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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 No.: 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) 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 [Akerberg, Caves and Frazer \(2015\)](#), in that its identification exploits more information from the optimizing 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 1998-2007. During this period, along with other major reforms including state

¹Recent 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. Indeed, 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)). 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 improves the target firm’s productivity in both the short and long run. However, we find that the long-run effect is typically smaller than the short-run effect. 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

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

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 contrast, 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 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 ownership. There are two common underlying assumptions of these studies: (1) the productivity process is exogenous with regard to the choice of foreign acquisition in the first-stage; and (2) the effect of foreign ownership is Hicks-neutral, meaning that it only affects the production function in a linear manner. In contrast, our econometric model relaxes these assumptions and allows the exploration of differences 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 \(2003\)](#), [Akerberg, 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.³

Our initial points of departure are papers by [De Loecker \(2013\)](#) and [Doraszelski and Jaumandreu \(2013\)](#), who extend productivity analysis to explore learning-by-exporting and R&D, respectively.⁴ 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.⁵

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 explicitly recover the productivity adjustment path of firms after the ownership change. This allows 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 between source countries of foreign investment (OCED versus HKMT).

The rest of the paper is organized as follows. In section 2, we describe the institu-

³See also reviews of this non-identification issue provided by [Bond and Söderbom \(2005\)](#), [Akerberg, Caves and Frazer \(2015\)](#), [Gandhi, Navarro and Rivers \(2020\)](#).

⁴These extensions date back to [Griliches \(1979\)](#)’s knowledge capital model in the productivity literature.

⁵For 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.

tional 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.

2 Foreign Investment in China from 1998-2007

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 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 (henceforth, **Tech**). We define the **Tech** group to include industries that involve relatively more sophisticated production processes. This group of in-

dustries 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). In the **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 OCED firms into one category, this increase is steep and consequently by 2007, foreign employment accounts for about 40% of the **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.⁶

3 The Model

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

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

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):

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

ω_{it} measures 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

⁶See Lu, Tao and Zhu (2017) for a review of FDI policy in China.

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:

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

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:⁷

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

The function $h(\cdot)$, 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 $f(\cdot)$, we simply suppose $h(\cdot)$ 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

⁷In 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.

(i.e., AR(1)) process given as:

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

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:

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

where $\mathbb{M}(\cdot)$ 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 well as state variables such as ownership status.⁸ A direct result from this assumption is that function $\mathbb{M}(\cdot)$ can be inverted to nonparametrically control for productivity based on observable inputs used:

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

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 their productivity for period t .
- The firm optimally chooses m_{it} , after which ε_{it} realizes and completely determines y_{it} .

⁸This 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 \(2003\)](#), [Akerberg, Caves and Frazer \(2015\)](#), [Gandhi, Navarro and Rivers \(2020\)](#).

- 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 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 $f(\cdot)$ 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 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 productivity 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 ownership 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 the productivity at the initial phase ($\frac{\partial f}{\partial v} + \gamma$), but the long-run productivity 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 $t \rightarrow \infty$. Figure 2 depicts possible productivity shock trajectories solely from foreign acquisitions when $0 < \rho < 1$. From this figure, we can predict how ownership status change affects the firm's productivity 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:

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

In other words, the productivity effect of foreign ownership is Hicks-neutral if and only if production function $f(\cdot)$ 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., $\frac{\partial f_1(\cdot)}{\partial k}$, $\frac{\partial f_1(\cdot)}{\partial l}$, $\frac{\partial f_1(\cdot)}{\partial m}$, 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 remain the same whether $v_{it} = 1$ or 0.⁹

Figure 3 depicts the marginal rate of technical substitution ($MRTS$) between two factors X and Y , where $X, Y \in \{K, L, M\}$, under two counterfactual scenarios: $v_{it} = 1$ versus $v_{it} = 0$, and under the assumption that the effect of foreign ownership is not Hicks-neutral. In this figure, when a firm has foreign ownership ($v_{it} = 1$), $MRTS_{XY}$ 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 and Y ($MRTS_{XY} = \frac{\partial f}{\partial x} / \frac{\partial f}{\partial y} \times \frac{Y}{X}$).¹⁰ In this case, foreign ownership has X -augmenting technology implications (relative to Y) and effectively increases the share of X (relative to Y) in total output derived from the production function.

Estimation Method

We follow the nonparametric identification and the two-stage estimation procedure by [Gandhi, Navarro and Rivers \(2020\)](#). In the first stage, we estimate the partial derivative of $f(\cdot)$ with respect to m_{it} . In the second stage, we integrate this partial derivative and recover the production function by combining it with the Markov productivity process.

The first stage makes use of 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} :

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

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

⁹Furthermore, 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.

¹⁰Here lowercase x and y are the natural logs of X and Y . Therefore, $MRTS_{XY} = \frac{MP_X}{MP_Y} = \frac{\partial F}{\partial X} / \frac{\partial F}{\partial Y} = \frac{(\frac{\partial f}{\partial x} \times \frac{F}{X}) / (\frac{\partial f}{\partial y} \times \frac{F}{Y})}{\frac{\partial f}{\partial x} / \frac{\partial f}{\partial y}} \times \frac{Y}{X}$.

us:

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

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

Taking the log and differencing with the production function $Y_{it} = \exp(f(k_{it}, l_{it}, m_{it}, v_{it})) \times \exp(\omega_{it} + \varepsilon_{it})$ in equation (1), we get:

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

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

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

where $\mathcal{E} = \mathbb{E}[s_{it}/D^{\mathcal{E}}(k_{it}, l_{it}, m_{it}, v_{it})]$. For estimation, we approximate $\log D^{\mathcal{E}}(\cdot)$ by the second-order polynomial sieves and solve the following least squares problem:

$$\min_{\theta} \sum_{i=1}^n \sum_{t=1}^T \left\{ \log s_{it} - \theta_0 - \sum_{0 \leq j_k + j_l + j_m \leq 1} \theta_{1, j_k, j_l, j_m} k_{it}^{j_k} l_{it}^{j_l} m_{it}^{j_m} v_{it} - \sum_{1 \leq j_k + j_l + j_m \leq 2} \theta_{2, j_k, j_l, j_m} k_{it}^{j_k} l_{it}^{j_l} m_{it}^{j_m} \right\}^2 \quad (13)$$

for $j_k, j_l, j_m \in \{0, 1, 2\}$, where θ denotes all the unknown parameters. Note that we exclude the v_{it}^2 term since v_{it} is binary.

In the second stage, we first numerically integrate $\frac{\partial}{\partial m_{it}} f(k_{it}, l_{it}, m_{it}, v_{it})$ to recover the

production function $f(\cdot)$ up to a constant addition $C(\cdot)$ as a function of k_{it} , l_{it} , and v_{it} :

$$\int \frac{\partial}{\partial m_{it}} f(k_{it}, l_{it}, m_{it}, v_{it}) dm_{it} = f(k_{it}, l_{it}, m_{it}, v_{it}) + C(k_{it}, l_{it}, v_{it}). \quad (14)$$

Replacing $f(\cdot)$ with its original form in equation (1), we have

$$\begin{aligned} \Psi_{it} &\equiv y_{it} - \varepsilon_{it} - \int \frac{\partial}{\partial m_{it}} f(k_{it}, l_{it}, m_{it}, v_{it}) dm_{it} \\ &= -C(k_{it}, l_{it}, v_{it}) + \omega_{it} \end{aligned} \quad (15)$$

and combining with the Markov process expression of ω_{it} in equation (5), we have

$$\Psi_{it} + C(k_{it}, l_{it}, v_{it}) = \rho \{\Psi_{it-1} + C(k_{it-1}, l_{it-1}, v_{it-1})\} + \gamma d_{it} + \eta_{it} \quad (16)$$

or

$$\Psi_{it} = -C(k_{it}, l_{it}, v_{it}) + \rho \Psi_{it-1} + \rho C(k_{it-1}, l_{it-1}, v_{it-1}) + \gamma d_{it} + \eta_{it}. \quad (17)$$

Making use of the exclusion restrictions described above, equation (17) is fully indentified, in the sense that $\mathbb{E}[\eta_{it} | C(k_{it}, l_{it}, v_{it}), C(k_{it-1}, l_{it-1}, v_{it-1}), d_{it}, \Psi_{it-1}] = 0$.

For estimation, once we solve equation (13), we obtain

$$\hat{\Psi}_{it} = y_{it} - \hat{\varepsilon}_{it} - \int \frac{\partial}{\partial m_{it}} \hat{f}(k_{it}, l_{it}, m_{it}, v_{it}) dm_{it} \quad (18)$$

with $\hat{\varepsilon}_{it} = \log s_{it} - \log \hat{D}^{\mathcal{E}}(k_{it}, l_{it}, m_{it}, v_{it})$, $\hat{\mathcal{E}} = (nT)^{-1} \sum_{i=1}^n \sum_{t=1}^T \exp(\hat{\varepsilon}_{it})$, and

$$\begin{aligned} &\int \frac{\partial}{\partial m_{it}} \hat{f}(k_{it}, l_{it}, m_{it}, v_{it}) dm_{it} \\ &= \frac{1}{\hat{\mathcal{E}}} \int \hat{D}^{\mathcal{E}}(k_{it}, l_{it}, m_{it}, v_{it}) dm_{it} \\ &= \frac{1}{\hat{\mathcal{E}}} \left\{ \hat{\theta}_0 m_{it} - \sum_{0 \leq j_k + j_l + j_m \leq 1} \frac{\hat{\theta}_{1, j_k, j_l, j_m}}{j_m + 1} k_{it}^{j_k} l_{it}^{j_l} m_{it}^{j_m + 1} v_{it} - \sum_{1 \leq j_k + j_l + j_m \leq 2} \frac{\hat{\theta}_{2, j_k, j_l, j_m}}{j_m + 1} k_{it}^{j_k} l_{it}^{j_l} m_{it}^{j_m + 1} \right\}. \end{aligned} \quad (19)$$

We approximate $C(k_{it}, l_{it}, v_{it})$ by the second-order polynomial sieves as

$$C(k_{it}, l_{it}, v_{it}) \approx \beta_0 + \sum_{0 \leq j_k + j_l \leq 1} \beta_{1, j_k, j_l} k_{it}^{j_k} l_{it}^{j_l} v_{it} + \sum_{1 \leq j_k + j_l \leq 2} \beta_{2, j_k, j_l} k_{it}^{j_k} l_{it}^{j_l} \quad (20)$$

for $j_k, j_l \in \{0, 1, 2\}$ and we run GMM estimation based on the following moment conditions:

$$\begin{aligned} \mathbb{E}[\eta_{it}] &= 0, \\ \mathbb{E}[\eta_{it} \Psi_{it-1}] &= 0, \\ \mathbb{E}[\eta_{it} d_{it}] &= 0, \\ \mathbb{E}[\eta_{it} k_{it}^{j_k} l_{it}^{j_l}] &= 0 \text{ for } 1 \leq j_k + j_l \leq 2 \text{ and } j_k, j_l \in \{0, 1, 2\}, \\ \mathbb{E}[\eta_{it} k_{it}^{j_k} l_{it}^{j_l} v_{it}] &= 0 \text{ for } 0 \leq j_k + j_l \leq 1 \text{ and } j_k, j_l \in \{0, 1\}. \end{aligned} \quad (21)$$

From equation (14), the production function estimate $\hat{f}(k_{it}, l_{it}, m_{it}, v_{it})$ is obtained by subtracting the estimated (20) from (19). In addition, estimated elasticities can be readily calculated since equations (19) and (20) are in polynomial forms.

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 A1 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.¹¹ Our foreign ownership

¹¹For 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

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).¹² 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 1st and 99th 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 identified 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 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

and Zhang (2014).

¹²Our 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.

productivity.

5 Results

Baseline

In the baseline specification, we combine HKMT and OCED firms, and treat them as one common type of foreign firms which share the same technology. Figure 4 describes the relationship between mean output $\hat{f}(\cdot)$ 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 manifests as 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 in Table 2 reports our estimates of the mean elasticities with respect to each input and the parameters of the Markov 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 **Tech** industries.¹³ We note that even though we do not impose any parametric assumptions on production function, the estimated mean elasticity of material is about 0.725, suggesting that the true production function differs from that of the Leontief form.¹⁴

In our baseline specification, we find that the mean effect of v is zero, which we interpret

¹³We 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.

¹⁴An implication of this result is that the use of a value-added production function cannot generally be justified.

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 2.6% 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 negative. 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 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. \(2018\)](#).¹⁵ 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 the 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 dummies for these two types of firms. The extended model is specified as follow:

$$y_{it} = f(k_{it}, l_{it}, m_{it}, v_{it}^{HKMT}, v_{it}^{OECD}) + \omega_{it} + \varepsilon_{it} \quad (22)$$

with Markov productivity process:

$$\omega_{it} = \rho\omega_{i,t-1} + \gamma_1 d_{it}^{HKMT} + \gamma_2 d_{it}^{OECD} + \eta_{it} \quad (23)$$

¹⁵Specifically, 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.

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 to private domestic firms. In contrast, the estimated productivity premium of OECD firms as compared to domestic firms is now much larger than in the baseline model. As in the baseline case, the labor productivity dominance of OECD as compared to HKMT and domestic firms disappears for very large firms.

Column 2 of Table 2 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 1.8% productivity shock and firms that switch to OECD ownership have an estimated 3.7% 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 HKMT 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 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 examine the non-Hicks-neutral implications of foreign ownership. We can then obtain the distributions of these elasticities with respect to labor, capital and material. Recall that if the foreign ownership productivity effect is neutral, these distributions should not be statistically different under $v_{it} = 1$ versus $v_{it} = 0$. To test for non-neutrality, Table 3 shows our simple paired t-test for these elasticities between OECD firms versus domestic firms that we estimated in (22).

Table 3 shows that OECD firms have higher product elasticity with respect to labor and capital on average compared to domestic firms. On the other hand, OECD firms have lower product 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.¹⁶ Table 4 compares the elasticity ratios of labor and capital, taking material as a 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. Table 4 shows that OECD firms have higher $MRTS$ than domestic firms. 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

¹⁶Furthermore, 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.

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 $VA = R - p_M M$ and $\frac{p_M M}{R} = \frac{\partial f}{\partial m}$, we have:

$$\log\left(\frac{VA}{R}\right) = \log\left(1 - \frac{p_M M}{R}\right) = \log\left(1 - \frac{\partial f}{\partial m}\right). \quad (24)$$

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

$$\begin{aligned} \log\left(\frac{wL}{VA}\right) &= \log\left(\frac{wL}{R} \frac{R}{VA}\right) = \log\left(\frac{wL}{R}\right) + \log\left(\frac{R}{VA}\right) \\ &= \log\left(\frac{\partial f}{\partial l}\right) - \log\left(1 - \frac{\partial f}{\partial m}\right). \end{aligned} \quad (25)$$

Here, w denotes the wage paid to workers.¹⁷ Based on our estimates of $\frac{\partial f}{\partial l}$ and $\frac{\partial f}{\partial m}$, equations (24)-(25) 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 (24) suggests that OECD ownership increases value-added share of total revenue by 11.78%. On the other hand, equation (25) suggests that OECD ownership decreases labor share of total value-added by 7.97%.

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-

¹⁷An underlying assumption in equation (25) 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. $\frac{wL}{R} = \frac{\partial f}{\partial l}$.

added share of Chinese high-tech exports.¹⁸ 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.¹⁹ Because 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.

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

¹⁸According 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.

¹⁹Characteristics 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.

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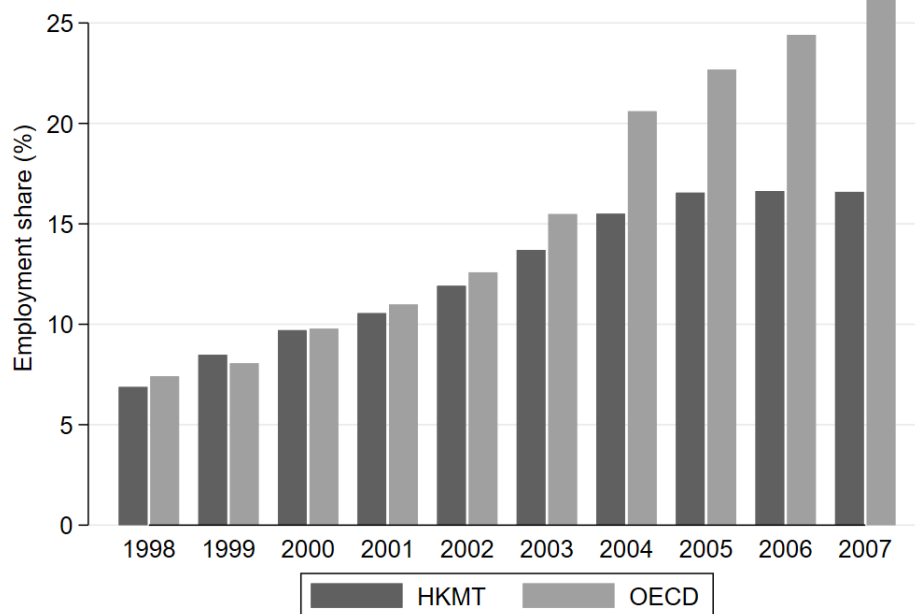
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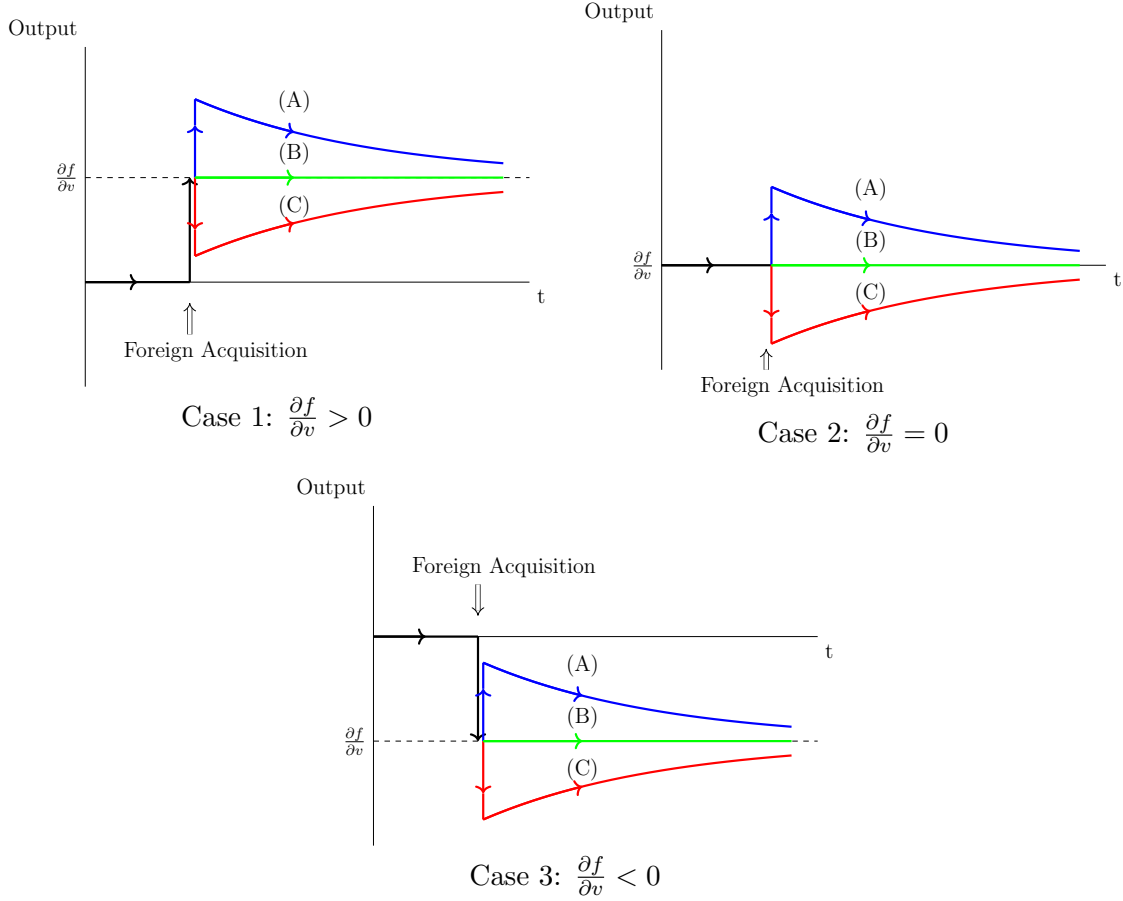
Figure 1: Employment Share of HKMT and OECD Firms from 1998 -2007 within **Tech** Industries



Note: The **Tech** 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).

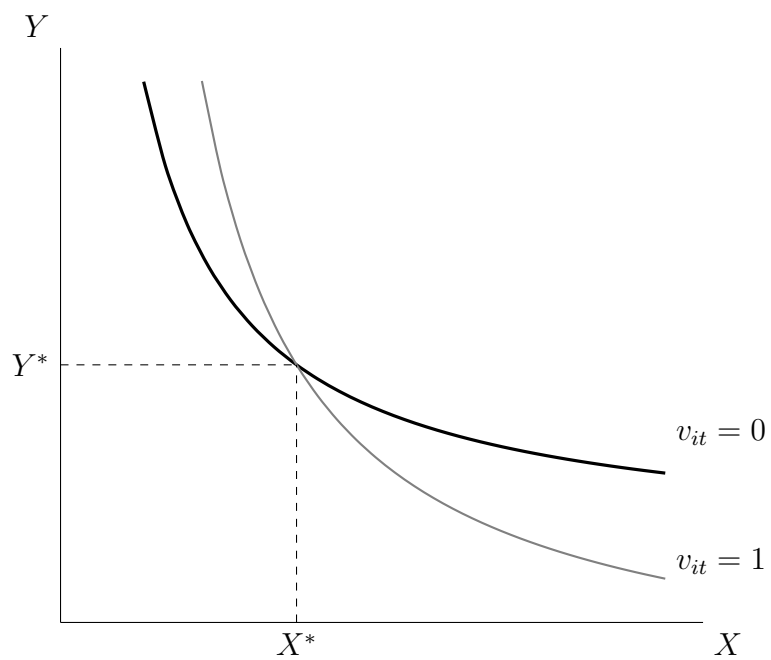
Source: The figure is based on authors' calculations using Annual Survey of Industrial Enterprises (ASIE).

Figure 2: Productivity Change after Foreign Acquisition (When $0 < \rho < 1$)



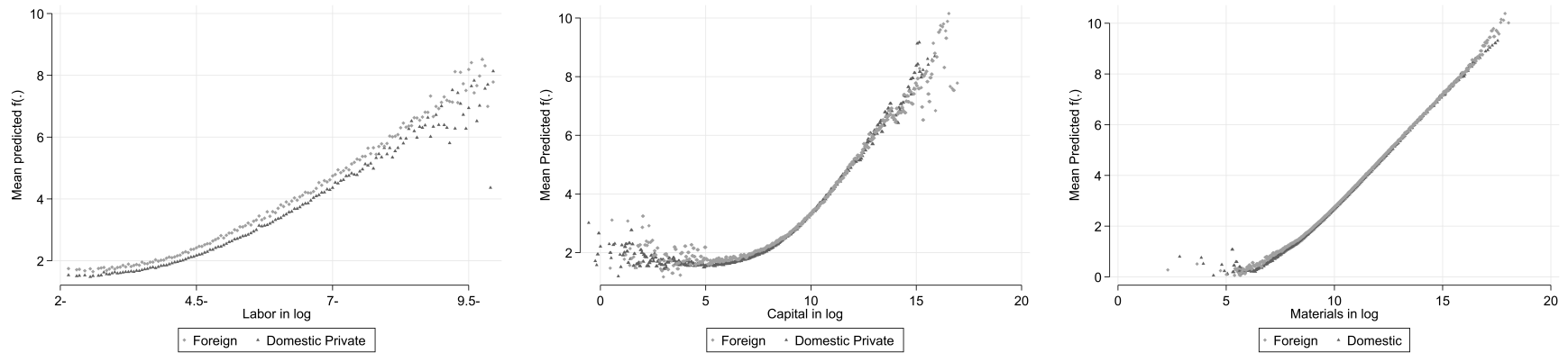
Note: The graphs illustrate three cases depending on the sign of $\frac{\partial f}{\partial v}$, which determines the magnitude of the long-run productivity effect. For each case, there are three potential productivity paths (A), (B) and (C) corresponding to the sign of γ . (A) corresponds to $\gamma > 0$. (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 and Y under the assumption that foreign acquisition ($v_{it} = 1$) is not Hicks-neutral when compared to domestic ownership ($v_{it} = 0$).

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



Note: The figures illustrate the relationship between mean output $\hat{f}(\cdot)$ 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 red point is obtained by averaging $\hat{f}(l, k_{it}, m_{it}, v_{it})$ for all i and i with $v_{it} = 1$; each blue point 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 , $f(\cdot)$ is estimated as described in Section 3.

Figure 5: Predicted Productivity Change after Foreign Acquisition

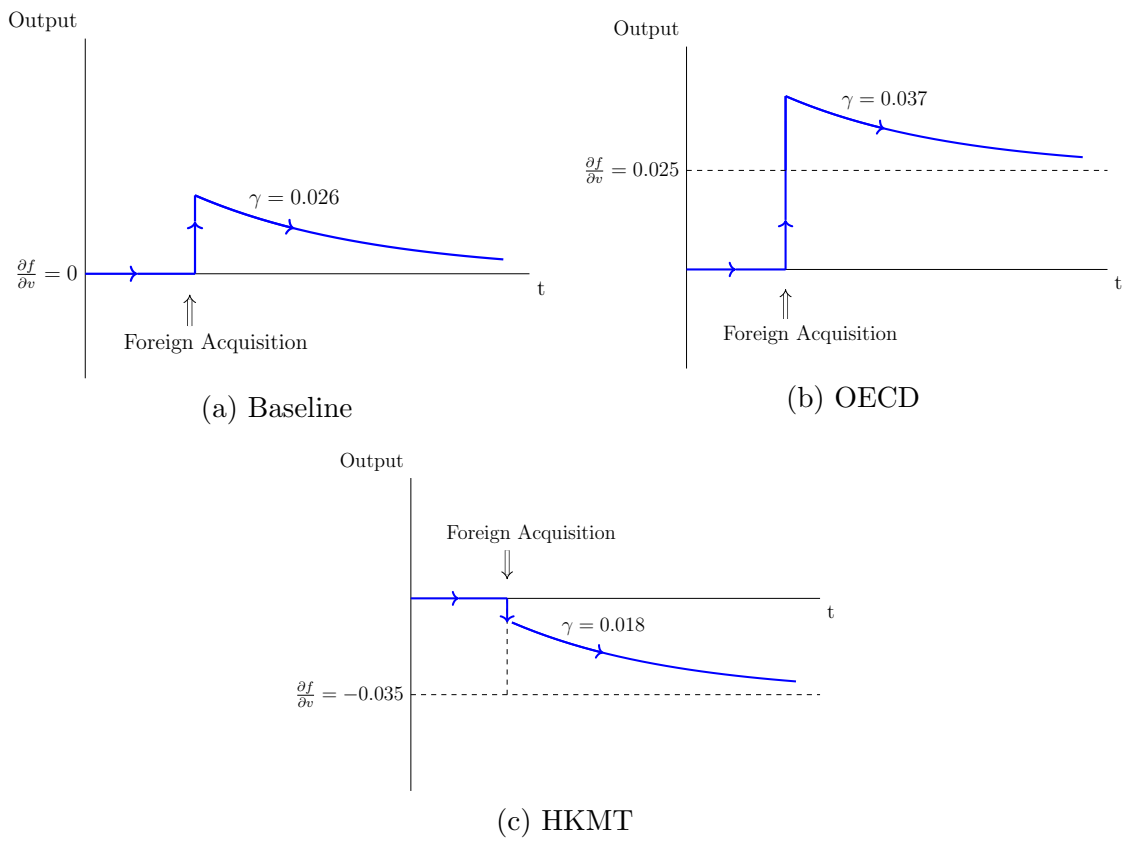
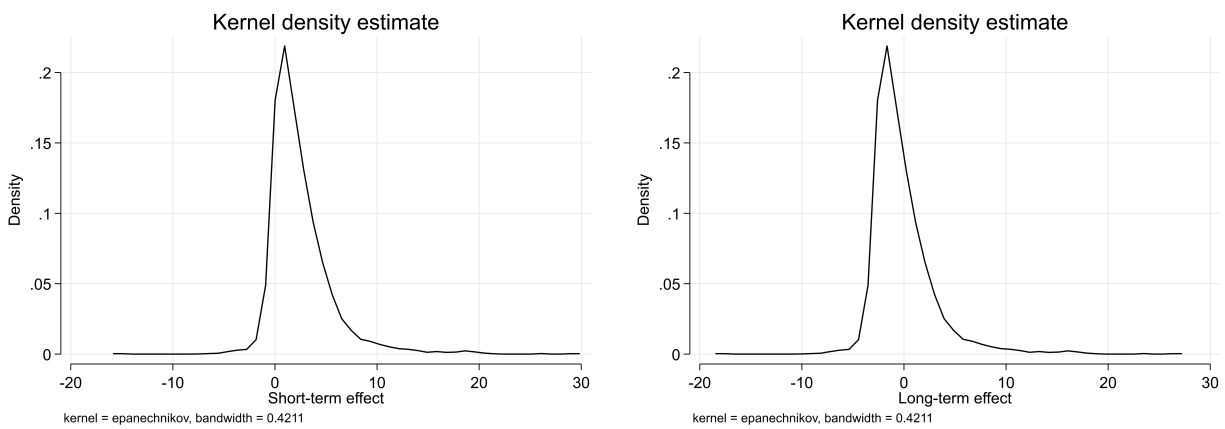
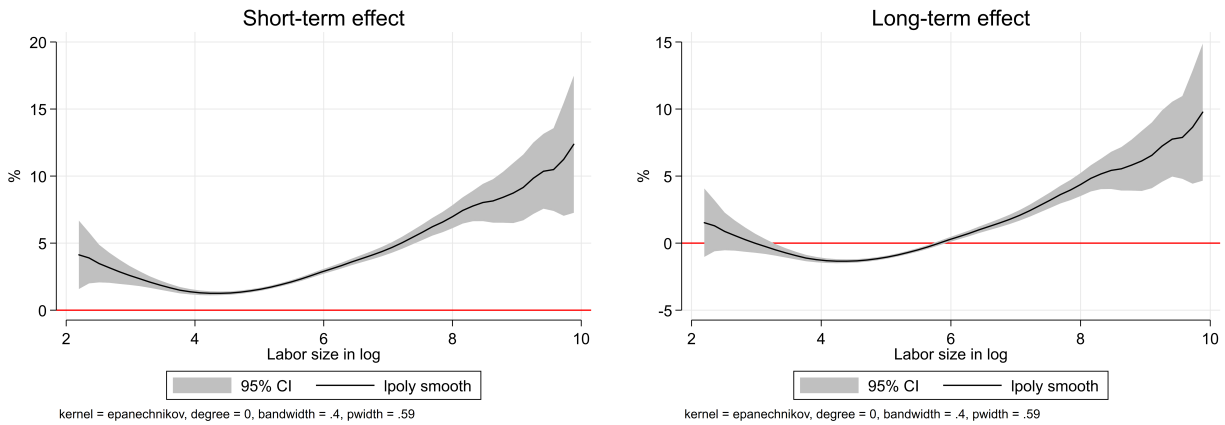


Figure 6: Distribution of Short-term and Long-term Productivity Effects of Firms Switching Ownership Status



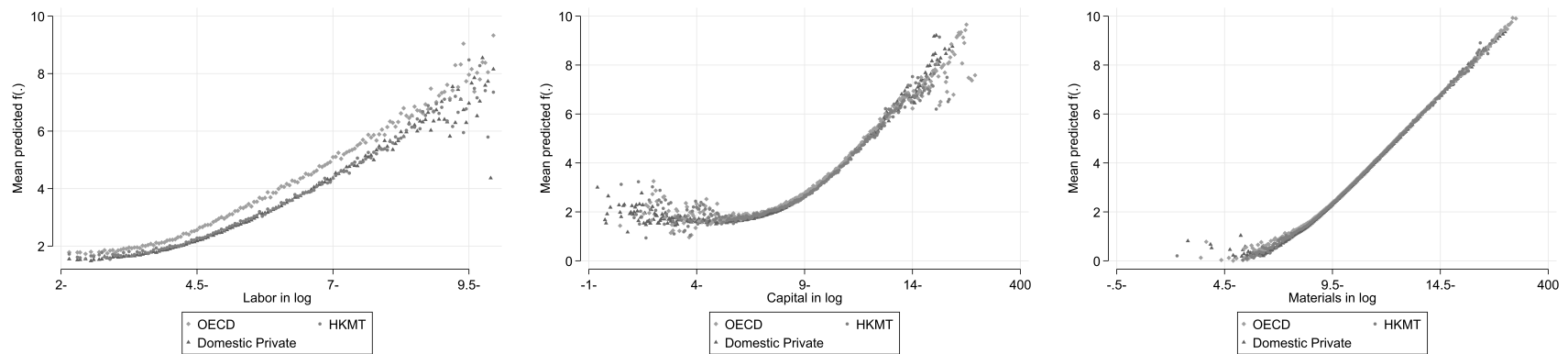
Note: The figures illustrate the distribution of short-term (left panel) and long-term (right panel) effects for firms switching ownership status from domestic ($v_{it} = 0$) to foreign ($v_{it} = 1$). Effects are measured in percentage points.

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



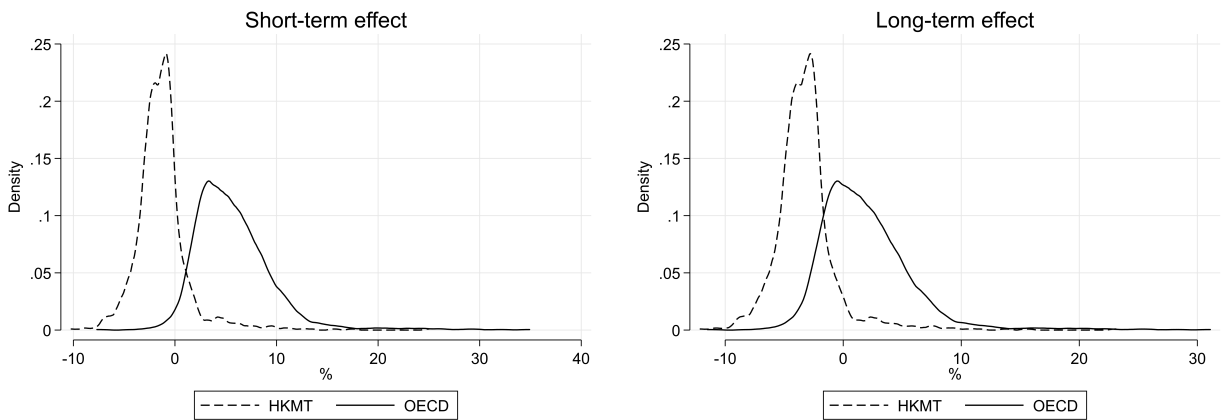
Note: The figures illustrate the heterogeneity of short-term (left panel) and long-term (right panel) estimated effects based on firm size (measured in log employment). The right graph is obtained by nonparametric regression of the long-term effect estimates $\frac{\partial \hat{f}}{\partial v}$ on log 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 $\hat{f}(\cdot)$ against Primary Inputs for OECD, HKMT and Domestic Firms in **Tech** Industries



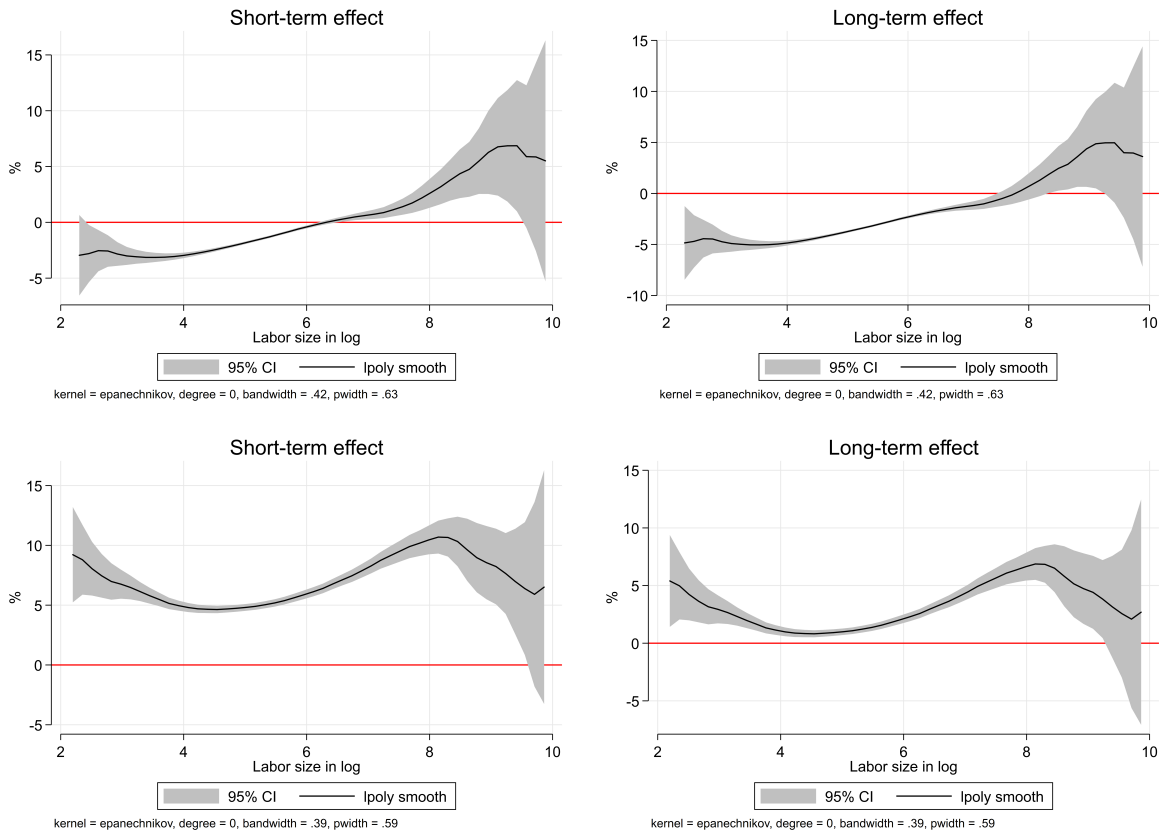
Note: The figures illustrate the relationship between mean output $\hat{f}(\cdot)$ and (log) primary inputs, labor, capital and material respectively, for OECD, HKMT and domestic firms. Each graph is obtained as Figure 4 based on the extended model in equations (22)-(23).

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			
	No.98	Pct98	No.07	Pct07	No.98	Pct98	No.07	Pct07
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 for **Tech** Industries

Mean Elasticities and Estimated Parameters	GNR1 (Baseline)	GNR2 (HKMT vs OECD)
$\partial f / \partial k$	0.091	0.090
$\partial f / \partial l$	0.105	0.106
$\partial f / \partial m$	0.725	0.725
$\partial f / \partial v$	-0.000	.
$\partial f / \partial v^{HKMT}$.	-0.035
$\partial f / \partial v^{OECD}$.	0.025
$\partial \omega / \partial d \equiv \gamma$	0.026*** (4.67)	.
$\partial \omega / \partial d^{HKMT} \equiv \gamma_1$.	0.018*** (2.58)
$\partial \omega / \partial d^{OECD} \equiv \gamma_2$.	0.037*** (5.42)
$\partial f / \partial v + \gamma$	0.026	.
$\partial f / \partial v^{HKMT} + \gamma_1$.	-0.017
$\partial f / \partial v^{OECD} + \gamma_2$.	0.063
ρ	0.895	0.899

Note: Bootstrap t-statistics are reported in brackets. Estimates without t-statistics are the means of their respective elasticities over i and t .

Table 3: Paired t-test for Differences between Counterfactual Elasticities (OECD)

Paired t-test	N	Mean ($v_{it} = 1$)	Mean ($v_{it} = 0$)	Difference	p-value
Labor Elasticity	424610	0.107	0.104	0.003	0.000
Capital Elasticity	424610	0.102	0.088	0.013	0.000
Material Elasticity	424610	0.658	0.696	-0.038	0.000
(Revenue) Return to Scale		0.867	0.888		
Markup		15.34 %	12.61 %		

Note: The table shows paired t-test results for elasticities computed for every firms in the sample under two counterfactuals: $v_{it} = 1$ versus $v_{it} = 0$. (Revenue) return to scale is sum of mean elasticities. Markups are inferred under the assumption of constant return to scale of physical production.

Table 4: Paired t-test for Elasticity Ratios under Factor Bias Counterfactuals (OECD)

Paired t-test	N	Mean ($v_{it} = 1$)	Mean ($v_{it} = 0$)	Difference	p-value
Labor/Material	424610	0.172	0.154	0.018	0.000
Capital/Material	424610	0.162	0.131	0.031	0.000

Note: The table shows paired t-test results for elasticity ratios under two counterfactuals: $v_{it} = 1$ versus $v_{it} = 0$. These elasticity ratios are $\frac{\partial f}{\partial l}(\cdot)/\frac{\partial f}{\partial m}(\cdot)$ and $\frac{\partial f}{\partial k}(\cdot)/\frac{\partial f}{\partial m}(\cdot)$ respectively.

Appendix

Table A1: 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