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Allocation Efficiency in China's State-owned, Private, and Foreign Sector Firms

Yoshihiro HASHIGUCHI*

March 2020

Abstract

Despite the fact many scholars have shown an interest in China's allocation efficiency, few studies have examined quantitative analysis of allocation efficiency within and between the state-owned and private sectors. To address this issue, this paper develops a quantitative measure of allocation efficiency, which is an extension of the dynamic Olley-Pakes productivity decomposition proposed by Melitz and Polanec (2015). The extended measure enables the simultaneous capture of the degree of misallocation within a group and between groups and parallel to capturing the contribution of entering and exiting firms to aggregate productivity growth. Using China's manufacturing firm-level data from 2003 to 2007, the author examine the efficiency of resource allocation within and between three ownership sectors (state-owned, domestic private, and foreign sectors). It is found that the between allocation efficiency tends to improve in industries wherein market shares move from the less-productive state sector to the more-productive private sector.

Keywords: Misallocation, Firm-level productivity, Structural estimation, China

JEL classification: D24, O47

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1 Introduction

Recent studies argued that the allocation of production resources among firms or sectors is a key driver behind the growth of aggregate total factor productivity (TFP) (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Bartelsman et al., 2013; Collard-Wexler and De Loecker, 2015). The shift in production resources from less productive to more productive units yields an increase in aggregate TFP, and resource allocation efficiency can be crucial to explaining countries' aggregate TFP. A well-functioning market economy has a function to allocate more production resources to more productive businesses. Because developing economies are generally found to have lower allocation efficiency than developed economies, improving resource allocation is expected to increase their aggregate TFP and GDP per capita.

In this paper, the author investigates the allocation of production resources in China's manufacturing sector. Several scholars have argued the degree of allocation efficiency in China. For example, Hsieh and Klenow (2009) used manufacturing firm-level data from 1998 to 2005 to measure the degree of misallocation and found that misallocation within an industry tended to decline over time. Chen, et al. (2011) used industry-level data from 1980 to 2008 and found that factor reallocation played a substantial role in increasing aggregate productivity from 1980 to 2000; however, after 2001, they found that allocation efficiency worsened and contributed to decreasing productivity growth. Brandt, et al. (2013) also used industry-level data by province from 1985 to 2007 and found that misallocation within provinces declined between 1985 and 1997 but increased in the last 10 years.

Although many researchers have maintained continuous interests in the allocation efficiency in China, little study has been done to actually explore resource allocation between ownership sectors. Since the 2000s, one debate has been over the state sector's advantageous access to capital resources compared with the private sector, a phenomenon called Guojin Mintui (i.e., the state advances, the private sector retreats). Such a favorable environment for the state sector may impede the growth of the private sector, causing resource allocation to deteriorate. Has China's resource allocation between the state and private sector been working efficiently? There are no definitive answers to this questions.

To address this issue, the author develops a quantitative measure of allocation efficiency, which is an extension of the dynamic Olley-Pakes productivity decomposition proposed by Melitz and Polanec (2015).[1)] The covariance measure was originally proposed by Olley and Pakes (1996), Melitz and Polanec (2015) extended it to capture the contributions of entering and exiting firms, calling it the dynamic Olley-Pakes (OP) productivity decomposition. However, the dynamic and non-dynamic (i.e., original) OP decomposition do not capture allocation efficiency between groups (e.g., ownership groups); they only capture allocation efficiency within a group. This paper attempts to extend the dynamic OP decomposition to a multi-group version to simultaneously capture the degree of allocation efficiency within a group and between groups and parallel to capturing the contribution of entering and exiting firms. Using this extended decomposition, the author examines the allocation efficiency within and between the state-owned,

[1)] There are two types of empirical measures of allocation efficiency: (1) the gap beween marginal product and the unit cost of input (Hsieh and Klenow, 2009; Petrin and Levinsohn, 2012) and (2) the covariance between a firm's market share and productivity (Olley and Pakes, 1996; Collard-Wexler and De Loecker, 2013; Melitz and Polanec, 2015). This paper attempts to extend the latter measure of allocation efficiency.

domestic private, and foreign sectors.

The data used for the quantitative analysis is based on China's manufacturing firm-level data from 2003 to 2007. The empirical analysis has two steps. First, firm-level productivity is estimated using a structural estimation method proposed by Gandhi, et al. (2016). Second, the productivity decomposition method is exploited to quantify the effect of misallocation on aggregate manufacturing productivity. As a result, allocation efficiency between the three ownership sectors (state-owned, domestic private, and foreign sectors) tends to improve in industries in which the market share moves from a less-productive state-owned sector to a more productive private sector. However, this efficiency tends to worsen in industries in which 1) the state-owned sector's TFP increases on relative basis despite decreases in its market share or 2) the private sector's TFP does not grow compared with other sectors despite increases in its market share.

The remainder of this paper is structured as follows. Section 2 describes the measure of allocation efficiency used in this study. Section 3 describes the TFP estimation procedure and the data sources, Section 4 reports the allocation efficiency in China, and Section 5 concludes.

2 Measure of Allocation Efficiency

The measure of allocation efficiency used in this paper is based on a productivity decomposition method originally developed by Olley and Pakes (OP; 1996) and extended by Melitz and Polanec (MP; 2015) to a dynamic version. Sections 2.1 and 2.2 review the OP and MP methods, and Section 2.3 describes the extended version of their methods. Section 4 reports the empirical results of allocation efficiency between ownership groups.

2.1 Olley-Pakes Decomposition

Let us consider aggregate productivity (Φ_t), which is defined as the weighted average of firm-level productivity: $\Phi_t = \sum_{i\in\Omega_t} s_{it}\phi_{it}$, where Ω_t is the set of firms at time t, ϕ_{it} is the firm-level log TFP, and s_{it} is firm i's share of output at time t. Olley and Pakes (1996) showed that aggregate productivity can be decomposed into the following two parts:

$$\begin{aligned}\Phi_t &= \sum_{i\in\Omega_t} s_{it}\phi_{it} = \frac{1}{N_t}\sum_{i\in\Omega_t}\phi_{it} + \sum_{i\in\Omega_t}\left(s_{it} - \frac{1}{N_t}\sum_{\iota\in\Omega_t} s_{\iota t}\right)\left(\phi_{it} - \frac{1}{N_t}\sum_{\iota\in\Omega_t}\phi_{\iota t}\right) \\ &= \mu_t + \mathrm{cov}_t\end{aligned} \tag{1}$$

where μ_t represents the unweighted mean productivity and cov_t is proportional to the covariance between market shares and productivity. cov_t represents the magnitude of allocation efficiency because it increases as more-productive firms have higher market shares, and conversely, it decreases as less productive firms have higher market shares. Olley and Pakes (1996) used plant-level panel data on the U.S. telecommunications equipment industry from 1974 to 1987 to estimate plant-level productivity for the industry and then exploited it to calculate OP decomposition. They found that the unweighted mean productivity (μ_t) did not change much since 1975, but the covariance term increased from 0.01 in 1974 to 0.32 in 1987. They concluded that a factor reallocation occurred from less-productive to more-productive plants.

2.2 Dynamic Olley-Pakes Decomposition

Melitz and Polanec (2015) extended the OP decomposition to capture the contribution of entering and exiting firms in aggregate productivity, which is called the dynamic Olley-Pakes productivity decomposition. They showed that the difference in the aggregate log TFP at times 1 and 2 ($\Delta\Phi = \Phi_2 - \Phi_1$) can be decomposed into the following parts: (1) unweighted TFP of firms surviving during the period, (2) the OP's covariance term calculated using surviving firms' log TFP and market shares, and (3) the contribution of entering and exiting firms during the period.

The dynamic Olley-Pakes (DOP) decomposition is derived as follows. First, the aggregate log TFP at time 1 (Φ_1) is decomposed into surviving firms' log TFP and exiting firms' log TFP at time 1:

$$\begin{aligned}\Phi_1 &= \sum_{i\in\Omega^S} s_{i1}\phi_{i1} + \sum_{i\in\Omega^X} s_{i1}\phi_{i1} \\ &= \Phi_1^S + s_1^X\left(\Phi_1^X - \Phi_1^S\right),\end{aligned} \tag{2}$$

where Ω^S and Ω^X denote the sets of surviving and exiting firms during the period and Φ_1^S and Φ_1^X are the aggregate log TFPs at time 1 for surviving and exiting firms, respectively:

$$\Phi_1^S = \sum_{i\in\Omega^S} \frac{s_{i1}}{\sum_{\iota\in\Omega^S} s_{\iota 1}}\phi_{i1}, \quad \Phi_1^X = \sum_{i\in\Omega^X} \frac{s_{i1}}{\sum_{\iota\in\Omega^X} s_{\iota 1}}\phi_{i1}, \quad s_1^X = \sum_{i\in\Omega^X} s_{i1}.$$

Similarly, the aggregate log TFP at time 2 is decomposed into surviving firms' log TFP at time 2 and entering firms' log TFP at time 2:

$$\begin{aligned}\Phi_2 &= \sum_{i\in\Omega^S} s_{i2}\phi_{i2} + \sum_{i\in\Omega^E} s_{i2}\phi_{i2} \\ &= \Phi_2^S + s_2^E\left(\Phi_2^E - \Phi_2^S\right),\end{aligned} \tag{3}$$

where Ω^E denotes the set of entering firms during the period and Φ_2^S and Φ_2^E are the aggregate log TFPs at time 2 for surviving firms and entering firms, respectively:

$$\Phi_2^S = \sum_{i\in\Omega^S} \frac{s_{i2}}{\sum_{\iota\in\Omega^S} s_{\iota 2}}\phi_{i2}, \quad \Phi_2^E = \sum_{i\in\Omega^E} \frac{s_{i2}}{\sum_{\iota\in\Omega^E} s_{\iota 2}}\phi_{i2}, \quad s_2^E = \sum_{i\in\Omega^E} s_{i2}.$$

Applying the OP decomposition to Φ_t^S ($t = 1, 2$) yields:

$$\begin{aligned}\Phi_t^S &= \frac{1}{N_S}\sum_{i\in\Omega^S}\phi_{it} + \sum_{i\in\Omega^S}\left(\frac{s_{it}}{\sum_{\iota\in\Omega^S} s_{\iota t}} - \frac{1}{N_S}\sum_{i\in\Omega^S}\frac{s_{it}}{\sum_{\iota\in\Omega^S} s_{\iota t}}\right)\left(\phi_{it} - \frac{1}{N_S}\sum_{i\in\Omega^S}\phi_{it}\right) \\ &= \mu_t^S + \mathrm{cov}_t^S,\end{aligned} \tag{4}$$

where N_S is the number of firms surviving during the period, μ_t^S is the unweighted mean productivity of surviving firms, and cov_t^S represents the magnitude of allocation efficiency among surviving firms. Substituting Equation (4) in Equations (2) and (3) and taking the difference of the aggregate log TFP ($\Delta\Phi = \Phi_2 - \Phi_1$) results in the DOP decomposition as follows:

$$\begin{aligned} \Delta\Phi &= \Delta\mu^S + \Delta\mathrm{cov}^S + s_2^E(\Phi_2^E - \Phi_2^S) + s_1^X(\Phi_1^S - \Phi_1^X) \\ &= \Delta\mu^S + \Delta\mathrm{cov}^S + ent + ext\,, \end{aligned} \tag{5}$$

where $\Delta\mu^S = \mu_2^S - \mu_1^S$, $\Delta\mathrm{cov}^S = \mathrm{cov}_2^S - \mathrm{cov}_1^S$, $ent = s_2^E(\Phi_2^E - \Phi_2^S)$, and $ext = s_1^X(\Phi_1^S - \Phi_1^X)$. The first term on right-hand side is the change in the unweighted average log TFP for surviving firms. The second term is the change in the covariance, which indicates the change in the magnitude of allocation efficiency among surviving firms. The contributions of entering and exiting firms appear in *ent* and *ext*, respectively, both of which are evaluated in comparison with the productivity of surviving firms as follows:

$$\begin{aligned} ent &\gtreqless 0 \text{ when } \Phi_2^E \gtreqless \Phi_2^S, \\ ext &\gtreqless 0 \text{ when } \Phi_1^S \gtreqless \Phi_1^X. \end{aligned}$$

Thus, the DOP decomposition method allows us to identify the contributions of entering and exiting firms.

Melitz and Polanec (2015) used firm-level panel data from the Slovenian manufacturing sector from 1995 to 2000 to estimate the parameters of a production function for the industry and then calculated the DOP decomposition using the estimated log TFP and the log of labor productivity. They found that the aggregate log TFP change ($\Delta\Phi$) from 1995 to 2000 is 0.4013 and is decomposed into the unweighted mean productivity for surviving firms ($\Delta\mu^S = 0.2758$), the covariance term change ($\Delta\mathrm{cov}^S = 0.0955$), and the contributions of entering and exiting firms ($ent = 0.0021$, $ext = 0.0279$). Their results indicate that the improvement in allocation efficiency added 10 percentage points to aggregate TFP growth during the five years.

2.3 Augmented Dynamic OP (ADOP) Decomposition

The OP and DOP decompositions allow us to quantify the degree of allocation efficiency within a group (e.g., an industrial sector). However, these quantifications can be augmented to a multi-group version to simultaneously capture the degree of allocation efficiency within a group and between groups. This section shows the augmented version of the DOP decomposition.

Let us consider that the number of groups is J and aggregate log TFP at time 1 is represented as:

$$\begin{aligned} \Phi_1 &= \sum\nolimits_{j=1}^{J} w_{j1} \sum_{i\in\Omega_{j1}} \frac{s_{i1}}{w_{j1}}\phi_{i1} \\ &= \sum\nolimits_{j=1}^{J} w_{j1}\,\tilde{\mu}_{j1}, \end{aligned}$$

where Ω_{j1} is the set of firms in group j at time 1, w_{j1} is group j's output share at time 1, and $\tilde{\mu}_{j1} = \sum_{i\in\Omega_{j1}}(s_{i1}/w_{j1})\phi_{it}$ is the weighted average log TFP for group j. Applying the OP decomposition to the above equation yields:

$$\begin{aligned}\Phi_1 &= \frac{1}{J}\sum\nolimits_{j=1}^{J}\tilde{\mu}_{j1} + \sum\nolimits_{j=1}^{J}\left(w_{jt} - \frac{1}{J}\sum\nolimits_{\kappa=1}^{J} w_{\kappa 1}\right)\left(\tilde{\mu}_{j1} - \frac{1}{J}\sum\nolimits_{\kappa=1}^{J}\tilde{\mu}_{\kappa 1}\right) \\ &= \frac{1}{J}\sum\nolimits_{j=1}^{J}\tilde{\mu}_{j1} + \tilde{\mathrm{cov}}_1\,,\end{aligned} \tag{6}$$

where $\tilde{\mathrm{cov}}_t$ represents the magnitude of inter-group allocation efficiency. This paper defines the first and second terms as "within-effect" and "between-effect," respectively. The weight $a_{ij1} = s_{i1}/w_{j1}$ can be written as

$$\begin{aligned}\sum\nolimits_{i\in\Omega_{j1}} a_{ij1} &= \sum\nolimits_{i\in\Omega_j^S} a_{ij1} + \sum\nolimits_{i\in\Omega_j^X} a_{ij1} \\ &= a_{j1}^S + a_{j1}^X = 1.\end{aligned}$$

where Ω_j^S and Ω_j^X denote the sets of surviving and exiting firms for group j, respectively. They can be decomposed into the weighted average log TFP of surviving firms and the contribution of exiting firms:

$$\begin{aligned}\tilde{\mu}_{j1} &= \sum_{i\in\Omega_j^S}\frac{a_{ij1}}{a_{j1}^S}\phi_{i1} + a_{j1}^X\left(\sum_{i\in\Omega_j^X}\frac{a_{ij1}}{a_{j1}^X}\phi_{i1} - \sum_{i\in\Omega_j^S}\frac{a_{ij1}}{a_{j1}^S}\phi_{i1}\right) \\ &= \Phi_{j1}^S + a_{j1}^X\left(\Phi_{j1}^X - \Phi_{j1}^S\right) \\ &= \Phi_{j1}^S - ext_j,\end{aligned} \tag{7}$$

where Φ_{j1}^S and Φ_{j1}^X denote the weighted average log TFP of surviving and exiting firms for group j, respectively, and $ext_j = a_{j1}^X\left(\Phi_{j1}^S - \Phi_{j1}^X\right)$ represents the contribution of exiting firms to group j's aggregate productivity $\tilde{\mu}_{j1}$. By exploiting the OP decomposition method, the first term of Equation (7) can be decomposed as:

$$\begin{aligned}\Phi_{j1}^S &= \frac{1}{N_{j1}^S}\sum_{i\in\Omega_j^S}\phi_{i1} + \sum_{i\in\Omega_j^S}\left(\frac{a_{ij1}}{a_{j1}^S} - \frac{1}{N_{j1}^S}\sum_{\iota\in\Omega_j^S}\frac{a_{\iota j1}}{a_{j1}^S}\right)\left(\phi_{i1} - \frac{1}{N_{j1}^S}\sum_{\iota\in\Omega_j^S}\phi_{\iota 1}\right) \\ &= \mu_{j1}^S + \mathrm{cov}_{j1}^S,\end{aligned} \tag{8}$$

where μ_{j1}^S is the simple average log TFP of surviving firms at time 1 and cov_{j1}^S is the degree of allocation efficiency within group j at time 1. Substituting Equations (8) and (7) in Equation (6) yields the following decomposition:

$$\Phi_1 = \underbrace{\frac{1}{J}\sum\nolimits_{j=1}^{J}\left(\mu_{j1}^S + \mathrm{cov}_{j1}^S - ext_j\right)}_{\textit{Within effect}} + \underbrace{\tilde{\mathrm{cov}}_1}_{\textit{Between effect}}\ . \tag{9}$$

Similarly, the aggregate log TFP at time 2 can be decomposed as follows:

$$\begin{aligned}
\Phi_2 &= \frac{1}{J}\sum\nolimits_{j=1}^{J} \tilde{\mu}_{j2} + \tilde{\text{cov}}_2 \\
&= \frac{1}{J}\sum\nolimits_{j=1}^{J} \left(\Phi_{j2}^{S} + a_{j2}^{E}\left(\Phi_{j2}^{E} - \Phi_{j2}^{S}\right)\right) + \tilde{\text{cov}}_2 \\
&= \underbrace{\frac{1}{J}\sum\nolimits_{j=1}^{J} \left(\mu_{j2}^{S} + \text{cov}_{j2}^{S} + ent_j\right)}_{\textit{Within effect}} + \underbrace{\tilde{\text{cov}}_2}_{\textit{Between effect}},
\end{aligned} \tag{10}$$

where $ent_j = a_{j2}^{E}\left(\Phi_{j2}^{E} - \Phi_{j2}^{S}\right)$ indicates the contribution of entering firms to aggregate productivity $\tilde{\mu}_{j2}$.

Finally, taking the difference between Φ_1 and Φ_2, the augmented dynamic OP (ADOP) decomposition is obtained:

$$\Delta\Phi = \underbrace{\frac{1}{J}\sum\nolimits_{j=1}^{J} \left(\Delta\mu_{j}^{S} + \Delta\text{cov}_{j}^{S} + ent_j + ext_j\right)}_{\textit{Within effect}} + \underbrace{\Delta\tilde{\text{cov}}}_{\textit{Between effect}} \tag{11}$$

where Δcov_j^S represents the changes in allocation efficiency among surviving firms within group j and $\Delta\tilde{\text{cov}}$ represents the changes in allocation efficiency between groups. When $J = 1$, Equation (10) reduces to the original dynamic OP decomposition.

In this paper, Equation (11) is used to decompose China's aggregate productivity and investigate the magnitude of allocation efficiency within and between ownership sectors. The empirical results are described in Section 4. Before reporting the results, the next section explains how to measure firm-level productivity (ϕ_{it}).

3 Production Function Estimation and Data Description

3.1 Production Function Estimation

Having clarified the measure of allocation efficiency in the previous section, showing the measure of firm-level productivity is required. This paper employs the nonparametric identification strategy proposed by Gandhi, et al. (GNR; 2016) to measure China's firm-level productivity. This method is built on the recent literature on production function estimation, such as Olley and Pakes (1996), Levinsohn and Petrin (LP; 2003), and Ackerberg, et al. (ACF; 2006). The Appendix A contains GNR's estimation methodology used in this study.

3.2 Data Description

The data used to estimate the production function are based on unbalanced firm-level panel data on China's manufacturing industry from 2003 to 2007, which are obtained from the annual survey of industrial enterprises conducted by the National Bureau of Statistics. The survey covers firms with sales higher than 5 million RMB in the mining, manufacturing, and public utilities industries, and the original database consists of 336,768 industry firms for 2007, which is the same number as that reported in the China Statistical Yearbook published in 2008 (p. 485). Firm IDs contained in the database are used to construct a panel of observations.[2)]

The production function variables are constructed as follows: Y_{it} is the total gross output, K_{it} is the total fixed assets, L_{it} is the number of employees, and M_{it} is the total intermediate inputs. The deflators for Y_{it} and M_{it} are based on the output and input deflators provided by Brandt, et al. (2012).[3)] The deflator for total fixed assets is constructed as follows.

(1) Firm-level total fixed-asset data at current prices are gathered by province. The province-level data are denoted by $\tilde{K}_{pt}$, where p denotes a province.
(2) The provincial nominal investment is calculated as $\tilde{I}_{it} = \tilde{K}_{pt} - (1 - \delta)\tilde{K}_{p,t-1}$. Following Brandt et al. (2012), the depreciation rate δ is set at 0.09.
(3) $\tilde{I}_{it}$ is deflated by a province-level investment deflator, which is obtained from the China Statistical Yearbook. Using the deflated investment (I_{pt}), provincial deflated fixed assets are calculated as $K_{pt} = (1 - \delta)K_{p,t-1} + I_{pt}$, where $K_{p0} = \tilde{K}_{p0}$.
(4) The deflator for total fixed assets by province can be calculated using $\tilde{K}_{pt}$ and K_{pt}.

The following firms are removed as outliers from the database: 1) firms with a non-positive value for Y_{it}, K_{it}, L_{it}, or M_{it}; 2) firms whose Y_{it}/L_{it} or K_{it}/L_{it} in t is more than 1000 times or less than 0.001 the value in $t - 1$; or 3) firms in Tobacco (industrial codes 161, 162, and 169) and nuclear-related industries (253 and 424). Table 1 shows the number of firms. Manufacturing firm-level data without outliers are used for the estimation.

[– Table 1 –]

Table 2 reports summary statistics of the panel data by ownership sector. “State” denotes state-owned firms, including state-owned enterprises and solely state-funded corporations. “Private+” denotes domestic and non-state-owned firms, including collective-owned firms (and other hybrids) and privately funded enterprises. “Foreign” denotes firms with funds from Hong Kong, Macao, and Taiwan and those that are purely foreign-funded enterprises. The State sector shows the smallest number of firms and a sharp decrease of 57% from 2003 to 2007, whereas the number of private and foreign firms increased during the four years. The Private+ sector has the largest number of firms, accounting for 76% of the total in 2007. However, its output per firm is nearly five times smaller than that of state-owned firms in 2007, indicating that most private firms operate as small entities compared with state and foreign firms. Note that the number of firms in 2004 increases 1.4 times compared to the previous year. Because Chinese economic census was conducted in 2004, the sample coverage has been probably expanded since 2004.

[– Table 2 –]

[2)] However, this IDs are often missing or changes over time. Hence, this paper creates a new series of firm IDs by using firm attributes, such as original firm IDs, firm names, and phone numbers. Firm-matching is conducted by R. The matching algorithm is described in Appendix B.

[3)] See their online appendix: `http://www.econ.kuleuven.be/public/n07057/china/`.

3.3 Estimates of Output Elasticities

The production function is separately estimated by industry using a three-digit industrial code.[4)] Appendix Tables A1–A4 report the estimates of the average output elasticities for each input and the sum of the elasticities for capital, labor, and intermediate inputs. The estimates of GNR's method are found to show lower average elasticities of intermediate inputs (η_M) than the OLS estimates in every industry. The difference between the GNR and OLS estimates of η_M is 0.32 on average, and the OLS estimates are approximately 1.55 times higher on average than the GNR estimates. These results are clearly expected and consistent with the estimation results in GNR (2016). The failure to control the endogenous bias from the correlation between flexible variables and unobservable productivity (ω_{it}) is known to lead to overestimates of the coefficients on flexible variables because positive productivity shocks are likely to increase the use of flexible inputs. The average elasticities of capital and labor as estimated by OLS are lower than the estimates based on the GNR method, which is also consistent with the empirical results in GNR (2016).

China's intermediate input elasticities shown in Appendix Tables A1–A4 are similar to Colombia's and Chile's as estimated by GNR (2016). The data used in GNR (2016) are based on five three-digit manufacturing industries (Food Products, Textiles, Apparel, Wood Products, Fabricated Metal Products), and their estimates of input elasticities for these industries are 0.54 for Colombia, and 0.55 for Chile, respectively. This paper's average elasticity for the nearly corresponding industries (131, 171, 181, 203, and 341) is 0.53, which is slightly smaller than the estimates of Colombia and Chile.

4 Allocation Efficiency

This section presents the results of the augmented dynamic OP (ADOP) decomposition using China's manufacturing firm-level productivity. These methods enable us to simultaneously quantify allocation efficiency within and between three ownership groups ($j \in \{$State (S), Private+ (P), and Foreign (F) sectors$\}$ ($J = 3$)). Because the three-digit industrial classification is relatively narrow, several industries have few or no firms in any of the three ownership sectors. To focus on the industries in which the three ownership sectors coexist, this analysis is conducted on the three-digit industrial sectors with more than 50 firms for each ownership sector. As a result, 75 industrial sectors are used for the analysis.[5)] The ADOP decomposition equation for sector i is written as

$$\Delta\Phi(i) = \frac{1}{3} \sum_{j \in \{S,P,F\}} \left[\Delta\mu_j^S(i) + \Delta\mathrm{cov}_j^S(i) + ent_j(i) + ext_j(i) \right] + \Delta\tilde{\mathrm{cov}}(i).$$

Note that i denotes a three-digit industrial sector and the ADOP decomposition applies separately for each $i = 1, 2, \ldots, 75$.

4)Industries 212, 214, 233, 402, and 423 are included in 211, 219, 232, 409, and 429, respectively. The estimation is implemented using R version 3.3.1 (R Development Core Team, 2009).

5)This sample selection may cause us to select industrial sectors where the state-owned firms are likely to survive in the market. It is necessary to keep in mind that there may exist the inequality of competitive conditions between the state and non-state sectors in such sectors.

4.1 Allocation Efficiency between Ownership Groups

[– Figure 1 –]

Figure 1 demonstrates the ADOP decomposition of the aggregate TFP growth from 2003 to 2007. The main driver of the aggregate TFP growth is $\Delta \text{cov}^S_j(i)$, changes in the simple average log TFP of surviving firms. The contribution of the within and between allocation efficiency $\Delta \text{cov}^S_j(i)$ and $\Delta \tilde{\text{co}}\text{v}(i)$ varies across sectors, and the median of these contribution is much smaller than those of $\Delta \text{cov}^S_j(i)$. This indicates that resource reallocation does not contribute significantly to increasing the aggregate productivity growth.

[– Figure 2 –]

Figure 2 presents the allocation efficiency between three ownership groups ($\Delta \tilde{\text{co}}\text{v}(i)$) during 2003–2007. This figure exhibits the plots of aggregate productivity changes $\Delta\Phi(i)$ and the changes in allocation efficiency between the three ownership groups, $\Delta \tilde{\text{co}}\text{v}(i)$. Although the average of $\Delta \tilde{\text{co}}\text{v}(i)$ is almost zero, it varies among industries, ranging from -0.167 to 0.109. In all, 42 industrial sectors are plotted in the positive area of the vertical axis ($\Delta \tilde{\text{co}}\text{v}(i) > 0$), indicating that these industries tend to improve resource allocation among the three ownership groups.

[– Figure 3 –]

To investigate the source of the variation in $\Delta \tilde{\text{co}}\text{v}(i)$, it is rewritten as follows:

$$
\begin{aligned}
\Delta \tilde{\text{co}}\text{v}(i) &= \sum_{j \in \{S,P,F\}} \left[x_{j2}(i)\, y_{j2}(i) - x_{j1}(i)\, y_{j1}(i) \right] \\
&= \sum_{j \in \{S,P,F\}} \left[y_{j2}(i)\, \Delta x_{j2}(i) + x_{j1}(i)\, \Delta y_{j2}(i) \right]
\end{aligned}
\tag{12}
$$

where $x_{jt}(i) = w_{jt}(i) - 1/J \sum_j w_{jt}(i)$ and $y_{jt}(i) = \tilde{\mu}_{jt}(i) - 1/J \sum_j \tilde{\mu}_{jt}(i)$ for $t = 1, 2$. For industry i and ownership sector j, $\Delta x_{jt}(i)$ is changes in market share and $\Delta y_{jt}(i)$ is changes in the centered aggregate productivity during 2003–2007. The relationship among the three variables ($\Delta \tilde{\text{co}}\text{v}$, Δx_{jt}, and Δy_{jt}) is plotted in Panels (A)–(C) of Figure 3 by ownership, where the horizontal axis is Δx_{jt}, and the vertical axis is Δy_{jt}. The red-colored plots denote industries with positive $\Delta \tilde{\text{co}}\text{v}$ values in Figure 2, whereas the blue-colored plots denote industries with negative $\Delta \tilde{\text{co}}\text{v}$ values.[6)]

As shown in Panel (A), the State sector's market shares decreased in most industrial sectors, and red plots in Panel (A) are primarily distributed in the third quadrant. This result indicates that resource allocation between ownership groups ($\Delta \tilde{\text{co}}\text{v}$) tends to improve in industries in which the State sector's market share and productivity both decrease. In contrast, the blue plots

[6)] Note that the first and third quadrants in Panels (A)–(C) indicate the positive relationship between the changes in market share and productivity. However, this positive relationship does not necessarily produce positive $\Delta \tilde{\text{co}}\text{v}$ values. As is clear from Equation (12), $\Delta \tilde{\text{co}}\text{v}$ does not necessarily become positive even if the sign of Δx_{j2} is the same direction as that of Δy_{j2} for each $j \in \{S, P, F\}$.

in Panel (A) are primarily distributed in the fourth quadrant, indicating that the resource allocation between ownership groups are likely to worsen in industries in which the State sector's market share decreases but productivity increases.

Panel (B) shows the relationship between the changes in the Private+ sector's market share and productivity. Contrary to Panel (A), the red and blue plots are primarily distributed in the first and second quadrants, respectively, indicating that the resource allocation between ownership groups tends to improve in industries in which the Private+ sector's market share and productivity both increase and worsen in industries in which the Private+ sector's market share increases but productivity decreases. In contrast, the Foreign sector (Panel (C)) does not show a clear relationship between red and blue plots.

In summary, the allocation efficiency between ownership sectors tends to improve in industries in which the market share moves from the less-productive State sector to the more-productive Private+ sector. In contrast, the allocation efficiency tends to worsen in industries in which 1) the State sector's productivity relatively increases despite a decrease in its market share or 2) the Private+ sector's productivity does not grow compared with the other sectors despite an increase in its market share.

4.2 Within-Effects for Each Ownership Group

[– Figure 4 –]

Figure 4 reports the histograms of the within-effects. The vertical axis defines the number of three-digit industrial sectors ($i = 1, 2, \dots, 75$). Panels (A), (B) and (C) show allocation efficiency $\Delta \mathrm{cov}_j^S(i)$, entry effects $ent_j(i)$, and exit effects $ext_j(i)$ within a group $j \in \{S, P, F\}$, respectively.[7)]

Panel (A) shows that the medians of these histograms is -0.006 (State), 0.02 (Private+), and 0.009 (Foreign), and that the shares of the number of sectors with $\Delta \mathrm{cov}_j^S(i) > 0$ are 46.1%, 64.5%, and 54.0%, respectively. Although the values of $\Delta \mathrm{cov}_j^S(i)$ are distributed broadly for each group, the Private+ group tends to improve its allocation efficiency among firms during 2003–2007. The entry effect in Panel (B) shows that the medians for each group are -0.003 (State), -0.018 (Private+), and -0.011 (Foreign), and the shares of the number of sectors with $ent_j(i) > 0$ are 46.1%, 31.6%, and 40.8%, respectively. This result indicates that new entry firms in all groups during 2003–2007 have, on average, lower productivity than existing firms for each group.] Consequently, they have a negative effect on aggregate productivity growth. In particular, new entry firms in the Private+ sector tend to show relatively low productivity compared to the other sectors. Furthermore, the exit effect of the Private+ group shown in Panel (C) is also small. The medians are 0.039 (State), 0.0061 (Private+), and 0.0095 (Foreign), and the shares of the number of sectors with $ext_j(i) > 0$ are 80.3%, 56.6%, and 64.5%, respectively, implying that relatively nonproductive firms in the Private+ group are not likely to exit the market.

7) Appendix Figures A1–A4 demonstrate the bar-plots of the decomposition into the ownership sectors by 3-digit industry.

In summary, the Private+ sector tends to have more industrial sectors improving allocation efficiency among firms, compared with State and Foreign sectors. However, the entry and exit effects for Private+ are very weak. In particular, the entry effect has negative values for many industrial sectors, indicating that new firms in the Private+ sector tend to be less productive than existing firms and drive down aggregate productivity growth.

5 Conclusions

Despite the fact many scholars have shown an interest in China's allocation efficiency, few studies have examined quantitative analysis of allocation efficiency within and between the state-owned and private sectors. The author addresses this issue, using China's manufacturing firm-level data and a new measure of allocation efficiency that is an extension of the productivity decomposition methods proposed by Olley and Pakes (1996) and Melitz and Polanec (2015). This new measure enables us to simultaneously capture the degree of misallocation within a group and between groups, and parallel to capturing the contribution of entering and exiting firms to aggregate TFP growth. Because the methods used by Olley and Pakes (1996) and Melitz and Polanec (2015) cannot capture the degree of allocation efficiency between groups, this new measure can be considered a group-wise extension of their methods.

It is found that misallocation between three ownership groups declined in 42 of the 75 three-digit industrial sectors, indicating that these industries improved resource allocation among the three ownership groups. Furthermore, misallocation tended to decline in industries wherein market shares move from the less-productive State sector to the more-productive Private+ sector. In contrast, misallocation tended to worsen in industries in which 1) the State sector's productivity relatively increases despite decreases in its market share or 2) the Private+ sector's productivity does not grow compared with that of the other sectors despite increases in its market share.

These empirical results lead us to conclude that resource allocation between State, Private+, and Foreign sectors tends to improve by allocating production resources to more productive private firms from less productive state-owned firms. In other words, industries in which less productive state-owned firms have greater market share are likely to be lower allocation efficiency. What is behind the behavior of allocation efficiency in China? According to previous studies, financial frictions are believed to be an important source of misallocation (Caggese and Cuñat, 2013; Midrigan and Xu, 2014). The main source of misallocation between ownership sectors could be attributed to unequal access to factor resources, such as capital from bank loans, subsidies, and land, between state-owned and non-state owned firms. A favorable environment for the state sector or a phenomenon "Guojin Mintui" (i.e., the state advances, the private sector retreats) may impede the growth of the private sector, causing resource allocation to deteriorate. Although identifying the source of misallocation is challenging, reexamining the equity of competitive conditions among firms in the financial market in terms of optimal resource allocation is crucially important.

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Table 1: Number of firms

	2003	2004	2005	2006	2007
The original number of firms [1]	196,220	276,474	271,835	301,960	336,768
Manufacturing firms [2]	181,225	257,075	251,556	279,309	313,046
Manufacturing firms without outliers [3]	173,186	246,821	243,922	272,119	306,427

[1] Number of sample firms of the original database, which includes firms in the mining, manufacturing, and public utilities industries.
[2] Number of manufacturing firms of the original database.
[3] Number of firms used for the estimation.

Table 2: Summary of Firm-level Panel Data[1]

		Average			
	Num	Y	K	L	M
All (2003)	173,186	71,374	23,197	275	54,829
All (2004)	246,821	65,016	19,068	225	49,679
All (2005)	243,922	78,505	21,838	239	59,292
All (2006)	272,119	86,894	22,779	228	65,253
All (2007)	306,427	96,697	23,316	220	72,432
State (2003)	14,458	115,053	69,480	597	88,769
State (2004)	13,407	108,548	59,460	461	83,433
State (2005)	9,758	170,049	85,542	597	130,147
State (2006)	8,319	211,790	104,574	623	162,019
State (2007)	6,122	335,632	145,929	792	261,067
Private+ (2003)	121,514	53,310	15,449	220	40,833
Private+ (2004)	178,917	48,180	13,422	180	36,808
Private+ (2005)	179,020	58,393	15,383	188	44,224
Private+ (2006)	204,527	64,353	15,713	178	48,399
Private+ (2007)	234,384	71,291	16,054	169	53,194
Foreign (2003)	37,214	113,387	30,514	330	87,346
Foreign (2004)	54,497	109,581	27,667	315	83,631
Foreign (2005)	55,144	127,596	31,521	341	95,673
Foreign (2006)	59,273	147,147	35,681	348	109,828
Foreign (2007)	65,921	164,841	37,749	348	123,313

[1] Outliers are excluded. Y, K, L, and M denote the average values of output, fixed capital, the number of labor, and intermediate inputs. These variables are constant prices at 2003. Num is the number of firms.

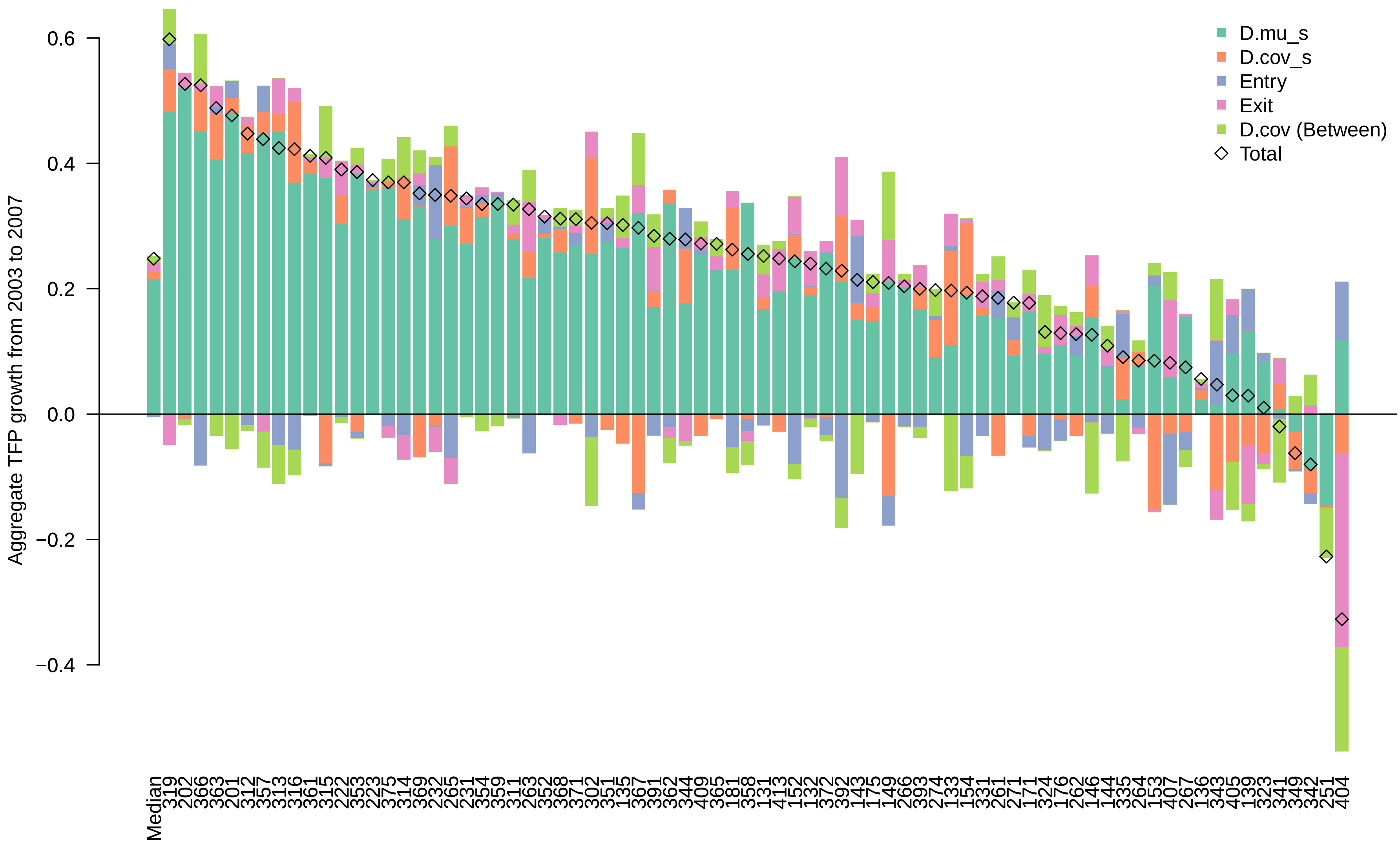
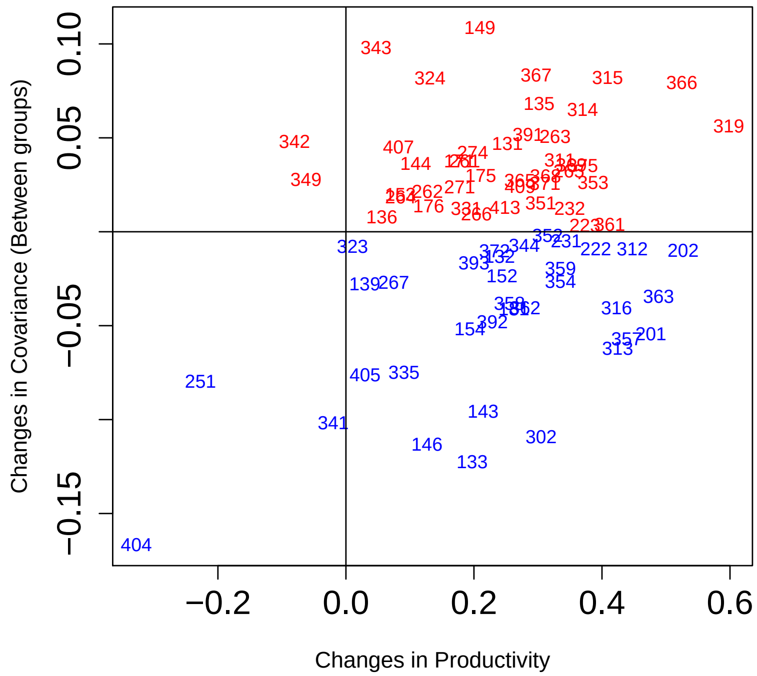


Figure 1: ADOP Decomposition of the aggregate TFP growth 2003–2007

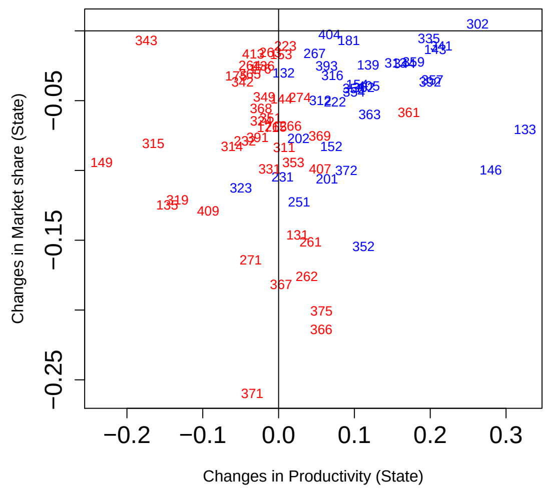
Notes: The horizontal axis shows the number of three-digit industrial sectors ($i = 1, 2, \ldots, 75$). $D.mu_s \equiv 1/J \sum \Delta\mu_j^S$, $D.cov_s \equiv 1/J \sum \Delta \mathrm{cov}_j^S$, $Entry \equiv 1/J \sum ent_j$, $Exit \equiv 1/J \sum ext_j$, and $D.cov(Between) \equiv \Delta\tilde{\mathrm{cov}}$.



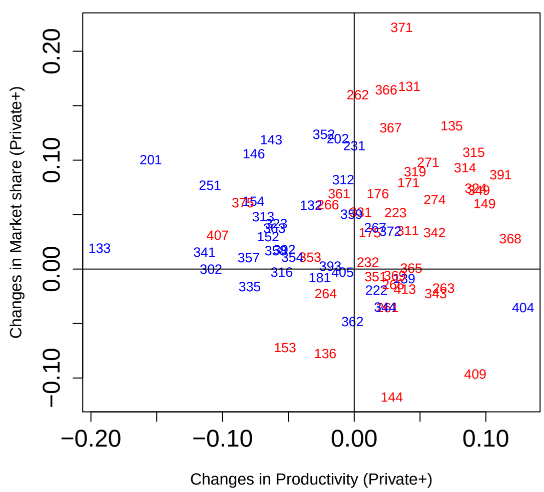
Plots of $\Delta\Phi(i)$ (horizontal axis) and $\Delta\tilde{\text{co}}\text{v}(i)$ (vetical axis), $i = 1, 2, ..., 75$.

Figure 2: Changes in allocation efficiency *between* ownership groups during 2004–2007

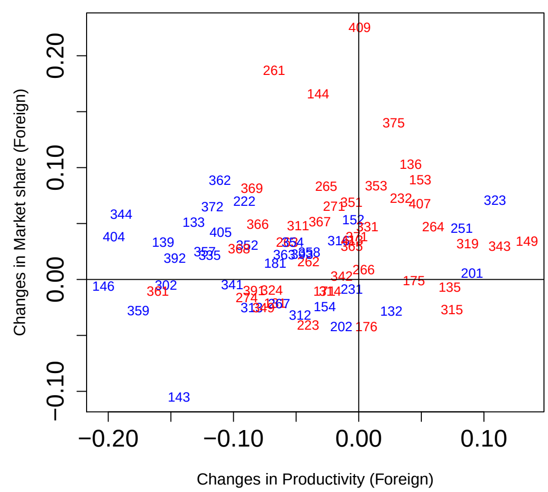
Notes: Red-colored plots denote industries with positive $\Delta\tilde{\text{co}}\text{v}$ values, whereas blue-colored plots denote industries with negative $\Delta\tilde{\text{co}}\text{v}$ values.



(A) Decomposition of $\Delta \tilde{cov}$ (State)



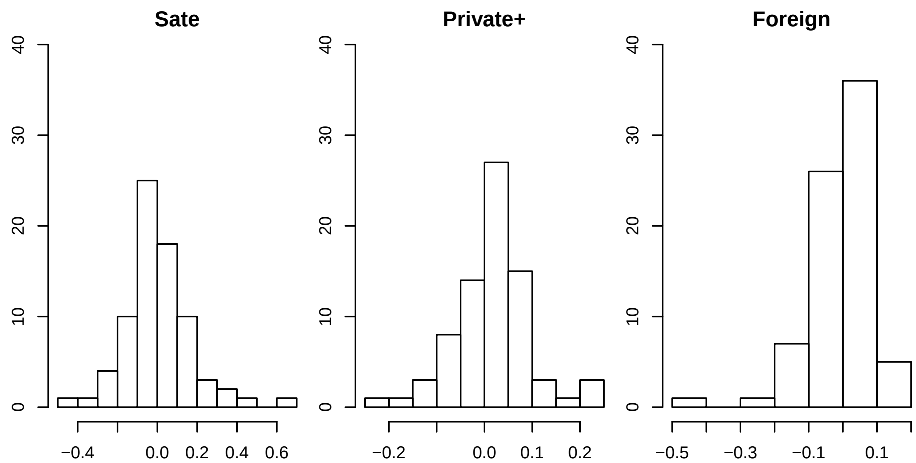
(B) Decomposition of $\Delta \tilde{cov}$ (Private+)



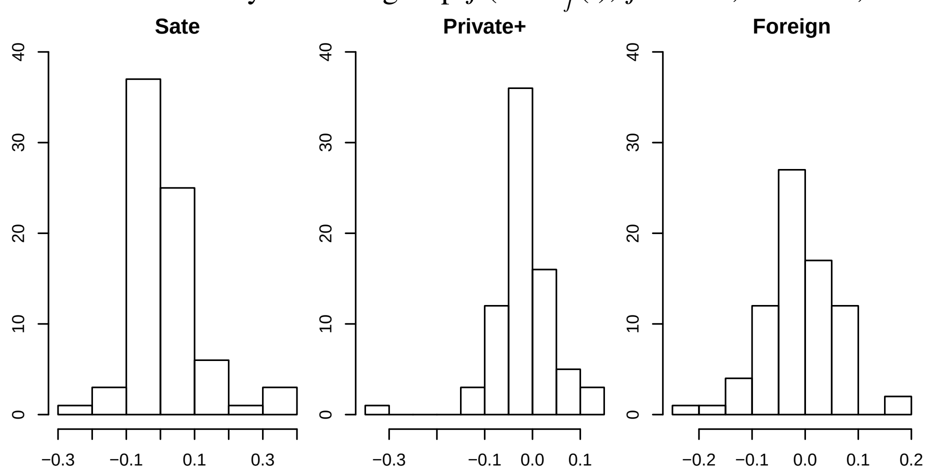
(C) Decomposition of $\Delta \tilde{cov}$ (Foreign)

Figure 3: Source of the variation in $\Delta \tilde{cov}(i)$ during 2004–2007

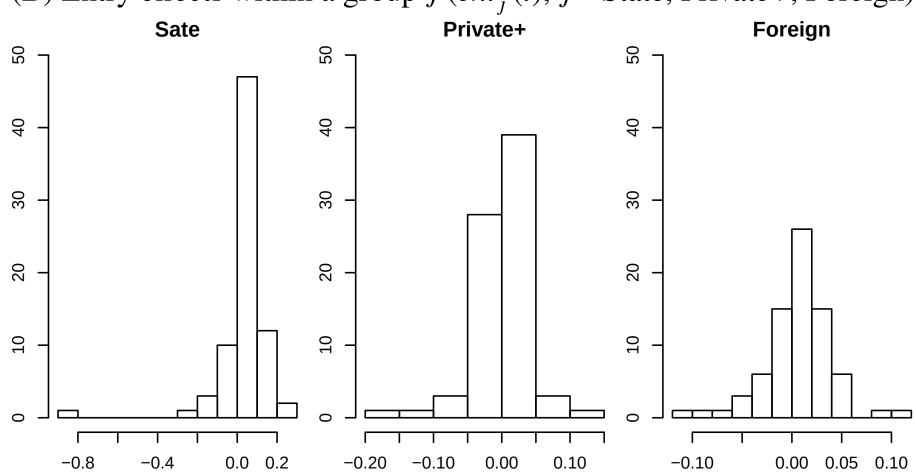
Notes: This figure shows the plots of changes in productivity (horizontal axis) and changes in market share (vertical axis) for (A) State, (B) Private+, and (C) Foreign sectors. Red-colored plots denote industries with positive $\Delta \tilde{cov}$ values in Figure 2, whereas blue-colored plots denote industries with negative $\Delta \tilde{cov}$ values.



(A) Allocation efficiency within a group j ($\Delta\text{cov}_j^S(i)$, j =State, Private+, Foreign)



(B) Entry effects within a group j ($ent_j^S(i)$, j =State, Private+, Foreign)



(C) Exit effects within a group j ($ext_j^S(i)$, j =State, Private+, Foreign)

Figure 4: Decomposition of the within-effect by ownership during 2003–2007

Notes: The vertical axis shows the number of three-digit industrial sectors (i = $1, 2, \ldots, 75$).

Appendix A: Production Function Estimation

Following GNR (2016), this section describes the framework of firm behavior and shows the identification strategy of the production function.

A.1 Model of Firm Behavior

Let us consider that firm i operates through discrete time t and produces output Y_{it} using capital K_{it}, labor L_{it}, and intermediate inputs M_{it}. The relationship between these inputs and output is assumed to be determined by a production function F and a Hicks neutral productivity shock ν_{it} as follows:

$$\begin{aligned} Y_{it} &= F(K_{it}, L_{it}, M_{it}) \exp\{\nu_{it}\} \\ &= F(K_{it}, L_{it}, M_{it}) \exp\{\omega_{it} + \varepsilon_{it}\}, \end{aligned} \tag{A.1}$$

where the productivity shock ν_{it} is decomposed as $\nu_{it} = \omega_{it} + \varepsilon_{it}$. It is assumed that ω_{it} is an anticipated productivity known to firm i, but unobservable to the econometrician,[8)] and ε_{it} represents an unanticipated productivity shock and/or measurement error that cannot be observed by firm i before making period t's decisions. Letting $\mathcal{I}_{it}$ denote the available information set of the firm in period t, the anticipated productivity (ω_{it}) is included in the information set ($\omega_{it} \in \mathcal{I}_{it}$), while ε_{it} is not included ($\varepsilon_{it} \notin \mathcal{I}_{it}$). Furthermore, ω_{it} is assumed to evolve over time according to the first-order Markov process and is decomposed into its conditional expectation given all information known to the firm in period $t-1$ and a residual (ξ_{it}). Thus, ω_{it} can be expressed as:

$$\begin{aligned} \omega_{it} &= \mathrm{E}(\omega_{it} \mid \mathcal{I}_{i,t-1}) + \xi_{it} \\ &= \mathrm{E}(\omega_{it} \mid \omega_{i,t-1}) + \xi_{it} \\ &= g(\omega_{i,t-1}) + \xi_{it}, \end{aligned} \tag{A.2}$$

where ξ_{it} is, by definition, uncorrelated to $g(\omega_{i,t-1})$ because it is defined as new information not available in period $t-1$, which is frequently referred to as an *innovation* at t. The innovation ξ_{it} and the ex post shock ε_{it} are assumed to be mean zero random variables.

The data generating process of capital, labor and intermediate inputs are assumed as follows: The amounts of capital and labor inputs are the function of $\mathcal{I}_{i,t-1}$, implying that these inputs are predetermined in period t and, then, the information set in period t includes the amounts of capital and labor in period t (i.e., $K_{it} \in \mathcal{I}_{it}$ and $L_{it} \in \mathcal{I}_{it}$). This means that these inputs are quasi-fixed inputs and that adjustment costs exist in capital and labor (e.g., hiring/firing, job training, or machine installation costs). Intermediate input depends on the information in period t and not to have dynamic implication. This implies that the choice of M_{it} is flexible in period t and is not included in the information set available in period t (i.e., $M_{it} \notin \mathcal{I}_{it}$). In other words, at each period t, given the levels of labor, capital inputs, and ω_{it}, firm i chooses the level of M_{it}.

8)The ω_{it} represents a firm's technology, information, knowledge, or situation that affects its productivity. For example, business management differences, deviations from expected machine breakdown rates in a particular period, or labor management problems.

A.2 Identification

A.2.1 Problem in the proxy approach

TFP is defined as $\exp\{\omega_{it} + \varepsilon_{it}\}$. Taking the logarithm for both sides of Equation (A.1) yields:

$$\begin{aligned} y_{it} &= f(k_{it}, l_{it}, m_{it}) + \omega_{it} + \varepsilon_{it}, \\ \log \mathrm{TFP}_{it} &= \omega_{it} + \varepsilon_{it}, \end{aligned} \tag{A.3}$$

where the lower-case letters denote the logs of their upper-case letters. Identifying $f(k_{it}, l_{it}, m_{it})$ is required to estimate TFP. However, since ω_{it} is correlated with k_{it}, l_{it}, and m_{it} under the data generating process described the previous section, the regression of y_{it} on inputs (k_{it}, l_{it}, and m_{it}) yields a biased estimate. To avoid this problem, LP (2003), ACF (2006), and Wooldridge (2009) employ a proxy approach as follows. Let us consider the demand function of intermediate inputs:

$$m_{it} = h(k_{it}, l_{it}, \omega_{it}). \tag{A.4}$$

Assuming that the intermediate demand function is strictly monotonic in ω_{it}, we obtain the anticipated productivity expressed by the inverted intermediate demand function:

$$\begin{aligned} \omega_{it} &= h^{-1}(k_{it}, l_{it}, m_{it}) \\ &= \phi_{it} - f(k_{it}, l_{it}, m_{it}) \\ &= g(\phi_{i,t-1} - f(k_{i,t-1}, l_{i,t-1}, m_{i,t-1})) + \xi_{it}, \end{aligned} \tag{A.5}$$

where $\phi_{it} = h^{-1}(k_{it}, l_{it}, m_{it}) + f(k_{it}, l_{it}, m_{it}) \equiv \phi(k_{it}, l_{it}, m_{it})$. The third equation of Equation (A.5) is derived using Equation (A.2). The key idea of the proxy approach is to replace ω_{it} with the inverted demand function. Substituting Equation (A.5) into Equation (A.3), we obtain

$$\begin{aligned} y_{it} &= \phi(k_{it}, l_{it}, m_{it}) + \varepsilon_{it} \\ &= f(k_{it}, l_{it}, m_{it}) + g(\phi_{i,t-1} - f(k_{i,t-1}, l_{i,t-1}, m_{i,t-1})) + \xi_{it} + \varepsilon_{it}. \end{aligned} \tag{A.6}$$

Because k_{it}, $k_{i,t-1}$, l_{it}, $l_{i,t-1}$, and $m_{i,t-1}$ are, by definition, uncorrelated with both ξ_{it} and ε_{it}, this orthogonality is exploited to identify the production function. The estimation procedure of the proxy approach has two steps: the first is to estimate ϕ_{it} and ε_{it} using the first equation of Equation (A.6), and the second is to identify the parameters of the production function using the results of the first step.

However, GNR (2016) shows that this proxy approach is not able to identify the production function under the above assumption of data generating process.[9)] The cause of it lies in the collinearity between inputs. Replacing ω_{it} in Equation (A.4) with the inverted demand function, we obtain

$$m_{it} = h(k_{it}, l_{it}, g(h(k_{i,t-1}, l_{i,t-1}, m_{i,t-1})) + \xi_{it}). \tag{A.7}$$

[9)] Although the original proxy strategy proposed by OP (1996) exploits investment variable, GNR (2016) shows that this strategy also raises similar identification problems.

Given the predetermined variables (k_{it}, $k_{i,t-1}$, l_{it}, $l_{i,t-1}$, and $m_{i,t-1}$), no source of variation exists in m_{it} except for the unobservable ξ_{it}, implying that the production function is non-parametrically under-identified.[10] GNR (2016) proposed an alternative approach to solving the identification problem based on gross output production functions, including both quasi-fixed inputs and flexible inputs. This paper employs their identification strategy.

A.2.2 Identification strategy

GNR (2016) found that the source of the under-identification lies in the elasticity of flexible inputs, that is, $\partial f(k_{it}, l_{it}, m_{it})/\partial m_{it}$ in this paper. The integration of the elasticity in terms of m_{it} can be expressed as

$$\int \frac{\partial f(k_{it}, l_{it}, m_{it})}{\partial m_{it}} dm_{it} = f(k_{it}, l_{it}, m_{it}) + \varphi(k_{it}, l_{it}) \tag{A.8}$$

where $\varphi(k_{it}, l_{it})$ is a function of k_{it} and l_{it}, which denotes an integral constant in terms of m_{it}. Using Equation (A.8), y_{it} can be rewritten as

$$y_{it} = \int \frac{\partial f(k_{it}, l_{it}, m_{it})}{\partial m_{it}} dm_{it} - \varphi(k_{it}, l_{it}) + \omega_{it} + \varepsilon_{it}. \tag{A.9}$$

If the integral of the flexible inputs elasticity is known, the proxy approach is able to identify the production function (GNR, 2016, Theorem 3). Based on this theorem, GNR proposed the following two-step identification strategy: (1) recovering the integral of the flexible inputs elasticity by using the firm's first-order condition; and (2) identifying the remaining function $\varphi(k_{it}, l_{it})$. Given these estimates, TFP can be identified.

A specific estimation procedure employed in this paper is as follows. Let us consider the firm's expected profit maximization problem with respect to M_{it} under the perfect competition in the intermediate input and output markets. The first-order condition of the problem is

$$P_t \frac{\partial F(K_{it}, L_{it}, M_{it})}{\partial M_{it}} \exp\{\omega_{it}\}\mathcal{E} = \rho_t, \tag{A.10}$$

where $\mathcal{E} \equiv \mathrm{E}(\exp\{\varepsilon_{it}\})$, and P_t and ρ_t denote the output and intermediate input prices, respectively. Multiplying both sides of Equation (A.10) by $M_{it}/P_t Y_{it}$ yields the revenue share of the intermediate input:

$$\begin{aligned} S_{it} \equiv \frac{\rho_t M_{it}}{P_t Y_{it}} &= \frac{\partial f(k_{it}, l_{it}, m_{it})}{\partial m_{it}} \frac{\mathcal{E}}{\exp\{\varepsilon_{it}\}} \\ &= \mathcal{B}(k_{it}, l_{it}, m_{it}) \exp\{-\varepsilon_{it}\}, \end{aligned} \tag{A.11}$$

where $\mathcal{B}(k_{it}, l_{it}, m_{it}) \equiv [\partial f(k_{it}, l_{it}, m_{it})/\partial m_{it}]\mathcal{E}$. Taking the logarithm of both sides of Equation (A.11) enables the share equation to be rewritten as:

$$s_{it} = \log\{\mathcal{B}(k_{it}, l_{it}, m_{it})\} - \varepsilon_{it}, \tag{A.12}$$

[10] For more details, refer to Theorems 1 and 2 in GNR (2016).

where $s_{it} \equiv \log S_{it}$. The ex post shock ε_{it} is, by definition, orthogonal to k_{it}, l_{it}, and m_{it}, so that $\log\{\mathcal{B}(k_{it}, l_{it}, m_{it})\}$ in Equation (A.12) can be non-parametrically identified using this orthogonal conditions. In practice, following GNR (2016), $\mathcal{B}(k_{it}, l_{it}, m_{it})$ is approximated by a polynomial series of degree 2:

$$\begin{aligned}\mathcal{B}(k_{it}, l_{it}, m_{it}) = &\beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_{kk} k_{it}^2 + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 \\ &+ \beta_{kl} k_{it} l_{it} + \beta_{km} k_{it} m_{it} + \beta_{lm} l_{it} m_{it}.\end{aligned} \tag{A.13}$$

Based on Equations (A.12) and (A.13), unknown parameters in Equation (A.13) and $\mathcal{E}$ are estimated by non-linear regression methods. Because the integral of the intermediate inputs elasticity is rewritten as

$$\begin{aligned}\int \frac{\partial f(k_{it}, l_{it}, m_{it})}{\partial m_{it}} dm_{it} &= \int \frac{\exp\{\log\{\mathcal{B}(k_{it}, l_{it}, m_{it})\}\}}{\mathcal{E}} dm_{it} \\ &= \Big(\beta_0 + \beta_k k_{it} + \beta_l l_{it} + \frac{\beta_m}{2} m_{it} + \beta_{kk} k_{it}^2 + \beta_{ll} l_{it}^2 + \frac{\beta_{mm}}{3} m_{it}^2 \\ &+ \beta_{kl} k_{it} l_{it} + \frac{\beta_{km}}{2} k_{it} m_{it} + \frac{\beta_{lm}}{2} l_{it} m_{it}\Big) \frac{m_{it}}{\mathcal{E}},\end{aligned} \tag{A.14}$$

this is recovered by replacing unknown parameters in Equation (A.14) with those non-linear regression estimates.[11)]

The second step identifies the remaining $\varphi(k_{it}, l_{it})$. Following GNR (2016), $\varphi(k_{i,t}, l_{i,t})$ is approximated by a polynomial series of degree 2 as follows:

$$\begin{aligned}\varphi(k_{i,t}, l_{i,t}) &= \alpha_k k_{it} + \alpha_l l_{it} + \alpha_{kk} k_{it}^2 + \alpha_{ll} l_{it}^2 + \alpha_{kl} k_{it} l_{it} \\ &= \mathbf{z}_{it} \boldsymbol{\alpha},\end{aligned} \tag{A.15}$$

where $\mathbf{z}_{it} = (k_{it}, l_{it}, k_{it}^2, l_{it}^2, k_{it} l_{it})$ and $\boldsymbol{\alpha} = (\alpha_k, \alpha_l, \alpha_{kk}, \alpha_{ll}, \alpha_{kl})'$. Let us define

$$\tilde{y}_{it} \equiv y_{it} - \int \frac{\partial f(k_{it}, l_{it}, m_{it})}{\partial m_{it}} dm_{it} - \varepsilon_{it}.$$

where $\tilde{y}_{it}$ is recovered using the estimates obtained in the first step. Then, given the observations, ω_{it} can be rewritten as a function of the unknown parameters $\boldsymbol{\alpha}$ as follows:

$$\begin{aligned}\omega_{it}(\boldsymbol{\alpha}) &= \tilde{y}_{it} + \mathbf{z}_{it} \boldsymbol{\alpha} \\ &= g(\tilde{y}_{i,t-1} + \mathbf{z}_{i,t-1} \boldsymbol{\alpha}) + \xi_{it} \\ &= g(\omega_{i,t-1}(\boldsymbol{\alpha})) + \xi_{it}\end{aligned} \tag{A.16}$$

Furthermore, the function $g(\cdot)$ is approximated by a third-order polynomial in $\omega_{i,t-1}(\boldsymbol{\alpha})$ such as

$$\begin{aligned}\omega_{it}(\boldsymbol{\alpha}) &= \delta_0 + \delta_1\, \omega_{i,t-1}(\boldsymbol{\alpha}) + \delta_2\, [\omega_{i,t-1}(\boldsymbol{\alpha})]^2 + \delta_3\, [\omega_{i,t-1}(\boldsymbol{\alpha})]^3 + \xi_{it} \\ &= \mathbf{w}_{i,t-1} \boldsymbol{\delta} + \xi_{it}\end{aligned} \tag{A.17}$$

where

$$\begin{aligned}\mathbf{w}_{i,t-1} &= [1, \omega_{i,t-1}(\boldsymbol{\alpha}), [\omega_{i,t-1}(\boldsymbol{\alpha})]^2, [\omega_{i,t-1}(\boldsymbol{\alpha})]^3] \\ \boldsymbol{\delta} &= [\delta_0, \delta_1, \delta_2, \delta_3]'.\end{aligned}$$

11) The $\mathcal{E} \equiv \mathrm{E}(\exp\{\varepsilon_{it}\})$ is recovered using the residual of the non-parametric regression ($\hat{\varepsilon}_{it}$).

The orthogonal conditions $\mathrm{E}(\mathbf{w}'_{i,t-1}\xi_{it}) = \mathbf{0}$ and $\mathrm{E}(\mathbf{z}'_{i,t-1}\xi_{it}) = \mathbf{0}$ can be used to estimate $\boldsymbol{\delta}$ and $\boldsymbol{\alpha}$, respectively. The specific steps are as follows: First, given the initial value of $\boldsymbol{\alpha}$, ξ_{it} is estimated as the residual of Equations (A.17); and the estimate of $\boldsymbol{\alpha}$ can then be obtained by minimizing the value of a function $f(\boldsymbol{\alpha}) = \hat{\mathbf{s}}'_{\mathbf{z}\xi}\,\hat{\mathbf{s}}_{\mathbf{z}\xi}$ with respect to $\boldsymbol{\alpha}$, where $\mathbf{s}_{\mathbf{z}\xi}$ denotes the sample analogue of the moment condition $\mathrm{E}(\mathbf{z}'_{i,t-1}\xi_{it})$:[12)]

$$\hat{\mathbf{s}}_{\mathbf{z}\xi} = \frac{1}{N}\sum\nolimits_{i\in N}\frac{1}{T_i}\sum\nolimits_{t\in T_i}\mathbf{z}'_{it}\,\hat{\xi}_{it}(\boldsymbol{\alpha}). \tag{A.18}$$

The estimate of $\boldsymbol{\alpha}$ is used to recover $\varphi(k_{i,t}, l_{i,t})$.

Having obtained the estimates of the integral of intermediate inputs elasticity (Equation (A.14)) and $\varphi(k_{i,t}, l_{i,t})$ in this identification strategy, TFP can be recovered.

[12)]The Nelder-Mead method is used for the minimization of $f(\boldsymbol{\alpha})$.

Appendix B: Firm-matching Algorithm

Step 0: Create new ID for each database.

Step 1: Matching between year t and year $t+1$ ($t = 2002, 2003, ..., 2007$)

0) $t = 2002$

1) Firm ID matching
If matched, the ID of Year $t+1$'s sample is overwritten with the year t's ID. Save matching samples, not matching samples, and duplicated samples.

2) Firm name matching using not matching samples and duplicated samples in 1).
If matched, the ID of Year $t+1$'s sample is overwritten with the year t's ID.
Save matching samples, not matching samples, and duplicated samples.

3) Firm ID & Firm name & Firm Tel matching using not matching samples and duplicated samples in 2).
If matched, the ID of Year $t+1$'s sample is overwritten with the year t's ID.
Save matching samples, not matching samples, and duplicated samples.

* Duplicated samples in 3) are considered as "Duplicated."

4) $t = t + 1$ and return to 1)

Step 2: Matching between year t and year $t+2$ ($t = 2002, 2003, ..., 2006$) using samples not matched in step 1

0) $t = 2002$

1) Firm ID matching
If matched, the ID of Year $t+2$'s sample is overwritten with the year t's ID.
Save matching samples, not matching samples, and duplicated samples.

2) Firm name matching using not matching samples and duplicated samples in 1).
If matched, the ID of Year $t+2$'s sample is overwritten with the year t's ID.
Save matching samples, not matching samples, and duplicated samples.

3) Firm ID & Firm name & Firm Tel matching using not matching samples and duplicated samples in 2).
If matched, the ID of Year $t+2$'s sample is overwritten with the year t's ID.
Save matching samples, not matching samples, and duplicated samples.

* Duplicated samples in 3) are considered as "Duplicated."

4) $t = t + 1$ and return to 1)

⋮

Step 5: Matching between year t and year $t+5$ ($t = 2002$) using samples not matched in the previous steps

0) $t = 2002$

1) Firm ID matching
If matched, the ID of Year $t + 5$'s sample is overwritten with the year t's ID.
Save matching samples, not matching samples, and duplicated samples.

2) Firm name matching using not matching samples and duplicated samples in 1).
If matched, the ID of Year $t + 5$'s sample is overwritten with the year t's ID.
Save matching samples, not matching samples, and duplicated samples.

3) Firm ID & Firm name & Firm Tel matching using not matching samples and duplicated samples in 2).
If matched, the ID of Year $t + 5$'s sample is overwritten with the year t's ID.
Save matching samples, not matching samples, and duplicated samples.

***** Duplicated samples in 3) are considered as "Duplicated."

Table A1: Average Input Elasticities of Output (1)

	GNR				OLS			
Industry	K	L	M	$K+L+M$	K	L	M	$K+L+M$
131	0.0713	0.2291	0.5269	0.8272	0.0116	0.0521	0.9264	0.9902
132	0.1447	0.3462	0.4550	0.9459	0.0144	0.0637	0.9306	1.0086
133	0.1731	0.2582	0.3757	0.8070	0.0147	0.0351	0.9257	0.9755
134	0.1242	0.1891	0.6689	0.9822	0.0271	0.0134	0.9520	0.9924
135	0.0958	0.3431	0.3628	0.8017	0.0085	0.0344	0.9454	0.9883
136	0.0873	0.1354	0.7161	0.9387	0.0206	0.0519	0.9315	1.0039
137	0.0824	0.1220	0.6367	0.8411	0.0204	0.0327	0.9095	0.9626
139	0.0741	0.1997	0.6210	0.8949	0.0145	0.0451	0.9238	0.9833
141	0.1269	0.2421	0.5738	0.9428	0.0266	0.0785	0.9102	1.0152
142	0.0652	0.1599	0.7000	0.9251	0.0156	0.0620	0.9268	1.0044
143	0.1230	0.2413	0.4973	0.8617	0.0250	0.0396	0.9172	0.9819
144	0.0873	0.1364	0.6949	0.9186	0.0088	0.0405	0.9437	0.9930
145	0.0674	0.1289	0.7024	0.8987	0.0200	0.0417	0.9241	0.9859
146	0.1538	0.1610	0.6199	0.9348	0.0173	0.0240	0.9449	0.9862
149	0.0996	0.2918	0.4991	0.8905	0.0131	0.0616	0.9112	0.9860
151	0.0947	0.2222	0.6861	1.0030	-0.0148	0.0757	0.9499	1.0109
152	0.1746	0.2693	0.4300	0.8740	0.0193	0.0541	0.9328	1.0061
153	0.1761	0.2787	0.5399	0.9946	0.0284	0.0469	0.9313	1.0065
154	0.0868	0.1410	0.6910	0.9188	0.0267	0.0627	0.9187	1.0080
171	0.1013	0.1913	0.5255	0.8181	0.0078	0.0511	0.9263	0.9852
172	0.0758	0.1160	0.6794	0.8712	0.0101	0.0369	0.9413	0.9882
173	0.1135	0.1508	0.6541	0.9183	0.0091	0.0288	0.9236	0.9615
174	0.0422	0.1223	0.7484	0.9129	0.0105	0.0470	0.9252	0.9827
175	0.1019	0.1895	0.4931	0.7846	0.0178	0.0514	0.9185	0.9877
176	0.0761	0.1309	0.6625	0.8695	0.0185	0.0817	0.8819	0.9821
181	0.1207	0.2753	0.4319	0.8280	0.0230	0.0967	0.8633	0.9830
182	0.0463	0.1903	0.6773	0.9139	0.0243	0.0840	0.8921	1.0004
183	0.0603	0.1380	0.6918	0.8902	0.0187	0.0706	0.8689	0.9583
191	0.0594	0.1637	0.6986	0.9217	0.0269	0.0603	0.8946	0.9818
192	0.0979	0.1505	0.6828	0.9312	0.0204	0.0906	0.8794	0.9904
193	0.0841	0.1285	0.6804	0.8930	0.0225	0.0457	0.9418	1.0100
194	0.1031	0.0866	0.5700	0.7597	0.0128	0.0238	0.9162	0.9529
201	0.1224	0.3116	0.3281	0.7621	0.0187	0.0651	0.8892	0.9731
202	0.0866	0.1216	0.6866	0.8948	0.0282	0.0266	0.9103	0.9652
203	0.1052	0.1534	0.5923	0.8509	0.0276	0.0679	0.8624	0.9579
204	0.0643	0.1736	0.7049	0.9428	0.0433	0.0732	0.8417	0.9582
211	0.0843	0.2388	0.5073	0.8304	0.0221	0.0620	0.9028	0.9869
213	0.0597	0.1637	0.7345	0.9579	0.0245	0.0523	0.9276	1.0044
219	0.0524	0.1839	0.7248	0.9610	0.0197	0.0690	0.8809	0.9696
221	0.1033	0.0980	0.7049	0.9063	0.0265	-0.0085	0.9478	0.9659
222	0.1531	0.2530	0.3982	0.8044	0.0030	0.0423	0.9396	0.9848
223	0.1463	0.2631	0.4144	0.8237	0.0223	0.0488	0.9152	0.9863
231	0.1404	0.2099	0.6164	0.9667	0.0557	0.0542	0.9014	1.0114
232	0.0910	0.2123	0.6437	0.9470	0.0243	0.0945	0.9186	1.0374
241	0.0659	0.1727	0.7082	0.9469	0.0333	0.0612	0.8996	0.9940
242	0.0541	0.1558	0.6719	0.8818	0.0248	0.0688	0.8920	0.9856
243	0.1003	0.1422	0.6887	0.9312	0.0211	0.0998	0.8818	1.0028
244	0.0545	0.1659	0.6747	0.8950	0.0250	0.0842	0.8701	0.9793
245	0.0543	0.0723	0.7595	0.8861	0.0334	0.0421	0.9189	0.9944
251	0.1909	0.1681	0.6342	0.9932	0.0174	0.0450	0.9198	0.9822

Table A2: Average Input Elasticities of Output (2)

	GNR				OLS			
Industry	K	L	M	$K+L+M$	K	L	M	$K+L+M$
251	0.1909	0.1681	0.6342	0.9932	0.0174	0.0450	0.9198	0.9822
252	0.1186	0.1465	0.6801	0.9452	0.0082	0.0600	0.8996	0.9678
261	0.1331	0.1504	0.6210	0.9045	0.0243	0.0345	0.9190	0.9778
262	0.1116	0.1309	0.6441	0.8866	0.0308	0.0373	0.9135	0.9815
263	0.0863	0.2334	0.5280	0.8477	0.0173	0.0451	0.9267	0.9891
264	0.0431	0.1702	0.6793	0.8926	0.0262	0.0367	0.9215	0.9844
265	0.2809	0.2972	0.1959	0.7740	0.0208	0.0435	0.9007	0.9650
266	0.1471	0.1175	0.5334	0.7980	0.0250	0.0462	0.9038	0.9750
267	0.1166	0.2041	0.4983	0.8190	0.0257	0.0353	0.9241	0.9851
271	0.1536	0.2261	0.5097	0.8894	0.0276	0.0462	0.9168	0.9906
272	0.1253	0.3686	0.4442	0.9381	0.0273	0.0898	0.8777	0.9948
273	0.0724	0.1521	0.5783	0.8028	0.0369	0.0671	0.8760	0.9799
274	0.1097	0.2899	0.4698	0.8694	0.0296	0.0656	0.9020	0.9972
275	0.1650	0.1677	0.6571	0.9898	0.0340	0.0752	0.9313	1.0404
276	0.1060	0.2100	0.5836	0.8996	0.0397	0.0942	0.8593	0.9933
277	0.1349	0.1837	0.4762	0.7948	0.0386	0.0421	0.9051	0.9858
281	0.1143	0.0541	0.7336	0.9021	0.0268	0.0113	0.9400	0.9781
282	0.0862	0.0924	0.7673	0.9458	0.0149	0.0311	0.9400	0.9859
291	0.0477	0.2733	0.6323	0.9533	-0.0053	0.0238	0.9538	0.9723
292	0.2399	0.0490	0.5302	0.8191	0.0355	0.0302	0.9128	0.9785
293	0.1430	0.0916	0.5877	0.8223	0.0382	0.0538	0.8721	0.9642
294	0.0835	0.1736	0.6627	0.9198	0.0177	0.0435	0.9182	0.9794
295	0.0853	0.1256	0.7049	0.9158	0.0223	0.1014	0.8797	1.0035
296	0.0807	0.2144	0.5812	0.8764	0.0003	0.0795	0.8879	0.9677
299	0.1112	0.1191	0.6060	0.8363	0.0452	0.0556	0.8668	0.9676
301	0.1392	0.0966	0.6381	0.8739	0.0258	0.0302	0.9299	0.9860
302	0.1306	0.1751	0.4660	0.7717	0.0154	0.0361	0.9224	0.9739
303	0.0567	0.1904	0.5556	0.8027	0.0261	0.0475	0.9048	0.9783
304	0.1012	0.2373	0.4083	0.7469	0.0181	0.0528	0.8906	0.9615
305	0.0594	0.1712	0.7436	0.9743	0.0004	-0.0089	0.9854	0.9769
306	0.1083	0.1366	0.6872	0.9321	0.0341	0.0463	0.8872	0.9676
307	0.0902	0.1657	0.6927	0.9486	0.0521	0.0766	0.8538	0.9825
308	0.0748	0.1431	0.6787	0.8966	0.0303	0.0765	0.8770	0.9839
309	0.0728	0.1179	0.6762	0.8669	0.0331	0.0593	0.8656	0.9580
311	0.1617	0.1194	0.5480	0.8291	0.0154	0.0246	0.9358	0.9758
312	0.1525	0.1476	0.5891	0.8891	0.0403	0.0148	0.9301	0.9851
313	0.1474	0.1329	0.5431	0.8233	0.0269	0.0286	0.9266	0.9821
314	0.1399	0.2175	0.4955	0.8530	0.0392	0.0454	0.8985	0.9831
315	0.0734	0.1107	0.6572	0.8414	0.0141	0.0509	0.9086	0.9735
316	0.0954	0.0666	0.6920	0.8539	0.0323	0.0102	0.9568	0.9992
319	0.1492	0.1396	0.4936	0.7824	0.0371	0.0167	0.9237	0.9775
321	0.1108	0.1531	0.6663	0.9302	0.0080	0.0426	0.9374	0.9879
322	0.0876	0.1412	0.7481	0.9769	0.0093	0.0447	0.9430	0.9970
323	0.2436	0.3123	0.3682	0.9241	0.0091	0.0591	0.9152	0.9834
324	0.0594	0.1838	0.6701	0.9133	0.0178	0.0425	0.9238	0.9842
331	0.1173	0.1989	0.5304	0.8466	0.0141	0.0600	0.9041	0.9782
332	0.1524	0.0395	0.6522	0.8440	0.0315	0.0707	0.8752	0.9774
333	0.0582	0.1050	0.7056	0.8687	0.0139	0.0367	0.9191	0.9697
334	0.0690	0.0807	0.7420	0.8916	0.0231	0.0393	0.9185	0.9809
335	0.1308	0.1361	0.6582	0.9251	0.0192	0.0492	0.9000	0.9684
341	0.0995	0.1794	0.5815	0.8604	0.0216	0.0694	0.8824	0.9735

Table A3: Average Input Elasticities of Output (3)

	GNR				OLS			
Industry	K	L	M	$K+L+M$	K	L	M	$K+L+M$
342	0.0852	0.1415	0.7040	0.9307	0.0302	0.0620	0.8909	0.9831
343	0.2250	0.2428	0.3852	0.8530	0.0277	0.0565	0.8853	0.9695
344	0.0579	0.4971	0.2150	0.7701	0.0060	0.0798	0.8762	0.9620
345	0.1370	0.2704	0.3894	0.7968	0.0231	0.0643	0.9062	0.9936
346	0.0929	0.1595	0.6347	0.8871	0.0422	0.0631	0.8518	0.9571
347	0.0623	0.1111	0.6963	0.8697	0.0129	0.0624	0.8937	0.9690
348	0.0959	0.1458	0.6256	0.8674	0.0190	0.0718	0.8785	0.9693
349	0.1232	0.1271	0.6210	0.8714	0.0293	0.0613	0.8751	0.9657
351	0.1011	0.1938	0.5664	0.8613	0.0124	0.0384	0.9108	0.9616
352	0.0765	0.1400	0.6389	0.8554	0.0221	0.0480	0.9154	0.9855
353	0.2140	0.1579	0.4363	0.8083	0.0207	0.0427	0.9063	0.9697
354	0.1398	0.2379	0.4828	0.8606	0.0246	0.0389	0.9118	0.9753
355	0.1423	0.0913	0.6369	0.8705	0.0352	0.0336	0.8937	0.9625
356	0.0709	0.1374	0.7103	0.9185	0.0203	0.0247	0.9191	0.9640
357	0.2344	0.3401	0.2104	0.7849	0.0281	0.0342	0.9067	0.9691
358	0.1402	0.1524	0.5194	0.8120	0.0397	0.0610	0.8885	0.9892
359	0.1156	0.1295	0.6307	0.8758	0.0225	0.0247	0.9260	0.9732
361	0.1080	0.0960	0.6019	0.8058	0.0261	0.0125	0.9190	0.9576
362	0.1109	0.1672	0.6252	0.9034	0.0472	0.0486	0.8636	0.9594
363	0.1212	0.1772	0.5462	0.8446	0.0247	0.0153	0.9658	1.0059
364	0.0854	0.1049	0.6899	0.8803	0.0260	0.0205	0.9246	0.9711
365	0.0395	0.1391	0.7019	0.8805	0.0105	0.0464	0.9055	0.9624
366	0.1698	0.3423	0.2646	0.7766	0.0375	0.0370	0.8632	0.9377
367	0.1163	0.2282	0.4994	0.8438	0.0183	0.0369	0.9435	0.9987
368	0.1763	0.2918	0.4467	0.9148	0.0449	0.0564	0.8705	0.9719
369	0.0924	0.1566	0.5862	0.8352	0.0313	0.0375	0.9003	0.9691
371	0.1375	0.1331	0.6066	0.8772	0.0231	0.0443	0.9062	0.9735
372	0.1902	0.3083	0.4306	0.9290	0.0313	0.0559	0.9063	0.9935
373	0.0595	0.1647	0.7458	0.9701	0.0167	0.0412	0.9231	0.9810
374	0.0763	0.2542	0.5672	0.8977	0.0169	0.0804	0.8851	0.9824
375	0.1113	0.2521	0.4982	0.8616	0.0122	0.1074	0.8586	0.9782
376	0.1674	0.1575	0.6040	0.9289	0.1050	0.0930	0.7712	0.9692
379	0.0173	0.1612	0.6226	0.8011	0.0167	0.0545	0.8809	0.9521
391	0.2044	0.2800	0.3466	0.8310	0.0115	0.0649	0.8978	0.9742
392	0.1784	0.3210	0.2521	0.7515	0.0230	0.0627	0.8825	0.9681
393	0.1827	0.1517	0.5009	0.8353	0.0289	0.0519	0.8987	0.9795
394	0.1091	0.1988	0.6339	0.9418	0.0278	0.0648	0.8763	0.9690
395	0.0705	0.1234	0.7288	0.9227	0.0172	0.0609	0.9119	0.9900
396	0.0650	0.1053	0.7326	0.9030	0.0188	0.0319	0.9326	0.9832
397	0.0698	0.2334	0.6168	0.9199	0.0228	0.0717	0.8887	0.9833
399	0.1239	0.3411	0.5066	0.9716	0.0262	0.0986	0.8638	0.9886
401	0.1810	0.2354	0.4320	0.8485	0.0254	0.0935	0.8213	0.9402
403	0.0941	0.1579	0.6366	0.8886	0.0157	0.0589	0.8787	0.9534
404	0.0968	0.3854	0.3308	0.8130	0.0342	0.0930	0.8193	0.9466
405	0.2839	0.3758	0.2264	0.8860	0.0571	0.0811	0.8264	0.9646
406	0.1123	0.1628	0.6387	0.9138	0.0413	0.0840	0.8570	0.9823
407	0.0741	0.2838	0.5475	0.9054	0.0236	0.0977	0.8656	0.9870
409	0.1429	0.1825	0.3999	0.7254	0.0393	0.0727	0.8343	0.9463
411	0.2216	0.1265	0.3740	0.7220	0.0333	0.0475	0.8850	0.9658
412	0.1472	0.3393	0.4212	0.9077	0.0171	0.0554	0.9132	0.9857

Table A4: Average Input Elasticities of Output (4)

Industry	GNR				OLS			
	K	L	M	$K + L + M$	K	L	M	$K + L + M$
413	0.0304	0.1740	0.6639	0.8683	0.0094	0.1140	0.8516	0.9750
414	0.0456	0.1954	0.6435	0.8845	0.0321	0.0872	0.8457	0.9649
415	0.0617	0.2516	0.5839	0.8972	0.0244	0.0824	0.8442	0.9509
419	0.1835	0.1313	0.4567	0.7715	0.0604	0.0395	0.8303	0.9302
421	0.0762	0.1501	0.6127	0.8389	0.0294	0.0798	0.8689	0.9781
422	0.0662	0.1218	0.7304	0.9184	0.0296	0.0477	0.9014	0.9787
429	0.1309	0.1567	0.5947	0.8823	0.0476	0.0534	0.8770	0.9780
431	0.0660	0.0753	0.6954	0.8367	0.0299	0.0327	0.8998	0.9624
432	0.0925	0.0851	0.6833	0.8609	0.0350	0.0602	0.8588	0.9540

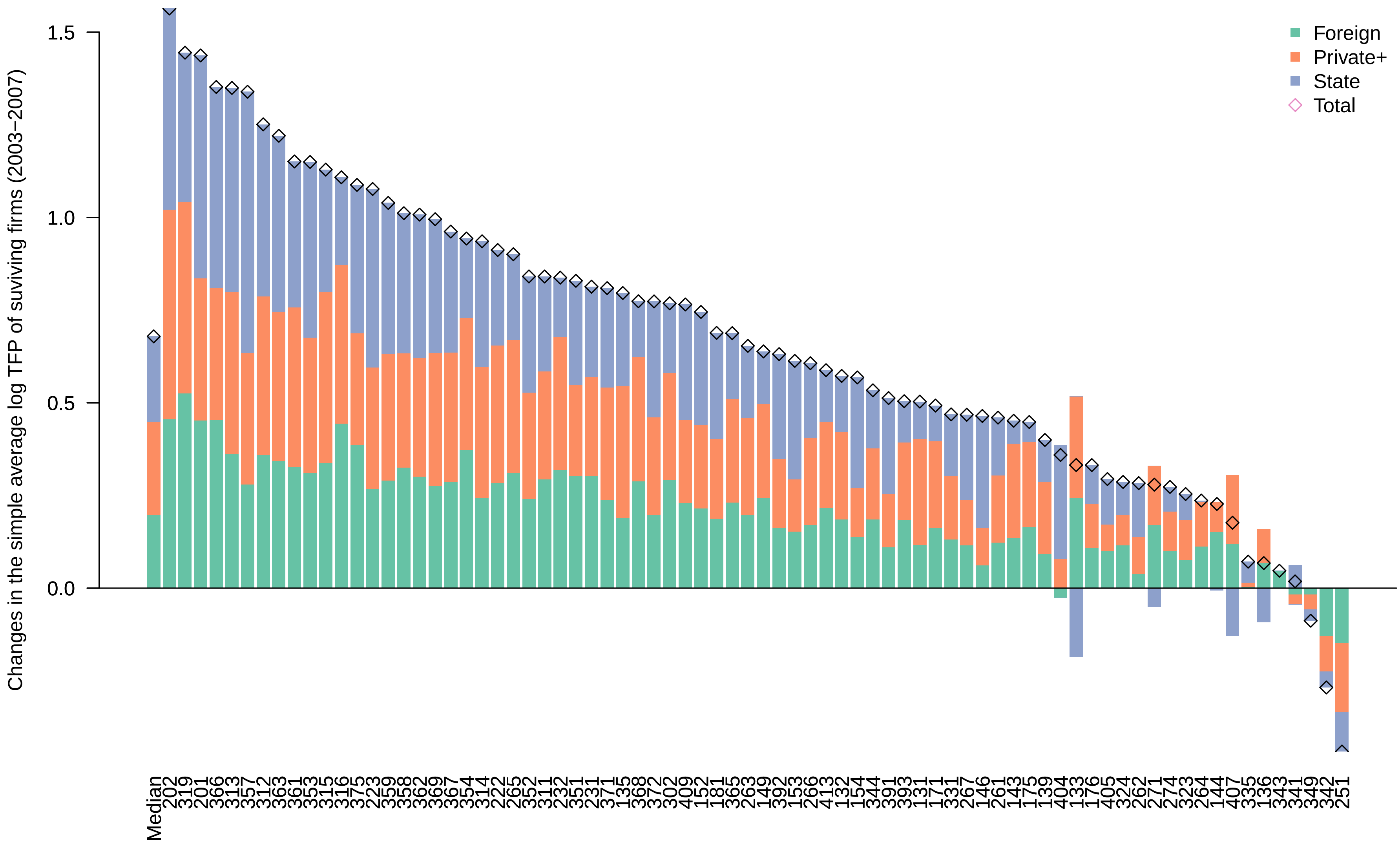


Figure A1: Decomposition of $1/J \sum \Delta\mu_j^S$ into State, Private+, and Foreign sectors

Notes: The horizontal axis shows the number of three-digit industrial sectors ($i = 1, 2, \ldots, 75$).

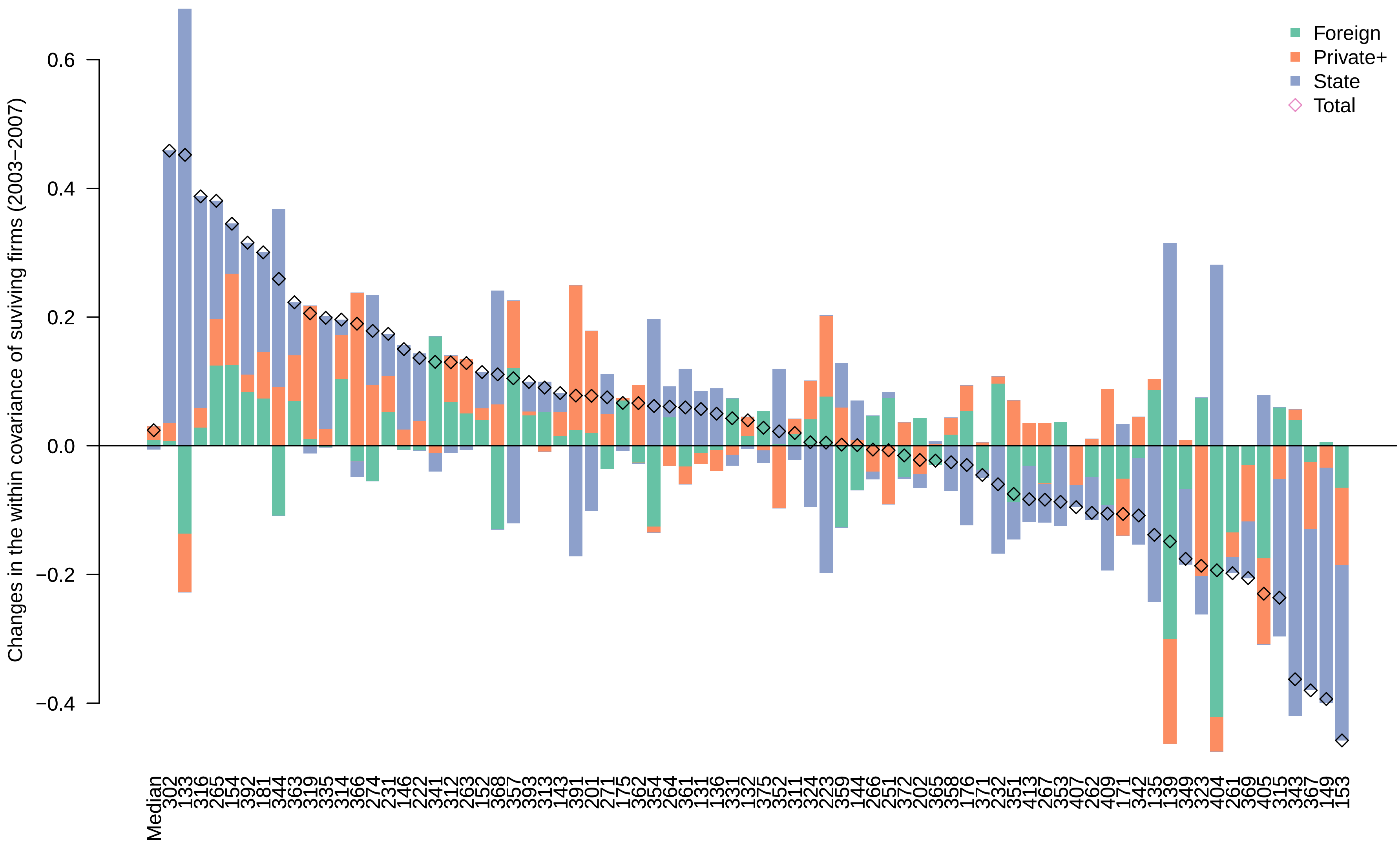


Figure A2: Decomposition of $1/J \sum \Delta \mathrm{cov}_j^S$ into State, Private+, and Foreign sectors

Notes: The horizontal axis shows the number of three-digit industrial sectors ($i = 1, 2, \ldots, 75$).

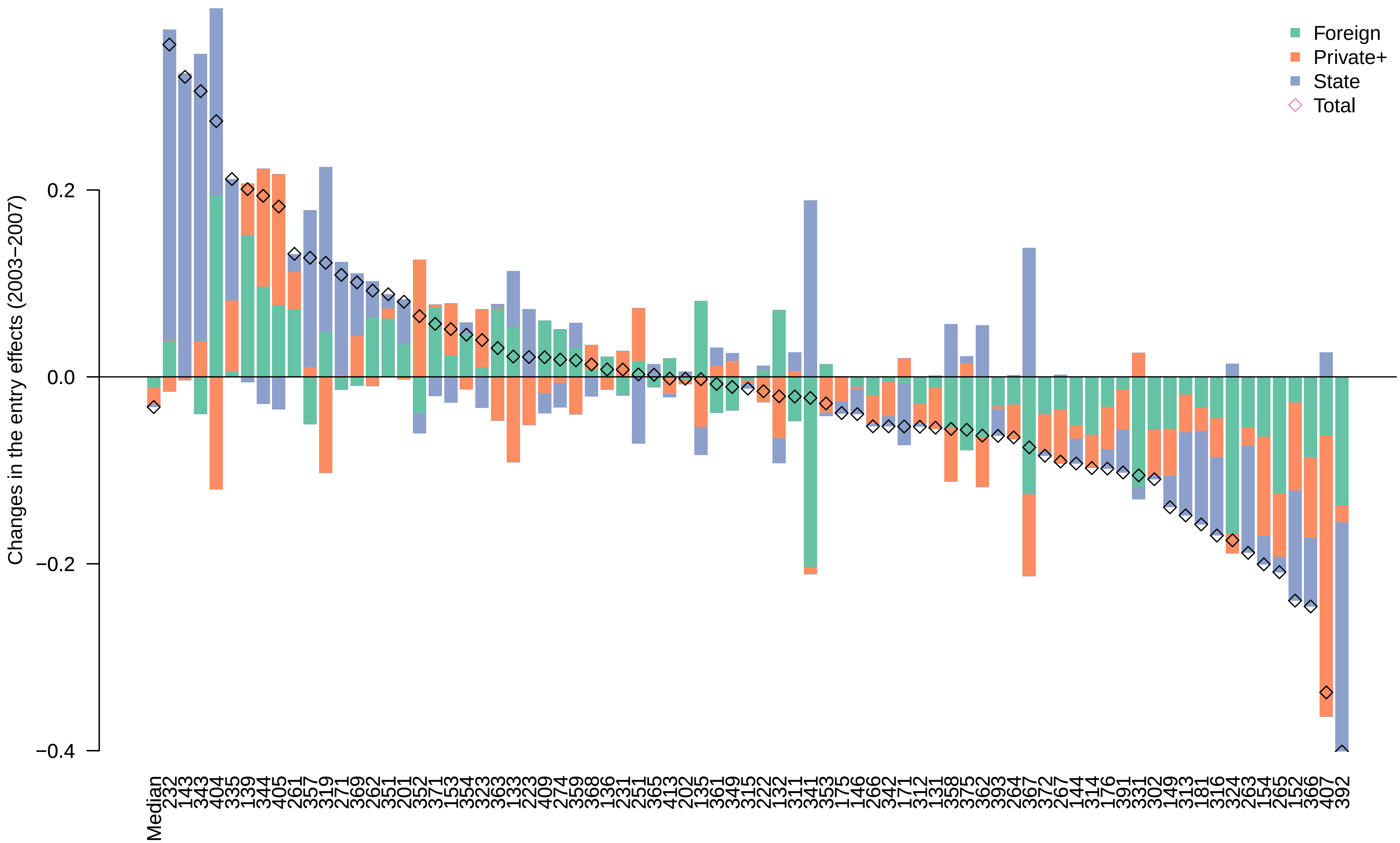


Figure A3: Decomposition of the Entry effect into State, Private+, and Foreign sectors

Notes: The horizontal axis shows the number of three-digit industrial sectors ($i = 1, 2, \ldots, 75$).

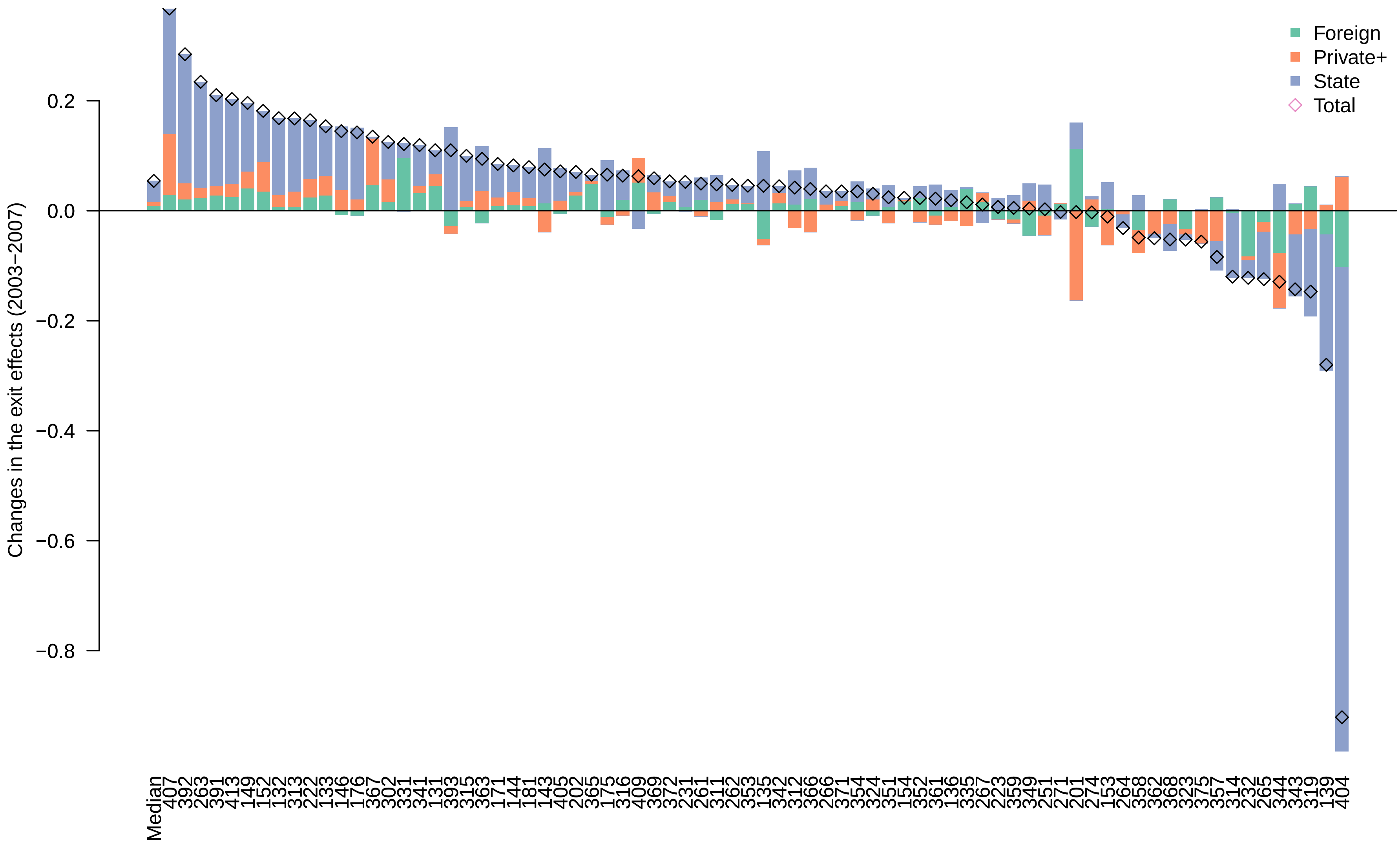


Figure A4: Decomposition of the Exit effect into State, Private+, and Foreign sectors

Notes: The horizontal axis shows the number of three-digit industrial sectors ($i = 1, 2, \ldots, 75$).