Outward Direct Investment and Firm Productivity: Evidence from Chinese Firms*

Wei Tian† Miaojie Yu‡

November 7, 2014

Abstract

This paper examines how Chinese firm productivity affects firms' outward direct investment (ODI) by using two novel data sets on the ODI decision and ODI volume. As there are fewer ODI firms than non-ODI firms, the estimations correct for rare-events bias and show that high-productivity firms are more likely to invest abroad. Conditional on firms engaging in ODI, a 10 percentage point increase in firm productivity leads to a 3.87 percent increase in firm ODI. By estimating an endogenous threshold of income in host countries, the threshold regressions find support for the Linder hypothesis on ODI volume to high-income countries.

JEL: F13, P51

Keywords: Outward Direct Investment, Firm Productivity, Linder Hypothesis, Rare-Events Corrections, Threshold Estimates

---

*We thank Qiang Chen, Yiping Huang, Anders Johansson, Zhiyuan Li, Kalina Manova, Ding Sai, Heiwai Tang, Yang Yao, and the participants in the seminar at the Chinese Academy of Social Sciences, the first China Trade Research Group (CTRG), and the CCER-CERC international conference at the Stockholm School of Economics. Financial support from the National Natural Science Foundation of China (No. 71001030) is gratefully acknowledged. All errors are ours.

†School of International Trade and Economics, University of International Business and Economics, Beijing, China. Email: wei.tian08@gmail.com.

‡Corresponding author. China Center for Economic Research (CCER), National School of Development, Peking University, Beijing 100871, China. Phone: +86-10-6275-3109, Fax: +86-10-6275-1474, Email: mjyu@nsd.pku.edu.cn.

1 Introduction

This paper investigates the connection between productivity and outward direct investment (ODI) of Chinese firms. As the second largest economy in the world, China's ODI is surging in the new century and plays a more and more important role in global direct investment. With a 50 percent annual growth rate, China's ODI has become economically significant enough to affect international investment (Rosen and Hanemann, 2009). China's non-financial ODI increased from \$29.9 billion in 2002 to \$326.5 billion in 2011, a more than tenfold increase during the period.[1] In 2012, China's ODI flow of \$87.8 billion accounted for around 6.5 percent of the global foreign direct investment (FDI) flows of \$1.35 trillion. China's non-financial ODI ranks third in the world, following the United States and Japan, and first among developing countries. The productivity of Chinese firms has also increased dramatically in the new century. Chinese firms have undergone at least 2.7 percent weighted average annual productivity growth from 1998 to 2006 (Brandt et al., 2012). The trend of rapid productivity growth was only slightly affected by the negative shock from the recent financial crisis (Feenstra et al., 2014). This raises two questions: Is firm productivity crucial to firms' ODI decision? If so, to what extent does firm productivity foster firm ODI?

Our main findings in this paper are threefold. First, by using a comprehensive ODI decision data set covering universal Chinese ODI manufacturing firms during 2000–08, we find that the higher is a firm productivity, the higher is the probability that the firm engages in ODI. This finding is qualitatively ascertained by firm ODI data in Zhejiang province, one of the largest ODI provincial sources in China, in 2006–08. Since only a very small proportion of firms in our large panel sample engaged in ODI activity, we correct for rare-events estimation downward bias. We use Zhejiang's ODI data and find a large marginal effect of firm productivity on the decision to engage in ODI. Second and equally important, as our Zhejiang ODI data set provides information on each firm's ODI volume and investing destinations, we are able to explore the

[1] China's nonfinancial investment (i.e., greenfield investment) outweighs the country's financial investment (i.e., investment from mergers and acquisitions). In 2011, China's nonfinancial investment accounted for 91.8 percent of its entire foreign investment. Thus, we focus on greenfield ODI in this paper.

intensive margin effect of a firm's productivity on its ODI. After controlling for endogeneity of firm productivity, we find strong evidence that firm productivity fosters ODI and the effect is statistically and economically significant. Conditional on the firm's engaging in ODI, a 10 percentage point increase in firm productivity leads to a 3.87 percent increase in firm ODI. Third, by allowing firm heterogeneity on choosing host destinations, we find that the role of a firm's productivity on its ODI flow differs by destination income. By estimating an endogenous threshold of income in host countries, our threshold regressions find support for the Linder hypothesis on ODI volume to high-income countries.

Our paper makes the following two contributions to the literature. First, it enriches our understanding of Chinese ODI behavior. Except for a fairly large micro-level literature on Chinese exports (see Qiu and Xue (2014) for a recent survey), not many papers investigate China's ODI, especially from the firm-level perspective, in large part because of lack of data. It has been only recently that China's government (more precisely, China's Ministry of Commerce) has released the universal, nationwide, firm-level ODI decision data (i.e., which firms engage in ODI activity). With this data set, we are now able to explore whether the well-accepted Melitz-type effects apply to China, the largest trading country in the world today. Based on Melitz (2003), Helpman et al. (2004) predict that, to enter foreign markets through foreign affiliates, firms have to pay extra high fixed costs to cover additional expenses, such as investigating the foreign market regulatory environment. Only profitable, high-productivity firms can do so. Our binary estimates find that the theoretical predictions of Helpman et al. (2004) work well in China. Thus, different from the mixed findings on Chinese exports and firm productivity,[2] we confirm that the standard Melitz findings apply to Chinese ODI firms.

More important, we explore the intensive margin on firm ODI flow, which is completely absent in previous studies because of the unavailability of data. As introduced in detail in the next section, although the Ministry of Commerce of China released the list of ODI firms

[2] Lu (2010) finds that Chinese exporters are less productive. However, Dai et al. (2012) and Yu (2014) argue that that finding was because of the presence of China's processing exporters, which are less productive than non-exporters and non-processing exporters. Once processing exporters are excluded, Chinese exporters are more productive than non-exporters, in line with the theoretical predictions of Melitz (2003).

(henceforth, the ODI decision data set), the data set does not report each firm's ODI volume in all years. To overcome this data challenge, we access a confidential ODI data set compiled by the department of commerce in Zhejiang province, which reports firms' ODI volume in addition to all other information covered in the ODI decision data set. Thanks to this novel data set, we are able to explore the intensive margin of firm ODI in China.

Second, our paper contributes to the literature on empirical identification. We adopt razor-edge econometric techniques to deal with the related empirical challenges; the techniques can be applied to other projects facing a similar problem or data constraints. An empirical challenge is rare-events estimation bias. As there are much fewer ODI firms than non-ODI firms in our ODI data sets (i.e., national ODI decision data and Zhejiang's ODI flow data), conventional binary estimates, like logit or probit, would face a downward estimation bias of firms' ODI probability, which will be discussed carefully. We adopt the rare-events logit method proposed by King and Zeng (2001, 2002) to correct for possible estimation bias. We find that the marginal effect of firm productivity on ODI probability with rare-events corrections is much larger than that without the corrections.

Another econometric innovation is that we use the endogenous threshold regressions developed by Hansen (1999, 2000). Recent studies find that the conventional Linder (1961) export hypothesis can extend to and work for ODI: high-income countries usually absorb more ODI (Fajgelbaum et al., forthcoming). We are particularly interested in whether firm productivity has a heterogeneous impact on firm ODI volume by destination income. The empirical challenge is where to set the line for high-income and low-income host countries. We take a different approach from previous studies that set the cutoff lines at a predetermined level as adopted from the World Bank. We instead allow firms to choose their endogenous cutoffs based on their productivity performance. Hence, we are able to estimate the endogenous average income threshold for firms' ODI decision. Our threshold regressions find strong support for the Linder hypothesis for ODI volume to high-income countries.

The present study is related to three strands of the literature on ODI. The first strand is firm heterogeneity of productivity and ODI. Inspired by Melitz (2003), Helpman et al. (2004) develop the concentration-proximity trade-off initiated by Markusen (1984) to find firms' sorting behavior: low-productivity firms self-select to sell in domestic markets, whereas high-productivity firms sell in domestic and foreign markets. However, only the most productive firms self-select to engage in ODI. The sorting pattern is mainly determined by the trade-off between transportation cost and the fixed cost of ODI. By assuming that firm production requires headquarter services and manufactured components, Antràs and Helpman (2004) ascertain that a firm's productivity ranking influences the firm's choice between outsourcing and ODI, which is confirmed by Federico (2009), who uses Italian manufacturing firm-level data. Yet, the sorting pattern proposed by Helpman et al. (2004) is challenged by Bhattacharya et al. (2010), who use data on the Indian software industry. Different from those findings in the services industry, we find that the predictions of Helpman et al. (2004) work well for Chinese firms.

The second strand is related to the literature on the nexus between exports and ODI. Early works, such as Froot and Stein (1991), find that depreciation in the host country would absorb more ODI because of the declining investment cost in the host countries. In search of the relationship between exports and ODI, Blonigen (2001) finds a possible substitution between Japanese ODI to the United States and Japanese exports of final goods to the United States in the automobile market, although intermediate goods are complementary. Recent works examine this nexus beyond the traditional concentration-proximity models. For instance, Oldenski (2012) explores the role of communication of complex information in the traditional proximity-concentration model of the decision between exports and ODI. She finds evidence that firms would prefer exporting if the activities require complex within-firm communication. Instead, firms would prefer choosing ODI if goods and services require direct communication with consumers. Based on Russ (2007), Ramondo et al. (2014) find that countries with less volatile fluctuations are served relatively more by foreign affiliates than by exporters. Similarly, inspired by Jovanovic (1982), Conconi et al. (2014) find that firms are more likely to export rather than engage in ODI when they face uncertainty of foreign market demand. So exporting and (horizontal) FDI may be complements in a dynamic setup, although they are substitutes in the static setting.

The third related strand of the literature is research on China's ODI. Because of the unavailability of micro-level data, previous works, such as Rosen and Hanemann (2009), examine the industrial characteristics of ODI but abstract away the role of firm activity. Huang and Wang (2011) argue that Chinese ODI firms have different objectives for their investment. In echoing this, Kolstad and Wiig (2012) find that Chinese ODI is attracted to three destinations: countries with lower institutional quality, countries that are rich in natural resources, and large markets. Most recent related works tend to explore what determines the ODI of Chinese firms. Using the same universal nationwide ODI decision data set, Wang et al. (2012) find that government support and the industrial structure of Chinese firms play an important role in interpreting the ODI decision of Chinese firms. Chen and Tang (2014) also find that firm productivity and the probability of firm ODI are positively correlated, yet, because of lack of data, they remain silent on the intensive margin of firms' ODI. Our present paper aims to fill this gap and take a step further to explore the income heterogeneity of firms' ODI.

The rest of the paper is organized as follows. Section 2 describes our data sample, followed by a careful scrutiny of measures of firm productivity. Section 3 examines the importance of firm productivity in the firm's ODI decision. Section 4 explores the role of firm productivity on the intensive margin of ODI flows. Section 5 discusses the firm's investment destination and Section 6 concludes.

2 Data and Measures

We rely on three data sets. The first data set provides the list of ODI firms in China since 1980. This data set is crucial for understanding firms' ODI decision. However, the data set does not report any ODI values. To examine the role of the intensive margin, we rely on the second firm-level ODI data set, which contains information on the universal firm-level ODI greenfield activity in Zhejiang province of China. Finally, we merge firm-level manufacturing production data with the two ODI data sets to explore the nexus between ODI and firm productivity.

2.1 ODI Decision Data

The nationwide data set of Chinese firms' ODI decisions was obtained from the Ministry of Commerce of China (MOC). MOC requires every Chinese ODI firm to report its detailed outward investment activity since 1980. To invest abroad, for any Chinese firm, whether it is a state-owned enterprise (SOE) or private firm, it is mandatory to apply to the MOC and its former counterpart, the Ministry of Foreign Trade and Economic Cooperation of China, for approval and registration. MOC requires such firms to provide the following information: the firm's name, the names of the firm's foreign subsidiaries, the type of ownership (i.e., SOE or private firm), the investment mode (e.g., trading-oriented affiliates, mining-oriented affiliates), and the amount of foreign investment (in U.S. dollars). Once a firm's application is approved by MOC, MOC will release the information mentioned above, as well as additional information, including the date of approval and the date of registration abroad. All such information can be downloaded freely from the MOC webpage except the amount of the firm's outward investment, which may be considered sensitive and confidential information to the firms.

The first year that the data were released by MOC was 1980. Since 1980, MOC has released information on new ODI firms every year. Thus, the nationwide ODI decision data indeed report ODI starters by year. However, since this data set does not report firms' ODI flows, researchers are not able to explore the intensive margin of firm ODI with this data set.

2.2 ODI Flow Data

To explore the intensive margin, we use our second data set, which is compiled by the Department of Commerce of Zhejiang Province. The most novel aspect of this data set is that it includes data on firms' ODI flows (in current U.S. dollars). The data set covers all firms with headquarters located (and registered) in Zhejiang and is a short, unbalanced panel from 2006 to 2008. In addition, the data set provides each firm's name, the city where it has its headquarters, type of ownership, industry classification, investment destination countries, stock share from

Chinese parent company, category of FDI (i.e., greenfield or merger & acquisition (M&A)). The database even reports specific modes of investment: foreign affiliates, foreign resource utilization, marketing network, processing trade, consulting service, real estate, research and development (R&D) center, trading company, and other unspecified types.

Although this data set seems ideal for examining the role of the intensive margin of firms' ODI, the disadvantage is also obvious: the data set is for only one province in China.[3] Regrettably, as is the case for many other researchers, we cannot access similar databases from other provinces. Still, we believe that Zhejiang's firm-level ODI flow data are a good proxy for understanding the universal Chinese firm's ODI flow for the following reasons.

First, the ODI flow from Zhejiang province is outstanding in the whole of China. Firms in Zhejiang have engaged in ODI since 1982. Such firms were the pioneers of Chinese ODI activity. As reported by MOC, only around 10 firms began to engage in ODI before 1982. Since then, Zhejiang has maintained a fast growth rate similar to that of other large eastern provinces, such as Guangdong, Jiangsu, and Shandong. In 2008, Zhejiang had 2,809 ODI firms (including greenfield firms and M&A firms), accounting for 21 percent of all ODI firms in China, and became the largest province in the number of FDI firms. In terms of FDI flow, Zhejiang's ODI also maintained a high plateau, ranking at the very top in the entire country from 2006 to 2009. As shown in Appendix Table 1, Zhejiang's ODI accounted for 16 percent of the country's ODI flow and became the largest ODI province in 2010.

Second, the distribution of type of ownership of ODI firms in Zhejiang province is consistent with that across the country. According to the *Statistical Bulletin of China's Outward Foreign Direct Investment* (2009) of Ministry of Commerce, 95 percent of all Chinese ODI firms are directly managed by local governments and most are private firms. In Zhejiang province, 70 percent of FDI firms are private firms.

Third, the distribution of Zhejiang ODI firms' destinations is similar to that of the whole

[3]To our knowledge, almost all previous work was not able to access nationwide universal outward FDI flow data, except Wang et al. (2012), who use nationwide firm-level outward FDI data to investigate the driving force of outward FDI of Chinese firms. However, the study uses data only from 2006 to 2007; hence, it cannot explore the possible effect of the financial crisis in 2008.

country. Up to 2009, Chinese ODI firms invested in 177 countries (regimes) and 71.4 percent of ODI volume was invested in Asia. Hong Kong is the most important destination for Chinese ODI firms.[4] This observation also applies to Zhejiang's ODI firms. Most FDI firms in Zhejiang invest in Asia, Europe, and North America. Hong Kong and the United States are the two destinations with the largest investments. The most common investment mode is to set up production affiliates and create a marketing network by establishing a trade-oriented office.

Fourth, the industrial distribution of Zhejiang's ODI firms is similar to that for the whole of China. According to the Statistical Bulletin of China's Outward Foreign Direct Investment (2009), the top two sectors for Chinese ODI firms are manufacturing and retail and wholesale, which accounted for 30.2 percent and 21.9 percent, respectively, of China's total ODI in 2009. These sectors are especially relevant for Zhejiang province's ODI firms. Manufacturing industry is the most important sector in which Zhejiang's firms invest abroad. In particular, Zhejiang's firms invest mostly in the garment, machinery, textile, mining, and electronics industries, in descending order. The lower module of Table 1 shows the number of ODI firms in 2006–08, resulting in a total of 1,270 ODI firm-year observations in the database.

[Insert Table 1 Here]

2.3 Firm-Level Production Data

Our last database is the firm-level production data compiled by China's National Bureau of Statistics in an annual survey of manufacturing enterprises. The data set covers around 162,885 firms in 2000 and 410,000 firms in 2008 and, on average, accounts for 95 percent of China's total annual output in all manufacturing sectors. The data set includes two types of manufacturing firms: universal SOEs and non-SOEs whose annual sales are more than RMB 5 million (or equivalently $830,000 under the current exchange rate). The data set is particularly useful for calculating measured TFP, since the data set provides more than 100 firm-level variables listed in the main accounting statements, such as sales, capital, labor, and intermediate inputs.

[4]Note that it is possible that some Chinese ODI firms take Hong Kong as an international investment expŕot since Hong Kong is a popular "tax haven." Such a phenomenon is beyond the scope of the present paper, although it would be interesting for future research.

As highlighted by Feenstra et al. (2014) and Yu (2014), some samples in this firm-level production data set are noisy and somewhat misleading, largely because of mis-reporting by some firms. To guarantee that our estimation sample is reliable and accurate, we screen the sample and omit outliers by adopting the following criteria. First, we eliminate a firm if its number of employees is less than eight workers, since otherwise such an entity would be identified as self-employed. Second, a firm is included only if its key financial variables (e.g., gross value of industrial output, sales, total assets, and net value of fixed assets) are present. Third, we include firms based on the requirements of the Generally Accepted Accounting Principles (GAAP).[5]

By using these two methods, we match Zhejiang's manufacturing firms with Zhejiang's ODI flow firms. As shown in the lower module of Table 1, of 1,270 ODI firm-year observations in Zhejiang province from 2006 to 2008, 407 ODI firms are engaging in manufacturing sectors, suggesting that around two-thirds of Zhejiang's ODI firms either serve in service sectors or are trading intermediates (Ahn et al., 2010). Table 2 reports the summary statistics of firms' characteristics for nationwide manufacturing firms and Zhejiang's manufacturing firms, respectively.

2.4 Data Merge

We then merge the two firm-level ODI data sets (i.e., nationwide ODI decision data and Zhejiang's ODI flow data) with the manufacturing production database. Although the two data sets share a common variable—the firm's identification number—their coding system is completely different. Hence, we use alternative methods to merge the three data sets. The matching procedure involves three steps. First, we match the three data sets (i.e., firm production data, nationwide ODI decision data, and Zhejiang ODI flow data) by using each firm's Chinese name and year. If a firm has an exact Chinese name in a particular year in all three data sets, it is considered an identical firm. Still, this method could miss some firms since the Chinese name for an identical company may not have the exact Chinese characters in the two data sets, although

[5] In particular, an observation is included in the sample only if the following observations hold: (1) total assets are higher than liquid assets; (2) total assets are larger than the total fixed assets and the net value of fixed assets; (3) the established time is valid (i.e., the opening month should be between January and December); and (4) the firm's sales must be higher than the required threshold of RMB 5 million.

they share some common strings. Our second step is to decompose a firm name into several strings referring to its location, industry, business type, and specific name, respectively. If a company has all identical strings, such a firm in the three data sets is classified as an identical firm.[6] Our second step is to decompose a firm name into several strings referring to its location, industry, business type, and specific name, respectively. If a company has all identical strings, such a firm in the three data sets is classified as an identical firm.[7] Finally, to avoid possible mistakes, all approximate string-matching procedures are double-checked by eyes.

By using these two methods, we match Zhejiang's manufacturing firms with Zhejiang's ODI flow firms. As shown in the lower module of Table 1, of 1,270 ODI firms-year in Zhejiang province from 2006 to 2008, 407 ODI firms are engaging in manufacturing sectors, suggesting that around two-third of Zhejiang ODI firms either serve in service sectors or are trading intermediates (Ahn et al., 2010). Table 2 reports the summary statistics of firms characteristics for national-wise manufacturing firms and Zhejiang's manufacturing firms, respectively.

[Insert Table 2 Here]

2.5 TFP Measures

The main interest of this paper is to investigate how firm productivity affects firm ODI. Hence, it is crucial to measure firm productivity accurately. In the literature, the most convenient way to measure productivity is to adopt labor productivity, which is appropriate when the research interest is on labor productivity and wages (Trefler, 2004). However, such an index faces several serious pitfalls because it ignores the role of capital used by a firm, which is crucial for a firm to determine its output productivity (De Loecker, 2011). Thus, we use total factor productivity (TFP) to measure firm productivity.

Traditionally, TFP is measured by the estimated Solow residual between the true data on

[6] For example, "Ningbo Hangyuan communication equipment trading company" shown in the ODI data set and "(Zhejiang) Ningbo Hangyuan communication equipment trading company" shown in the National Bureau of Statistics of China production data set are the same company but do not have exactly the same Chinese characters.

[7] In the example above, the location fragment is "Ningbo," the industry is "communication equipment," the business type is "trading company," and the specific name is "Hangyuan."

output and its fitted value using the OLS approach. However, the OLS approach suffers from two problems, namely, simultaneity bias and selection bias.[8] Following Amiti and Konings (2007) and Yu (2014) in assuming a Cobb-Douglas production function, we adopt the augmented Olley-Pakes semi-parametric approach to deal with simultaneity bias and selection bias in measured TFP. In particular, we tailor the standard Olley-Pakes approach to fit the data for China with the following extensions.

First, we estimate the production function for exporting and non-exporting firms separately in each industry. The idea is that different industries may use different technology; hence, firm TFP must be estimated for each industry. Equally important, even within an industry, exporting firms may use completely different technology than non-exporting firms. For example, some processing exporters only receive imported material passively (Feenstra and Hanson, 2005) and hence do not have their own technology choice. We hence include an export dummy to allow different TFP realization between exporting firms and non-exporting firms.[9]

Second, we use deflated prices at the industry level to measure TFP. Previous studies, such as De Loecker (2011), stressed the estimation bias of using monetary terms to measure output when estimating the production function. In that way, one actually estimates an accounting identity. Hence, we use different price deflators for inputs and outputs. Admittedly, it would be ideal to adopt firm-specific prices as the deflators. Unfortunately, the firm-level data set does not provide sufficient information to measure prices of products. Following previous studies, such as Goldberg et al. (2010), we adopt industry-level input and output deflators for TFP measures. As in Brandt et al. (2012), the output deflators are constructed using "reference

[8] Note that these two biases arise for the following reasons: First, only a few parts of TFP changes can be observed by the firm early enough for it to change its input decision to maximize profit. Thus, the firm's TFP may have reverse endogeneity in its input factors. The firm's maximized choice becomes biased without this consideration. Second, the firm's dynamic behavior also generates selection bias. With international competition, low-productivity firms will collapse and exit the market, whereas high-productivity firms will stay in the market (Melitz, 2003). The observations in the panel data set include firms that have already survived. Low-productivity firms that have collapsed are excluded from the sample, suggesting that the samples in the estimations are not randomly selected, hence generating estimation bias.

[9] Note that we are not able to include a processing dummy in the full data sample, since processing information is only available in the released China's customs data set during the period 2000–06, but our sample extends to 2008.

price" information from China's Statistical Yearbooks, whereas input deflators are constructed based on output deflators and China's national Input-Output Table (2002).

Third, it is important to construct the real investment variable when using the Olley-Pakes (1996) approach.[10] As usual, we adopt the perpetual inventory method to investigate the law of motion for real capital and real investment. The nominal and real capital stocks are constructed as in Brandt et al. (2012). Rather than assigning an arbitrary number for the depreciation ratio, we use the exact firm's real depreciation provided by the Chinese firm-level data set.[11] Figure 1 shows that the average annual productivity of ODI firms is larger than that of non-ODI firms during 2000–08.

[Insert Figure 1 Here]

3 Productivity and the Extensive Margin of ODI

This section discusses how a firm's productivity affects the firm's decision to engage in ODI (i.e., the extensive margin). Before running regressions, we provide several preliminary statistical tests to enrich our understanding of the difference in productivity between ODI and non-ODI firms, following a careful scrutiny of the effect of firm productivity on the decision to engage in ODI.

3.1 Descriptive Analysis on Productivity Differences

Previous studies, like Helpman et al. (2004), find that firms' sales decision can be sorted by their productivity. Low-productivity firms serve in domestic markets, high-productivity firms export, and higher-productivity firms engage in ODI. Eaton et al. (2011) also find that higher-productivity firms are usually larger. If so, we would observe that, compared with non-ODI firms, ODI firms on average are larger, more productive, and export more. The first module of

[10] In the literature, the Levinsohn and Petrin (2003) approach is also popular in constructing TFP in which materials (i.e., intermediate inputs) are used as a proxy variable. This approach is appropriate for firms in countries not using a large amount of imported intermediate inputs. However, such an approach may not directly apply to China, given that Chinese firms substantially rely on imported intermediate inputs, which have prices that are significantly different from those of domestic intermediate inputs (Helpern et al., 2011).

[11] Note that even with the presence of exporting behavior, the data still exhibit a monotonic relationship between TFP and investment.

Table 3 checks the difference between non-ODI and ODI firms on their TFP, labor, sales, and exports. Compared with non-ODI firms, ODI firms are found to be more productive, hire more workers, sell more, and export more. The t-values for these variables are strongly significant at the conventional statistical level.

[Insert Table 3 Here]

The upper part of Table 4 shows that ODI firms are more productive than non-ODI firms by year during the sample period 2000–08.[12] The productivity difference between ODI firms and non-ODI firms roughly declines over the period (especially after 2004), suggesting that ODI firms may not enjoy much productivity gain via learning from investing. To see whether productivity is an important cause of firms' ODI, we compare several key firm characteristics between non-ODI firms and ODI starters in the lower part of Table 3. Once again, we observe that ODI starters have higher productivity, hire more workers, sell more, and even export more than those that have never engaged in ODI, indicating that ODI firms had predominantly high productivity before engaging in ODI.

However, the simple t-test comparisons thus far may not be sufficient to conclude that ODI firms are more productive than their counterparts, since ODI firms may be very different from non-ODI firms in terms of size (number of employees and sales) and experience in foreign markets. As seen from Table 3, ODI firms on average have larger exports, suggesting that ODI firms have already penetrated to foreign markets.

We follow Imbens (2004) and perform propensity score matching (PSM) by choosing the number of firm employees, firm sales, and firm exports as covariates. Each ODI firm is matched to its most similar non-ODI firm. Since there are observations with identical propensity score values, the sort order of the data could affect the results. We thus perform a random sort before adopting the PSM approach. Table 4 reports the estimates for average treatment for the

[12] Note that TFP in 2008 is calculated and estimated differently. As in Feenstra et al. (2014), we use deflated firm value added to measure production and exclude intermediate inputs (materials) as one kind of factor input. However, we are not able to use value added to estimate firm TFP in 2008, since it is absent in the data set. We instead use industrial output to replace value added in 2008. Thus, we have to be cautious in comparing TFP in 2008 with TFP in previous years.

treated (ATT) by year. The coefficient of ATT for all ODI manufacturing firms is 0.114 and highly statistically significant, suggesting that, overall, productivity for ODI firms is higher than that for similar non-ODI firms during the period 2000–08.

[Insert Table 4 Here]

3.2 Extensive Margin of ODI

To examine whether firm productivity plays a key role in the firm's decision to engage in FDI, we consider the following empirical specification:

$$\Pr(ODI_{it} = 1) = \beta_0 + \beta_1 \ln TFP_{it} + \boldsymbol{\theta}\mathbf{X} + \varpi_i + \eta_t + \varepsilon_{it}, \tag{1}$$

where $\ln TFP_{it}$ is the log productivity of firm i in year t. $\mathbf{X}$ denotes other firm characteristics, such as firm size (produced by firm's log of employment) and types of ownership (i.e., multinational firms or SOEs).[13] For instance, SOEs might be less likely to invest abroad because of low efficiency (Hsieh and Klenow, 2009). In addition, larger firms are more likely to invest abroad because they may have an additional advantage to realize increasing returns to scale. Inspired by Oldenski (2012), we also include a firm export indicator in the estimations, since an exporting firm could find it easier to invest abroad, given that it would have an information advantage on foreign markets compared with non-exporting firms. Finally, the error term is decomposed into three components: (1) firm-specific fixed effects to control for time-invariant factors such as firm location[14]; (2) year-specific fixed effects η_t to control for firm-invariant factors such as Chinese RMB appreciation; and (3) an idiosyncratic effect ε_{it} with normal distribution $\varepsilon_{it} \sim N(0, \sigma_i^2)$ to control for other unspecified factors.

We start from a simple linear probability model (LPM) to conduct our empirical analysis. The attractiveness of the LPM method is that it can make it easier to address the fixed ef-

[13] Here, a firm that has investment from foreign countries or Hong Kong/Macao/Taiwan is defined as a foreign firm, following Feenstra et al. (2014).

[14] We first estimate using firm-specific fixed effects and then industry-specific fixed effects, given our sample has only a three-year time span, and the within-group variation would be reduced too much with the implementation of firm-specific fixed effects.

fects. Many nonlinear estimators, including probit, may be biased in the presence of incidental parameters (Angrist and Pischke, 2009). The well-known drawback of using the linear probability model is that there is no justification for why the specification is linear. In addition, the predicted probability could be less than zero or greater than one, which does not make sense. We therefore report the LPM estimates by including two-digit Chinese industry classification (CIC) level industry-specific fixed effects in column 1 of Table 5 and firm-specific fixed effects in column 2.[15] We then compare the estimate results with the probit and logit estimations using two-digit CIC-level fixed effects in columns 3 and 4, respectively.[16]

The first four columns of Table 5 show that higher-productivity firms are more likely to engage in ODI. As expected, larger firms are more likely to invest abroad, whereas SOEs are less likely to do so. Exporting firms are more likely to engage in ODI by employing their information advantage (Oldenski, 2012). A striking finding is that multinational firms are less likely to engage in ODI activity. One possible reason is that multinational firms are more likely to engage in global value chain or processing trade and hence focus more on exporting (Yu, 2014).

[Insert Table 5 Here]

3.3 Estimates with Rare Events Corrections

Our estimations above may still face some bias. As observed from Tables 1 and 2, of the total 1,526,167 observations, only 0.44 percent of firms engage in outward investment. Thus, our sample exhibits the features of rare events that occur infrequently but may have important economic implications. As highlighted by King and Zeng (2001, 2002), standard econometric methods such as logit and probit would underestimate the probability of rare events, although maximum likelihood estimators are still consistent. To see this, consider a simplified logit

[15] Note that the coefficients of export (SOE, foreign) indicator are still present in the fixed-effects estimates since exporting firms (SOEs, foreign firms) could switch to non-exporting firms (non-SOEs, non-foreign firms) during the sample period.

[16] Note that the coefficients shown in the probit estimates are not marginal effects.

regression of the ODI dummy on firm TFP.

$$\Pr(ODI_{it} = 1) = \Lambda(\beta_1 \ln TFP_{it}) = \frac{\exp(\beta_1 \ln TFP_{it})}{1 + \exp(\beta_1 \ln TFP_{it})}, \tag{2}$$

where $\Lambda(\cdot)$ is the logistic cumulative density function (henceforth CDF). Since $\hat{\beta}_1 > 0$, as shown in columns (1)-(4) of Table 5, the probability of $ODI_{it} = 1$ is positively associated with firm TFP; most of the zero-ODI observations will be to the left and the observation with $ODI_{it} = 1$ will be to the right with little overlap. Since there are around 1.5 million observations with zero ODI, the standard binary estimates can easily estimate the illustrated probability density function curve without error, as shown by the solid line in Figure 2.[17] However, since only 0.44 percent of the observations have positive ODI, any standard binary estimates of the dashed density line for firm TFP when $ODI_{it} = 1$ will be poor. Because the minimum of the observed rare ODI sample is larger than that of the unobserved ODI population, the cutting point that best classifies non-ODI and ODI would be too far from the density of observations with $ODI_{it} = 1$. This will cause a systematic bias toward the left tail and result in an underestimation of the rare events with $ODI_{it} = 1$ (See King and Zeng (2001, 2002) for a detailed discussion).

As recommended by King and Zeng (2001, 2002), the rare-events estimation bias can be corrected as follows. We first estimate the finite sample bias of the coefficients, $bias(\hat{\boldsymbol{\beta}})$, to obtain the bias-corrected estimates $\hat{\boldsymbol{\beta}} - bias(\hat{\boldsymbol{\beta}})$, where $\hat{\boldsymbol{\beta}}$ denotes the coefficients obtained from the conventional logistic estimates.[18] Column 5 in Table 5 reports the logit estimates with rare-events corrections. The coefficient of firm TFP is slightly larger than its counterpart in column 4, suggesting that the estimation bias is not so severe. The coefficient of the SOE indicator in column 5 is relatively larger, in absolute terms, than its counterpart in column 4, whereas the coefficients of the other variables do no show much change.

An alternative approach to correct possible rare-events estimation errors is to use the complementary log-log model.[19] The idea is the distributions of standard binary nonlinear models,

[17] To illustrate the idea in a simple way, the distribution curves are drawn to be normal, although this need not be the case.

[18] Chen (2014) also adopts this method to explore how negative climate shocks (e.g., severe drought, locust plagues) affected peasant uprisings.

[19] The CDF of the complementary log-log model is $C(\mathbf{X}'\boldsymbol{\beta}) = 1 - \exp(-\exp(\mathbf{X}'\boldsymbol{\beta}))$ with margin effect

such as probit and logit, are symmetric to the original point. So the speed of convergence toward the probability that $ODI_{it} = 1$ is the same as that for $ODI_{it} = 0$. This violates the feature of the rare events, which exhibit faster convergence toward the probability that $ODI_{it} = 1$. The complementary log-log model can address this issue, since the model has a left-skewed extreme value distribution, which also exhibits a faster convergence speed toward the probability that $ODI_{it} = 1$ (Cameron and Trivedi, 2005). The complementary log-log model in column 6 in Table 5 shows that the coefficient of firm TFP is fairly close to its counterparts in conventional logit estimates and rare-events logit estimates, suggesting once again that the estimation bias caused by the property of "rare events" is not so severe in our estimates. One possible reason is that the number of observations with positive ODI is still quite large (N = 6,673) in absolute number, although it only accounts for a small proportion in the whole sample.

Finally, to examine the entry of ODI firms, we only include firms that never employed FDI and FDI starters in columns 7 to 9 in Table 5. Similarly, we start from the logit estimation, as a comparison with the following rare-events logit estimates and complementary log-log estimates. As seen from columns 7 to 9, high-productivity firms are still found to be more likely to invest abroad.

3.4 Endogeneity of Firm Productivity

The specifications in Table 5 face a possible endogeneity problem. Firms that engage in outward investment may be able to absorb better technology or gain managerial efficiency from host countries (Oldenski, 2012), which in turn boosts firm productivity. We use two approaches to address such reverse causality.

To mitigate the endogeneity issue, we adopt an instrumental variable approach in which firms' R&D expenses are an instrument. The economic rationale is straightforward. With more investment in new technology, firms will have higher productivity (Bustos, 2011). However, firms with more R&D expenses will not necessarily have more ODI: the simple correlation between firm ODI and firm R&D expenses is close to nil (0.07), as shown in the sample. In the first-stage

$\exp(-\exp(\mathbf{X}'\boldsymbol{\beta}))\exp(\mathbf{X}'\boldsymbol{\beta})\boldsymbol{\beta}$.

estimation, we regress log R&D expenses as an excluded variable on firm TFP,[20] as well as other included variables such as indicators of SOE, foreign, exporter, and log labor. The bottom module of Table 6 shows that the coefficient of log firm R&D expenses is positively correlated with firm TFP and strongly significant at the conventional statistical level. As suggested by King and Zeng (2001, 2002), the fitted value of firm TFP obtained in the first stage then serves as a new variable in the second-stage nonlinear binary estimates, including logit in column 1, rare-events logit in column 2, and complementary log-log in column 3. Of course, the standard errors of all coefficients are required to be bootstrapped. After correcting the rare-events estimates bias, the coefficient of fitted firm TFP in the rare-events logit in column 2 is found to be slightly larger than the regular logit estimates, suggesting that regular binary estimates face a downward bias.

There is still a concern about whether firm R&D expenses strictly satisfy the requirement of the "exogenous" restriction of the instrumental variable, since firm TFP might reversely affect the firm's R&D expenses in a dynamic catch-up scenario: Low-productivity firms may input more R&D expenses to boost their productivity so they can catch up with high-productivity firms. More important, mainstream firm-heterogeneity trade theory, such as Melitz (2003), suggests that firm productivity is ex ante randomly drawn from a distribution. But the conventional TFP measure is essentially a Solow residual and hence an ex post measure. So there is a possible mismatch between the theoretical foundation and the empirical evidence.

Inspired by Feenstra et al. (2014), we address this issue by constructing an alternative measure of firm ex ante TFP. To motivate this from the Olley-Pakes specification, consider a Cobb-Douglas gross production function:

$$\ln Y_{it} = \alpha_K \ln K_{it} + \alpha_L \ln L_{it} + \mu_{it}, \tag{3}$$

where Y_{it}, K_{it}, and L_{it} represent value-added, capital, and labor for firm i in year t, respectively. The standard Olley-Pakes approach is to take the difference between log gross output and log

[20]Since many observations in the sample have zero R&D expenses, we define the variable of log firm R&D here as $\log(1 + R\&D)$, where $R\&D$ refers to the firm's R&D expenses, to allow observations with zero R&D expenses in the sample.

factor inputs times their estimated coefficients:

$$TFP_{it}^{OP} = \ln Y_{it} - \hat{\alpha}_K \ln K_{it} + \hat{\alpha}_L \ln L_{it}.$$

Clearly, firm productivity TFP_{it}^{OP} is correlated with *ex post* productivity shock ϵ_{it} caused by possible technology spillover and managerial efficiency (Qiu and Yu, 2014).

We can instead construct an *ex ante* productivity measure TFP_{it}^{OP2} by taking advantage of firm investment I_{it} (the proxy variable used in the conventional Olley-Pakes estimates), which depends on the *ex ante* productivity measure in a polynomial functional form: $I_{it} = g(TFP_{it}^{OP2}, \ln K_{it})$. We invert this equation to obtain $TFP_{it}^{OP2} = g^{-1}(I_{it}, \ln K_{it})$. Feenstra *et al.* (2014) shows that the *ex ante* TFP measure is independent of the *ex post* productivity shock ϵ_{it} and more consistent with the spirit of Melitz (2003), which requires that firms randomly draw productivity at the very beginning. Columns (4) to (6) of Table 6 replace the conventional Olley-Pakes TFP with the ex-ante TFP measures and still obtain similar results as before.[21]

We now turn to discuss the marginal effect of our estimations to consider the economic magnitude of the effect of firm productivity. As shown in Table 6, the estimated coefficients of firm TFP vary from 0.280 to 0.334, suggesting that a one-point increase in firm productivity would increase the odds ratio of firms engaging in ODI by 32 to 39 percent, given that exp(0.28) = 1.32 and exp(0.33) = 1.39. As firm average TFP increases from 3.11 in 2000 to 4.97 in 2008, firm productivity improvement raises the odds ratio of firms engaging in ODI by 60 to 72 percent during this period.

[Insert Table 6 Here]

4 Intensive Margin of ODI

Thus far, we can safely conclude that high-productivity Chinese manufacturing firms are more likely to engage in ODI. We now turn to explore the role of firm productivity on ODI flow. Since

[21] Note that the number of observations in columns 4 to 6 in Table 6 is greater than in columns 1 to 3 because data on firm R&D expenses are unavailable for 2008.

we only have Zhejiang province's ODI flow data, we start by examining whether our previous findings based on nationwide ODI decision data hold for Zhejiang's ODI manufacturing firms.

Table 7 picks up this task. By controlling for firm-specific fixed effects, the linear probability model estimates in column 1 confirm that Zhejiang's high-productivity manufacturing firms are more likely to engage in ODI during the sample period 2006–08. The logit estimates in column 2 yield similar findings with a slightly larger coefficient of firm TFP. Of 102,785 manufacturing firms during the sample period, there are only 407 ODI manufacturing firms, as shown in the lower module of Table 1. That is, the probability of ODI is only 0.39 percent, suggesting that firm ODI activity is also a rare event in Zhejiang province during the sample period and the standard logit estimation results may have a downward bias. In Table 7, we again correct for such bias by using rare-events logit estimates in column 3 and complementary log-log estimates in column 4. The estimated coefficients of firm productivity are much larger than their counterparts in columns 1 and 2, indicating that the downward bias in the regular estimates is fairly large. The increases in the odds ratio caused by firm productivity are similar to their counterparts in Table 5.

[Insert Table 7 Here]

To examine the effects of firm productivity on ODI flow, we introduce a bivariate sample selection model, or equivalently, a Type-2 Tobit model (Cameron and Trivedi, 2005). The Type-2 Tobit specification includes: (1) an ODI participation equation,

$$ODI_{it} = \begin{cases} 0\, if\ U_{it} < 0 \\ 1\, if\ U_{it} \geq 0 \end{cases}, \tag{4}$$

where U_{it} denotes a latent variable faced by firm i; and (ii) an "outcome" equation whereby the firm's ODI flow is modeled as a linear function of other variables. In particular, we use a logit model to estimate the following selection equation:

$$\begin{aligned} \Pr(ODI_{ijt} &= 1) = \Pr(U_{it} \geq 0) = \Lambda(\gamma_0 + \gamma_1 \ln \widehat{TFP}_{it} + \gamma_2 SOE_{it} \\ &+\gamma_3 FIE_{it} + \gamma_4 FX_{it} + \gamma_5 \ln L_{it} + \xi_j + \lambda_t) \end{aligned} \tag{5}$$

where $\Lambda(.)$ is the logistic CDF. In addition to the logarithm of firm productivity, a firm's ODI decision is also affected by other factors, such as the firm's ownership (whether it is an SOE or a multinational firm), export status (FX_{it} equals one if a firm exports and zero otherwise) and size (measured by the logarithm of the number of employees). Our estimations here include three steps. Because ODI firms may improve their productivity via investment abroad, in the first step, we run a preliminary regression where the dependent variable, $\ln TFP_{it}$, is regressed on firm log R&D expenses, the other variables that appeared in the ODI participation equations, and firm-level indicators. As in Feenstra et al. (2014), we use the predicted variable $\ln\widehat{TFP}_{it}$ to proxy firm productivity in Equ. (5).

For the second step, our Type-2 Tobit model requires an excluded variable that affects the firm's ODI decision but does not affect its ODI flow (Cameron and Trivedi, 2005). Here the firm's export indicator (FX_{it}) serves this purpose, since the literature finds that a firm's export status matters for its ODI decision but may not be directly related to ODI flow, because exports of intermediate goods and exports of final goods affect firm ODI flow in different directions (Blonigen, 2001). The simple correlation between ODI flow and export status is close to nil (0.04) and ascertains that the export indicator can serve as an excluded variable in the third-step Heckman estimates. For the third step, we include the two-digit CIC industrial ξ_j and year dummies λ_t to control for other unspecified factors. Note that we also include rare-events logit estimates in the ODI decision equation to avoid possible downward bias, which occurs in the regular logit estimates.

Table 8 reports the estimation results for the bivariate sample selection model. From the second-step rare-events logit estimates of equation 3, as shown in column 2, high-productivity firms are more likely to engage in ODI. Similarly, as predicted, exporting firms are more likely to engage in ODI. We then include the computed inverse Mills ratio obtained in the second-step rare-events logit estimates in the third-step Heckman estimation as an additional regressor in column 3. We also include firm export share (i.e., firm exports over firm sales) as an additional regressor. It turns out that the estimated coefficients have exactly identical signs as obtained in the second-step estimates. Finally, since most pure exporters are processing firms and have different profit maximization behavior compared with ordinary exporters or non-exporters (see Feenstra and Hanson (2005) and Yu (2014) for careful discussions), column 4 drops pure exporters and obtains similar results as before. Thus, after controlling for the endogenous ODI selection, we find that high-productivity firms are not only more likely to engage in ODI, but also invest more in foreign countries.

Our final step is to discuss the economic magnitudes of productivity improvement. As shown in the Type-2 Tobit estimates in column 4, the coefficient of firm TFP (in log) is 0.005, suggesting that a 10 percentage point increase in firm productivity leads to an increase of 0.05 percent in firm ODI. Such a magnitude seems too small at first glance, but this is mainly because there are too many observations with zero ODI, or equivalently, firm ODI activities are still rare events. However, it is possible that ODI firms would gain more from productivity improvement and invest more abroad once they have experience in ODI. So we are particularly interested in the effects of firm productivity on firm ODI flow, conditional on the firm's already engaging in ODI activities. Column 5 of Table 8 picks up this task. By restricting our sample to positive ODI firms, the coefficient of firm log TFP increases to 0.387, indicating that, conditional on the firm engaging in ODI, a 10 percentage point increase in firm productivity leads to an increase of 3.87 percent in firm ODI.

[Insert Table 8 Here]

5 Investment Destination

Thus far, we have found evidence that high-productivity firms are more likely to invest abroad. Once a firm invests, the higher is its productivity, the more the firm invests abroad. But it is also interesting to ask whether firm productivity matters for host countries' income. Interestingly, the literature offers divergent answers to this question. Head and Ries (2003) use Japanese data and find that firms investing in poor countries have even lower productivity than do non-FDI firms. However, studies like Damijan et al. (2007) find that the income level of the host country has no significant effect on Slovenian firms' ODI decision.

We consider a multinomial logit model to explore the role of firm productivity in the decision to engage in ODI to different income destinations. We first split our sample into two groups, low-income countries and high-income countries, by using predetermined income threshold suggested by the World Bank. The base category of our multinomial logit regression is non-ODI firms, so the probability that firm i chooses to invest in country j (poor or rich) is as follows:

$$\Pr(ODI_{it} = j|\mathbf{X}_{it}) = \begin{cases} \frac{1}{1+\sum_{k=2}^{3}\exp(\mathbf{X}_{it}\beta_k)} & (j \text{ is without ODI}) \\ \frac{\exp(\mathbf{X}_{it}\beta_j)}{1+\sum_{k=2}^{3}\exp(\mathbf{X}_{it}\beta_k)} & (j \text{ is ODI to poor } or \text{ to rich countries}) \end{cases}, \tag{6}$$

where the regressors $\mathbf{X}_{it}$ include firm productivity and other control variables, such as export status, firm size (i.e., log firm labor), and firm ownership (i.e., SOE or multinational). We start our regressions with a predetermined income threshold in Table 9. According to the World Bank's classifications in 2008, a country with per capita GDP less than \$3,855 is classified as a lower-middle-income country, whereas a country with per capita GDP greater than \$10,000 is classified as a high-income country. We hence start our multinomial logit estimates by defining ODI destination countries with income less than \$3,855 as poor countries. After controlling for year-specific fixed effects and industry-specific fixed effects, the coefficient of firm productivity is positive and statistically significant for firms investing in rich countries and negative and insignificant for firms investing in poor countries. These findings hold when we increase the income threshold to \$10,000, as shown in columns 3 and 4 of Table 9. The economic rationale is straightforward. Chinese ODI firms have different motivations for their ODI behavior. Some firms seek foreign markets, whereas some seek foreign sourcing for natural resources (Huang and Wang, 2011). As high-income foreign markets are usually highly competitive, only high-productivity firms are able to invest and seek local markets there. By contrast, firms investing in poor destinations are not mainly seeking foreign markets; instead, the firms may be interested in natural resources or cheaper labor in the host countries. The latter is especially true for firms in labor-intensive industries, such as textiles and garments. For instance, Chinese ODI firms that invest in Africa (e.g., Ethiopia and Madagascar) mostly are low-productivity firms in labor-intensive industries (see Shen (2013) for a detailed discussion).

[Insert Table 9 Here]

5.1 Threshold Estimates of the Linder Hypothesis

Beyond the conventional wisdom that ODI is determined by a proximity-concentration trade-off, Fajgelbaum et al. (forthcoming) argue that the per capita income of host countries is positively correlated with market size. With trade costs, firms are more likely to engage in ODI rather than export when host markets are large (Markusen, 1984). Thus, the standard Linder hypothesis, which stresses that high-income countries have relatively large trade volume, applies to firm ODI behavior: high-income countries usually absorb more ODI. Our final exercise is to see whether the Linder hypothesis for ODI works in China.

The first necessary step to perform this task is to classify destination country groups by income. A common and simple way is to use the classification of the World Bank, as in Table 9. However, such a classification suffers from two pitfalls. First, the threshold varies by year. There are no clear and time-invariant cutoffs for the income groups. Second, even if the cutoffs are fixed, the effect of firm productivity on firm ODI may not exactly correspond to the predetermined income cutoffs. That is, host countries' per capita GDP is an endogenous threshold for ODI firms in response to productivity movement.

To overcome these empirical challenges, Hansen (1999, 2000) provides an econometric approach that considers endogenous threshold regressions. To motivate this, consider an empirical specification with a country's per capita GDP ($pcgdp$) as a threshold variable:

$$\begin{cases} ODI_{it} = \boldsymbol{\beta}\mathbf{X}_{it} + \epsilon_{it} \, if \;\, pcgdp_{it} < T \\ ODI_{it} = \boldsymbol{\theta}\mathbf{X}_{it} + \epsilon_{it} \, if \;\, pcgdp_{it} \geq T \end{cases}, \tag{7}$$

where T is the threshold parameter to be estimated. ODI_{it} is firm i's ODI flow in year t. $\mathbf{X}_{it}$ refers to all regressors, including firm productivity. Without loss of generality, ϵ_{it} is i.i.d with normal distribution: $\epsilon_{it}\tilde{}N(0, \sigma_i^2)$. By using an indicator function $I(\cdot)$, we can re-express Equ.

(7) as:

$$ODI_{it} = \boldsymbol{\beta}\mathbf{X}_{it} \cdot I(pcgdp_{it} < T) + \boldsymbol{\theta}\mathbf{X}_{it} \cdot I(pcgdp_{it} \geq T) + \epsilon_{it}.$$

As this is a nonlinear regression, we can use the nonlinear squares approach to minimize the sum of squared residuals. Since the estimators also include the threshold parameter $\hat{T}$, the most convenient computational method to obtain the linear squares estimate is via concentration. Thus, the optimal threshold parameter $\hat{T}$ is chosen to minimize the concentrated sum of square errors function so that $\hat{T} = \arg\min\ SSR(\beta(T), \theta(T), T)$. Based on this, Hansen (1999, 2000) developed an asymptotic distribution theory for the threshold regression estimates.

Table 10 presents the threshold regression results. By comparison, we start from a regression without considering the threshold effect in columns 1 and 2. By abstracting away all other variables, we see that firm TFP is positively correlated to firm log ODI flow, as shown in column 1. The specification in column 2 yields similar results by controlling industry-specific fixed effects and year-specific fixed effects. The threshold regression results are reported in columns 3 and 4. The estimated threshold parameter of host countries' log per capita GDP is 10.73 (or equivalently, per capita GDP is $45,524). As before, the coefficient of firm productivity is positive and statistically significant for high-income ODI destinations. However, for low-income host countries, where per capita GDP is lower than the estimated threshold, the effect of firm productivity on firm ODI flow is statistically insignificant, suggesting that firm productivity is not a crucial determinant of firm ODI flow. This finding is robust even when we control for year-specific fixed effects and industry-specific fixed effects in columns 5 and 6, suggesting that the Linder hypothesis for ODI volume to high-income destination countries holds but may not exist for ODI volume to low-income countries. This result ascertains that Chinese firms' investment in poor countries may not be labeled as "horizontal" ODI: seeking foreign markets may not be a top priority for these firms (Kolstad and Wilg, 2012).

[Insert Table 10 Here]

6 Concluding Remarks

This paper is one of the first to explore the role of firm productivity on Chinese ODI volume. The rich data set enables the determination of whether a firm engages in ODI and the examination of the effect of firm productivity on the ODI flow. In this paper we find that the more productive is the Chinese firm, the higher is its probability to engage in ODI. After controlling for the endogeneity of firm productivity, we find that firm productivity raises firm ODI significantly in the economic and statistical senses. Conditional on a firm's engaging in ODI, a 10 percentage point increase in firm productivity leads to a 3.87 percent increase in firm ODI. By estimating an endogenous threshold of income in host countries, our threshold regressions find support for the Linder hypothesis of ODI volume to high-income countries.

Our paper also has policy implications. Owing to recent impotent domestic demand and excess supply in China (Yao and Yu, 2009), Chinese firms are eager to sell their products abroad. However, Chinese products in some industries, such as textiles, still face strong trade barriers, such as import quotas and special safeguards. Thus, ODI becomes an alternative means for China's firms to export. Our findings emphasize that firms should exert great efforts to boost their productivity to invest abroad.

References

[1] Ahn, JaeBin, Amit Khandelwal, and Shang-jin Wei (2010), "The Role of Intermediaries in Facilitating Trade," *Journal of International Economics* 84(1), pp. 73-85.

[2] Amiti, Mary, and Jozef Konings (2007), "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia," *American Economic Review* 97(5), pp. 1611-1638.

[3] Angrist, Joshua, and Jörn-Steffen Pischke (2009), *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton University Press.

[4] Antràs, Pol and Elhanan, Helpman (2004), "Global Sourcing," *Journal of Political Economy* 112, pp. 552-580.

[5] Bhattacharya Rudrani, Ila Patnaik, and Ajay Shah (2010), "Productivity and Outbound FDI in Software Services: a Reversal of the HMY Model," working paper, National Institute of Public Finance and Policy, New Delhi.

[6] Blonigen, Bruce (2001), "In Search of Substitution between Foreign Production and Exports," *Journal of International Economics* 53(1), pp. 81-104.

[7] Brandt, Loren, Johannes Van Biesebroeck, and Yifan Zhang (2012), "Creative Accounting or Creative Destruction? Firm-level Productivity Growth in Chinese Manufacturing?" *Journal of Development Economics*, 97, pp. 339-351.

[8] Bustos, Paula (2011), "Trade Liberalization, Exports and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinean Firms," *American Economic Review* 101(1), pp. 304-340.

[9] Cameron, Colin and Pravin Trivedi (2005), *Microeconometrics: Methods and Applications*, Cambridge University Press.

[10] Chen, Qiang (2014), "Climate Shocks, State Capacity, and Peasant Uprisings in North China during 25-1911 CE.," *Economica*, forthcoming.

[11] Chen, Wenjie and Heiwai Tang (2014), "The Dragon is Flying West: Micro-Level Evidence of Chinese Outward Direct Investment," Asian Development Review, 31(2), pp. 109-140.

[12] Conconi, Paola, André Sapir, and Maurizio Zanardi (2014), "The Internationalization Process of Firms: from Exports to FDI", mimeo, Lancaster University Management School.

[13] Corcos, Gregory, Delphine Irac, Giordano Mion, and Thierry Verdier (2013), "The Determinants of Intrafirm Trade: Evidence from French Firms," *Review of Economics and Statistics*, 95(3), pp. 825-838.

[14] Dai, Mi, Madhura Maitra, and Miaojie Yu (2012), "Unexceptional Exporter Performance in China? The Role of Processing Trade," mimeo, Peking University.

[15] Damijan, Joze P, Saso Polanec and Janez Prasnikar (2007), "ODI and Productivity: Micro-evidence from Slovenia," *The World Economy*, 30 (1), pp. 135–155.

[16] De Loecker, Jan (2011), "Product Differentiation, Multiproduct Firms, and Estimating the Impact of Trade Liberalization on Productivity," *Econometrica*, 79(5), pp. 1407–1451.

[17] Eaton Jonathan, Samuel Kortum, and Francis Kramarz (2011), "An Anatomy of International Trade: Evidence from French Firms," *Econometrica* 79(5), pp. 1453-1498.

[18] Fajgelbaum Pablo, Gene Grossman, and Elhanan Helpman (forthcoming), "A Linder Hypothesis for Foreign Direct Investment," *Review of Economic Studies.*

[19] Federico, Stefano (2009), "Outsourcing versus Integration at Home and Abroad," working paper, Bank of Italy.

[20] Feenstra, Robert and Gordon Hanson (2005),"Ownership and Control in Outsourcing to China: Estimating the Property-Rights Theory of the Firm," *Quarterly Journal of Economics* 120(2), pp. 729-762.

[21] Feenstra, Robert, 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), pp.729-744.

[22] Froot, Kenneth and Jeremy Stein (1991), "Exchange Rates and Foreign Direct Investment: An Imperfect Capital Markets Approach", *Quarterly Journal of Economics*, 1191-1217.

[23] Goldberg, Pinelopi, Amit Khandelwal, Nina Pavcnik, and Petia Topalova (2010), "Imported Intermediate Inputs and Domestic Product Growth: Evidence from India," *Quarterly Journal of Economics* 125 (4), pp. 1727-1767.

[24] Hansen, Bruce (1999), "Threshold effects in non-dynamic panels: Estimation, testing and inference," *Journal of Econometrics* 93, 345-368.

[25] Hansen, Bruce (2000), "Sample Splitting and Threshold Estimation," Econometrica 68(3), pp. 575-603.

[26] Head, Keith and John Ries (2003), 'Heterogeneity and the FDI versus Export Decision of Japanese Manufacturers,' *Journal of the Japanese International Economies* 17(4), pp. 448–67.

[27] Helpern, Laszlo, Miklos Koren, and Adam Szeidl (2010), "Imported Inputs and Productivity," University of California, Berkeley, Mimeo.

[28] Helpman, Elhanan, Marc J. Melitz and Steven R. Yeaple (2004), "Export vs. FDI," *American Economic Review* 94(1), pp. 300–16.

[29] Hsieh, Chang-Tai and Peter Klenow (2009), "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economic*s 124(4), pp. 1403-48.

[30] Huang, Yiping and Bijun Wang (2011), "Chinese Outward Direct Investment: Is There a China Model?" *China & World Economy* 19(4), pp. 1-21.

[31] Imbens, Guido (2004), "Nonparametric Estimation of Average Treatment Effects Under Exogeneity: A Review," *Review of Economics and Statistics* 86(1), pp. 4-29.

[32] Jovanovic, Boyan J.(1982), "Selection and the Evolution of Industry," Econometrica 50, pp. 649-670.

[33] King, Gary and Langche Zeng (2001), "Logistic Regression in Rare Events Data," *Political Analysis* 9(2), pp. 137-163.

[34] King, Gary and Langche Zeng (2002), "Estimating Absolute, Relative, and Attributable Risks in Case-Control Studies," *Statistics in Medicine* 21, pp. 1409-1427.

[35] Kolstad Ivar and Arne Wilg (2012), "What determines Chinese ODI?" *Journal of World Business*, 47(1), pp. 26-34.

[36] Levinsohn, James and Amil Petrin (2003), "Estimating Production Functions Using Inputs to Control for Unobservable," *Review of Economic Studies* 70(2), pp. 317-341.

[37] Lin, Justin, Fang Cai, and Zhou Li (2004), *The China Miracle: Development Strategy and Economic Reform*, Chinese University of Hong Kong.

[38] Linder, Staffen Burenstam (1961), *An Essay on Trade and Transformation*, Stockholm: Almqvist and Wiksell.

[39] Lu Dan (2010), "Exceptional Exporter Performance? Evidence from Chinese Manufacturing Firms," mimeo, University of Chicago.

[40] Markusen, James R. (1984), "Multinationals, Multi-Plant Economies, and the Gains from Trade," *Journal of International Economics* 16 (3-4), pp. 205-26.

[41] Melitz, Marc (2003), "The Impact of Trade on Intra-industry Reallocations and Aggregate Industry Productivity," *Econometrica* 71(6), pp. 1695–725.

[42] Oldenski, Lindsay (2012), "Export Versus FDI and the Communication of Complex Information,"*Journal of International Economics* 87, 312-322.

[43] Olley, Steven and Ariel Pakes (1996), "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica* 64(6), pp. 1263-1297.

[44] Poncet, Sandra (2009), "Inward and ODI in China," in *China and the World Economy: consequences and challenges*, edited by David Greenaway, Chris Milner and Shuyie Yao, Palgrave. Londres, UK.

[45] Qiu, Larry, D. and Ying Xue (2014), "Understanding China's Foreign Trade: a Literature Review (I)," *China Economic Journal*, 7(2), pp. 168-186.

[46] Qiu, Larry D. and Miaojie Yu (2014), "Managerial Efficiency and Product Decision: Evidence from Chinese Firms," mimeo, CCER, Peking University.

[47] Ramondo, Natalia, Veronica Rapporport, Kim J. Ruhl (2014), "The Proximity-Concentration Tradeoff under Uncertainty," *Review of Economic Studies*, forthcoming.

[48] Rosen H. Daniel and Thilo Hanemann (2009), "China' Changing Outbound Foreign Direct Investment Profile: Drivers and Policy Implications," Peterson Institute of International Economics, Policy Brief, PB09-14.

[49] Russ (2007), "The Endogeneity of the Exchange Rate as a Determinant of FDI: A Model of Money, Entry, and Multinational Firms," *Journal of International Economics* 71(2), pp. 344-372.

[50] Shen, Xiaofang (2013), "Private Chinese Investment in Africa: Myths and Realities," mimeo, Johns Hopkins University.

[51] Trefler, Daniel (2004), "The Long and Short of the Canada-U.S. Free Trade Agreement", *American Economic Review* 94(3), pp. 870-895.

[52] Van Biesebroeck, Johannes (2005), "Exporting Raises Productivity in Sub-Saharan African Manufacturing Firms," *Journal of International Economics* 67(2), pp. 373-391.

[53] Wang Chengqi, Junjie Hong, Mario Kafouros, Agyenim Boateng (2012), "What Drives ODI of Chinese Firms? Testing the Explanatory Power of Three Theoretical Frameworks," *International Business Review*, 21(3). pp. 425-438.

[54] Yao, Yang and Miaojie Yu (2009) "Labor, Demography, and the Export-Oriented Growth Model in China," *Journal of Comparative Economic Studies* 5(1), pp. 61-78.

[55] Yu, Miaojie (2014), "Processing Trade, Tariff Reductions, and Firm Productivity: Evidence from Chinese Firms," forthcoming, *Economic Journal*.

Table 1: ODI Share in Number of Manufacturing Firms (2000-08)

Firm type	2000	2001	2002	2003	2004	2005	2006	2007	2008
					Nation-wide ODI decision data				
Mfg. firms	84,974	100,091	110,522	129,720	200,989	198,285	248,601	258,246	222,312
ODI mfg. firms	197	340	444	587	972	984	1081	1140	1018
ODI share (%)	0.23	0.34	0.40	0.45	0.48	0.49	0.43	0.44	0.46
					Zhejiang's ODI flow data				
Mfg. firms							35,887	39,465	27,433
ODI firms							424	419	427
ODI mfg. Firms							113	163	131
ODI share (%)							0.31	0.41	0.48

Source: Ministry of Commerce of China and authors' calculations.

Note: ODI share (%) is obtained by dividing the number of ODI manufacturing firms by the number of manufacturing firms for nationwide and in Zhejiang province, respectively. For Zhejiang firms, the ODI decision data are available every year during the sample but the ODI flow data are available only for 2006–08, for which there are 1,270 ODI firms in Zhejiang and 407 of them are manufacturing firms.

Table 2: Summary Statistics of Key Variables

Variable	Mean	Std. dev.	Min	Max
Full Sample (2000-08)				
Firm TFP (Olley-Pakes)	3.61	1.18	0.61	6.57
Firm ODI indicator	0.004	0.066	0	1
Firm export indicator	0.29	0.451	0	1
SOE indicator	0.05	0.219	0	1
Foreign indicator	0.20	0.402	0	1
Firm log labor	4.78	1.115	1.61	13.25
Sample of Zhejiang Province (2006-08)				
Firm TFP (Olley-Pakes)	4.08	0.94	1.88	6.34
Firm ODI indicator	0.003	0.05	0	1
Firm export indicator	0.42	0.49	0	1
Firm log ODI	3.27	1.53	0	8.61
SOE indicator	0.002	0.047	0	1
Foreign indicator	0.16	0.366	0	1
Firm log labor	4.45	0.983	2.08	10.16
Log of per-capita GDP in destination	9.78	1.39	6.20	11.19

Table 3: Difference between Non-ODI and ODI Firms

	TFP		# of Employees		Sales		Export	
Firm type	# obs	Mean	# obs	Mean	# obs	Mean	# obs	Mean
			ODI Firms vs. Non-ODI Firms					
Non-ODI firms	1,134,760	3.604	1,519,380	4.776	1,519,206	96,971	1,519,392	17,242
ODI firms	5,459	3.899	6,763	5.970	6,763	1,464,885	6,763	538,097
Difference		-0.294***		-1.193***		-1367913***		-520,854***
		(-18.37)		(-88.03)		(-103.3)		(-86.71)
			ODI Starters vs. Non-ODI Firms					
Non-ODI Firms	1,134,760	3.604	1,519,380	4.776	1,525,097	102422	1,519,392	17,242
ODI starters	918	4.049	1,058	5.877	1,058	967849	1,058	224,354
Difference		-0.445***		-1.100***		-865427		-207,111***
		(-11.40)		(-32.22)		(-25.81)		(-20.81)

Note: Numbers in parentheses are t-values. *** denotes significance at the 1% level.

Table 4: TFP Difference between Non-FDI and FDI Firms Using Propensity Score Matching

Firm productivity (TFP)	2000	2001	2002	2003	2004	2005	2006	2007	2008	All Years
ODI firms	3.309	3.317	3.507	3.558	3.409	3.733	3.772	3.888	5.304	3.899
Unmatched non-ODI firms	3.109	3.001	3.216	3.282	3.064	3.420	3.540	3.658	4.966	3.604
Difference	0.200**	0.316***	0.291***	0.276***	0.345***	0.313***	0.232***	0.230***	0.338***	0.294***
	(2.01)	(4.17)	(4.49)	(6.07)	(8.72)	(9.02)	(6.95)	(6.99)	(10.35)	(18.37)
Matched non-ODI firms	3.127	3.045	3.247	3.402	3.225	3.586	3.662	3.792	5.128	3.784
Average treatment	0.182	0.272***	0.260***	0.068**	0.184***	0.147***	0.106***	0.096*	0.176	0.114***
on the treated (ATT)	(1.32)	(2.47)	(2.80)	(2.32)	(3.10)	(2.89)	(2.16)	(1.95)	(1.32)	(3.82)
Obs. in the ATT estimates	39,344	46,966	51,772	105,367	151,600	170,944	194,197	221,381	158,648	1,140,219

Note: Numbers in parentheses are t-values. ***(**, *) denotes significance at the 1% (5%, 10%) level. The table reports firm TFP difference between ODI and non-ODI firms. The first row is unmatched whereas the second is the average treatment on the treated (ATT) approach using propensity score matching (PSM). The treated group is ODI firms, whereas the control group is non-ODI firms. Firm size (in log labor), exports, and sales are used as covariates to obtain the propensity score. Since there are observations with identical propensity score values, the sort order of the data could affect the results. The sort order is made to be random before adopting the PSM approach.

Table 5: Effects of Firm Productivity on ODI Decision (2000-08)

Regressand: ODI indicator	Full sample						ODI starters & non-ODI		
Econometric method:	LPM	LPM	Probit	Logit	Rare events logit	Comp. log-log	Logit	Rare events logit	Comp. log-log
Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Firm TFP	0.001***	0.001***	0.085***	0.239***	0.240***	0.239***	0.210***	0.212***	0.212***
	(20.76)	(12.34)	(14.47)	(15.18)	(15.32)	(15.49)	(5.29)	(5.35)	(5.50)
SOE indicator	-0.006***	-0.004***	-0.516***	-1.370***	-1.395***	-1.382***	-1.059***	-1.036***	-1.076***
	(-19.68)	(-7.86)	(-12.31)	(-11.74)	(-11.96)	(-11.97)	(-3.43)	(-3.36)	(-3.50)
Foreign indicator	-0.004***	-0.002***	-0.187***	-0.531***	-0.531***	-0.527***	-0.528***	-0.526***	-0.526***
	(-17.81)	(-9.04)	(-14.35)	(-15.30)	(-15.28)	(-16.31)	(-6.25)	(-6.23)	(-6.73)
Log firm labor	0.004***	0.005***	0.238***	0.619***	0.618***	0.609***	0.608***	0.608***	0.606***
	(40.78)	(63.17)	(53.64)	(56.61)	(56.56)	(59.27)	(23.09)	(23.08)	(23.75)
Export indicator	0.009***	0.004***	0.523***	1.477***	1.476***	1.468***	1.528***	1.527***	1.526***
	(39.56)	(21.98)	(41.75)	(40.01)	(40.00)	(42.95)	(17.14)	(17.13)	(18.47)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firmixed effects	No	Yes	No	No	No	No	No	No	No
Number of observations	1,140,219	1,140,219	1,139,076	1,139,076	1,140,217	1,140,217	1,087,940	1,135,676	1,135,676

Note: The regressand is the ODI indicator. Numbers in parentheses are t-values. *** denotes significance at the 1% level. Estimates in columns 1 and 2 are linear probability model (LPM). Column 3 is probit estimates, whereas columns 4 and 7 are logit estimates. Columns 5 and 8 are rare-events logit estimates. Columns 6 and 9 are complementary log-log estimates. Estimates in columns 1 to 6 include the full samples, whereas those in columns 7 to 9 only include ODI starters and never-ODI firms.

Table 6: Endogeneity Estimates of Firm Productivity on ODI Decision (2000-08)

Econometric method:	IV estimates (2000-2007)			Alternative TFP measure		
Regressand: ODI indicator	Logit	Rare events logit	Comp. log-log	Logit	Rare events logit	Comp. log-log
	(1)	(2)	(3)	(4)	(5)	(6)
Fitted firm TFP	0.321***	0.334***	0.332***			
	(15.39)	(16.55)	(15.68)			
Ex-ante firm TFP				0.281***	0.284***	0.280***
				(14.74)	(14.96)	(14.10)
SOE indicator	-1.205***	-1.234***	-1.227***	-1.364***	-1.388***	-1.375***
	(-9.03)	(-9.27)	(-9.32)	(-11.68)	(-11.88)	(-11.90)
Foreign indicator	-0.482***	-0.479***	-0.475***	-0.535***	-0.534***	-0.530***
	(-11.68)	(-11.62)	(-12.36)	(-15.39)	(-15.38)	(-16.41)
Log firm labor	0.587***	0.584***	0.575***	0.623***	0.622***	0.612***
	(45.93)	(45.89)	(46.52)	(56.37)	(56.32)	(59.56)
Export indicator	1.512***	1.513***	1.507***	1.474***	1.474***	1.466***
	(34.38)	(34.39)	(36.73)	(39.95)	(39.95)	(42.90)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	789,700	790,480	790,480	1,139,026	1,140,167	1140,167
		First-Stage Regression				
IV: Log Firm R&D Expenses		0.010***		–	–	–
		(14.99)				

Notes: The regressand is the ODI indicator. Numbers in parentheses are bootstrapped t-values. *** denotes significance at the 1% level. Estimates in columns 1 and 4 are logit estimates, whereas those in columns 3 and 5 are rare-events logit estimates. Columns 3 and 6 are complementary log-log estimates. Columns 1 to 3 use ex ante TFP (refers to TFP2) to proxy firm productivity. Estimates in columns 4 to 6 include two-step estimations: In the first-stage, log of firm R&D serves as the instrument of conventional TFP to obtain fitted TFP, which is used in the second-stage estimates.

Table 7: Extensive Margin Estimates for Zhejiang Firms (2006-08)

Econometric method: Regressand: ODI indicator	LPM	Logit	Rare events logit	Comp. log-log
	(1)	(2)	(3)	(4)
Firm TFP	0.001***	0.078**	0.238***	0.237***
	(6.50)	(2.58)	(2.71)	(2.78)
SOE indicator	-0.003	-0.337	-0.400	-0.854
	(-0.77)	(-0.90)	(-0.40)	(-0.84)
Foreign indicator	-0.002***	-0.063	-0.163	-0.167
	(-3.92)	(-1.20)	(-1.10)	(-1.13)
Log firm labor	0.003***	0.239***	0.657***	0.653***
	(14.41)	(11.64)	(12.19)	(11.44)
Export indicator	0.003***	0.671***	2.111***	2.128***
	(8.62)	(10.64)	(9.70)	(9.78)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	No	Yes	Yes
Firm fixed effects	Yes	No	No	No
Number of observations	100,847	100,743	100,847	100,847

Note: The regressand is the ODI indicator. Numbers in parentheses are t-values. ***(**) denotes significance at the 1% (5%) level.

Table 8: Type-2 Heckman Estimates for Zhejiang Firms (2006-08)

Heckman estimates:	First-step	Second-step	Third-step		
Regressand:	Firm TFP	ODI indicator	Log ODI flow		
Econometric Method:	OLS	Rare events logit	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)
Fitted firm TFP	–	0.480***	0.005***	0.005***	0.387***
		(3.73)	(3.49)	(3.46)	(4.37)
SOE indicator	-0.304*	-0.330	0.023	0.022	1.569*
	(-1.70)	(-0.33)	(0.50)	(0.49)	(1.71)
Foreign indicator	0.057	-0.369**	-0.004*	-0.004	0.341
	(1.25)	(-2.10)	(-1.70)	(-1.46)	(0.95)
Log firm labor	-0.148***	0.694***	0.008***	0.009***	0.353
	(-14.08)	(9.96)	(4.47)	(4.54)	(0.62)
Export indicator	0.066***	1.685***	–	–	–
	(5.83)	(6.99)			
Export-sales ratio			0.003	0.004	-0.189
			(0.67)	(0.96)	(-0.41)
Inverser mills ratio			-0.004**	-0.004**	0.131
			(-2.56)	(-2.29)	(0.26)
Log firm R&D expenses	0.007***	–	–	–	–
	(3.70)				
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	No	No	No	No
Pure exporters included	Yes	Yes	Yes	No	No
Number of observations	73,634	73,634	73,634	70,934	175
R-squared	0.01	-	0.01	0.01	0.22

Note: The regressand is shown in the column heads. Numbers in parentheses are bootstrapped t-values. ***(**,*) denotes significance at the 1% (5%, 10%) level. Estimates in this table include three steps. The first-step fixed-effect OLS estimates, in column 1, regress firm TFP on its determinants to obtain the fitted value of firm TFP, which serves as the regressand in the second step. The second step, in column 2, is the rare-events logit estimates, for which the fitted value is used to construct the inverse Mills ratio. Estimates in columns 3 to 5 include the inverse Mills ratio and firm export-sales ratio as additional regressors. Estimates in columns 1 to 3 include the full sample in Zhejiang province during 2006–08. Column 4 drops pure exporters, whereas column 5 drops pure exporters and zero ODI observations.

Table 9: Multinomial Logit Estimates of the ODI Decision by Destination Income (2006-08)

Predetermined income threshold	GDPPC=$3,885		GDPPC=$10,000	
Regressand: ODI decision	ODI to poor	ODI to rich	ODI to poor	ODI to rich
	(1)	(2)	(3)	(4)
Firm TFP	-0.092	0.298***	-0.068	0.328***
	(-0.44)	(3.12)	(-0.37)	(3.30)
Log of labor	0.584***	0.674***	0.698***	0.654***
	(4.26)	(11.52)	(6.72)	(10.50)
Export indicator	1.163***	2.431***	1.568**	2.387***
	(2.86)	(9.07)	(4.41)	(8.60)
SOE indicator	-16.48***	-0.612	-15.80***	-0.401
	(-33.38)	(-0.62)	(-36.64)	(-0.40)
Foreign indicator	-0.223	-0.159	-0.477	-0.092
	(-0.56)	(-1.00)	(-1.42)	(-0.56)
Year-specific fixed effects	Yes	Yes	Yes	Yes
Industry-specific fixed effects	Yes	Yes	Yes	Yes
Number of observations	100,847		100,847	

Note: The regressand is the ODI indicator. Numbers in parentheses are t-values. ***(**) denotes significance at the 1% (5%) level. The sample in this table covers Zhejiang manufacturing firms during 2006–08. Two-digit Chinese industry classification industry-specific fixed effects are included in all the estimations.

Table 10: Threshold Estimates by Income of Host Countries (2006-08)

Estimated threshold: Log GDPPC=10.726	Without threshold		With threshold			
			Low	High	Low	High
Regressand: Firm log ODI flow	(1)	(2)	(3)	(4)	(5)	(6)
Firm TFP	0.209***	0.254***	0.067	0.395***	0.107	0.460***
	(2.29)	(2.61)	(0.67)	(2.43)	(1.00)	(2.68)
Constant	2.500***	2.303***	2.945***	1.977***	2.767***	1.588***
	(6.37)	(5.24)	(6.69)	(2.78)	(5.50)	(2.04)
Year fixed effects	No	Yes	No	No	Yes	Yes
Industry fixed effects	No	Yes	No	No	Yes	Yes
Number of observations	251	251	165	86	165	86
(Joint) R-squared	0.023	0.038	0.061		0.082	

Note: The regressand is firm log ODI flow. Numbers in parentheses are t-values. *** denotes significance at the 1% level. Estimates in this table are threshold estimates a la Hanson (2000) by using ODI destination income as the threshold. Estimates in columns 1 and 2 are standard OLS estimates without considering the heteroskedasticity of the threshold. Columns 4 to 6 are estimated by using the estimated threshold (log per capita GDP is 10.726). Joint R-squareds are reported in columns 4 to 6. Columns 5 and 6 include CIC two-digit industry-level fixed effects and year-specific fixed effects. The 95% confidence interval estimates for each variable are not reported to save space, although they are available upon request.

6.1 On-line Appendix (not for publication): TFP Measures

Econometricians have tried hard to address the empirical challenge of measuring TFP, but were unsuccessful until the pioneering work by Olley and Pakes (1996). In the beginning, researchers used two-way (*i.e.*, firm-specific and year-specific) fixed effects estimations to mitigate simultaneity bias. Although the fixed effect approach controls for some unobserved productivity shocks, it does not offer much help in dealing with reverse endogeneity and remains unsatisfactory. Similarly, to mitigate selection bias, one might estimate a balanced panel by dropping those observations that disappeared during the period of investigation. The problem is that a substantial part of the information contained in the dataset is wasted, and the firm's dynamic behavior is completely unknown.

Fortunately, the Olley–Pakes methodology makes a significant contribution in addressing these two empirical challenges. By assuming that the expectation of future realization of the unobserved productivity shock, υ_{it}, relies on its contemporaneous value, firm i's investment is modeled as an increasing function of unobserved productivity and log capital, $k_{it} \equiv \ln K_{it}$. Following previous works, such as van Biesebroeck (2005) and Amiti and Konings (2007), the Olley–Pakes approach was revised by adding the firm's export decision as an extra argument in the investment function since most firms' export decisions are determined in the previous period:

$$I_{it} = \tilde{I}(\ln K_{it}, \upsilon_{it}, EF_{it}), \tag{8}$$

where EF_{it} is a dummy to measure whether firm i exports in year t. Therefore, the inverse function of (8) is $\upsilon_{it} = \tilde{I}^{-1}(\ln K_{it}, I_{it}, EF_{it})$.[22] The unobserved productivity also depends on log capital and the firm's export decisions. Accordingly, the estimation specification (3) can now be written as:

$$\ln Y_{it} = \beta_0 + \beta_l \ln L_{it} + g(\ln K_{it}, I_{it}, EF_{it}) + \epsilon_{it}, \tag{9}$$

where $g(\ln K_{it}, I_{it}, EF_{it})$ is defined as $\beta_k \ln K_{it} + \tilde{I}^{-1}(\ln K_{it}, I_{it}, EF_{it})$. Following Olley and Pakes (1996) and Amiti and Konings (2007), fourth-order polynomials are used in log-capital, log-investment, firm's export dummy, and import dummy to approximate $g(\cdot)$.[23] In addition, since the firm dataset is from 2000 to 2006, we include a WTO dummy (*i.e.*, one for a year after 2001

[22] Olley and Pakes (1996) show that the investment demand function is monotonically increasing in the productivity shock υ_{ik}, by making some mild assumptions about the firm's production technology.

[23] Using higher order polynomials to approximate $g(\cdot)$ does not change the estimation results.

and zero for before) to characterize the function $g(\cdot)$ as follows:

$$g(k_{it}, I_{it}, EF_{it}) = (1 + EF_{it}) \sum_{h=0}^{4} \sum_{q=0}^{4} \delta_{hq} k_{it}^{h} I_{it}^{q}. \tag{10}$$

After finding the estimated coefficients $\hat{\beta}_m$ and $\hat{\beta}_l$, we calculate the residual R_{it} which is defined as $R_{it} \equiv \ln Y_{it} - \hat{\beta}_l \ln L_{it}$.

The next step is to obtain an unbiased estimated coefficient of β_k. To correct the selection bias, Amiti and Konings (2007) suggest estimating the probability of a survival indicator on a high-order polynomial in log-capital and log-investment. One can then accurately estimate the following specification:

$$R_{it} = \beta_k \ln K_{it} + \tilde{I}^{-1}(g_{i,t-1} - \beta_k \ln K_{i,t-1}, \hat{p}r_{i,t-1}) + \epsilon_{it}, \tag{11}$$

where $\hat{p}r_i$ denotes the fitted value for the probability of the firm 's exit in the next year. Since the specific "true" functional form of the inverse function $\tilde{I}^{-1}(\cdot)$ is unknown, it is appropriate to use fourth-order polynomials in $g_{i,t-1}$ and $\ln K_{i,t-1}$ to approximate that. In addition, (11) also requires the estimated coefficients of the log-capital in the first and second term to be identical. Therefore, non-linear least squares seem to be the most desirable econometric technique. Finally, the Olley–Pakes type of TFP for each firm i in industry j is obtained once the estimated coefficient $\hat{\beta}_k$ is obtained:

$$TFP_{it}^{OP} = \ln Y_{it} - \hat{\beta}_k \ln K_{it} - \hat{\beta}_l \ln L_{it}. \tag{12}$$

Appendix Table 1: ODI Share of Zhejiang Province

Year	ODI(mil. US$)	Share of Total ODI(%)	Ranking by Province
2006	191.65	8.52	4
2007	458.98	10.22	2
2008	505.58	8.23	2
2009	782.07	8.36	5
2010	2,621.39	16.06	1

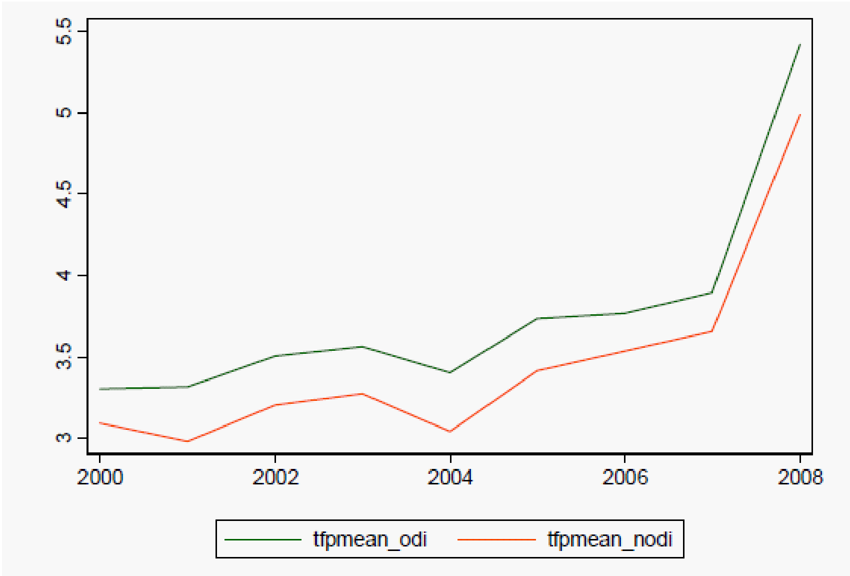
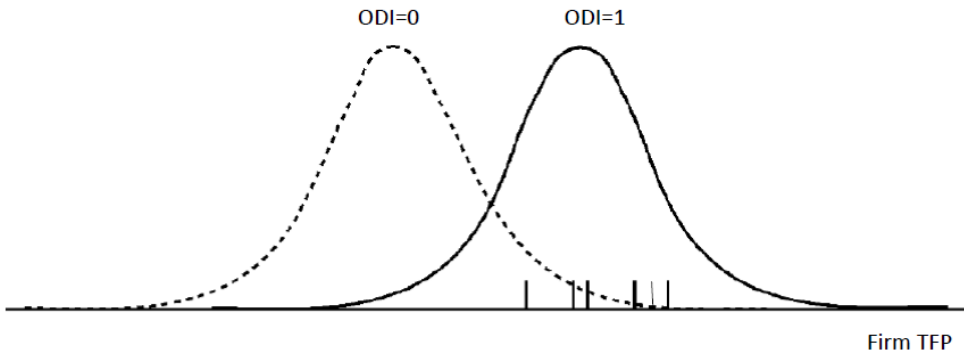


Figure 1: Firm Productivity for ODI firms vs. Non-ODI Firms (2000-2008)



Note: Samples are sorted by firm TFP. The short vertical line represents rare observations with ODI=1 whereas the many observations with ODI=0 are not drawn. The solid (dotted) curve refers to the probability density with ODI=1(ODI=0). The cutting points that best classify ODI=0 and ODI=1 would be too far to the right as argued in the text.

Figure 2: Rare Events of ODI Firms

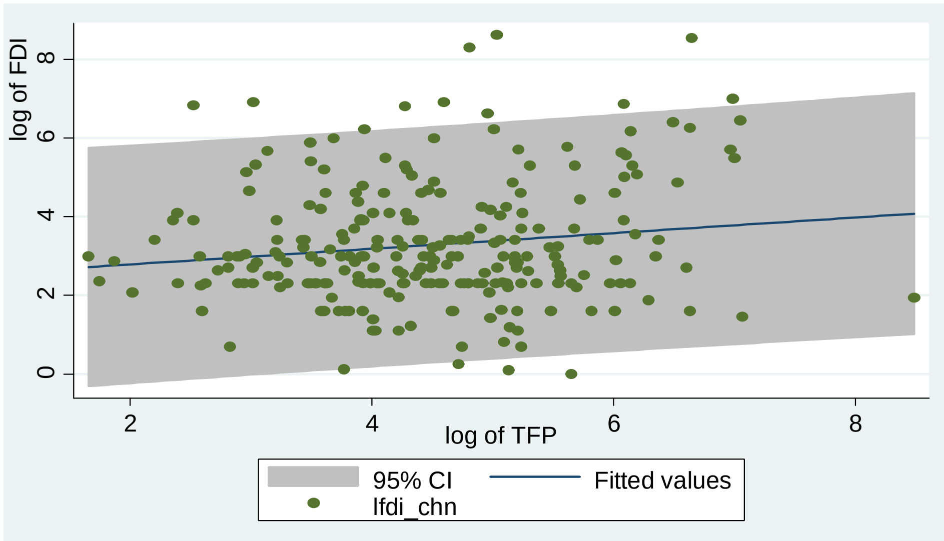


Figure 3: Firm Productivity and Zhejiang's ODI Flow (2006-2008)