Outward FDI and Domestic Input Distortions: Evidence from Chinese Firms[*]

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Abstract. We examine how domestic distortions affect firms' production strategies abroad by documenting two puzzling findings using Chinese firm-level data of manufacturing firms. First, private multinational corporations (MNCs) are *less* productive than state-owned MNCs, while they are more productive than state-owned enterprises overall. Second, there are disproportionately fewer state-owned MNCs than private MNCs. We build a model to rationalize these findings by showing that discrimination against private firms domestically incentives them to produce abroad. The model shows that selection reversal is more pronounced in industries with more severe discrimination against private firms, which receives empirical support.

JEL: F12, F14, F23, O53.

Keywords: Outward FDI, Multinational Corporations, Institutional Distortion.

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1 Introduction

Foreign direct investment (FDI) and the emergence of multinational corporations (MNCs) are dominant features of the world economy nowadays.[1] Therefore, understanding the behavior of MNCs and patterns of FDI is important for the analysis of the aggregate productivity and resource allocation.

The sharp increase in outward FDI from developing countries in the past decade has been phenomenal, and this is especially true for China. The UNCTAD World Investment Report (UNCTAD 2015) shows that outward FDI flows from developing economies have already accounted for more than 33 percent of overall FDI flows, up from 13 percent in 2007. Furthermore, despite the fact that global FDI flows plummeted by 16 percent in 2014, MNCs from developing economies invested almost US$468 billion abroad in 2014, an increase of 23 percent over the previous year.[2] As the largest developing country in the world, China has seen an astonishing increase in its outward FDI flows in the past decade. In 2015, China's outward FDI reached the level of 9.9 percent of the world's total FDI flows, which made China the second largest home country of FDI outflows globally. In addition, manufacturing outward FDI from China is becoming more important in China' total outward FDI flows. Its share in China's total outward FDI has increased from 9.9% in 2012 to 18.3% in 2016.[3] In sum, patterns of China's manufacturing outward FDI flows need to be explored, given its importance for the world economy.

This study investigates the patterns of China's outward FDI of manufacturing firms, through the lens of domestic input market distortions. It has been documented that discrimination against private firms is a fundamental issue for the Chinese economy. For instance, state-owned enterprises (SOEs) enjoy preferential access to financing from state-owned banks (Dollar and Wei 2007; Song, Storesletten, and Zilibotti 2011; Khandelwal, Schott, and Wei 2013; Manova, Wei, and Zhang 2015). Moreover, Khandelwal, Schott, and Wei (2013), and Bai, Krishna, and Ma (2017) document that private firms had been treated unequally by the Chinese government in the exporting market. In short, it is natural to link the behavior of Chinese MNCs to domestic distortions in China.

To the best of our knowledge, there is little work studying how institutional distortions at home affect firms' investment patterns abroad. The reason is that developed economies have been the home countries of outward FDI for many decades, and their economies are much less likely to be subject to distortions compared with developing economies. By contrast, various distortions are fundamental features of developing countries. For instance, size-dependent policies and red tape have been shown to

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[1]MNCs refer to firms that own or control production of goods or services in countries other than their home country. FDI includes mergers and acquisitions, building new facilities, reinvesting profits earned from overseas operations and intra-company loans.

[2]The UNCTAD World Investment Report also demonstrates that FDI stock from developing economies to other developing economies grew by two-thirds, from US$1.7 trillion in 2009 to US$2.9 trillion in 2013. It also reports that transition economies now represent nine of the 20 largest investor economies globally (UNCTAD 2015).

[3]See Statistical Bulletin of China's Outward Foreign Direct Investment (2015 and 2016).

generate substantial impacts on firm growth and resource allocation in India (Hsieh and Klenow 2009, 2014). The government discriminates against private firms in China (Huang 2003, 2008; Brandt, Tombe, and Zhu 2013). Moreover, there is already anecdotal evidence documenting how private firms in China circumvent these distortions by doing business abroad. For instance, the key to the success of Geely automobile company (a private car maker in China) was to expand internationally even at early stages of its development (e.g., the purchase of Volvo in 2010). Thus, distortions in the domestic market do seem to affect firms' decisions concerning going abroad.

We document three stylized facts of China's MNCs in manufacturing sectors to motivate our theory. First, although private non-MNCs are more productive than state-owned non-MNCs on average, private MNCs are actually *less productive* than state-owned MNCs on average. Moreover, when look at the productivity distribution of state owned MNCs and private MNCs, we find that at each percentile, state-owned MNCs have higher (normalized) TFP compared to private MNCs. Second, compared with private firms, the fraction of firms that undertake outward FDI is smaller among SOEs. Finally, the relative size of MNCs (i.e., average size of MNCs divided by average size of non-exporting firms) is *smaller* among private firms than among SOEs.

These findings are counterintuitive. First, SOEs are much larger than private firms in China, and larger firms are more likely to become MNCs. Furthermore, it has been documented that SOEs receive substantial support from the Chinese government for investing abroad. Thus, why are there so few SOEs that actually invested abroad in the data? Finally, it has been documented that SOEs are less productive than private firms in China (e.g., Brandt, Van Biesebroeck, and Zhang 2012; Khandelwal, Schott, and Wei 2013). Our data also show this pattern when we look at non-exporting and exporting (but non-multinational) firms. Why is this pattern reversed when we focus on MNCs?

To rationalize these puzzling findings, we build a model based on Helpman, Melitz, and Yeaple (2004) (henceforth, HMY) and highlight two economic forces: institutional arbitrage and selection reversal. Two key departures we make from HMY are the addition of capital (or land) used in the production process and asymmetric distortions across border. Specifically, we assume that private firms pay a higher capital rental price (and land price) when *producing* domestically (compared with SOEs), while all firms pay the same input prices when they produce abroad. The existence of the input price wedge comes from the capital and land markets, as the banking sector is dominated by state-owned banks and land is largely owned by the government in China. In our data, private firms pay higher interest rates and unit land price than SOEs, which is equivalent to an implicit input tax levied on private firms. When firms produce abroad, at least a part of the input price wedge ceases to exist, as the capital and land markets in foreign economies are not controlled by the Chinese government. In other words, the domestic input price (relative to the foreign input price) private firms face is higher than that of SOEs.[4]

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[4]It is plausible that the distortion in the input market shows up as a subsidy to SOEs. In this scenario, SOEs have *less* of an

As a result of this asymmetry, there is an extra incentive for private firms to produce abroad, since they can circumvent the input market distortion that exists *only* domestically by becoming MNCs (i.e., institutional arbitrage). Absent the domestic distortion, there would be no difference in the selection into the (domestic and) FDI market, since SOEs and private firms face the same domestic (and foreign) market environment. When there is a domestic distortion, selection into the domestic market is tougher for private firms. However, since they receive an extra benefit from producing abroad (i.e., not just the saving on the variable trade cost), the incentive of becoming a MNC is higher for them. This leads to less tough selection into the FDI market for private firms, which is termed as selection reversal in this paper. This reversal rationalizes why there are disproportionately fewer MNCs among SOEs than among private firms and why private MNCs are less productive than state-owned MNCs.

In addition to explaining the stylized facts, our model yields several additional empirical predictions. First, conditional on other firm-level characteristics, a private firm sells *disproportionately more* in the foreign market because of the nonexistence of distortion abroad. Second, as the distortion exists in the capital and land markets (rather than in the labor market), the selection reversal for state-owned MNCs is more pronounced in capital intensive industries and in industries in which the (industry-level) interest rate (or land price) differential between private firms and SOEs is larger. We present supporting evidence for these additional predictions.

It might be true that Chinese firms can borrow money from domestic banks to finance a part of their outward FDI projects. Thus, the discrimination against private firms in the credit market might still exist even when private firms invest abroad. However, even if this is true for a fraction of firms in our study, the discrimination against private firms in the land market is limited to the domestic market as firms cannot move land abroad to do investment. Importantly, we find evidence that the selection reversal is more pronounced in industries in which the unit land price differential (between private firms and SOEs) is larger. Therefore, the asymmetric distortion in the land market across border plays a role in affecting Chinese firms' FDI decisions.

The data set of outward FDI used in this paper is a representative sample of China's outward FDI projects, as the ministry of commerce of China requires all outward FDI deals whose investment amounts are higher than USD 10 million to be reported to the ministry. Admittedly, our data set loses small outward FDI projects which are most likely to be conducted by private firms.[5] Naturally, the exclusion of small private outward FDI deals would prevent us from finding the selection reversal. Given that we do find the selection reversal, this pattern should be more pronounced if we used an universal data set which includes small outward FDI deals.

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incentive to undertake FDI, since the relative domestic input price they face is lower, which is the same as in our main model. This situation results in tougher selection into the FDI market for SOEs as well, which leads to the same empirical predictions.

[5]Shen (2013) and Chen, Dollar, and Tang (2016) draw the same conclusion that outward FDI projects conducted by private firms are substantially underreported in the data set provided by the ministry of commerce.

It is important to stress that Chinese firms have different motives to undertake outward FDI. In this paper, we focus on manufacturing FDI and exclude outward FDI projects in the construction and mining sectors for two reasons. First, manufacturing firms' investment behavior is more related to firm performance and profit-driven.[6] Second, the canonical model of FDI (i.e., HMY) and asymmetric distortions across border fit well into the case of manufacturing MNCs from China. In particular, the share of manufacturing FDI in total outward FDI is much larger within China's investment into developed economies than within its investment into developing economies.[7] As developed economies probably have fewer distortions than developing economies, our story fits better into manufacturing MNCs from China.

We also use several sub-samples of our data sets to exclude alternative hypotheses for the selection reversal pattern. First, we find that the selection reversal does not hold, when we compare private exporting firms to state-owned exporting firms. Given that exporting does not allow private firms to escape from domestic input distortions, this finding excludes an alternative hypothesis related to discriminations in the output market. Second, we find that the selection reversal pattern still exists, even after we exclude merger and acquisition (M&A)-type FDI projects or FDI projects to tax heaven economies from our analysis. As the motive of acquiring better technologies and brands is more pronounced for *M&A*-type FDI (compared to greenfield-type FDI) and the motive of shifting profits is more pronounced for FDI into tax heaven economies, these two types of motives cannot explain our empirical finding of selection reversal.

Although we focus on how a particular type of asymmetric institutional treatment affects economic outcomes, the insights of this study apply to other circumstances as well. For instance, a rising number of talented and wealthy French people moved abroad because of the increasing tax rates in France.[8] This serves as a perfect example of institutional arbitrage. In India, red tape has forced many talented entrepreneurs to leave the country and start their businesses abroad as well.[9]

This study aims to speak to the literature on FDI and MNCs. In research on vertical FDI, Helpman (1984) insightfully points out how the difference in factor prices across countries affects patterns of vertical FDI. Antràs (2003, 2005) and Antràs and Helpman (2004) emphasize the importance of contractual frictions for shaping the pattern of FDI and outsourcing. In research on horizontal FDI, Markusen (1984) postulates the concentration-proximity trade-off, which receives empirical support from Brainard (1997). More recently, HMY (2004) develop a model of trade and FDI with heterogeneous firms. Our study contributes to this literature by pointing out another motive for firms to engage in FDI.

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[6]Shen (2013) and Chen, Dollar, and Tang (2016) find empirical support for this argument.

[7]According to Statistical Bulletin of China's Outward Foreign Direct Investment (2015), the share of manufacturing FDI in total outward FDI is 26.3% for China's investment into the U.S. and 19.7% for China's investment into EU. Note that the average share of manufacturing FDI in total outward FDI is 13.7% across all countries.

[8]See http://www.france24.com/en/20150808-france-wealthy-flee-high-taxes-les-echos-figures.

[9]Readers interested in studying anecdotal evidence of this can find it at http://www.thehindu.com/news/national/red-tape-forces-top-indian-entrepreneurs-to-shift-overseas/article7367731.ece.

This study is also related to the literature that substantiates the existence of resource misallocation in developing economies. Hsieh and Klenow's (2009) pioneering work substantiates substantial resource misallocation in China and India. Midrigan and Xu (2014), Moll (2014), and Gopinath et al. (2017) study the aggregate impact of financial frictions on firm productivity and investment. Guner, Ventura, and Xu (2008), Restuccia and Rogerson (2008), and Garicano, Lelarge, and Van Reenen (2016) explore the impact of size-dependent policies on aggregate productivity.[10] Our work contributes to this research area by showing a link between domestic distortions and firms' behavior in the global market.

The third related literature is the research on distortions in China and FDI decisions of Chinese firms (Brandt, Tombe, and Zhu 2013; Bai, Hsieh, and Song 2015). Using a similar data set to ours, Shen (2013) and Chen, Dollar, and Tang (2016) study the motives and consequences of China's outward FDI into Africa. Using the same data set, Tian and Yu (2015) document the sorting pattern of Chinese MNCs, but abstract away from the difference between state-owned MNCs and private MNCs. Compared with the existing work, our paper links firms' outward FDI decisions to domestic distortions.

2 Data and Stylized Facts

2.1 Data

There are four main data sets used in the present paper, in which we introduce as follows. Detailed discussions of the four data sets can be found in Online Appendix A.

Annual Survey of Industrial Firms Data. Our first data set is a production data set of Chinese manufacturing firms from 2000 to 2013, which comes from the Annual Survey of Industrial Firms (ASIF) complied by the National Bureau of Statistics (NBS) of China. All SOEs and "above-scale" non-SOEs (i.e., private firms) are included in the data set.[11]

FDI Decision Data. The nationwide data set of Chinese firms' FDI decisions was obtained from the Ministry of Commerce of China (MOC). MOC requires every Chinese MNC to report its investment activity abroad since 1980, if it is above USD 10 million. To invest abroad, every Chinese firm is required by the government to apply to the MOC for approval, or for registration if no approval is needed.[12] In addition, the nationwide FDI decision data report FDI starters by year.

Firm Land Price Data. To explicitly show the price discrimination against private firms in input factor markets, we use a comprehensive and novel firm-level data set of land price which is collected

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[10]For a synthesis of work on misallocation and distortion, see Restuccia and Rogerson (2013).

[11]The "above-scale" firms are defined as firms with annual sales of RMB 5 million (or equivalently, about US$830,000) or more before 2010 and with RMB 10 million afterward.

[12]Note that the SOEs directly controlled by central government are also required to report their FDI deals. This is why our data samples include such firms like CNPC(China national petroleum corporation), CPCC(China petroleum chemical corporation), and China resource corporation.

from the official website of China's land transaction monitoring system operated and maintained by the Ministry of Land and Resources. This monitoring system contains detailed information of land transactions, including land area, deal price, assigner and assignee.

Orbis Data. Finally, we use the Orbis data from Bureau Van Dijk from 2005 to 2014, since they contain detailed financial information on foreign affiliates of Chinese MNCs. For the data before 2011, we merge our ASIF data with the Orbis data by matching the names in Chinese. For the data after 2011, we merge our ASIF data with the Orbis data using (Chinese) parent firms' trade registration number which is contained in both data sets after 2011. We use the merged data set to study how Chinese MNCs allocate their sales across border.

Data Merge. We merge the firm-level FDI and land price data sets with the manufacturing production database. Although the three data sets share a common variable—the firm's identification number—their coding systems are 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 by using each firm's Chinese name and year. If a firm has an exact Chinese name in all three data sets in a particular year, 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 three data sets, although 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. If a company has all identical strings in the three data sets, such a firm is classified as an identical firm. Finally, all approximate string-matching procedures are double-checked manually.

[Insert Table 1 Here]

We show the matching quality of our data in Table 1, and detailed discussions can be found in Online Appendix A. In short, we are able to match $21\% - 42\%$ of manufacturing MNCs reported in the statistical bulletin to our ASIF data between 2006 and 2010. Furthermore, the matching quality has improved substantially afterwards. In addition, our matched sample exhibits the same trend as in the statistical bulletin: The proportion of state-owned MNCs is decreasing over years.

Although our firm-level data set covers 2000-13, we use data for 2000-08 to conduct our main empirical analysis, as the data after 2008 lack information on (parent) firm's value-added and use of materials, which dis-enables us to estimate firm productivity (a key variable in our empirical analysis). We instead use data after 2008 for robustness checks in Online Appendix. As highlighted by Feenstra, Li and Yu (2014), some observations in this firm-level production data set are noisy and 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 criteria a là Feenstra, Li and Yu (2014).[13]

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[13]For details, see Online Appendix A.

2.2 Measures

The SOE indicator and measured firm productivity are the two key variables used in the paper. This subsection describes how we construct these two measures.

2.2.1 SOE Measures

We define SOEs using two methods. The first one is to adopt the official definition of SOEs, as reported in the *China City Statistical Yearbook*(2006), by using information on firm's legal registration. A firm is classified as an SOE if its legal registration identification number belongs to the following categories: state-owned sole enterprises, state-owned joint venture enterprises, and state-owned and collective joint venture enterprises. State-owned limited corporations are excluded from SOEs by this measure. As this is the conventional measure widely used in the literature, we thus adopt such a measure as the default measure to conduct our empirical analysis. Table 1 of Online Appendix provides summary statistics for the SOE dummy used in this study.[14]

Recently, Hsieh and Song (2015) introduce a broader definition of SOEs and suggest defining a firm as an SOE when its state-owned equity share is greater than or equal to 50 percent. Along this line, we introduce an alternative way to define SOEs following their suggestion. As a result, a firm is defined as an SOE if either (1) it is classified as a SOE using the conventional measure; or (2) its state-owned equity share is greater than or equal to 50 percent. We use such a broadly defined SOE dummy in our robustness checks.

2.2.2 TFP Measures

First and foremost, we estimate firm TFP using the augmented Olley-Pakes (1996) approach as adopted in Yu (2015). Compared with the standard Olley-Pakes (1996) approach, our approach has five new elements. First, we estimate the production function for MNCs and non-MNCs in each industry, separately, since these two types of firms may adopt different technology.[15] Second, we use detailed industry-level input and output prices to deflate firm's input use and revenue in our productivity estimation. As the revenue-based TFP may pick up differences in price-cost markup and prices across firms (De Loecker and Warzynski, 2012), an ideal method is to use firm-specific price deflators to construct quantity-based TFP. However, such data are not available in China. To mitigate this problem, we follow Brandt, Van Biesebroeck, and Zhang (2012) to use four-digit Chinese Industrial Classification (CIC)-level input and output prices to deflate firm's input use and revenue. Once industry-level price deflators are well defined

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[14]For details, see Online Appendix A.

[15]As a robustness check, we also pool MNCs and non-MNCs together and, in the inversion step of the productivity estimation, re-estimate the production function by including a dummy variable for MNC status. The results generated by this alternative method do not change our subsequent empirical findings, as shown by Table 2 of Online Appendix.

and the price-cost markup is positively associated with true efficiency, revenue-based TFP captures the true efficiency of the firm reasonably well (Bernard et al., 2003).

Third, we take the effect of China's accession to the WTO (on firm performance) into account, as Chinese firms may export more or do more outward FDI due to the expansion of foreign markets after 2001. We thus include a WTO dummy in the inversion step of our productivity estimation. Fourth and similarly, we also include a processing export dummy in the inversion step as processing exporters and non-processing firms may use different technology (Feenstra and Hanson, 2005). Last and most importantly, we also add a SOE indicator and an export indicator into the control function in the first-step Olley-Pakes estimates. In particular, we include the SOE indicator (and the export indicator) and its interaction terms with log-capital and log-investment to approximate the fourth-order polynomials in the inversion step of the TFP estimates.

As stressed in Arkolakis (2010), firm TFP cannot be directly comparable across industries. We thus calculate the relative TFP ($RTFP$) by normalizing our augmented Olley-Pakes TFP in each industry. As suggested by Ghandi, Navarro and Rivers (2016), the correct identification of the flexible input elasticities should be based on the estimation of gross output production functions. Thus, all the TFP measures are conducted by using gross output production function.[16]

Although we control for the SOE indicator in the productivity estimation described above, it might still be unclear whether the TFP difference between SOE and private firms is caused by input factor distortions (or any other factors). If input factor distortions play an essential role in determining firms' input use, it should be observed that SOEs are more capital intensive even within each narrowly defined industry (after controlling for firm size and other year-variant factors), as SOEs can access working capital at lower cost. Inspired by this intuition, we first regress the capital-labor ratio of the firm on its size (proxied by firm sales), industry fixed effects (at the finest four-digit CIC level), and year fixed effects, to obtain firm-level clustered residuals. We then interact these residuals with log-capital and log-investment as additional variables in the fourth-order polynomials used in the inversion step of the TFP estimates. We thus re-estimate our augmented relative TFP, taking into consideration the input distortions ($RTFP^{Distort}$). Finally, we also consider another specification ($RTFP_{SOE}^{Distort}$) by including the firm-level clustered residuals and the SOE indicator (with interactions with log-capital and log investment) in the inversion step of the TFP estimates for robustness checks.

2.3 Stylized Facts

The main purpose of this subsection is to document three stylized facts using the merged data sets. As our interest is to explore how resource misallocation (across firm type) at home affects Chinese firms'

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[16]We thank a referee for pointing this out.

outward FDI behavior, we compare state-owned MNCs with private MNCs when stating these stylized patterns.

2.3.1 Stylized Fact One: Productivity Premium for State-Owned MNCs

Table 2 reports the difference in our augmented Olley-Pakes TFP estimates between SOEs and private firms. Simple *t*-tests in columns (1) and (3) show that, among non-MNCs and non-exporting firms, private firms are more productive than SOEs. To confirm this finding, we perform nearest-neighbor propensity score matching, by choosing a dummy variable for capital-intensive industries and the the year as covariates.[17] To avoid the case in which multiple observations have the same propensity score, we perform a random sorting before matching. Columns (2) and (4) present the estimates for average treatment for the treated for private firms. Again, the coefficients of the productivity difference between SOEs and private firms are highly significant, suggesting that non-multinational (and non-exporting) SOEs are less productive than non-multinational (and non-exporting) private firms. The findings for non-MNCs are consistent with other studies, such as Hsieh and Song (2015).

By contrast, a *selection reversal* is found when we focus on MNCs only. That is, private MNCs (i.e., *private* parent firms) are on average *less productive* than state-owned MNCs (i.e., state-owned parent firms), which is shown in column (5) in Table 2. To confirm this finding, we focus on the productivity difference between private and state-owned MNCs that are engaged in FDI and exporting as well.[18] Column (7) reveals the same pattern. In Columns (6) and (8), we perform nearest-neighbor propensity score matching, by choosing a dummy variable for capital-intensive industries, a dummy variable for rich destination economies, outward FDI mode (i.e., horizontal, vertical, or R&*D* seeking) and the year as covariates. The results reported in these two columns confirm our finding that private MNCs private MNCs) are on average less productive than state-owned MNCs, even after we have controlled for aggregate-level factors. For more details, see Online Appendix B.

The lower module of Table 2 presents evidence of the selection reversal using a broadly defined SOE indicator à la Hsieh and Song (2015). Compared with the numbers of MNCs and SOEs shown in the upper module, there are more SOEs engaged in outward FDI and more firms classified as SOEs when we use the broadly defined SOE dummy.

[Insert Table 2 Here]

In order to validate our finding further, we run simple OLS regressions. Specifically, we first regress

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[17]In Melitz-type models (Melitz 2003; Helpman, Melitz, and Yeaple 2004), firm size is a sufficient statistic for productivity. The model we will present is an extension of Helpman, Melitz, and Yeaple (2004). Therefore, we do not use firm sales or employment as our covariates in the propensity score matching.

[18]In reality, some Chinese MNCs engage in outward FDI and exporting. This is especially true for firms that undertake distribution FDI by setting up trade office abroad to promote exports. See Tian and Yu (2015) for detailed discussions.

the estimated TFP on the SOE indicator, the interaction term between SOE indicator and MNC indicator, and the firm fixed effects. Detailed disscisions can be found in Online Appendix A. In short, we find that the selection reversal holds in the regression results, as the own coefficient of the SOE indicator and its interaction term with MNC indicator are negatively (and positively) significant, respectively.

Table 3 reports number of MNCs by types of ownership and the consequent fraction of MNCs during the sample year. There are 566 broad-defined state-owned MNCs in our sample between 2000 and 2013, which double its counterpart when SOEs are measured in a conventional way. Still, the evidence shows that private MNCs are less productive than state-owned MNCs, although private non-MNCs are more productive than state-owned MNCs.

[Insert Table 3 Here]

Our first stylized fact is robust to different TFP measures as shown in Table 4. Columns (1), (4) and (7) report relative TFP for all firms, non-MNCs, and MNCs, respectively. Firm's relative TFP is obtained by scaling down firm TFP in each industry after normalizing the TFP of the most productive firm in that industry to one (see Arkolakis 2010; Groizard, Ranjan, and Rodriguez-Lopez. 2015). After normalization, we calculate the relative TFP of firms in each industry. The TFP measure used in columns (2), (5) and (8), $RTFP^{distort}$, takes firm's input factor distortions into account when we estimate firm's relative TFP. The alternative firm TFP measure, $RTFP^{distort}_{soe}$, reported in columns (3), (6) and (9), puts the SOE dummy, distortion residuals and their interaction terms with other firm-level key variables into TFP estimations, as discussed above. Again, our findings are robust to the different TFP measures. Our data clearly exhibit selection reversal in the sense that private MNCs are less productive than state-owned MNCs.

Equally interestingly, we then look at the productivity difference between state-owned and private MNCs industry by industry. To do so, we separate all industries into two categories: capital-intensive and labor-intensive industries, according to the official definition adopted by the National Statistical Bureau of China.[19] The lower module of Table 4 shows that a productivity premium for state-owned MNCs exists in capital-intensive industries. This finding is important, as it shows that selection reversal exists in industries with more severe distortions in the input market.[20]

[Insert Table 4 Here]

To verify that input distortion plays an essential role in interpreting the productivity premium of state-own MNCs (compared to private MNCs), we need to make sure that both SOEs and private firms

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[19]In particular, among the 28 CIC two-digit industries, the following industries are classified as labor-intensive sectors: processing of foods (code: 13), manufacture of foods (14), beverages (15), textiles (17), apparel (18), leather (19), and timber (20).

[20]Section 4 shows that the input price wedge mainly exists in the credit (i.e., capital) market.

have similar productivity dispersions (also implied by our model in the next section). Admittedly, the productivity distribution of SOEs might have a different level of dispersion compared to that of private firms, and the productivity distribution may change during the era of SOE reforms (see, e.g., Lardy, 2004; Hsieh and Song, 2015). However, we show that the productivity distribution of state-own MNCs first-order stochastically dominates that of private MNCs in Online Appendix A (i.e., state-owned MNCs are more productive than private MNCs at each percentile of the distribution).

Finally, as all of the TFP estimates are essentially based on the Olley-Pakes approach, which use investment as a proxy for TFP. A possible concern with the Olley-Pakes approach that uses investment as a proxy in the first stage is that investment in developing countries like China is lumpy and the existence of too many zeros can create bias. However, this is not a problem in our estimations as discussed in Feenstra, Li, and Yu (2014). In particular, we have already dropped those bizarre observations in our sample following the General Accepted Accounting Principle (GAAP) criteria. Also, the most recent advances on TFP estimation and identification such as Ghandi, Navarro and Rivers (2016) suggest that adopting the gross output production functions can better mitigate this potential problem. Therefore, all TFP estimates in the present paper adopt the approach of the gross output production function. Still, for the sake of completeness, we report simple labor productivity (defined as value-added per employee) and Levinsohn-Petrin (2003) TFP in Online Appendix Table 3. Once again, we see that state-owned non-MNCs are less productive than private non-MNCs. But the opposite is true for MNCs: State-owned MNCs are more productive than private MNCs. In short, our first empirical finding is robust.

2.3.2   Stylized Fact Two: Smaller Fraction of State-Owned MNCs

Columns (3) and (6) of Table 3 present our second stylized fact. That is, the fraction of MNCs is larger among private firms than among SOEs. Again, this finding is robust to different definitions we use to construct the SOE indicator and the different time periods we focus on. When using a broadly defined SOE indicator, we find that more firms are classified as SOEs whereas the number of state-owned MNCs does not change much for the sample of 2000-08. For the period of 2000-2013, the share of MNCs increases both among SOEs and among private firms compared to the period of 2000-08. In all four cases (two time periods and two definitions of SOEs), there are always disproportionately more MNCs among private firms than among SOEs. On the one hand, this finding is puzzling, since SOEs are larger firms which should be more likely to invest abroad. Furthermore, the Chinese government has supported its SOEs' investing abroad for many years, known as the Going-Out strategy. On the other hand, such an observation is consistent with our first finding. Namely, as state-owned MNCs are more productive than private MNCs, the fraction of SOEs engaged in FDI should be smaller (i.e., tougher selection).

2.3.3 Stylized Fact Three: Larger Relative Size Premium for State-Owned MNCs

Our last stylized fact is related to the relative size premium of state-owned MNCs. The conventional view is that SOEs are larger in size, which is usually measured by log employment or log sales. Our data also exhibit such features, as shown in Table 4 of Online Appendix.

More importantly, the size premium for state-owned MNCs holds in the relative sense as well. Table 5 shows that the ratio of average log employment of multinational parent firms to that of non-exporting firms is larger among SOEs than among private firms. Table 5 reports the result obtained from the comparison between the relative size of state-owned MNCs and that of private MNCs. The relative size is measured by l_o^j/l_d^j where l_o^j and l_d^j are the average log employment of MNCs and that of non-exporting firms for firm type j (i.e., private or state-owned). The year-average ratio in the first column shows that the relative size of private MNCs is significantly smaller than that of SOEs. As few SOEs were engaged in outward FDI before 2005, we report the year-average ratio up to a particular year in Table 5 as well. All columns suggest larger relative size for state-owned MNCs. To sum up, our third stylized fact states that the absolute and relative sizes of private MNCs (compared with non-exporting firms) are smaller than those of state-owned MNCs.

[Insert Table 5 Here]

Thus far, we have established three interesting empirical findings. In what follows, we will present a model to rationalize these findings. Furthermore, the model yields several additional empirical predictions, which will be shown to be consistent with the data.

3   Model

We modify the standard horizontal FDI model proposed by HMY (2004) to rationalize the empirical findings documented so far. We study how discrimination against private firms in the input market affects the sorting pattern of MNCs and their size premium at the intensive margin. At the same time, we investigate how the difference in foreign investment costs impacts the investment behavior of private MNCs and state-owned MNCs at the extensive margin.[21]

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[21]Major predictions of the canonical horizontal FDI model a la HMY (2004) are consistent with our empirical findings documented in Table 2. For instance, average productivity of MNCs is higher than that of non-multinational firms (see columns (3) and (5) of the table). Moreover, after the propensity score matching, we find that average productivity of non-multinational firms (domestic firms plus exporting but non-multinational firms) is higher than that of domestic firms (see columns (2) and (4) of the table).

3.1 Setup

There is one industry populated by firms that produce differentiated products under conditions of monopolistic competition à la Dixit and Stiglitz (1977). Each variety is indexed by ω, and Ω is the set of all varieties. Consumers derive utility from consuming these differentiated goods according to

$$U = \Big[\int_{\omega \in \Omega} q(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \Big]^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where $q(\omega)$ is the consumption of variety ω, and σ is the constant elasticity of substitution between differentiated goods.

Entrepreneurs can enter the industry by paying a fixed cost, f_e, in terms of the unit of goods produced by the firm.[22] After paying the entry cost, the entrepreneur receives a random draw of productivity, φ, for her firm. The cumulative density function of this draw is assumed to be $F(\varphi)$. Once the entrepreneur observes the productivity draw, she decides whether or not to stay in the market as there is a fixed cost to produce, f_D (in terms of the units of the goods produced by the firm).

After entering and choosing to stay in the domestic market, each entrepreneur also chooses whether to serve the foreign market. There are two options for doing this, the first of which is exporting. Exporting entails a variable trade cost, $\tau (\geq 1)$, and a fixed exporting cost, f_X. The second way is to set up a plant in the foreign country and produce there directly. The cost of doing this is fixed and denoted by f_I. Both fixed costs of serving the foreign market are in terms of the units of the goods produced by the firm.

Similar to Bernard, Redding, and Schott (2007), there are two factors of production, capital (or land) and labor, and the production function takes the following constant-elasticity-of-substitution form:

$$q(k, l) = \varphi \Big(k^{\frac{\mu-1}{\mu}} + l^{\frac{\mu-1}{\mu}} \Big)^{\frac{\mu}{\mu-1}}, \tag{2}$$

where k and l are capital (or land) and labor inputs respectively, and φ is the productivity draw the firm receives. Parameter $\mu (\geq 1)$ is the elasticity of substitution between capital and labor.

We assume that there are two types of firms in the economy: private firms and SOEs.[23] The key innovation of the model is to introduce a wedge between the input price paid by SOEs and by private enterprises when they produce *domestically*. Specifically, it is assumed that private firms pay a capital rental price (or the unit land price) $c (> 1)$ times as high as what SOEs pay when they *produce* domestically. However, firms pay the same wage and capital rental price (or the unit land price) when producing

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[22]We follow Bernard, Redding, and Schott (2007) to choose this specification in order to make various fixed costs have the same capital (or land) intensity as the variable cost.

[23]We do not take a stance on why some firms become SOEs (or private enterprises), since the predictions of the model do not depend on this.

abroad.[24]

Based on equation (2), we derive total variable cost and total fixed cost as

$$TVC(q, \varphi) = \frac{qr}{\varphi(1 + \omega^{\mu-1})^{\frac{1}{\mu-1}}} \tag{3}$$

and

$$FC(r, w) = \frac{f_i r}{(1 + \omega^{\mu-1})^{\frac{1}{\mu-1}}}, \tag{4}$$

where r and w are the capital rental price (or the unit land price) and the wage rate and $i \in \{D, X, I\}$. Variable $\omega = \frac{r}{w}$ is relative price of capital (or land). Capital (or land) intensity in equilibrium is given by $\frac{l(w,r)w}{k(w,r)r} = \omega^{\mu-1}$. As long as $\mu > 1$, a higher relative price of capital leads to lower capital (or land) intensity. This property is utilized in our productivity estimation.

3.2 Domestic Production, Exporting, and FDI

We derive firm profit and revenue as follows. Based on equation (1), the demand function for variety ω can be derived as

$$q(\omega) = \frac{p(\omega)^{-\sigma}}{P^{1-\sigma}} E, \tag{5}$$

where E is the total income of the economy and P is the ideal price index and defined as

$$P \equiv \left[\int_{\Omega(\omega) \in \Omega} p^{1-\sigma}(\omega) M dF(\omega) \right]^{\frac{1}{1-\sigma}},$$

where M is the total mass of varieties in equilibrium. The resulting revenue function is

$$R(q) = q^{\frac{\sigma-1}{\sigma}} E^{\frac{1}{\sigma}} P^{\beta}, \qquad \beta \equiv \frac{\sigma - 1}{\sigma}. \tag{6}$$

We derive SOE's operating profit of domestic production and exporting first. Since both types of production use domestic factors only, their operating profits are given by

$$\pi_{SD}(\varphi) = \frac{D_H}{\sigma} \left(\frac{\beta\varphi}{r_H} \right)^{\sigma-1} (1 + \omega_H^{\mu-1})^{\frac{\sigma-1}{\mu-1}} \tag{7}$$

and

$$\pi_{SX}(\varphi) = \pi_{SD}(\varphi) + \frac{D_F}{\sigma} \left(\frac{\beta\varphi}{\tau r_H} \right)^{\sigma-1} (1 + \omega_H^{\mu-1})^{\frac{\sigma-1}{\mu-1}}, \tag{8}$$

---

[24]We will show that there is evidence for the existence of an input price wedge in the credit land markets, but not in the labor market. Since buying capital usually requires a substantial amount of borrowing, we assume that private firms pay a higher capital rental price than SOEs.

where $D_i \equiv P_i^{\sigma-1} E_i$ and $i \in \{H, F\}$. Subscripts S, D, X, H and F refer to SOE, domestic production, exporting, home country and foreign country respectively. For private firms, the operating profits are

$$\pi_{PD}(\varphi) = \frac{D_H}{\sigma}\left(\frac{\beta\varphi}{cr_H}\right)^{\sigma-1}(1 + (c\omega_H)^{\mu-1})^{\frac{\sigma-1}{\mu-1}} \tag{9}$$

and

$$\pi_{PX}(\varphi) = \pi_{PD}(\varphi) + \frac{D_F}{\sigma}\left(\frac{\beta\varphi}{\tau cr_H}\right)^{\sigma-1}(1 + (c\omega_H)^{\mu-1})^{\frac{\sigma-1}{\mu-1}}. \tag{10}$$

Firm's revenue is $R_{ij}(\varphi) = \sigma\pi_{ij}(\varphi)$ where $i \in \{S, P\}$ and $j \in \{D, X\}$.

We can derive the exit cutoff and the exporting cutoff for SOEs and private firms respectively:

$$\bar{\varphi}_{SD} = \frac{r_H(\sigma r_H f_D/D_H)^{\frac{1}{\sigma-1}}}{\beta\left(1 + \omega_H^{\mu-1}\right)^{\frac{\sigma}{(\sigma-1)(\mu-1)}}}; \quad \bar{\varphi}_{SX} = \tau\frac{r_H(\sigma r_H f_X/D_F)^{\frac{1}{\sigma-1}}}{\beta\left(1 + \omega_H^{\mu-1}\right)^{\frac{\sigma}{(\sigma-1)(\mu-1)}}};$$

$$\bar{\varphi}_{PD} = \frac{cr_H(\sigma cr_H f_D/D_H)^{\frac{1}{\sigma-1}}}{\beta\left(1 + (c\omega_H)^{\mu-1}\right)^{\frac{\sigma}{(\sigma-1)(\mu-1)}}}; \quad \bar{\varphi}_{PX} = \tau\frac{cr_H(\sigma cr_H f_X/D_F)^{\frac{1}{\sigma-1}}}{\beta\left(1 + (c\omega_H)^{\mu-1}\right)^{\frac{\sigma}{(\sigma-1)(\mu-1)}}}.$$

Note that $\bar{\varphi}_{PD} > \bar{\varphi}_{SD}$ and $\frac{\bar{\varphi}_{PX}}{\bar{\varphi}_{PD}} = \frac{\bar{\varphi}_{SX}}{\bar{\varphi}_{SD}}$.

Now, we discuss the case of FDI. Following HMY, we assume that the firm uses foreign factors to produce after setting up a plant in the foreign country.[25] In addition, foreign factors are used to pay for the fixed FDI cost.[26] Thus, the operating profit of firms that engage in FDI is:

$$\pi_{SO}(\varphi) = \pi_{SD}(\varphi) + \frac{D_F}{\sigma}\left(\frac{\beta\varphi}{r_F}\right)^{\sigma-1}(1 + \omega_F^{\mu-1})^{\frac{\sigma-1}{\mu-1}}; \tag{11}$$

$$\pi_{PO}(\varphi) = \pi_{PD}(\varphi) + \frac{D_F}{\sigma}\left(\frac{\beta\varphi}{r_F}\right)^{\sigma-1}(1 + \omega_F^{\mu-1})^{\frac{\sigma-1}{\mu-1}}. \tag{12}$$

When both SOEs and private firms produce abroad, they face the same factor prices. The FDI cutoffs are pinned down by the following indifference conditions (between exporting and engaging in FDI):

$$\frac{f_I r_F}{(1 + \omega_F^{\mu-1})^{\frac{1}{\mu-1}}} - \frac{f_X r_H}{(1 + \omega_H^{\mu-1})^{\frac{1}{\mu-1}}} = \frac{D_F}{\sigma}\left(\beta\bar{\varphi}_{SO}\right)^{\sigma-1}\left[\frac{(1 + \omega_F^{\mu-1})^{\frac{\sigma-1}{\mu-1}}}{r_F^{\sigma-1}} - \frac{(1 + \omega_H^{\mu-1})^{\frac{\sigma-1}{\mu-1}}}{(\tau r_H)^{\sigma-1}}\right] \tag{13}$$

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[25]In our data set of Chinese MNCs from Zhejiang, we checked whether firms increased their foreign investment after the initial investment and ended up with few cases. The finding is that at least a substantial fraction of factors used in foreign production (including capital and land) is sourced from the foreign country.

[26]It is worth stressing that our theoretical predictions will hold well independent of this assumption. In Online Appendix D, we allow for FDI fixed cost to be paid using domestic factors, and private firms do not face discrimination when they pay the FDI fixed cost using domestic factors. In both cases, our theoretical results are still preserved.

and

$$\frac{f_I r_F}{(1 + \omega_F^{\mu-1})^{\frac{1}{\mu-1}}} - \frac{f_X c r_H}{(1 + (c\omega_H)^{\mu-1})^{\frac{1}{\mu-1}}} = \frac{D_F}{\sigma}\left(\beta\bar{\varphi}_{PO}\right)^{\sigma-1}\left[\frac{(1 + \omega_F^{\mu-1})^{\frac{\sigma-1}{\mu-1}}}{r_F^{\sigma-1}} - \frac{(1 + (c\omega_H)^{\mu-1})^{\frac{\sigma-1}{\mu-1}}}{(c\tau r_H)^{\sigma-1}}\right]. \quad (14)$$

It is evident that selection into FDI is tougher for *SOEs* than for private firms (i.e., $\bar{\varphi}_{SO} > \bar{\varphi}_{PO}$), as the opportunity cost of engaging in FDI is smaller for private firms than for SOEs.

3.3   Domestic Distortion and Patterns of Outward FDI

In this subsection, we discuss how the existence of domestic distortions in the capital and land markets affects the patterns of outward FDI at the extensive and intensive margins.

Proposition 1 *Sorting Patterns of Private Firms and SOEs (Extensive Margin):*

1. *The exit cutoff and exporting cutoff are higher for private firms than for SOEs. However, the cutoff for becoming an MNC is lower for private firms than for SOEs (i.e., selection reversal).*

2. *Conditional on the initial productivity draw (and other firm-level characteristics), private firms are more likely to become MNCs.*

3. *Assume that the truncated distribution of the productivity draw for private firms (weakly) first order stochastically dominates (FOSD) that of SOEs, or the two conditional probability density functions (PDFs) satisfy the (weak) monotone likelihood ratio property (MLRP) with:*

$$\frac{\partial}{\partial\varphi}\left(\frac{f_P(\varphi|\varphi \geq \varphi_0)}{f_S(\varphi|\varphi \geq \varphi_0)}\right) \geq 0 \quad \forall \varphi \geq \varphi_0,$$

   where $f_P(\varphi|\varphi \geq \varphi_0)$ and $f_S(\varphi|\varphi \geq \varphi_0)$ are the truncated probability density functions of the pro-ductivity draw for private firms and SOEs respectively. Then, the fraction of MNCs is larger among private firms than among SOEs. Furthermore, simple average productivity of private firms is greater than that of SOEs overall.

4. *Assume that both types of firms draw productivities from the same distribution (which trivially satisfies weak FOSD property). Then the (simple) average productivity of private MNCs is smaller than that of state-owned MNCs (i.e., productivity premium for state-owned MNCs).*

   Proof. See Online Appendix C. ∎

   The intuition for the above proposition is as follows. First, since there is discrimination against private firms at home, it is more difficult for private firms to survive and export. As a result, the exit

cutoff and the exporting cutoff are higher for these firms. Absent the choice of exporting, the FDI cutoff would be the same for SOEs and for private firms, as they would face the same benefit and costs of doing FDI in the relative sense. However, since the firm at the FDI cutoff compares exporting with FDI, the (opportunity) cost of engaging in FDI is smaller for private firms than for SOEs.[27] As a result, the FDI cutoff is lower for private firms than for SOEs. Online Appendix Table 8 shows that the selection reversal holds, as the estimated productivity at 1% (and 5%) percentile is higher for state-owned MNCs than for private MNCs. If we make assumptions on the distribution of the productivity draws, the selection reversal leads to an average productivity premium for state-owned MNCs, and the above theoretical results rationalize the first two stylized facts.[28] Finally, Table 6 and Online Appendix Tables 5-6 in the next section show the lower probability of becoming an MNC for SOEs.

We next discuss how a variation in the level of domestic distortion affects the sorting pattern of private MNCs and state-owned MNCs differently using the following proposition.

Proposition 2 *Cross-Industry Variations:*

1. *In industries with more severe distortion (i.e., c ↑), the productivity premium of state-owned MNCs is larger. Moreover, SOEs are less likely to produce abroad in industries with more severe distortion than SOEs in industries with less severe distortion.*

2. *Assume that the production function is Cobb-Douglas with capital and labor. Then, the productivity premium of state-owned MNCs is more pronounced in capital intensive industries. Furthermore, SOEs are less likely to engage in FDI (compared with private firms) in capital intensive industries.*

   Proof. See Online Appendix C. ∎

The intuition for the above proposition is straightforward. Since the asymmetric distortion disincentives SOEs to produce abroad, the selection into the FDI market becomes more stringent for SOEs (than for private firms) in industries with more severe discrimination against private firms. Furthermore, as the distortion exists in the capital market, we expect a more stringent selection into the FDI market for SOEs (than for private firms) in capital intensive industries. We will provide empirical evidence for these two predictions in what follows.

Finally, we discuss how domestic distortion affects the sorting patterns of MNCs at the intensive margin.

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[27]Exporting does not eliminate the distortion private firms face in the domestic market.

[28]The selection reversal holds irrespective of the distribution of the initial productivity draw. The average productivity premium for state-owned MNCs exists, if SOEs and private firms draw productivity from the same distribution. However, the assumption of the same productivity distribution is not required. What we need is that a lower cutoff on the productivity draw implies a smaller average productivity (i.e., a relationship between the marginal productivity and the inframarginal productivity). This is why we need MLRP for part 3 of the above proposition.

Proposition 3 *Sorting Pattern of Private Firms and SOEs (Intensive Margin):*

1. *Suppose the initial productivity draw follows a Pareto distribution with the same shape parameter for private firms and SOEs. Then, the relative size of private MNCs in the domestic market (i.e., compared with private non-exporting firms) is smaller than that of state-owned MNCs (i.e., compared with non-exporting SOEs).*

2. *Conditional on productivity and other firm-level characteristics, the ratio of foreign sales to domestic sales is higher for private MNCs than for state-owned MNCs.*

   Proof. See Online Appendix C. ∎

The intuition for Proposition 3 is straightforward. Since there is an extra benefit for private firms to produce abroad, they produce and sell more in the foreign market. This effect is another key result of our model, for which we provide empirical support in the next section. The first part of Proposition 3 receives strong statistical support from Table 5. As the table shows, the relative size of private MNCs is smaller than that of state-owned multinational firms. We will provide evidence for the second part of the above proposition in what follows.

4   Evidence

Our theoretical model yields three empirical propositions. Some of the predictions of the propositions have already been shown to be consistent with the stylized facts presented in Section 2, others are still waiting for empirical examination, which is the purpose of this section.

4.1   FDI Decision and Firm Ownership

Most of the predictions of Proposition 1 have been shown to be consistent with the empirical results in Tables 2-5. Only part 2 of Proposition 1 needs further empirical examination. The nationwide FDI data only contain the information of the first year when firms began to undertake FDI in a given country (i.e., no information on whether firms exited from FDI in a particular country after entry). Therefore, the estimations in Table 6 and the other tables include non-MNCs and current MNCs every year.

Table 6 reports the estimation results starting from a linear probability model (LPM) in which the regressand is an indicator of outward FDI. As the outward FDI data set only reports the first year when a firm engages in outward FDI in a given country, we assume that a firm will continue to engage in outward FDI afterward.[29] That is, the FDI indicator equals one once a firm engages in FDI and zero otherwise.

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[29]It is important to note that our findings remain unchanged even without imposing such an assumption and with only FDI starters' being examined. This can be seen from Table 5 of Online Appendix.

To explore whether SOEs are less likely to engage in FDI, we include an SOE indicator in the regression, as well as several key firm characteristics, such as firm size (i.e., log employment), firm-level TFP, and exporting status. Equally importantly, we include industry-specific fixed effects and year-specific fixed effects to control for unobservable time-invariant and industry-invariant factors.[30] The SOE indicator is shown to be negative and statistically significant in column (1), suggesting that SOEs are indeed less likely to engage in outward FDI. The magnitude of the SOE indicator is too small, which is probably due to a well-known pitfall of LPM: The predicted probability could be greater than one or less than zero.

To overcome this drawback, we report the logit estimates in column (2) by controlling for a rich set of fixed effects with interactions of industry and year dummies, which yield qualitatively the same results as for the LPM model. Particularly, compared with private firms, SOEs are less likely to engage in outward FDI. For such a nonlinear probability model, firm-specific fixed effects cannot be included in the regression. Instead, we control for year-specific and industry-specific fixed effects in all the rest of the regressions.

Our estimates include foreign-invested enterprises (FIEs), which are firms that receive direct investment from foreign entities. However, if a FIE has a dominant share of foreign stakes, it is directly controlled by its foreign headquarters. Our model does not consider such firms, as FIE's headquarters are not located in the home country. Thus, we drop FIEs from the sample in all regressions, and columns (3) to (10) in Table 6 report the results. After dropping the FIE sample, the logit estimates in column (3) still show that SOEs are less likely to engage in outward FDI, conditioning on other firm-level characteristics.

There are two important caveats here. First, as shown in row (3) of Table 1, less than 1 percent of manufacturing firms undertook FDI in most of the sample years. Within MNCs, a small fraction of them are SOEs. As highlighted by King and Zeng (2001), standard binary nonlinear models, such as logit or probit models, underestimate the probability of rare events. To address this concern, King and Zeng recommend using the rare-event logit approach, which corrects for possible downward bias.[31] Column (4) in Table 6 reports the logit estimates with rare-event corrections. The key coefficient of the SOE indicator is much larger than its counterparts in columns (2) and (3) in absolute value. Equally importantly, the coefficient is still negative and statistically significant, ascertaining that SOEs are less likely to engage in outward FDI.

The rare-event feature of our FDI data also generates another problem, that the probability distribution of state-owned MNCs engaging in FDI exhibits faster convergence toward the true probability that SOEs engage in foreign investment. Standard logit or probit estimates cannot deal with this problem. We

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[30]In principle, we can control for firm-specific fixed effects. However, since there are only few ODI deals per Chinese MNC over 2000-13, there are not enough degrees of freedom to identify the coefficient on the SOE indicator with firm-specific fixed effects. We thus add industry-specific fixed effects in the LPM estimates.

[31]Rare-events estimation bias can be corrected as follows. We first estimate the finite sample bias of the coefficients, $bias(\hat{\beta})$, to obtain the bias-corrected estimates $\hat{\beta} - bias(\hat{\beta})$, where $\hat{\beta}$ denotes the coefficients obtained from the conventional logistic estimates.

thus run complementary log-log regressions in the rest of Table 6, which allows for faster convergence toward rare events. Column (5) of Table 6 reports the complementary log-log regression by dropping foreign firms. Column (6) adopts the broadly defined SOE indicator in the regression. Clearly, our key results are robust regardless of different SOE definitions.

There may be a worry that some Chinese firms may invest in tax haven destination economies, such as Hong Kong and the Cayman Islands, due to the motive of tax evasion or profit shifting.[32] Consequently, our model and its underlying story cannot be applied to those firms. Column (7) of Table 6 thus drops observations of outward FDI in tax haven destinations.[33] Similarly, it is also possible that some Chinese firms may establish trading offices in their exporting destinations to promote market-specific exports (Tian and Yu 2015). Such distribution-oriented outward FDI is *not* the focus of our model, and our theory does not apply to this type of FDI. Column (8) thus drops the sample of distribution-oriented FDI.

Next, as shown in row (2) of Table 1, China's outward FDI increases rapidly after 2004, when the government adopted policies to encourage firms to go abroad. It is also true that a large wave of privatization of SOEs took place after 1998 (Hsieh and Song, 2015). We thus drop SOE switching firms from the sample and focus on observations from 2004 to 2008 in columns (9) and (10) of Table 6. The coefficient of the SOE indicator in column (9) is larger than its counterpart in column (8), suggesting that private firms were more likely to go abroad after 2004. Still, there may be a worry that our story fits better into the case of greenfield FDI rather than M&A-type FDI, as the latter usually targets at better technology or seeks famous brand names of the targeted firms. We thus drop the M&A–type FDI in column (10) and the estimation still yields the same results: SOEs are less likely to engage in outward FDI.[34]

[Insert Table 6 Here]

Finally, we provide two additional robustness checks. First, we rerun all the regressions in Table 5 of Online Appendix by setting the FDI indicator to one only in the first year when the Chinese manufacturing firm became an MNC (i.e., the indicator for starting FDI). The results reported in Appendix Table 5 show that our findings in Table 6 are not driven by subsequent entries into the outward FDI market. Second, the inclusion of *destination*-specific fixed effects and *affiliates*' industry-specific fixed effects does not change our findings in Table 6 either, though the value of the estimated coefficients changes somewhat. The results are reported in Appendix Table 6 of Online Appendix. In total, our finding of a lower probability of SOEs' conducting outward FDI is robust to different estimation methods, various specifications, and different time spans.

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[32]See Garetto, Oldenski, and Ramondo (2016) for this point.

[33]The tax haven regions include the Bahamas, Bermuda, the Cayman Islands, Hong Kong, Luxembourg, Macao, Monaco, Panama, the Virgin Islands, and Switzerland.

[34]To identify M&A–type FDI, we manually merge the outward FDI data set with the M&A–type FDI data compiled by Thomson Reuters, by using the identical names of Chinese parent firms.

4.2 Input Market Distortions

Our theoretical model is built on the premise that, compared with SOEs, private firms have to bear higher input costs in the domestic market. Although this assumption seems to be widely accepted, we provide direct evidence for it in this subsection.

Previous work suggests that Chinese SOEs access working capital by paying a lower interest rate than what private firms pay (Feenstra, Li, and Yu 2014). Similarly, SOEs acquire land at a lower market price than private firms, which is especially true in the manufacturing sector (Tian, Sheng, and Zhang 2015). To investigate whether these conjectures are supported by the data, we first construct a measure of firm-level interest rate by dividing the firm's interest expenses by its current liabilities (in each year), both of which are available in the ASIF data set over the period of 2000-08 (but not after 2008). We then regress this measure on the narrowly defined SOE indicator in columns (1) and (2) in Table 7. If our underlying assumption that SOEs access external working capital at a lower cost than private firms is supported by the data,[35] we should observe that the SOE indicator has a negatively significant coefficient.

This outcome is exactly what we observe in Table 7. Estimates in columns (1)-(3) include year-specific and industry-specific fixed effects. In addition, columns (2)-(3) control for province-specific fixed effects and other key firm characteristics, such as firm TFP, log employment of the firm, foreign indicator, and export indicator. The key coefficient, the SOE indicator, is always negative and statistically significant, when we use the short-term liabilities to calculate the interest rate (in column (1) and (2)). It is possible that SOEs may have higher long-term liabilities than private firms. Thus, using the short-term liabilities as the denominator to measure interest rate might under-estimate the interest rate of the SOEs. To address this concern, column (3) of Table 7 measures the firm-level interest rate using the ratio of interest payment to *total* liabilities, which include both short-term loans and long-term loans. It turns out that the SOE indicator is still negative and statistically significant under this alternative specification of firm-level interest rate. Its absolute magnitude is around 0.09, suggesting that private firms pay annual interest rate 9 percent higher than SOEs, and hence bear higher capital cost than SOEs.[36]

Still, one may have a concern that private firms could use domestic credits to finance costs associated with FDI projects. If so, they would still face discrimination even when investing abroad. Admittedly, we cannot rule out this possibility without further information on firm's credit allocation. However, a better investigation is to check whether private firms acquire land at a higher unit cost than SOEs. If so, whether the land market distortion plays a role when private firms engage in outward FDI.

Thus, columns (4)-(8) in Table 7 go further to check whether SOEs acquire land at lower costs. By

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[35]We find similar results when SOEs are measured in a broad way à la Hsieh and Song (2015).

[36]The relative interest rate differential between SOEs and private firms is plausible if the firms' informal finance is taken into account. Private firms usually have to finance their working capital from informal financial markets due to severe credit constraints (see Lardy 2014). Our magnitude is close to Song, Storesletten,and Zilibotti (2011) and Midrigan and Xu (2014) which find that private firms pay roughly 9% − 10% higher interest rate than SOEs.

controlling for industry-specific and year-specific fixed-effects, respectively, we first regress firm-level unit land price on the SOE indicator over the period of 2000-13 in column (4). Columns (5) and (6) add other firm-level controls such as firm TFP, log employment, the foreign indicator, and the export indicator. Since there may be a concern that land market discrimination could reversely induce firm churning (i.e., switching from private firms to SOEs or vice versa), column (6) regresses the unit land price on the one-year lag of SOE indicator to avoid possible simultaneous bias. The regression results in Table 7 show that the coefficient of SOE indicator is always negatively significant. Thus, private firms do seem to pay higher unit land price than SOEs.

Compared with the interest rate estimates in columns (1)-(3), the numbers of observations drop dramatically in columns (4)-(6) due to the usual imperfect matching between the production data set and the land price data set. To overcome such a problem, we use the prefectural-level data of land purchase for robustness checks.[37] We first construct a variable of SOE intensity, which is defined as the number of SOEs divided by the number of total manufacturing firms in the city. Our theory predicts that a city with a higher SOE intensity is expected to have a lower average price of land, conditioning on other prefecture-level characteristics. Estimations whose results are reported in columns (7) and (8) regress average land price at the prefectural city level on SOE intensity. Particularly, columns (7) and (8) control for both year-specific and city-specific fixed-effects, respectively. Still, it is possible that aggregate demand for land in each city affects the price of land in the city. columns (7) and (8) thus control for cities' total land sales. In all cases, the coefficient of SOE intensity is negative and statistically significant, suggesting that SOEs pay lower unit land price on average and hence bear lower land costs than private firms.

[Insert Table 7 Here]

4.3 Channels and Sectoral Heterogeneity

Part 1 of Proposition 2 hints that the selection reversal is heterogeneous across sectors. Specifically, the productivity premium of state-owned MNCs will be more pronounced in industries with severe distortions. Similarly, we should observe that SOEs are less likely to produce abroad in these sectors compared to SOEs in sectors with less severe distortions. To verify these predictions, we regress the firm outward FDI indicator on the SOE indicator and its interaction with the industry-level input price differential which is first measured by the interest rate differential, followed by the difference in the unit land price. For this difference-in-differences regression, our model predicts a negatively significant coefficient of

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[37]Data are from China's *Land and Resources Statistical Yearbook* (various years). As in Tian, Sheng, and Zhang (2015), we only use data on land sales for land that is sold or granted by market channels, including agreement, auction, bidding, and listing. We exclude land transfers to SOEs through direct government leasing and allocation. Thus, the coefficients in the last two estimates in Table 7 shall be understood as the lower bound of the measured distortion.

the SOE dummy and of its interaction with the (positive) industry-level input price differential. The economic rationale is evident: Compared to SOEs in other industries, SOEs in industries with more severe credit and/or land market distortions against private firms are less likely to undertake outward FDI projects, as they receive even better treatments in the domestic input markets than their counterparts in other sectors. Indeed, the interaction between SOE and industrial input price differential is crucial to testing our hypothesis, as it shows the effect of input price distortions on the likelihood of SOEs' investing abroad directly.

To check whether the credit market plays an important role in shaping the pattern of firm's selection reversal, columns (1)-(6) of Table 8 report the estimation results using the interest rate to measure the input price. The industrial input price differential here is calculated as the difference between the (high-level) average interest rate paid by private firms and the (low-level) average interest rate paid by SOEs within the same industry-year cell. After controlling for industry and year fixed effects, separately, and other key firm-level variables, we find that the SOE indicator and its interaction term with the industry-level interest rate differential are both negative and statistically significant. These results suggest that the credit market distortion is an important reason why SOEs are less likely to go abroad. Such a key finding is robust to different specifications. Particularly, we drop the sample of FIEs in column (2) and the sample of outward FDI to tax haven destinations in column (3). We also drop the sample of distribution-oriented FDI in columns (4) and (5) and narrow the time window to 2004-08 in column (6).[38] All the estimation results suggest that the credit market distortion is an important factor for us to interpret the pattern of Chinese firms' selection reversal.

As mentioned above, one may worry that private firms still suffer from domestic credit market distortions if they use domestic credits to finance FDI fixed cost and/or variable cost. To mitigate such a concern, we go further to examine the channel of land market distortions, which would be a cleaner experiment as firms cannot move their domestic land input abroad.

To do so, we first obtain firm's total cost of acquiring land during the sample period of 2000-13 which is time-*invariant*, as firms could acquire land unevenly and infrequently across years. We then calculate the 3-digit CIC industry-level difference in the unit land price paid by private firms and by SOEs. Both its own term (of the industrial land price differential) and its interacted term with the SOE indicator are included in columns (7)-(11) of Table 8.

Similar to columns (1)-(6), columns (7)-(11) include important firm-level control variables such as firm's log employment and the export dummy. Columns (7)-(9) cover the entire sample period of 2000-13. Columns (8)-(11) drop observations with tax-haven FDI destination countries, and columns (9)-(11) drop foreign firms from the regressions. Column (10) includes the sample of 2000-08 so that it can

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[38]In column (5), we use the ratio of firm's interest payment to its total liabilities to calculate firm-level interest rate.

be directly compared to column (3) with the measure of interest rates.[39] We also control for industry and year fixed-effects respectively in all regressions. In particular, we include the interacted industry-year fixed-effects in column (11) of Table 8. All the specifications in columns (7)-(11) of Table 8 yield the same findings: SOEs are less likely to engage in outward FDI. More importantly, SOEs in industries with more severe land market distortions are less likely to undertake outward FDI than SOEs in industries with less severe land market distortions (i.e., the negative interaction term). This is the key evidence we provide for our explanation for the selection reversal pattern.

[Insert Table 8 Here]

4.4 Capital Intensity and Pattern of Outward FDI

Part 2 of Proposition 2 implies that, compared with private firms, SOEs are less likely to engage in outward FDI in capital-intensive industries. This subsection provides evidence for this prediction. By definition, firms in capital-intensive industries have higher demand for working capital. Accordingly, domestic input distortions against private firms favor SOEs more in such industries. If domestic input distortions are the fundamental driving force for explaining the behavior of Chinese firms' outward FDI, SOEs in capital-intensive industries should be unlikely to undertake outward FDI. By contrast, such a phenomenon may not exist in labor-intensive industries.

To check this out, we run the following difference-in-differences regression and focus on the difference between capital-intensive sectors and labor-intensive sectors. Specifically, we interact the dummy variable for the firm's being in the capital-intensive sector and the dummy variable for firm's being in the labor-intensive sector with the SOE dummy in our Logit regressions.[40] The interacted coefficient between the SOE indicator and the labor-intensive indicator shows how the state ownership affects the likelihood of investing abroad for the parent firms from labor intensive industries. Similarly, the interacted coefficient between SOE indicator and labor-intensive shows how the state ownership affects the likelihood of investing abroad for the parent firms from capital intensive industries. Column (1) in Table 9 shows that SOEs are less likely to engage in outward FDI in capital-intensive industries. By contrast, the SOE indicator is insignificant for parent firms from labor-intensive sectors. This finding is robust to different specifications, such as dropping foreign firms, dropping SOE switching firms, dropping FDI to tax haven destinations, or using a shorter time period (2004-08).

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[39]The number of observations in column (10) is substantially higher than that in column (3), as the land price differential used in column (10) is time-invariant and hence exists in all 3-digit CIC industries whereas the interest rate used in column (3) is time-variant and some industry-year pairs have missing observations.

[40]Note that our specification is the same as the specification of $OFDI_{it} = \beta_1 SOE_{it} + \beta_2 SOE_{it} \times Kdummy + ...$, since it is equal to $OFDI_{it} = (\beta_1 + \beta_2)SOE_{it} \times Kdummy + \beta_1 SOE_{it} \times (1 - Kdummy)$ where $Kdummy$ denotes capital-intensive indicator, which equals one minus labor-intensive indicator. As we don't include parent-firm fixed effects in the regression, the perfect collinearity problem does not arise here.

It is worth discussing why the key coefficient of the SOE indicator is insignificant in labor-intensive sectors. In China, the cost of labor has increased dramatically after 2004. Accordingly, some firms in labor-intensive sectors established foreign affiliates in other least-cost, labor-abundant countries, such as Bangladesh, Ethiopia, and Vietnam (Shen 2013). Such firms sought global sourcing instead of global markets (Antràs 2016), which is out of the scope of the current paper.

[Insert Table 9 Here]

4.5 Estimates at the Intensive Margin

We now provide evidence for Proposition 3. Table 5 provides evidence for part 1 of the proposition. Part 2 of Proposition 3 states that the ratio of foreign sales to domestic sales is higher for private MNCs than for state-owned MNCs. Data on sales of foreign affiliates are unavailable in the Chinese firm-level ASIF data set. Thus, we merged the ASIF data set with the Orbis data set, which contain information on sales and revenue of (domestic and foreign) affiliates of Chinese MNCs. Unfortunately, the matching rate for the two data sets between 2005 and 2010 is extremely low, as we merge our ASIF data with the Orbis data by matching firms' names in Chinese.[41] For the data between 2011 and 2013, we merge our ASIF data with the Orbis data using the trade registration number of the (Chinese) parent firms, as this information is contained in both data sets. In Orbis data, 11,000 observations (i.e., affiliate-year pairs) have non-missing values for sales, revenue, and employment. Among these affiliates, roughly 30% of them are in manufacturing sectors. Since we can only identify FDI starters (between 2011 and 2013) in our outward FDI data set, we managed to match roughly 750 affiliate-year observations for the two data sets between 2011 and 2013. The data between 2011 and 2013 are the data we use to implement following empirical analysis.

Table 10 regresses log sales (or log revenue) of each domestic or foreign affiliate of Chinese MNCs in a given year on a dummy variable for being a private (parent) firm, a dummy variable for being a foreign affiliate, and characteristics of the parent firm. Importantly, we add an interaction term between the two dummy variables: $Private_{i,t} \times Foreign_{j,t}$ where i, j and t refer to parent firm (private or state-owned), affiliate and year respectively. As expected, the regression results show that private parent firms have smaller affiliates on average, and foreign affiliates are smaller than domestic affiliates on average. What is interesting is that the size difference between the domestic affiliate and the foreign affiliate (of the same parent firm) is smaller among private MNCs than among state-owned MNCs, as the coefficient

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[41]The main reason responsible for the low matching rate is that firms' names are in Chinese in our ASIF data, while they are in English in Orbis data. As English translations of a firm's Chinese name can be multiple, it is extremely challenging to match observations from the two independent data sets (e.g., the company whose English name is Lenovo currently should be translated into "Legend" based on its Chinese name). We identify a matched observation, when the English translation of the firm's name exactly matches the characters of its Chinese name, the non-matched firms are probably random and should not affect our empirical results.

of $Private_{i,t} \times Foreign_{j,t}$ is positively significant. This is exactly what part 2 of Proposition 3 predicts: The ratio of foreign sales to domestic sales is higher for private MNCs than for state-owned MNCs.

[Insert Table 10 Here]

4.6 Outward FDI Data between 2000 and 2013

In this subsection, we expand the time horizon of our sample to 2000-13. The major reason is the number of state owned MNCs is small before 2008, as the total number of manufacturing outward FDI projects is not too big before 2008. As there are much more manufacturing outward FDI projects after 2008, the inclusion of outward FDI data until 2013 can alleviate the concern that the small number of state owned MNCs might affect our estimation results. [42] Moreover, the quality of our data matching becomes better after 2010, and the importance of China's manufacturing outward FDI (in China's total outward FDI) is increasing with time. Therefore, using outward FDI data after 2009 provides crucial robustness checks for our previous empirical findings. However, the drawback of using the longer time-series data set is that we cannot estimate firm productivity accurately. The reason is that China's firm-level production data report neither value added nor purchase of intermediate inputs after 2008. Without knowing these key variables, we cannot precisely estimate TFP or calculate labor productivity (i.e., value added per worker). Because of these substantial restrictions on the data, we do not use the data for 2000-13 as our main data set. Instead, we use the longer time-series data for robustness checks only and relegate detailed discussions into Online Appendix E.

The empirical findings based on the sample from 2000 to 2013 are qualitatively the same as our previous findings. In particular, We still find that SOEs are less likely to invest abroad after we control for important firm-level characteristics and a variety of fixed effects. In addition, this pattern is more pronounced in sectors that have larger interest rate differentials (between SOEs and private firms) and in sectors that are more capital-intensive. In total, both the short sample and the long sample of our outward FDI data lead to the same empirical findings emphasized in this paper.

5 Concluding Remarks

In this study, we utilize data on Chinese MNCs to investigate how distortions (i.e., discrimination against private firms) in the domestic market affect firms' FDI decisions. We document three puzzling stylized facts. First, private MNCs are less productive than state-owned MNCs, although private non-MNCs are more productive than state-owned non-MNCs. Second, SOEs are less likely to undertake FDI, although

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[42]We have taken into account this issue in Table 5 and Table 5 of Online Appendix by using the rare event Logit regression.

they are larger and receive various supports from the government for investing abroad. Third, the relative size of state-owned MNCs (compared with non-exporting firms) is larger than that of private MNCs.

We then build a model to rationalize these findings and highlight a key channel through which distortions affect firms' FDI decisions. Distortions in the domestic market incentives private firms to invest and produce abroad, which results in less tough selection into the FDI market for them. In addition, compared with state-owned MNCs, private MNCs allocate output disproportionately more in the foreign market, and their size increases disproportionately when they become MNCs. Finally, the selection reversal and productivity premium for state-owned MNCs are more pronounced in capital-intensive industries and in industries with more severe discrimination against private firms. All the empirical predictions of the model receive support from the data.

We argue that alternative hypotheses rather than the input market distortion cannot be used to rationalize our finding of selection reversal. First, a price wedge in the domestic product market (between private firms and SOEs) would lead to *no* difference in the selection into FDI market between the two types of firms, as the cost and benefit of doing FDI would be the same (for the two types of firms) in this case. Next, profit shifting motive of private firms cannot be used to rationalize the selection reversal, as our result holds for the sub-sample that drops Chinese FDI projects into tax heavens economies. Finally, technology-seeking and brand-seeking motives of private firms cannot be used to rationalize the selection reversal, as our result holds for the sub-sample that drops *M&A*-type FDI.[43]

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[43]We discuss the role played by the fixed FDI cost in our model and relegate the proof of the result to Online Appendix D.

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Table 1: FDI Share in Chinese Manufacturing Firms (2000-12)

Firm type	2000	2002	2004	2006	2008	2010	2012
(1) Manufacturing firms	83,579	110,498	199,873	194,201	158,220	306,366	283,018
(2) FDI mfg. parent firms (in our sample)	5	9	56	562	867	1945	5501
(3) FDI share (%)	0.01	0.01	0.03	0.29	0.55	0.64	1.94
(4) FDI mfg. parent firms (in the bulletin)	–	–	–	2670	3650	4654	6744
(5) Matching Percentage (%)	–	–	–	21.1	23.8	41.8	81.6
(6) FDI mfg. SOEs share (%, in our sample)	20.0	22.2	5.35	3.02	1.49	1.23	1.81
(7) FDI SOEs share (%, in the bulletin)	–	–	–	26.0	16.1	10.2	9.1

Note: Data on China's MNCs were obtained from the Ministry of Commerce of China. FDI share in row (3) is obtained by dividing the number of FDI manufacturing firms in row (2) by the number of manufacturing firms in row (1). That is, (3) = (2)/(1). Matching percentage in row (5) equals the number of FDI manufacturing parent firms in our sample divided by number of FDI manufacturing parent firms in the bulletin (i.e., (5) = (2) / (4)). Numbers of FDI manufacturing parent firms in the bulletin before 2006 in column (4) are unavailable. FDI manufacturing SOEs share in row (6) reports the percentage share of state-owned manufacturing MNCs among all manufacturing MNCs in our sample. FDI SOEs share in row (7) denotes the percentage share of state-owned MNCs among all MNCs in the bulletin.

Table 2: Selection Reversal: State-owned MNCs Are More Productive than Private MNCs

Category	Non-MNCs				MNCs			
	all firms		with exports only		all firms		with exports only	
PSM Matching	unmatched	matched	unmatched	matched	unmatched	matched	unmatched	matched
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(i) Private firms	3.62	3.56	3.60	3.77	4.28	4.10	4.28	4.15
(ii) SOE	3.06	3.06	3.27	3.26	4.48	4.62	4.76	4.90
Difference=(i)-(ii)	0.56***	0.50***	0.33***	0.51***	-0.20*	-0.52*	-0.48***	-0.75**
	(94.19)	(47.85)	(27.20)	(27.75)	(-1.67)	(-1.68)	(-3.30)	(-2.08)
			Ownership defined by state share					
(iii) Private firms	3.63	3.56	3.60	3.77	4.28	4.09	4.28	4.12
(iv) SOE	3.07	3.06	3.27	3.27	4.53	4.66	4.78	4.90
Difference=(iii)-(iv)	0.56***	0.50***	0.33***	0.50***	-0.25**	-0.57*	-0.50***	-0.78**
	(97.56)	(50.05)	(28.35)	(28.60)	(-2.11)	(-1.84)	(-3.53)	(-2.17)

Note: Columns (1)-(4) show that private firms have higher TFP than SOEs among non-MNCs with all firms and with exports only, respectively. A dummy variable for capital-intensive industries and year are used as covariates to obtain the propensity score for Non-MNCs in columns (2) and (4). Columns (5)-(8) show that private MNCs are less productive than state-owned MNCs with all firms and with exports only, respectively. A dummy variable for capital-intensive industries, a dummy variable for rich destination economies, outward FDI mode and year are used as covariates to obtain the propensity score for MNCs in columns (6) and (8). In Rows (iii) and (iv) private firms and SOEs are defined by using the state share in firm's ownership a là Hsieh and Song (2015). The numbers in parentheses are *t*-values. *** (**, *) denotes the significance at 1 percent (5 percent, 10 percent). TFP is measured by the augmented Olley-Pakes TFP, see the text for details.

Table 3: Selection Reversal: Disproportionately More Private MNCs

Category	2000-08			2000-13		
	# of MNCs	# of All firms	Fraction of MNCs	# of MNCs	# of All firms	Fraction of MNCs
MNCs	(1)	(2)	(3)	(4)	(5)	(6)
(i) Private firms	3,623	1,335,514	0.27%	21,426	2,287,915	0.94%
(ii) SOE	104	40,612	0.25%	270	66,192	0.41%
Ownership defined by state share						
(iii) Private firms	3,622	1,097,322	0.33%	21,130	2,273,486	0.93%
(iv) SOE	105	43,512	0.24%	566	80,621	0.70%

Note: Column (3) reports the fraction of MNCs that is obtained by dividing column (1) by column (2) for year 2000-08. Similarly, column (6) reports the fraction of MNCs that is obtained by dividing column (4) by column (5) for year 2000-13. Clearly, the share of MNCs is smaller among SOEs than among private firms, which is consistent with part 3 of Proposition 1. In Rows (iii) and (iv) private firms and SOEs are defined by using the state share in firm's ownership a là Hsieh and Song (2015). Note that we lose some observations when defining SOEs using the state share in firm's ownership, as some firms did not report their state shares in our data. Refer to the texts for details.

Table 4: Productivity Premium of State-owned MNC by Different Types of Relative TFP (2000-08)

Category Measures of RTFP	All Firms			Non-MNC Firms			MNC Firms		
	RTFP^{OP}	$\text{RTFP}^{Distort}$	$\text{RTFP}^{Distort}_{soe}$	RTFP^{OP}	$\text{RTFP}^{Distort}$	$\text{RTFP}^{Distort}_{soe}$	RTFP^{OP}	$\text{RTFP}^{Distort}$	$\text{RTFP}^{Distort}_{soe}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(i) Private firms	0.506	0.494	0.497	0.505	0.494	0.497	0.616	0.500	0.503
(ii) SOE	0.412	0.478	0.481	0.411	0.479	0.481	0.650	0.528	0.532
Difference=(i)-(ii)	0.094***	0.016***	0.016***	0.094***	0.015***	0.016***	-0.034*	-0.028***	-0.029***
	(93.95)	(46.42)	(46.29)	(97.07)	(46.53)	(46.40)	(-1.69)	(-2.69)	(-2.73)
			Capital-Intensive Industries Only						
(iii) Private firms	0.509	0.500	0.503	0.509	0.500	0.503	0.624	0.505	0.509
(iv) SOE	0.422	0.477	0.480	0.422	0.477	0.480	0.676	0.525	0.529
Difference=(iii)-(v)	0.087***	0.023***	0.023***	0.087***	0.023***	0.023***	-0.052**	-0.020*	-0.020*
	(78.03)	(59.05)	(59.54)	(78.28)	(59.14)	(59.62)	(-2.39)	(-1.65)	(-1.64)

Notes: Number in parenthesis are t-value. ***(**,*) denotes the significance at 1(5, 10)%, respectively. Columns (1)-(3) show that private firms have higher relative TFP than SOEs for all firms. Similarly, columns (4)-(6) show that private non-MNC firms have higher relative TFP than SOE non-MNC firms. Columns (7)-(9) show that private MNC firms are *less* productive than state-owned MNCs. Columns (1), (4) and (7) are relative Olley-Pakes TFP. Columns (2), (5) and (8) are relative TFP featured with input factor distortions. Columns (3), (6) and (9) are relative TFP featured with input factor distortions and interacted SOE dummy with other polynomials. The upper module includes all sample whereas the bottom one includes capital-intensive industries only, which account for around three quarters of the entire sample.

Table 5: Relative Size Premium for SOEs

Year coverage	Avg.	≤ 2001	≤ 2002	≤ 2003	≤ 2004	≤ 2005	≤ 2006	≤ 2007	≤ 2008
		relative size of MNCs to non-exporting firms (l_o/l_d)							
(1) Private Firms	4.50	4.59	4.59	4.56	4.54	4.53	4.52	4.51	4.50
(2) SOE	5.48	5.65	5.64	5.58	5.55	5.53	5.51	5.49	5.48
Size Difference=(1)-(2)	-0.97***	-1.06***	-1.05***	-1.02***	-1.01***	-1.00***	-0.99***	-0.98***	-0.98***
	(-488.1)	(-234.0)	(-283.5)	(-329.0)	(-374.1)	(-400.1)	(-430.4)	(-445.5)	(-466.6)

Note:This table reports the difference in relative firm size between private MNCs and state-owned MNCs. Firm size is measured by log employment. The table shows that the relative size of FDI firms to non-exporting firms is smaller for private firms than that for SOEs. This finding is consistent with part 1 of Proposition 3 that relative size of MNCs is smaller for private firms than for SOEs. The numbers in parentheses are t-values. *** (**, *) denotes significance at the 1 percent (5 percent, 10 percent) level.

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Table 6: Private Firms Are More Likely to Undertake FDI

Regressand: FDI Indicator	LPM	Logit	Logit	Rare Event Logit			Complementary Log-Log			
Year coverage:	2000-2008								2004-2008	
SOE defined:	narrow	narrow	narrow	narrow	narrow	broad	narrow	narrow	narrow	narrow
Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SOE Indicator	-0.002**	-0.454*	-0.757***	-1.306***	-0.693***	-0.682***	-1.179***	-0.532*	-0.703***	-0.662**
	(-2.41)	(-1.85)	(-2.88)	(-12.63)	(-2.81)	(-2.88)	(-3.26)	(-1.73)	(-2.68)	(-2.56)
Firm TFP	0.009***	1.333*	1.716**	4.237***	1.838**	1.843**	1.552*	1.603	2.360***	2.500***
	(4.14)	(1.80)	(2.00)	(18.50)	(2.25)	(2.26)	(1.66)	(1.28)	(4.25)	(4.96)
Log Firm Labor	0.003***	0.589***	0.623***	0.588***	0.587***	0.587***	0.565***	0.734***	0.574***	0.567***
	(6.55)	(10.85)	(9.78)	(38.49)	(8.86)	(8.86)	(7.86)	(8.21)	(9.37)	(11.03)
Export Indicator	0.004***	0.900***	1.142***	1.102***	1.145***	1.145***	1.167***	0.736***	1.145***	1.174***
	(7.42)	(4.45)	(6.03)	(26.01)	(6.03)	(6.03)	(5.43)	(3.81)	(5.82)	(6.49)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Foreign Firms Dropped	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tax Haven Dropped	No	No	No	No	No	No	Yes	No	No	No
Distr. FDI Dropped	No	No	No	No	No	No	No	Yes	No	No
Switching SOE Dropped	No	No	No	No	No	No	No	No	Yes	Yes
M&A Deals Dropped	No	No	No	No	No	No	No	No	No	Yes
Observations	1,136,603	1,135,467	895,209	896,314	895,209	895,210	894,815	893,754	701,277	701,204

Note: The regressand is the FDI indicator. All columns include industry-specific fixed effects and year-specific fixed effects. The numbers in parentheses are t-values clustered at the firm level. *** (**) denotes significance at the 1 percent (5 percent) level. Columns (1)-(2) include foreign-invested firms whereas all other columns drop those firms. Columns (1)-(8) cover data over the period of 2000-2008 whereas Columns (9)-(10) cover data over the period of 2004-2008. Column (6) uses broadly defined SOE. Column (7) drops outward FDI to tax haven destinations. Column (8) drops distribution-oriented FDI (i.e., Distr. FDI). Column (9) drops the switching SOEs (i.e., switching from SOEs to private firms). Column (10) drops both switching SOEs and merge & acquisition deals. In all columns,TFP is measured by augmented Olley-Pakes controlling for input price distortion and SOE status.

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Table 7: Distortions in Input Factors Markets

Regressand	Measured Firm Interest Rates			Firm-Level Unit Land Price			City-Level Unit Land Price	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SOE Indicator	-0.134*	-0.174***	-0.089**	-9.39***	-6.78***			
	(-1.90)	(-3.34)	(-2.28)	(-4.43)	(-3.02)			
One-year Lag of SOE Indicator						-11.43***		
						(-4.47)		
SOE Intensity							-54.53*	
							(-1.84)	
One-year Lag of SOE Intensity								-48.97*
								(-1.67)
Other Firm Factors Controls	No	Yes	Yes	No	Yes	Yes	No	No
Year-specific Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-specific Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-specific Fixed Effects	No	Yes	Yes	No	No	No	No	No
City-specific Fixed Effects	No	No	No	No	No	No	Yes	Yes
Year coverage		2000-08			2000-13			2000-08
Number of Obs.	1,119,454	1,119,446	1,136,049	208,320	157,810	103,826	1,489	1,306
R-squared	0.01	0.01	0.01	0.07	0.07	0.08	0.13	0.15

Note: Columns (1)-(3) and (7)-(8) cover the period of 2000-08 whereas columns (4)-(6) cover the period of 2000-13. The regressand in columns (1)-(3) is the firm-level interest rate calculated as the ratio of firm's interest expenses to current liabilities in columns (1) and (2) and to total liabilities in column (3). The regressand in columns (4)-(6) is the firm-level price of land purchased from the government. This is defined as the ratio of the firm's total spending on land acquisition to the area of land it purchases. The regressand in columns (7)-(8) is the prefectural city-level price of land purchased by firms from the government. This is defined as the ratio of government's total land revenue to its land area in each prefectural city. The SOE intensity in columns (7)-(8) is defined as the number of SOEs divided by the total number of manufacturing firms within each prefectural city. All columns control for year-specific and industry-specific fixed effects, respectively. Columns (2) and (3) add other controls of firm-level characteristics such as log firm labor, foreign indicator, export dummy, and province-specific fixed effects. Columns (5)-(6) add other controls of firm-level characteristics such as firm's capital-labor ratio, foreign indicator, and export dummy. Columns (6) uses the lag of SOE indicator whereas column (8) uses the lag of SOE intensity in the regressions. The numbers in parentheses are *t*-values. *** (**, *) denotes significance at the 1 percent (5 percent, 10 percent) level.

Table 8: Logit Estimates on Channels

Measure of Input Price	Measured Firm-Level Interest Rate						Firm-Level Land Price				
Regressand: FDI Indicator	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
SOE Indicator	-0.264**	-0.488***	-0.994***	-0.290**	-0.250**	-0.254**	-0.638***	-1.069***	-1.343***	-1.850***	-1.855***
	(-2.33)	(-4.22)	(-6.36)	(-2.09)	(-1.97)	(-2.11)	(-7.67)	(-8.42)	(-10.46)	(-6.61)	(-6.60)
SOE Indicator × Ind. Input Price Diff.	-0.638*	-0.886**	-0.948*	-1.033**	-0.817**	-0.767*	-0.003**	-0.006***	-0.006***	-0.006***	-0.006**
	(-1.69)	(-2.41)	(-1.90)	(-2.19)	(-2.10)	(-1.89)	(-2.10)	(-4.01)	(-4.35)	(-2.76)	(-2.36)
Ind. Input Price Diff.	0.019	0.057	0.079*	0.090	0.127	0.019	0.001	0.001***	0.001***	0.001**	0.001**
	(0.54)	(1.56)	(1.84)	(1.30)	(0.80)	(0.53)	(1.35)	(3.27)	(3.40)	(2.34)	(2.24)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Foreign Firms Included	Yes	No	No	No	No	Yes	Yes	Yes	No	No	No
Tax Haven Included	Yes	Yes	No	Yes	Yes	Yes	Yes	No	No	No	No
Distribution FDI Included	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year Coverage	2000-08	2000-08	2000-08	2000-08	2000-08	2004-08	2000-13	2000-13	2000-13	2000-08	2004-08
Observations	1,121,845	879,003	873,150	829,655	832,741	883,712	2,278,062	2,200,723	1,750,939	1,005,294	739,082

Note: The regressand is the FDI indicator. The numbers in parentheses are *t*-values. *** (**) denotes significance at the 1 percent (5 percent) level. Input prices in columns (1)-(6) are measured by firm-level interest rate whereas those in columns (7)-(11) are firm-level unit land price. The measured interest rate is calculated as the ratio of firm's interest expenses to current liabilities in columns (1)-(4) and (6) and to total liabilities in columns (5). In particular, the industry interest rate (or unit land price) differential (i.e., Ind. Input Price Diff.) is measured by the average industry-level interest rate (unit land price) paid by private firms minus that paid by SOEs in each 3-digit CIC industries by year. Columns (1)-(5), (10) cover data over 2000-08 whereas Columns (6) and (11) cover data over 2004-08. Columns (7)-(9) cover data over 2000-13. Columns (2)-(5) and (9)-(11) drop foreign firms. Columns (3), (8)-(11) drop FDI to tax haven destination countries. Columns (4) and (5) drop distribution FDI. All columns include other firm-level controls such as firm TFP (in columns (1)-(6) only), log employment and export indicator. All regressions include industry-specific fixed-effects and year-specific fixed-effects whereas column (11) even controls the industry-year specific fixed-effects.

Table 9: Logit Estimates by Sectors

Sectoral Category:	2000-08			2004-08	
Regressand: FDI Indicator	(1)	(2)	(3)	(4)	(5)
SOE Indicator ×	-0.276	-0.290	-0.690	-0.180	-0.170
Labor-intensive Indicator	(-0.68)	(-0.70)	(-1.36)	(-0.44)	(-0.35)
SOE Indicator ×	-0.475*	-0.754***	-1.257***	-0.834***	-0.646**
Capital-intensive Indicator	(-1.73)	(-2.70)	(-2.98)	(-3.09)	(-2.35)
Firm Relative TFP	1.305*	1.837**	1.551*	2.328***	2.069***
	(1.81)	(2.25)	(1.66)	(4.20)	(3.82)
Log Firm Labor	0.582***	0.587***	0.565***	0.570***	0.539***
	(11.18)	(8.84)	(7.85)	(9.61)	(19.46)
Export Indicator	0.896***	1.146***	1.167***	1.152***	1.297***
	(4.44)	(6.03)	(5.43)	(5.93)	(18.71)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Foreign Firms Dropped	No	Yes	Yes	Yes	Yes
Tax Haven Destinations Dropped	No	No	Yes	No	No
SOE switching firms dropped	No	No	No	No	Yes
Observations	1,135,468	895,210	894,816	707,154	554,768

Note: The regressand is the FDI indicator. All columns include industry-specific fixed effects and year-specific fixed effects. The numbers in parentheses are t-values clustered at the firm level. *** (**) denotes significance at the 1 percent (5 percent) level. Columns (1)-(3) cover observations during years 2000-08 whereas columns (4)-(5) cover observations during years 2004-08. Columns (1) keeps foreign invested firms whereas the other columns drop foreign invested firms. Columns (3) drops outward FDI to tax-haven regions. Columns (5) drops SOE switching firms. The relative TFP in columns (1)-(5) are measured by augmented Olley-Pakes controlling for input price distortion and SOE status Labor intensive sectors indicator equals one if firm's Chinese industrial classification is higher than 20 and zero otherwise.

Table 10: Ratio of Foreign Sales to Domestic Sales is Higher for Private MNCs

Regressand:	(1) log(sales)	(2) log(revenue)	(3) log(sales)	(4) log(revenue)	(5) log(sales)	(6) log(revenue)	(7) log(sales)	(8) log(revenue)
Private Indicator × Foreign Indicator	1.223***	1.103***	1.338***	1.111***	1.213***	1.088***	1.326***	1.088***
	(9.92)	(7.91)	(7.51)	(5.78)	(9.72)	(7.57)	(7.65)	(5.58)
Private Indicator	-1.546***	-1.405***	-1.567***	-1.380***	-1.496***	-1.356***	-1.541***	-1.342***
	(-7.35)	(-5.48)	(-5.01)	(-3.38)	(-6.97)	(-5.03)	(-5.12)	(-3.30)
Foreign Indicator	-2.518***	-2.323***	-4.362***	-4.190***	-2.217***	-2.013***	-4.032***	-3.816***
	(-3.81)	(-2.94)	(-8.95)	(-6.82)	(-3.55)	(-2.64)	(-7.82)	(-5.66)
Log Total Assets$_{parent}$	0.855***	0.906***	0.802***	0.901***	0.688***	0.749***	0.670***	0.777***
	(11.39)	(10.05)	(7.48)	(6.25)	(7.76)	(4.82)	(5.84)	(4.34)
Log Exports$_{parent}$			0.181	0.0767			0.133	0.0283
			(1.04)	(0.44)			(0.79)	(0.16)
Log Current Liability$_{parent}$					0.168*	0.160	0.131	0.129
					(1.80)	(1.02)	(1.38)	(0.74)
Parent Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	713	733	586	604	678	698	559	577
R-squared	0.896	0.875	0.897	0.865	0.903	0.881	0.900	0.868

Note: Observation are affiliate-year pairs between 2012 and 2014, and log(*sales*) and log(*revenue*) are log sales and log revenue of each (domestic or foreign) affiliate of Chinese MNCs in a given year. Orbis data of affiliates between 2012-2014 are merged to ASIF data of parent firms between 2011-2013 (i.e., one year lag). Specifically, we merge our ASIF data with the ORBIS data using (Chinese) parent firms' trade registration number (in China) whose information is contained by both data sets after 2011. Both MNC starters and incumbents (after 2011) are included into the regression. Standard errors are clustered at the parent firm level. *** (**, *) denotes significance at the 1 percent (5 percent, 10 percent) level, and *t* statistics are reported in parentheses.