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November 2015

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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. This measure empirically assesses the degree of misallocation in China using manufacturing firm-level data from 2004 to 2007. Misallocation among industrial sectors has been found to increase over time, and allocation efficiency within an industry has been found to worsen in industries that use more capital and have firms with relatively higher state-owned market shares. Allocation efficiency among three ownership sectors (state-owned, domestic private, and foreign sectors) tends to improve in industries wherein the market share moves from a less-productive state-owned sector to a 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). Their argument is that the shift in production resources from less productive to more productive units yields an increase in aggregate TFP and that resource allocation efficiency is crucial to explaining countries' aggregate TFP. A well-functioning market economy can 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. Therefore, developing an appropriate measure of allocation efficiency and theoretically and empirically investigating the sources of misallocation are crucial to implementing better economic policies.

In this paper, the author develops an extended quantitative measure of allocation efficiency. Two types of empirical measures of allocation efficiency have been used in previous studies: (1) the dispersion of firm-level productivity (Hsieh and Klenow, 2009) 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). According to Bartelsman et al. (2013), the covariance measure is a robust theoretical and empirical measure to assess the effect of misallocation. 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., industrial sectors, ownership groups); they only capture allocation efficiency within a group. This paper attempts to extend the 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.

The extended productivity decomposition method is applied to China's manufacturing firm-level data from 2004 to 2007. Several scholars estimated the degree of allocation efficiency in China. However, some debate has occurred over its recent trend. For example, Hsieh and Klenow (2009) used manufacturing firm-level data from 1998 to 2005 to measure the degree of misallocation. They found that misallocation within an industry tended to decline over time. Meanwhile, 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. Has China's allocation efficiency worsened since the 2000s? What is the extent of its allocation efficiency among industrial sectors and ownership groups? The investigations into China's allocation efficiency remain insufficient.

This paper addresses these questions using the extended measure of allocation efficiency. The empirical analysis has two steps. First, firm-level productivity is estimated using a structural estimation method proposed by Gandhi et al. (2013). Second, the productivity decomposition method is exploited to quantify the effect of misallocation on aggregate manufacturing productivity. Hence, misallocation between industrial sectors is revealed as increasing over time, and changes in misallocation between industrial groups have a more significant effect on aggregate TFP growth than effect of misallocation changes within an industry. Misallocation within an industry is found to increase in industries that use more capital and have firms with relatively higher state-owned market shares. However, allocation efficiency between 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 Section 4 presents the data sources and estimation results of productivity. Section 5 reports the allocation efficiency in China, and Section 6 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 5.2 reports the empirical results of China's allocation efficiency.

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 at time 1 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:

$$ent \lesseqgtr 0 \text{ when } \Phi_2^E \lesseqgtr \Phi_2^S,$$
$$ext \lesseqgtr 0 \text{ when } \Phi_1^S \lesseqgtr \Phi_1^X.$$

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 Extension of the OP and Dynamic OP Decompositions

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 OP and DOP decomposition.

2.3.1 Augmented OP (AOP) Decomposition

Let us consider that the number of groups is J and aggregate productivity is represented as:

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

where Ω_{jt} is the set of firms in group j at time t, w_{jt} is group j's output share at time t, and $\tilde{\mu}_{jt} = \sum_{i\in\Omega_{jt}}(s_{it}/w_{jt})\phi_{it}$ is the weighted average log TFP for group j. Applying the OP decomposition to the above equation yields:

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

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 $\tilde{\mu}_{jt}$ in the within-effect can be decomposed as:

$$\begin{aligned}\tilde{\mu}_{jt} &= \frac{1}{N_{jt}} \sum_{i\in\Omega_{jt}} \phi_{it} + \sum_{i\in\Omega_{jt}} \left(\frac{s_{it}}{w_{jt}} - \frac{1}{N_{jt}} \sum_{\iota\in\Omega_{jt}} \frac{s_{\iota t}}{w_{jt}} \right) \left(\phi_{it} - \frac{1}{N_{jt}} \sum_{\iota\in\Omega_{jt}} \phi_{\iota t} \right) \\ &= \mu_{jt} + \text{cov}_{jt}\,, \end{aligned} \tag{7}$$

where N_{jt} is the number of firms in group j at time t. Substituting Equation (7) in Equation (6) yields the augmented OP (AOP) decomposition as follows:

$$\Phi_t = \underbrace{\frac{1}{J}\sum\nolimits_{j=1}^{J} \mu_{jt} + \frac{1}{J}\sum\nolimits_{j=1}^{J} \text{cov}_{jt}}_{\textit{Within effect}} + \underbrace{\tilde{\text{cov}}_t}_{\textit{Between effect}} \,. \tag{8}$$

The first term in Equation (8) is the unweighted mean productivity, and cov_{jt} and $\tilde{\text{cov}}_t$ represent the degree of allocation efficiency within group j and between groups, respectively. When $J = 1$, Equation (8) reduces to the original OP decomposition. Taking the difference in Equation (8) yields:

$$\Delta\Phi = \frac{1}{J}\sum\nolimits_{j=1}^{J} \Delta\mu_j + \frac{1}{J}\sum\nolimits_{j=1}^{J} \Delta\text{cov}_j + \Delta\tilde{\text{cov}}\,. \tag{9}$$

2.3.2 Augmented Dynamic OP (ADOP) Decomposition

The dynamic OP decomposition is also extended to a multi-group case. First, as in the case of the OP decomposition, the aggregate log TFP at time 1 can be decomposed into within- and between-effects:

$$\Phi_1 = \frac{1}{J}\sum\nolimits_{j=1}^{J} \tilde{\mu}_{j1} + \tilde{\text{cov}}_1\,, \tag{10}$$

where $\tilde{\mu}_{j1} = \sum_{i\in\Omega_{j1}} (s_{i1}/w_{j1})\phi_{i1}$ and $\tilde{\text{cov}}_1 = \sum_{j=1}^{J} (w_{j1} - w_1^*)(\tilde{\mu}_{j1} - \tilde{\mu}_1^*)$. w_1^* and $\tilde{\mu}_1^*$ denote simple averages of w_{j1} and $\tilde{\mu}_{j1}$, 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:

$$\begin{aligned}\tilde{\mu}_{j1} &= \sum_{i\in\Omega_j^S} \frac{a_{ij1}}{a_{j1}^S}\phi_{i1} + a_{j1}^X \left(\sum_{i\in\Omega_j^X} \frac{a_{ij1}}{a_{j1}^X}\phi_{i1} - \sum_{i\in\Omega_j^S} \frac{a_{ij1}}{a_{j1}^S}\phi_{i1} \right) \\ &= \Phi_{j1}^S + a_{j1}^X \left(\Phi_{j1}^X - \Phi_{j1}^S \right) \\ &= \Phi_{j1}^S - ext_j, \end{aligned} \tag{11}$$

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 (11) can be decomposed as:

$$\begin{aligned}\Phi_{j1}^{S} &= \frac{1}{N_{j1}^{S}}\sum_{i\in\Omega_j^S}\phi_{i1} + \sum_{i\in\Omega_j^S}\left(\frac{a_{ij1}}{a_{j1}^{S}} - \frac{1}{N_{j1}^{S}}\sum_{\iota\in\Omega_j^S}\frac{a_{\iota j1}}{a_{j1}^{S}}\right)\left(\phi_{i1} - \frac{1}{N_{j1}^{S}}\sum_{\iota\in\Omega_j^S}\phi_{\iota 1}\right)\\ &= \mu_{j1}^{S} + \mathrm{cov}_{j1}^{S},\end{aligned} \tag{12}$$

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 (12) and (11) in Equation (10) yields the following decomposition:

$$\Phi_1 = \underbrace{\frac{1}{J}\sum_{j=1}^{J}\left(\mu_{j1}^{S} + \mathrm{cov}_{j1}^{S} - ext_j\right)}_{\textit{Within effect}} + \underbrace{\tilde{\mathrm{cov}}_1}_{\textit{Between effect}}. \tag{13}$$

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

$$\begin{aligned}\Phi_2 &= \frac{1}{J}\sum_{j=1}^{J}\tilde{\mu}_{j2} + \tilde{\mathrm{cov}}_2\\ &= \frac{1}{J}\sum_{j=1}^{J}\left(\Phi_{j2}^{S} + a_{j2}^{E}\left(\Phi_{j2}^{E} - \Phi_{j2}^{S}\right)\right) + \tilde{\mathrm{cov}}_2\\ &= \underbrace{\frac{1}{J}\sum_{j=1}^{J}\left(\mu_{j2}^{S} + \mathrm{cov}_{j2}^{S} + ent_j\right)}_{\textit{Within effect}} + \underbrace{\tilde{\mathrm{cov}}_2}_{\textit{Between effect}},\end{aligned} \tag{14}$$

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:

$$\Delta\Phi = \underbrace{\frac{1}{J}\sum_{j=1}^{J}\left(\Delta\mu_{j}^{S} + \Delta\mathrm{cov}_{j}^{S} + ent_j + ext_j\right)}_{\textit{Within effect}} + \underbrace{\Delta\tilde{\mathrm{cov}}}_{\textit{Between effect}} \tag{15}$$

where $\Delta\mathrm{cov}_j^S$ represents the changes in allocation efficiency among surviving firms within group j and $\Delta\tilde{\mathrm{cov}}$ represents the changes in allocation efficiency between groups. When $J = 1$, Equation (14) reduces to the original dynamic OP decomposition. The definition of $\Delta\tilde{\mathrm{cov}}$ in Equation (15) is the same as that of Equation (9).

In this paper, Equations (9) and (15) are used to decompose China's aggregate productivity and investigate the magnitude of allocation efficiency. The empirical results are described in Section 5. Before reporting the results, the next section explains how to measure firm-level productivity (ϕ_{it}).

3 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 structural estimation method proposed by Gandhi et al. (GNR; 2013) 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). Following GNR (2013), this section describes the framework of firm behavior and shows the identification strategy of the production function.

3.1 Model of Firm Behavior

Let us consider that firm i operates through discrete time t and produces output using labor L_{it}, capital K_{it}, and intermediate inputs M_{it}. The firm's anticipated output Q_{it} is assumed to depend on these inputs, and the anticipated productivity level ω_{it}. ω_{it} represents a firm's technology, information, knowledge, or situation that affects its productivity; this can be observed by firm i, but not by the econometrician. For example, ω_{it} represents business management differences, deviations from expected machine breakdown rates in a particular period, or labor management problems.

At the beginning of each period, firm i can observe ω_{it}, which affects current and future input decisions. The relationship between Q_{it} and the inputs in period t is expressed as:

$$Q_{it} = F(K_{it}, L_{it}, M_{it}) \exp\{\omega_{it}\}, \tag{16}$$

$$Y_{it} = Q_{it} \exp\{\varepsilon_{it}\}, \tag{17}$$

$$\therefore\ Y_{it} = F(K_{it}, L_{it}, M_{it}) \exp\{\omega_{it} + \varepsilon_{it}\}, \tag{18}$$

where $F(\cdot)$ is a production function and Y_{it} is the measured output observed by the econometrician. The difference between Q_{it} and Y_{it} is ε_{it}, representing an unanticipated productivity shock and/or measurement error that cannot be observed by firm i before making period t's input decisions. TFP is defined as $\exp\{\omega_{it} + \varepsilon_{it}\}$. Taking the logarithm for both sides of Equation (18) yields:

$$\begin{aligned} y_{it} &= f(k_{it}, l_{it}, m_{it}) + \omega_{it} + \varepsilon_{it}, && (19) \\ \log \mathrm{TFP}_{it} &= \omega_{it} + \varepsilon_{it}, \end{aligned}$$

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.

As in OP (1996), LP (2003), ACF (2006), and GNR (2013), assumptions about the dynamics of productivity and the timing of input decisions are required to identify the production function. First, the anticipated productivity ω_{it} evolves over time according to the first-order Markov process and is decomposed into its conditional expectation given all information ($\Theta_{i,t-1}$) known by the firm at $t-1$ and a residual (ξ_{it}). Thus, ω_{it} can be expressed as:

$$\begin{aligned} \omega_{it} &= \mathrm{E}(\omega_{it} \mid \Theta_{i,t-1}) + \xi_{it} \\ &= \mathrm{E}(\omega_{it} \mid \omega_{i,t-1}) + \xi_{it} \\ &= g(\omega_{i,t-1}) + \xi_{it}, \end{aligned} \tag{20}$$

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. Equation (19) can be rewritten as:

$$y_{it} = f(k_{it}, l_{it}, m_{it}) + g(\omega_{i,t-1}) + \xi_{it} + \varepsilon_{it}. \tag{21}$$

For the timing of input decisions, as with GNR, labor and capital inputs at t are assumed to be decided at or before $t-1$, implying that these inputs are quasi-fixed inputs and that adjustment costs exist in labor and capital (e.g., hiring/firing, job training, or machine installation costs). Under these timing assumptions, labor and capital inputs can be regarded as state variables for firms, and they are orthogonal to the innovation at t, i.e., $\mathrm{E}(\xi_{it} \mid k_{it}, l_{it}) = 0$. This moment condition is required to identify the elasticities associated with labor and capital inputs.

The intermediate input M_{it} is assumed to be a flexible input, which is variable in each period and does not have dynamic implications. Therefore, its level at t does not affect the firm's profit in the future. At the beginning of each period, given the levels of labor, capital inputs, and ω_{it}, firm i chooses the level of M_{it}. Consequently, M_{it} is an implicit function of K_{it}, L_{it}, ω_{it}, and the output and intermediate input prices. This result implies two points. First, M_{it} is an endogenous variable because it partly depends on ω_{it}, which cannot be observed by the econometrician. Second, no source of cross-sectional variation exists in M_{it} other than the remaining inputs: K_{it}, L_{it}, and ω_{it}. In other words, M_{it} is "collinear" with the other productive inputs. As a result, the identification problem arises with flexible input, which was pointed out by Marschak and Andrews (1944), Bond and Söderbom (2005), ACF (2006), and GNR (2013). To address this problem, ACF (2006) suggested strategies using value-added production functions to remove flexible inputs, such as an intermediate input, whereas Wooldridge (2009) proposed the use of lagged inputs decisions as instruments. However, GNR (2013) argued that these solutions are incomplete and showed that TFP estimates based on value-added functions have significant bias and that Wooldridge's approach does not solve the collinearity problem. GNR (2013) 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.

3.2 Identification

For estimation purposes, a translo-type production function is used for $f(k_{it}, l_{it}, m_{it})$:

$$\begin{aligned} y_{it} &= \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} \\ &\quad + \beta_{kk} k_{it}^2 + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 \\ &\quad + \beta_{kl} k_{it} l_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} \\ &\quad + \omega_{it} + \varepsilon_{it}, \end{aligned} \tag{22}$$

where a constant term of the production function is included in ω_{it}. GNR's identification strategy consists of two stages. The first stage involves estimating parameters associated with the intermediate input by using the firm's first-order condition with respect to M_{it} under perfect competition in the input and output markets:

$$P_t F_M(K_{it}, L_{it}, M_{it}) \exp\{\omega_{it}\} = \rho_t, \tag{23}$$

where $F_M(\cdot) = \partial F(\cdot)/\partial M_{it}$, and P_t and ρ_t denote the output and intermediate input prices, respectively. Multiplying both sides of Equation (23) by $M_{it}/P_t Y_{it}$ yields the revenue share of the intermediate input:

$$
\begin{aligned}
S_{it} = \frac{\rho_t M_{it}}{P_t Y_{it}} &= P_t F_M(K_{it}, L_{it}, M_{it}) \frac{M_{it}}{P_t Y_{it}} \exp\{\omega_{it}\} \\
&= F_M(K_{it}, L_{it}, M_{it}) \frac{M_{it}}{F(K_{it}, L_{it}, M_{it}) \exp\{\omega_{it} + \varepsilon_{it}\}} \exp\{\omega_{it}\} \\
&= F_M(K_{it}, L_{it}, M_{it}) \frac{M_{it}}{F(K_{it}, L_{it}, M_{it})} \frac{1}{\exp\{\varepsilon_{it}\}} \\
&= G(K_{it}, L_{it}, M_{it}) \frac{1}{\exp\{\varepsilon_{it}\}},
\end{aligned}
\tag{24}
$$

where $G(\cdot)$ is the elasticity of the anticipated output with respect to M_{it}. Taking the logarithm of both sides of Equation (24) enables the share equation to be rewritten as:

$$
s_{it} = \log \Gamma_{it} - \varepsilon_{it}, \tag{25}
$$

where $s_{it} = \log S_{it}$ and $\Gamma_{it} = G(K_{it}, L_{it}, M_{it})$. Because ε_{it} is the ex post shock that is, by definition, uncorrelated with the input decisions, $\log \Gamma_{it}$ can be identified by the non-parametric regression of s_{it} on $\log \Gamma_{it}$.[1)] The estimates $\hat{\Gamma}_{it}$ and $\hat{\varepsilon}_{it} = s_{it} - \log \hat{\Gamma}_{it}$ are used to identify the parameters in Equation (22). Based on the production function in Equation (22), the elasticity associated with M_{it} can be written as:

$$
e_{it}(\boldsymbol{\theta}_1) = \beta_m + \beta_{mm} 2 m_{it} + \beta_{km} k_{it} + \beta_{lm} l_{it}, \tag{26}
$$

where $\boldsymbol{\theta}_1 = (\beta_m, \beta_{mm}, \beta_{km}, \beta_{lm})'$. Given the observation, because Equation (26) depends only on the parameters associated with M_{it}, we can recover $\boldsymbol{\theta}_\mathbf{1}$ by minimizing the distance between $\hat{\Gamma}_{it}$ and $e_{it}(\boldsymbol{\theta}_\mathbf{1})$:

$$
\min_{\theta_1} \sum_t \sum_i \left[\hat{\Gamma}_{it} - e_{it}(\boldsymbol{\theta}_\mathbf{1}) \right]^2 . \tag{27}
$$

The second stage identifies the remaining parameters associated with k_{it} and l_{it} by using the moment conditions $\mathrm{E}(\xi_{it} \mid k_{it}, l_{it}) = 0$. Given the estimates for $\hat{\boldsymbol{\theta}}_1$ and $\hat{\varepsilon}_{it}$ obtained in the first stage, ω_{it} can be written as:

$$
\begin{aligned}
\omega_{it} &= y_{it} - \hat{\beta}_m m_{it} - \hat{\beta}_{mm} m_{it}^2 - \hat{\beta}_{km} k_{it} m_{it} - \hat{\beta}_{lm} l_{it} m_{it} - \hat{\varepsilon}_{it} \\
&\quad - \beta_k k_{it} - \beta_l l_{it} - \beta_{kk} k_{it}^2 - \beta_{ll} l_{it}^2 - \beta_{kl} k_{it} l_{it} \\
&= y_{it} - \mathbf{z}_{1it} \hat{\boldsymbol{\theta}}_1 - \mathbf{z}_{2it} \boldsymbol{\theta}_2 - \hat{\varepsilon}_{it} \\
&= \tilde{y}_{it} - \mathbf{z}_{2it} \boldsymbol{\theta}_2
\end{aligned}
\tag{28}
$$

where $\tilde{y}_{it} = y_{it} - \mathbf{z}_{1it} \hat{\boldsymbol{\theta}}_1 - \hat{\varepsilon}_{it}$, and:

$$
\begin{aligned}
\mathbf{z}_{1it} &= \begin{bmatrix} m_{it} & m_{it}^2 & k_{it} m_{it} & l_{it} m_{it} \end{bmatrix}, \\
\mathbf{z}_{2it} &= \begin{bmatrix} k_{it} & l_{it} & k_{it}^2 & l_{it}^2 & k_{it} l_{it} \end{bmatrix}, \\
\boldsymbol{\theta}_\mathbf{2} &= \begin{bmatrix} \beta_k & \beta_l & \beta_{kk} & \beta_{ll} & \beta_{kl} \end{bmatrix}' .
\end{aligned}
$$

1) In this paper, $\log \Gamma_{it}$ is approximated by a third-order polynomial in k_{it}, l_{it}, and m_{it}.

Given the estimates $\hat{\boldsymbol{\theta}}_1$ and $\hat{\varepsilon}_{it}$, ω_{it} is a function of $\boldsymbol{\theta_2}$. Consequently, ξ_{it} in Equation (20) can be written as:

$$\xi_{it}(\boldsymbol{\theta_2}) = \omega_{it}(\boldsymbol{\theta_2}) - g(\omega_{i,t-1}(\boldsymbol{\theta_2})). \tag{29}$$

Because ξ_{it} is, by definition, orthogonal to k_{it} and l_{it}, the moment condition $\mathrm{E}(\mathbf{z}_{2it}\,\xi_{it}) = \mathbf{0}$ can be used to identify $\boldsymbol{\theta_2}$. Using the sample analogue of the moment condition,

$$\mathbf{s}_{\mathbf{z}_2\xi} = \frac{1}{N}\sum\nolimits_{i\in N}\frac{1}{T_i}\sum\nolimits_{t\in T_i}\mathbf{z}_{2it}\,\xi_{it}(\boldsymbol{\theta_2}) = \mathbf{0}, \tag{30}$$

the estimate of $\boldsymbol{\theta}_2$ can be identified. The specific steps are as follows. Given the initial value of $\boldsymbol{\theta_2}$, $\hat{\xi}_{it}$ is non-parametrically estimated using Equations (28) and (29), and $\hat{\boldsymbol{\theta}}_2$ can then be obtained by minimizing the value of a function $\varphi(\boldsymbol{\theta_2}) = \hat{\mathbf{s}}'_{\mathbf{z}_2\xi}\,\hat{\mathbf{s}}_{\mathbf{z}_2\xi}$ with respect to $\boldsymbol{\theta}_2$.[2)] Having obtained the estimates of $\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_2$ in this identification strategy, TFP can be recovered as follows:

$$\widehat{\mathrm{TFP}}_{it} = \exp\{y_{it} - \mathbf{z}_{1it}\hat{\boldsymbol{\theta}}_1 - \mathbf{z}_{2it}\hat{\boldsymbol{\theta}}_2\}. \tag{31}$$

4 Data and Estimation Results

4.1 Data Description

The data used for the estimation are based on unbalanced firm-level panel data on China's manufacturing industry from 2004 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.[3)]

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).[4)] 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.

[2)] $g(\omega_{i,t-1}(\boldsymbol{\theta_2}))$ in Equation (29) is approximated by a third-order polynomial in $\omega_{i,t-1}(\boldsymbol{\theta_2})$. The Nelder-Mead method is used for the minimization of $\varphi(\boldsymbol{\theta_2})$.

[3)] 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, the names of legal representatives, phone numbers, and city codes. Firm-matching is conducted by STATA. It is based on but is not the same as the algorithm in Brandt et al. (2012). Their algorithm is described in their online appendix:
`http://www.econ.kuleuven.be/public/n07057/china/`.

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

(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}.

Firms with a non-positive value for Y_{it}, K_{it}, L_{it}, and M_{it} are dropped from the database.

Table 1: Summary Statistics

		Average			
	Num	Output	Fixed assets	Labor	Intermediate
All (2004)	246403	68843.1	22764.7	225.6	53252.3
All (2005)	243333	83349.6	26578.3	238.5	63594.3
All (2006)	271446	92161.9	27710.6	227.9	69865.5
All (2007)	306452	101843.7	28564.3	218.9	76821.5
State (2004)	13464	115096.4	71827.8	463.5	88494.6
State (2005)	9793	179316.1	107357.2	596.6	136711.4
State (2006)	8468	221442.7	131736.6	617.7	170184.0
State (2007)	6157	347542.9	190751.0	781.9	269392.1
Private+ (2004)	177744	51451.8	16101.9	180.6	39631.0
Private+ (2005)	178467	62454.1	18763.9	188.0	47801.3
Private+ (2006)	203758	68820.2	19217.4	177.6	52368.6
Private+ (2007)	234338	75686.2	19678.1	168.4	56955.1
Foreign (2004)	55195	113565.5	32252.7	312.5	88520.0
Foreign (2005)	55073	133997.6	37537.0	338.2	101771.1
Foreign (2006)	59220	153987.6	42058.0	345.2	115722.1
Foreign (2007)	65957	171842.9	44995.9	345.8	129428.7

Table 1 reports summary statistics on the panel data by ownership sector.[5] "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 54% from 2004 to 2007, whereas the number of private and foreign firms increased during the three 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.

4.2 TFP and Output Elasticities

The production function in Equation (22) is separately estimated by industry using a three-digit industrial code.[6] 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

[5] The tobacco industry is excluded from the database.

[6] Tobacco (industrial codes 161, 162, and 169), and nuclear-related industries (253 and 424) are eliminated from the sample. Industries 212, 214, 233, 402, and 423 are included in 211, 219, 232, 409, and 429, respectively. The estimation is implemented using R version 3.0.0 (R Development Core Team, 2009).

OLS estimates of η_M is 0.155 on average, and the OLS estimates are approximately 1.21 times higher on average than the GNR estimates. These results are clearly expected and consistent with the estimation results in GNR (2013). 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 (2013).

China's intermediate input elasticities shown in Appendix Tables A1–A4 are higher than Colombia's and Chile's as estimated by GNR (2013). The data used in GNR (2013) are based on five three-digit manufacturing industries, and their estimates of input elasticities for these industries are 0.71 (Food Products), 0.56 (Textiles), 0.53 (Apparel), 0.53 (Wood Products), and 0.54 (Fabricated Metal Products) for Colombia, and 0.69, 057, 0.58, 0.62, and 0.53 for Chile, respectively. Compared with this paper's estimates of the nearly corresponding industries (131, 171, 181, 203, and 341), Colombia's and Chile's estimates are lower in every case, indicating that China's manufacturing production depends more on intermediate inputs.

5 Allocation Efficiency

This section presents the results of the augmented OP and dynamic OP (AOP and ADOP) decomposition using China's manufacturing firm-level productivity. These methods enable us to simultaneously quantify allocation efficiency within a group and between groups. The definition of group j is required for this analysis. Section 5.1 shows the results based on the group defined as having 159 three-digit industrial sectors ($j = 1, 2, \ldots, J; J = 159$), and Section 5.2 reports the results based on the group defined as having three ownership sectors (j = State, Private+, Foreign; $J = 3$).

5.1 Allocation Efficiency of 3-digit Industrial Sectors

Table 2 reports the results of the AOP and ADOP decomposition based on the group of three-digit industrial sectors ($J = 159$). The change rate of the aggregate log TFP from 2004 to 2007 is 10.80%, and its annual average is 2.70%. Annual TFP growth rates tend to decrease annually, such as 4.36% for 2004–05, 3.93% for 2005–06, and 2.51% for 2006–07. These figures are smaller than those estimated by Brandt, et al (2012), who showed that the annual average growth of aggregate TFP is 2.85% for a gross output production function from 1998 to 2007 (Brandt, et al., 2012, Table 2). However, the sample periods and estimation methods of this paper differ from their paper, and these results indicate the possibility that China's manufacturing TFP growth tended to slow after 2004.

The ADOP decomposition reveals that new entering firms during 2004–2007 decreased aggregate manufacturing TFP by −1.20% points, whereas exiting firms increased it by 0.6% points. In the case of Slovenian manufacturing, the contribution of entering and exiting firms during 1995–2000 was 0.21% and 2.79% points, respectively (Melitz and Polanec, 2015). The contribution of China's exiting firms on productivity is positive; however, the magnitude is much smaller than that in Slovenia's case. These results indicate that entering firms in China are less efficient than surviving firms, whereas the exiting firms are slightly more inefficient

Table 2: TFP Decomposition (J = 159: three-digit industrial code)

(I) Augmented Olley-Pakes Decomposition

	Total		Within		Between
	$\Delta\Phi$	$J^{-1}\sum_j \Delta\tilde{\mu}_j$			$\Delta\tilde{\mathrm{cov}}$
			$J^{-1}\sum_j \Delta\mu_j$	$J^{-1}\sum_j \Delta\mathrm{cov}_j$	
2004–2005	0.0436	0.0619	0.0524	0.0095	−0.0183
2005–2006	0.0393	0.0494	0.0510	−0.0015	−0.0101
2006–2007	0.0251	0.0221	0.0367	−0.0146	0.0030
2004–2007	0.1080	0.1334	0.1401	−0.0066	−0.0254

(II) Augmented Dynamic Olley-Pakes Decomposition

	Total		Within				Between
	$\Delta\Phi$	$J^{-1}\sum_j \Delta\tilde{\mu}_j$					$\Delta\tilde{\mathrm{cov}}$
			$J^{-1}\sum_j \Delta\mu_j^S$	$J^{-1}\sum_j \Delta\mathrm{cov}_j^S$	$J^{-1}\sum_j ent_j$	$J^{-1}\sum_j ext_j$	
2004–2005	0.0436	0.0619	0.0551	0.0080	−0.0037	0.0025	−0.0183
2005–2006	0.0393	0.0494	0.0553	−0.0013	−0.0066	0.0020	−0.0101
2006–2007	0.0251	0.0221	0.0395	−0.0115	−0.0075	0.0016	0.0030
2004–2007	0.1080	0.1334	0.1347	0.0047	−0.0120	0.0060	−0.0254

than are surviving firms. However, the average productivity gap between exiting and surviving firms is quite small, compared with Slovenia's case. The entry and exit of manufacturing firms does not seem to contribute to the increase in aggregate TFP growth in China.

The contribution of allocation efficiency between groups ($\Delta\tilde{\mathrm{cov}}$) to the aggregate manufacturing TFP growth is −0.0254 for 2004–2007. If $\Delta\tilde{\mathrm{cov}}$ was zero during 2004–2007, the aggregate log TFP change rate ($\Delta\Phi$) would increase to 13.34% in Panel (I) and 13.47% in Panel (II), and these annual averages would be 3.34% and 3.37%, respectively. These results indicate that resource allocation among three-digit industrial sectors tends to worsen during this period, although the annual change rates increase over time. In contrast, the changes in the average allocation efficiency within each group are −0.0066 (AOP decomposition) and 0.0047 (ADOP decomposition), which indicate opposite signs for AOP and ADOP and small magnitudes. The changes in allocation efficiency between the groups are found to affect the aggregate TFP changes more than those of the within-group allocation efficiency. The increase in misallocation between industrial sectors reduces aggregate TFP growth during 2004–2007 by annual average of 0.635% points.

Because the within allocation efficiency shown in Table 2 is the average of 159 three-digit sectors, the magnitude of the within effect for each sector is likely to vary among sectors. Figure 1 shows a histogram of AOP and ADOP's covariance terms within each sector ($\Delta\mathrm{cov}_j$ and $\Delta\mathrm{cov}_j^S$), which indicates that not all industries have negative values. However, the range is from approximately 0.20 to −0.25 (without industry 379), and the number of sectors having positive values is 87 industries for the AOP decomposition and 99 industries for the ADOP decomposition. Furthermore, Panel (III) in the figure indicates a gap between the AOP and ADOP covariance terms. Considering the meaning of this gap is useful. AOP's covariance change includes the contributions of both surviving firms and exiting-entering firms to the degree of allocation efficiency. In contrast, for ADOP, the focus is only on the change in allocation efficiency among surviving firms. Consequently, the difference in $\Delta\mathrm{cov}_j - \Delta\mathrm{cov}_j^S$ implies the contributions of exiting firms and entering firms to the change in the allocation efficiency within sector j. A positive gap leads to the interpretation that exiting and/or entering firms contribute

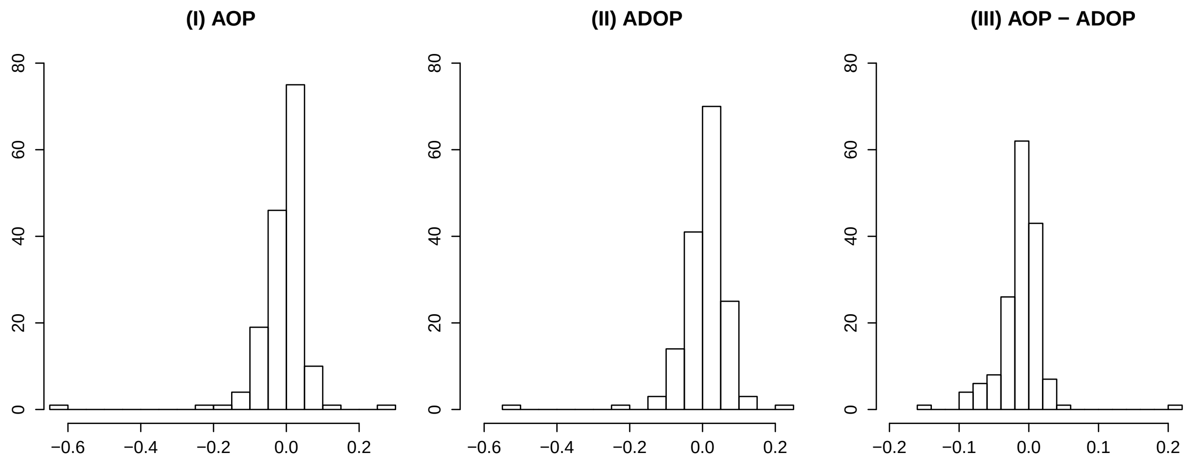


Figure 1: Allocation efficiency within each industrial sector.
Notes: The vertical axis represents the number of three-digit industrial sectors. The horizontal axis is defined as Δcov_j for panel (I), Δcov_j^S for panel (II), and $\Delta\text{cov}_j - \Delta\text{cov}_j^S$ for panel (III).

to improving allocation efficiency. As shown in Panel (III) of Figure 1, the gap differs among sectors and ranges from −0.16 to 0.21. The average is −0.011, and 107 of 159 sectors (67%) are plotted in the negative area, indicating that a firm's entry to and/or exit from the market does not necessarily contribute to improving China's manufacturing allocation efficiency.

What causes the difference in the within allocation efficiency (Δcov_j and Δcov_j^S) among industrial sectors? Chen, et al. (2011) argued that the changes in China's allocation efficiency have a negative relationship with the capital-labor ratio and the market shares of state-owned firms. Brandt et al. (2013) found that the misallocation of capital between state and non-state sectors tended to increase after 1997. These findings indicate that misallocation is expected to increase in relatively capital intensive industries, and/or in industries dominated by state-owned firms. Furthermore, it is possible that the spatial concentration of industries contributes to improving allocation efficiency because spatial concentration is likely to enhance competition among firms. Thus, less-productive firms are expected to exit the market and, consequently, production resources are allocated to more productive firms.

To explore the factors that change the variations in allocation efficiency, a regression analysis is conducted, using three-digit industrial sectors. The explained variables are the changes of within-allocation efficiencies (Δcov_j and Δcov_j^S) during 2004–2007. The explanatory variables are market share by ownership (State, Private+, and Foreign), aggregate industry-level capital-labor ratio, and the Ellison-Glaeser (EG) industry-concentration index (Ellison and Glaeser, 1997). The market shares are measured using gross output, and the EG index is based on county-level regions and the number of firm-level employees, such as:

$$EG_j = \frac{\sum_{m=1}^{M}(s_{jm} - s_{*m})^2 - \left(1 - \sum_{m=1}^{M} s_{*m}^2\right) H_j}{\left(1 - \sum_{m=1}^{M} s_{*m}^2\right)\left(1 - H_j\right)}, \tag{32}$$

where i, j, and m denote firm, industry, and county, respectively, and:

$$s_{jm} = \frac{x_{jm}}{\sum_{m=1}^{M} x_{jm}}, \quad s_{*m} = \frac{\sum_{j=1}^{J} x_{jm}}{\sum_{j=1}^{J}\sum_{m=1}^{M} x_{jm}}, \quad H_j = \sum_{i\in j}^{N_j}\left(\frac{x_{i\in j}}{\sum_{i\in j} x_{i\in j}}\right)^2,$$

where x is the number of employees. All explanatory variables are based on observations in 2004.

Table 3: Regression results

Explained variables:		Δcov_j^S	Δcov_j
Regressors	Coef.		
Output share (State, 2004)	α_s	0.052	0.030
		(0.049)	(0.044)
Output share (Private+, 2004)	α_p	0.171***	0.159***
		(0.028)	(0.029)
Output share (Foreign, 2004)	α_f	0.071**	0.058*
		(0.024)	(0.023)
Ellison-Glaeser Index (2004)	α_{EG}	−0.393	0.010
		(0.250)	(0.193)
$\log K/L$ (2004)	α_{KL}	−0.026***	−0.027***
		(0.006)	(0.006)
Likelihood ratio tests (p-value)			
Null: $\alpha_s = \alpha_p$		0.008	0.004
Null: $\alpha_s = \alpha_f$		0.644	0.504
Null: $\alpha_p = \alpha_f$		0.000	0.000
Sample size: 158			

Notes: The sample is based on the number of three-digit industrial sectors, except sector #379. Asterisks ***, **, and * indicate significant levels at 0.1%, 1%, and 5%, respectively.

Table 3 reports the regression results.[7)] The market shares of private and foreign firms have positive and significant coefficients, while the market share of state-owned firms is insignificant. The $\log K/L$ has a significantly negative relationship with changes in allocation efficiency. The coefficients of EG index show negative values that are not significant for Δcov_j^S and Δcov_j. Contrary to expectations, the spatial concentration of industries does not have a positive effect on the improvement in allocation efficiency. These results indicate that changes in allocation efficiency tend to improve in industries with private firms having higher market shares, and/or in relatively labor intensive industries.

Exploring the magnitude of the allocation efficiency level is also useful. Table 4 provides the level of covariance terms within an industry and between industries. A comparison of panels (I) and (II) shows a small difference and the same tendency. Industry averages of the within-industry covariance terms fall between 0.22–0.24. These figures are not very small compared with those of other countries. According to Bartelsman et al. (2013; Table 1), the covariance term averages during 1993–2001 for eight countries were 0.51 (United States), 0.15 (UK), 0.28 (Germany), 0.24 (France), 0.30 (Netherlands), 0.16 (Hungary), -0.03 (Romania), and 0.04 (Slovenia). China's manufacturing sector is at the same level as Germany's. However, the

[7)]Because the sector #397 has negative extreme values for Δcov_j^S and Δcov_j, as shown in Figure 1, the sector is eliminated from the regression analysis.

between-industry covariance terms are very low, indicating negative values for several years and implying that improving the allocation efficiency between industries can make a significant contribution to increasing aggregate manufacturing TFP growth.

Table 4: Level of the covariance terms ($J = 159$)

(I) Augmented OP decomposition

t	$J^{-1}\sum_j \text{cov}_{jt}$	$\tilde{\text{cov}}_t$
2004	0.2387	0.0377
2005	0.2482	0.0194
2006	0.2467	0.0093
2007	0.2321	0.0123

(II) Augmented MP decomposition

		$J^{-1}\sum_j \text{cov}^S_{jt}$		$\tilde{\text{cov}}^S_t$	
$t = 1$	$t = 2$	$t = 1$	$t = 2$	$t = 1$	$t = 2$
2004	2005	0.2324	0.2404	0.0377	0.0194
2005	2006	0.2421	0.2408	0.0194	0.0093
2006	2007	0.2368	0.2253	0.0093	0.0123
2004	2007	0.2269	0.2316	0.0377	0.0123

In summary, allocation efficiency between industries worsened during 2004–2007, and a variation existed in the changes of within-industry allocation efficiency among industrial sectors. The within-allocation efficiency worsened for the sectors that use more capital and have firms with relatively higher state-owned market shares. These findings are consistent with those of Chen, et al. (2011) and Brandt, et al. (2013).

5.2 Allocation Efficiency of Ownership Groups by Industrial Sector

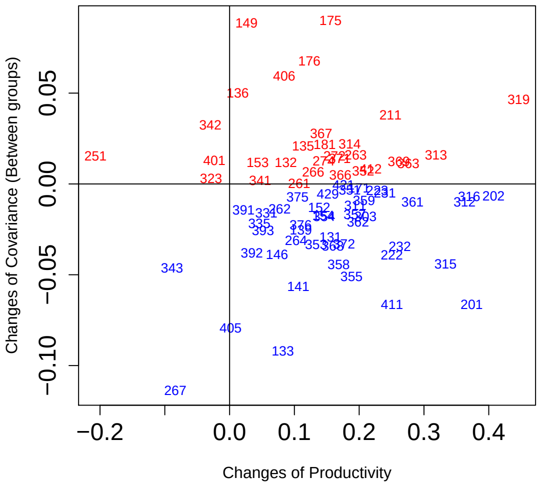
The previous section showed the degree of allocation efficiency within each industrial sector and between industrial sectors. This section focuses on the allocation efficiency of ownership groups by three-digit industrial sector. The ownership groups are defined as $j \in$ {State (S), Private+ (P), and Foreign (F) sectors} ($J = 3$). Section 4 provides a definition of each sector. The author examines the extent of allocation efficiency within each ownership group and between groups using the three-digit industrial sector, and the following ADOP decomposition equation:

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

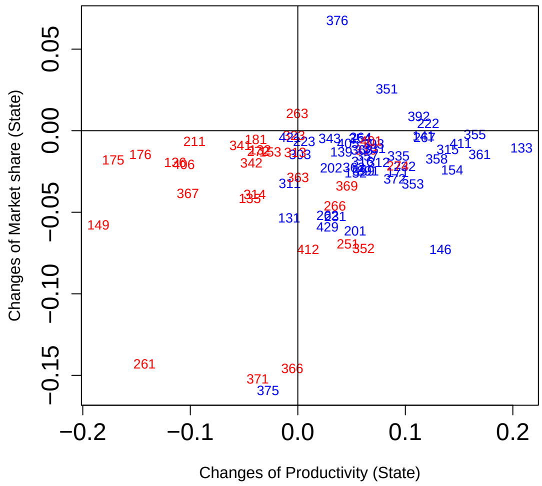
Note that i denotes a three-digit industrial sector in this section and the ADOP decomposition applies separately for each $i = 1, 2, \ldots, I^*$. Because the three-digit industrial classification is relatively narrow, several industries have few or no firms in any of the three ownership sectors. To 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, $I^* = 75$ industrial sectors are used in this section.

5.2.1 Allocation Efficiency between Ownership Groups

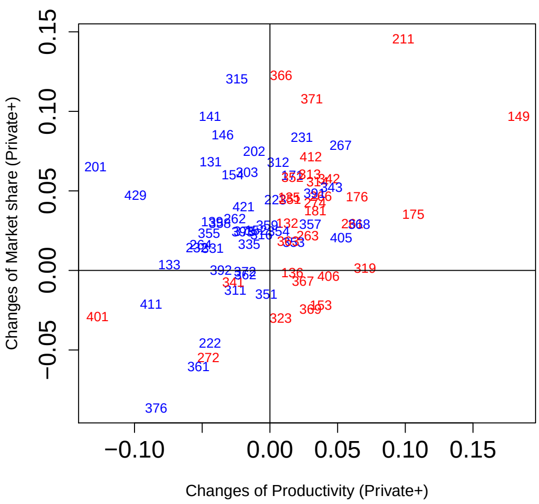
Figure 2 presents the allocation efficiency between three ownership groups ($\Delta\tilde{\text{cov}}(i)$) during 2004–2007. Panel (A) of Figure 2 exhibits the plots of aggregate productivity changes $\Delta\Phi(i)$,



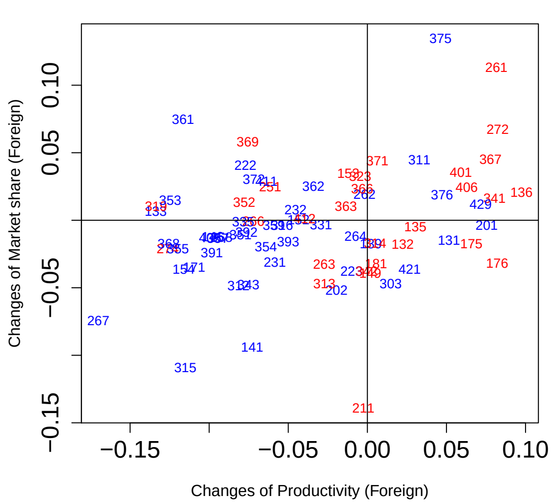
(A) Plots of ΔΦ (horizontal axis) and Δcõv (vertical axis)



(B) Decomposition of Δcõv (State)



(C) Decomposition of Δcõv (Private+)



(D) Decomposition of Δcõv (Foreign)

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

Notes: Red-colored plots denote industries with positive Δcõv values in Panel (A), whereas blue-colored plots denote industries with negative Δcõv values.

and the changes in allocation efficiency between the three ownership groups, $\Delta\tilde{\text{cov}}(i)$. Although the average of $\Delta\tilde{\text{cov}}(i)$ is almost zero (-0.007), it varies among industries, ranging from -0.114 to 0.09. In all, 30 industrial sectors are plotted in the positive area of the vertical axis ($\Delta\tilde{\text{cov}}(i) > 0$), indicating that these industries tend to improve resource allocation among the three ownership groups.

To investigate the source of the variation in $\Delta\tilde{\text{cov}}(i)$, it is rewritten as follows (suppress i to ease notation):

$$\begin{aligned}\Delta\tilde{\text{cov}} &= \sum_{j\in\{S,P,F\}} (x_{j2}y_{j2} - x_{j1}y_{j1}) \\ &= \sum_{j\in\{S,P,F\}} (y_{j2}\Delta x_{j2} + x_{j1}\Delta y_{j2})\end{aligned} \tag{33}$$

where $x_{jt} = w_{jt} - 1/J\sum_j w_{jt}$ and $y_{jt} = \tilde{\mu}_{jt} - 1/J\sum_j \tilde{\mu}_{jt}$ for $t = 1, 2$. Δx_{jt} and Δy_{jt} denote changes in the demeaned aggregate productivity and market share for each ownership sector during 2004–2007. The relationship among the three variables ($\Delta\tilde{\text{cov}}$, Δx_{jt}, and Δy_{jt}) is plotted in Panels (B)–(D) of Figure 2 by ownership. The red-colored plots denote industries with positive $\Delta\tilde{\text{cov}}$ values in Panel (A), whereas the blue-colored plots denote industries with negative $\Delta\tilde{\text{cov}}$ values.[8)]

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

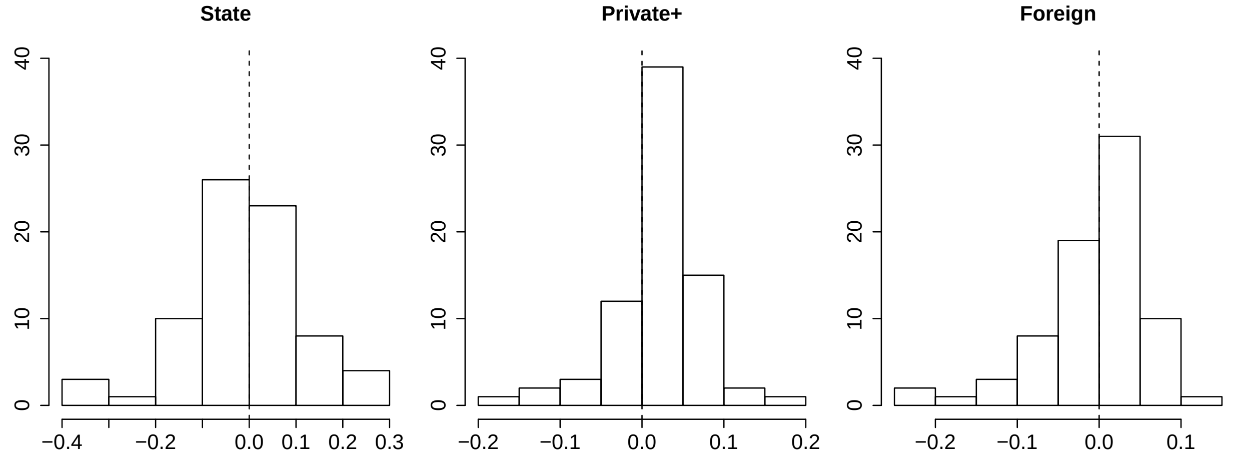
Panel (C) shows the relationship between the changes in the Private+ sector's market share and productivity. Contrary to Panel (B), the red and blue plots are primarily distributed in the first and second quadrants, respectively, indicating that the resource allocation between ownership groups tends 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 (D)) 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.

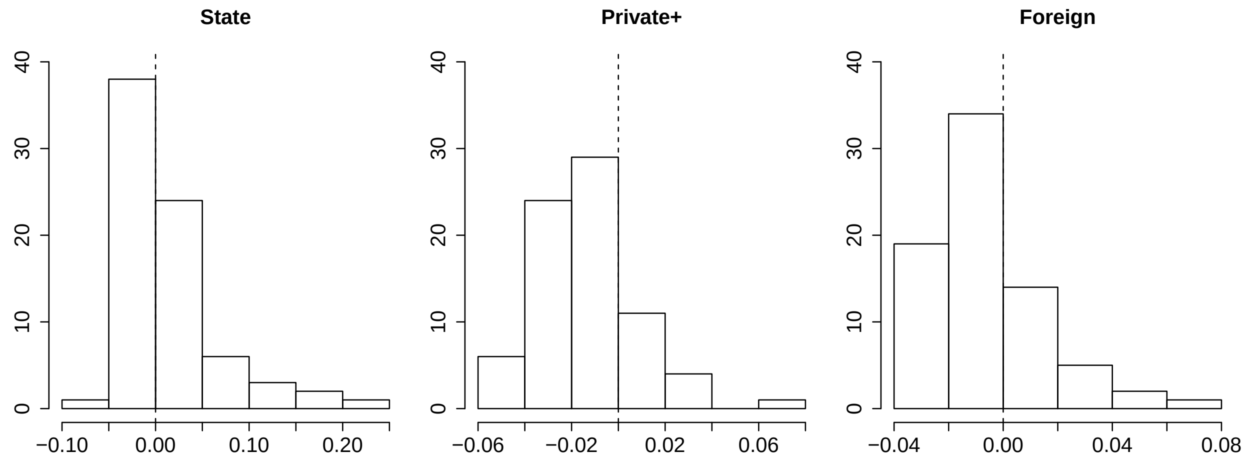
5.2.2 Within-Effects for Each Ownership Group

Figure 3 reports the histograms of the within-effects. The vertical axis defines the number of three-digit industrial sectors ($i = 1, 2, \ldots, 75$). Panels (A), (B) and (C) show allocation

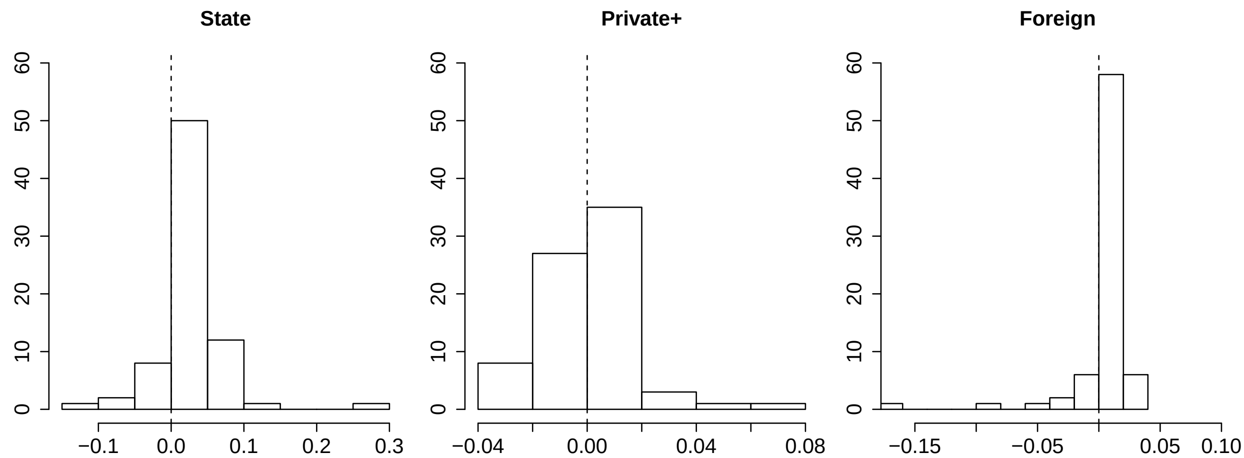
[8)]Note that the first and third quadrants in Panels (B)–(D) indicate the positive relationship between the changes in market share and productivity. However, this positive relationship does not necessarily produce positive $\Delta\tilde{\text{cov}}$ values. As is clear from Equation (33), $\Delta\tilde{\text{cov}}$ does not necessarily become positive even if the sign of Δx_{j2} is the same direction as that of Δy_{j2} for each $j \in \{S, P, F\}$.



(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 3: Decomposition of the within-effect by ownership during 2004–2007

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

efficiency $\Delta\text{cov}_j^S(i)$, entry effects $ent_j^S(i)$, and exit effects $ext_j^S(i)$ within a group $j \in \{S, P, F\}$, respectively.

Panel (A) shows that the means of these histograms is -0.007 (State), 0.020 (Private+), and -0.007 (Foreign), and that the shares of the number of sectors with $\Delta\text{cov}_j^S(i) > 0$ are 46.7%, 76.0%, and 56%, respectively. Although the values of $\Delta\text{cov}_j^S(i)$ are distributed broadly for each group, the Private+ group tends to improve its allocation efficiency among firms during 2004–2007. The entry effect in Panel (B) shows that the means for each group are 0.019 (State), -0.14 (Private+), and -0.007 (Foreign), and the shares of the number of sectors with $ent_j^S(i) > 0$ are 48.0%, 21.3%, and 29.3%, respectively. This result indicates that new entry firms in the Private+ and Foreign groups during 2004–2007 have, on average, lower productivity than existing firms for each group. Consequently, they have a negative effect on aggregate productivity growth. Furthermore, the exit effect of the Private+ group shown in Panel (C) is also small. The means are 0.026 (State), 0.0019 (Private+), and 0.003 (Foreign), and the shares of the number of sectors with $ext_j^S(i) > 0$ are 85.3%, 53.3%, and 85.3%, respectively, implying that relatively nonproductive firms in the Private+ group are not likely to exit the market.

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.

6 Conclusions

Are changes in resource allocation important to driving the growth of aggregate TFP? Answering this question requires a quantitative measure of allocation efficiency. This paper provides 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.

The measure of allocation efficiency is applied to China's manufacturing firm-level data from 2004 to 2007. This paper uses two definitions of groups: (1) 159 industrial groups based on a three-digit industrial classification and (2) three ownership groups (State, Private+, Foreign sectors). Firm-level productivity used to calculate productivity decomposition is estimated using a structural estimation method proposed by Gandhi et al. (2013). The main findings of this paper are summarized as follows:

1. New entering and exiting firms did not contribute significantly to the increase in growth of aggregate manufacturing TFP.

2. Misallocation between 159 industrial sectors tended to increase during 2004–2007, which reduced aggregate TFP growth during 2004–2007 by an annual average of 0.635% points. The changes in allocation efficiency within each industrial sector during 2004–2007 varied widely among sectors. However its average is almost zero, indicating that the within-effects do not significantly affect aggregate TFP growth.

3. Misallocation within an industrial sector was found to increase for sectors using more capital and having firms with relatively higher state-owned market shares. These findings are consistent with those of Chen, et al. (2011) and Brandt, et al. (2013).

4. Misallocation between three ownership groups declined in 30 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.

5. The Private+ sector has more industrial sectors improving the within-allocation efficiency among firms compared with the State and Foreign sectors. However, the entry and exit effects for the Private+ sector were very small. In particular, the entry effect has negative values for many industrial sectors, indicating that new firms in the Private+ sector tended to be less productive than existing firms, driving down aggregate productivity growth.

These empirical results lead us to conclude that misallocation in China's manufacturing sector tended to increase during 2004–2007 that, particularly the increase in misallocation between industrial sectors had a significant negative effect on aggregate TFP growth. Furthermore, allocation efficiency tended to improve in industrial sectors in which 1) the production process is not capital intensive and 2) non-state-owned firms are relatively productive and have higher market share than state-owned firms.

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 increase in misallocation in China 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. 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. In addition, as Brandt et al. (2013) argued, regional policies such as Xibu Kaifa (i.e., develop the great west) may be related to the increase in misallocation. If the government promotes the reallocation of investment resources toward less-productive sectors, doing so should worsen resource allocation.

Identifying the source of misallocation is challenging, but misallocation worsened in China's manufacturing sector during 2004–2007, in accordance with the findings of this paper. Therefore, reexamining the regional development policies and the equity of competitive conditions among firms in the financial market in terms of optimal resource allocation is crucially important.

Finally, the difference should be noted between the two measures for allocation efficiency: 1) the covariance type, originally developed by Olley and Pakes (1996), and 2) the dispersion type, discussed by Hsieh and Klenow (2009). The former assesses the degree of allocation efficiency using the relationship between market share and productivity, whereas the latter uses the degree of dispersion (e.g., standard deviations) of firm-level productivity within a sector as the measure of allocation efficiency. A higher covariance measure indicates more-efficient resource allocation, whereas a lower dispersion measure indicates more-efficient resource allocation. However, these two measure are likely to provide inconsistent results because the decrease in the dispersion might lead to a decline in the covariance. What are the main sources of this inconsistency? Although this issue is beyond the scope of this paper, it must be resolved.

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Table A1: Average Input Elasticities of Output (1)

	GNR				OLS			
Industry	K	L	M	$K+L+M$	K	L	M	$K+L+M$
131	0.0634	0.1994	0.7289	0.9916	0.0065	0.0541	0.9216	0.9822
132	0.0702	0.1924	0.7616	1.0241	0.0168	0.0582	0.9322	1.0072
133	0.0863	0.1448	0.7445	0.9755	0.0030	0.0322	0.9367	0.9719
134	0.1172	0.1136	0.7209	0.9516	0.0460	0.0168	0.9315	0.9943
135	0.0617	0.1796	0.7224	0.9637	0.0002	0.0376	0.9514	0.9892
136	0.0734	0.1418	0.7513	0.9665	0.0186	0.0510	0.9283	0.9978
137	0.0664	0.1029	0.7238	0.8930	0.0207	0.0327	0.9043	0.9577
139	0.0610	0.1380	0.7099	0.9088	0.0095	0.0481	0.9140	0.9716
141	0.0813	0.1797	0.7242	0.9852	0.0226	0.0821	0.9063	1.0111
142	0.0783	0.1523	0.7357	0.9663	0.0147	0.0518	0.9294	0.9959
143	0.0847	0.1638	0.7174	0.9659	0.0271	0.0567	0.9052	0.9890
144	0.0757	0.1577	0.7388	0.9721	-0.0006	0.0493	0.9432	0.9919
145	0.0610	0.1449	0.7369	0.9428	0.0158	0.0450	0.9261	0.9868
146	0.1027	0.1234	0.7238	0.9500	0.0232	0.0205	0.9521	0.9958
149	0.0748	0.1632	0.7159	0.9539	0.0187	0.0653	0.9043	0.9884
151	0.0897	0.1875	0.7183	0.9955	-0.0161	0.0556	0.9445	0.9841
152	0.0971	0.1914	0.6619	0.9504	0.0094	0.0690	0.9209	0.9993
153	0.1222	0.1941	0.7016	1.0179	0.0265	0.0619	0.9225	1.0109
154	0.0826	0.1570	0.7173	0.9570	0.0318	0.0602	0.9220	1.0141
171	0.0560	0.1539	0.7647	0.9746	0.0075	0.0514	0.9280	0.9870
172	0.0424	0.1032	0.7496	0.8952	-0.0032	0.0303	0.9457	0.9728
173	0.0627	0.1342	0.7247	0.9216	0.0091	0.0378	0.9155	0.9624
174	0.0600	0.1317	0.7896	0.9812	0.0092	0.0452	0.9250	0.9794
175	0.0640	0.1391	0.7617	0.9649	0.0174	0.0574	0.9194	0.9942
176	0.0627	0.1582	0.7451	0.9659	0.0190	0.0838	0.8790	0.9818
181	0.0718	0.1672	0.7189	0.9578	0.0225	0.0977	0.8583	0.9785
182	0.0565	0.1947	0.7277	0.9788	0.0214	0.0769	0.8786	0.9768
183	0.0778	0.1057	0.7241	0.9077	0.0231	0.0765	0.8708	0.9703
191	0.0655	0.2402	0.7489	1.0546	0.0100	0.0597	0.9180	0.9876
192	0.0735	0.1879	0.7306	0.9920	0.0194	0.0913	0.8741	0.9847
193	0.0861	0.1732	0.7528	1.0122	0.0205	0.0255	0.9246	0.9706
194	0.0749	0.0877	0.7667	0.9293	0.0165	0.0114	0.9088	0.9367
201	0.0542	0.2121	0.7218	0.9880	0.0179	0.0836	0.8978	0.9993
202	0.0860	0.1464	0.7348	0.9671	0.0221	0.0318	0.9173	0.9713
203	0.0583	0.1632	0.7274	0.9489	0.0198	0.0789	0.8634	0.9621
204	0.0599	0.1880	0.7341	0.9820	0.0318	0.0753	0.8561	0.9632
211	0.0562	0.1642	0.7333	0.9536	0.0197	0.0593	0.9040	0.9830
213	0.0745	0.1517	0.7723	0.9985	0.0286	0.0425	0.9237	0.9949
219	0.0643	0.1974	0.7521	1.0138	0.0229	0.0827	0.8596	0.9653
221	0.0603	0.0893	0.7392	0.8888	-0.0010	0.0254	0.9511	0.9755
222	0.0734	0.1677	0.7600	1.0011	0.0030	0.0393	0.9435	0.9858
223	0.0711	0.1493	0.7592	0.9797	0.0206	0.0594	0.9047	0.9847
231	0.1018	0.1601	0.7199	0.9817	0.0516	0.0599	0.9082	1.0197
232	0.0572	0.2268	0.7089	0.9928	0.0222	0.1212	0.8961	1.0394
241	0.0621	0.1441	0.7566	0.9628	0.0298	0.0582	0.9022	0.9902
242	0.0652	0.1575	0.7462	0.9690	0.0245	0.0683	0.8833	0.9760
243	0.0419	0.1001	0.7378	0.8798	0.0149	0.1067	0.8669	0.9885
244	0.0498	0.1578	0.7346	0.9422	0.0270	0.0853	0.8739	0.9862
245	0.0541	0.1714	0.7740	0.9995	0.0361	0.0371	0.9193	0.9925
251	0.1181	0.0982	0.7644	0.9807	0.0216	0.0335	0.9280	0.9831

Table A2: Average Input Elasticities of Output (2)

	GNR				OLS			
Industry	K	L	M	$K+L+M$	K	L	M	$K+L+M$
252	0.1122	0.0821	0.7190	0.9134	0.0055	0.0351	0.9166	0.9573
261	0.0825	0.1177	0.7385	0.9387	0.0196	0.0362	0.9228	0.9786
262	0.0940	0.1021	0.7336	0.9298	0.0254	0.0349	0.9179	0.9781
263	0.0547	0.1988	0.7315	0.9851	0.0107	0.0491	0.9313	0.9912
264	0.0882	0.1380	0.7605	0.9867	0.0246	0.0374	0.9217	0.9837
265	0.1134	0.1100	0.7676	0.9910	0.0184	0.0432	0.9097	0.9712
266	0.1022	0.1127	0.7246	0.9395	0.0239	0.0504	0.8965	0.9708
267	0.0896	0.1262	0.7334	0.9492	0.0282	0.0341	0.9294	0.9916
271	0.0896	0.1727	0.7284	0.9907	0.0149	0.0454	0.9213	0.9816
272	0.0867	0.1940	0.6718	0.9525	0.0019	0.1003	0.8855	0.9877
273	0.0487	0.1650	0.6903	0.9040	0.0446	0.0668	0.8543	0.9657
274	0.0535	0.2078	0.6538	0.9152	0.0278	0.0797	0.8999	1.0074
275	0.1050	0.1914	0.6879	0.9843	0.0300	0.0759	0.9308	1.0367
276	0.0471	0.2479	0.6476	0.9425	0.0126	0.1263	0.8707	1.0096
277	0.1270	0.1847	0.7056	1.0172	0.0321	0.0667	0.8909	0.9897
281	0.0957	0.1136	0.7657	0.9750	0.0273	0.0116	0.9476	0.9864
282	0.0807	0.0481	0.7924	0.9212	0.0114	0.0284	0.9465	0.9862
291	0.0412	0.0785	0.7467	0.8664	-0.0206	0.0093	0.9770	0.9657
292	0.0798	0.1088	0.7500	0.9386	0.0343	0.0291	0.9068	0.9703
293	0.0815	0.1279	0.7174	0.9268	0.0279	0.0583	0.8923	0.9785
294	0.0406	0.1606	0.7384	0.9395	0.0023	0.0445	0.9463	0.9931
295	0.0930	0.1371	0.7401	0.9703	0.0365	0.0883	0.8887	1.0135
296	0.0928	0.1572	0.7398	0.9898	0.0014	0.0494	0.9180	0.9688
299	0.1128	0.1091	0.7310	0.9529	0.0368	0.0674	0.8678	0.9720
301	0.0793	0.1124	0.7751	0.9668	0.0177	0.0433	0.9243	0.9854
302	0.0790	0.1374	0.7646	0.9810	0.0096	0.0391	0.9161	0.9648
303	0.1075	0.1662	0.7455	1.0192	0.0312	0.0528	0.8950	0.9790
304	0.0454	0.1314	0.7755	0.9522	0.0134	0.0570	0.8981	0.9685
305	0.0603	0.1454	0.7878	0.9934	-0.0015	0.0108	0.9770	0.9863
306	0.0965	0.1083	0.7533	0.9580	0.0357	0.0430	0.8964	0.9750
307	0.1021	0.1732	0.7509	1.0262	0.0497	0.0840	0.8518	0.9855
308	0.0718	0.1530	0.7614	0.9861	0.0275	0.0798	0.8826	0.9899
309	0.0791	0.1006	0.7529	0.9327	0.0315	0.0570	0.8656	0.9541
311	0.0950	0.0974	0.7332	0.9256	0.0140	0.0286	0.9301	0.9727
312	0.0801	0.1136	0.7401	0.9339	0.0275	0.0322	0.9313	0.9909
313	0.1103	0.1261	0.6973	0.9338	0.0208	0.0387	0.9178	0.9773
314	0.1040	0.1765	0.7294	1.0099	0.0384	0.0595	0.8938	0.9917
315	0.0980	0.1042	0.6922	0.8943	0.0148	0.0633	0.9006	0.9787
316	0.0955	0.1138	0.7221	0.9313	0.0348	0.0098	0.9473	0.9919
319	0.0903	0.1270	0.7249	0.9421	0.0374	0.0260	0.9170	0.9803
321	0.0839	0.1355	0.7424	0.9618	0.0119	0.0439	0.9296	0.9854
322	0.0861	0.0609	0.7697	0.9168	0.0167	0.0234	0.9493	0.9895
323	0.0865	0.1462	0.7770	1.0097	0.0105	0.0564	0.9213	0.9882
324	0.0670	0.1305	0.7297	0.9272	0.0161	0.0505	0.9242	0.9908
331	0.0706	0.1202	0.7456	0.9364	0.0135	0.0511	0.9123	0.9768
332	0.1061	-0.0025	0.6946	0.7982	0.0185	0.0630	0.8942	0.9757
333	0.0786	0.0983	0.7422	0.9191	0.0128	0.0279	0.9319	0.9726
334	0.0714	0.1358	0.7749	0.9821	0.0189	0.0465	0.9223	0.9877
335	0.0740	0.0947	0.7844	0.9531	0.0136	0.0414	0.9218	0.9768
341	0.0841	0.1503	0.7447	0.9791	0.0224	0.0690	0.8878	0.9791

Table A3: Average Input Elasticities of Output (3)

	GNR				OLS			
Industry	K	L	M	$K+L+M$	K	L	M	$K+L+M$
342	0.0805	0.1268	0.7377	0.9450	0.0332	0.0627	0.8824	0.9783
343	0.0963	0.1509	0.7603	1.0075	0.0243	0.0527	0.8974	0.9744
344	0.0676	0.1155	0.7736	0.9567	0.0146	0.0599	0.9049	0.9794
345	0.0941	0.1437	0.7603	0.9981	0.0209	0.0540	0.9033	0.9783
346	0.1101	0.1111	0.7417	0.9629	0.0415	0.0810	0.8395	0.9620
347	0.0618	0.1161	0.7576	0.9355	0.0179	0.0646	0.8787	0.9612
348	0.0737	0.1036	0.7587	0.9361	0.0201	0.0558	0.8871	0.9630
349	0.0770	0.0986	0.7531	0.9286	0.0302	0.0543	0.8741	0.9586
351	0.0612	0.1450	0.7308	0.9369	0.0011	0.0489	0.9126	0.9627
352	0.0841	0.1286	0.7250	0.9378	0.0295	0.0501	0.9137	0.9933
353	0.0847	0.2072	0.7482	1.0401	0.0167	0.0545	0.8990	0.9702
354	0.0886	0.1248	0.7407	0.9541	0.0285	0.0327	0.9130	0.9742
355	0.1090	0.1529	0.7272	0.9891	0.0385	0.0458	0.8835	0.9679
356	0.0671	0.1418	0.7560	0.9649	0.0351	0.0389	0.9116	0.9856
357	0.0873	0.1693	0.7414	0.9980	0.0207	0.0478	0.9061	0.9746
358	0.0927	0.1439	0.7434	0.9800	0.0382	0.0689	0.8886	0.9957
359	0.0807	0.1055	0.7507	0.9370	0.0216	0.0324	0.9187	0.9727
361	0.1013	0.1506	0.7216	0.9735	0.0191	0.0348	0.9071	0.9611
362	0.0957	0.1591	0.7141	0.9689	0.0500	0.0696	0.8577	0.9773
363	0.0517	0.2190	0.7237	0.9945	0.0184	0.0290	0.9555	1.0029
364	0.0655	0.1210	0.7296	0.9161	0.0167	0.0365	0.9313	0.9845
365	0.0486	0.1188	0.7453	0.9127	0.0108	0.0456	0.9045	0.9609
366	0.0864	0.1643	0.7086	0.9592	0.0314	0.0550	0.8605	0.9468
367	0.0499	0.1574	0.7319	0.9392	0.0084	0.0457	0.9388	0.9929
368	0.1239	0.1767	0.6791	0.9797	0.0521	0.0679	0.8685	0.9885
369	0.0619	0.1883	0.7120	0.9621	0.0245	0.0683	0.8948	0.9876
371	0.1036	0.1659	0.7094	0.9789	0.0268	0.0479	0.9060	0.9808
372	0.0837	0.1787	0.7386	1.0010	0.0212	0.0637	0.9069	0.9917
373	0.0597	0.1330	0.7775	0.9702	0.0148	0.0401	0.9243	0.9792
374	0.0525	0.1364	0.7953	0.9843	0.0244	0.0603	0.8977	0.9824
375	0.0716	0.1907	0.7099	0.9722	0.0060	0.1141	0.8559	0.9760
376	0.1880	0.1024	0.6312	0.9216	0.0996	0.0775	0.7880	0.9651
379	0.1005	0.1390	0.7047	0.9442	0.0242	0.0662	0.8738	0.9642
391	0.0877	0.1614	0.7573	1.0063	0.0041	0.0608	0.9060	0.9710
392	0.0914	0.1608	0.7361	0.9883	0.0233	0.0555	0.8907	0.9694
393	0.1069	0.1199	0.7665	0.9933	0.0308	0.0481	0.8979	0.9769
394	0.0946	0.1439	0.7637	1.0022	0.0210	0.0547	0.8831	0.9588
395	0.0687	0.1776	0.7767	1.0230	0.0120	0.0657	0.9079	0.9855
396	0.0391	0.1043	0.7634	0.9068	-0.0018	0.0383	0.9422	0.9787
397	0.0838	0.1579	0.7695	1.0112	0.0195	0.0659	0.8866	0.9720
399	0.0776	0.1952	0.7147	0.9876	0.0263	0.1081	0.8499	0.9844
401	0.0758	0.2030	0.7182	0.9970	0.0152	0.1089	0.8292	0.9533
403	0.1068	0.1534	0.7349	0.9951	0.0367	0.0762	0.8401	0.9530
404	0.0699	0.1789	0.7348	0.9836	0.0228	0.1064	0.8245	0.9537
405	0.1089	0.1737	0.7036	0.9862	0.0442	0.0905	0.8335	0.9682
406	0.1012	0.1455	0.7319	0.9786	0.0405	0.0884	0.8547	0.9836
407	0.0529	0.1717	0.7740	0.9986	0.0221	0.1057	0.8593	0.9871
409	0.0599	0.1550	0.7136	0.9286	0.0294	0.0782	0.8384	0.9461
411	0.0757	0.1692	0.7121	0.9570	0.0230	0.0608	0.8947	0.9785
412	0.1003	0.1883	0.6966	0.9852	0.0297	0.0653	0.8857	0.9807

Table A4: Average Input Elasticities of Output (4)

Industry	GNR				OLS			
	K	L	M	$K + L + M$	K	L	M	$K + L + M$
413	0.0577	0.1592	0.7105	0.9273	0.0204	0.1097	0.8291	0.9592
414	0.0952	0.1821	0.7154	0.9927	0.0256	0.0688	0.8694	0.9638
415	0.0540	0.1844	0.7370	0.9754	0.0436	0.0713	0.8444	0.9594
419	0.1318	0.0332	0.7012	0.8662	0.1157	0.0305	0.7934	0.9396
421	0.0701	0.1289	0.7169	0.9159	0.0287	0.0871	0.8574	0.9732
422	0.0656	0.1458	0.7631	0.9746	0.0352	0.0401	0.9097	0.9849
429	0.1245	0.1203	0.7062	0.9510	0.0596	0.0632	0.8603	0.9831
431	0.0774	0.0868	0.7719	0.9361	0.0365	0.0383	0.8885	0.9633
432	0.0485	0.0931	0.7475	0.8891	0.0211	0.0686	0.8541	0.9438