

Technology Gap, Reverse Technology Spillover and Domestic Innovation Performance in Outward Foreign Direct Investment: Evidence from China

Hong Jin, Chongyang Zhou, Yanrui Wu, Ruicheng Wang, Dora Marinova*

Abstract: *This research adds to the literature studying the effects of outward foreign direct investment (OFDI) on domestic innovation performance and the moderating effect of a technology gap between host and home countries. New definitions of observed technology gap and expected technology gap are proposed. An observed technology gap captures the existing differences in technology level between establishments, regions or countries. An expected technology gap is an indication of the effort of imitating and learning from technology leaders. The corresponding measures and effects of observed and expected technology gaps on OFDI-induced reverse technology spillover are analyzed. OFDI in developed countries promotes innovation performance. However, OFDI in emerging markets hampers innovation performance. It is also found that regions with a wider observed technology gap and a narrower*

*Hong Jin, Associate Professor, University of Science and Technology of China, China. Email: hongjin@ustc.edu.cn; Chongyang Zhou, Ph.D. student, University of Science and Technology of China, China. Email: zhoucy@mail.ustc.edu.cn; Yanrui Wu, Professor, University of Western Australia, Australia. Email: yanrui.wu@uwa.edu.au; Ruicheng Wang, Ph.D. student, Nanjing University of Science and Technology, China. Email: w_wangruicheng@163.com; Dora Marinova, Professor, Curtin University, Australia. Email: D.Marinova@curtin.edu.au.

expected technology gap can benefit more from OFDI.

Keywords: innovation performance; outward foreign direct investment; reverse technology spillover; technology gap

JEL Codes: O21, O30, O32, O33

I. Introduction

The United Nations Conference on Trade and Development (UNCTAD) *2017 World Investment Report* witnessed a surge of outward foreign direct investment (OFDI) by emerging market multinational corporations (EMMNCs). From 2000 to 2016, the amount of OFDI made by EMMNCs surged from US\$91bn to US\$383bn with their proportion of global foreign direct investment (FDI) flows increasing from 7.82 percent to 28 percent. In 2016, Chinese OFDI rose by 44 per cent to reach US\$183bn, making China the second largest outward foreign direct investor for the first time.

The rise of OFDI in emerging economies has given scholars the opportunity to justify the effects of reverse spillover. Different from “strategic asset seeking” OFDI theory (Hill et al., 1990), Fosfuri et al. (2001) put forward the theory of emerging economy business without advantages: their OFDI was not to utilize their advantages, but to approach new technologies and knowledge. Many scholars since have contended that OFDI made by emerging economies represents knowledge-seeking behavior, aimed at learning cutting edge technology from advanced economies to promote domestic

productivity and innovation performance.

Scholars concluded that FDI-induced technology spillover is contingent on a technology gap between the host and home countries (Findlay, 1978; Wang and Blomström, 1992; Sjöholm, 1999; Keller and Yeaple, 2009). However, a consistent conclusion about the relationship between technology gap and technology spillover has not been made. A stream of literature considers a technology gap as the observed and existing differences among establishments, regions or countries (Findlay, 1978; Blomström and Sjöholm, 1999; Keller and Yeaple, 2009), while the other stream considers a technology gap to be a reflection of the effort of establishments or regions learning from technology leaders and exploiting technology spillover (Glass and Saggi, 1998; Pittiglio et al., 2016). Thus, building a rigorous theoretical framework to differentiate these two terms and to investigate the moderating effects of a technology gap on the technology spillover process is worthwhile.

In contrast to the large amount of research on the effects of a technology gap on inward FDI spillover (Blomström and Sjöholm, 1999; Sjöholm, 1999), little research has been conducted regarding the relationship between a technology gap and reverse technology spillover through OFDI. In this paper, clear and explicit definitions of observed and expected technology gaps are proposed. The different effects of host countries are also distinguished, after a division of OFDI in developed countries and emerging markets. As a result, and based on Chinese provincial level data, this paper is one of the few to clearly examine the moderating impact of a technology gap on the

effects of OFDI on domestic innovation performance in the context of emerging markets.

The rest of the paper proceeds as follows. In Section II, we review the relevant literature. In Section III, we describe the dataset and main variables. In Section IV, regression results are reported. We conduct several robustness checks in Section V. Finally, we summarize the findings of the research, outline theoretical and practical implications and highlight the limitations.

II. Literature Review

1. Outward Foreign Direct Investment (OFDI) and Reverse Technology Spillover

Emerging market multinational corporations may not possess as relatively strong technological resources as their counterparts from developed countries; therefore, some scholars have suggested that OFDI of EMMNCs may not be driven by strategic asset exploitation but instead, are driven by strategic asset seeking (Bhaumik et al., 2016). EMMNCs with an interest in knowledge acquisition may actively invest in markets that are rich in technological resources (Huang and Zhang, 2017). Anderson et al. (2015) argued that the acquisition of strategic assets for imitation and exploitation provides one plausible explanation for EMMNCs' OFDI.

Technology-seeking OFDI is more likely to pursue tacit knowledge than explicit and observable knowledge. Although EMMNCs can gain access to patent knowledge through an open and fair technology exchange market, they have to be present in host

countries in order to learn from the advanced skills and experience of the research and development (R&D) personnel, which is non-standardized and difficult to codify.

Important micromechanisms for reverse technology spillover have also been identified. First, EMMNCs can acquire new technology related to core business or technology to compensate for their technical disadvantages through mergers and acquisitions, improve their technology portfolio and ultimately enhance their competitiveness (Dunlap et al., 2016). Alliances with local firms, such as joint ventures, provide an important way to gain access to a more open and wider range of knowledge resources (Katila and Ahuja, 2002). Second, enterprises in high-tech industries are increasingly active in forming alliances with the suppliers, distributors, customers, and even competitors in their innovation ecosystems. R&D strategic alliances enable alliance partners to achieve R&D resource sharing and learning. Alliance partners can share technology and patents, reduce the minimum necessary time for new product development and share the high development and investment cost of fixed asset investment. The problem of path-dependency could be avoided through joint problem solving and communication among partners. Third, R&D internationalization enables EMMNCs to take advantage of the location advantages of the host country in science and technology resources. They employ subsidiaries to seek diversified technology inputs and programs, cross-cultural teams, and complementary resources to make full use of global labor division. Other mechanisms include imitation and learning from local companies and the benefits from forward and backward linkages with local firms.

However, the positive effects of OFDI on domestic innovation performance cannot be taken for granted (Zhou et al., 2018). World R&D expenditure is highly concentrated in a number of leading MNCs of developed countries (Li et al., 2017). Thus, locating close to such companies may help EMMNCs gain access to new technology and knowledge. However, EMMNCs may also invest in emerging markets to gain access to natural resources and markets (Wang and Hu, 2017). Innovation performance varies between countries. Compared to developed countries, emerging markets are poorly equipped with human capital endowment or R&D inputs to produce sophisticated patents or technology. The innovation capacity of emerging markets is limited, thus cooperation with local firms often cannot provide the knowledge resources or human capital that EMMNCs need to exploit creative resources. Investment in emerging markets may not be beneficial to domestic innovation performance. Li et al. (2017) suggested that the reverse technology spillover is greater for EMMNCs that invest in Organization for Cooperation and Development (OECD) countries compared to non-OECD countries. OFDI substitutes foreign activities for domestic activities and therefore domestic investment is reduced (Herzer and Schrooten, 2008; Tsung et al., 2017). Because the total amount of capital available to invest is limited in emerging markets, more OFDI means less domestic investment. Domestic innovation performance may suffer from the decreased domestic investment. Several empirical contributions reflect this phenomenon (Herzer and Schrooten, 2008). You and Solomon (2015) provided evidence of substitution between OFDI and domestic investment.

Tsung et al. (2017) found that China exhibits short-term and long-term unidirectional causality running from domestic investment to OFDI.

2. The Role of the Technology Gap

Findlay (1978) proposed the problem of the technology gap when studying the influencing factors of technology spillover. He posited that the potential for positive spillover is higher with a wider technology gap between host and home country firms, as the marginal return of new knowledge is greater for firms that have more room to “catch up” than it is for firms that are already competitive (Wang and Blomström, 1992; Blomström and Sjöholm, 1999; Sjöholm, 1999). Jordaan (2013) argued that a large technology gap makes it more likely for local suppliers to experience positive FDI spillover.

However, a smaller technology gap may reflect the stronger learning ability and potential of local enterprises, that is, the ability to absorb and utilize the knowledge that spills over. Local enterprises cannot benefit from technology transfer without reaching a minimum technology or human capital threshold level or without sufficient investment in cultivating absorptive capacity (Glass and Saggi, 1998). Pittiglio et al. (2016) found that domestic firms with at least a basic technology level find it easier to adapt to improved technologies.

Alternatively, some scholars believe that a moderate technology gap is most suitable (Kokko et al., 1996). A moderate technology gap not only provides a good

example for home country firms to learn from and imitate, but also is not too difficult to learn. Local enterprises are more adept at absorbing knowledge, skills and technology with a moderate technology gap.

The inconclusive findings so far in the literature may reflect the theoretical ambiguities of a technology gap. The two different notions of “technology gap”, namely, observed and expected, are often confused and used as synonyms in extant literature. Thus, measures of the two notions are not differentiated. Castellani and Zanfei (2007) argued that intra-industry heterogeneity in productivity (similar to the observed technology gap in this research) and investment in R&D or innovative behavior (expected technology gap) are two different notions.

A technology gap, as the observed differences in knowledge, technology and managerial skills, exists between home and host country enterprises. It only reflects the objective distance of technical efficiency, knowledge or technology level, managerial skills and, therefore, productivity between host and home country firms. Thus, an observed technology gap describes the objective situation of how far a firm or a region lies behind another. With the expansion of an observed technology gap, home country enterprises are equipped with more space to learn, imitate, and undertake knowledge and technology transfer. An observed technology gap provides a learning space for followers but it does not explain whether, when and how followers will finally catch up to the leaders. The observed differences provide EMMNCs with good opportunities to imitate and learn. Although an observed technology gap alone does not explain a firm’s

concrete capacity to learn and imitate, it constitutes the foundation for the firm to benefit from technology spillover. If the observed technology gap is too small, the limited learning space is not sufficient to promote EMMNCs' technological progress.

However, an expected technology gap reflects enterprises' ability to learn from cutting-edge technology and skills from foreign firms. Firms with a smaller expected technology gap are more adept at imitating and learning and have a stronger motivation to catch up to the leaders (Kokko et al., 1996). An expected technology gap does not explain the objective difference in technology level, but it displays firms' capacity and effort for technology catch up. When facing a huge observed technology gap, firms with a smaller expected technology gap are better at absorbing sophisticated technology from upstream and downstream enterprises or competitors. Firms with a smaller expected technology gap are more adept at organizational learning and internalizing external knowledge (Kokko et al., 1996). When EMMNCs operate in foreign countries, those with strong organizational learning capacity and a small expected technology gap can function as effective centers for the internal transfer of tacit knowledge. EMMNCs' innovation can benefit from local expertise, human capital endowment, market demand, cooperation with local enterprises, and economies of scale and scope, especially in regard to knowledge management. Therefore, EMMNCs are required to be equipped with strong dynamic capacity. Investment in R&D, human capital and technological infrastructure stimulates the process of learning.

III. Data, Variables and Methodology

1. Data

China has become the world's second largest outward foreign direct investor. Considering the availability of appropriate data, a balanced panel dataset for 31 provinces and municipalities over the period 2004–2014 is employed in this study. Firm level statistics are not used because of data limitations. In the existing literature, the most commonly used firm level data is the Chinese Annual Survey of Industrial Firms during 1998–2007. This database is clearly outdated for our study of OFDI, which according to the *Statistical Bulletin of China's Outward Foreign Direct Investment* only became significant after 2007. For this reason, this article focuses on the effects of a technology gap on OFDI and domestic innovation performance from a macro point of view, rather than from a micro view. After ruling out tax shelters, 21 main destinations of Chinese OFDI were selected and divided into two categories: developed countries and emerging markets. The 11 developed countries are: Australia, Canada, France, Germany, Japan, the Netherlands, the Republic of Korea, Singapore, Sweden, the United Kingdom and the United States. The emerging markets include 10 countries: Brazil, India, Indonesia, Iran, Kazakhstan, Mongolia, Pakistan, the Russian Federation, South Africa and Thailand. In 2014, the aggregate volume of Chinese non-financial OFDI stock in these 21 countries was US\$87.37bn, comprising 69.60 percent of the sum of Chinese OFDI in 2014 after ruling out tax avoidance investment.

The basis for division into two categories lies in the following. First, China ranked

25 in the 2016 Global Innovation Index (Dutta et al., 2016). In our sample, countries ranked ahead of China are considered as developed countries while countries ranked behind China are considered as emerging markets. Second, this division is consistent with the World Bank’s classification of high-income, low-income and middle-income countries, and the International Monetary Fund’s division of advanced economies and emerging and developing countries. This classification is also consistent with the United Nations 2016 work on development (UNDP, 2016).

2. Variables

Regional patent intensity, which is the number of patent applications per million people, was employed to calculate the innovation performance of a region, denoted as Inv_{it} .

Based on the measuring method proposed by De La Potterie and Lichtenberg (2001), international technology spillover is induced through three main channels: OFDI, FDI and imports. Reverse technology spillover through OFDI in developed countries can be measured by the R&D capital stock China gains from a host country through OFDI:

$$S_t^{OFDI_1} = \sum_j \frac{OFDI_{1,jt}}{k_{jt}} S_{jt}^d, \quad (1)$$

where S_t^{OFDI} represents the R&D capital stock China gains from its OFDI to country j in year t . $OFDI_{jt}$ represents the flow of Chinese OFDI to country j in year t . S_{jt}^d is the R&D capital stock of country j in year t . k_{jt} is the gross fixed asset formation of country j in year t .

Country j 's R&D capital stock, S_{jt}^d , is a stock variable that is calculated by the perpetual inventory method:

$$S_{jt}^d = (1 - \delta)S_{j(t-1)}^d + R\&D_{jt}, \quad (1)$$

where S_{jt}^d is the gross R&D capital stock and δ is the depreciation rate, which takes the value of five percent (Coe et al., 2009). $R\&D_{jt}$ is the R&D capital input of country j in year t . The R&D capital stock in the base year 2004 is calculated according to the perpetual inventory method:

$$S_{j,2004} = \frac{S_{j,2004}}{\delta + g}, \quad (3)$$

where g is the average annual growth over 2004–2014. Similarly, reverse technology spillover through OFDI in emerging markets, $OFDI_{2,jt}$, can be calculated.

The foreign R&D capital stock embodied in inward FDI, S_t^{FDI} , is computed as follows:

$$S_t^{FDI} = \sum_j \frac{FDI_{jt}}{k_{jt}} S_{jt}^d, \quad (4)$$

where FDI_{jt} is the flow of FDI of China from country j in year t .

The import-embodied foreign R&D capital stock, S_t^{IM} , is constructed as follows:

$$S_t^{IM} = \sum_j \frac{IM_{jt}}{y_{jt}} S_{jt}^d, \quad (5)$$

where IM_{jt} is the flow of Chinese imports of goods and services from country j in year t and y_{jt} is country j 's GDP.

Export is also an important channel of international technology spillover (Bai et al., 2017). As in the calculation above, the export-embodied foreign R&D capital stock, S_t^{EX} , is constructed as follows:

$$S_t^{EX} = \sum_j \frac{EX_{jt}}{y_{jt}} S_{jt}^d, \quad (2)$$

where EX_{jt} is the flow of Chinese exports of goods and services to country j in year t and y_{jt} is country j 's GDP.

Because the OFDI, FDI and import data for a specific host country are not available at province level, the proportion of a region's OFDI, FDI, imports and exports to China's whole volume is utilized to calculate technology spillover:

$$S_{it}^{OFDI} = \frac{OFDI_{it}}{\sum_i OFDI_{it}} \times S_t^{OFDI} \quad (7)$$

$$S_{it}^{OFDI_1} = \frac{OFDI_{1,it}}{\sum_i OFDI_{1,it}} \times S_t^{OFDI_1} \quad (8)$$

$$S_{it}^{OFDI_2} = \frac{OFDI_{2,it}}{\sum_i OFDI_{1,it}} \times S_t^{OFDI_2} \quad (9)$$

$$S_{it}^{FDI} = \frac{FDI_{it}}{\sum_i FDI_{it}} \times S_t^{FDI} \quad (10)$$

$$S_{it}^{IM} = \frac{IM_{it}}{\sum_i IM_{it}} \times S_t^{IM} \quad (11)$$

$$S_{it}^{EX} = \frac{EX_{it}}{\sum_i EX_{it}} \times S_t^{EX} \quad (12)$$

SD_{it} is measured by domestic R&D input stock of region i in year t . The perpetual inventory method is used to calculate the R&D input stock for each year.

Differences in labor productivity (Amable, 1993) are calculated to measure the observed technology gap between China and developed countries, OTG_{1it} . These are measured by the ratio of labor productivity in developed countries to Chinese provinces. The labor productivity of each developed country is calculated by the real GDP divided by total employment. We then use the weighted average of developed countries' labor productivity to better illustrate the observed technology gap. That is:

$$OTG_{1it} = \frac{\frac{y_{jt}}{Emp_{jt}} \times \frac{OFDI_{jt}}{\sum OFDI_{jt}}}{\frac{y_{it}}{Emp_{it}}}, \quad (13)$$

where y_{it} represents real GDP of region i in year t , Emp_{it} represents total employment in region i in year t and Emp_{jt} represents total employment in host country j in year t . Similarly, the observed technology gap between China and emerging markets, OTG_{2it} , is measured by the ratio of the weighted average of labor productivity in emerging markets to Chinese provinces.

Differences in capital intensity (Kokko, 1994) are calculated to measure the expected technology gap between China and developed countries, ETG_{1it} . These are measured by the ratio of capital intensity in developed countries to Chinese provinces.

That is:

$$ETG_{1it} = \frac{\frac{Fix_{jt}}{Emp_{jt}} \times \frac{OFDI_{jt}}{\sum OFDI_{jt}}}{\frac{Fix_{it}}{Emp_{it}}}, \quad (14)$$

where Fix_{it} represents fixed capital stock of region i in year t and Fix_{jt} represents fixed capital stock of host country j in year t . Similarly, we calculate the gap in capital intensity between China and emerging markets, ETG_{2it} . All nominal values in this paper have been converted into real values in 2004 and into purchasing power parity prices for international comparison. Table 1 provides an overview of the main variables. We take logarithms of variables Inv , S^{OFDI_1} , S^{OFDI_2} , S^{FDI} , S^{IM} , S^{EX} and SD . Descriptive statistics of the main variables are reported in Table 2.

Table 1. Description of Main Variables

Variable	Proxy	Source
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<i>Inv</i>	Regional patent intensity	<i>China Statistical Yearbook on Science and Technology</i>
S^{OFDI_1}	OFDI-embodied foreign R&D capital stock from developed countries	<i>Statistical Bulletin of China's Outward Foreign Direct Investment, World Bank Database, UNCTAD Database</i>
S^{OFDI_2}	OFDI-embodied foreign R&D capital stock from emerging markets	<i>Statistical Bulletin of China's Outward Foreign Direct Investment, World Bank Database, UNCTAD Database</i>
S^{FDI}	FDI-embodied foreign R&D capital stock	<i>World Bank Database, UNCTAD Database</i>
S^{IM}	Import-embodied foreign R&D	<i>World Bank Database, UNCTAD Database</i>
S^{EX}	Export-embodied foreign R&D	<i>World Bank Database, UNCTAD Database</i>
<i>SD</i>	Domestic R&D input stock	<i>China Statistical Yearbook on Science and Technology</i>
OTG_1	Observed technology gap between China and developed countries	<i>World Bank Database, China Statistical Yearbook</i>
OTG_2	Observed technology gap between China and emerging markets	<i>World Bank Database, China Statistical Yearbook</i>
ETG_1	Expected technology gap between China and developed countries	<i>World Bank Database, China Labor Statistical Yearbook</i>
ETG_2	Expected technology gap between China and emerging markets	<i>World Bank Database, China Labor Statistical Yearbook</i>

Notes: OFDI, outward foreign direct investment; R&D, research and development; UNCTAD, United Nations Conference on Trade and Development

Table 2. Descriptive Statistics for Main Variables

Variable	N	Mean	SD	Min	Max
<i>Inv</i>	341	4.3576	7.5297	0.0833	53.6169
S^{OFDI_1} (thousand)	341	2757.55	4803.27	0.00	41181.39
S^{OFDI_2} (thousand)	341	858.97	1490.36	0.00	13268.21
S^{FDI} (thousand)	341	9722348.45	14700021.11	54454.26	83100570.95
S^{IM} (thousand)	341	192458.40	645689.92	45.21	5671689.03
S^{EX} (thousand)	341	192217.80	629981.43	357.02	6644390.71
<i>SD</i> (million)	341	153544.56	180914.84	1464.22	940158.51
OTG_1	341	0.1279	0.0927	0.0146	0.4125
OTG_2	341	0.3748	0.2641	0.0510	1.1868

ETG_1	341	0.7369	0.6769	0.0414	2.9069
ETG_2	341	6.5138	5.5421	0.4843	24.7649

Note: SD, standard deviation.

3. Method

In line with many previous studies, we base our model on the knowledge production function (KPF):

$$Inv_{it} = A \times (SD_{it})^{\beta_1}. \quad (3)$$

We extend this classic model to study R&D input and the effects of several other factors on innovation performance:

$$INV_{it} = A \times (SD_{it})^{\beta_1} \times (S_{it}^{FDI})^{\beta_2} \times (S_{it}^{IM})^{\beta_3} \times (S_{it}^{EX})^{\beta_4} \times (S_{it}^{OFDI_1})^{\beta_5} \times (S_{it}^{OFDI_2})^{\beta_6}, \quad (4)$$

where $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$, and β_6 are all parameters to be estimated.

Considering the non-linear relationship between technology gap and innovation performance (Lai et al., 2009), we assume that domestic innovation performance is a piecewise function of a technology gap. That is, the coefficient of a technology gap remains unchanged until the technology gap reaches a threshold. Two common approaches are usually adopted for studying the relationship between a technology gap and technology spillover. One method is the exogenous grouping model, which divides the samples into two or more subsamples according to some perceived proxies for technology gap after an ad hoc value (e.g. the median) from the observations is selected. A comparison is then made of the effects of spillover across the subsamples (Liu, 2008). However, the exogenously imposed splitting of samples has faced criticism. As shown

by Hansen (2000), we run into serious inference problems if econometric estimators are generated from such exogenous sample-splitting procedures. Another method is to introduce a linear interaction term between the OFDI variable and a proxy for the technology gap. However, there are three discernible shortcomings. First, it cannot evaluate the exact threshold value. Second, the linear interaction term is based on the hypothesis, namely technology spillover effects are monotonously increasing (or decreasing) with the technology gap, which, may not be the truth. Third, the introduction of an interaction term may cause serious multiple collinearity, which would expand the estimators' variance and thus lower estimation efficiency.

In order to avoid possible bias from an artificially set threshold, we therefore employ Hansen's endogenous threshold model to develop a more flexible specification. This method is useful for checking the existence of a threshold value and identifying the exact threshold value rather than adopting an ad hoc and arbitrary method of exogenously splitting the samples or introducing a linear interaction term between the OFDI variable and a proxy for the technology gap. We start by checking the existence of the threshold effect and estimate the threshold value of a technology gap between China and developed countries. The single-threshold model is as follows:

$$\begin{aligned}
 \ln Inv_{it} = & \mu_i + \beta_1 \times \ln SD_{it} + \beta_2 \times \ln S_{it}^{FDI} + \beta_3 \times \ln S_{it}^{IM} + \\
 & \beta_4 \times \ln S_{it}^{EX} + \alpha_1 \times \ln S_{it}^{OFDI_1} I(Gap_{it} \leq \theta_1) + \alpha_2 \times \\
 & \ln S_{it}^{OFDI_1} I(Gap_{it} > \theta_1) + \gamma \times \ln S_{it}^{OFDI_2} + \varepsilon_{it},
 \end{aligned} \tag{15}$$

where technology gap (GAP_{it}) is the threshold variable, and θ is the threshold value

to be estimated. $I(\cdot)$ is an indicator function. Similarly, we can check the existence of a threshold effect and estimate the threshold value of a technology gap between China and emerging markets.

Similarly, a double-threshold model can be established as follows:

$$\begin{aligned} \ln Inv_{it} = & \mu_i + \beta_1 \times \ln SD_{it} + \beta_2 \times \ln S_{it}^{FDI} + \beta_3 \times \ln S_{it}^{IM} + \\ & \beta_4 \times \ln S_{it}^{EX} + \alpha_1 \times \ln S_{it}^{OFDI_1} I(Gap_{it} \leq \theta_1) + \alpha_2 \times \\ & \ln S_{it}^{OFDI_1} I(\theta_1 < Gap_{it} \leq \theta_2) + \alpha_3 \times \ln S_{it}^{OFDI_1} I(Gap_{it} > \theta_2) + \\ & \gamma \times \ln S_{it}^{OFDI_2} + \varepsilon_{it}. \end{aligned} \quad (5)$$

IV. Empirical Results

1. Regression Results: Observed Technology Gap

First, to avoid a spurious estimated relationship, a unit root test is employed to check the stationarity of data, which shows that the raw data are not stable. Cointegration techniques are thus used, in which a cointegration relationship between variables is found. The results of cointegration tests are reported in Table 3.

Table 3. Results of Cointegration Tests

	Statistic	P-value
Modified Dickey–Fuller test	-3.4309	0.0003***
Dickey–Fuller test	-7.0773	0.0000***
Augmented Dickey–Fuller test	-1.2280	0.1007*
Unadjusted modified Dickey–Fuller test	-4.7898	0.0000***
Unadjusted Dickey–Fuller test	-7.6239	0.0000***
Lags	1.39 (Newey–West)	
Augmented lags	1	

Notes: * and *** indicate significance at 10 and 1 percent levels, respectively.

Granger causality tests are performed to check the causal relationships between domestic innovation performance and reverse technology spillover through OFDI in developed countries and emerging markets. The results are reported in Table 4, from which we conclude that reverse technology spillover through OFDI in developed countries and emerging markets Granger cause domestic innovation performance.

Table 4. Results of Granger Causality Tests

Null hypothesis	F-statistic	P-value
Reverse technology spillover through OFDI in developed countries does not Granger cause domestic innovation performance	6.8825	0.0012**
Domestic innovation performance does not Granger cause reverse technology spillover through OFDI in developed countries	0.0343	0.9663
Reverse technology spillover through OFDI in emerging markets does not Granger cause domestic innovation performance	13.9766	0.0000***
Domestic innovation performance does not Granger cause reverse technology spillover through OFDI in emerging markets	0.1530	0.8582

Notes: ** and *** indicate significance at 5 and 1 percent levels, respectively. OFDI, outward foreign direct investment.

A Hausman test is used to check if our sample fits an endogenous threshold regression model. A p-value close to 0 shows that our sample fits the model very well. We start by examining the effect of the observed technology gap, OTG_{1it} and OTG_{2it} , on the relationship between domestic innovation performance and OFDI, both in developed countries and emerging markets, respectively. Table 5 reports the F-statistics and p-values of the threshold effect. Single-threshold effects are statistically significant at the 1 percent level, while double-thresholds effects are insignificant. Therefore, a

single-threshold effect model fits our sample. Estimated threshold values and confidence intervals are reported in Table 6.

In Table 7, Model 1 shows that when an observed technology gap is less than the threshold value 22.63, a 1 percent increase in OFDI spillover from developed countries will lead to a 0.069 percent increase in regional patent intensity. However, when an observed technology gap exceeds the threshold value, a 1 percent increase in OFDI spillover from developed countries will lead to a 0.1372 percent increase in regional patent intensity. These findings tend to indicate that EMMNCs with wider observed technology gaps have more room to catch up. A wider observed technology gap provides EMMNCs with favorable opportunities to learn from local competitors in developed countries. Compared to firms that are already competitive, firms with a wider observed technology gap can promote technical progress through learning and imitating, as they have more space to make technological progress. Therefore, they can benefit more from a reverse technology spillover compared to EMMNCs with a narrower observed technology gap.

Model 1 also displays a negative relationship between OFDI in emerging markets and domestic innovation performance. Domestic innovation is hampered by OFDI in emerging markets. Chinese MNCs cannot learn much technology from emerging markets. A “crowding out” effect, that is, when domestic investment is substituted by OFDI, may exist (Tsung et al., 2017).

From Model 2 in Table 7, when an observed technology gap exceeds the threshold

value 6.46, the coefficient of OFDI in emerging markets is insignificant. However, when the observed technology gap is less than the threshold value, the coefficient of OFDI in emerging markets is negative and significant. The change in coefficient shows that EMMNCs with a wider observed technology gap suffer less from OFDI in emerging markets because even compared to emerging markets they still have room to learn and imitate.

Table 5. Threshold Effects Test: Observed Technology Gap

Observed technology gap	Test	F-statistics	P-value
Between China and developed countries	Single-threshold	60.44	0.00***
	Double-thresholds	9.81	0.40
Between China and emerging markets	Single-threshold	42.04	0.00***
	Double-thresholds	13.63	0.25

Notes: P-values are the results of the bootstrap simulation for 300 times in this table. *** indicates significance at 1 percent.

Table 6. Estimated Threshold Values and Their Confidence Intervals: Observed Technology Gap

Observed technology gap	Threshold	Estimated values	95 percent confidence interval
Between China and developed countries	θ_1	22.63	[21.86, 23.51]
Between China and emerging markets	θ_2	6.46	[5.83, 7.29]

Table 7. Estimated Parameters for Single-threshold: Observed Technology Gap

Model 1	Observed technology gap between China and developed countries	Model 2	Observed technology gap between China and emerging markets
Constant	-15.8121*** (-10.51)	Constant	-16.3633*** (-10.69)
$\ln S^{OFDI_1}$ ($OTG_{1it} \leq 22.63$)	0.0690*** (2.96)	$\ln S^{OFDI_1}$	0.1031*** (4.39)
$\ln S^{OFDI_1}$	0.1372***	$\ln S^{OFDI_2}$	-0.0907***

$(OTG_{1it} > 22.63)$	(5.79)	$(OTG_{2it} \leq 6.46)$	(-3.74)
$\ln S^{OFDI_2}$	-0.0597**	$\ln S^{OFDI_2}$	-0.0242
	(-2.49)	$(OTG_{2it} > 6.46)$	(-0.93)
$\ln S^{FDI}$	0.1289**	$\ln S^{FDI}$	0.1242*
	(1.98)		(1.87)
$\ln S^{IM}$	0.0228	$\ln S^{IM}$	0.0319
	(0.48)		(0.65)
$\ln S^{EX}$	0.0633	$\ln S^{EX}$	0.0424
	(1.34)		(0.88)
$\ln SD$	1.2222***	$\ln SD$	1.2924***
	(13.46)		(14.30)
R^2	0.88	R^2	0.85

Notes: Figures in parentheses are t-statistics. *, ** and *** indicate significance at 10, 5 and 1 percent levels, respectively.

2. Regression Results: Expected Technology Gap

As in the above procedure, we try different models, from a single-threshold to a double-threshold model. The single-threshold effects are statistically significant at the 1 percent level, while the double-threshold effects are insignificant. Estimated threshold values and confidence intervals are reported in Table 9.

In Model 3 from Table 10, we can conclude that when an expected technology gap is less than the threshold value 3.78, a 1 percent increase in OFDI spillover from developed countries will lead to a 0.097 percent increase in regional patent intensity. However, when an expected technology gap exceeds the threshold value, a 1 percent increase in OFDI spillover from developed countries will lead to a 0.0521 percent increase in regional patent intensity. EMMNCs with a narrower expected technology gap understand better the value of knowledge and are more skilled in internalizing and adapting such knowledge. Knowledge transfer channels between subsidiaries and

headquarters are more effective for EMMNCs with a narrower expected technology gap as they have stronger organization learning ability and dynamic capacity. The process of internalizing external knowledge is important for EMMNCs to utilize the location advantage in developed countries. The main goal of their OFDI in developed countries is knowledge asset-seeking, thus firms with a narrower expected technology gap are more competent at learning advanced technology from local firms and finally achieve the goal of technological progress.

For OFDI in emerging markets, OFDI spillover has a negative effect on domestic innovation performance when an expected technology gap exceeds the threshold value 0.507. But with the expected technology gap being narrowed down, the negative effect becomes insignificant. This shows that with improvement in regional capital intensity, the crowding out effect of OFDI in emerging markets is relieved. As OFDI in such countries could be seen as a substitute of domestic investment, there will not be a serious problem if the available resource of investment for both domestic and abroad becomes much more abundant.

The results for several control variables are worth noting. First, FDI significantly promotes domestic innovation performance, although the correctness and effectiveness of the Chinese government's strategy of "exchanging technology with market" has always been questioned (Zhao and Zhang, 2010). Second, import-embodied and export-embodied technology spillovers do not promote domestic innovation performance. They may not serve as the main channel for international knowledge

transfer. Third, R&D capital stock improves domestic innovation performance, consistent with the results of previous research implying the importance of domestic R&D investment (Liu and Agbola, 2014).

Table 8. Threshold Effects Test: Expected Technology Gap

Expected technology gap	Test	F-statistics	P-values
Between China and developed countries	Single-threshold	37.39	0.00***
	Double-threshold	9.64	0.41
Between China and emerging markets	Single-threshold	28.04	0.01***
	Double-threshold	10.14	0.31

Notes: P-values are the results of the bootstrap simulation for 300 times. *** indicates significance at 1 percent.

Table 9. Estimated Threshold Values and Their Confidence Intervals: Expected Technology Gap

Expected technology gap	Threshold	Estimated values	95 percent confidence interval
Between China and developed countries	θ_1	3.78	[369, 3.91]
Between China and emerging markets	θ_2	0.41	[0.39, 0.45]

Table 10. Estimated Parameters for Single-threshold: Expected Technology Gap

Model 3	Expected technology gap between China and developed countries	Model 4	Expected technology gap between China and emerging markets
Constant	-15.6501*** (-9.75)	Constant	-16.4626*** (-10.35)
$\ln S^{OFDI_1}$ ($ETG_{1it} \leq 3.78$)	0.0970*** (4.10)	$\ln S^{OFDI_1}$	0.0837*** (3.49)
$\ln S^{OFDI_1}$ ($ETG_{1it} > 3.78$)	0.0521** (2.10)	$\ln S^{OFDI_2}$ ($ETG_{2it} \leq 0.41$)	-0.0213 (-0.78)
$\ln S^{OFDI_2}$	-0.0346 (-1.35)	$\ln S^{OFDI_2}$ ($ETG_{2it} > 0.41$)	-0.0664*** (-2.67)

$\ln S^{FDI}$	0.1633** (2.44)	$\ln S^{FDI}$	0.1681** (2.49)
$\ln S^{IM}$	0.0145 (0.29)	$\ln S^{IM}$	0.0158 (0.32)
$\ln S^{EX}$	0.0791 (1.63)	$\ln S^{EX}$	0.0739 (1.51)
$\ln SD$	1.1703*** (11.25)	$\ln SD$	1.2397*** (12.20)
R^2	0.85	R^2	0.85

Notes: Figures in parentheses are t-statistics. *, ** and *** indicate significance at 10, 5 and 1 percent levels, respectively.

V. Robustness Check

In this section, we conduct three robustness checks. First, readers may question the division of developed countries and emerging markets. Therefore, a new division of the host countries is made according to the 2016 Bloomberg Innovation Index (BII) (Coy and Lu, 2016). China ranked 21 in the 2016 BII. Making a new division, countries ranked ahead of China are considered as technology-leading countries and those ranked behind China are seen as technology-lagging countries. The main results remain consistent with our prior research and are reported in Tables 11–16.

Table 11. Robustness Check of Threshold Effects Test: Observed Technology Gap

Observed technology gap	Test	F-statistics	P-values
Between China and technology-leading countries	Single-threshold	65.21	0.00***
	Double-thresholds	11.74	0.36
Between China and technology-lagging countries	Single-threshold	41.43	0.00***
	Double-thresholds	20.38	0.11

Notes: P-values are the results of the bootstrap simulation for 300 times. *** indicates significance at 1 percent.

Table 12. Robustness Check of Estimated Threshold Values and Their Confidence Intervals: Observed Technology Gap

Observed technology gap	Threshold	Estimated values	95 percent confidence interval
Between China and technology-leading countries	θ_1	22.63	[21.86, 23.50]
Between China and technology-lagging countries	θ_2	6.46	[5.83, 6.52]

Table 13. Robustness Check of Estimated Parameters for Single-threshold: Observed Technology Gap

Model 5	Observed technology gap between China and developed countries	Model 6	Observed technology gap between China and emerging markets
Constant	-16.3850*** (-11.16)	Constant	-17.1238*** (-11.39)
$\ln S^{OFDI_1}$ ($OTG_{1it} \leq 22.63$)	0.0537*** (2.61)	$\ln S^{OFDI_1}$	0.0848*** (3.99)
$\ln S^{OFDI_1}$ ($OTG_{1it} > 22.63$)	0.1237*** (5.66)	$\ln S^{OFDI_2}$ ($OTG_{2it} \leq 6.46$)	-0.0718*** (-3.26)
$\ln S^{OFDI_2}$	-0.0443** (-2.08)	$\ln S^{OFDI_2}$ ($OTG_{2it} > 6.46$)	-0.0036 (-0.16)
$\ln S^{FDI}$	0.1342** (2.04)	$\ln S^{FDI}$	0.1402** (2.07)
$\ln S^{IM}$	0.0307 (0.64)	$\ln S^{IM}$	0.0428 (0.87)
$\ln S^{EX}$	0.0517 (1.10)	$\ln S^{EX}$	0.0303 (0.63)
$\ln SD$	1.2686*** (14.26)	$\ln SD$	1.3397*** (14.89)
R ²	0.86	R ²	0.85

Notes: Figures in parentheses are t-statistics. *, ** and *** indicate significance at 10, 5 and 1 percent levels, respectively.

Table 14. Robustness Check of Threshold Effects Test: Expected Technology Gap

Expected technology gap	Test	F-statistics	P-values
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Between China and technology-leading countries	Single-threshold	41.86	0.00***
	Double-threshold	10.14	0.34
Between China and technology-lagging countries	Single-threshold	28.70	0.00***
	Double-threshold	10.63	0.34

Notes: P-values are the results of the bootstrap simulation for 300 times. *** indicates significance at 1 percent.

Table 15. Robustness Check of Estimated Threshold Values and Their Confidence Intervals: Expected Technology Gap

Expected technology gap	Threshold	Estimated values	95 percent confidence interval
Between China and technology-leading countries	θ_1	3.78	[3.69, 3.91]
Between China and technology-lagging countries	θ_2	0.41	[0.39, 0.45]

Table 16. Robustness Check of Estimated Parameters for Single-threshold: Expected Technology Gap

Model 7	Expected technology gap between China and developed countries	Model 8	Expected technology gap between China and emerging markets
Constant	-16.0049*** (-10.09)	Constant	-17.1478*** (-10.97)
$\ln S^{OFDI_1}$ ($ETG_{1it} \leq 4.303$)	0.0803*** (3.79)	$\ln S^{OFDI_1}$	0.0628*** (2.94)
$\ln S^{OFDI_1}$ ($ETG_{1it} > 4.303$)	0.0335 (1.54)	$\ln S^{OFDI_2}$ ($ETG_{2it} \leq 0.507$)	-0.0028 (-0.12)
$\ln S^{OFDI_2}$	-0.0153 (-0.68)	$\ln S^{OFDI_2}$ ($ETG_{2it} > 0.507$)	-0.0447** (-2.02)
$\ln S^{FDI}$	0.1768*** (2.62)	$\ln S^{FDI}$	0.1815*** (2.65)
$\ln S^{IM}$	0.0218 (0.44)	$\ln S^{IM}$	0.0252 (0.50)
$\ln S^{EX}$	0.0708 (1.47)	$\ln S^{EX}$	0.0620 (1.27)

$\ln SD$	1.1848*** (11.29)	$\ln SD$	1.2851*** (12.72)
R^2	0.85	R^2	0.84

Notes: Figures in parentheses are t-statistics. *, ** and *** indicate significance at 10, 5 and 1 percent levels, respectively.

Second, we employ a separate measure for the observed technology gap, regional GDP per capita, and a different measure for the expected technology gap, human capital. Differences in regional GDP per capita reflect a region's average productivity, which has been employed as an indicator of an observed technology gap in extant literature. Differences in regional GDP per capita between China and developed countries, $PGDP_{1it}$, are measured by the ratio of weighted average GDP per capita of developed countries to Chinese regions:

$$PGDP_{1it} = \frac{\frac{y_{jt}}{Pop_{jt}} \times \frac{OFDI_{jt}}{\sum OFDI_{jt}}}{\frac{y_{it}}{Pop_{it}}}, \quad (6)$$

where Pop_{it} represents the population of region i in year t and Pop_{jt} represents the population of DC j in year t . Similarly, the difference in regional GDP per capita between China and emerging markets can be calculated.

Differences in human capital, as an indicator of an expected technology gap measures regions' difference in capacity to undertake technology transfer. A region's ratio of the population with tertiary education is employed as a measure of human capital stock. Differences in human capital stock between China and developed countries, HC_{1it} , are measured by the ratio of weighted average of human capital stock in developed countries to Chinese regions:

$$HC_{1it} = \frac{\frac{Pop_{jt}^*}{Pop_{jt}} \times \frac{OFDI_{jt}}{\sum OFDI_{jt}}}{\frac{Pop_{it}^*}{Pop_{it}}}, \quad (7)$$

where Pop_{it}^* represents the population that has completed tertiary education of region i in year t and Pop_{jt}^* represents the population that has completed tertiary education of country j in year t . Similarly, we can obtain the difference in human capital stock between China and emerging markets. The results of Hansen's endogenous threshold regression remain largely the same and are available upon request.

Foreign direct investment may have spatial spillover effects (Thang et al., 2016). To account for these spatial spillover effects, neighboring regions' FDI technology spillover is employed as an explanatory variable. The results show that the spatial spillover effect of FDI is not significant.

Finally, we also test if different depreciation rates of R&D capital stock would impact our results. We replicate our analysis by including different depreciation rates: 5, 9.6 and 15 percent. Similar results are observed. Detailed results of all robustness tests are available upon request.

VI. Discussion and Conclusion

Using regional panel data from China, we examined the effects of OFDI on domestic innovation performance. We found that the relationship between OFDI-induced reverse technology spillover and domestic innovation performance is contingent on observed and expected technology gaps, adding to the debate under what circumstances

OFDI-induced reverse technology spillover can improve domestic innovation performance.

The empirical analysis provides evidence that reverse technology spillover through OFDI in developed countries has a positive and significant impact on regional innovation, whereas OFDI in emerging markets has a negative impact on regional innovation. When an expected technology gap is narrowed down, the negative effect becomes insignificant. These findings confirm the positive effect of “knowledge-seeking” OFDI of EMMNCs in developed countries. These findings have important policy implications in that they encourage emerging countries to make OFDI to advanced and technology-leading countries. Policymakers should promote the *Go Global* policy actively. On the business side, EMMNCs should conduct knowledge-seeking OFDI to reap the advantages of investment in developed countries. However, EMMNCs’ blind investment in technology-lagging countries may cause disadvantageous effects as a result of the crowding out of domestic investment.

Consistent with the theory of “advantage of backwardness,” a wider observed technology gap provides home country enterprises with greater learning room to catch up to host country enterprises. However, a narrower expected technology gap enables home country enterprises to assimilate and internalize cutting-edge technology. On the one hand, the results reemphasize the importance of investment in technology-leading countries. On the other hand, close attention should be paid to narrowing an expected technology gap to a certain threshold. For emerging markets, increasing education

training for human capital and instituting policies to promote fixed asset investment are effective measures to strengthen learning ability. Policy should also stimulate R&D investment and innovative behavior, technology infrastructure construction, technical serviceability and intellectual property protection for local enterprises. As an emerging economy, China's factor-driven economic development relies heavily on investment, not only domestically but also worldwide. As a result, fixed asset investment is of particular significance to China. While a wider observed technology gap provides Chinese regions with good opportunities to learn technology and imitate in order to reap greater benefits from spillover, China's expected technology gap with developed countries needs to be further narrowed.

Future studies can extend our research in several ways. First, future studies could investigate the influence mechanism of a technology gap among different industries and check whether the existing conclusions can be applied to those industries as well. Second, several other factors, such as industry competition, may influence reverse technology spillover through OFDI and should be considered. Finally, the role and impact of the Chinese government in promoting OFDI needs to be examined.

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