Outward FDI and Efficiency in Within-Firm Resource Allocation - Evidence from Firm-Level Data of China

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Abstract: With the rapid expansion of outward foreign direct investment (OFDI) in China over the last two decades, OFDI has become an increasingly important way of internationalization for firms. This paper documents how firms’ OFDI and its different patterns may affect their internal resource allocation efficiency by adopting PSM-DID method and using firm-level data of China. Our results show that China's OFDI significantly improves the overall efficiency of resource allocation within enterprises, which has a time lag effect. Furthermore, we find that different patterns of firms’ OFDI display significant heterogeneity in their performances. All results remain robust when we replace key variables with different indexes, change the matching method, recalculate parameter, and change the sample size. The key implication of the paper is that both the value and the pattern of OFDI of Chinese enterprises do have significant influences on its internal resource allocation.

Keywords: Outward FDI; Foreign Direct Investment; Resource Allocation; PSM-DID; Firm Internationalization; China

JEL code: F21, D24, E25

1. Introduction

At the beginning of the 21st century, China put forward the development strategy of "Going out", after experiencing a stage of rapid development stimulated by import and export trade and utilization of foreign capital (Xu, Li, Jiang, & Chen, 2020). Not surprisingly, China has witnessed a rapid increase in the flows of outward foreign direct investment (OFDI) and the numbers of multinational enterprises (MNEs) since the introduction of this policy.[1] According to the 2019 Statistical Bulletin of China's Outward Foreign Direct Investment, China's OFDI flow was 14.16 billion dollars, ranking second in the world, indicating that OFDI has gradually become an increasingly important way for China to be involved in the global economy. With China's Belt and Road initiatives further introduced, China's "Going out" strategy has turned into a new engine for pushing forward a new round of opening-up strategy. It is widely accepted that OFDI can play an important role in economic development (Murthy, 2015). OFDI is not only a key mode of internationalization, but also an important way for enterprises to make full use of domestic and foreign markets, in order to improve resource allocation. Therefore, we believe that it is pertinent and relevant to consider the impact of China's OFDI on resource allocation, thus contributing to the FDI literature.

It has been documented that resource misallocation is often a fundamental issue for the Chinese economy (Dollar & Wei, 2007; Manova, Wei, & Zhang, 2015; Bai, Hsieh, & Song, 2016). Some studies (e.g., Hsieh & Klenow, 2009; Wu, 2018) found that improving the efficiency of resource allocation can have great potential to promote China's economic growth. As a result, the issue of resource allocation has received much attention in the recent literature. Many existing studies have extensively examined the cause and consequence of resource misallocation from the perspectives of domestic market distortion and policy intervention in China. However, it seems that relatively few studies have investigated whether and how the internationalization of firms could contribute to improving the allocation efficiency. Related works have found that not only the value, but also the pattern of OFDI are indeed crucial factors to better understanding how and why China has become one of the most important emerging economies in the global market (Clegg, Lin, H., Voss, H., Yen, I., & Shih, Y., 2016). Against this background, this paper focuses on investigating whether and how different patterns of Chinese firms' OFDI contribute to the improvement of internal resource allocation efficiency with our novel firm-level data. We find empirical evidence that the internationalization of firms' OFDI and its patterns can provide an important role in improving resource misallocation in China. Thus, our study has key implications for both academics and policy makers.

Our paper is grounded in two key strands of literature. The first strand of literature is related to resource misallocation. New and growing studies surveyed by Restuccia and Rogerson (2008) have highlighted that the efficiency of resource allocation is an important

[1] Please refer to Ma et al. (2020) for a detailed description of Chinese companies' internationalization and a general understanding of the current OFDI in China.

factor in explaining total factor productivity (TFP) differences across countries. Thus, an efficient reallocation of resources across firms can strongly contribute to economic growth (Restuccia & Rogerson, 2008; Hsieh & Klenow, 2009; Wu, 2018). Many studies have discussed the misallocation across firms measured by the dispersion of TFP in line with the seminal work of Hsieh and Klenow (2009). Meanwhile, the crucial role of resource allocation within-firm has generally been overlooked to some extent. However, Bloom (2009) found that the resource allocation within-firm can be significant in determining macro-outcomes, such as business cycle fluctuation, TFP, and growth. The importance of resource allocation within-firm is also highlighted by Bernard, Redding, and Schott (2012), who examine endogenous product selection within-firm and point out that resource allocation within-firm may be more important than resource allocation across firms. A growing stream of studiesin the field of international trade, explores changes between different productive products within-firm, using disaggregated trade data in the context of different countries (see for example, Bernard et al., 2012 (USA); Goldberg et al., 2010 (India); Iacovone & Javorcik, 2010 (Mexico); and Tan et al., 2015 (China)).

There tends to be a lack of research that investigates resource allocation by considering investment changes between branches in the same firm (Matvos & Seru, 2011; Midrigan & Xu, 2014). In the context of China, Brandt et al. (2013) provide stylized facts of factor misallocation across time, space, and sector in China. Although there exist several studies that attempt to address resource misallocation existing in China, most of them focus only on domestic factors, government involvement, and specific policies (Tan et al., 2015; Deng & Wang, 2016; Chen, 2019; Cong et al., 2019). To the best of our knowledge, there seem to be very few existing studies which have directly considered the impact of China's internationalization via OFDI on the internal resource allocation, especially from the micro-level perspective.

The second strand of literature in our paper is OFDI from emerging economies (EEs). Commonly abbreviated as BRICs (Brazil, Russia, India, China), these emerging economies are increasingly important players in the global OFDI process, and they have recently attracted much attention from the economic literature (e.g., Kaushal, 2018; Mohanty & Sethi, 2019). Many related studies (e.g., Nocke & Yeaple, 2007; Deng, 2009; Buckley et al., 2007; Wang et al., 2012; Ramasamy et al., 2012) have examined the patterns, motivations, and mode selections of EEs' OFDI. Mainly due to the lack of OFDI in firm-level data, the research on the impact of OFDI on the domestic performance of EEs has received relatively little attention (Chen et al., 2012; Gerschewski, 2013). However, empirical evidence indicates that there is existing significant heterogeneity regarding firms' participation in OFDI. Firm-level data does help to improve investigation on OFDI (Amighini et al., 2014). Recent studies, therefore, have put more efforts to conduct research based on firm-level data (Amighini et al., 2014; Chen & Tang, 2014). Most of the evidence (e.g., Boateng et al., 2008;

Stiebale & Trax, 2011; Cozza et al., 2015; Edamura et al., 2014) have found that the patterns of OFDI matter on the effect on the firms' performance for EEs' firms, in general, and, more specifically, Chinese companies. Hence, there is a need for more detailed information on firms' OFDI data to better understand the effects of OFDI on resource allocation within-firm. Thanks to our unique dataset, we can discuss the impact of Chinese firms' OFDI on internal resource allocation efficiency to distinguish the roles of different types of OFDI on firms' allocation efficiency.

This study aims to fill the existing research gaps by examining how OFDI affects resource allocation efficiency within-firm, and what are the heterogeneous impacts of Chinese firms' OFDI via different patterns, imposed on the internal resource allocation efficiency of firms. Therefore, this paper helps to enhance our understanding of existing knowledge of Chinese resource allocation and enriches the field of research on the relationship between OFDI and firm's performance in the context of China. Further, it also has some useful and relevant policy implications. It is well known that many OFDI enterprises tend to lack international experience despite the rapid growth of OFDI in China, which leads to the high failure rate and low profits of foreign investment of Chinese enterprises. A more challenging issue nowadays is that the world grapples with the effects of the COVID-19 global pandemic. According to the recent UNCTAD special edition of its investment trends monitor on March 8 in 2020, COVID-19 could shrink global FDI by 5% to 15%, and new greenfield projects and M&As could result in a sharp slowdown. Therefore, our research on the enterprise level, deeply analyzing the impact of the specific OFDI behaviors of enterprises on the allocation of resources within enterprises, will provide key references for the specific strategy guiding the "Going out" of Chinese enterprises. In addition, our study provides a theoretical basis and rationale for the more efficient implementation of "Going out" policy for the Chinese government.

The remainder of the paper is organized as follows: Section 2 outlines the data description, and the measures of resource allocation efficiency within-firm. In Section 3, we describe the identification method and the empirical model. Section 4 presents our heterogeneity and robust tests. Finally, we provide the key conclusions, policy recommendations, and limitations of the study.

2. Data description and Measurements for within-firm resource allocation efficiency

2.1 Data description

Consistent with the objectives of our paper, we rely and focus on three types of databases:

(1) Industrial Enterprise Database (IED): This firm-level production dataset is collected and maintained by the National Bureau of Statistics of China (NBSC). It is a comprehensive dataset collecting detailed information for all state-owned enterprises (SOEs) and

non-state-owned enterprises with annual sales above five million renminbi in China between 1998 and 2007. This dataset is currently widely used by Chinese and Western literature (Brandt et al., 2012), and is also considered to provide the most reliable data in China (Cai and Liu 2009). Following Feenstra et al. (2014), we first drop those firm-level observations for which the indexes of enterprise ID, total output, total assets, sales revenue, intermediate inputs, fixed assets, and the number of employees are partly missing, and drop those observations which violate generally accepted accounting standards. After excluding invalid samples, there are 556,492 enterprises and 1,976,281 total observations from 1998 to 2007.

(2) Dataset of China Outward Foreign Investment Directory is provided by the Ministry of Commerce of China (hereinafter referred to as "Outbound Investment Directory"(OID)). It records the information of Chinese firms conducting OFDI and coversthe name of the parent company and its subsidiary, the country of destination, the year of approval of OFDI, and the scope of business. The Chinese government has not provided official OFDI statistics until 2002 when NBSC and the former Ministry of Foreign Trade and Economic Cooperation jointly established China's first "Outbound Direct Investment Statistical System". In consideration of the reliability of the data and the consistency of the caliber, we limit the OFDI sample of this study to the companies that made their initial OFDI from 2002 to 2007.

(3) The third and final dataset about OFDI mode in our paper is obtained based on manual data collection. The largest difficulty in this study is the data construction of OFDI mode (one of our key variables of interest), as the OID does not provide related information. In terms of data collection procedures, we collected the entry mode and the equity mode for firms' OFDI through the parent companies' websites, listed company annual reports and media public reports, etc. Specifically, the entry mode of firms' subsidiaries is identified as "mergers and acquisitions" (M&A), if the message in the channels explicitly includes words, such as "mergers and acquisitions", "mergers", or "acquisitions". If the terms regarding the subsidiary company is expressed as "establish", "found", "build" or "newly established" in the information, it is regarded as "greenfield investment". In terms of equity modes, this is identified as "wholly-owned equity" (WOE), if the message clearly described the subsidiary as "wholly-owned equity". If the information is closely related to "joint venture equity"(JV), then it would be regarded as "joint venture subsidiary". When no relevant information is found, firm's OFDI mode is treated as “missing” in our paper.

In order to find out the firms which conduct OFDI during the sample period, we merged the first two datasets (i.e., IED and OID) by using the firms' names, for which are the only item comparable between the two datasets. However, the Chinese names of enterprises in both datasets are often misleading due to typing errors, misreporting, and different abbreviations. The potential risks by matching its original parent names in both datasets are that we could not only lose many valuable sample firms, but some OFDI enterprises might be recognized as non-OFDI enterprises by mistake, which would result in serious bias. Therefore, we need to carefully deal with the original enterprises' names in both datasets prior to matching them. After cleaning both datasets, the number of matched samples is increased by about 8.2% compared with the number of samples matched simply by using its original parent names. With this merged dataset and the mode dataset of firms' OFDI, we obtain our estimation samples. The matching panel data from 2002-2007 contains 1,374 parent companies that conducted initial OFDI during this period, and 1,934 subsidiaries established by OFDI. The average numbers of destination countries where subsidiaries of each parent company locate are 1.11, with 10 the maximum number of countries. The initial OFDI destination of 902 companies (about 65.6%) locates in developing countries, for another 431 companies (about 31.4%) it locates in developed countries[2]. In addition, 41 companies (about 2.98%) had mixed destinations for investments (i.e., investment both in developed and developing countries). In terms of the initial OFDI during 2002-2007, there are 31 firms explicitly adopting the M&A mode, and 731 firms explicitly adopting the greenfield investment model. As for the equity mode, 631 companies adopt the WOE mode, and another 112 companies adopt JV mode. This unique dataset of OFDI mode enables our research to provide in-depth insights into the heterogeneous effects of OFDI on within-firm resource allocation efficiency.

A new classification system for industry codes (GB/T 4754-2002) was adopted in 2003. Consistent with Brandt et al. (2012), we convert the industry codes in the 2003-2007 data to the old classification system to achieve consistency in the industry codes for the entire sample period (2001-2007).

2.2 Resource allocation within-firm (RA)

Following the ideas put forward by Hsieh and Klenow (2009), we consider an economy composed of many sectors that include many plants producing differentiated products, which could be combined into a sector aggregate accordingly.

$$Y_j = \left(\sum_{i=1}^{M_j} Y_{ij}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma-1}{\sigma}} \tag{1}$$

Where, Y_{ij} stands for the output of firm i in sector j and σ represents product substitution within sector.

Each firm in sector j is assumed to produce adhering to a Cobb-Douglas production function.

$$Y_{ij} = A_{ij} K_{ij}^{\beta_j^k} L_{ij}^{\beta_j^l} \tag{2}$$

In the above C-D function, A_{ij} is total factor productivity; L_{ij} is the input of labor;

[2] Here, developed countries include 22 OECD countries, such as the United States, France, the United Kingdom, Japan, Germany, Canada, Italy, Sweden, Finland, Denmark, Norway, the Netherlands, Belgium, Sweden, Austria, Australia, New Zealand, Greece, Iceland, Ireland, Portugal and Spain. The remaining countries are defined as developing countries.

K_{ij} is the input of capital; β_j^l and β_j^k represent the output elasticity of labor and capital, respectively. Without the distortion of production factor, the marginal output of factor will be equal to the rate of return of each factor. However, as documented by Hsieh and Klenow (2009), the actual allocation may deviate from the efficient allocation when production factor is distorted. Therefore, factor distortion will drive wedges between marginal output of factor and its rate of factor return.

A firm subjected to factor distortions will maximize its profit in the following formula:

$$Max\{P_{ij}Y_{ij} - \left(1 + \tau_{l_{ij}}\right) w_{ij}L_{ij} - \left(1 + \tau_{k_{ij}}\right) rK_{ij}\} \tag{3}$$

F.O.C for formula (3), we come to the following equation (4) and (5):

$$MRPL_{ij} = \frac{d(P_{ij}Y_{ij})}{dL_{ij}} = w_{ij}\left(1 + \tau_{l_{ij}}\right) = \frac{\sigma - 1}{\sigma} * \frac{\beta_j^l P_{ij}Y_{ij}}{L_{ij}} \tag{4}$$

$$MRPK_{ij} = \frac{d(P_{ij}Y_{ij})}{dK_{ij}} = r\left(1 + \tau_{k_{ij}}\right) = \frac{\sigma - 1}{\sigma} * \frac{\beta_j^k P_{ij}Y_{ij}}{K_{ij}} \tag{5}$$

Where for firm i in sector j, $MRPL_{ij}$ and $MRPK_{ij}$ represent marginal revenue product of labor and capital, respectively. P_{ij} is firm's sale price; w_{ij} and r denote the return of units of labor and capital, respectively. $\tau_{l_{ij}}$ and $\tau_{k_{ij}}$ are wedges measuring deviations from efficient labor and capital allocation, respectively. Following Hsieh and Klenow (2009), we assume that the r is 10% and σ is 3.

Misallocation can be inferred from differences between the marginal output value of various factors of production within or across firms. According to the expression in Eq. (4) and (5), we can yield $\tau_{l_{ij}}$ and $\tau_{k_{ij}}$. Whatever the reasons are for the wedges, an efficient firm will equate the marginal output value between each factor. Hence we can construct resource allocation index (RA1) to measure the efficiency of factor allocation within-firm as follows:

$$RA1_{ij} = \left[\tau_{l_{ij}} - \tau_{k_{ij}}\right] = \left|\frac{MRPK_{ij}}{r} - \frac{MRPL_{ij}}{w_{ij}}\right| \tag{6}$$

According to the law of diminishing marginal returns of factor, when the marginal output value of labor is higher than the marginal output value of capital, an enterprise would tend to reduce labor input and increase capital input to improve its profit, and vice versa. Therefore, RA1 could efficiently capture within-firm efficiency of resource allocation. The larger the value of RA1 is the less within-firm resource allocation efficiency would be.

In addition, we could combine both factors' distortion to construct another aggregated distortion index (RA2) suggested by Obsfield (2011) as follows:

$$RA2_{ij} = \beta_j^l \tau_{l_{ij}} + \beta_j^k \tau_{k_{ij}} \tag{7}$$

Therefore, RA2 indicator reflects the overall resource allocation efficiency of an enterprise, which consists of both labor distortion and capital distortion. The larger the value of $RA2$ is the worse the performance of within-firm efficiency of resource allocation would be.

2.3 Internal resource allocation efficiency of Chinese enterprises

In this section, we document stylized facts regarding within-firm resource allocation efficiency with whole samples, and separated samples of OFDI vs. non-OFDI firms. With the measures of within-firm resource allocation efficiency as RA1 and RA2, in the first place, we compute the internal resource allocation efficiency of Chinese enterprises from 2000 to 2007. Table 1 presents the summary statistics of overall performances among Chinese enterprises in within-firm resource allocation efficiency (RA1 and RA2), labor distortion (τ_l) and capital distortion (τ_k) for the whole samples and the subsamples of OFDI and non-OFDI. Statistics display that both the mean of RA1 and the mean of RA2 in Table 1 show an increasing trend from 2000 to 2007. Further, the average capital distortion is always larger than the absolute value of average labor distortion whether in the whole samples or in the OFDI and non-OFDI subsamples during this period. When we compare RA1 or RA2 in the two subgroups between OFDI and non-OFDI in Table 1, it shows that OFDI companies have relatively lower RA than those of non-OFDI companies, which indicates that firms' OFDI may improve the efficiency of resource allocation within the enterprises. However, this conclusion needs to be further confirmed by the following rigorous empirical tests.

Table 1: Statistics of enterprise resource allocation efficiency and factor distortion

Year		2000	2001	2002	2003	2004	2005	2006	2007
Whole Samples	RA1	1.7976	1.9256	2.1693	2.4851	2.6851	2.4056	2.6590	2.8831
	RA2	0.0530	0.0622	0.0728	0.0901	0.1004	0.0845	0.0974	0.1069
	τ_l	-0.5271	-0.5221	-0.5172	-0.4978	-0.5037	-0.5100	-0.5326	-0.5508
	τ_k	0.9260	1.0900	1.2998	1.6302	1.8348	1.5412	1.8157	2.0273
OFDI	RA1	1.5651	1.8857	1.9072	2.0918	2.3195	1.7017	1.9508	2.1605
	RA2	0.0449	0.0614	0.0599	0.0729	0.0803	0.0495	0.0638	0.0729
	τ_l	-0.4729	-0.4685	-0.4936	-0.4680	-0.5096	-0.4887	-0.5037	-0.4892
	τ_k	0.7806	1.1239	1.1221	1.2829	1.4734	0.8651	1.1244	1.3343

Non-OFDI	RA1	1.9001	1.9428	2.2828	2.6428	2.8374	2.6740	2.9536	3.1998
	RA2	0.0565	0.0625	0.0784	0.0971	0.1087	0.0979	0.1114	0.1217
	τ_l	-0.5510	-0.5453	-0.5274	-0.5098	-0.5012	-0.5182	-0.5446	-0.5778
	τ_k	0.9902	1.0754	1.3769	1.7694	1.9853	1.7990	2.1032	2.3310

Source: Calculated by the authors

3. Identification and empirical model

3.1 PSM-DID method

Our empirical strategy is to identify the causal effect of OFDI on firm's RA. Let $RA_{t,i}^1$ be the efficiency of resource allocation of OFDI of firm i in period t, while $RA_{t,i}^0$ denotes resource allocation efficiency of firm i in time period t if the firm does not conduct OFDI. The causal effect of OFDI of firm i on RA is then defined as:

$$\pi = \mathrm{E}\left(RA_{t,i}^1 \middle| X_{t-1,i}, OFDI_{t,i} = 1\right) - \mathrm{E}\left(RA_{t,i}^0 \middle| X_{t-1,i}, OFDI_{t,i} = 1\right) \tag{8}$$

Where $\mathrm{OFDI}_{t,i}$ is a dummy variable, taking the value of one if the firm's initial OFDI occurs in the year t, zero otherwise; $X_{t-1,i}$ contains a set of once-lagged control variables.

The fundamental problem of the causal inference above is that the quantity $\mathrm{RA}_{t,i}^0$ is unobservable, as the firm i at time period t have initially conducted OFDI (i.e., for which we only observe $\mathrm{RA}_{t,i}^1$). Therefore, causal inference relies on the construction of the counterfactual for the second term in Eq. (8). An important feature of the accurate construction of the counterfactual is the selection of a valid control group.

We employ matching techniques constructing control groups, which are expected to achieve matches of OFDI and non-OFDI firms that are similar to each other with respect to a range of observable characteristics. It is desirable to perform the matching on the basis of a single index that captures all the information from those variables. We adopt the method of propensity score matching as suggested by Rosenbaum and Rubin (1983). Using probit model to identify the probability of OFDI conditional on a series of covariates observed before OFDI occurs. Then the unobservable second term in Eq. (8) can be matched from the corresponding non-OFDI firm with the closest scores, which is denoted as $\mathrm{E}\left(\mathrm{RA}_{t,i}^0 \middle| \mathrm{X}_{t-1,i}, \mathrm{OFDI}_{t,i} = 0\right)$. As our dataset is a panel, we can release the strong assumption of selection on observables by combining the matching technique with a difference-in-differences (DID) estimator (Blundell and Costa Dias 2000). Now, the causal effect of OFDI for firm i on RA in the implication of Eq. (8) can be replaced by the following formula:

$$\widehat{\pi}\,(\mathrm{DID}) = \mathrm{E}\left(\Delta RA_{t,i}^1 \middle| X_{t-1,i}, OFDI_{t,i} = 1\right) - \widehat{\mathrm{E}}\left(\Delta RA_{t,i}^0 \middle| X_{t-1,i}, OFDI_{t,i} = 0\right) \tag{9}$$

Where, $\Delta RA_{t,i}^1$ and $\Delta RA_{t,i}^0$ denote the change of RA of OFDI firm i and that of its corresponding non-OFDI firm, respectively.

The choice of covariates is followed by the empirical literature on the determinants of firm's OFDI. Existing literature suggests that the determinants of firm's OFDI decision include TFP, capital intensity (KL), firm size (SIZE), firm age (AGE), firm profit (PROFIT), Export Intensity (EX), Financing Constraints (FINANCE), Ownership Structure (STATE) and Political Relations (AFFILIATION). Among the covariates mentioned above, TFP is measured by the LP method suggested by Levinsohn and Petrin (2003)[3]; Capital intensity (KL) is defined as the ratio of net fixed assets to the total number of employees of the firm. Our proxies of the size of the enterprise (SIZE) and the age of the enterprise (AGE) are the logarithm of the company's sales and the number of years of establishment of the enterprise, respectively. The profit of the enterprise (PROFIT) is defined as the ratio of the firm's operating profit to sales; the export intensity (EX) is measured as the share of the export delivery value to sale; Financing constraints (FINANCE) is defined as the ratio of interest expenses to fixed assets; Ownership structure (STATE) is measured by the ratio of state-owned paid-in capital to the total paid-in capital of the enterprise. As a measure of the degree of the political association (AFFILIATION), we adopt the method suggested by Wang et al. (2012), and based on the affiliation relationship of enterprise, from central, province, city, county, assign score from 5 to 1 accordingly. The greater the score is, the more intense the political connection would be.

In this paper, we apply the nearest neighbor matching method to conduct year-by-year matching with the 1: 3 matching ratio. Thus, some companies could serve as control groups for multiple treatment groups. After the matching, we obtain 4,849 samples of treatment group and 11,849 samples of the control group. Figure 1 illustrates the identification strategy. It clearly shows that the two groups have generally similar trends before one year of the initial OFDI, but a visible divergence in trend of RA1 after then. It makes sense that the divergence may appear some periods ahead of initial OFDI as an individual firm's behavior is likely to change in anticipation of its coming OFDI. Therefore, it would be a better choice to regard one year before OFDI as the effective starting point (solid vertical line in Figure 1) in order to find a proper treatment group. These similar trends in RA1 before -1 year between treatment group and control groups alleviate the concern that our treatment group and control groups are ex ante incomparable, which provides support to the satisfaction of our DID identifying assumption. Meanwhile, the treatment group is more efficient in allocating resources than the constructed control group after -1 year, which implies that OFDI can significantly improve within-firm efficiency of resource allocation.

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[3] A key issue in the estimation of production functions is the correlation between unobservable productivity shocks and input levels, which yields inconsistent estimates under OLS. Both Olley and Pakes (1996) and Levinsohn and Petrin (2003) methods are now widely used to solve this issue. We first apply LP method to calculate TFP, and then use OP method for robustness test.

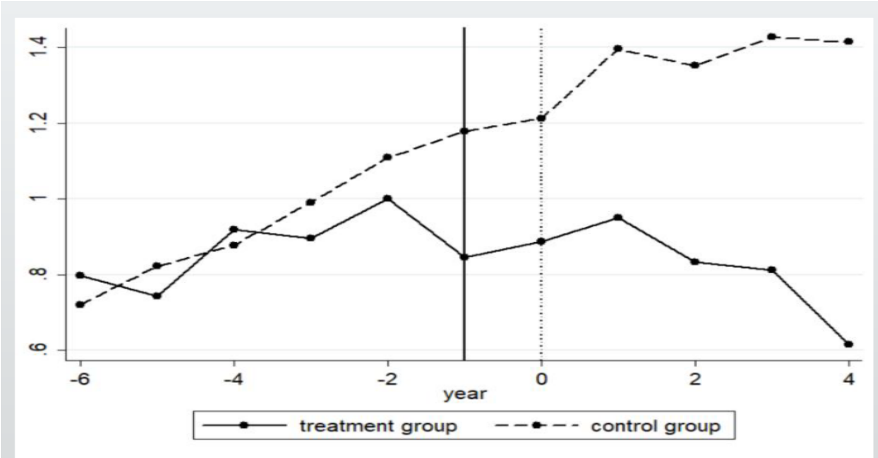

Figure 1: control group vs. treatment group

(Note: the initial year of firm's OFDI is defined as the origin year 0 on horizontal line, then, -1 represents 1 year before OFDI occurs, -2 is 2 years before OFDI, however, +1 means 1 year after the first OFDI happens, +2 is 2 years after the first OFDI happens, and so on.)

3.2 Estimation model and results

3.2.1. Baseline model

In order to examine the impact of OFDI on the efficiency of resource allocation within an enterprise, we adopt the following regression equation as our baseline specification:

$$RA1_{it} = \beta_0 + \beta_1 OFDI_i + \beta_2 POST_t + \beta_3 OFDI_i * POST_t + \beta_4 X_{it-1} + \delta_t + \mu_j + \theta_p + \varepsilon_{ijpt} \quad (10)$$

Where, i、j、p and t respectively denote firm, industry, region and year. $OFDI_i$ is a dummy variable, the value of $OFDI_i$ is 1 for treatment group and 0 for control group; X_{it-1} is control variables with once-lagged which include covariates we defined before; $POST_t$ is time dummy variable of OFDI, the value is 1 after -1 year of the initial OFDI, otherwise, the value is 0. The coefficient of the interaction item of $OFDI_i$ and $POST_t$ (i.e. DID) reflects the impact of OFDI on the efficiency of resource allocation within the enterprise. δ_t、μ_j and θ_p represent time dummy, industry dummy and region dummy, respectively, and ε_{ijpt} refers to random error terms.

3.2.2 Estimation and placebo test

We firstly estimate the baseline specification (10), the result of which confirms our former conclusion that firm's OFDI can improve internal resource allocation efficiency. The regression results for the baseline specification (10) are reported in Table 2. We start with a simple DID specification that includes only year, industry and region dummy in column (1) of Table 2. Our regressor of interest, β_3, is negative and statistically significant, suggesting OFDI could improve RA1. In column (2) of Table 2, we then include all control variables.

Evidently, our results are found to be robust to these additional controls. After that, we add the interaction items of OFDI and initial OFDI year (POST_1), OFDI and +1 year after OFDI (POST_2), OFDI and +2 years after OFDI (POST_3)[4], and OFDI and +3 years after OFDI (POST_4) accordingly in the baseline model (10) to analyze the time dynamic effect of OFDI on the within-firm resource allocation efficiency, that is, whether the OFDI has a sustainable impact. The results without and with control variables are presented in column (3) and (4) of Table 2, respectively. As can be seen in column (3) and (4), the coefficients of interaction items of OFDI and POST_1, OFDI and POST_2, OFDI and POST_3 are insignificant and negative; whereas the coefficients of the interaction OFDI and POST_4 is statistically significant and negative, suggesting that there is a lag effect of OFDI on the improvement of within-firm resources allocation efficiency. It is understandable as it always takes time for a firm to reorganize the production activities in reality.

One issue is that our treatment and control groups could be systematically different *ex ante*, which may spuriously generate the impact of OFDI imposed on RA1. That is, the parallel trend hypothesis for DID identification is not satisfied. To alleviate this concern, we conduct placebo test. Based on the baseline model, we add both the interaction item of OFDI and OFDI one year before (OFDI*POST_pre1), and the interaction item of OFDI and OFDI two year before (OFDI*POST_pre2)[5]. We report the results in column (5) of Table 2. The coefficients of the interaction item of OFDI and OFDI one year before (OFDI*POST_pre1) and the interaction item of OFDI and OFDI two year before (OFDI*POST_pre2) are both found to be statistically insignificant, suggesting little expectation effect in much earlier years before a firm conducting OFDI and illustrating that improvement in efficiency of resource allocation is indeed due to the OFDI of enterprises. We further add to the interactive items of OFDI and 1 year after OFDI (POST_1), OFDI and 2 years after OFDI (POST_2), OFDI and three years after OFDI (POST_3) and OFDI and four years after OFDI (POST_4), and relevant results are presented in column (6) of Table 2. It indicates that the parallel trend hypothesis for DID identification is satisfied as the interaction items of OFDI with both one and two years before are still robustly insignificant.

Table 2: Benchmark result analysis and placebo test

Variables	Baseline model		Time dynamics		Placebo test	
	RA1		RA1		RA1	
	(1)	(2)	(3)	(4)	(5)	(6)
OFDI	-0.3702**	-0.4496***	-0.3687**	-0.4485***	-0.4232***	-0.4219***
	(0.1460)	(0.1376)	(0.1461)	(0.1377)	(0.1564)	(0.1564)

4 Based on our $POST_t$ setting, one year after (POST_1) refers to the 0 initial year of OFDI. Two year after (POST_2) refers to +1 year of initial OFDI, and so on.

5 Based on our POST setting, one year before (POST_pre1), is equal to -2 year of initial OFDI. Two year before((POST_pre2), is equal to -3 year of initial OFDI, and so on.

POST	0.5647***	0.5924***	0.5587***	0.5738***	0.5993***	0.5807***
	(0.1582)	(0.1532)	(0.1645)	(0.1592)	(0.1570)	(0.1626)
OFDI*POST	-0.6837***	-0.6807***	-0.6584***	-0.5968***	-0.7071***	-0.6227***
	(0.1521)	(0.1441)	(0.1658)	(0.1557)	(0.1788)	(0.1918)
OFDI*POST_1			0.0544	0.0335		0.0324
			(0.1647)	(0.1624)		(0.1625)
OFDI*POST _2			-0.0299	-0.1522		-0.1534
			(0.1624)	(0.1530)		(0.1530)
OFDI*POST _3			-0.0836	-0.2355		-0.2366
			(0.2054)	(0.1915)		(0.1916)
OFDI*POST _4			-0.7457***	-0.6458***		-0.6475***
			(0.2339)	(0.2372)		(0.2371)
OFDI*POST_pre1					0.0278	0.0279
					(0.2028)	(0.2029)
OFDI*POST_pre2					-0.1529	-0.1542
					(0.1590)	(0.1590)
Controls	N	Y	N	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y
Industry dummy	Y	Y	Y	Y	Y	Y
Region dummy	Y	Y	Y	Y	Y	Y
Constant	3.2414***	1.6408*	3.2366***	1.6276*	1.6328*	1.6194*
	(0.6659)	(0.8377)	(0.6659)	(0.8379)	(0.8396)	(0.8398)
Observation	15,402	15,189	15,402	15,189	15,189	15,189
R^2	0.0939	0.1739	0.0940	0.1741	0.1739	0.1741

Note: the robust standard error is clustered by firm. * p <0.1, ** p <0.05, *** p <0.01, same for all following tables

3.2.3 Labor distortion and capital distortion

As illustrated in section 2.2, RA2 is aggregated distortion index to measure resource allocation efficiency within-firm. We first replace the dependent variable in equation (10) with RA2. Then, we examine whether the effect of OFDI on improving the efficiency of enterprise resource allocation is mainly achieved through reducing labor distortion or capital distortion. To address this issue, we replace the explained variables in equation (10) with labor distortion （$\tau_{l_{ij}}$） and capital distortion （$\tau_{k_{ij}}$） ,respectively. The results are presented in Table 3. Among them, the dependent variables in columns (1) and (2) are RA2, the dependent variables in columns (3) and columns (4) are labor distortions, and for columns (5) and (6), they are capital distortions. In addition, we only control the time, industry and region dummy in the odd columns, and further add all the control variables in the even columns. The coefficients of interaction terms of OFDI and POST are still significantly negative for RA2, which is consistent with the baseline regression. However, the coefficients of interaction terms of DID are negative, but not significant for $\tau_{l_{ij}}$, while it is significantly negative for $\tau_{k_{ij}}$, which demonstrates that the improvement of within-firm efficiency is mainly contributed by improving capital distortions rather than labor distortion. One possible explanation for this outcome is that capital misallocation is much more severe than labor market distortion in China. As we know, most loans in China are generally still dominated by state-owned banks (Zhang, Wang, Liu, & Fu, 2020). Thus, capital misallocation seems widespread due to government and policy intervention (Wu, 2018). It could help to ease capital misallocation when firms turn into international market via OFDI. However, compared to the inefficient financial market, the Chinese government began to reform labor market much earlier. China has experienced a massive labor migration since the mid-1990s, which might partly explain why OFDI has not the same effect on reducing labor distortion as on capital distortion.

Table 3: Labor distortion and capital distortion

Variables	RA2		$\tau_{l_{ij}}$		$\tau_{k_{ij}}$	
	(1)	(2)	(3)	(4)	(5)	(6)
OFDI	-0.0232***	-0.0291***	-0.0276	-0.0660**	-0.3807**	-0.4788***
	(0.0081)	(0.0077)	(0.0318)	(0.0307)	(0.1511)	(0.1425)
POST	0.0318***	0.0333***	0.0240	0.0199	0.5070***	0.5277***
	(0.0093)	(0.0091)	(0.0374)	(0.0358)	(0.1613)	(0.1555)
OFDI*POST	-0.0322***	-0.0316***	-0.0022	-0.0054	-0.7055***	-0.6804***
	(0.0085)	(0.0081)	(0.0297)	(0.0291)	(0.1549)	(0.1457)
Controls	N	Y	N	Y	N	Y
Year	Y	Y	Y	Y	Y	Y
Industry	Y	Y	Y	Y	Y	Y
Region	Y	Y	Y	Y	Y	Y
Constant	0.0762**	-0.1133**	-1.0040***	-2.1480***	2.3899***	-0.0923
	(0.0324)	(0.0465)	(0.0869)	(0.1391)	(0.6798)	(0.8716)
Observations	15,402	15,189	15,402	15,189	15,402	15,189
R^2	0.1158	0.1871	0.2814	0.3290	0.1434	0.2265

4. Heterogeneous and robust test

4.1 Heterogeneity test

4.1.1. OFDI mode

When undertaking OFDI in a foreign country, a firm can choose different modes of entry. Generally speaking, an investor may choose entry mode, either performing M&A with an existing firm or setting up a new venture (i.e. greenfield investment); or choose equity modes of ownership equity, such as WOE or JV[6]. In this section, we will examine how these

[6] Further, it can be four possible combinations including M&A-WOE, M&A-JV, greenfield – WOE and greenfield

different modes of OFDI can impose an effect on within-firm resource allocation efficiency.

There is often much missing information related to firms' OFDI mode. Generally, the value of firms implementing international M&A or WOE tends to be greater, which are more likely to be reported by the media. We thus replace missing information about entry mode with greenfield investment and replace missing information about equity mode with JV in order to keep our samples as sufficient as possible. In robust test, we will take this issue into consideration again. The results of entry mode and equity mode are presented in column (1) and (2) of Table 4, respectively, as the decision of entry mode and equity mode is usually closely related. To avoid the possible ambiguous explanation of results coming from one dimension, we further combine entry mode and equity mode into four types of mode, which include Mode_1 (M&A - JV), Mode_2 (M&A - WOE); Mode_3 (greenfield - WOE) and Mode_4 (greenfield - JV). The results are presented in column (3) of Table 4, where Mode_2 is treated as the reference group[7]. The regression results from Table 4 show that all the coefficients of DID are still negative and significant. However, the coefficients of three-way interaction items (OFDI*POST*Greenfield and OFDI*POST*WOE) are both insignificant in column (1) and column(2),which might imply that there is no significant heterogeneity in the effect of different entry modes or equity modes. However, when we consider both entry mode and equity mode, the coefficient of three-way interaction items of Mode_1 becomes negative and statistically significant in 5% level. This reflects that the entry mode with different equity choice does have heterogeneous effect on the resource allocation for a firm. More specifically, when we put the coefficient of the reference group (Mode_2) into overall consideration, those firms via M&A with JV (Mode_1) have a statistically better performance than those via M&A with WOE (Mode_2). Those firms with the mode choice of greenfield-WOE (Mode_3) might also perform better than firms with the mode of greenfield-JV (Mode_4), but it is not statistically significant. In other words, for firms conducting M&A, JV may be a better choice for ownership; however, for firms conducting greenfield, WOE may be a better choice for ownership according to our results.

Table 4: Mode of OFDI

	Entry mode	Equity mode	Entry & Equity mode
	RA1	RA1	RA1
Variables	(1)	(2)	(3)
OFDI	-0.4503***	-0.4512***	-0.4518***
	(0.0961)	(0.0961)	(0.0962)
POST	0.2014	0.5621***	0.5839***
	(0.2707)	(0.1465)	(0.1390)
OFDI*POST	-0.7677**	-0.5823***	-0.7072**

– JV from two dimensions of entry mode and equity mode.

[7] The sample size of firms with M&A-WOE mode is the smallest in the total sample

	(0.3226)	(0.1552)	(0.3205)
OFDI*POST*Greenfield	0.0885		
	(0.3224)		
OFDI*POST*WOE		-0.2291	
		(0.1800)	
OFDI*POST*Mode_1			-0.9272**
			(0.3717)
OFDI*POST*Mode_3			-0.0661
			(0.3147)
OFDI*POST*Mode_4			0.1210
			(0.3178)
Controls	Y	Y	Y
Year dummy	Y	Y	Y
Industry dummy	Y	Y	Y
Region dummy	Y	Y	Y
Constant	1.6085***	1.6499***	1.6281***
	(0.4929)	(0.4931)	(0.4935)
Observations	15,189	15,189	15,189
R-squared	0.1741	0.1740	0.1741

4.1.2. Destination of OFDI

It has been suggested by many studies that different destinations of OFDI, developed or developing countries, generate different impacts on the performance of home countries. Based on our data sample, many firms enter into more than one destination via OFDI. In this section, we investigate how OFDI of different destinations imposes influences on within-firm resource allocation efficiency. According to its destination, we category our samples into three types: developed countries, developing countries, and mixed. Relevant results are presented in Table 5. Column (1) and (2) of Table 5 are the results of regression without and with the number of destinations, respectively. The evidence from the results in Table 5 shows that the coefficients of DID are still negative, but not significant now. However, the coefficients of three-way interaction items in Column (1) and (2) of Table 5 are negative in 5% significant level for developed destination. In contrast, the coefficients of three-way interaction term in Column (1) and (2) of Table 5 are negative but not significant for developing destination. These results indicate that there do exist significant heterogeneous effect on internal efficiency gain from the different choice of destination, and those firms investing into developed destinations (also for firms investing into mixed destinations, which are treated as a reference group) can play better performance on internal efficiency improvement than only investing into developing destinations. These results are consistent with previous research findings that Chinese firms benefit more from developed countries than from developing countries.

Table 5: Destination country of OFDI

	Without the number of destinations	With the number of destinations
Variables	RA1	RA1
	(1)	(2)
OFDI	-0.4468***	-0.4462***
	(0.0965)	(0.0967)
POST	-0.2185	-0.2372
	(0.2754)	(0.2951)
OFDI*POST*Developed	-0.7870**	-0.7855**
	(0.3665)	(0.3665)
OFDI*POST*Developing	-0.5541	-0.5523
	(0.3564)	(0.3559)
OFDI*POST	-0.0438	-0.0456
	(0.3473)	(0.3474)
Number of destinations		0.0146
		(0.0880)
Controls	Y	Y
Year dummy	Y	Y
Industry dummy	Y	Y
Region dummy	Y	Y
Constant	1.5220***	1.5107***
	(0.4998)	(0.5066)
Observations	15,066	15,066
R-squared	0.1758	0.1758

4.1.3. Branch types of OFDI

According to OID provided by the Ministry of Commerce of China, there are different branch types of OFDI. Jiang and Jiang (2014) found that different branch types of OFDI can have different impacts on the performance of parent companies. It is commonly classified by four branch types of OFDI: “representative office” (Type_1), “trade” (Type_2), “R&D” (Type_3), and “trade + R&D” (Type_4). Following the approach generally applied in a Chinese study (Jiang and Jiang 2014), we distinguish between the different types of OFDI based on the keywords involved in the information of business scope from OID. More specifically, we consider the OFDI firms as Type_1, when description of business scope of OFDI firm only includes keywords, such as service, representative office, consulting, non-operating management, leasing, investment management, and investment consulting, etc. In China, the major purpose of setting up “representative office” in foreign countries is often to collect information for trade and to provide better trade service. We consider the OFDI firms as Type_2, when description only covers keywords, such as trade, sales, import and export, purchase and sale, retail, and wholesale etc. Meanwhile, those firms with keywords that only include development, scientific research, research and design, etc. are defined as Type_3. If description in the business investment scope of the enterprise both includes the keywords in Type_2 and Type_3, we define these firms as Type_4. The estimation results of four types of OFDI are reported in Table 6, where Type_3 of OFDI is treated as a reference group[8]. From Table 6, we can see that the coefficient of DID becomes insignificant, but all coefficients of three-way interaction items (OFDI*POST*Type_1, OFDI*POST*Type_2 and OFDI*POST*Type_4) are becoming very significant. That is, firms with branches of Type_1, Type_2 and Type_4 can induce the efficiency improvement within-firm except those with pure R&D branch. This is consistent with previous research in terms of export contributions to improving the efficiency of resource allocation of enterprises (Metliz, 2003; Bernard et al., 2011; Qiu & Zhou, 2013; Mayer et al., 2014). As branches of Type_1, Type_2 and Type_4 are all related to trade, they would be, thus, beneficial for the improvement of within-firm resource allocation efficiency by promoting exports. As for the result of firms with only pure R&D branch abroad, we conjecture that the resource allocation may be affected due to its strategic motivation or its different objectives.

Table 6: Branch types of OFDI

Variables	RA1 (1)	RA1 (2)
OFDI	-0.3479***	-0.4304***
	(0.1051)	(0.1005)
POST	0.2900	0.3075
	(0.2082)	(0.1999)
OFDI*POST	0.3260	0.3166
	(0.3992)	(0.3882)
OFDI*POST*Type_1	-1.3826***	-1.3104***
	(0.4261)	(0.4109)
OFDI*POST*Type_2	-1.0786**	-1.0471**
	(0.4263)	(0.4147)
OFDI*POST*Type_4	-0.9855**	-1.0184**
	(0.4144)	(0.4027)
Controls	N	Y
Year dummy	Y	Y
Industry dummy	Y	Y
Region dummy	Y	Y
Constant	3.2047***	1.6450***

[8] As the share of firms with branches of Type_3 is less than 10 percent of the total sample, what more, other three types of branch are all related with trade

	(0.4006)	(0.5302)
Observations	14,617	14,415
R-squared	0.0955	0.1771

4.2 Robust tests

To provide further support on the validity of our specification, we conduct several robustness checks.

First, we change the matching ratio. More specifically, we replace the matching ratio of 1: 3 with 1: 1, and re-estimate the baseline regression. The regression results are presented in column (1) of Table 7. The estimated result obtained is consistent with the evidence presented in the previous baseline regression results.

Second, we change the method for calculating the output elasticity of factor. Here, we replace LP method with OP method as proposed by Olley and Pakes (1996). We recalculate RA1 and RA2 with the new output elasticity of factor, and repeat the baseline regression. We report the corresponding results of the regression in columns (2) and (3) of Table 7. The results remain similar.

Third, we drop missing samples of mode. It may be of concern that we treat those samples without entry mode information as greenfield and treat those samples without equity mode information as JV in previous Section 4.1.1 may bias our results. To mitigate this concern, we restrict the sample to firms that have explicit information of both entry and equity mode, and conduct regression again. The regression results are presented in columns (4) of Table 7. The coefficient of DID is still negative and statistically significant, and the coefficients for three-way interaction terms of Mode_1 and Mode_3 keep negative the same as the previous results. Therefore, we may conclude that those firms with M&A entry mode, JV equity may be a better ownership choice than WOE, but we still need to be more cautious about this conclusion, as now the coefficient for three-way interaction term is becoming statistically insignificant.

Finally, we consider change in rental price. It may be problematic that our results could be sensitive to the assumption of rental price (r) and product substitution elasticity(σ) in our measures of RA. To consider this, we change the way to calculate r but still keep σ as 3[9]. We calculate the rental price by firm's interest expenditure over its debt[10] rather than assuming 10%. Based on new rental price r, we obtain our new RA1. Then, we estimate the baseline model with the change of RA1. As it is showed in column (5) for Table 7, our finding is still

9 The reason is that σ is generally between 3 to 10 in competitive manufacturing according to Broda and Weinstein (2006), Hendel and Nevo (2006). In addition, the market can become more efficient with σ increase (Gong & Hu, 2013), and firms can improve the efficiency of resource allocation with more efficient market. Thus, take a low bound 3 for σ is the most conservative choice.

10 From 1999 to 2007, the legal minimum interest rate of financial institution' loan was set above 5% in China. Therefore, following the way suggested by Shi and Xian (2012), the rental price, which is less than 5%, will be replaced with the average interest rate of loans by each types of ownership in each year.

robust with new RA1.

Table 7: Robust tests

Variables	Matching with 1:1	OP method for RA		Drop missing samples for mode	Change of r
	RA1	RA1_OP	RA2_OP	RA1	RA1
	(1)	(2)	(3)	(4)	(5)
OFDI	-0.4074**	-0.2106**	-0.0130***	-0.5060***	-0.8199***
	(0.1847)	(0.0838)	(0.0043)	(0.1379)	(0.2714)
POST	0.5470**	0.2487***	0.0117**	0.4096**	1.0840***
	(0.2177)	(0.0958)	(0.0052)	(0.2039)	(0.3006)
OFDI*POST	-0.6666***	-0.4243***	-0.0151***	-0.6778**	-1.2230***
	(0.1991)	(0.0921)	(0.0043)	(0.3411)	(0.2790)
OFDI*POST*Mode_1				-0.6360	
				(0.4086)	
OFDI*POST*Mode_3				-0.0515	
				(0.3191)	
OFDI*POST*Mode_4				-0.4085	
				(0.3412)	
Constant	1.9527*	0.9744*	-0.1320***	1.8547**	2.8060*
	(1.0103)	(0.5034)	(0.0234)	(0.8414)	(1.6044)
Controls	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y
Industry dummy	Y	Y	Y	Y	Y
Region dummy	Y	Y	Y	Y	Y
Observations	8,050	15,189	15,189	7,526	15,157
R-squared	0.1683	0.1220	0.1659	0.1890	0.1791

5. Conclusions, policy recommendations and limitations

Empirical evidence on the effect of firms’ internationalization on resource allocation is relatively scarce, particularly in terms of the internationalization process of OFDI. This is one of the first empirical papers that explores the impact of enterprises' OFDI behavior on the efficiency of resource allocation within-firm by adopting PSM-DID method and using firm-level data of China. Our results show that China's OFDI can significantly improve the overall efficiency of resource allocation within enterprises, which has a time lag effect. Furthermore, we find that different patterns of firms’ OFDI display significant heterogeneity in their performances. More specifically, those firms conducting M&A entry mode with the ownership of JV, in general, perform the best in our paper. Firms investing into developed destinations or mixed destinations (both developed and developing destinations) can perform much better on internal efficiency improvement than those only investing into developing destinations. When OFDI is categorized by its branch types, we find those firms which set up the types of branch related with trade, such as representative office, trading or trade plus R&D, are more likely to have better internal resources allocation efficiency gains. Our regression results also provide empirical evidence that the improvement of the efficiency of the internal resource allocation by Chinese OFDI is mainly achieved by alleviating the capital distortion of enterprises.

Our study provides several key policy implications. First, we suggest that the Chinese government is well advised to create a better environment to encourage competent and promising enterprises to invest abroad. In addition, we recommend Chinese enterprises leveraging the attractive opportunities of "one belt, one road", thus actively benefiting from the advantages of OFDI to improve the efficiency of internal resource allocation. Secondly, as different modes, destinations, and branch types of OFDI can generate different effect on internal resource allocation, Chinese enterprises should make thoroughly considerations on the choice of modes, destinations, and branch types of OFDI according to their actual conditions, in order to avoid following others blindly and achieving the intended purposes of OFDI.

One main limitation of our study relates to the timeframe of the paper in that our sample is restricted to 2007. The intermediate input data from the Chinese Industrial Enterprise Database has not been publicly available since 2007. Therefore, it is impossible for us to calculate the output elasticity of labor and capital (β_j^l and β_j^k accordingly), which are the necessary parameters to measure our key variable of RA. However, the purpose of this paper focuses on exploring the role of the firms' OFDI behavior on the improvement of internal resource allocation, rather than solving a specific problem in the current OFDI. China's OFDI has developed very rapidly in the past decades. It would be beneficial to be able to explain the reality with more recent data. Thus, we believe that this provides potential scope for future research using additional data in the future.

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