Dynamic and Non-Neutral Productivity Effects of Foreign Ownership: A Nonparametric Approach*

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Abstract

This paper studies two novel productivity characteristics of foreign acquisition on high-tech manufacturing firms: the dynamic and the non-Hicks-neutral effects. A dynamic productivity effect of foreign ownership arises when adoption of foreign technology and management practices takes time to fully realize. Furthermore, these dynamic adjustments may be capital or labor augmenting as adoption of advanced production technologies tends to have non-neutral productivity implications in developed countries. We propose and implement an econometric framework to estimate both effects using firm-level data from China's manufacturing sector. Our framework extends the nonparametric productivity framework developed by Gandhi, Navarro and Rivers (2020), in which identification is achieved using a firm's first-order conditions and timing assumptions. We find strong evidence of dynamic and non-neutral effects from foreign ownership, with significant differences across investment sources. Investment from OECD sources is found to provide a long-term productivity boost for all but the largest recipients, while that from Hong Kong, Macau and Taiwan does not raise performance. These findings have implications for China's declining labor share and for the rising domestic value-added content of its high-tech exports.

JEL Codes: F23, D24, L25, C51, F61, P33, L60.

Keywords: Foreign direct investment, productivity dynamics, non-Hicks-neutral effect, China's manufacturing sector, nonparametric model.

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1 Introduction

The impact of foreign ownership and foreign acquisition on domestic firms' performance has long been a central topic in empirical studies of globalization (see for example Aitken and Harrison (1999), Javorcik (2004), Haskel, Pereira and Slaughter (2007)). Contemporary increases in foreign direct investment (FDI) and domestic manufacturing productivity, especially in China, have kept alive debate concerning causal links between these two observed phenomena. Voluminous empirical work examining the relationship, however, has focused mainly on short-term and Hicks-neutral effects of foreign investment on the production processes of domestic firms. In this paper, we study two novel productivity effects of foreign ownership and foreign acquisition on domestic firms' production function: the *dynamic* and the *non-Hicks-neutral* effects. The former captures the long-term gain or loss from foreign ownership, while the latter provides insight into the labor market impact of FDI-led manufacturing growth. Our empirical context is China's high-tech manufacturing sectors from 1998-2007 and we allow for differential effects of foreign investment across investment sources.

Dynamic productivity effects of foreign ownership arise because adoption of foreign technology and management practices often takes time to fully realize. To fix ideas, consider a domestic firm that is acquired by a foreign partner with advanced technological capability. Absorption of this technology by the acquired firm requires structural transformation in both production and non-production processes. As this adjustment takes time, changes in measured performance may not be fully realized immediately after the acquisition, but accumulate gradually over a longer time horizon. Accounting for this dynamic adjustment provides a more comprehensive picture of how foreign investment affects domestic firm productivity.

Furthermore, since non-Hicks-neutral gains accrue from advanced production technologies deployed in developed countries, which are often found to be capital or labor augmenting, the same technology may have similar effects in developing economies when being transferred through foreign investment. Biased technological change is considered a leading cause of many structural transformations in the labor markets of developed countries. For example, Oberfield and Raval (2014) and Lawrence (2015) identify biased technological change as a major factor in the secular decline of labor share in the US.[1] If foreign investment carries advanced foreign technology content, such investment acts as a firm-level technological shock that alters the production function of recipient domestic firms, with potentially aggregate implications for the host country.

In this paper, we propose a unifying econometric framework to estimate both the dynamic and non-Hicks-neutral productivity effects of firm-level foreign investment. To achieve these goals, we first include the foreign ownership status as an input choice in a nonparametric production function. This allows us to identify the non-linear effects of foreign investment on firms' production function, permitting us to test for non-Hicks-neutral productivity effects. Secondly, we also include the foreign acquisition variable (i.e. a switch from domestic to foreign ownership) in the Markov productivity process so that we can distinguish the productivity dynamic paths before and after the major ownership change. Overall, our econometric framework extends a recent nonparametric identification result for production function estimation proposed by Gandhi, Navarro and Rivers (2020) (henceforth, GNR). The GNR method is distinguished from other existing methods, such as Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves and Frazer (2015), in that its identification exploits more information from the optimizating behavior of firms rather than imposing a functional-form assumption on production functions, enabling us to explore the full impact of foreign ownership on a firm's production process.

We apply this new framework to a panel dataset of Chinese high-tech manufacturing firms from 1998 to 2007. During this period, along with other major reforms including state

[1]Recent evidence of biased technological change is also documented by Doraszelski and Jaumandreu (2018) using panel data of Spanish manufacturing plants. More broadly, Karabarbounis and Neiman (2013) document a global trend of declining labor share, not only in developed countries but also in developing countries.

enterprise restructuring and its 2001 accession to the World Trade Organization, China experienced annual inflows of over $40 billion in foreign investment, almost all in manufacturing industries.[2] Contemporaneously, China's manufacturing sectors sustained high rates of productivity growth (Brandt, Biesebroeck and Zhang (2012)). This provides an ideal context to investigate the impacts of foreign investment on Chinese firms' productivity.

Our analysis focuses on high-tech manufacturing because these are sectors where foreign partners likely have a technological advantage over Chinese domestic firms. We also further explore the differential impacts of foreign investment based on origin: investment from Organization for Economic Co-operation and Development (henceforth, OECD) member countries versus that from Hong Kong, Macau and Taiwan (henceforth, HKMT). This empirical interest is motivated by recent evidence that HKMT firms are not more productive than private domestic Chinese firms.[3] Indeed, Huang, Jin and Qian (2013) find that HKMT firms tend to underperform as compared to other FDI firms on metrics such as return on asset and return on equity, and that their performance deteriorates in post acquisition periods.[4] Our analysis supports past findings that HKMT investment has different effects on productivity as compared to OECD investment, and we are also able to compare the dynamics of these impacts and their non-Hicks-neutral implications.

We offer three main results. First, in our baseline model, we show that foreign acquisition of a Chinese private firm in high-tech industries improves the target firm's productivity in

[2]Value obtained from Naughton (2006), figure 17.1. During this time period, foreign direct investment inflows averaged between 3 and 4 percent of Chinese GDP.

[3]An unknown share of HKMT firms are actually mainland Chinese firms that establish headquarters in neighboring locations to enjoy favorable tax treatment reserved for foreign investors (Du, Harrison and Jefferson (2012)). This phenomenon is referred to as round-trip FDI in Huang (2003). Even though round-trip FDI was believed to be substantial, especially from periods between 1986 and 1998, it is unlikely that it fully explains our results. HKMT investment played an important role in transferring technology, financing production activities, especially for Chinese exports, and most likely had a positive effect on firm productivity during this period. During our sample period from 1998 to 2007 however, HKMT investment may have played a different role, especially in technology transfer, and thus had different implications for productivity. We thank the anonymous referees for pointing this out.

[4]In Huang, Jin and Qian (2013), HKMT investment in China is coined as ethnically Chinese economies (ECEs) investment. They find that, in contrast to conventional belief, ethnically-tied investment Hong Kong, Macau and Taiwan underinvest in factors that may bear long-term benefits such as human capital and technology.

both the short and long run, with the long-run effect typically smaller than the short-run effect.[5] Furthermore, the long-run productivity effect varies significantly across firm sizes: larger firms generally benefit from foreign ownership while smaller firms do not. Secondly, when we distinguish foreign investment coming from HKMT versus OECD-member states, we find no productivity premium relative to domestic ownership from HKMT acquisition, but a larger than average premium from OECD firm ownership. Interestingly, the production technology of HKMT-acquired firms, which manifests as output elasticities with respect to production inputs, are remarkably similar to those of private domestic firms. Finally, and importantly, we find strong evidence of non-Hicks-neutral impacts of OECD ownership on China's high-tech manufacturing sectors. In particular, we find that foreign technology embedded in OECD investment has both labor- and capital-augmenting implications.

Foreign Ownership and Productivity

The relationship between foreign ownership and firm productivity has been studied extensively in the literature. In most cases, researchers investigate the short-term and Hicks-neutral productivity effects, and empirical results are mixed. For example, Djankov and Hoekman (2000), Harris (2002), Harris and Robinson (2003), Conyon et al. (2002), Girma and Gorg (2007), Arnold and Javorcik (2009), Girma et al. (2015) find that foreign-invested firms (and foreign affiliates) have higher productivity than do their domestic counterparts. In the case of foreign acquisition, foreign investment is found to boost the productivity of domestic recipient firms. In constrast, other studies such as Griffith (1999), Benfratello and Sembenelli (2006), Fons-Rosen et al. (2013), Wang and Wang (2015) find that foreign ownership typically has no or a very small positive productivity effect post acquisition.

This paper introduces a new econometric framework for exploring the productivity impacts of foreign acquisition, a contribution made evident by a brief review of prior empirical approaches. The most common empirical strategy in recent studies is a two-stage approach,

[5] Productivity implications of foreign acquisition may differ substantially in other sectors, where a technology gap between OECD firms and Chinese firms may not be present.

where in the first stage the researcher estimates a structural measure of firms' performance (i.e. total factor productivity (TFP)), while in the second stage the researcher combines a difference-in-difference estimator with propensity score matching to identify an average treatment effect of foreign ownership on firms' performance. For instance, Arnold and Javorcik (2009) employ this strategy and find that foreign investment substantially improve productivity of recipient plants in Indonesia, with an average effect of about 13.5% three years after acquisition. Wang and Wang (2015) implement this strategy to study the effect of foreign acquisition compared to domestic acquisition, finding no significant productivity advantage due to foreign equity participation. Girma and Gorg (2007) and Girma et al. (2015) apply the same strategy to UK and Chinese manufacturing, respectively, and arrive at similar qualitative conclusions. Most closely related to our paper, Kamal (2015) employs this two-stage approach to compare productivity differences between HKMT and OECD-owned firms in China and finds productivity premium of OECD owership. There are often two common underlying assumptions in these studies: (1) the productivity process is exogenous with regard to the choice of foreign acquisition in the first-stage (see also Loecker (2013)'s critics of this stage in the context of learning by exporting); and (2) the effect of foreign ownership is Hicks-neutral, meaning that it only enters the production function in a linear manner. In contrast, our econometric model relaxes these assumptions and allows the exploration of different productivity dimensions that are not feasible with previous empirical strategies.

Our Approach

Our econometric framework builds on a dynamic model of firm behavior introduced in the productivity estimation literature. This model and its structural estimation have been developed by a series of papers including Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg, Caves and Frazer (2015) (henceforth, OP, LP and ACF, respectively) and Gandhi, Navarro and Rivers (2020). Both the ACF and GNR methods draw insights from LP in that the levels of static inputs are determined based on firms' current realization of productivity and hence, contain information about this unobserved characteristic. These observed static inputs can then be used to nonparametrically control for productivity. ACF combines this information with a Leontief functional-form assumption to identify the production function. GNR extracts information from static inputs taking a different angle. In addition to using the *levels* of static inputs to control for productivity, GNR exploits *static input shares* and the first order conditions to provide additional sources of information for identification. This source of additional information allows GNR to overcome the nonparametric non-identification issue of the classic OP and LP approaches for the gross output production function.[6]

Our initial points of departure are papers by Loecker (2013) and Doraszelski and Jaumandreu (2013), who extend productivity analysis to explore learning-by-exporting and R&D, respectively.[7] Most closely related to our paper is Chen et al. (2020) who extend GNR's nonparametric framework to study productivity dynamics of privatization in China. GNR estimates a gross output production function and allows for flexible nonlinearities in both production technology and productivity growth. Therefore, the GNR method serves our purpose by making estimation of the dynamic and non-Hicks-neutral effects feasible. Our identification is obtained by the firm's first-order condition for profit maximization with respect to material and by the timing assumptions of firm's actions. We do not distinguish between revenue productivity (denoted as TFPR) and physical productivity (TFP) as we are interested in the general performance of firms, which might include firm-specific market power as well.[8]

Our approach offers several advantages. First, by including the choice of foreign acquisition and allowing this choice to affect future productivity through a Markov process, we

[6]See also reviews of this non-identification issue provided by Bond and Söderbom (2005), Ackerberg, Caves and Frazer (2015), Gandhi, Navarro and Rivers (2020).

[7]These extensions date back to Griliches (1979)'s knowledge capital model in the productivity literature.

[8]For a survey regarding the distinction between TFPR and TFP, see Loecker and Goldberg (2014). In this paper, we use the term "productivity" to refer to firms' overall performance.

explicitly recover the productivity adjustment path of firms after the ownership change. This enables us to compare short-term versus long-term effects of foreign ownership and foreign acquisitions. Secondly, by estimating a nonparametric production function, we can account for the full heterogeneity of the production function. This feature is particularly important since even within a narrowly defined industry, firms with different ownership types and different scales of production may exhibit substantial heterogeneity in production technology. Finally, our framework is easily extendable to study other dimensions of ownership changes such as distinguishing effects from different sources of foreign investment (OECD versus HKMT).

The rest of the paper is organized as follows. In section 2, we describe the institutional background of foreign investment in China's manufacturing sectors from 1998-2007. In section 3, we propose our empirical approach and estimation strategy. Section 4 details our dataset. Section 5 presents and discusses our results, while section 6 draws broader implications of our findings. We provide additional details on benchmarking and data source in the Appendix.

2 Foreign Investment in China from 1998 to 2007

Table 1 shows aggregate shares of firm and employment by ownership type in 1998 and 2007. Two clear trends can be seen from this table. The first trend is the rapid growth in China's private sector. In addition to robust entry of new firms, the Chinese government pursued a substantial program of state-owned enterprise (SOE) reform, the implications of which are studied by Chen et al. (2020). The second trend is a sharp increase in foreign investment in China's manufacturing sectors during this period, with the number of HKMT-owned firms almost doubling while those with OECD investors tripling in number. The employment share of foreign-invested firms increases markedly from 6.7% to 13% for HKMT firms and from 5% to 15% for OECD firms between 1998 and 2007. Taken together, the table has two important implications. First, the number of foreign firms grows proportionally to the total number of firms in China's manufacturing during this sample period. Secondly, the scale of foreign firms is larger than that of average domestic firms. In 2007, foreign activities, measured by employment shares, account for almost 30% of Chinese manufacturing, highlighting their importance in Chinese manufacturing sector during the sample period. These magnitudes suggest that the impact of foreign investment on productivity is an important aspect of China's post-WTO-accession development.

The increase in economic activity of foreign firms reveals much more interesting patterns in several particular industries. Figure 1 captures employment share of HKMT firms and OECD firms in *high-tech* industries over time. We define the high-tech group to include industries that involve relatively more sophisticated production processes. This group of industries includes 2-digit manufacturing of: general-purpose machinery (35), special-purpose machinery (36), transportation equipments (37), electrical machinery (39), communication equipment and computers (40), and precision instruments (41). Our definition of the high-tech industries is very closely related to China's official "High-tech Industry Statistical Classification Catalog" (Guo Tong Zi [2002] No.33).[9] In the high-tech group, the share of foreign employment increases markedly from about 7% to 16% for HKMT firms and from about 8% to 25% for OECD firms. Again, if one were to combine HKMT and OECD firms into one category, this increase is steep and consequently by 2007, foreign employment accounts for about 40% of the high-tech industries. Another interesting pattern captured by Figure 1 is that there is an abrupt surge in the employment share of OECD firms after 2003. This surge is potentially due to a major overhaul of China's FDI policy in 2002 following China's WTO accession giving preferences to the high-tech sectors.[10]

[9] Although there are some differences between the two classifications, we present the robustness of our results to this alternative official classification in section 5.

[10] See Lu, Tao and Zhu (2017) for a review of FDI policy in China.

3 The Model

We start with an augmented model of a nonparametric production function. Consider the following production function:

$$y_{it} = f(k_{it}, l_{it}, m_{it}, v_{it}) + \omega_{it} + \varepsilon_{it}, \tag{1}$$

where $y_{it}, k_{it}, l_{it}, m_{it}$ are the natural logs of output (Y_{it}), capital (K_{it}), labor (L_{it}), and material (M_{it}) of firm i in year t. v_{it} indicates the ownership status of the firm, whether domestic (D) or foreign (F):

$$v_{it} = \begin{cases} 1 \text{ if Foreign (F)} \\ 0 \text{ if Domestic (D).} \end{cases} \tag{2}$$

ω_{it} measures (Hicks-neutral) productivity of the firm. We interpret this term as firm's overall performance rather than physical productivity in order to avoid the need to identify firm markups, which is difficult in Chinese firm-level data due to the lack of firm-level price information. ε_{it} is a random measurement error and fully exogenous. In this model, the indicator variable v_{it} captures fundamentally different technology (heterogeneity) between foreign firms (F) and domestic firms (D). We treat this v_{it} as an input into the production processes of firms and allow it to be correlated with productivity ω_{it}.

The second extended feature of this model is the Markov productivity process. Specifically, we consider the Markovian productivity:

$$\omega_{it} = h(\omega_{i,t-1}, d_{it}) + \eta_{it}, \tag{3}$$

where d_{it} indicates if the firm switches ownership status from domestic to foreign between the periods $(t-1)$ and t. If the firm's ownership status changes, this indicator variable equals 1. Otherwise, this indicator equals 0. In particular, d_{it} is defined as:[11]

$$d_{it} = \begin{cases} 1 \text{ if } v_{i,t-1} = 0 \text{ and } v_{it} = 1 \\ 0 \text{ otherwise .} \end{cases} \tag{4}$$

The function $h(.)$, which captures the expected productivity of the firm at the beginning of period t, is allowed to be nonparametric.

The structures in equations (1)-(4) combined allow us to capture the short-run and long-run effects on productivity of firms due to ownership change. Here, we interpret v_{it} as the *permanent shift* in productivity trajectory between domestic and foreign firms. On the other hand, d_{it} captures the *initial productivity shock* of firms who switch ownership as compared to firms who do not, conditioning on the same level of past productivity $\omega_{i,t-1}$. Though we maintain the nonparametric specification for the production function $f(.)$, we simply let $h(.)$ to be linear, which is a widely used specification in the productivity literature. Specifically, we assume that the Markov productivity is a linear autoregressive of order one (i.e., AR(1)) process given as:

$$\omega_{it} = \rho\omega_{i,t-1} + \gamma d_{it} + \eta_{it}. \tag{5}$$

When the Markov process is stationary (i.e. $|\rho| < 1$), the initial productivity shock will die out over time.

Next, we follow the productivity literature in imposing the scalar unobservability assumption:

$$m_{it} = \mathbb{M}(k_{it}, l_{it}, v_{it}, \omega_{it}), \tag{6}$$

where $\mathbb{M}(.)$ is strictly monotone in ω_t, conditioning on all other inputs and state variables. Intuitively, equation (6) implies that more productive firms use more material to produce more output, conditioning on the same market environments and on all other inputs as

[11] In the data, there are a few firms that switch ownership from foreign to domestic. Therefore, in principle, we can include another indicator for this type of switch. However, these cases are very few and we exclude domestic acquisitions in this study.

well as state variables such as ownership status.[12] A direct result from this assumption is that function $\mathbb{M}(.)$ can be inverted to nonparametrically control for productivity based on observable inputs used:

$$\omega_{it} = \mathbb{M}^{-1}(k_{it}, l_{it}, v_{it}, m_{it}). \tag{7}$$

We also need timing assumptions to identify our production function. The formal timing assumptions follow GNR and Chen et al. (2020). We describe the timing of firm's actions as:

- At the end of period $(t-1)$, the firm chooses (k_{it}, l_{it}, v_{it}) and whether to exit at t.
- At the beginning of period t, η_{it} (and hence ω_{it}) realizes. The firm observes its productivity for period t.
- The firm optimally chooses m_{it}, after which ε_{it} realizes and completely determines y_{it}.
- At the end of period t, the firm chooses $(k_{i,t+1}, l_{i,t+1}, v_{i,t+1})$ and whether to exit at $(t+1)$, repeating the same process.

Based on this timing structure, we have classified inputs based on their information sets. Specifically, we first assume that k_{it}, l_{it} and v_{it} are dynamic inputs that belong to the information set of the firm at the end of period $(t-1)$, which we denote as $\mathbb{I}_{i,t-1}$. This assumption creates exclusion restrictions between these dynamic inputs and the productivity shock η_{it} as well as the random measurement error ε_{it}. Additionally, we assume that m_{it} is a static input that belongs to the information set in period t, which we denote as $\mathbb{I}_{it}$, but not $\mathbb{I}_{i,t-1}$. This means that m_{it} is allowed to be correlated with η_{it}. However, since m_{it} is not correlated with the random measurement error ε_{it} by construction, this creates another exclusion restriction for us to identify the elasticity with respect to this input. Intuitively, capital and labor are assumed to be sticky inputs: they take time to plan, implement and

[12]This assumption can be shown to hold under various market structures when firms solve a static optimization problem with respect to material. See expositions of this assumption in Levinsohn and Petrin (2003), Ackerberg, Caves and Frazer (2015), Gandhi, Navarro and Rivers (2020).

go into actual production. On the other hand, firms are assumed to have full flexibility in adjusting material corresponding to their temporal productivity shocks.

Dynamic Interpretation

It is important to clarify how we interpret the dynamics in our augmented model. As we discussed above, the term v_{it} is the foreign ownership status indicator and hence it captures the heterogeneity in production technology between foreign-owned versus domestic firms. More precisely, we specify that v_{it} captures the permanent change in the production function $f(.)$ so that it can describe the permanent productivity shift for firms that switch ownership from being purely domestic to having foreign equity participation (i.e., a permanent difference between two long-run equilibrium levels). On the other hand, the term d_{it} indicates the moment of ownership change so that it captures the initial productivity shock on ω_{it}. Under the stationarity of ω_{it}, this initial shock eventually disappears and helps us to distinguish between the short-term and the long-term productivity effects. The immediate productivity effect on firms switching ownership status is reflected by the total effect from v_{it} and d_{it}, whereas the permanent effect comes from v_{it} only.

Interestingly, the (residual) output paths of firms after foreign acquisitions can vary depending on the directions of the effects of v_{it} and d_{it}, and their relative magnitudes. For instance, we suppose the marginal effects from foreign owndership are positive: $\frac{\partial y_{it}}{\partial v_{it}} = \frac{\partial f}{\partial v} > 0$ in equation (1) and $\frac{\partial \omega_{it}}{\partial d_{it}} = \gamma > 0$ in equation (5). When ω_{it} is a stationary Markov process with drift (i.e., $|\rho| < 1$ in equation (5)), then the ownership change yields overshooting in output at the initial phase ($\frac{\partial f}{\partial v} + \gamma$), but the long-run effect from the ownership change after the t^{th} period is $\frac{\partial f}{\partial v} + \gamma \rho^t$, which becomes $\frac{\partial f}{\partial v}$ as the time after foreign acquisition $t \to \infty$. Figure 2 depicts possible (residual) output change trajectories solely from foreign acquisitions when $0 < \rho < 1$. From this figure, we can predict how ownership status change affects the firm's output over time once we estimate the marginal effects $\frac{\partial y_{it}}{\partial v_{it}}$ and $\frac{\partial \omega_{it}}{\partial d_{it}}$.

Non-Hicks-neutral Effects

We now distinguish between Hicks-neutral and non-Hicks-neutral effects. In our framework, the effect of foreign ownership is Hicks-neutral if and only if the production function in equation (1) can be rewritten in the following form:

$$y_{it} = f_1(k_{it}, l_{it}, m_{it}) + f_2(v_{it}) + \omega_{it} + \varepsilon_{it}. \tag{8}$$

In other words, the productivity effect of foreign ownership is Hicks-neutral if and only if production function $f(.)$ is additively separable between the main inputs (k_{it}, l_{it}, m_{it}) and the ownership indicator v_{it}. An implication of the specification in equation (8) is that the elasticities with respect to capital, labor, material, i.e., $\frac{\partial f_1(.)}{\partial k}$, $\frac{\partial f_1(.)}{\partial l}$, $\frac{\partial f_1(.)}{\partial m}$, are not functions of ownership, v_{it}. Importantly, since the specification in equation (8) is nested within our nonparametric model in equation (1), we can test for the additive separability of v_{it} in the production function by comparing our estimated elasticities under two counterfactual scenarios: when $v_{it} = 1$ versus when $v_{it} = 0$. If the effect of foreign ownership is Hicks-neutral, elasticities with respect to other inputs should remains the same whether $v_{it} = 1$ or 0.[13]

Figure 3 depicts the marginal rate of technical substitution $(MRTS)$ between two input factors X_1 and X_2, where $X_1, X_2 \in \{K, L, M\}$, under two counterfactual scenarios: $v_{it} = 1$ verus $v_{it} = 0$, and under the assumption that the effect of foreign ownership is not Hicks-neutral. In this figure, when a firm has foreign ownership ($v_{it} = 1$), $MRTS_{12}$ is larger as compared to the case where the same firm is domestically owned ($v_{it} = 0$), conditioning on the same input mix of X_1 and X_2 ($MRTS_{12} = \frac{\partial f}{\partial x_1} / \frac{\partial f}{\partial x_2} \times \frac{X_2}{X_1}$).[14] In this case, foreign ownership has X_1-augmenting technology implications (relative to X_2) and effectively increases the

[13] Furthermore, we can compute the labor share, capital share and material share in a counterfactual exercise where we remove all the foreign investment in China's manufacturing sector in our sample period.

[14] Here lowercase x_1 and x_2 are the natural logs of X_1 and X_2. Therefore, $MRTS_{12} = \frac{MP_{X_1}}{MP_{X_2}} = \frac{\partial Y}{\partial X_1} / \frac{\partial Y}{\partial X_2} = \frac{\partial \log Y}{\partial \log X_1} / \frac{\partial \log Y}{\partial \log X_2} \times \frac{X_2}{X_1} = \frac{\partial y}{\partial x_1} / \frac{\partial y}{\partial x_2} \times \frac{X_2}{X_1} = \frac{\partial f}{\partial x_1} / \frac{\partial f}{\partial x_2} \times \frac{X_2}{X_1}$.

share of X_1 (relative to X_2) in total output derived from the production function.

Identification and Estimation

We follow the nonparametric identification and the two-step estimation procedure by Gandhi, Navarro and Rivers (2020).

For the identification, we use the the first order condition (FOC) of the firm's profit maximization problem. Firm i maximizes its profit at the period t with respect to material M_{it}:

$$\max_{M_{it}} P_t \mathbb{E}\left[\exp\left(f\left(k_{it}, l_{it}, m_{it}, v_{it}\right) + \omega_{it} + \varepsilon_{it}\right) | \mathbb{I}_{it}\right] - p_t M_{it}, \tag{9}$$

where $\mathbb{I}_{it}$ denotes the firm's information set at the beginning of t. P_t and p_t are respectively prices of output and material which the firm takes as given. Since M_{it} does not have any dynamic implications and only affects current period profits, the FOC of this problem gives us:

$$P_t \frac{\partial \exp\left(f\left(k_{it}, l_{it}, m_{it}, v_{it}\right)\right)}{\partial M_{it}} \exp\left(\omega_{it}\right) \mathcal{E} - p_t = 0, \tag{10}$$

where $\mathcal{E} \equiv \mathbb{E}\left[\exp\left(\varepsilon_{it}\right) | \mathbb{I}_{it}\right] = \mathbb{E}\left[\exp\left(\varepsilon_{it}\right)\right]$.

Taking log of equation (10) and differencing with the production function $Y_{it} = \exp\left(y_{it}\right)$ in equation (1), we get:

$$\begin{aligned} \log s_{it} &\equiv \log \frac{p_t M_{it}}{P_t Y_{it}} \\ &= \log \mathcal{E} + \log\left(\frac{\partial}{\partial m_{it}} f\left(k_{it}, l_{it}, m_{it}, v_{it}\right)\right) - \varepsilon_{it} \\ &\equiv \log D^{\mathcal{E}}\left(k_{it}, l_{it}, m_{it}, v_{it}\right) - \varepsilon_{it}. \end{aligned} \tag{11}$$

In equation (11), s_{it} denotes the material share of total revenue which we can obtain directly from the firm-level data. Intuitively, it implies that material share is informative about the elasticity of output with respect to material in firm's production function, i.e.,

$\frac{\partial}{\partial m_{it}} f\left(k_{it}, l_{it}, m_{it}, v_{it}\right)$. From Theorem 2 of GNR, we can identify $\frac{\partial}{\partial m_{it}} f\left(k_{it}, l_{it}, m_{it}, v_{it}\right)$ as

$$\frac{\partial}{\partial m_{it}} f\left(k_{it}, l_{it}, m_{it}, v_{it}\right) = \frac{D^{\mathcal{E}}\left(k_{it}, l_{it}, m_{it}, v_{it}\right)}{\mathcal{E}}, \tag{12}$$

where $\mathcal{E} = \mathbb{E}\left[D^{\mathcal{E}}\left(k_{it}, l_{it}, m_{it}, v_{it}\right)/s_{it}\right]$ from equation (11).

We then integrate the partial derivative $\frac{\partial}{\partial m_{it}} f\left(k_{it}, l_{it}, m_{it}, v_{it}\right)$ to recover the production function $f(.)$ up to a constant addition $C(.)$ as a function of k_{it}, l_{it}, and v_{it}:

$$\int \frac{\partial}{\partial m_{it}} f\left(k_{it}, l_{it}, m_{it}, v_{it}\right) dm_{it} = f\left(k_{it}, l_{it}, m_{it}, v_{it}\right) + C\left(k_{it}, l_{it}, v_{it}\right). \tag{13}$$

Plugging the expression of $f(.)$ from equation (13) into the production function equation (1), we define

$$\begin{aligned} \Psi_{it} &\equiv y_{it} - \varepsilon_{it} - \int \frac{\partial}{\partial m_{it}} f\left(k_{it}, l_{it}, m_{it}, v_{it}\right) dm_{it} \\ &= -C\left(k_{it}, l_{it}, v_{it}\right) + \omega_{it} \end{aligned} \tag{14}$$

and combining with the Markov process expression of ω_{it} in equation (7), we have

$$\Psi_{it} = -C\left(k_{it}, l_{it}, v_{it}\right) + \rho\left\{\Psi_{it-1} + C\left(k_{it-1}, l_{it-1}, v_{it-1}\right)\right\} + \gamma d_{it} + \eta_{it}. \tag{15}$$

Making use of the exclusion restrictions described above, equation (15) is fully indentified, in the sense that $\mathbb{E}[\eta_{it}|k_{it}, k_{it-1}, l_{it}, l_{it-1}, v_{it}, v_{it-1}, d_{it}, \Psi_{it-1}] = 0$.

For estimation, based on the identification results above, we apply the standard series estimation in two steps. In the first step, we nonparametrically estimate the partial derivative of $f(.)$ with respect to m_{it}. In the second step, we integrate this partial derivative and recover the production function by combining it with the Markov productivity process.

More precisely, in the first step, we approximate $D^{\mathcal{E}}(.)$ by the second-order polynomial sieves and solve the following least squares problem from equation (11):

$$\min_{\theta} \sum_{i=1}^{n} \sum_{t=1}^{T} \left\{ \log s_{it} - \log \left[\theta_0 + \sum_{0 \leq j_k + j_l + j_m \leq 1} \theta_{1,j_k,j_l,j_m} k_{it}^{j_k} l_{it}^{j_l} m_{it}^{j_m} v_{it} + \sum_{1 \leq j_k + j_l + j_m \leq 2} \theta_{2,j_k,j_l,j_m} k_{it}^{j_k} l_{it}^{j_l} m_{it}^{j_m} \right] \right\}^2 \tag{16}$$

for $j_k, j_l, j_m \in \{0, 1, 2\}$, where θ denotes the vector of all the unknown parameters. Note that we exclude the v_{it}^2 term since v_{it} is binary. From equation (12), the estimate of the partial derivative $\frac{\partial}{\partial m_{it}} f(k_{it}, l_{it}, m_{it}, v_{it})$ is then obtained as

$$\frac{\partial}{\partial m_{it}} \hat{f}(k_{it}, l_{it}, m_{it}, v_{it}) = \frac{\hat{D}^{\mathcal{E}}(k_{it}, l_{it}, m_{it}, v_{it})}{\hat{\mathcal{E}}}, \tag{17}$$

where $\hat{\mathcal{E}} = (nT)^{-1} \sum_{i=1}^{n} \sum_{t=1}^{T} \exp(\hat{\varepsilon}_{it})$, $\hat{\varepsilon}_{it} = \log s_{it} - \log \hat{D}^{\mathcal{E}}(k_{it}, l_{it}, m_{it}, v_{it})$, and $\hat{D}^{\mathcal{E}}$ is from the nonlinear least squares in equation (16).

In the second step, we have

$$\hat{\Psi}_{it} = y_{it} - \hat{\varepsilon}_{it} - \int \frac{\partial}{\partial m_{it}} \hat{f}(k_{it}, l_{it}, m_{it}, v_{it})\, dm_{it}$$

from equation (14), where

$$\begin{aligned} & \int \frac{\partial}{\partial m_{it}} \hat{f}(k_{it}, l_{it}, m_{it}, v_{it})\, dm_{it} \qquad (18) \\ = \;& \frac{1}{\hat{\mathcal{E}}} \int \hat{D}^{\mathcal{E}}(k_{it}, l_{it}, m_{it}, v_{it})\, dm_{it} \\ = \;& \frac{1}{\hat{\mathcal{E}}} \left\{ \hat{\theta}_0 m_{it} - \sum_{0 \leq j_k + j_l + j_m \leq 1} \frac{\hat{\theta}_{1,j_k,j_l,j_m}}{j_m + 1} k_{it}^{j_k} l_{it}^{j_l} m_{it}^{j_m+1} v_{it} - \sum_{1 \leq j_k + j_l + j_m \leq 2} \frac{\hat{\theta}_{2,j_k,j_l,j_m}}{j_m + 1} k_{it}^{j_k} l_{it}^{j_l} m_{it}^{j_m+1} \right\} \end{aligned}$$

from equation (17), where the parameter estimates are from the nonlinear least squares in equation (16). We now approximate $C(k_{it}, l_{it}, v_{it})$ by the second-order polynomial sieves and obtain

$$\hat{C}(k_{it}, l_{it}, v_{it}) = \hat{\beta}_0 + \sum_{0 \leq j_k + j_l \leq 1} \hat{\beta}_{1,j_k,j_l} k_{it}^{j_k} l_{it}^{j_l} v_{it} + \sum_{1 \leq j_k + j_l \leq 2} \hat{\beta}_{2,j_k,j_l} k_{it}^{j_k} l_{it}^{j_l} \tag{19}$$

for $j_k, j_l \in \{0, 1, 2\}$, where the parameter estimates are from GMM estimation based on the following moment conditions:

$$\begin{aligned}
\mathbb{E}\left[\eta_{it}\right] &= 0, \\
\mathbb{E}\left[\eta_{it}\Psi_{it-1}\right] &= 0, \\
\mathbb{E}\left[\eta_{it}d_{it}\right] &= 0, \\
\mathbb{E}\left[\eta_{it}k_{it}^{j_k}l_{it}^{j_l}\right] &= 0 \;\text{ for } 1 \leq j_k + j_l \leq 2 \text{ and } j_k, j_l \in \{0,1,2\}, \\
\mathbb{E}\left[\eta_{it}k_{it}^{j_k}l_{it}^{j_l}v_{it}\right] &= 0 \;\text{ for } 0 \leq j_k + j_l \leq 1 \text{ and } j_k, j_l \in \{0,1\}.
\end{aligned}$$

From equation (13), the production function estimate $\hat{f}\left(k_{it}, l_{it}, m_{it}, v_{it}\right)$ is obtained by subtracting the estimated function in (19) from that in (18):

$$\hat{f}\left(k_{it}, l_{it}, m_{it}, v_{it}\right) = \int \frac{\partial}{\partial m_{it}} \hat{f}\left(k_{it}, l_{it}, m_{it}, v_{it}\right) dm_{it} - \hat{C}\left(k_{it}, l_{it}, v_{it}\right).$$

In addition, estimated elasticities can be readily calculated since equations (18) and (19) are in polynomial forms. For inferences, we follow GNR in computing nonparametric bootstrap standard errors, clustered by firms, for all of our reported statistics.

4 Data

Our data are drawn from the Annual Survey of Industrial Enterprises (ASIE) in China from 1998 to 2007. This is a panel survey data covering all industrial firms with sales above 5 million Renminbi (RMB). The survey encompasses more than 90% of industrial activities in China. Table B1 in the Appendix summarizes aggregate statistics of this panel dataset by year, which matches the official published data from the Chinese government and ensures the quality of our dataset. We follow Brandt, Biesebroeck and Zhang (2012) and Brandt, Biesebroeck and Zhang (2014) in basic data cleaning procedures and in constructing our capital stock series using the perpetual inventory method.[15] Our foreign ownership definitions are based on the official registration types recorded in the dataset. The official threshold of foreign capital share to be categorized as foreign ownership is 25%. In our dataset, however, more than 75% of foreign firms have a foreign capital share above 30%.

As previously mentioned, our empirical applications focus on the designated high-tech industries in China. Therefore, we keep only a sample of six 2-digit industries, including: general-purpose machinery (35), special-purpose machinery (36), transportation equipment (37), electrical machinery (39), communication equipment and computers (40) and precision instruments (41). Since we are mainly interested in comparing foreign-owned firms with private domestic firms, we drop all the observations that are registered as state-owned enterprises (SOE).[16] We drop all firms that switch their ownership status back and forth between domestic and foreign more than once in the panel. There are 70 firms belong to this category from the raw data. Outliers in terms of capital, labor, material and material share are also excluded from our sample (outside of the corresponding 1^{st} and 99^{th} percentiles). These procedures leave us with 126,387 panels spanning the 10-year period. Roughly 25% of total firm-year observations are registered as foreign firms and 75% are registered as domestic firms.

A firm is identified as switching from domestic to foreign-owned in period t if it is registered as (domestically) privately-owned in period $t-1$ and as foreign-owned in period t. Since our data allow us to further classify foreign-owned firms into HKMT versus OECD-owned, a (domestically) privately-owned firm in period $t-1$ is indentified as switching to HKMT-type if it is HKMT-owned in period t, and as OECD-type if it is OECD-owned in period t. During our sample period, a total of 2,192 firms switch ownership status from

[15]For basic cleaning procedures, we drop all firms with missing or negative values of the main variables, including revenue, fixed assets, employment, material, and wage-bill. We drop all firms that employ fewer than 8 workers. Real capital stocks are constructed based on procedures as specified in Brandt, Biesebroeck and Zhang (2014).

[16]Our identification exploits the profit-maximizing behavior of firms, thus it is more plausible to compare private domestic with foreign-owned firms. Furthermore, there are very few transitions between SOE firms and foreign firms in our sample period.

domestic to foreign, in which 1,079 firms switch to HKMT-type and 1,113 firms switch to OECD-type. Overall, the number of switchers is small relative to the entire sample size, yet it is enough to identify the dynamic effects of a change in foreign ownership status on productivity.

5 Results

Baseline

In the baseline specification, we combine HKMT and OECD firms, and treat them as one common type of foreign firms which share the same technology. Figure 4 describes the relationship between mean output $\hat{f}(.)$ and production inputs. There are two notable patterns from Figure 4. First, conditioning on the same amount of labor used, foreign firms produce more output compared to private domestic firms. Nevertheless, such a premium disappears when conditioning on capital and material. Our estimation thus suggests that technology associated with foreign ownership is labor-augmenting technology (i.e., v_{it} primarily interacts with l_{it}). Secondly, in the first graph, foreign dominance in labor production appears to be largest among firms of middle size. For some of the largest firms, such dominance is not evident, implying that large domestic firms are technologically comparable to foreign firms.

Column (1) of Table 2 reports the mean elasticities with respect to each input and the parameters of the productivity process. Overall, our model delivers reasonable estimates of mean elasticities with respect to capital, labor and material. The ratio of the capital over labor elasticity is close to 1, reflecting the relatively capital intensive nature of the high-tech industries.[17] We note that even though we do not impose any parametric assumptions on production function, the estimated mean elasticity of material is 0.692, suggesting that the

[17] We estimate our model for the textile-related industries and find a much lower ratio. For Textiles (17), this ratio is 0.75. For Garments (18) and Leather (19), this ratio is 0.5. More results regarding these sectors are available upon request.

true production function differs from that of the Leontief form.[18]

In our baseline specification, we find that the mean effect of v is zero, which we interpret as evidence against a long-term effect on productivity of changing ownership status from domestic to foreign. The coefficient for d is positive and significant, suggesting a strong initial positive productivity shock to firms who switch ownership status. In particular, firms that switch ownership status have on average a 2.7% short-term productivity effect as compared to firms who do not, subject to the same Markov process and past productivity $\omega_{i,t-1}$. This is consistent with the previous literature, which documents the existence of positive productivity shock of foreign acquisition.

Since we consider a nonparametric production function, we can further recover heterogeneity of the productivity effects. Based on the estimated marginal effects of v and d, panel (a) in Figure 5 depicts the productivity dynamics of our baseline model for all the foreign firms (i.e., both HKMT and OECD firms) as in Figure 2. Figure 6 depicts the densities of long-term and short-term productivity effects of all the domestic firms after the foreign acquisition. We can see that the mode of short-term effects is positive whereas that of long-term effects is near zero. It suggests that most domestic firms have some short-term productivity premium after foreign acquisition, though this premium disappears over time and hence the evidence of long-term premium is weak. However, both of them are slightly skewed to the right, which implies that there exist firms with large positive productivity effects both in short term and long term.

Figure 7 shows how the long-term and short-term productivity effects are related to the firm size, measured by log of employment. They show that for firms of smaller size ($log(L) \leq 6$), the long-term effect of foreign ownership is negative, implying that their production processes do not interact well with foreign technology. On the other hand, firms of larger size benefit substantially from foreign ownership. The long-term productivity premium for these firms is as large as about 10%. One potential explanation for such heterogeneity

[18] An implication of this result is that the use of a value-added production function cannot generally be justified.

is that larger firms often have better absorptive capacity, and hence are better equipped to take advantage of foreign technology and management practices. This result resonates the recent findings by Fons-Rosen et al. (2018).[19] For the short-run effect, our model predicts that all firms generate some productivity gains from foreign ownership, with gains ranging from 2% to 13%.

In sum, from our baseline specification which combines all the HKMT and OECD firms as one type, we show that the long-term effect of foreign investment is small on average and substantially heterogenous across firm sizes. On the other hand, we find robust evidence of a strong positive initial productivity shock when firms switch from domestic to foreign ownership status.

HKMT versus OECD Ownership

As noted in section 1, some evidence suggests that HKMT firms are in fact mainland Chinese firms, yet they establish their headquarters in offshore locations to access favorable policies for foreign investments. If this is the case, unlike OECD ownership, HKMT ownership should not bring more productivity gain to recipient firms as compared to other private domestic firms with comparable characteristics. To examine this hypothesis and demonstrate the usefulness of our framework, we extend our baseline model by separating HKMT ownership from OECD ownership and compare their technology as well as productivity changes after acquisitions.

Specifically, we allow HKMT firms to behave differently than OECD firms by incorporating separate foreign ownership dummies for these two types of firms. The extended model is specified as follow:

$$y_{it} = f(k_{it}, l_{it}, m_{it}, v_{it}^{HKMT}, v_{it}^{OECD}) + \omega_{it} + \varepsilon_{it} \tag{20}$$

[19] Specifically, they find that FDI only benefits domestic firms that share similar technology to foreign firms, even though in their context, the productivity effects occur through horizontal spillovers rather than direct transfers of technology through foreign ownership as in this paper.

with Markov productivity process:

$$\omega_{it} = \rho\omega_{i,t-1} + \gamma_1 d_{it}^{HKMT} + \gamma_2 d_{it}^{OECD} + \eta_{it} \tag{21}$$

We report results for this extension in column (2) of Table 2 and in Figures 8-10. Strikingly, as illustrated in Figure 8, we find that HKMT firms' production technology and productivity are almost identical and indistinguishable to that of private domestic firms. On the other hand, the estimated productivity premium of OECD firms as compared to domestic firms is now much larger than in the baseline model. Nonetheless, the labor productivity dominance of OECD as compared to HKMT and domestic firms disappears for very large firms as in the baseline case.

Column (2) of Table 2 also shows that HKMT firms have negative long-term productivity effect from foreign investment, while OECD firms have positive long-term effect. Therefore, foreign acquisition makes HKMT firms perform worse than domestic firms in the long-run, if other things are equal. There are positive initial productivity shocks among firms who switch their ownership status to either HKMT or OECD type, although the productivity shock is stronger for OECD acquisitions. Firms that switch to HKMT ownership have an estimated 2% productivity shock and firms that switch to OECD ownership have an estimated 3.9% productivity shock compared to firms that do not switch. Based on the estimated marginal effects of v and d, panels (b) and (c) in Figure 5 depict the productivity dynamics of the OECD and HKMT firms, respectively, as in Figure 2, where we have $\hat{\rho}$ of about 0.9 for all the cases.

The positive productivity shock of OECD firms becomes more apparent when it is disentangled from that of HKMT firms. Figure 9 shows the distributions of the short-term and long-term productivity effects from foreign ownership similar to Figure 6. We can easily see the difference between foreign ownership types: the distribution of HKMT effects is primarily negative, while the distribution of OECD effects is mainly positive. Figure 10 illustrates the long-term and short-term effects with respect to firm size as in Figure 7. The top two panels show that HMKT firms are mostly less productive than private domestic firms, and that a switch to HKMT type will not generate productivity gains either for short-term or long-term. In fact, the results indicate that HKMT firm's performance deteriorates over time in post acquisition periods. These results support the view that ethnically-tied HKMT investment might have reduced economic efficiency, possibly by privileging insiders at the expense of outsiders, consistent with the findings in Huang, Jin and Qian (2013), though in terms of productivity rather other performance metrics. In contrast, the bottom panels of Figure 10 demonstrate strong patterns of both short-term and long-term productivity gains for firms receiving investment from OECD sources. The long-term effect ranges from 2% to more than 5%, while the short-term effect ranges from 5% to above 10%. As for the baseline case, this productivity gain is largest for the moderately sized firm. However, even for OECD investment, the foreign productivity gain mostly disappears for firms of very large size ($log(L)$ close to 10 in this case).

Non-Hicks-neutral Implications

After estimating the model, we can compute the counterfactual elasticities of each firm and obtain the distributions of these elasticities with respect to labor, capital and material. We then examine the non-Hicks-neutral implications of foreign ownership. Recall that if the foreign ownership productivity effect is neutral, these distributions should not be statistically different under $v_{it}^{OECD} = 1$ versus $v_{it}^{OECD} = 0$. We use our estimated results from the extended version of our model in (20) to test for non-Hicks-neutrality hypothesis between OECD firms versus other types of firms. To test for non-neutrality, Tables 3-4 respectively presents our results for two statistical tests that we performed: (1) simple paired (mean) t-test and (2) Kolmogorov-Smirnov (KS) test for the difference between the distributions of counterfactual elasticities.

The first three rows of Table 3 show that OECD firms have higher average output elasticity with respect to labor and capital compared to domestic firms. On the other hand, OECD firms have lower output elasticity with respect to material on average. The differences are all statistically significant. These results imply that foreign technology involves more labor and capital but less material.[20] The next two rows of Table 3 compare the elasticity ratios of labor and capital, taking material as the normalized input. As we hold the input ratios fixed for each firm, differences in these elasticity ratios essentially reflect differences in $MRTS$, which directly maps to input factor shares. We further test for the differences in the distribution of these elasticities as well as elasticity ratios using KS test in Table 4. Our KS test confirms the significant difference in distribution between these quantities under the two counterfactual scenarios.[21]

Results from Tables 3-4 show that OECD firms have higher $MRTS$ than domestic firms in both labor-material and capital-material pairs. Ceteris paribus, this implies that labor share and capital share of total output are higher in OECD firms as compared to domestic firms. However, since the magnitude of difference is larger for capital, capital-augmenting technology dominates labor-augmenting technology among OECD firms. These facts combined deliver two implications: (1) value-added share of total revenue increases and (2) labor share of total value-added decreases (relative to capital share) due to foreign ownership.

We calculate (average) counterfactual value-added (VA) shares of total revenue and labor shares of total value-added as follow. First, since $VA = R - pM$ and $\frac{pM}{R} = \frac{\partial f}{\partial m}$, where R is the total revenue and p is the material price, we have:

$$\log(\frac{VA}{R}) = \log(1 - \frac{pM}{R}) = \log(1 - \frac{\partial f}{\partial m}). \tag{22}$$

As a result, difference in the natural logs of value-added shares translates directly to the

[20] Furthermore, if we impose constant return to scale (CRS) assumption on the physical production function, we can infer markups induced by different ownership status. Table 3 shows that having OECD ownership increases firms' markups.

[21] Since KS test is sensitive to outliers, we trim observations outside of the 1^{th} and 99^{th} range of the estimated labor, capital, and material elasticities before implementing both of our tests. Our paired (mean) t-test results remain robust without trimming these observations.

difference in the natural logs of $(1 - \frac{\partial f}{\partial m})$ under two counterfactuals ($v_{it} = 1$ versus $v_{it} = 0$). Secondly, using similar arguments, we could also compute the difference in the natural logs of labor share of total value-added as follow:

$$\begin{aligned} \log(\frac{wL}{VA}) &= \log(\frac{wL}{R}\frac{R}{VA}) = \log(\frac{wL}{R}) + \log(\frac{R}{VA}) \\ &= \log(\frac{\partial f}{\partial l}) - \log(1 - \frac{\partial f}{\partial m}). \end{aligned} \tag{23}$$

Here, w denotes the wage paid to workers.[22] Based on our estimates of $\frac{\partial f}{\partial l}$ and $\frac{\partial f}{\partial m}$, equations (22)-(23) allow us to compute average counterfactual value-added share of total revenue and labor share of total value-added. Plugging in the mean values of our estimated elasticities from Table 3, equation (22) suggests that OECD ownership increases value-added share of total revenue by 11.3%. On the other hand, equation (23) suggests that OECD ownership decreases labor share of total value-added by 7.56%.

Our evidence suggests that foreign investment is non-Hicks-neutral biased and may have contributed substantively to the decline of Chinese manufacturing labor share during this sample period. Biased technological change introduced by foreign investment into China's high-tech manufacturing may also help to explain the observed growth in the domestic value-added share of Chinese high-tech exports.[23] As noted above, our estimates imply that foreign technology involves more labor and capital inputs relative to material. Foreign-invested firms were expanding presence in China's high-tech sector during our sample period: their share of total high-tech sales rose from 27.5% in 1995 to 44% in 2005. By 2005, foreign-invested firms provided almost two-thirds of China's total high-tech export value.[24] Because

[22] An underlying assumption in equation (23) is that, without any endogenous form of labor market distortion, labor share of total revenue can be approximated by the revenue elasticity with respect to labor i.e. $\frac{wL}{R} = \frac{\partial f}{\partial l}$.

[23] According to the OECD-WTO Trade in Value-Added Project, in 1995 around three-quarters of the total value of China's information and computer technology exports reflected foreign content but by 2011 this had fallen to just over half, with similar large declines seen in other high-tech sectors, such as electrical machinery and transport equipment. See https://www.oecd.org/sti/ind/tiva/CN_2015_China.pdf.

[24] Characteristics of the high-tech sector for 1995 are drawn from Huang (2003), Table 1.4, which is based on data from China's Third Industrial Census. Comparable numbers for 2005 are calculated by the authors from the Annual Survey of Industrial Enterprises, which is described in the text.

foreign technology raises the contribution of domestic labor relative to imported materials, foreign investment may have contributed to the rising domestic value-added share in high-tech exports.

Benchmarking Results

To put our nonparametric approach into perspective, we compare our estimation results with other studies that examine a similar question using alternative empirical approaches. Two of such studies are Wang and Wang (2015) and Kamal (2015), which exploit changes in foreign ownership using the Chinese firm-level dataset in the same period as ours. Both of these studies estimate structural measures of productivity in the first stage and employ a difference-in-differences research design in the second stage. Wang and Wang (2015) compare productivity differences of foreign-acquired firms versus domestic-acquired firms to estimate the "purified" effect of foreign acquisitions. In their study, they combined both HKMT-type and OECD-type acquisitions into one category as the treatment group, and find no long-run productivity effect of foreign ownership. This finding corresponds very well to our baseline model results in column (1) of Table 2, indicating that our nonparametric procedure is able to appropriately control for both observable and unobservable differences across firm types.[25]

Nonetheless, in Wang and Wang (2015), when distinguishing between the two treatment types (HKMT-type versus OECD-type), they do not detect any significant difference in productivity effects between different FDI sources. This finding contradicts to our results in the extended model in column (2) of Table 2 and those in Kamal (2015), which adopts similar empirical approach to Wang and Wang (2015). Kamal (2015) compares purely OECD-acquired firms versus HKMT-acquired firms, thus using different sets of control and treatment group, and finds very large productivity differences between OECD-acquired firms and HKMT-acquired firms. She finds that this difference ranges from 11.7% (after the first year) to 27.8% (after the second year post-acquisition). On this heterogeneity dimension, our results

[25] They do find initial productivity shock of 6.2%, which is qualitatively consistent but larger than our 2.7% estimate. However, their estimated effect dies out right after the first year post-acquisition.

are qualitatively consistent with findings in Kamal (2015) in that the performance of OECD-acquired firms and HKMT-acquired firms diverges in post-acquisition periods and reaching 6% productivity differences in the long run.

Overall, our results reconcile with the findings in both Wang and Wang (2015) and Kamal (2015), though the empirical approach employed in these studies appears to be sensitive to the choice of treatment and control groups. To provide addtional benchmarking, we estimate versions of our models using ordinary least squares (OLS), fixed effect regression (FE), and linearized GNR, and report these results in the appendix Table A1. OLS does not account for the endogeneity due to the unobservable productivity term and thus biases the estimates of elasticities and other model parameters. As we better handle endogeneity, the estimates improve and approach our main results in Table 2.

Robustness to Alternative Classification of High-Tech Industries

Our classification for the group of high-tech industries in previous sections may appear subjective. To investigate the robustness of our results regarding the interpretation of high-tech industries, we re-estimate our models using an alternative official classification based on China's "High-tech Industry Statistical Classification Catalog" (Guo Tong Zi [2002] No.33). This official classification is quite similar to our proposed classification, except that it does not include 2-digit industries: general-purpose machinery (35) and electrical machinery (39), while entailing pharmaceutical manufacturing (27).[26] Table 5 reports our estimation results corresponding to this alternative classification of the high-tech industries.

Across the two estimation models, the robustness results remain very similar to our main results in Table 2. Output elasticities with respect to capital and labor increase slightly, while that of material decreases slightly. This is due to the fact that general-purpose machinery (35) and electrical machinery (39) command higher shares of material usage, while

[26]There are more detailed differences regarding subcategories within these industries. We provide the list of 4-digit industries listed in this document in the appendix B.1 and relevant official documents in the suplemental materials.

pharmaceutical manufacturing (27) uses less material and more capital as well as labor. Our main parameters of interest also remain highly consistent. In the baseline model, we still find that foreign ownership overall does not bring any long-run productivity premium as compared to private domestic firms. On the other hand, when distinguishing between the sources of foreign ownership (HKMT versus OECD), we analogously find that only OECD ownership increases long-run productivity, with the magnitude of the effect is 2.6%. HKMT firms perform worse in the long-run with productivity loss of 4.2%, in similar range to what we obtained in Table 2. We also find evidence of initial productivity shocks for OECD acquisitions of magnitude of 2%, while that of HKMT acquisitions is not statistically significant. Nonetheless, the implied immediate effects remain statistically significant, indicating similar productivity trajectories for both types of foreign acquisition as in our main results. In sum, our estimation results for the alternative classification of high-tech industries remain robust.

6 Conclusion

In this paper, we study the dynamic and non-Hicks-neutral productivity effects of foreign ownership in China's high-tech manufacturing industries from 1998-2007. To this end, we propose an econometric framework that extends a recent nonparametric productivity analysis by Gandhi, Navarro and Rivers (2020). We include a foreign ownership variable in the production function as well as an acquisition choice variable in the productivity dynamics. Our approach enables us to recover the productivity adjustment path after foreign acquisitions to distinguish short-term and long-term effects, and to study the bias of foreign technology embedded in foreign ownership.

We find that foreign ownership brings both short-term and long-term productivity gains in general, although the long-term effect is smaller than the short-term effect. This is mostly the result of positive productivity shock upon foreign acquisitions. We also find that these effects display substantial heterogeneity across firm sizes. Domestic medium-sized enterprises gain the most from access to foreign investment, while the largest firms see no productivity boost.

Finally, in the context of China, our empirical analysis demonstrates that HKMT ownership does not bring productivity gain in the long run compared to their domestic counterparts and only OECD acquisition delivers persistent productivity premia. Comparing OECD-invested firms with domestic firms, we find that OECD technology is biased, meaning that it is both labor- and capital-augmenting. Thus, the foreign-investment productivity boost raises the marginal products of capital and labor relative to materials. This factor bias may offer further insights into China's falling labor share and rising domestic valued-added in high-tech exports.

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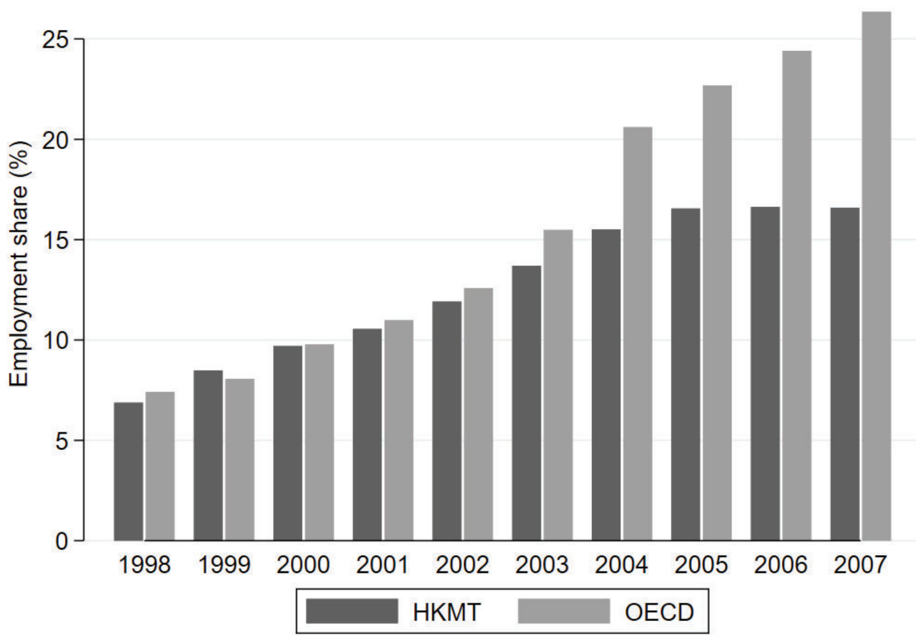
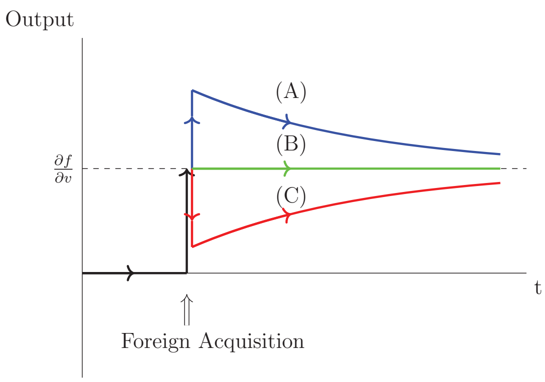
Figure 1: Employment Share of HKMT and OECD Firms from 1998 -2007 within High-tech Industries

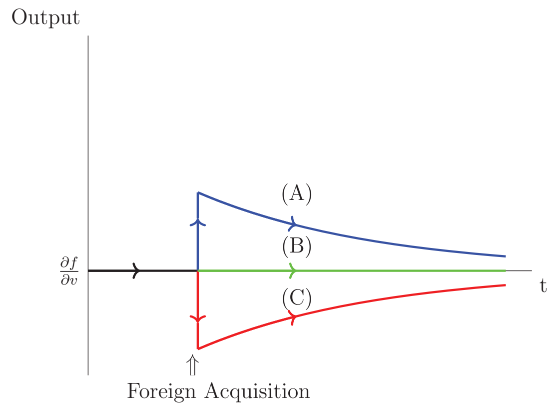


Note: The high-tech industry group comprises 2-digit manufacturing of: general-purpose machinery (35), special-purpose machinery (36), transportation equipments (37), electrical machinery (39), communication equipments and computers (40) and precision instruments (41).
Source: The figure is based on authors' calculations using Annual Survey of Industrial Enterprises (ASIE).

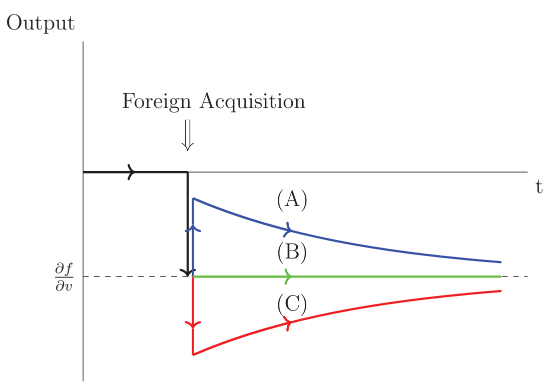
Figure 2: Possible Output Trajectories after Foreign Acquisition (When $0 < \rho < 1$)



Case 1: $\frac{\partial f}{\partial v} > 0$



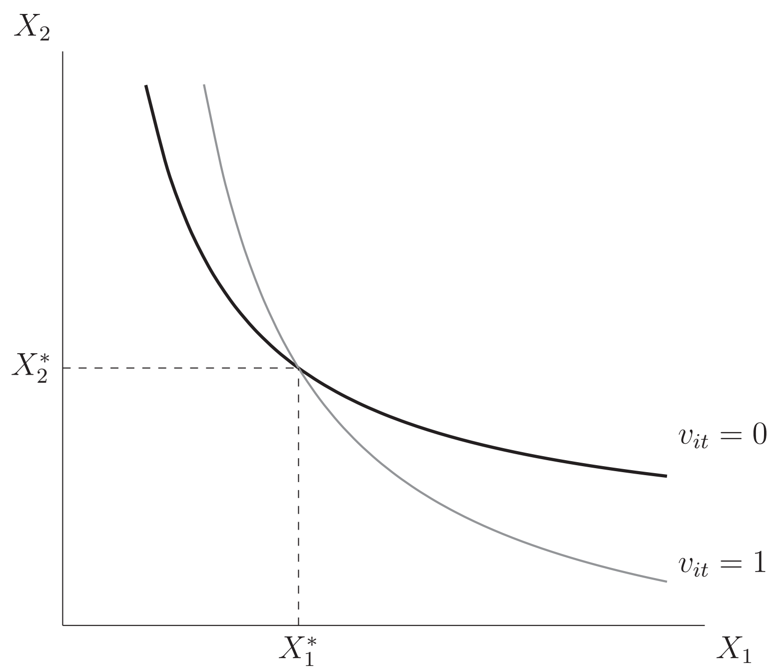
Case 2: $\frac{\partial f}{\partial v} = 0$



Case 3: $\frac{\partial f}{\partial v} < 0$

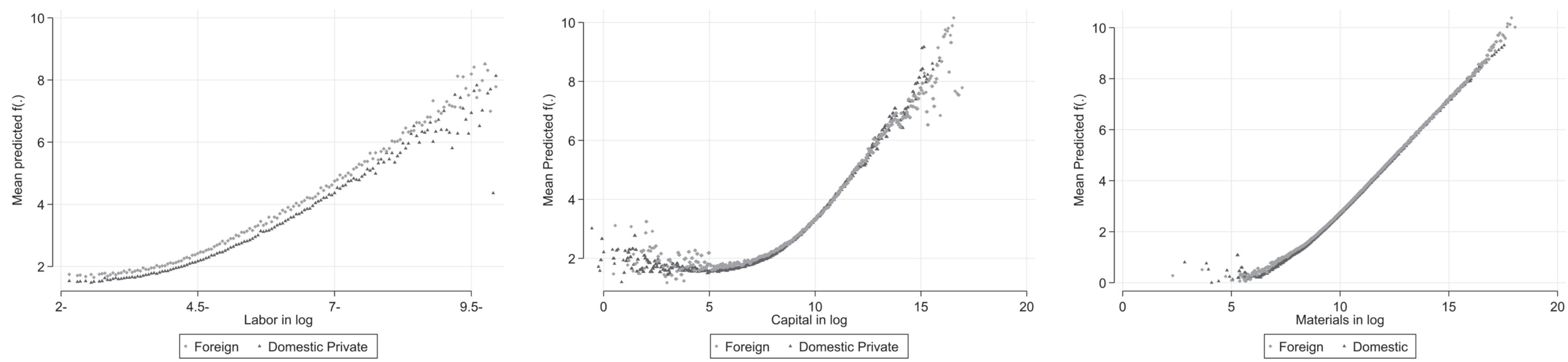
Note: The graphs illustrate three cases depending on the sign of $\frac{\partial f}{\partial v}$, which determines the magnitude of the long-run productivity effect. For each case, there are three potential productivity paths (A), (B) and (C) corresponding to the sign of γ: (A) corresponds to $\gamma > 0$. (B) corresponds to $\gamma = 0$. (C) corresponds to $\gamma < 0$.

Figure 3: Marginal Rate of Technical Substitution ($MRTS$) under Factor Biased Counterfactuals



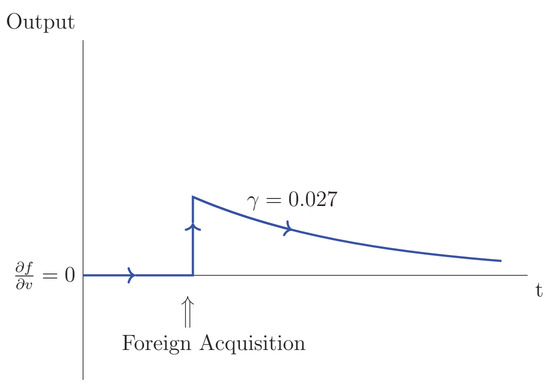
Note: The figure illustrates the marginal rate of technical substitution ($MRTS$) between two factors X_1 and X_2 under the assumption that foreign acquisition ($v_{it} = 1$) is not Hicks-neutral when compared to domestic ownership ($v_{it} = 0$).

Figure 4: Mean $\hat{f}(.)$ against Primary Inputs for Foreign versus Domestic Ownership in **Tech** Industries

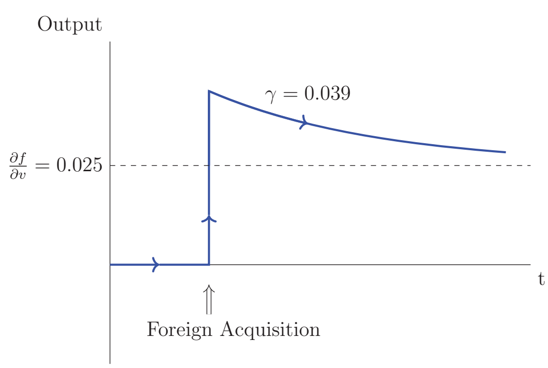


Note: The figures illustrate the relationship between mean output $\hat{f}(.)$ and (log) primary inputs, labor, capital and material respectively, for foreign and domestic firms. In the first graph, at each given level of (log) labor l, each diamond is obtained by averaging $\hat{f}(l, k_{it}, m_{it}, v_{it})$ for all i and i with $v_{it} = 1$; each triangle is obtained by averaging $\hat{f}(l, k_{it}, m_{it}, v_{it})$ for all i and i with $v_{it} = 0$. The second and the third graphs are obtained in the same way, but at given (log) capital and (log) material, respectively. For each i and t, $f(.)$ is estimated as described in section 3.

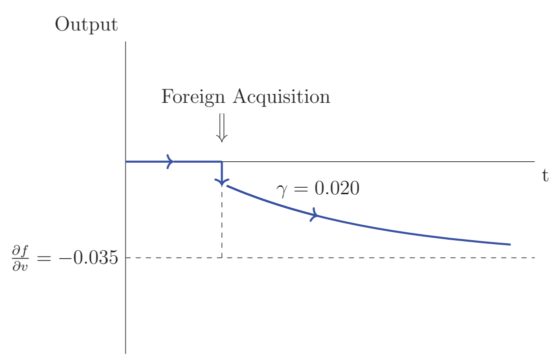
Figure 5: Predicted Output Change after Foreign Acquisition



(a) Baseline

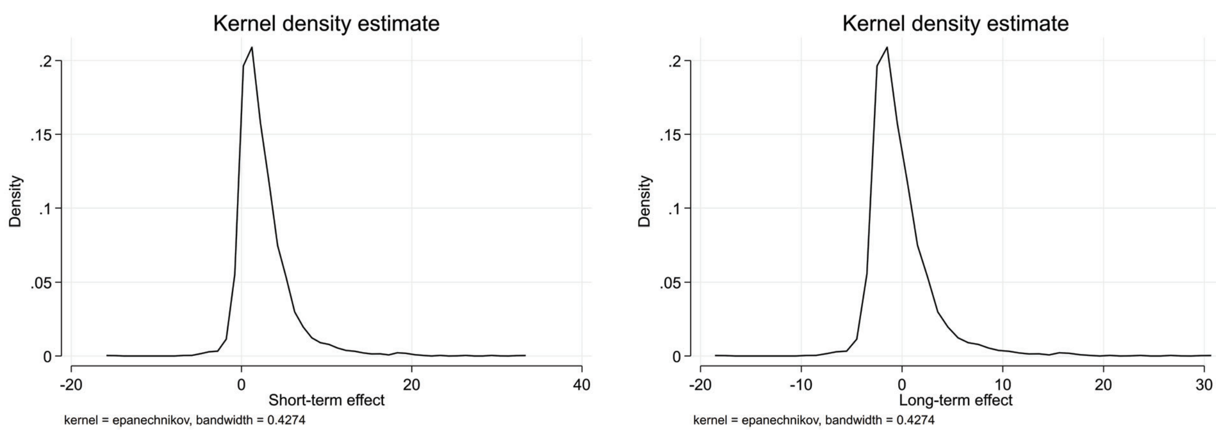


(b) OECD



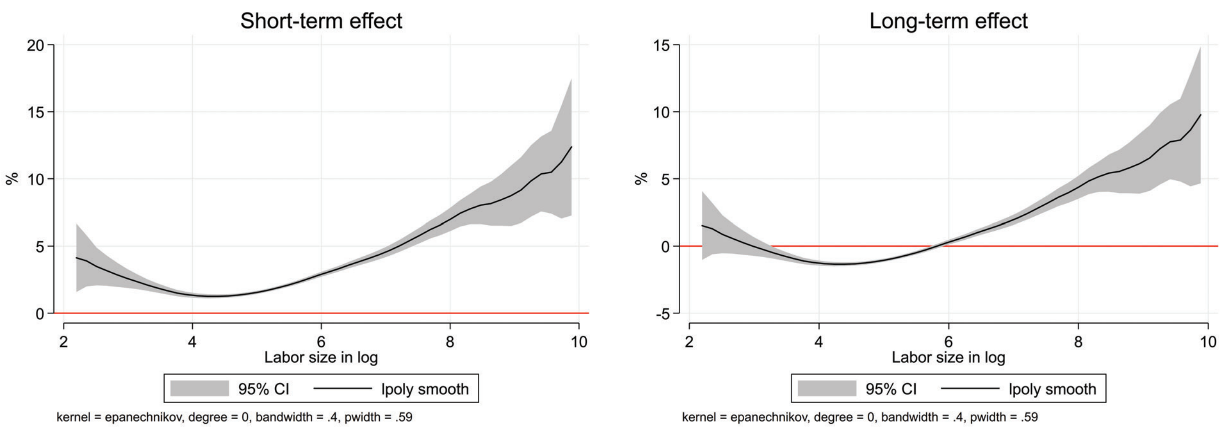
(c) HKMT

Figure 6: Distribution of Short-term and Long-term Productivity Effects of Firms Switching Ownership Status



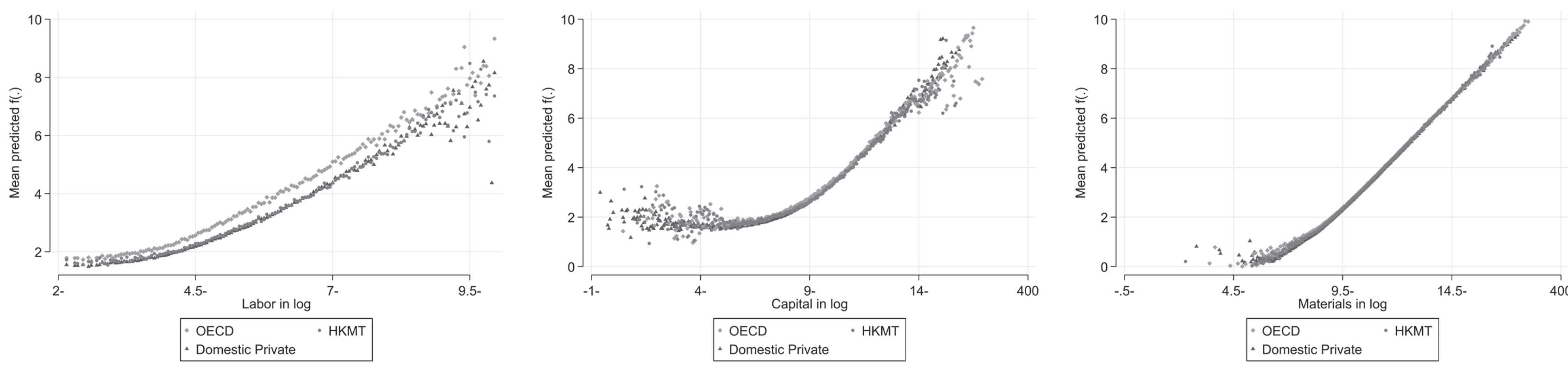
Note: The figures illustrate the distribution of short-term (left panel) and long-term (right panel) effects for firms switching ownership status from domestic ($v_{it} = 0$) to foreign ($v_{it} = 1$). Effects are measured in percentage points.

Figure 7: Productivity Effects by Firm Size (in Log Employment)



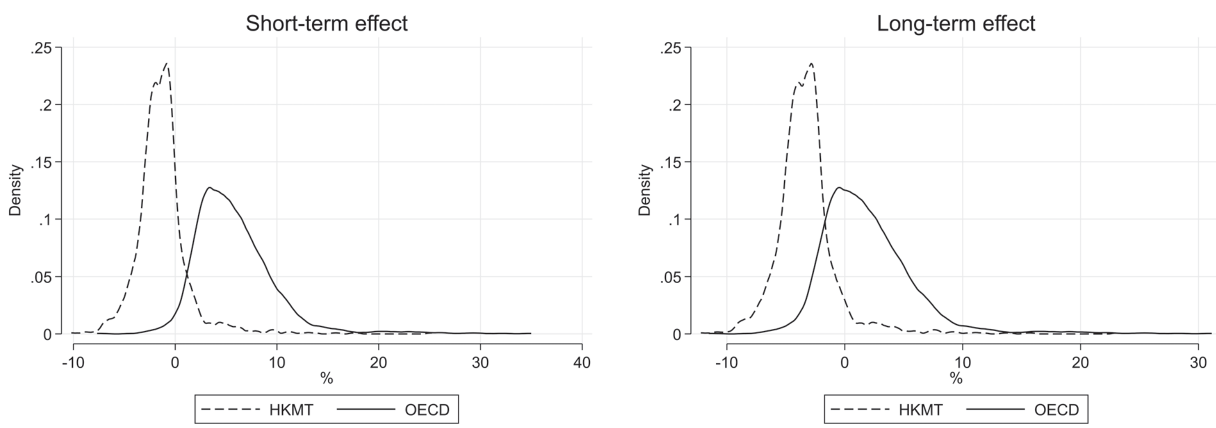
Note: The figures illustrate the heterogeneity of short-term (left panel) and long-term (right panel) estimated effects based on firm size (measured in log employment). The right graph is obtained by nonparametric regression of the long-term effect estimates $\frac{\partial \hat{f}}{\partial v}$ on log employment for all i and t. The left graph is a vertical shift of it by the size of short-term effect estimate $\hat{\gamma}$.

Figure 8: Mean $\hat{f}(.)$ against Primary Inputs for OECD, HKMT and Domestic Firms



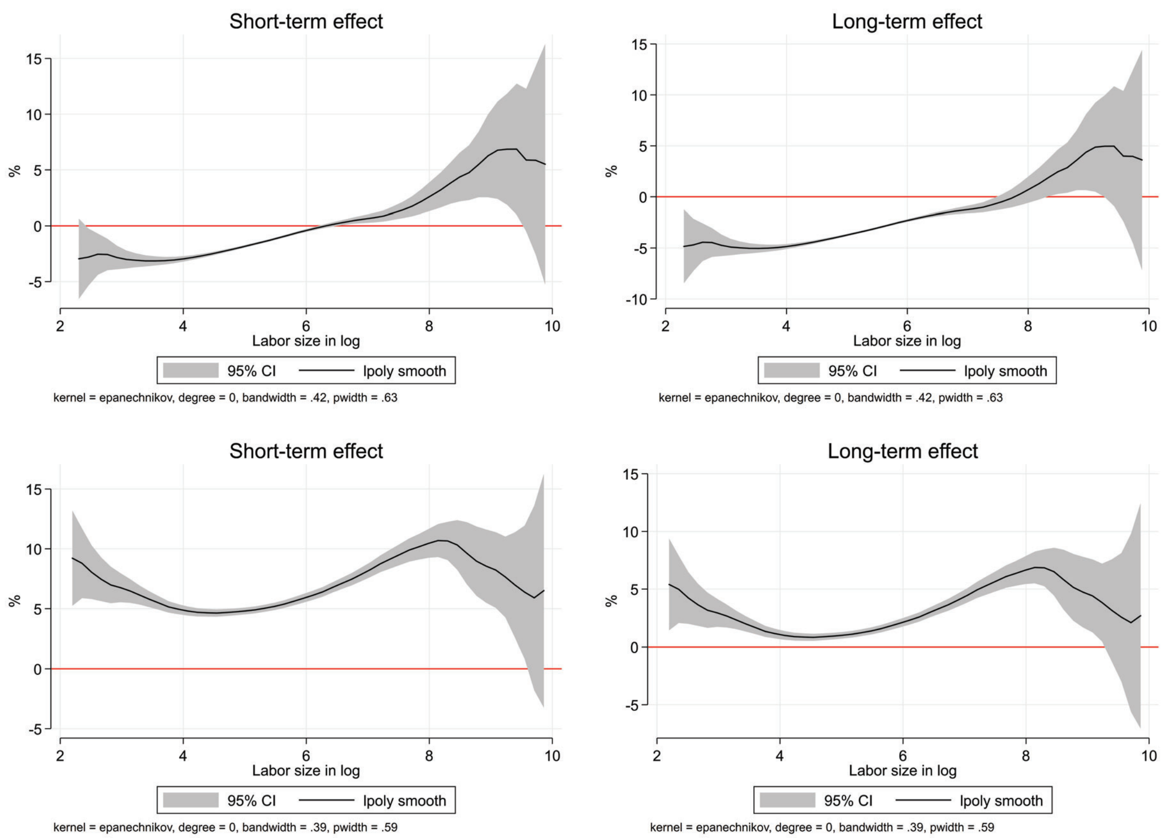
Note: The figures illustrate the relationship between mean output $\hat{f}(.)$ and (log) primary inputs, labor, capital and material respectively, for OECD, HKMT and domestic firms. Each graph is obtained as Figure 4 based on the extended model in equations (20)-(21).

Figure 9: Distribution of Short-term and Long-term Productivity Effects of Firms Switching Ownership Status (HKMT versus OECD)



Note: The figures illustrate the estimated distribution of short-term (left panel) and long-term (right panel) effects for firms switching ownership status from domestic to HKMT or OECD firms. Effects are measured in percentage points.

Figure 10: Productivity Effects by Firm Size for HKMT (Top) and OECD (Bottom) Investments



Note: The figures illustrate the heterogeneity of short-term (left) and long-term (right) estimated effects based on firm size (measured in log employment). The graphs are obtained by nonparametric regressions as in Figure 7. The top panels illustrate short-term and long-term effects for HKMT firms. The bottom panels illustrate short-term and long-term effects for OECD firms.

Table 1: Firms and Employment by Ownership Category in 1998 and 2007

Ownership	Number of Firms				Employment			
	1998 (Count)	1998 (Share)	2007 (Count)	2007 (Share)	1998 (Count)	1998 (Share)	2007 (Count)	2007 (Share)
SOE	39,477	33	9,463	3.6	27	57	11	17
Hybrid/Collective	42,297	35	32,414	12	11	24	10	16
Private	18,770	16	170,888	66	3.3	7.1	24	39
Foreign - HKMT	11,480	**9.5**	22,164	**8.5**	3.2	**6.7**	8.2	**13**
Foreign - OECD	8,228	**6.8**	25,753	**9.9**	2.3	**5**	9.5	**15**
Total	120,252	100	260,682	100	47	100	63	100

Note: The foreign equity threshold is 25% for both HKMT and OECD firms.
Source: The table is based on authors' calculations using Annual Survey of Industrial Enterprises (ASIE).

Table 2: The Model Estimates

Mean Elasticities & Estimated Parameters	Baseline (1)	HKMT vs. OECD (2)
Production Function Elasticities (Mean)		
$\partial f/\partial k$	0.091 (0.001)	0.090 (0.001)
$\partial f/\partial l$	0.105 (0.002)	0.106 (0.001)
$\partial f/\partial m$	0.692 (0.001)	0.692 (0.001)
Initial Productivity Shocks		
$\partial \omega/\partial d \equiv \gamma$	0.027^{***} (0.008)	.
$\partial \omega/\partial d^{HKMT} \equiv \gamma_1$	.	0.020^{**} (0.0096)
$\partial \omega/\partial d^{OECD} \equiv \gamma_2$	.	0.039^{***} (0.008)
Immediate Effects (Mean)		
$\partial f/\partial v + \gamma$	0.027^{***} (0.005)	.
$\partial f/\partial v^{HKMT} + \gamma_1$	.	-0.015^{***} (0.0055)
$\partial f/\partial v^{OECD} + \gamma_2$	.	0.064^{***} (0.006)
Long-run Effects (Mean)		
$\partial f/\partial v$	-0.000 (0.009)	.
$\partial f/\partial v^{HKMT}$	.	-0.035^{***} (0.009)
$\partial f/\partial v^{OECD}$	.	0.025^{***} (0.007)
ρ	0.896 (0.004)	0.898 (0.003)

Note: Nonparametric clustered bootstrap standard errors with 100 replications are reported in parentheses. Bootstrap samples are drawn at the firm level, which follows the approach by Lee, Mukherjee and Ullah (2019). Estimates, except for $(\gamma, \gamma_1, \gamma_2)$, are the means of their respective elasticities over i and t. Stars indicate conventional statistical significance for parameters we test against zeros (*** p<0.01, ** p<0.05, * p<0.1).

Table 3: Paired t-test for Differences in Means of Counterfactual Elasticities and Elasticity Ratios (OECD vs. Other Firms)

Paired t-test	N	Mean ($v_{it}^{OECD} = 1$)	Mean ($v_{it}^{OECD} = 0$)	Difference	p-value
Elasticities					
Labor Elasticity	376,115	0.107	0.103	0.004	0.000
Capital Elasticity	376,115	0.103	0.09	0.013	0.000
Material Elasticity	376,115	0.665	0.701	-0.035	0.000
Elasticity Ratios					
Labor/Material	376,115	0.166	0.149	0.017	0.000
Capital/Material	376,115	0.16	0.131	0.03	0.000
(Revenue) Return to Scale	376,115	0.875	0.894	-0.018	0.000
Markup	376,115	15.5%	12.2%	3.3%	0.000

Note: The table shows paired t-test results for the means of elasticities and elasticity ratios computed for every firms in the sample under two counterfactuals: $v_{it}^{OECD} = 1$ versus $v_{it}^{OECD} = 0$. The elasticity ratios are $\frac{\partial f}{\partial l}(.)/\frac{\partial f}{\partial m}(.)$ and $\frac{\partial f}{\partial k}(.)/\frac{\partial f}{\partial m}(.)$ respectively. (Revenue) return to scale is sum of mean elasticities. Markups are inferred under the assumption of constant return to scale of physical production. The test is performed after trimming observations outside of the 1^{th} and 99^{th} percentile range of the estimated labor, capital, and material elasticities.

Table 4: Kolmogorov-Smirnov Test for Differences in CDFs of Counterfactual Elasticities and Elasticity Ratios (OECD vs. Other Firms)

Kolmogorov-Smirnov Test	N	K-S Difference Statistics	p-value
Elasticities			
Labor Elassticity	376,115	0.85	0.000
Capital Elasticity	376,115	0.86	0.000
Material Elasticity	376,115	0.63	0.000
Elasticity Ratios			
Labor/Material	376,115	0.79	0.000
Capital/Material	376,115	0.81	0.000

Note: The table shows the paired Kolmogorov-Smirnov test results for the equivalence between the CDFs of elasticities and elasticity ratios computed for every firms in the sample under two counterfactuals: $v_{it}^{OECD} = 1$ versus $v_{it}^{OECD} = 0$. The elasticity ratios are $\frac{\partial f}{\partial l}(.)/\frac{\partial f}{\partial m}(.)$ and $\frac{\partial f}{\partial k}(.)/\frac{\partial f}{\partial m}(.)$ respectively. The test is performed after trimming observations outside of the 1^{th} and 99^{th} percentile range of the estimated labor, capital, and material elasticities.

Table 5: The Model Estimates for Alternative Definition of High-tech Industries

Mean Elasticities & Estimated Parameters	Baseline	HKMT vs. OECD
	(1)	(2)
Production Function Elasticities (Mean)		
$\partial f/\partial k$	0.109	0.107
	(0.002)	(0.002)
$\partial f/\partial l$	0.124	0.125
	(0.003)	(0.003)
$\partial f/\partial m$	0.657	0.657
	(0.002)	(0.001)
Initial Productivity Shocks		
$\partial \omega/\partial d \equiv \gamma$	0.018	.
	(0.011)	
$\partial \omega/\partial d^{HKMT} \equiv \gamma_1$	.	0.011
		(0.016)
$\partial \omega/\partial d^{OECD} \equiv \gamma_2$	.	0.020*
		(0.012)
Immediate Effects (Mean)		
$\partial f/\partial v + \gamma$	0.011	.
	(0.009)	
$\partial f/\partial v^{HKMT} + \gamma_1$	.	-0.030**
		(0.015)
$\partial f/\partial v^{OECD} + \gamma_2$	.	0.046***
		(0.010)
Long-run Effects (Mean)		
$\partial f/\partial v$	-0.007	.
	(0.008)	
$\partial f/\partial v^{HKMT}$	.	-0.042***
		(0.010)
$\partial f/\partial v^{OECD}$	.	0.026***
		(0.010)
ρ	0.831	0.836
	(0.006)	(0.006)

Note: Nonparametric clustered bootstrap standard errors with 100 replications are reported in brackets. Bootstrap samples are drawn at the firm level, which follows the approach by Lee, Mukherjee and Ullah (2019). Estimates, except for $(\gamma, \gamma_1, \gamma_2)$, are the means of their respective elasticities over i and t. The alternative definition of the high-tech industry group is based on China's "High-tech Industry Statistical Classification Catalog" (Guo Tong Zi [2002] No.33). Stars indicate conventional statistical significance for parameters we test against zeros (*** p<0.01, ** p<0.05, * p<0.1).

Appendix

A Benchmark Models

OLS and Fixed Effect Regression

OLS estimation of the baseline model is obtained by running the following regression:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_v v_{it} + \gamma d_{it} + \varepsilon_{it}. \tag{A1}$$

Similarly, for the extended version of the model, we run the following regression:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_{v1} v_{it}^{HKMT} + \beta_{v2} v_{it}^{OECD} + \gamma_1 d_{it}^{HKMT} + \gamma_2 d_{it}^{OECD} + \varepsilon_{it}. \tag{A2}$$

We run these regressions both with and without firm fixed effects. The results are shown in columns (1)-(2) and (4)-(5) of Table A1.

In columns (1) and (4), OLS estimates bias the output elasticities with respect to inputs. In particular, the OLS estimation underestimates capital and labor elasticities (β_k and β_l), while overestimates material elasticity (β_m). It also expectedly overestimates the long-run (β_v) as well as short-run ($\beta_v + \gamma$) productivity effects of foreign ownership, which typically appears as a correlation in the data.

When correcting for individual heterogeneity by firm fixed effects (columns (2) and (5) of Table A1), the biases become less severe, though still are quite substantial. In particular, estimates of β_k and β_l increase while that of β_m decreases. Here, we also see that the estimates of long-run as well as short-run productivity effects decrease.

Linear GNR

In the linear regressions above, we do not allow for the productivity process to evolve following a Markov process. To allow or this possibility, we estimate the linearized version of our GNR models as follow (see also this linearized version of similar models in Chen et al. (2020)):

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_v v_{it} + \omega_{it} + \varepsilon_{it}, \tag{A3}$$

where

$$\omega_{it} = \rho\omega_{i,t-1} + \gamma d_{it} + \eta_{it}. \tag{A4}$$

Based on the linearized production function in equation (A3), the first GNR stage reduces to:

$$\log(s_{it}) = \log \mathcal{E} + log(\beta_m) - \varepsilon_{it}, \tag{A5}$$

while the second stage reduces to running the following regression:

$$\Psi_{it} = (\beta_k k_{it} + \beta_l l_{it} + \beta_v v_{it}) + \rho\Psi_{it-1} - \rho(\beta_k k_{i,t-1} + \beta_l l_{i,t-1} + \beta_v v_{i,t-1}) + \gamma d_{it} + \eta_{it}. \tag{A6}$$

We adopt a similar procedure for the linearized version of our extended (HKMT vs. OECD) model.

The linear GNR model results in columns (3) and (6) of Table A1 get closer to our main results in Table 2. There are still some remaining biases in estimates of β_k, β_m, and ρ. Nevertheless, in column (3), the long-run effects now disappear and equal to zero, which is similar to the nonparametric GNR model. Here, the linear GNR model does not detect initial productivity shock as in our main results. Column (6) does not detect long-run productivity effect of OECD ownership and initial productivity shock for HKMT acquisitions. However, it reveals initial productivity shock for OECD acquisitions and long-run productivity loss of HKMT ownership. Overall, we take these results combined as a good benchmark for our preferred models and results in the main text of the paper.

Table A1: Linear OLS and Linear GNR Benchmark Estimates

Elasticities & Estimated Parameters	Baseline			HKMT vs. OECD		
	OLS	OLS	Linear GNR	OLS	OLS	Linear GNR
	(1)	(2)	(3)	(4)	(5)	(6)
Production Function Elasticities						
β_k	0.039	0.071	0.069	0.038	0.071	0.068
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
β_l	0.028	0.074	0.106	0.031	0.074	0.107
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
β_m	0.899	0.857	0.678	0.897	0.857	0.678
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Initial Productivity Shocks						
γ	0.008	0.011	0.004	.	.	.
	(0.006)	(0.006)	(0.007)			
γ_1	.	.	.	0.013	0.018**	-0.006
				(0.010)	(0.009)	(0.009)
γ_2	.	.	.	0.007	0.002	0.018*
				(0.009)	(0.009)	(0.010)
Immediate Effects						
$\beta_v + \gamma$	0.029***	0.020***	-0.000	.	.	
	(0.007)	(0.006)	(0.005)			
$\beta_{v1} + \gamma_1$ (HKMT)	.	.	.	-0.005	0.015*	-0.018***
				(0.010)	(0.008)	(0.007)
$\beta_{v2} + \gamma_2$ (OECD)	.	.	.	0.062***	0.026***	0.019**
				(0.009)	(0.009)	(0.008)
Long-run Effects						
β_v	0.020***	0.009*	-0.004	.	.	
	(0.001)	(0.005)	(0.005)			
β_{v1} (HKMT)	.	.	.	-0.017***	-0.003	-0.013**
				(0.001)	(0.005)	(0.006)
β_{v2} (OECD)	.	.	.	0.056***	0.024***	0.001
				(0.002)	(0.005)	(0.006)
ρ	.	.	0.884	.	.	0.882
			(0.002)			(0.002)
Firm FE	.	Yes	.	.	Yes	.

Note: Robust standard errors are reported in brackets for OLS regressions. For linear GNR estimation, we report nonparametric clustered bootstrap standard errors with 100 replications. Stars indicate conventional statistical significance for parameters we test against zeros (*** p<0.01, ** p<0.05, * p<0.1).

B Addtional Materials

B.1 High-tech Industry Statistical Classification Catalog (Guo Tong Zi [2002] No.33)

2-digit industries (and their subcategories) that are included in the China's official "High-tech Industry Statistical Classification Catalog" (Guo Tong Zi [2002] No.33):

- (25) Petroleum Processing: 253
- (26) Raw Chemical: 2665
- (27) Pharmaceutical Manufacturing: 2710, 2720, 2730, 2740, 2750, 2760, 2770
- (36) Special-purpose Machinery: 3681, 3682, 3683, 3684, 3685, 3686, 3689
- (37) Transportation Equipments: 3761, 3762, 3769
- (40) Communication Equipment and Computers:
  - (401): 4011, 4012, 4013, 4014, 4019
  - (402): all
  - (403): 4031, 4032, 4039
  - (404): 4041, 4042, 4043
  - (405): 4051, 4052, 4053, 4059
  - (406): 4061, 4062
  - (407): 4071, 4072
  - (409): all
- (41) Precision Instruments:
  - (411): 4111, 4112, 4113, 4114, 4115, 4119
  - (412): 4121, 4122, 4123, 4124, 4125, 4126, 4127, 4128, 4129
  - (414): 4141
  - (415): 4154, 4155
  - (419): 4190

In our estimation of the models with alternative classification, we drop 2-digit industries (25) and (26) due to the small number of observations and likely different technologies.

B.2 Aggregate Data Summary

Table B1: Aggregate Summary Statistics (Monetary Values in Trillion RMB)

Year	Number of Firms	VA	Sales	Output	Employment	Export	Fixed Assets (Net)
1998	165118	1.94	6.54	6.77	56.44	1.08	4.41
1999	162033	2.16	7.06	7.27	58.05	1.15	4.73
2000	162882	2.54	8.37	8.57	53.68	1.46	5.18
2001	171256	2.83	0.00	9.54	54.41	1.62	5.54
2002	181557	3.30	10.86	11.08	55.21	2.01	5.95
2003	196220	4.20	13.95	14.23	57.48	2.69	6.61
2004	279092	0.00	19.78	20.17	66.22	4.05	7.97
2005	271835	7.22	24.69	25.16	69.31	4.77	8.95
2006	301961	9.11	31.08	31.66	73.49	6.05	10.58
2007	336768	11.70	39.76	40.51	78.75	7.34	12.34