Table 5 presents the results for the FDI spillovers and local firms' innovation with human capital diversity and R&D diversity as threshold variables. The dependent variables for Models 1 and 2 are new product sales, while for Models 3 and 4 are TFP.

Hypothesis 1 proposes a non-linear effect of human capital diversity in the FDI spillovers process. In Models 1 and 3, when human capital diversity is lower than the first threshold (Human capital diversity  $< \theta_1$ ), the coefficients of FDI are positive and significant ( $\beta = 0.140$ ,  $p < 0.05$  in model 1;  $\beta = 0.829$ ,  $p < 0.01$  in model 3). When human

**Table 3** Test of threshold effects

Dependent variable	Independent variable	Threshold variable	Threshold test	F-statistics	P-value	Critical values		
						90%	95%	99%
New product sales	FDI	HC diversity	Test for single threshold	31.23***	0.000	11.263	15.429	16.304
			Test for double threshold	22.30***	0.000	13.614	15.439	19.588
			Test for triple threshold	14.15	0.560	23.929	29.890	49.193
		R&D diversity	Test for single threshold	29.20***	0.000	6.441	8.280	9.912
			Test for double threshold	3.39	0.360	6.173	7.359	10.793
			Test for triple threshold	3.16	0.510	7.689	10.154	12.566
TFP	FDI	HC diversity	Test for single threshold	1777.59***	0.000	19.919	24.067	24.888
			Test for double threshold	487.23***	0.000	13.830	16.573	18.973
			Test for triple threshold	198.44	0.460	233.699	246.013	264.412
		R&D diversity	Test for single threshold	75.74***	0.000	8.137	11.371	14.680
			Test for double threshold	6.52	0.170	7.218	8.676	12.228
			Test for triple threshold	5.75	0.200	6.851	9.130	14.430

Notes (1) HC diversity represents human capital diversity. (2) P-value and critical values are the results of the bootstrap simulation for 1000 times.; (3)\*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1

**Table 4** Estimated threshold values and their confidence intervals

Dependent Variable	Independent variable	Threshold variable	Threshold	Estimated value	95% confidence interval
New product sales	FDI	HC diversity	First threshold ( $\theta_1$ )	0.067	[0.061, 0.071]
			Second threshold ( $\theta_2$ )	0.593	[0.583, 0.598]
TFP	FDI	R&D diversity	First threshold ( $\theta_1$ )	0.304	[0.278, 0.320]
			First threshold ( $\theta_1$ )	0.324	[0.318, 0.325]
	R&D diversity	Second threshold ( $\theta_2$ )	0.557	[0.551, 0.562]	
		First threshold ( $\theta_1$ )	0.114	[0.086, 0.129]	

*Note* (1) HC diversity represents human capital diversity. (2) The threshold value is estimated by the grid search method proposed in Hansen (1999)



capital diversity is between the first threshold and the second threshold ( $\theta_1 < \text{Human capital diversity} \leq \theta_2$ ), the coefficients of FDI are positively significant and larger than those below the first threshold ( $\beta = 0.241$ ,  $p < 0.01$  in model 1;  $\beta = 0.201$ ,  $p < 0.01$  in model 3), which indicates that a 1 unit increase of FDI presence can be translated into 24.1% increase of local firms' new product sales or 20.1% increase of TFP. Once the human capital diversity exceeds the second threshold ( $\text{Human capital diversity} > \theta_2$ ),

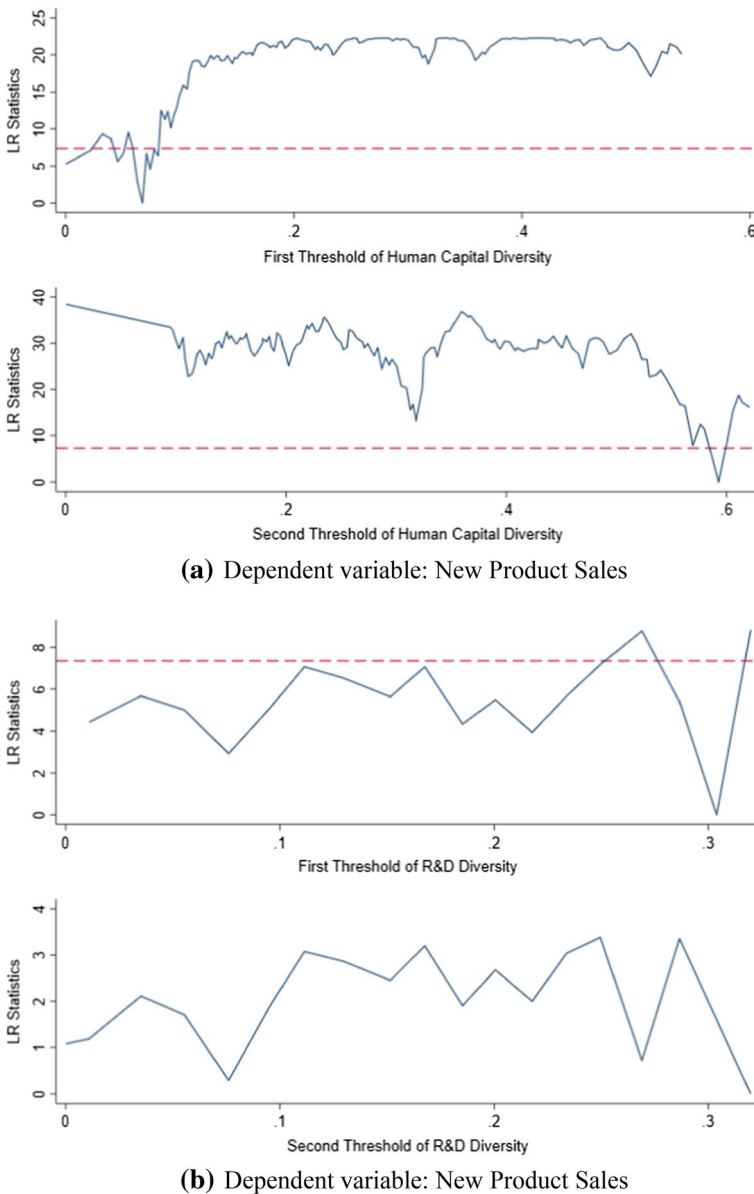


Fig. 1 5% critical value construction of the thresholds

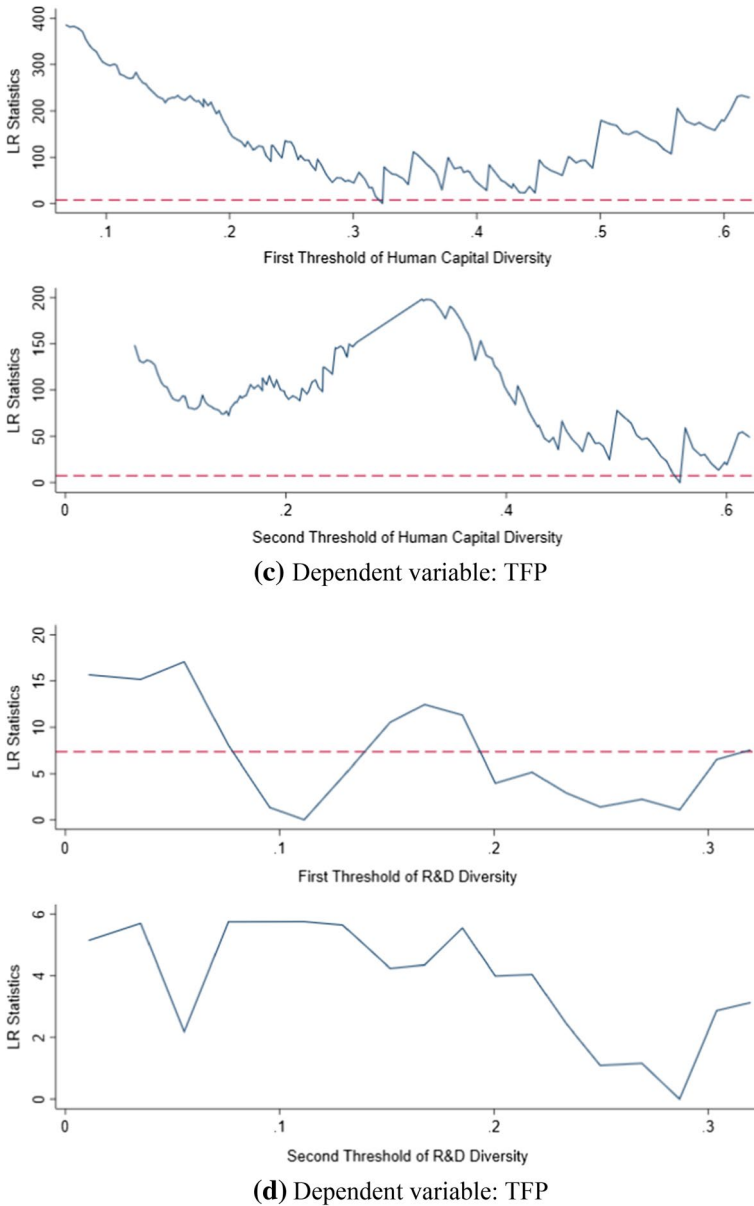


Fig. 1 (continued)

FDI begins to have negative but insignificant impacts on local firms' new product sales and TFP ( $\beta = -0.154, p > 0.1$  in model 1;  $\beta = -0.072, p > 0.1$  in model 3). The coefficients suggest that at a higher level of human capital diversity, local firms' innovation would not significantly benefit from FDI spillovers. The results confirm a non-linear moderating role of human capital diversity in the relationship between FDI spillovers and local firm innovation performance, which supports hypothesis 1.

**Table 5** FDI and local firm innovation: the threshold role of human capital and R&D diversity (panel endogenous threshold analysis)

Variables	New product sales		TFP	
	(1)	(2)	(3)	(4)
Firm size	0.065*** (0.014)	0.067*** (0.014)	0.154*** (0.005)	0.833*** (0.032)
Firm age	-0.444*** (0.027)	-0.446*** (0.027)	-0.073*** (0.008)	-0.243*** (0.043)
R&D intensity	1.570*** (0.179)	1.535*** (0.180)	0.472*** (0.050)	2.959*** (0.281)
ROA	0.375*** (0.048)	0.373*** (0.048)	-0.023 (0.015)	-0.110 (0.081)
Market competition	0.109 (0.092)	0.113 (0.092)	0.003 (0.033)	0.154 (0.221)
HC diversity	0.198*** (0.052)	0.072* (0.039)	0.042** (0.020)	0.085*** (0.016)
R&D diversity	0.169*** (0.045)	0.132** (0.062)	0.039*** (0.009)	0.022** (0.011)
FDI $\times I(HCdiversity \leq \theta_1)$	0.140** (0.069)		0.829*** (0.105)	
FDI $\times I(\theta_1 < HCdiversity \leq \theta_2)$	0.241*** (0.077)		0.201*** (0.018)	
FDI $\times I(HCdiversity > \theta_2)$	-0.154 (0.105)		-0.072 (0.096)	
FDI $\times I(R\&Ddiversity \leq \theta_1)$		0.391*** (0.118)		0.859*** (0.218)
FDI $\times I(R\&Ddiversity > \theta_1)$		-0.129 (0.091)		-0.093 (0.078)
Constant	1.358*** (0.066)	1.357*** (0.066)	1.112*** (0.017)	2.906*** (0.094)
Percent of OBS below the first threshold	35.13%	89.71%	64.99%	86.63%
Percent of OBS between thresholds	53.21%	N/A	20.72%	N/A
Percent of OBS above the second threshold	11.66%	10.29%	14.29%	13.37%
Year dummy	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes
Observations	35,622	35,622	35,622	35,622
R-squared	0.090	0.110	0.206	0.178
Number of firm	5,937	5,937	5,937	5,937

Notes (1) HC diversity represents human capital diversity; (2) The explanatory variables are lagged for one year; (3) Robust standard errors in the parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Hypotheses 2 predicts the threshold effect of R&D diversity on the relationship between FDI spillovers and local firms' innovation. In Model 2 and 4, when the diversity of R&D is below the threshold ( $R\&D\ diversity \leq \theta_1$ ), the coefficients of FDI are positive and significant at 1% level ( $\beta = 0.391$ ,  $p < 0.01$  in model 2;  $\beta = 0.859$ ,  $p < 0.01$  in model 4), which indicates that The coefficients suggest that 1 unit increase of FDI presence would lead to

39.1% increase of local firms' new product sales or 85.9% increase of TFP. After the diversity exceeds the threshold ( $R\&D\ diversity > \theta_1$ ), the coefficients of FDI turn to negative and insignificant ( $\beta = -0.129$ ,  $p > 0.1$  in model 2;  $\beta = -0.093$ ,  $p > 0.1$  in model 4), which suggests that a too high level of R&D diversity would not facilitate the absorption of FDI spillovers and improve local innovation. The results confirm the non-linear contingency effect of R&D diversity on FDI spillovers. Hypothesis 2 is thus supported.

### 4.3 Robustness tests

We conduct several tests to check the robustness of our results. We first refer to an alternative method to examine the non-linear role of human capital diversity and R&D diversity. We follow Girma (2005) and include the interactions between the square terms of our moderating variables and FDI in the estimations. Moreover, reverse causation might present between FDI and local firms' innovation performance. We thus employ the widely used system-GMM model to solve the unobserved and dynamic endogeneity issues (Blundell & Bond, 1998). We use the first differences of the second and third lags and lagged levels of dependent and explanatory variables as instruments variables. We rely on the Arellano-Bond (AR) test to examine the first or second-order serial correlation and Hansen's J test to check the overall validity of our instruments. Our dynamic panel model is expressed as:

$$Y_{it} = \beta_1 Y_{it-1} + \beta_2 FDI_{it} + \beta_3 DIV_{it} + \beta_5 FDI_{it} \times DIV_{it} + \beta_6 FDI_{it} \times DIV_{it}^2 + \gamma X_{it} + \varepsilon_{it} \quad (13)$$

Table 6 presents the system-GMM estimation results. We first only include the control variables and then add FDI and its interactions with the moderating variables subsequently. The dependent variable for Models 1–3 is the volume of new product sales, while Models 4–6 is the TFP. We observe that the Hansen J values are insignificant across models and the AR tests indicate that only first-order AR(1) error terms are serially correlated. The tests indicate appropriate system-GMM estimations. As shown in Models 2 and 5, the coefficients for the interaction terms between FDI and the square of human capital diversity are negative and significant at 1% level ( $\beta = -1.944$ ,  $p < 0.01$  in model 2;  $\beta = -2.657$ ,  $p < 0.05$  in model 5). Moreover, in Models 3 and 6, the coefficients for the interaction terms between FDI and the square of R&D diversity are also negative and significant at 1% level ( $\beta = -1.797$ ,  $p < 0.01$  in model 3;  $\beta = -1.460$ ,  $p < 0.01$  in model 6). The results all suggest a non-linear impact of human capital diversity and R&D diversity on the relationship between FDI spillovers and local firms' innovation performance, which further supports our hypotheses.

Second, we use an alternative measurement of the diversity, which is the widely used Blau's index of heterogeneity (Blau, 1977), and calculated as  $1 - \sum p_i^2$ , where  $p$  is the proportion of a group in the  $i$ th category. The number of thresholds, signs and significant levels remain unchanged for human capital diversity and R&D diversity, respectively. Third, we consider alternative time periods for our estimation. For example, we construct our balanced panels from 2010 to 2015, or from 2009 to 2014 and the results are consistent with our main findings. Fourth, we use alternative measurements of FDI, such as the industrial share of foreign firms' R&D investment or sales, and the results are consistent with our previous findings. Finally, we substitute our control variables with different computations. For instance, we calculate the level of R&D activities as the ratio of R&D expenditure over total sales and measure size as firms' total employment. The results for these different controls are still robust. For brevity, results are available upon request.

**Table 6** Robustness test: FDI and innovation: the role of human capital and R&D diversity (system GMM estimation)

Variables	New product sales			TFP		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable (t-1)	0.476*** (0.022)	0.193*** (0.058)	0.175*** (0.054)	1.038*** (0.068)	1.094*** (0.084)	1.112*** (0.069)
Firm size	0.011 (0.016)	0.016 (0.026)	0.025 (0.018)	0.059*** (0.006)	0.058*** (0.006)	0.055*** (0.006)
Firm age	- 0.275*** (0.031)	- 0.571*** (0.075)	- 0.542*** (0.052)	- 0.151*** (0.010)	- 0.152*** (0.014)	- 0.152*** (0.011)
R&D intensity	0.921*** (0.216)	0.435 (0.324)	0.809*** (0.290)	- 0.959*** (0.086)	- 1.038*** (0.096)	- 1.022*** (0.092)
ROA	0.292*** (0.050)	0.339*** (0.080)	0.320*** (0.054)	0.085*** (0.019)	0.090*** (0.021)	0.092*** (0.020)
Market competition	- 0.110 (0.082)	- 0.983** (0.382)	- 0.832*** (0.277)	- 0.035 (0.031)	- 0.027 (0.043)	- 0.029 (0.034)
FDI		0.989*** (0.213)	1.133*** (0.110)		- 0.364** (0.151)	0.061 (0.049)
HC diversity		1.218 (1.242)			1.210*** (0.431)	
HC diversity square		- 3.301*** (0.711)			- 4.089*** (1.272)	
FDI×HC diversity		3.225*** (1.060)			1.367** (0.611)	
FDI×HC diversity square		- 1.944*** (0.632)			- 2.657*** (0.817)	
R&D diversity			4.749*** (1.337)			0.166** (0.068)
R&D diversity square			- 4.044*** (1.131)			- 1.351*** (0.203)
FDI×R&D diversity			1.923*** (0.664)			0.617*** (0.105)
FDI×R&D diversity square			- 1.797*** (0.592)			- 1.460*** (0.298)
Constant	0.874*** (0.070)	0.374*** (0.055)	0.326*** (0.049)	0.145* (0.083)	0.179 (0.126)	0.038 (0.087)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
AR(1)	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	0.389	0.394	0.328	0.757	0.964	0.963
Hansen	0.162	0.177	0.193	0.225	0.359	0.412
Observations	35,622	35,622	35,622	35,622	35,622	35,622
Number of firm	5,937	5,937	5,937	5,937	5,937	5,937

Notes: (1) HC diversity represents human capital diversity; (2) Standard errors in the parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

## 5 Discussion and conclusions

### 5.1 Discussion

FDI is a critical external knowledge source for emerging market firms to upgrade their technology, however, local firms need to effectively build up their capabilities to absorb FDI knowledge. This paper examines how a firm's structures of human capital and R&D strategy affect its absorption of the FDI spillovers. We employ a unique dataset of Chinese firms in Beijing Zhongguancun science park from 2009 to 2015, and the panel endogenous threshold models to test our hypotheses. Our results confirm that the FDI knowledge spillovers is contingent on the threshold effects of local firms' human capital diversity and R&D strategy diversity. We observe that human capital diversity has two thresholds. When human capital is both below the first threshold and between the two thresholds, FDI spillovers have positive impacts on local firms' new product innovation and TFP. However, after exceeding the second threshold, FDI spillovers turn to insignificant and negative effects. In contrast, R&D strategy diversity only has one threshold. When R&D strategy diversity is below the threshold, the knowledge transferred from FDI spillovers is positively associated with local firms' innovation performance, while above the threshold, FDI has an insignificantly negative impact.

Based on our analysis, this paper makes two main contributions. Firstly, although existing studies have acknowledged the importance of human capital and R&D in identifying and assimilating FDI knowledge, most of them mainly focus on the impact of their volume or stock (Rojec & Knell, 2018). We make the first attempt to distinguish the human capital and R&D strategies into different types and providing more empirical evidence on how their compositions influence the local absorptive capacity. More specifically, concerning the human capital, we consider a firm's entire employees composition according to their educational background and employ a large-N quantitative database, which complements existing studies either using qualitative data to investigate the effect of individual-level knowledge or focusing on the diversity of the top management team in shaping local capabilities. Besides, we are the first to differentiate certain types of R&D strategies and explain their structure in the absorption of FDI spillovers. Indeed, some previous studies have investigated the diversity of R&D strategies in the improvement of industrial innovation performance, however, they have not considered its role in learning FDI advanced technology (Lin, 2014, Bae & Han, 2020). Our paper thus extends the theoretical framework and evidence and makes an essential attempt to offer a more comprehensive understanding of the impact of firms' human capital structures and R&D strategies.

Secondly, we contribute to the literature on absorptive capacity by providing a threshold framework for the role of human capital and R&D strategy diversity. Previous studies have indicated the possible negative impact of too much diversity; however, they fail to confirm a threshold relation and to identify the specific turning point of the thresholds (Østergaard et al., 2011; Roberson et al., 2017). Moreover, to what extent the diversity of human capital and R&D strategies can influence the local absorption of FDI knowledge spillovers also has not been investigated. Using the panel endogenous threshold model, we confirm two specific thresholds for human capital diversity and one threshold value for R&D strategy diversity in helping local firms to learn from FDI technology. Our study thus not only emphasizes a firm's efforts in introducing different types of employees and R&D but also underlines the importance of avoiding allocating their efforts evenly upon sub-categories within the two resources.

## 5.2 Practical implications

Our study also has several practical implications. On the one hand, this paper contributes to more evidence that FDI spillovers promote local firms' innovation, which suggests that policymakers need to introduce more FDI and encourage significant knowledge flows and knowledge transferring (Ning et al., 2016b; Zhang et al., 2014). On the other hand, our findings underline the importance of the structure of local firms' human capital and R&D strategies in absorbing FDI spillovers (Cohen & Levinthal, 1990; Lund Vinding, 2006). Managers can, therefore, introduce different types of employees and investing in various R&D to benefit from the mixing of them. However, too much diversity of human capital and R&D might not always help the absorption of FDI knowledge. A higher diversity requires a firm's efforts to manage internal interactions and resource allocation, so that constrains the contributions of the diversity to local absorptive capacity (Lin, 2014; Østergaard et al., 2011). With too diversified human capital and R&D, local firms would not benefit from FDI spillovers. Managers thus need to bypass a too diverse composition of human capital and R&D. It is also important for local organizations to find ways to ease the internal communication and minimize the management costs when faced with the problem of being too diversified to make full use of human capital and R&D.

## 5.3 Limitations and future research directions

There are also some limitations and these can be served as considerations for future research. Firstly, our 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, we still need additional evidence by combining other science parks or industrial clusters (Hobbs et al., 2017; Ubeda et al., 2019). Secondly, in this paper, we assume implicitly that human capital diversity is measured only as the number of different types of employees according to their educational background and level. However, other alternatives, such as employees' task or work experience, ethnic composition, or professional occupations, also need to be considered to proxy the firm's human capital diversity (Bogers et al., 2018; Mohammadi et al., 2017). Due to data limitations in the statistical census of firms in ZSP, this paper is unable to distinguish details regarding the specific demographic and structural diversity of a firm's human capital. Thirdly, regarding R&D diversity, in our database, we lack data on the R&D outsourcing contractors, so we cannot identify the impact of local firms' R&D corporations with foreign firms. Moreover, we are unable to distinguish the complementary or substitutional relationship among the different types of R&D strategy, so it might be better to find a more comprehensive index to capture their structures. Nevertheless, our study still provides a useful insight and framework on how local organizations should approach the effectiveness of human capital structure and R&D strategies to promote their absorptive capacity. Future studies can extend our arguments with a more comprehensive dataset and investigate these non-linear relationships.

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## Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.

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