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Learning by Outward FDI: Evidence from Chinese Manufacturing Enterprises

Summary: Using firm-level data of Chinese manufacturing enterprises between 1998 and 2007, we investigate the existence and channels of "learning by outward FDI". Difference-in-differences estimation reveals that productivity of Chinese parent firms is significantly improved by their outward foreign direct investment and the learning effects form a "V" shape in the following years. There is no significant difference in learning effects between state-owned enterprises and non-state-owned enterprises; neither do we find any evidence that investing in countries with advanced technology gives more learning effects. In addition, we find that learning effects mainly come from technology transfer, technology spillovers and an enlarged production scale.

Key words: Outward foreign direct investment, Learning effects, Learning channels, Difference-in-difference estimator.

JEL: D24, F21, F23.

China is one of the leading sources of foreign direct investment (FDI) and has generated the third-largest FDI outflow since 2013 after the US and Japan. This new and important phenomenon, especially its effects on Chinese domestic firms' rapid progress of internalization, has attracted lots of academic studies. Ping Deng (2009) points out that it is urgent for Chinese MNEs as a latecomer to engage in technology sourcing and strategic assets seeking so as to catch up with the global giants. Evidence (see, e.g., Magnus Blomström and Fredrik Sjöholm 1999; Beata S. Javorcik 2004; Sourafel Girma 2005) shows that FDI plays an important role in international knowledge and technology spillovers. Therefore, Chinese parent firms may receive reverse technology spillovers and correspondingly improve their productivity.

In this paper, we denote the above effects as the learning effects, which refer to the acceleration of absorbing and creating technical knowledge and other non-technical information through outward foreign direct investment (OFDI), so as to promote the enterprise productivity. Although lots of studies (Fukunari Kimura and Kozo Kiyota 2006; Giorgio B. Navaretti, Davide Castellani, and Anne-Célia Disdier 2010; Alexander Hijzen, Sebastien Jean, and Thierry Mayer 2011) estimate OFDI-related technology diffusion and productivity performance in developed countries, relatively little empirical research has been carried out on efficiency changes induced by OFDI in developing countries. In this work, we focus on the OFDI efficiency of parent firms and use a propensity score matching (PSM) technique in combination with a difference-in-differences (DiD) estimator to answer the following questions. First, do Chinese parent firms become more efficient after they invest abroad, namely, are there the learning effects? Second, if there are the learning effects, what factors will influence the learning effects? Finally, through what channels can the Chinese parent firms acquire the learning effects? To conduct the empirical investigation, we draw on data from two sources: China Annual Survey of Manufacturing Firms (1998-2007) and Directories of Foreign Investment Enterprises (Institutions) from Ministry of Commerce of China.

The remainder of this article is arranged as follows: Section 1 is the literature review. The estimation strategy is discussed in Section 2 and data are reported in Section 3. Section 4 presents empirical findings and discussions of these results. Section 5 then concludes.

1. Related Empirical Literature and Theoretical Foundation

Foreign direct investment (FDI) has raised much attention in recent years due to its important role in international knowledge and technology flow. The existence of international technology spillovers and the channels of technology spillovers are two main topics in this field. Lots of empirical research have been devoted to these topics (for example, Ari Kokko, Ruben Tansini, and Mario C. Zejan 1996; Blomström and Sjöholm 1999; Javorcik 2004; Girma 2005; Zhiqiang Liu 2008; Laura Alfaro et al. 2010). These studies greatly enrich the research of international technology spillovers through FDI. However, little attention has been paid to reverse technology spillovers, which is defined as the technology spillovers from the host countries to the investing countries. Only recently have some researchers examined the performance of the OFDI enterprises which are mainly from the developed countries (see Kimura and Kiyota 2006; Navaretti, Castellani, and Disdier 2010; Hijzen, Jean, and Mayer 2011).

In the past several years, foreign direct investment from the developing countries has been growing at a staggering pace. Compared with the OFDI enterprises from the developed countries, those enterprises from the developing countries typically make efforts to seek for advanced technology (Frank R. Lichtenberg and Bruno Van P. de la Potterie 1998). Through their efforts, they can receive reverse technology spillovers and therefore are able to better improve productivity. As mentioned in the previous section, we define these effects as the learning effects, which refer to the acceleration of absorbing and creating technical knowledge and other non-technical information through OFDI so as to promote the enterprise productivity.

A lot of research has been conducted on the learning effects of enterprises from the developing countries. A recent case study by Sunil Mani (2013) looks at the experience of three leading domestic automotive firms. He finds that outward investments have resulted in considerable knowledge transfers from and to the parent companies based in India. Dierk Herzer (2011) examines the long-run relationship between outward FDI and total factor productivity for a sample of 33 developing countries over the period from 1980 to 2005. They discover that outward FDI has, on average, a robust positive long-run effect on total factor productivity in developing countries. For Chinese MNEs, Wei Zhao, Ling Liu, and Ting Zhao (2010) observe that Chinese outward direct investments have had beneficial spillover effects in improving total factor productivity growth over the period of 1991 to 2007. To the best of our knowledge, it is the only empirical research on Chinese firms' OFDI and their total factor productivity. In addition, there is also a lack of empirical research on the performance of OFDI enterprises from the developing countries (Herzer 2011). The strand of research has been restricted to the analysis of the whole host economy or industries with a lack of micro-level evidence. Moreover, the existing literature, based on a fixed effects model, has not well solved the endogeneity problem. Namely, enterprises' decisions about whether to invest outward or not are inevitably influenced by "self-selection", which raises questions about the reliability of the estimated results. In this paper, we address this problem by explicitly defining the counterfactual using PSM technique and DiD estimator.

Nuno Crespo and Maria P. Fontoura (2007) identify five main channels of FDI spillovers: demonstration, imitation, labor mobility, exports, competition, backward and forward linkages with domestic firms. Host enterprises could gain spillovers through these channels. What are the channels of OFDI through which parent firms could learn technology from host firms or oversea subsidiaries?

First, parent firms from the developing countries could establish joint ventures with their local partners or get advanced technology by M&A to bridge the technological gap with their competitors in the host country. M&A enables enterprises to gain fame, human capital and market channels of the acquired enterprises (Freek Vermeulen and Harry Barkema 2001; Wilbur Chung and Juan Alcácer 2002), and offer more opportunities for the OFDI enterprises to acquire external knowledge (Andrew C. Inkpen 2000). Japanese enterprises set up joint ventures with local American companies to bridge the technology gap (Hideki Yamawaki 1993), and M&A has promoted Indian automobile industry (Jaya P. Pradhan and Neelam Singh 2008). This is the direct channel of getting technology transfer.

Second, both Horizontal FDI and Vertical FDI could lead to a technology transfer to parent firms, in particular if MNEs locate their plants in knowledge-intensive areas (Rene Belderbos, Elissavet Lykogianni, and Reinhilde Veugelers 2008). Enterprises from the developing countries normally pay more attention to establish contact with local rival companies compared to those from the developed countries (Organisation for Economic Co-operation and Development - OECD 2006). By joining the local supply system in the developed countries, subsidiaries or branches can obtain the intermediate products of high quality, so as to realize the technology spillovers (Javorcik 2004). By cooperating with local innovation leader, laboratory and university, subsidiaries or branches can obtain more technology spillovers. Enterprises can keep up with the forefront of industry development through the employment of local designers, high quality engineers and technicians (Jarle Moen 2005). Accompanied with an increase in inputs of R&D funding and staff training of parent company, this technology can be transferred to home country. By using NBER patent citation data, Shireen AlAzzawi (2012) find that OFDI enterprises from technology-following countries make more R&D investments to improve productivity. This phenomenon has also been proved in Taiwan (Kun-Ming Chen and Shu-Fei Yang 2013).

Last, the scale effect also has impacts on efficiency. We expect that an increase in output due to OFDI enables parent firms to better exploit economies of scale. Some researchers (John R. Baldwin and Wulong Gu 2003) suggest that Horizontal OFDI might have a replacement effect, namely, the production of parent firms may be reduced, resulting in a loss of productivity. Nonetheless, evidence shows that technology sourcing OFDI is providing services rather than products in the host country. Branches of MNEs may purchase the services of R&D, design, marketing, finance or products from parent firms, leading to increased production of parent firms (Herzer 2011).

To this end, we conclude that learning effects may take place through: (i) direct technology transfer from host firms or oversea subsidiaries to parent firms; (ii) adverse technology spillovers to parent firms through employee training and R&D expenditure; (iii) expanded production scale which allows parent firms to better exploit scale economies.

2. Data

The main data in this study come from two sources which use different identity codes. Therefore, we match the data to create a unique firm-level data set containing firm-level information and firm-level outward investment information. We first use Directory of Foreign Investment Enterprises (Institutions) released by the Ministry of Commerce (MOFCOM) of China. This directory includes the information of all OFDI enterprises since 1980, such as the firm's name, the certificated number, the type of ownership (i.e., stated-owned enterprises (SOE) or private firm), the host country of investment, business scope, and approval date. However, firms' OFDI flows, considered confidential to firms, are not included in this data set.

We obtained all the other necessary firm information and characteristics from our second data source, the China Annual Survey of Manufacturing Firms (1998-2007), maintained by the National Bureau of Statistics (NBS) of China. These surveys are the most comprehensive firm-level datasets in China because it includes all state-owned and non-state-owned industrial enterprises with annual sales above RMB 5 million (about US$782 thousand under current exchange rate), accounting for about 90% of China's total industrial output value. The data set provides more than 100 variables including firms' basic information and all operation and performance variables, such as firms' identification, age, industry affiliation, location, ownership, output, added value, fixed capital, employment, intermediate inputs and export sales, etc. It is a rich source for measuring total factor productivity (TFP), which is used to represent firm's productivity and is the independent variable in our estimation.

By comparing these two datasets, we can update the information about outward investment in China Annual Survey of Manufacturing Firms (1998-2007). The China Annual Survey of Manufacturing Firms provides yearly data, which are counted by the end of each year. Therefore, we use the data in the year following a firm's

OFDI approval as the firm's first year record. We use sequential recognition method to encode the enterprise (Loren Brandt, Johannes V. Biesebroeck, and Yifan Zhang 2012). For sample outliers, we adopt the approach in Hongbin Cai and Qiao Liu (2009) and Robert C. Feenstra, Zhiyuan Li, and Miaojie Yu (2011). First, we remove the missing observations of key index (for example, total assets, number of employees, the total industrial output value, net value of fixed assets and sales). Second, we eliminate observations which don't meet the scale requirement, namely, observations with number of employees less than 8. In addition, we delete observations which are obviously incompatible with accounting principles, for instance, when their total assets are less than current assets, or total assets are less than the net value of fixed assets, or the cumulative depreciation is less than current depreciation. We choose enterprises with continuity of operation from 1998 to 2007 for the convenience of comparison. As a result, we have observations of 31763 companies for 10 years[1]. This sample consists of a treatment group and control group 1.

Firm-level productivity is of our primary interest in our study. We use TFP as the measurement of a firm's productivity performance (which is the most widely used productivity indicator in the literature). Regular ordinary least square (OLS) productivity estimator will possibly cause simultaneity bias and selection bias, which is based on coefficients estimation on capital and labor (George S. Olley and Ariel Pakes 1996; James Levinsohn and Amil Petrin 2003). Olley-Pakes method and Levinsohn-Petrin method assume that capital or intermediate input is more actively responsive to unobserved productivity than labor, which could control for the possible simultaneity bias and selection bias. However, Chinese firms usually adjust their labor input in face of a productivity shock, since the labor cost is low in China. So we calculate TFP by Levinsohn and Petrin (henceforth L-P) estimator in most of the case. To check the robustness of our results, we also employ Olley-Pakes (henceforth O-P) estimator for TFP and use labor productivity as the productivity measurement.

We describe the relevant variables in what follows. Capital intensity is given by fixed assets *per capita*. Enterprise size is measured by number of employees by the end of the year. Export firm is a dummy with value 1 indicating that a firm has an export delivery bigger than zero, and 0 otherwise. Ownership is 1 when the enterprise registration type is state-owned; it is 0 otherwise. Foreign capital includes capital from Hong Kong, Macao and Taiwan together with so called foreign capital. We take Beijing city as a reference, so the regional dummy variables corresponding to each of the provinces and cities of the estimated coefficient reflect differences in these areas and Beijing. We generate industry dummy variables in two digits in accordance to the national industry classification. We label equipment manufacturing, transportation equipment manufacturing, electrical machinery and equipment manufacturing industry and communication equipment, computers and other electronic equipment manufacturing industry as technology intensive industry. Finally, labor efficiency is measured by sales *per capita*. Other variables are self-evident. Table 1 lists descriptive statistics of main variables, among which the core variable is the log of L-P type TFP.

[1] Discontinuous sample does not affect the results of this article, as shown in the regression results in the robust test section.

Some empirical research show that OFDI firms are more productive than those who do not undertake foreign investment, which will potentially cause the self-selection problem (Elhanan Helpman, Marc J. Melitz, and Stephen R. Yeaple 2004; Navaretti, Castellani, and Disdier 2010). In order to address this problem, we construct two control groups to assess the differences between the two groups. One control group consists of all the enterprises which didn't make outward investment during the sample duration (hereinafter referred to as the group 1). The other control group is constructed through PSM method (hereinafter referred to as the group 2). This method identifies some firms that had similar tendency to invest in foreign countries but have chosen not to invest abroad. Using these firms as a control group allows us to carry out a counterfactual comparison showing how investing abroad would have impacted the firms had they chosen to invest in foreign countries.

Table 1 Descriptive Statistics of Main Variables

Variables	Description	Min	Max	Mean	S.E.
Log(TFP)	Logarithm of TFP	-2.408	14.892	6.690	1.142
Log(kinte)	Logarithm of capital intensity	-5.910	14.135	3.838	1.233
Log(size)	Logarithm of size	2.197	12.025	5.488	1.145
Log(newpv)	Logarithm of new product value	-0.158	18.226	9.635	2.189
Log(mexpe)	Logarithm of management fee	-0.327	17.035	7.742	1.705
Log(trafe)	Logarithm of training expense	-0.977	12.125	2.736	1.613
Log(rd)	Logarithm of R&D expense	-0.654	15.764	5.230	2.486
Log(labef)	Logarithm of labor efficiency	-3.763	13.520	5.062	1.084

Notes: Log(tfp) denotes the firm-level total factor productivity estimated by Levinsohn and Petrin (2003) method.

Source: Authors' statistic analysis based on the National Bureau of Statistics of China (2013)[2].

According to Marco Caliendo and Sabine Kopeinig (2008), the first step of PSM is to estimate the propensity score using Probit (or Logit) model. We include firm characteristics such as TFP (one year earlier of OFDI), size of a firm (in terms of output), capital intensity, stated-owned enterprise dummies, industry dummies, region dummies and year dummies in calculating the propensity score for the tendency of investing abroad[3]. Estimation model is $Logit(ofdi_{it}=1)=\Phi(h((x_{i(t-1)}))$. According to the propensity score, we choose the matched enterprises as our control group 2.

Finally, we obtain a new sample containing the treatment group and control group 2, with observations of 1680 companies for 10 years. The distribution of enterprises with outward foreign investment between 1998 and 2007 is summarized in Table 2.

2 **National Bureau of Statistics of China.** 2013. http://www.resset.cn/nlc (accessed November 30, 2013).

3 The PSM method is not entirely satisfactory in controlling for self-selection bias because of its strong assumption. However, it has been proven useful and is widely adopted in the literature. While we utilize this method, we have included as many firm characteristics as possible to address the potential issue of the PSM method.

Table 2 Distribution of Enterprises with Outward Foreign Direct Investment

Year	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Totality	16	9	16	16	38	56	170	803	1148	1254
Industrial firms	0	0	2	3	4	13	45	257	329	385
Sequential	0	0	2	3	4	12	42	257	326	358
Continuous	0	0	1	1	1	4	15	65	73	83

Notes: "Totality" represents the number of enterprises which have invested outward in China Annual Survey of Manufacturing Firms (1998-2007) after matching with Directories of Foreign Investment Enterprises (Institutions) from Ministry of Commerce of China; "Industrial firms" represents the number of industrial firms each year; "Sequential" represents the number of enterprises after using sequential recognition method (Brandt, Biesebroeck, and Zhang 2012); "Continuous" represents the number of enterprises with continuous operation from 1998 to 2007.

Source: Authors' statistic analysis.

3. Estimation Strategy

By combining the two data sets, we are with relatively abundant data which allow us to investigate both the existence and the channels of the learning effects. In order to identify the learning effects of foreign direct investment, we employ the DiD estimator. We exploit two sources of variations: time variation (before and after a critical date) and cross-sectional variation (the treatment group and the control group).

Our identification strategy relies on the comparison of outcome variables of the enterprises in the treatment group with the same variables of those in the control group before and after the action of investment abroad. In this paper, we take enterprises with outward investment as the treatment group. To make the results more credible, we construct two control groups. One consists of all the enterprises which don't make outward investment during the sample duration (control group 1); the other one is from PSM (control group 2). Enterprises from control group 2 have similar tendency as enterprises from the treatment group to invest outward. The basic comparison can be conducted as follows.

First, we construct two dummy variables, $ofdi_i$ and $post_{it}$ as follows:

$$ofdi_i = \begin{cases} 1 & \text{if enterprise belongs to treatment group;} \\ 0 & \text{otherwise;} \end{cases} \tag{1}$$

$$post_{it} = \begin{cases} 1 & \text{enterprise has invested outward;} \\ 0 & \text{otherwise;} \end{cases} \tag{2}$$

where subscript i and t represent enterprise and time, respectively. Since the China Annual Survey of Manufacturing Firms provides yearly data, we treat the record in the year following the outward investment approval as the first year record. We regard this year as $t = 1$. Thus if a firm has invested outward, $t \geq 1$ correspondingly. Since different firms may choose different time for outward foreign direct investment, values of the variable post it differ among firms at the same time.

Second, we compare the productivity performance variable. Take total factor productivity (TFP)[4] for example. TFP_{it} is the TFP of enterprise i at time t. We calcu-

[4] We use TFP as the measurement of a firm's productivity performance. This is the most widely used indicator in the literature.

late TFP by L-P method except for robustness check. $\Delta TFP_{\mathrm{i}}^{1}$ and $\Delta TFP_{\mathrm{i}}^{0}$ represent the variation of TFP between $post_{it}=0$ and $post_{it}=1$ of enterprises from the treatment group and the control group, respectively. The effect of investing outward is given by Equation (3):

$$\gamma = E(\gamma_{\mathrm{i}} \mid post_{it}=1) = E(\Delta TFP_{i}^{1} \mid post_{it}=1) - E(\Delta TFP_{i}^{0} \mid post_{it}=1). \tag{3}$$

Obviously, $E(\Delta TFP_{i}^{0} \mid post_{it}=1)$ is unobservable. We use $E(\Delta TFP_{i}^{0} \mid post_{it}=0)$ to represent $E(\Delta TFP_{i}^{0} \mid post_{it}=1)$, changing Equation (3) to Equation (4):

$$\gamma = E(\gamma_{\mathrm{i}} \mid post_{it}=1) = E(\Delta TFP_{i}^{1} \mid post_{it}=1) - E(\Delta TFP_{i}^{0} \mid post_{it}=0). \tag{4}$$

Finally, the quasi-natural experiment is given by Equation (5) in DiD estimator:

$$y_{\mathrm{it}} = \gamma_{i} + \gamma_{t} + \gamma_{1}.ofdi_{i}.post_{it} + \gamma_{2}Control_{it} + \varepsilon_{it}. \tag{5}$$

Subscript i and t represent enterprise and time respectively in Equation (5). γ_{i} is the individual fixed effect. γ_{t} is the time effect. For most of the time y_{it} is the logarithm of TFP. When checking the channels of learning by outward FDI, we examine the effects of outward FDI on mediator variables. At that time, y_{it} represents the logarithm of size, new product value, management fee, training expense and R&D expense, respectively. When we are doing robustness checks in Table 3, y_{it} represents logarithm of labor efficiency. ε_{it} is the random disturbance term. $post_{t}$ and $ofdi_{i}$ have the same meaning as described above. $Control_{it}$ represents other time-varying controls.

With panel data for multiple groups, we conduct several validity checks following Joshua D. Angrist and Jörn-Steffen Pischke (2009) and Michael Lechner (2011). First, one might be concerned that different industries in the treatment group and their counterparts in the control group may follow different time trends. To address this concern, we allow for the possibility that different industries have different time trends. Our findings remain robust to the inclusion of industry-specific time trends, implying that our DiD estimations are valid. For more details, please see Subsection 4.1 to Subsection 4.5.

Second, the validity of our DiD estimator hinges upon the assumption that the treatment and control groups are comparable before the treatment occurs. A check on whether there is any difference in time trends between the treatment and control groups before the occurrence of outward investment needs to be conducted. For more details, please see Subsection 4.6. Besides, we use PSM method to construct control group 2, making the treatment and the control group more comparable.

Third, the validity of our DiD estimator hinges upon the assumption that there is no sample selection bias in our estimation. To alleviate the concern, we conduct a robustness check by using the full sample to estimate. For more details, please see Subsection 4.6.

Fourth, to address the concern that our results may be affected by the efficiency of measurement, we use another two measurements, one is called O-P (Olley and Pakes 1996) method and the other is labor efficiency. For more details, please see Subsection 4.6.

In order to check the lagged effect, the ownership effect, and the host country effect of the learning effects, Equation (5) can be extended to Equation (6) and Equation (7):

$$TFP_{\mathrm{it}}=\gamma_i+\gamma_t+\gamma_1.ofdi_i.post1_{it}+\gamma_1.ofdi_i.post2_{it}+\gamma_1.ofdi_i.post3_{it}+\gamma_2 Control_{it}+\varepsilon_{it}\,. \quad (6)$$

$post1_{it}$, $post2_{it}$ and $post3_{it}$ in Equation (6) indicate that the observation is one, or two, or three years after the enterprise invests outward, respectively.

$$TFP_{\mathrm{it}}=\gamma_i+\gamma_t+\gamma_1.ofdi_i\cdot post_{it}+\gamma_1.ofdi_i\cdot post_{it}\cdot attributes_{it}+\gamma_2 Control_{it}+\varepsilon_{it}\,. \quad (7)$$

$attributes_{it}$ in Equation (7) represents the characteristics of firms with outward FDI such as whether the firm is state owned, to which kind of country the firm has invested, etc.

As noted in Section 1, enterprises gain the learning effects by investing outward through many channels including M&A, technology transfer, and economies of scale. By including some mediator variables, the comparison results of Equation (5) and Equation (7) can give us more insights:

$$TFP_{\mathrm{it}}=\gamma_i+\gamma_t+\gamma_1.ofdi_i.post_{it}+\gamma_2 Control_{it}+\gamma_3 intermediate+\varepsilon_{it}\,. \quad (8)$$

In Equation (8), many variables has been treated as mediator variables such as logarithm of firm size, new product value, management fee, training expense, and R&D expense. The regression results in Subsection 4.5 show that our findings remain robust to the inclusion of industry-specific time trends. Other validity checks of results examined in Subsections 4.3 - 4.5 have been done in Subsection 4.6. Due to space limitation, we do not present all the results in this article[5].

4. Empirical Findings

In this section, we first provide four baseline empirical findings regarding the existence of the learning effects by outward FDI and how the learning effects vary in Subsections 4.1 - 4.4. We then identify learning channels in Subsection 4.5. We carry out a series of robustness checks on the validity of our DiD estimator and address other econometric concerns in Subsection 4.6.

4.1 The Learning Effects of Outward FDI

Table 3 presents the basic regression results. Results in columns 1, 3 and 5 of Table 3 are based on control group 1, and those in columns 2, 4 and 6 are based on control group 2. We find that by investing outward, the productivity of parent firms has been significantly improved. Although the coefficients of regression using control group 2

[5] These results are available upon request.

are smaller than with control group 1, all results are significantly positive. One problem of concern is that industries in the treatment group and their counterparts in the control group may follow different time trends. To address this concern, we allow for industry-specific time trends in our estimation, i.e., the inclusion of additional control $\gamma_i \times t$. The estimation results are reported in columns 5 - 6. Our findings remain robust when including industry-specific time trends, which implies that our DiD estimations are valid.

Table 3 The Existence of the Learning Effects

	Dependent variable: log(tfp)					
	Group 1 (1)	Group 2 (2)	Group 1 (3)	Group 2 (4)	Group 1 (5)	Group 2 (6)
Ofdi × post	0.124***	0.096**	0.115***	0.087**	0.150***	0.106***
	(0.044)	(0.043)	(0.044)	(0.043)	(0.043)	(0.043)
Other time-varying controls	No	No	Yes	Yes	Yes	Yes
Industry-time trend	No	No	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	6.249***	6.758***	6.207***	6.688***	6.205***	6.689***
	(0.004)	(0.015)	(0.005)	(0.019)	(0.005)	(0.019)
R-squared	0.160	0.218	0.161	0.223	0.174	0.243
Observations	317,630	16800	317,630	16800	317,630	16800

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively; standard errors are reported in parenthesis.

Source: Authors' estimation.

4.2 The Lagged Learning Effects

In order to identify the lagged learning effects, we add the independent variable lagged one, two and three periods in regressions. Results introduced in columns 1, 3 and 5 of Table 4 are based on control group 1, and those in columns 2, 4 and 6 are based on control group 2. Compared with the results in Table 3, the learning effects of the first year is higher than the average effect over the years after outward investment.

The significant learning effects indicate that Chinese enterprises can rapidly absorb the useful management experience and technology in the international market. That explains why they can quickly improve their own TFP. Comparing the coefficients of leaning effects in the consecutive three years, we can see a "V" trend. Namely, the high effects decline in the second year, then recover to a higher level in the following years. The estimated coefficients of the second and third years are not all statistically significant, so we cannot make a clear conclusion. Comparing the standard deviation of the coefficient, we found that the statistical insignificance is largely driven by the rapidly rising standard deviation. That means the lack of observation attributes to this result, as verified in Table 2. The main reason for the decrease of TFP in the second year could be the high expenditure on R&D and the employee training fee of parent firms after outward FDI, which can cause high input cost in production and correspondingly bring down the firms' TFP growth rate in the short-term. Nonetheless, parent firms' TFP will increase in the long-run. Unfortunately, although the V-shaped pattern suggested by the three lags may persist longer, we could not examine the lagged effect longer than 3 years because of data limitation (which would lead to unreliable results). As we can see in Table 2, most of the outward investment happened after 2004. Further examination is warranted when data become available.

Table 4 The Lagged Learning Effects

	Dependent variable: log(tfp)					
	Group 1 (1)	Group 2 (2)	Group 1 (3)	Group 2 (4)	Group 1 (5)	Group 2 (6)
Ofdi × post1	0.160***	0.137***	0.152***	0.130**	0.181***	0.138***
	(0.053)	(0.051)	(0.053)	(0.051)	(0.052)	(0.051)
Ofdi × post2	0.122*	0.098	0.115	0.092	0.157**	0.121*
	(0.071)	(0.069)	(0.071)	(0.069)	(0.070)	(0.068)
Ofdi × post3	0.197	0.168	0.184	0.153	0.233*	0.192
	(0.141)	(0.136)	(0.141)	(0.153)	(0.140)	(0.135)
Other time-varying controls	No	No	Yes	Yes	Yes	Yes
Industry-time trend	No	No	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	6.249***	6.758***	6.207***	6.689***	6.205***	6.689***
	(0.004)	(0.015)	(0.005)	(0.019)	(0.005)	(0.019)
R-squared	0.160	0.219	0.161	0.224	0.174	0.243
Observations	317,630	16800	317,630	16800	317,630	16800

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively; standard errors are reported in parenthesis.

Source: Authors' estimation.

4.3 State-Owned Enterprises vs Non-State-Owned Enterprises

Literature (for example, Yadong Luo and Rosalie L. Tung 2007; Carlos Rodríguez and Ricardo Bustillo 2011) shows that Chinese state-owned enterprises (SOEs) have a unique way of investing abroad. Therefore, there may be differences in the learning effects between SOEs and non-SOEs. Table 5 presents the baseline regression results of the learning effects concerning ownership. The variable owner in Table 5 stands for ownership, which is defined in Section 3. If the registration type of an enterprise is state-owned, the variable owner takes the value of 1, otherwise it is 0. The comparison of Table 3 and Table 5 indicates that the learning effects of SOEs have no significant difference from the learning effects of non-SOEs. This result remains robust regardless of the sample we use and the relevant variables we control for.

Table 5 SOEs vs Non-SOEs

	Dependent variable: log(tfp)					
	Group 1 (1)	Group 2 (2)	Group 1 (3)	Group 2 (4)	Group 1 (5)	Group 2 (6)
Ofdi × post	0.120***	0.092**	0.111**	0.084*	0.150***	0.109**
	(0.045)	(0.044)	(0.045)	(0.044)	(0.044)	(0.044)
Ofdi × post × Owner	0.078	0.072	0.083	0.082	-0.002	-0.044
	(0.201)	(0.193)	(0.201)	(0.193)	(0.200)	(0.191)
Other time-varying controls	No	No	Yes	Yes	Yes	Yes
Industry-time trend	No	No	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	6.249***	6.758***	6.207***	6.689***	6.205***	6.689***
	(0.004)	(0.015)	(0.005)	(0.020)	(0.005)	(0.019)
R-squared	0.160	0.218	0.161	0.223	0.174	0.243
Observations	317,630	16800	317,630	16800	317,630	16800

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively; standard errors are reported in parenthesis.

Source: Authors' estimation.

4.4 Host Countries with Advanced Technology vs Host Countries without Advanced Technology

As one of the important channels of international technology spillovers, FDI promotes knowledge and technology flow worldwide (Lee Branstetter 2000). The direction and strength of technology flow are affected by the characteristics of two sides of international economic cooperation. By studying the outward investment experience of Swedish enterprises, Pär Hansson (2005) points out that only the investment in the Central and Eastern European countries (regions) has promoted the production efficiency of home enterprises.

Chinese OFDI can be roughly divided into three kinds according to the motivation of investment: resource seeking, market seeking and technology seeking, which directly determine the kind of host country of the investment (Deng 2009). In this subsection, we focus on technology seeking outward investment, which is invested in the developed countries and NIEs.

In Table 6, variable country indicates whether a country belongs to countries with advanced technology[6]. The comparison of Table 3 and Table 6 indicates that investing in countries with advanced technology has negative impacts on the learning effects. Although the coefficient is not statistically significant, the overall results give us confidence to make the speculation that the technology gap between the investing country and the host country has a negative impact on the learning effects. Parent firms' capability of absorbing technology is probably insufficient to overcome the negative impact of the technology gap.

Table 6 Host Countries with Advanced Technology vs Host Countries without Advanced Technology

	Dependent variable: log(tfp)					
	Group 1 (1)	Group 2 (2)	Group 1 (3)	Group 2 (4)	Group 1 (5)	Group 2 (6)
Ofdi × post	0.142**	0.103**	0.128**	0.094**	0.145**	0.113**
	(0.057)	(0.046)	(0.057)	(0.046)	(0.056)	(0.046)
Ofdi × post × country	-0.043	-0.048	-0.031	-0.044	-0.013	-0.045
	(0.088)	(0.119)	(0.088)	(0.119)	(0.088)	(0.118)
Other time-varying controls	No	No	Yes	Yes	Yes	Yes
Industry-time trend	No	No	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	6.249***	6.758***	6.207***	6.688***	6.205***	6.689***
	(0.004)	(0.015)	(0.005)	(0.019)	(0.005)	(0.019)
R-squared	0.160	0.218	0.161	0.223	0.174	0.243
Observations	317,630	16800	317,630	16800	317,630	16800

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively; standard errors are reported in parenthesis.

Source: Authors' estimation.

[6] Countries with advanced technology include 27 nations of the European Union, the US, Canada, Japan, New Zealand, Norway, Switzerland, South Korea, India and Singapore. The reason we include India is that India has advanced technology in areas such as electronic information. We exclude Australia and Israel as our outward investment in these countries focused on the natural resource extraction industries.

4.5 Channels of Learning through Outward FDI

As we have discussed in Section 1, there are three channels for a firm to get the learning effects by conducting outward FDI. In the following paragraphs, we examine these channels in three aspects. First, we want to know if the learning effects mainly depend on technology transfer. Second, we investigate the other two aspects to see how outward investment can be a stimulus to efficiency improvement.

According to Reuben M. Baron and David A. Kenny (1986), there are three steps to test a mediator variable. Since we have regressed the independent variable (OFDI) on the dependent variable (TFP) and found that parent firms have TFP improved after investing abroad, we only need to regress the mediator variables (technology transfer, technology spillovers, and production scale expansion) on the independent variable, and to regress the dependent variable on both the mediator variables and the independent variable. In other words, we want to confirm that the independent variable is a significant predictor of the mediator variables, and also to confirm that a mediator variable is a significant predictor of the dependent variable controlling for the independent variable.

First, by M&A or establishing joint ventures, enterprises can directly get advanced production technology. That's a way to quickly upgrade parent firms' technology and productivity. Because we cannot get data of every sample firm's activity of M&A or establishing joint ventures, we use new product value as the measurement of channel one, i.e., getting direct technology transfer. In most cases, parent firms could produce more new products because of getting advanced technology by M&A or establishing joint ventures. In columns 1-2 of Table 7, the positive and significant coefficients show that new product value of parent firms are improved after investing outward. When we regress the dependent variable (TFP) on both the mediator variable (new product value) and the independent variable, the results (columns 1-2 in Table 8) show that new product value is actually a mediator variable. Since the coefficients of our core independent variable decreases but is still positive, we conclude that it is a partial mediated variable (Michael E. Sobel 1986). This means that the action of investing abroad leads the parent firms to increase the production of new products; correspondingly, these activities raise the production efficiency and therefore enhance parent firms' TFP.

Table 7 The Effects of Outward FDI on Mediator Variables

	Dependent variable: log(newpv)		Dependent variable: log(mexpe)		Dependent variable: log(size)	
	Group 1 (1)	Group 2 (2)	Group 1 (3)	Group 2 (4)	Group 1 (5)	Group 2 (6)
Ofdi × post	0.285**	0.212*	0.338***	0.221***	0.240***	0.134***
	(0.120)	(0.122)	(0.045)	(0.046)	(0.027)	(0.029)
Other time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry-time trend	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	8.969***	9.790***	7.104***	7.749***	5.329***	6.091***
	(0.027)	(0.085)	(0.005)	(0.021)	(0.003)	(0.013)
R-squared	0.578	0.234	0.578	0.626	0.028	0.139
Observations	40015	3617	314,626	16723	317,630	16800

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively; standard errors are reported in parenthesis.

Source: Authors' estimation.

Table 8 Estimations Combined with Mediator Variables

	Dependent variable: log(tfp)					
	Group 1 (1)	Group 2 (2)	Group 1 (3)	Group 2 (4)	Group 1 (5)	Group 2 (6)
Ofdi × post	0.146**	0.115*	0.066	0.045	0.061	0.052
	(0.067)	(0.046)	(0.042)	(0.042)	(0.042)	(0.041)
Newpv	0.142***	0.138***				
	(0.003)	(0.011)				
Mexpe			0.234***	0.252***		
			(0.002)	(0.007)		
Size					0.371***	0.405***
					(0.003)	(0.012)
Other time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry-time trend	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	5.489***	6.008***	4.543***	4.741***	4.227***	6.091***
	(0.033)	(0.114)	(0.013)	(0.060)	(0.016)	(0.013)
R-squared	0.221	0.318	0.221	0.297	0.217	0.300
Observations	40015	3617	314,626	16723	317,630	16800

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively; standard errors are reported in parenthesis.

Source: Authors' estimation.

Second, parent firms have to spend on employee training and R&D so that they could absorb adverse technology spillovers and upgrade firms' productivity. There is fierce competition in the international market which urges enterprises to actively absorb the international advanced technology and management experience. They have to make more efforts to enhance their R&D capability and pay more attention to human capital accumulation. On the one hand, the internationalization strategy of enterprises requires firms to face harsher competition and challenges in product quality and standard of services. On the other hand, investing outward makes more qualified R&D resources available. It's more convenient for firms to use local technology and human capital to make technology innovation. We can verify this connection by analyzing the causal effect of management expense, efficiency and outward investment. In columns 3 and 4 of Table 7, we see that management expense increases after firms' outward investment. This may be attributed to the stimulus of outward investment, as shown in columns 3 and 4 of Table 8. We can see that the coefficient of logarithm of management expense is statistically significant. Compared to results in Table 3, the standard deviation of the interaction term doesn't have a significant change, but the coefficient of the interaction term is no longer statistically significant. We speculate that because of outward investment, management expense expands, which contributes to productivity improvement.

A variety of other costs exists in the index of management expense but is not directly related to productivity. We thus apply two other specific indicators, training expenses and R&D investment, to make further examination. We use the panel data from 2005 to 2007 due to data availability and the estimation results are summarized in Table 9 and Table 10. The results show that an increase in employee training expense is beneficial to parent firms' TFP because it accelerates firms' accumulation of human capital. In addition, increasing investment in R&D is also beneficial to parent firms' TFP because it enhances their research capability. We conclude that investing abroad will promote the parent firms to increase employee training and R&D expenditure, and these activities correspondingly raise parent firms' TFP.

Table 9 Further Checks on Mediator Variables

	Dependent variable: log(rd)	Dependent variable: log(trafe)
	(1)	(2)
Ofdi × post	0.250*	0.174***
	(0.114)	(0.041)
Other time-varying controls	Yes	Yes
Industry-time trend	Yes	Yes
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Constant	5.381***	2.800***
	(0.020)	(0.011)
R-squared	0.020	0.038
Observations	161866	300672

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively; standard errors are reported in parenthesis.

Source: Authors' estimation.

Table 10 Further Estimations Combined with Mediator Variables

	Dependent variable: log(tfp)	
	(1)	(2)
Ofdi × post	-0.032	-0.009
	(0.044)	(0.034)
Log(rd)	0.012***	
	(0.001)	
Log(trafe)		0.062***
		(0.002)
Other time-varying controls	Yes	Yes
Industry-time trend	Yes	Yes
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Constant	6.579***	6.246***
	(0.492)	(0.179)
R-squared	0.050	0.072
Observations	161866	300672

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively; standard errors are reported in parenthesis.

Source: Authors' estimation.

Third, the expansion of market and enterprise size due to OFDI makes it easier for enterprises to achieve economies of scale. The expansion of the scale creates favorable conditions for innovation and development. Firms can carry out R&D using profit gained from the enlarged market. By reallocation of research expense, they can also reduce marginal researching cost. At the same time, the expansion of enterprise size is an attraction to human capital. We can verify this connection by analyzing the causal effect of enterprise size, efficiency and outward investment.

In columns 5 and 6 of Table 7, after outward investment, size of enterprises increases. This may be attributed to the stimulus of outward investment, as shown in columns 5 and 6 in Table 8. We can see that the coefficient of logarithm of enterprise size is statistically significant. Compared to Table 3, the standard deviation of the interaction term doesn't have a significant change, but the coefficient of the interaction term is no longer statistically significant. We speculate that because of outward investment, enterprises' size expands, and this expansion contributes to parent firms' TFP improvement.

4.6 Robustness Checks

In this section, we conduct a series of robustness checks on the aforementioned DiD estimation results for all the relevant outcome variables examined mainly in Subsections 4.1 - 4.2.

First, the validity of our DiD estimator hinges upon the assumption that the treatment and control groups are comparable before the treatment occurs. To check specifically whether there is any difference in time trends between the treatment and control groups before the initiation of outward investment, we conduct a robustness check by including an additional variable $ofdi_i.pre_{it}$, where $pre_{it}=1$ if $t \in \{t-2, t-1\}$, and 0 otherwise. Since the China Annual Survey of Manufacturing Firms provides yearly data which are counted by the end of each year, we treat the record in the year following the OFDI approval as the first year record. Thus, the record in the approval year cannot be regarded as either pre-trend or post-trend effect. When $t=0$, it means that the investment is happening. The estimation results are summarized in Table 11. Clearly, there is no evidence of any differential time trends between the treatment and control groups before the initiation of outward investment, lending support to the validity of our DiD estimations. Our main findings on the learning effects also remain robust.

Second, the validity of our DiD estimator hinges upon the assumption that there are no sample selection bias in our estimation. To alleviate the concern, we conduct a robustness check by using the full sample to estimate. The estimation results are summarized in Table 12. Clearly, there is no significant difference in the results between the full sample and the continuous sample, lending support to the validity of our DiD estimations. Our main findings on the learning effects also remain robust with the full sample.

Table 11 Robustness Check of Differential Time Trends before Investment

	Dependent variable: log(tfp)			
	Group 1 (1)	Group 2 (2)	Group 1 (3)	Group 2 (4)
Ofdi × post	0.126***	0.088**		
	(0.044)	(0.044)		
Ofdi × post1			0.162***	0.131**
			(0.053)	(0.051)
Ofdi × post2			0.126**	0.094
			(0.071)	(0.070)
Ofdi × post3			0.194	0.154
			(0.141)	(0.136)
Ofdi × pre	0.078	0.006	0.083	0.061
	(0.053)	(0.052)	(0.053)	(0.042)
Other time-varying controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Constant	6.249***	6.688***	6.207***	6.689***
	(0.004)	(0.020)	(0.005)	(0.020)
R-squared	0.161	0.223	0.161	0.224
Observations	317,630	16800	317,630	16800

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively; standard errors are reported in parenthesis.

Source: Authors' estimation.

Table 12 Robustness Check Using Full Sample

	Dependent variable: log(tfp)			
	(1)	(2)	(3)	(4)
Ofdi × post	0.068***		0.058**	
	(0.026)		(0.026)	
Ofdi × post1		0.099***		0.091***
		(0.030)		(0.030)
Ofdi × post2		0.008		-0.0003
		(0.044)		(0.044)
Ofdi × post3		0.066		0.041
		(0.097)		(0.098)
Ofdi × pre	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Constant	5.749***	5.749***	5.778***	5.778***
	(0.003)	(0.003)	(0.003)	(0.003)
R-squared	0.117	0.117	0.114	0.114
Observations	1951499	1951499	1951499	1951499

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively; standard errors are reported in parenthesis.

Source: Authors' estimation.

Third, to address the concern that our results may be affected by measurement efficiency, we adopt two other measurements of firm efficiency, one is called O-P method and the other is labor efficiency. The estimation results are summarized in Table 13. Obviously, the results verified that our main findings on the learning effects also remain robust.

Table 13 Robustness Check with Other Measurements of Efficiency

	Dependent variable: log(tfp_op)		Dependent variable: log(labef)	
	Group 1	Group 2	Group 1	Group 2
	(1)	(2)	(3)	(4)
Ofdi × post	0.021***		0.107***	
	(0.012)		(0.032)	
Ofdi × post1		0.022		0.141***
		(0.014)		(0.038)
Ofdi × post2		0.028		0.062
		(0.020)		(0.052)
Ofdi × post3		0.054		0.177*
		(0.039)		(0.103)
Other time-varying controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Constant	1.496***	1.496***	6.924***	6.924***
	(0.002)	(0.002)	(0.012)	(0.123)
R-squared	0.020	0.020	0.354	0.354
Observations	221512	221512	317406	317406

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively; standard errors are reported in parenthesis.

Source: Authors' estimation.

5. Conclusion

As the role of developing countries in international direct investment is increasingly important, the request for us to conduct theoretical analysis and empirical test of OFDI from different angles becomes increasingly urgent. The case of China is a good start point.

In this paper, we study the learning effects of outward direct investment from developing countries using data from China Annual Survey of Manufacturing Firms (1998-2007) and Directories of Foreign Investment Enterprises (Institutions) from Ministry of Commerce of China. We use DiD estimation, which compares the outcome variables for the enterprises in the treatment group with the same variables for those in the control groups before and after the action of outward investment.

We find that Chinese parent firms' productivity are significantly improved by their OFDI and the learning effects form a "V" shape in the following years. There is no significant difference on the learning effects between state-owned enterprises and non-state-owned enterprises. Moreover, we find that the learning effects mainly come from direct technology transfer, adverse technology spillovers by employee training and R&D expenditure, and an expanded production scale.

References

AlAzzawi, Shireen. 2012. "Innovation, Productivity and Foreign Direct Investment-Induced R&D Spillovers." *The Journal of International Trade and Economic Development*, 21(5): 615-653. http://dx.doi.org/10.1080/09638199.2010.513056

Alfaro, Laura, Chanda Areendam, Kalemli-Ozcan Sebnem, and Sayek Selin. 2010. "Does Foreign Direct Investment Promote Growth? Exploring the Role of Financial Markets on Linkages." *Journal of Development Economics*, 91(2): 242-256. http://dx.doi.org/10.1016/j.jdeveco.2009.09.004

Angrist, Joshua D., and Jörn-Steffen Pischke. 2009. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton: Princeton University Press.

Baldwin, John R., and Wulong Gu. 2003. "Export-Market Participation and Productivity Performance in Canadian Manufacturing." *Canadian Journal of Economics*, 36(3): 634-657. http://dx.doi.org/10.1111/1540-5982.t01-2-00006

Baron, Reuben M., and David A. Kenny. 1986. "The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic and Statistical Considerations." *Journal of Personality and Social Psychology*, 51(6): 1173-1182. http://dx.doi.org/10.1037/0022-3514.51.6.1173

Belderbos, Rene, Elissavet Lykogianni, and Reinhilde Veugelers. 2008. "Strategic R&D Location by Multinational Firms: Spillovers, Technology Sourcing, and Competition." *Journal of Economics and Management Strategy*, 17(3): 759-779. http://dx.doi.org/10.1111/j.1530-9134.2008.00194.x

Blomström, Magnus, and Fredrik Sjöholm. 1999. "Technology Transfer and Spillovers: Does Local Participation with Multinationals Matter?" *European Economic Review*, 43(4-6): 915-923. http://dx.doi.org/10.1016/S0014-2921(98)00104-4

Brandt, Loren, Johannes V. Biesebroeck, and Yifan Zhang. 2012. "Creative Accounting or Creative Destruction? Firm-Level Productivity Growth in Chinese Manufacturing." *Journal of Development Economics*, 97(2): 339-351. http://dx.doi.org/10.1016/j.jdeveco.2011.02.002

Branstetter, Lee. 2000. "Vertical Keiretsu and Knowledge Spillovers in Japanese Manufacturing: An Empirical Assessment." *Journal of the Japanese and International Economies*, 14(2): 73-104. http://dx.doi.org/10.1006/jjie.2000.0444

Cai, Hongbin, and Qiao Liu. 2009. "Competition and Corporate Tax Avoidance: Evidence from Chinese Industrial Firms." *The Economic Journal*, 119(537): 764-795. http://dx.doi.org/10.1111/j.1468-0297.2009.02217.x

Caliendo, Marco, and Sabine Kopeinig. 2008. "Some Practical Guidance for the Implementation of Propensity Score Matching." *Journal of Economic Surveys*, 22(1): 31-72. http://dx.doi.org/10.1111/j.1467-6419.2007.00527.x

Chen, Kun-Ming, and Shu-Fei Yang. 2013. "Impact of Outward Foreign Direct Investment on Domestic R&D Activity: Evidence from Taiwan's Multinational Enterprises in Low-Wage Countries." *Asian Economic Journal*, 27(1): 17-38. http://dx.doi.org/10.1111/asej.12000

Chung, Wilbur, and Juan Alcácer. 2002. "Knowledge Seeking and Location Choice of Foreign Direct Investment in the United States." *Management Science*, 48(12): 1534-1554. http://dx.doi.org/10.1287/mnsc.48.12.1534.440

Crespo, Nuno, and Maria P. Fontoura. 2007. "Determinant Factors of FDI Spillovers - What Do We Really Know?" *World Development*, 35(3): 410-425. http://dx.doi.org/10.1016/j.worlddev.2006.04.001

Deng, Ping. 2009. “Why Do Chinese Firms Tend to Acquire Strategic Assets in International Expansion?” *Journal of World Business*, 44(1): 74-84. http://dx.doi.org/10.1016/j.jwb.2008.03.014

Feenstra, Robert C., Zhiyuan Li, and Miaojie Yu. 2014. “Exports and Credit Constraints under Incomplete Information: Theory and Evidence from China.” *Review of Economics and Statistics*, 96(4): 729-744. http://dx.doi.org/10.1162/REST_a_00405

Girma, Sourafel. 2005. “Absorptive Capacity and Productivity Spillovers from FDI: A Threshold Regression Analysis.” *Oxford Bulletin of Economics and Statistics*, 67(3): 281-306. http://dx.doi.org/10.1111/j.1468-0084.2005.00120.x

Hansson, Pär. 2005. “Skill Upgrading and Production Transfer within Swedish Multinationals.” *The Scandinavian Journal of Economics*, 107(4): 673-692. http://dx.doi.org/10.1111/j.1467-9442.2005.00428.x

Helpman, Elhanan, Marc J. Melitz, and Stephen R. Yeaple. 2004. “Export versus FDI with Heterogeneous Firms.” *American Economic Review*, 94(1): 300-316. http://dx.doi.org/10.1257/000282804322970814

Herzer, Dierk. 2011. “The Long-Run Relationship between Outward Foreign Direct Investment and Total Factor Productivity: Evidence for Developing Countries.” *The Journal of Development Studies*, 47(5): 767-785. http://dx.doi.org/10.1080/00220388.2010.509790

Hijzen, Alexander, Sebastien Jean, and Thierry Mayer. 2011. “The Effects at Home of Initiating Production Abroad: Evidence from Matched French Firms.” *Review of World Economics*, 147(3): 457-483. http://dx.doi.org/ 10.1007/s10290-011-0094-x

Inkpen, Andrew C. 2000. “Learning through Joint Ventures: A Framework of Knowledge Acquisition.” *Journal of Management Studies*, 37(7): 1019-1044. http://dx.doi.org/10.1111/1467-6486.00215

Javorcik, Beata S. 2004. “Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers Through Backward Linkages.” *American Economic Review*, 94(3): 605-627. http://dx.doi.org/10.1257/0002828041464605

Kimura, Fukunari, and Kozo Kiyota. 2006. “Exports, FDI, and Productivity: Dynamic Evidence from Japanese Firms.” *Review of World Economics*, 142(4): 695-719. http://dx.doi.org/10.1007/s10290-006-0089-1

Kokko, Ari, Ruben Tansini, and Mario C. Zejan. 1996. “Local Technological Capability and Productivity Spillovers from FDI in the Uruguayan Manufacturing Sector.” *The Journal of Development Studies*, 32(4): 602-611. http://dx.doi.org/10.1080/00220389608422430

Lechner, Michael. 2011. “The Estimation of Causal Effects by Difference-in-Difference Methods.” University of St. Gallen Discussion Paper 2010-28.

Levinsohn, James, and Amil Petrin. 2003. “Estimating Production Functions Using Inputs to Control for Unobservables.” *Review of Economic Studies*, 70(2): 317-341. http://dx.doi.org/10.1111/1467-937X.00246

Lichtenberg, Frank R., and Bruno Van P. de la Potterie. 1998. “International R&D Spillovers: A Comment.” *European Economic Review*, 42(8): 1483-1491. http://dx.doi.org/10.1016/S0014-2921(97)00089-5

Liu, Zhiqiang. 2008. “Foreign Direct Investment and Technology Spillovers: Theory and Evidence.” *Journal of Development Economics*, 85(1-2): 176-193. http://dx.doi.org/10.1016/j.jdeveco.2006.07.001

Luo, Yadong, and Rosalie L. Tung. 2007. "International Expansion of Emerging Market Enterprises: A Springboard Perspective." *Journal of International Business Studies*, 38(4): 481-498. http://dx.doi.org/10.1057/palgrave.jibs.8400275

Mani, Sunil. 2013. "Outward Foreign Direct Investment from India and Knowledge Flows, the Case of Three Automotive Firms." *Asian Journal of Technology Innovation*, 21(sup1): 25-38. http://dx.doi.org/10.1080/19761597.2013.819232

Moen, Jarle. 2005. "Is Mobility of Technical Personnel a Source of R&D Spillovers?" *Journal of Labor Economics*, 23(1): 81-114. http://dx.doi.org/10.1086/425434

Navaretti, Giorgio B., Davide Castellani, and Anne-Célia Disdier. 2010. "How Does Investing in Cheap Labour Countries Affect Performance at Home? Firm-Level Evidence from France and Italian." *Oxford Economic Papers*, 62(2): 234-260. http://dx.doi.org/10.1093/oep/gpp010

Olley, George S., and Ariel Pakes. 1996. "The Dynamics of Productivity in the Telecommunications Equipment Industry." *Econometrica*, 64(6): 1263-1297. http://dx.doi.org/10.2307/2171831

Organisation for Economic Co-operation and Development. 2006. *Investment for Development: Investment Policy Co-operation with Non-OECD Economics*. Paris: OECD Publishing.

Pradhan, Jaya P., and Neelam Singh. 2008. "Outward FDI and Knowledge Flows: A Study of the Indian Automotive Sector (November 2008)." *International Journal of Institutions and Economies*, 1(1): 155-186.

Rodríguez, Carlos, and Ricardo Bustillo. 2011. "A Critical Revision of the Empirical Literature on Chinese Outward Investment: A New Proposal." *Panoeconomicus*, 58(Special Issue): 715-733. http://dx.doi.org/10.2298/PAN1105715R

Sobel, Michael E. 1986. "Some New Results on Indirect Effects and Their Standard Errors in Covariance Structure Models." *Sociological Methodology*, 16: 159-186. http://dx.doi.org/10.2307/270922

Vermeulen, Freek, and Harry Barkema. 2001. "Learning through Acquisitions." *Academy of Management Journal*, 44(3): 457-476. http://dx.doi.org/10.2307/3069364

Yamawaki, Hideki. 1993. "International Competitiveness and the Choice of Entry Mode: Japanese Multinationals in the US and European Manufacturing Industries." Research Institute of Industrial Economics Working Paper 424.

Zhao, Wei, Ling Liu, and Ting Zhao. 2010. "The Contribution of Outward Direct Investment to Productivity Changes within China, 1991-2007." *Journal of International Management*, 16(2): 121-130. http://dx.doi.org/10.1016/j.intman.2010.03.003

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