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Decomposition of Aggregate Productivity Growth with Unobserved Heterogeneity

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Abstract

Aggregate productivity growth and the role of input reallocation have been hotly debated. Yet, it has received little attention as to how the measurement of reallocation relies on the commonly-made assumption that a production technology is uniform within an industry. To quantify the effects of unobserved heterogeneity in production technology, we estimate a random-coefficient Cobb-Douglas production function. We identify plant type from the distribution of the intermediate inputs to sales ratio using the first order condition without permanent distortions in intermediate input markets. The empirical analysis uses plant-level data from the Census of Manufacture. We find that accounting for unobserved heterogeneity lowers the volatility of technical efficiency and reallocation contributions. For knitted garments industry that features large dispersion in the intermediate input share, the average growth rate of the reallocation component over the 5-year period after the bubble burst in Japan is -0.5% with heterogeneity, while it is 0.4% without heterogeneity.

Keywords: Productivity, Resource reallocation, Unobserved heterogeneity
JEL classification: E23, O47

[1]This study is conducted as a part of the “Microeconometric Analysis of Firm Growth” project undertaken at the Research Institute of Economy, Trade and Industry (RIETI). This study utilizes the micro data of the questionnaire information based on the “Census of Manufacture” which is conducted by the Ministry of Economy, Trade and Industry (METI). We would like to thank Kyoji Fukao, Kaoru Hosono, Kozo Kiyota, Daisuke Miyakawa, Masayuki Morikawa, Hisamitsu Saito, Makoto Yano, and seminar participants at RIETI and Ryukoku University for their helpful comments. Toshiyuki Matsuura helped us to better understand the Census of Manufacture data set. The third author gratefully acknowledges financial support from JSPS Grant-in-Aid for Young Scientists B No.16K21004. All remaining errors are our own.

1 Introduction

Improvement in productivity is key for economic growth in the long run. Recently, economists have been trying to understand sources of aggregate productivity growth (APG) through within-plant increases in technical efficiency and between-plant reallocation of inputs (e.g., Hsieh and Klenow (2009)). One important limitation in the previous empirical analysis is that plants are assumed to have the same production function within narrowly defined industries. However, for example, because of different degrees of automation and outsourcing or the presence of different products within the same industry codes, production technologies can be heterogenous across plants beyond Hicks neutral technical efficiency. Ignoring such heterogeneity can lead to mismeasurement of technical efficiency and reallocation growths, which could bias policy evaluations. To quantify the potential biases, we estimate a random-coefficient Cobb-Douglas production function and apply the production function estimates to a decomposition of APG.

We consider a random-coefficient Cobb-Douglas production function with a finite number of unobservable technology types and estimate it by the classification estimator proposed by Kasahara et al. (2017). The classification estimator builds on the two-step estimation method that Gandhi et al. (2013) propose to address a nonparametric identification problem of the widely used Levinsohn-Petrin estimator. Assuming that intermediate inputs are flexible, consider the optimal intermediate input choice that maximizes the (short-run) profit. With the Cobb-Douglas specification, the first order condition (FOC) implies that the persistent dispersion in the ratio of the intermediate input cost to sales is explained by the distribution of the coefficient on intermediate inputs adjusted by the variance of the ex post residuals.

The classification estimator exploits this FOC relation to identify the type-specific coefficient on the intermediate input and plant's type probability distribution. One important identifying assumption is that there is no permanent distortion in the intermediate input markets, which cannot be separately identified from the coefficient on intermediate inputs without additional data.

We leverage a decomposition method by Petrin and Levinsohn (2012) (henceforth PL). PL define aggregate productivity growth by the change in aggregate final demand minus the change in aggregate expenditures on primary inputs and show that the APG can be decomposed into the contributions of technical efficiency and factor reallocation across production units such as plants. The estimation of the technical efficiency and reallocation components requires reliable estimates of the production function at the micro level, because those components are determined by aggregating plant-level Hicks neutral technical efficiency growth and the plant-level gap between the elasticity of output with respect to a given input factor and its expenditure to sales ratio.

Using data from the Japanese Census of Manufacture, we first document the dispersion of the intermediate input share within 4 digit industry codes. The 90th-10th percentile ratio of the intermediate input share is large, ranging from 3 to 9, for many industries such as knitted garments, auxiliary equipment for internal combustion engines, home comfort, clothes treatment and cleaner, miscellaneous household electric appliances, video recording and duplicating equipment, electric audio equipment, resistorscapacitors transformers and composite parts and motor vehicles parts and accessories. Furthermore, the histogram of the intermediate input share is bimodal for several industries including knitted garments, electric audio equipment and video recording and duplicating equipment. In contrast, bread and corrugated board boxes have low dispersion in the intermediate input share with the 90th-10th percentile ratios of 1.9 and 1.7, respectively.

To examine the role of unobserved heterogeneity for the measurement of technical efficiency and reallocation components, we focus on knitted garments, motor vehicles parts and accessories and corrugated boxes. The knitted garments industry has a bimodal distribution of intermediate input share with the 90th-10th percentile ratio of 8.2. The motor vehicles parts and accessories has the largest number of observations among all industries and relatively large dispersion in intermediate input share with the 90th-10th percentile ratio of 3.0. The corrugated boxes has the smallest 90th-10th percentile ratio in the intermediate input share among the 30 largest industries in terms of the sample size.

The empirical results show that taking into account unobserved heterogeneity lowers the volatility of the technical efficiency and reallocation contributions. For example, for the knitted garments industry, the standard deviation of the technical efficiency growth rate and that of the reallocation growth rate are 2.3 % and 1.0% with heterogeneity (3 unobserved types), while they are 3.3 % and 1.9% without heterogeneity. Furthermore, for the knitted garments industry, the average growth rate of the reallocation component over the 1992-1996 period, the period after the bubble burst in Japan in 1991, is -0.5% with heterogeneity, while it is 0.4% without heterogeneity. For the motor vehicles parts and accessaries industry, the average growth rate of the reallocation component over the 1987-1992 period is 0.7 % with heterogeneity, while it is -1.8% without heterogeneity. On the other hand, for the corrugated board boxes industry, taking into account unobserved heterogeneity does not affect the APG decomposition substantially.

The rest of this paper is organized as follows. Section 2 describes the PL decomposition of APG. Section 3 explains the empirical specification of production function and the estimation procedure by classification. Section 4 explains the data and descriptive statistics. Section 4 presents empirical results. Section 5 concludes.

2 APG and Its Decomposition

We fist describe the decomposition of aggregate productivity growth (APG) proposed by Petrin and Levinsohn (2012) (henceforth PL) in a general case. There are $\#N_t$ plants. Let Q_{it} denote plant i's output at t. The production technology is given by $Q_{it} = Q_{it}(X_{it}, M_{it})\omega_{it}$ where $X_{it} = (X_{i1t}, \dots, X_{i\#Kt})$ is the vector of $\#K$ primary inputs used by plant i at t, $M_{it} = (M_{i1t}, \dots, M_{i\#Jt})$ denotes the vector of plant $j = 1, \dots, \#J$'s output used as an intermediate input by plant i and ω_{it} represents Hicks neutral technical efficiency at plant i at t. Let Y_{it} denote the amount of output from plant i that goes to final demand. Then $Y_{it} = Q_{it} - \sum_j M_{jit}$. Following PL, we define APG_t by

$$APG_t \equiv \sum_{i=1}^{\#N_t} P_{it} dY_{it} - \sum_{i=1}^{\#N_t} \sum_{k=1}^{\#K} W_{ikt} dX_{ikt},$$

where P_{it} denotes the price of plant i's output at t and W_{ikt} is the price of the kth primary input used by plant i at t. Let VA_{it} denote plant i's value added at t, defined by $VA_{it} \equiv P_{it}Q_{it} - \sum_j P_{jt}M_{jit}$. Then, $\sum_i P_{it}Y_{it} = \sum_i VA_{it}$. Also, define dVA_{it} by $dVA_{it} \equiv P_{it}dQ_{it} - \sum_j P_{jt}dM_{jit}$. Then,

$$APG_t = \sum_{i=1}^{\#N_t} dVA_{it} - \sum_{i=1}^{\#N_t} \sum_{k=1}^{\#K} W_{ikt} dX_{ikt}.$$

PL show that APG_t can be decomposed into technical efficiency and factor reallocation terms as follows.

$$APG_t = \underbrace{\sum_i \sum_k \Big(P_{it}\frac{\partial Q_{it}}{\partial X_k} - W_{ikt}\Big) dX_{ikt} + \sum_i \sum_j \Big(P_{it}\frac{\partial Q_{it}}{\partial M_j} - P_{jt}\Big) dM_{ijt}}_{\text{Reallocation}} + \underbrace{\sum_i P_{it}\frac{\partial Q_{it}}{\partial \omega} d\omega_{it}}_{\text{Technical efficiency}}$$

Now consider the growth rate formulation. Define APG_{Gt} by $APG_{Gt} \equiv APG_t / \sum_i P_{it}Y_{it} = APG_t / \sum_i VA_{it}$. Then,

$$APG_{Gt} = \sum_i D^v_{it} d\ln VA_{it} - \sum_i D^v_{it} \sum_k s^v_{ikt} d\ln X_{ikt},$$

where $D_{it}^v \equiv VA_{it}/\sum_i VA_{it}$ and $s_{ikt}^v \equiv W_{ikt}X_{ikt}/VA_{it}$. The growth-rate version of the PL decomposition reads

$$APG_{Gt} = \sum_i \sum_k D_{it}(g_{ikt} - s_{ikt}) d\ln X_{ikt} + \sum_i \sum_j D_{it}(g_{ijt} - s_{ijt}) d\ln M_{ijt} + \sum_i D_{it} d\ln \omega_{it},$$

where g_{ikt} is the elasticity of plant i's output with respect to the kth primary input, i.e. $g_{ikt} = (\partial Q_{it}/\partial X_k)(X_{ikt}/Q_{it})$, g_{ijt} is the elasticity of plant i's output with respect to the jth intermediate input, $s_{ikt} = W_{ikt}X_{ikt}/(P_{it}Q_{it})$, $s_{ijt} = P_{ijt}M_{ijt}/(P_{it}Q_{it})$ and D_{it} is the Domar weight defined by $D_{it} = P_{it}Q_{it}/\sum_i VA_{it}$.

3 Production Function

This section explains the empirical specification of production function we employ in our analysis. Denote the log values of $(Q_{it}, L_{it}, K_{it}, M_{it})$ by $(q_{it}, \ell_{it}, k_{it}, m_{it})$. There are J different technology types and each plant belongs to one of J types. In what follows, the superscript j denotes plant's technology type. Let π^j denote the probability of belonging to type j. Plant's production technology is represented by the following (industry-specific) random-coefficient Cobb-Douglas production function.[1] For each type $j = 1, \ldots, J$,

$$q_{it} = \beta_t^j + \beta_m^j m_{it} + \beta_\ell^j \ell_{it} + \beta_k^j k_{it} + \omega_{it} + \epsilon_{it}, \tag{1}$$

where ω_{it} and ϵ_{it} represent Hicks neutral technical efficiency terms. The term ω_{it} follows a first order autoregressive process.

$$\omega_{it} = \rho^j \omega_{it-1} + \eta_{it}, \tag{2}$$

where $E[\eta_{it}|\omega_{it-1}] = 0$. L_{it} and K_{it} are predetermined while M_{it} is flexible, chosen after η_{it} is observed. The term ϵ_{it} represents an i.i.d. ex-post shock that is not known

[1]The coefficients are industry specific. For simplicity, we suppress the industry subscript.

when M_{it} is chosen. Specifically, $\epsilon_{it}|x_{it}, i \in \mathcal{I}^j \overset{iid}{\sim} N(0, (\sigma_\epsilon^j)^2)$ for $j = 1, ..., J$ where $\mathcal{I}^j := \{i : j^*(i) = j\}$ and $j^*(i)$ is the true type of plant i.

Kasahara et al. (2017) prove nonparametric identifiability of a finite mixture model in a more general setting. Following Gandhi et al. (2013), their identification argument exploits the first order condition with respect to flexible intermediate input. With the above Cobb-Douglas specification, the first order condition (in log) reads

$$s_{it} = \ln \beta_m^j + 0.5(\sigma_\epsilon^j)^2 - \epsilon_{it}, \tag{3}$$

where $s_{it}^m = \ln \frac{P_{it}^M M_{it}}{P_{it} Q_{it}}$ with P_{it}^M representing the intermediate good price.[2] Without additional data, we cannot separately identify heterogeneity in production technology and permanent distortion. Therefore, we assume no permanent distortion in the intermediate input markets and attribute persistent dispersion in the intermediate input share to production technology heterogeneity.

We estimate the random-coefficient Cobb-Douglas production function by the classification method proposed by Kasahara et al. (2017). Briefly, the estimation proceeds as follows: 1. Estimate $\theta_1 := (\pi^j, \beta_m^j, \sigma_\epsilon^j)_{j=1}^J$ using the FOC with respect to intermediate input by MLE; 2. Classify plants into J different technology types by posterior type probabilities; 3. Given $\hat{\theta}_1$, estimate $\theta_2 := (\beta_t^j, \beta_\ell^j, \beta_k^j)_{j=1}^J$, separately for each type, by GMM. In what follows, we treat J as known and report results for various values of J. Appendix A explains how to compute APG and its components with discrete time data and production function estimates.

[2]This first order condition also assumes perfect competition in the input and output goods markets. We can alternatively consider a case where each producer produces differentiated products facing a demand function with constant price elasticity. In that case, however, we cannot separately identify the (type-specific) price elasticity of demand and the coefficient β_m^j.

4 Data Description

We use the Japanese Census of Manufacture that collects plant-level production input/output data for the manufacturing industry in Japan. The survey uses different questionnaires for small and large plants: 1. Plants with 30 or more employees (Kou file); 2. 4-29 employees (Otsu file); 3. 1-3 employees (Otsu file, surveyed every 5 years). The questionnaire for large plants of 30+ employees is more detailed. For example, detailed inventory data (finished products, material, fuel) are available for large plants but not for small plants. All plants with 4+ employees report their book values of fixed assets every year up to 2000. However, from 2000, small plants have to report the fixed asset data every 5 years only.

Flow data on shipments and various production costs refer to calendar year (from January 1st to December 31st each year). The number of employees refers to the value in the end of the year, while the stock of fixed asset refers to the beginning of the period. Both the beginning and end of the period values are reported for inventory. Appendix B explains the detailed construction of the variables we use in the empirical analysis.

Our data set covers 1986-2010.[3] Although the Ministry of Economy, Trade and Industry (METI) provides data from 1980 in the electric format, we can construct panel data only from 1986 because the METI does not provide converter files, which are necessary to construct panel data, prior to 1986.[4]

[3] See Shimpo and Omori (2005), Abe et al. (2012) and Yukimoto (2015) for the construction of the panel data.

[4] Shimpo and Omori (2005) construct converter files for 1981-1985 on their own.

4.1 Heterogeneity in the Intermediate Input Share

Table 1 reports the 90th-10th percentile ratios for intermediate and labor expenditure shares for the 30 largest industries in terms of the number of observations. The columns designated by $\frac{PM_{it}}{PQ_{it}}$, $\frac{WL_{it}}{PQ_{it}}$ and $\frac{PM_{it}}{(PM_{it}+WL_{it})}$ report the 90th-10th percentile ratios of the intermediate input expenditure to sales ratio, the labor cost to sales ratio and the ratio of the intermediate input to the sum of intermediate input and labor costs in the pooled sample, respectively. The columns designated by $\overline{\left(\frac{PM_{it}}{PQ_{it}}\right)}_i$, $\overline{\left(\frac{WL_{it}}{PQ_{it}}\right)}_i$ and $\overline{\left(\frac{PM_{it}}{(PM_{it}+WL_{it})}\right)}_i$ report the 90th-10th percentile ratios of the corresponding variables replacing the individual observations with the plant-specific averages over time.

The 90th-10th percentile ratio of the intermediate input share varies across industries ranging from 1.7 for corrugated board box to 9.5 for textile business, work, sport clothing and school uniforms including, bonded fabrics and lace products. The column on $\overline{\left(\frac{PM_{it}}{PY_{it}}\right)}_i$ shows that the variation in the plan-specific averages accounts for around 80 percent of the variation in the pooled raw data for most of the selected industries. This suggests that the dispersion in the intermediate input share is persistent. The variation in the intermediate input share may come from heterogeneity in markup rates rather than heterogeneity in production technology. To control for the markup rates, we also report the ratio of the intermediate input expenditure to the sum of the intermediate input and labor expenditure ($\frac{PM_{it}}{PM_{it}+WL_{it}}$). The dispersion of the intermediate input to cost ratio ($\frac{PM_{it}}{PM_{it}+WL_{it}}$) tends to be large in the industries with large dispersion in the the intermediate input share ($\frac{PM_{it}}{PQ_{it}}$). The exception is the medical product preparations industry in which the markup heterogeneity across plants could be substantial.

To examine the importance of unobserved heterogeneity in production technology, we pick the following three industries for the empirical analysis: 1. Knitted garments;

2. Motor vehicles parts and accessories; 3. Corrugated board boxes. The knitted garments industry features large dispersion in the intermediate input share with the 90th-10th percentile ratio of 8.2. Furthermore, Figure 1 shows that the distribution of the intermediate input share is bimodal. The motor vehicles parts and accessories industry has a modest 90th-10th percentile ratio of the intermediate input share of 3.0. However, this industry has the largest number of observations and consequently industry-level sales is one of the largest. The corrugated board boxes industry has the smallest 90th-10th percentile ratio of the intermediate input share in Table 1. Figures 2 and 3 show the distribution of the intermediate input share for the motor vehicles parts and accessories and corrugated board boxes industries.

4.2 Sample Selection

We exclude observations if at least one of the following criteria applies: 1. the input, output or cost data are missing; 2. the plant has less than 30 employees; 3. the input or output data are outliers (top and bottom 0.5%). We impose the second criterion because capital stock data (in book value) are not available in a continuous manner for small plants from 2000.

5 Results

This section reports results of the APG decomposition analysis for knitted garments, motor vehicles parts and accessories and corrugated board boxes. Our main focus is to examine how the measurement of technical efficiency and reallocation contributions change when we take into account unobserved heterogeneity in production technologies beyond Hick neutral productivity term.

5.1 Estimation of Production Function

5.1.1 Knitted Garments

Table 2 reports the production function estimates for $J = 1$, 3 and 5. With $J > 1$, the coefficients $\hat{\beta}_m^j$, $\hat{\beta}_\ell^j$ and $\hat{\beta}_k^j$ are substantially different across types. When $J = 3$, $\hat{\beta}_m^j$ are estimated at 0.08, 0.29 and 0.58. The type with $\hat{\beta}_m^j = 0.08$ features the lowest capital intensity $\hat{\beta}_k^j/\beta_\ell^j$ of 0.071 among the three types. The type with $\hat{\beta}_m^j = 0.29$ features the highest capital intensity of 0.29. The type with $\hat{\beta}_m^j = 0.58$ has the largest size $\pi^j = 0.41$.

With $J = 1$, $\hat{\beta}_m^j = 0.2$. This value is substantially lower than the weighted averages of $\hat{\beta}_m^j$'s over types with $J > 1$. As Table 4 shows, the standard deviation of $\hat{\epsilon_{it}}$ is larger with $J = 1$ than $J > 1$. In the estimation of the intermediate input share equation (3), the larger $\hat{\sigma}_\epsilon^j$ tends to push $\hat{\beta}_m^j$ downward, partially accounting for the low estimate of β_m with $J = 1$.

Table 3 reports the mean and standard deviation of selected variables by type for $J = 3$. The mean of log gross output, intermediate input, labor input and capital stock monotonically increase from Type 1 to Type 3. However, the type-specific distributions of those variables tend to have larger overlaps than those of the intermediate input share s_{imt}, suggesting that the observable characteristics do not fully explain the type classification.

5.1.2 Motor Vehicles Parts and Accessories

Table 5 reports the results of the production function estimation for $J = 1$, 3 and 5. Overall, the returns to scale is a little above one and higher than that for the knitted garments industry. But it decreases with the number of unobserved components. Similar to knitted garments, the estimated value of $\hat{\beta}_m^j$ for $J = 1$ is lower than the weighted averages of $\hat{\beta}^j_m$'s across types for $J > 1$. With $J = 3$, the capital intensity $\hat{\beta}^j_k/\hat{\beta}^j_\ell$ is the highest for the type with the lowest $\hat{\beta}^j_m$.

As in the knitted garments industry, Table 6 shows that the plant size tends to increase from Type 1 to Type 3 as β^j_m increases. However, the overlaps in the distribution of gross output and input variables across types are large relative to that in the distribution of the intermediate input share, suggesting that the classification is not fully explained by the selected observable characteristics.

5.1.3 Corrugated Board Boxes

Table 7 reports the production function estimates for the corrugated board boxes industry for $J = 1$, 3 and 5. For $J > 1$, the variation in $\hat{\beta}^j_m$ is small relative to the other industries examined above. In addition, the estimates for $J = 1$ are close to the corresponding weighted averages over different types for $J > 1$. For example, $\beta^j_m = 0.544$ with $J = 1$, while the corresponding weighted average of β^j_m is 0.573 with $J = 3$.

5.2 Decomposition of APG

5.2.1 Knitted Garments

Figures 4 and 5 show the overall patterns of the growth of the knitted garments industry. Figure 4 reports that the number of plants, including small ones, declines from about 4000 in 1990 to about 1500 in 2010. The number of large plants also declines from over 1000 to around 200. Figure 5 reports that gross output and employment decline over time. The large plants account for around 60 percent of gross output and employment and the fraction is stable over time.

Figure 6 reports the changes in APG and its components over time. The left panel shows that APG is negative from 1991 for the knitted garments industry. As it is expected from the declining trend in the number of plants, the net entry effect is negative. Within the operating plants, the changes in APG are driven by the changes in the value added growth, while being partially offset by the negative labor growth. Table 8 shows that the average APG over the 1987-2008 period is -2.2% in which the average APG for operating plants is -0.8% and the average net entry contribution is -1.5%.

Figure 7 reports the technical efficiency and reallocation contributions to APG for $J = 1$ and 3. Both technical efficiency and reallocation contributions become less volatile with $J = 3$ than $J = 1$. Table 9 reports the average growth rates of the technical efficiency and reallocation components for 1987-1991, 1992-1996, 1997-2001, 2002-2008 and 1987-2008 and the standard deviation of the growth rates of the two components over the 1987-2008 period. The absolute values of the average growth rates over the subperiods are smaller with $J = 3$ than $J = 1$. The standard deviation of the growth rates of the technical efficiency component over the 1987-2008 period is 3.3% with $J = 1$ while it is 2.3% with $J = 3$. The standard deviation of the growth rate of the reallocation component is 1.9% with $J = 1$, while it is 1.0% with $J = 3$. Furthermore, the reallocation contribution tends to be negative with $J = 3$ in the 1990s, while it tends to be positive with $J = 1$ over the same period. Table 9 shows that the reallocation contribution is -0.5% with $J = 3$ over the 1992-1996 period, while it is 0.4% with $J = 1$.

Figure 8 decompose the reallocation contribution by input factors. The reallocation contribution of intermediate input is negative in the 1980s and positive 2-5 percent for most of the 1990s and 2000s with $J = 1$, while it is mostly negative or negligible with $J = 3$. It is likely because $\hat{\beta}_m^j$ with $J = 1$ is lower than the weighted average over types with $J = 3$, which makes the weighted average of the difference between $\hat{\beta}_m^j$ and $\bar{s}_{imt}$ negative, and the intermediate input growth is negative over the

1990s. In contrast to the intermediate input, the reallocation contribution of capital stock is positive up to 1992 and negative for the rest of the period with $J = 1$. With $J = 3$, the reallocation contribution, while having the same sign with $J = 1$ for most of the periods, is much smaller in absolute value. The labor reallocation effects are similar for $J = 1$ and 3, taking negative values for most of the periods.

5.2.2 Motor Vehicles Parts and Accessories

Motor Vehicles Parts and Accessories has the largest number of observations at the 4 digit level. This industry is likely to include a variety of products but cannot decompose further. Figures 9 shows that the number of plants is relatively stable over time with the number of small plants with less than 30 employees declining from 1992 and that of large plants stable or slightly increasing from 2000. Figure 10 reports the changes in log real output and the number of employees. The growth rate of real output is positive from 1986 to 1991, the bubble period in Japan, turns negative or close zero from 1992 to 1997, becomes positive from 2000 to 2007, sharply drop in 2008 and 2009 because of the global financial crisis and recovers in 2010. The growth rate of the number of employees in this industry changes in a similar manner with real output. The large plants with more than 30 employees account for around 90 percent of real output and employment, with the fraction slightly increasing in the 2000s.

Table 8 shows that the average APG over the 1987-2008 period is 2.8% in which the average APG for operating plants is 3.5% and the average net entry contribution is -0.6%. Figure 11 reports annual movements of APG and its components. Over the sample period, APG is relatively low or negative from 1992 to 1998 after the collapse of the bubble in Japan. The net entry effects are small but negative in 2000s. Within the staying plants, the value added growth drives the changes in APG except for that labor input noticeably increases from 2003 to 2007.

Figure 12 reports the contributions of technical efficiency and reallocation to APG for $J = 1$ and 3. Both technical efficiency and reallocation contributions become less volatile with $J = 3$. As shown in Table 9, the standard deviation of the growth rate of the technical efficiency component over time is 6.0% with $J = 1$ while it is 4.5% with $J = 3$. The standard deviation of the growth rate of the reallocation component is 3.1% with $J = 1$, while it is 1.3% with $J = 3$. For most of the sample years except for 1987-1991, the signs of the measured contributions are the same with and without unobserved heterogeneity. For the 1987-1991 period, which is the bubble period in Japan, Table 9 shows that the average growth rate of the reallocation component is 0.7% with $J = 3$, while it is -1.8% with $J = 1$. Figure 13 reports the reallocation contributions by input factors. The reallocation contributions become less volatile not only for intermediate inputs but also labor and capital inputs.

5.2.3 Corrugated Board Boxes

As Table 1 shows, the corrugated board boxes industry has the lowest intermediate input share in the 30 largest industries by sample size. For comparison purpose, we examine APG of this industry.

Table 8 shows that the average APG over the 1987-2008 period is -0.8% in which the average APG for operating plants is 0.2% and the average net entry contribution is -1.0%. Figure 14 reports the annual movements of APG and its components. Figure 15 reports the contributions of technical efficiency and reallocation to APG. Figure 16 decompose the reallocation contribution by factor inputs. Both Figures 15 and 16 show that the decomposition results are similar for $J = 1$ and $J = 3$, strikingly different from the patterns observed for knitted garments and motor vehicles parts and accessories.

6 Conclusion

This article examines how unobserved heterogeneity in production technology affects the measurement of the technical efficiency and reallocation contributions to APG. To do so, we conduct the PL decomposition of APG with a random-coefficient Cobb-Douglas production function. Using the Japanese Census of Manufacture, we first document that many industries defined at the 4 digit level feature large and persistent heterogeneity in the ratio of intermediate input expenditure to sales. In view of the first order condition with respect to the flexible intermediate inputs, the persistent heterogeneity in the intermediate input share implies heterogeneity in production technology beyond Hicks neutral technical efficiency.

To characterize the importance of unobserved heterogeneity in production technology, we analyze knitted garments, motor vehicles parts and accessaries and corrugated board boxes industries. The first two industries feature a relatively large 90th-10th percentile ratio in the intermediate input share, while the corrugated board boxes industry has the smallest 90th-10th percentile ratio among the 30 largest industries by sample size. The estimation results show that accounting for unobserved heterogeneity lowers the volatility of technical efficiency and reallocation contributions for knitted garments and motor vehicles parts and accessories, while there is almost no impact for corrugated board boxes. Furthermore, for the knitted garments industry, the average growth rate of the reallocation component over the 1992-1996 period, which is the 5-year period after the bubble burst in Japan, is -0.5% with heterogeneity, while it is 0.4% without heterogeneity. Similarly, for the motor vehicles parts and accessaries industry, the average growth rate of the reallocation component over the 1987-1992 period is 0.7 % with heterogeneity, while it is -1.8% without heterogeneity.

There are various issues left for future research. First, production technologies may be changing over time. For example, energy-efficient technologies have been developed over time. Therefore, it is important to extend the production function to allow for time-varying coefficients. Second, plants with different technology types may respond to aggregate shocks differently. Therefore, to examine the effects of aggregate shocks, such as the recent global financial crisis, on APG, it will be important to account for unobserved heterogeneity. Third, we plan to conduct more detailed policy evaluations using the present analytical framework. Various deregulation policies in electricity, fuel, labor and financial markets are expected to promote reallocation of the corresponding input factors to achieve more efficient allocations, while competition policies may affect individual plant's productivity more directly. To evaluate effectiveness of such policies, it is indispensable to have accurate measurement of technical efficiency and reallocation contributions to APG.

A Appendix: Discrete Time Approximation of APG

APG_{Gt} from $t-1$ to t is given by $APG_{Gt}[t-1,t] = \int_{t-1}^{t} APG_{Gt} dt$. Let $\mathcal{S}_t$, $\mathcal{E}_t$ and $\mathcal{X}_t$ denote the set of plants operating from period $t-1$ to t, the set of plants entering between $t-1$ and t and the set of plants exiting between $t-1$ and t, respectively. We do not consider the cases where plants make multiple entries and exits between $t-1$ and t. Let $\mathcal{N}_t = \mathcal{S}_t \cup \mathcal{E}_t \cup \mathcal{X}_t$. Applying Tornquist approximation, we can write

$APG_{Gt}[t-1,t]$ as follows.[5]

$$\begin{aligned}
APG_{Gt}[t-1,t] &\simeq \sum_{i\in\mathcal{S}_t}\bar{D}^v_{it}\Delta\ln VA_{it} - \sum_{i\in\mathcal{S}_t}\bar{D}^v_{it}\sum_k \bar{s}^v_{ikt}\Delta\ln X_{ikt} \\
&+ \sum_{i\in\mathcal{E}_t} D_{it}(1-\sum_k s_{ikt} - \sum_j s_{ijt}) - \sum_{i\in\mathcal{X}_t} D_{it-1}(1-\sum_k s_{ikt-1} - \sum_j s_{ijt-1}) \\
&\simeq \underbrace{\sum_{i\in\mathcal{S}_t}\sum_k \bar{D}_{it}(g_{ikt}-\bar{s}_{ikt})\Delta\ln X_{ikt} + \sum_{i\in\mathcal{S}_t}\sum_j \bar{D}_{it}(g_{ijt}-\bar{s}_{ijt})\Delta\ln M_{ijt}}_{\text{Reallocation}} \\
&+ \underbrace{\sum_{i\in\mathcal{S}_t}\bar{D}_{it}\Delta\ln\omega_{it}}_{\text{Technical efficiency}} \\
&+ \underbrace{\sum_{i\in\mathcal{E}_t} D_{it}(1-\sum_k s_{ikt} - \sum_j s_{ijt})}_{\text{Entry}} - \underbrace{\sum_{i\in\mathcal{X}_t} D_{it-1}(1-\sum_k s_{ikt-1} - \sum_j s_{ijt-1})}_{\text{Exit}},
\end{aligned}$$

where $\bar{D}^v_{it} = (D^v_{it} + D^v_{it-1})/2$, $\bar{D}_{it} = (D_{it} + D_{it-1})/2$, $\bar{s}^v_{ikt} = (s^v_{ikt} + s^v_{ikt-1})/2$, $\bar{s}_{ikt} = (s_{ikt} + s_{ikt-1})/2$ and $\bar{s}_{ijt} = (s_{ijt} + s_{ijt-1})/2$ and Δ is the first difference operator from period $t-1$ to t, that is, $\Delta x_{it} = x_{it} - x_{it-1}$.

Using the estimates of the production function (1), we compute $APG_{Gt}[t-1,t]$ and its components as follows.

$$\begin{aligned}
APG_{Gt}[t-1,t] &\simeq \sum_{i\in\mathcal{S}_t}\bar{D}^v_{it}\Delta\ln VA_{it} - \sum_{i\in\mathcal{S}_t}\bar{D}^v_{it}(\bar{s}^v_{i\ell t}\Delta\ell_{it} + \bar{s}^v_{ikt}\Delta k_{it}) \\
&+ \sum_{i\in\mathcal{E}_t} D_{it}(1-s_{ikt}-s_{i\ell t}-s_{imt}) - \sum_{i\in\mathcal{X}_t} D_{it-1}(1-s_{ikt-1}-s_{i\ell t-1}-s_{imt-1}) \\
&\simeq \sum_{i\in\mathcal{S}_t}\sum_{j=1}^{J}\bar{D}_{it}(\hat{\beta}^j_\ell - \bar{s}_{i\ell t})\Delta\ell_{it} + \sum_{i\in\mathcal{S}_t}\sum_{j=1}^{J}\bar{D}_{it}(\hat{\beta}^j_k - \bar{s}_{ikt})\Delta k_{it} \\
&+ \sum_{i\in\mathcal{S}_t}\sum_{j=1}^{J}\bar{D}_{it}(\hat{\beta}^j_m - \bar{s}_{imt})\Delta m_{it} + \sum_{i\in\mathcal{S}_t}\sum_{j=1}^{J}\bar{D}_{it}\Delta(\hat{\omega}_{it} + \hat{\epsilon}_{it}) \qquad (4) \\
&+ \sum_{i\in\mathcal{E}_t} D_{it}(1-s_{ikt}-s_{i\ell t}-s_{imt}) - \sum_{i\in\mathcal{X}_t} D_{it-1}(1-s_{ikt-1}-s_{i\ell t-1}-s_{imt-1}).
\end{aligned}$$

[5] See Kwon et al. (2015) for the derivation of the formula.

B Appendix: Variable Construction

This section explains variable construction.

B.1 Gross Output

Let PQ_{ist} denote the nominal value of gross output of plant i in sector s in time t. We define PQ_{ist} by the sum of shipments, revenues from repairing and fixing services, and revenues from performing subcontracted work. We deflate PQ_{ist} by the industry specific gross output deflator (base year 2000) provided by JIP Database 2011. Let Q_{ist} denote the real value of gross output of plant i in sector s in time t.

B.2 Intermediate Inputs

Let PM_{ist} denote the nominal value of intermediate inputs of plant i in sector s in time t. We define PM_{ist} by the sum of raw material, fuel, electricity, and subcontracting expenses for consigned production. We deflate PM_{ist} by the industry specific intermediate input deflator (base year 2000) provided by JIP Database 2011. Let M_{ist} denote the real intermediate inputs.

B.3 Labor Inputs

We define labor inputs, L_{it}, by the number of employees.

B.4 Capital Inputs

We construct the capital stock data for each plant by the perpetual inventory method. First, we compute nominal investment, PI_{ist}, by

$$PI_{ist} = BK_{ist+1} - BK_{ist} + \mathit{Depreciation}_{ist},$$

where BK_{ist} and $\mathit{Depreciation}_{ist}$ represent the book value of tangible fixed asset (all tangible fixed asset less land) at the beginning of time t for plant i in sector s and the depreciation amount of the tangible fixed asset in year t.[6] Then, we deflate PI_{ist} by the industry-specific investment deflator (base year 2000) provided by JIP Database 2015. Let P^I_{st} and I_{ist} denote the industry-specific investment deflator and real investment, respectively.

Next we construct the real value of capital stock, K_{ist}, by the perpetual inventory method. As the initial value of the capital stock, in 1986 or in the entry year of a given plant, we use the book value of tangible fixed asset converted into the constant price of 2000. Thus, $K_{ist_{0i}} = BK_{ist_{0i}}/P^I_{st_{0i}}$, where t_{0i} represent plant i's entry year and $P^I_{st_{0i}}$ is the industry-specific investment deflator. Then, using $\{I_{ist}\}_{ist}$, we construct capital stock data for each plant as follows.

$$K_{ist} = (1 - \delta_{st-1})K_{ist-1} + I_{ist-1},$$

where δ_{st-1} is the industry-time specific depreciation rate provided by JIP Database 2015, which is based on the US NIPA. If K_{ist} is missing or negative, we reset K_{ist} to BK_{ist}/P^I_{st}.

B.5 Labor Cost

We define labor cost by total salaries and denote it by WL_{ist}.

[6] Alternatively, we can use flow data on capital acquisition and removal to compute nominal investment. But there are more missing values in those data.

B.6 Capital Cost

We compute the capital cost for each plant by multiplying real capital stock by the industry-specific nominal rental price of capital provided by JIP Database 2015. Let RK_{ist} and P^{KS}_{st} denote the capital cost and the nominal rental price of capital. Then, $RK_{ist} = P^{KS}_{st} K_{ist}$.

B.7 Value Added

We compute value added, VA_{ist}, by $VA_{ist} = PQ_{ist} - PM_{ist}$.

B.8 Real Value Added

We define the real value added, denoted by RVA_{ist}, by $RVA_{ist} = Q_{ist} - M_{ist}$.

C Appendix: Tables

Table 1: Intermediate and Labor Cost Shares

Industry	$\frac{PM_{it}}{PQ_{it}}$	$\overline{\left(\frac{PM_{it}}{PQ_{it}}\right)}_i$	$\frac{WL_{it}}{PQ_{it}}$	$\overline{\left(\frac{WL_{it}}{PQ_{it}}\right)}_i$	$\frac{PM_{it}}{(PM_{it}+WL_{it})}$	$\overline{\left(\frac{PM_{it}}{(PM_{it}+WL_{it})}\right)}_i$
Meat products	2.442	1.963	7.018	5.84	1.621	1.552
Dairy products	2.038	1.873	4.917	4.137	1.326	1.305
Salted products	2.247	1.852	4.735	3.92	1.546	1.449
Bread	1.869	1.625	2.892	2.501	1.696	1.56
Pastries & cakes	2.437	2.137	3.418	2.976	1.719	1.611
Food & related prod.	2.336	2.001	3.568	3.067	1.664	1.546
Men's & boy's outer	5.992	4.618	3.591	3.058	5.188	4.334
Ladies & girls outer	8.227	6.206	3.123	2.577	6.821	5.324
Business & sport clothing	9.459	6.897	5.565	4.903	8.472	6.326
Knitted garments	8.167	6.002	5.118	4.373	6.917	5.286
Wooden furniture	2.128	1.822	3.163	2.746	1.558	1.457
Corrugated board boxes	1.692	1.487	2.714	2.351	1.301	1.266
Printing	2.664	2.212	3.285	2.874	1.968	1.831
Medical product prep.	5.419	4.283	9.283	7.9	1.899	1.702
Industrial plastic products	2.366	1.871	3.221	2.547	1.589	1.455
Mechanical rubber products	2.977	2.303	3.546	3.001	2.006	1.782
Concrete products	2.537	2.063	3.145	2.578	1.733	1.567
Construction-use metal prod.	2.792	2.163	5.014	3.911	1.695	1.541
Architectural metal prod.	3.414	2.386	5.361	4.289	2.08	1.865
Plate & sheet metal	2.532	2.017	3.539	2.978	1.916	1.727
Stamped & pressed metal	2.218	1.862	3.141	2.706	1.635	1.52
Semiconductor	2.713	2.07	4.083	2.946	1.93	1.715
Molds & dies	3.21	2.46	2.597	2.107	2.266	1.942
Relay switches etc	2.559	2.091	3.592	2.936	1.984	1.788
Equip. for engines	4.989	3.686	6.556	5.302	4.028	3.341
Home comfort	4.245	3.156	6.631	5.237	3.016	2.614
Video recording equipment	7.378	4.984	9.227	7.048	5.609	4.146
Electric audio equipment	7.951	5.362	7.923	6.091	6.306	4.478
Resistors etc	6.757	4.4	6.081	4.649	5.164	3.727
Motor vehicles parts	3.047	2.458	4.651	3.848	2.148	1.921

Notes. Each entry is the 90th-10th percentile ratio of the corresponding variable. The sample is restricted to the observations with non-missing (y_{it}, ℓ_{it}, k_{it}, m_{it}, $w\ell_{it}$) and 30+ employees.

Table 2: Estimates of Production Function (1)

Estimation by Classification									
	GNR	Random Coefficients Model							
	$J=1$	$J=3$			$J=5$				
		Type 1	Type 2	Type 3	Type 1	Type 2	Type 3	Type 4	Type 5
β_m^j	0.198	0.084	0.287	0.582	0.062	0.142	0.281	0.527	0.697
β_ℓ^j	0.535	0.786	0.580	0.335	0.873	0.762	0.625	0.387	0.213
β_k^j	0.318	0.056	0.167	0.039	0.061	0.058	0.147	0.088	0.034
$\beta_m^j + \beta_\ell^j + \beta_k^j$	1.050	0.926	1.034	0.956	0.995	0.962	1.053	1.001	0.944
β_k^j / β_ℓ^j	0.594	0.071	0.287	0.117	0.070	0.076	0.236	0.228	0.158
π^j	1.000	0.289	0.304	0.407	0.168	0.136	0.257	0.292	0.147
No. of Obs.	15627								
No. of plants	1297								

Notes. Knitted Garment. The sample is restricted to the observations with 1. non-missing (y_{it}, ℓ_{it}, k_{it}, m_{it}, $w\ell_{it}$); 2. 30+ employees; 3. y_{it}, k_{it}, m_{it}, and PM_{it}/PY_{it} between the 0.5th and the 99.5 percentiles; 4. more than 4 periods in the sample (between the first entry/exit).

Table 3: Descriptive Statistics By Type When $J=3$

	Type 1	Type 2	Type 3
y_{it}	9.584	10.080	11.099
	(0.555)	(0.706)	(0.706)
m_{it}	7.279	8.871	10.509
	(0.944)	(0.969)	(0.791)
ℓ_{it}	3.956	3.996	4.069
	(0.410)	(0.416)	(0.477)
k_{it}	8.561	9.084	9.740
	(1.171)	(1.058)	(1.090)
s_{imt}	0.135	0.351	0.606
	(0.103)	(0.148)	(0.118)
$s_{i\ell t}$	0.637	0.457	0.227
	(0.235)	(0.190)	(0.113)
s_{ikt}	0.069	0.064	0.046
	(0.081)	(0.059)	(0.052)

Notes. Knitted Garment. Each entry refers to the average of the corresponding variable. The standard deviation is in parentheses.

Table 4: Estimates of Production Function (1)

	Estimation by Classification								
	GNR	Random Coefficients Model							
	$J = 1$	$J = 3$			$J = 5$				
		Type 1	Type 2	Type 3	Type 1	Type 2	Type 3	Type 4	Type 5
Std. Dev. $\hat{\omega}_{it} + \hat{\alpha}_t^j$	1.078	0.767	0.584	0.265	0.897	0.410	0.579	0.257	0.185
Std. Dev. $\hat{\epsilon}_{it}$	0.831	0.697	0.458	0.204	0.793	0.332	0.468	0.201	0.120
Corr$(\hat{\epsilon}_{it}, \hat{\epsilon}_{it-1})$	0.919	0.762	0.683	0.702	0.732	0.654	0.647	0.585	0.587
No. of Obs.	15627								
No. of plants	1297								

Notes. Knitted Garment. The sample is restricted to the observations with 1. non-missing (y_{it}, ℓ_{it}, k_{it}, m_{it}, $w\ell_{it}$); 2. 30+ employees; 3. y_{it}, k_{it}, m_{it}, and PM_{it}/PY_{it} between the 0.5th and the 99.5 percentiles; 4. more than 4 periods in the sample (between the first entry/exit).

Table 5: Estimates of Production Function (1)

	Estimation by Classification								
	GNR	Random Coefficients Model							
	$J = 1$	$J = 3$			$J = 5$				
		Type 1	Type 2	Type 3	Type 1	Type 2	Type 3	Type 4	Type 5
β_m^j	0.412	0.198	0.504	0.686	0.108	0.356	0.481	0.616	0.743
β_ℓ^j	0.429	0.618	0.419	0.226	0.598	0.608	0.413	0.307	0.171
β_k^j	0.242	0.333	0.130	0.089	0.388	0.131	0.156	0.103	0.076
$\beta_m^j + \beta_\ell^j + \beta_k^j$	1.084	1.149	1.053	1.001	1.094	1.094	1.050	1.026	0.990
β_k^j / β_ℓ^j	0.564	0.539	0.310	0.395	0.649	0.215	0.377	0.335	0.441
π^j	1.000	0.226	0.367	0.407	0.088	0.197	0.205	0.303	0.207
No. of Obs.	52404								
No. of plants	3449								

Notes. Motor vehicles parts and accessories. The sample is restricted to the observations with 1. non-missing (y_{it}, ℓ_{it}, k_{it}, m_{it}, $w\ell_{it}$); 2. 30+ employees; 3. y_{it}, k_{it}, m_{it}, and PM_{it}/PY_{it} between the 0.5th and the 99.5 percentiles; 4. more than 4 periods in the sample (between the first entry/exit).

Table 6: Descriptive Statistics By Type When $J = 3$

	Type 1	Type 2	Type 3
y_{it}	11.321	12.146	12.833
	(1.279)	(1.123)	(1.166)
m_{it}	9.977	11.474	12.454
	(1.730)	(1.181)	(1.195)
ℓ_{it}	4.301	4.553	4.819
	(0.738)	(0.837)	(0.920)
k_{it}	10.486	11.462	11.776
	(1.702)	(1.356)	(1.457)
s^m_{it}	0.336	0.531	0.700
	(0.217)	(0.118)	(0.099)
s^ℓ_{it}	0.363	0.226	0.153
	(0.268)	(0.150)	(0.082)
s^k_{it}	0.092	0.085	0.061
	(0.125)	(0.119)	(0.063)

Notes. Motor vehicles parts and accessories. Each entry refers to the average of the corresponding variable. The standard deviation is in parentheses.

Table 7: Estimates of Production Function (1)

Estimation by Classification									
	GNR	Random Coefficients Model							
	$J = 1$	$J = 3$			$J = 5$				
		Type 1	Type 2	Type 3	Type 1	Type 2	Type 3	Type 4	Type 5
β^j_m	0.544	0.342	0.540	0.658	0.197	0.494	0.551	0.623	0.706
β^j_ℓ	0.294	0.506	0.297	0.235	0.561	0.334	0.288	0.260	0.204
β^j_k	0.173	0.330	0.187	0.098	0.363	0.221	0.174	0.124	0.089
$\beta^j_m + \beta^j_\ell + \beta^j_k$	1.011	1.178	1.023	0.991	1.121	1.049	1.013	1.008	0.999
β^j_k/β^j_ℓ	0.588	0.651	0.629	0.418	0.646	0.662	0.603	0.477	0.437
π^j	1.000	0.116	0.418	0.467	0.040	0.230	0.228	0.303	0.200
No. of Obs.	11441								
No. of plants	744								

Notes. Corrugated Board Boxes. The sample is restricted to the observations with 1. non-missing (y_{it}, ℓ_{it}, k_{it}, m_{it}, $w\ell_{it}$); 2. 30+ employees; 3. y_{it}, k_{it}, m_{it}, and PM_{it}/PY_{it} between the 0.5th and the 99.5 percentiles; 4. more than 4 periods in the sample (between the first entry/exit).

Table 8: Average APG Over 1987-2008

	APG	APG (Stayer)	Net Entry
Knitted garments	-2.2%	-0.8%	-1.5%
Motor vehicles parts and accessories	2.8%	3.5%	-0.6%
Corrugated board boxes	-0.8%	0.2%	-1.0%

Notes. The sample is restricted to the observations with 1. non-missing (y_{it}, ℓ_{it}, k_{it}, m_{it}, $w\ell_{it}$); 2. 30+ employees; 3. y_{it}, k_{it}, m_{it}, and PM_{it}/PY_{it} between the 0.5th and the 99.5 percentiles; 4. more than 4 periods in the sample (between the first entry/exit).

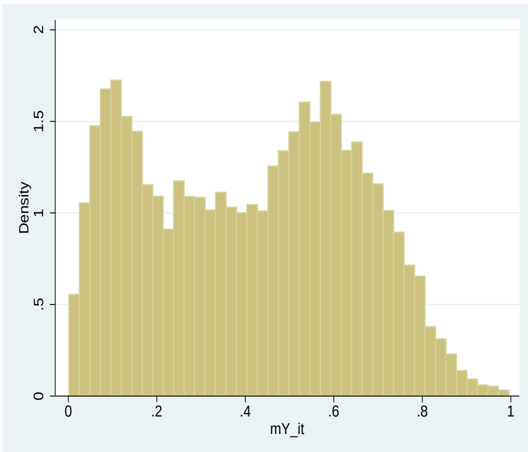
Table 9: Decomposition of APG

	Knitted garments				Motor vehicles parts and accessories				Corrugated board boxes			
	Technical Efficiency		Reallocation		Technical Efficiency		Reallocation		Technical Efficiency		Reallocation	
	$J=1$	$J=3$	$J=1$	$J=3$	$J=1$	$J=3$	$J=1$	$J=3$	$J=1$	$J=3$	$J=1$	$J=3$
Average												
1987-1991	3.7%	2.4%	-1.7%	-0.4%	8.9%	6.4%	-1.8%	0.7%	2.4%	2.0%	0.0%	0.4%
1992-1996	-2.3%	-1.5%	0.4%	-0.5%	-0.6%	-0.2%	0.4%	0.0%	-1.8%	-1.8%	0.3%	0.3%
1997-2001	-1.7%	-1.2%	-0.9%	-1.4%	2.7%	2.2%	-0.9%	-0.4%	1.3%	1.4%	-0.3%	-0.4%
2002-2008	-0.2%	-0.2%	-0.6%	-0.6%	5.5%	4.3%	-0.2%	1.0%	0.1%	0.4%	0.2%	-0.1%
1987-2008	-0.1%	-0.1%	-0.7%	-0.7%	4.3%	3.3%	-0.6%	0.4%	0.5%	0.5%	0.1%	0.0%
SD												
1987-2008	3.3%	2.3%	1.9%	1.0%	6.0%	4.5%	3.1%	1.3%	4.0%	4.1%	1.1%	1.2%

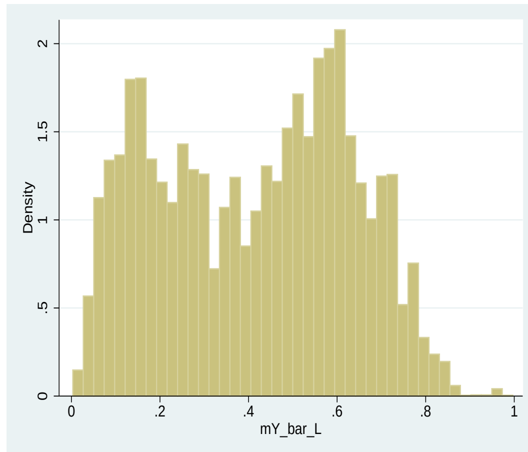
Notes. In the upper panel designated by Average, each entry reports the average growth rate of a given variable over the specified period. In the panel designated by SD, each entry reports the standard deviation of the growth rates of a given variable over the 1987-2008 period.

D Appendix: Figures

Figure 1: Distribution of Intermediate Input Share



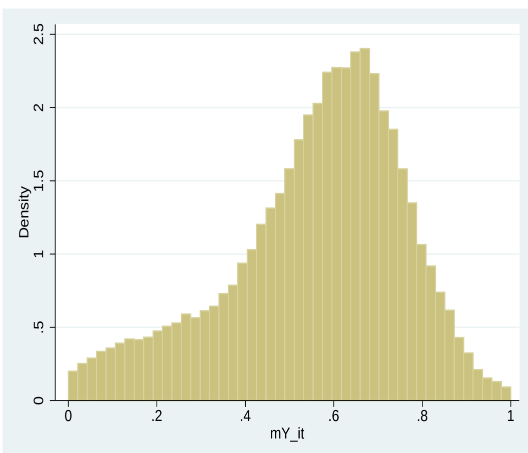
(a) $\frac{PM_{it}}{PY_{it}}$



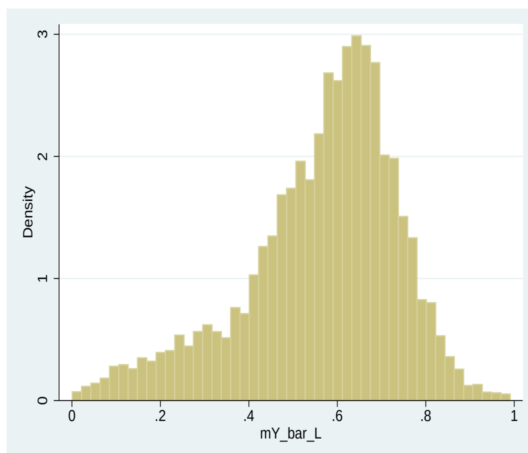
(b) $\frac{1}{T_i}\sum_{t=1}^{T_i}\frac{PM_{it}}{PY_{it}}$

Notes. Knitted Garment

Figure 2: Distribution of Intermediate Input Share



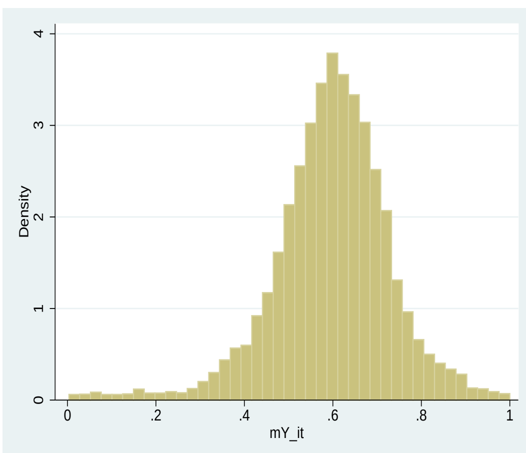
(a) $\frac{PM_{it}}{PY_{it}}$



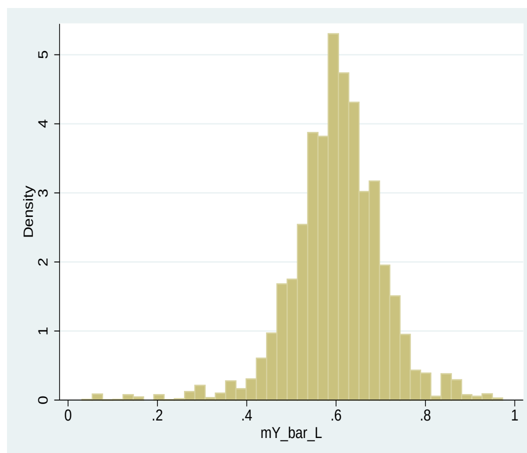
(b) $\frac{1}{T_i}\sum_{t=1}^{T_i}\frac{PM_{it}}{PY_{it}}$

Notes. Motor vehicles parts and accessories.

Figure 3: Distribution of Intermediate Input Share



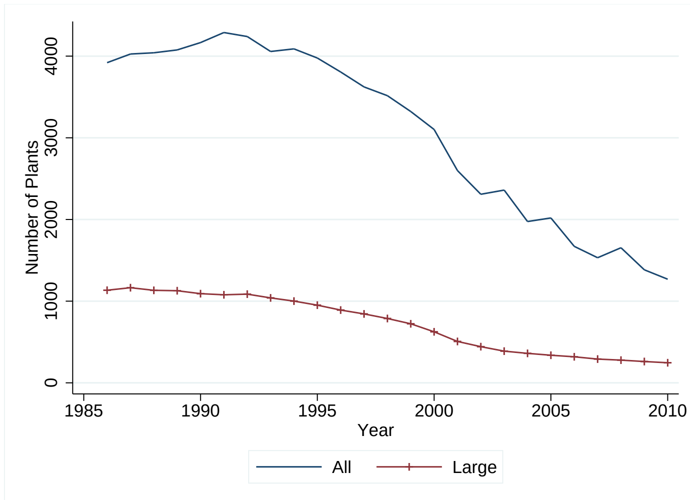
(a) $\frac{PM_{it}}{PY_{it}}$



(b) $\frac{1}{T_i}\sum_{t=1}^{T_i}\frac{PM_{it}}{PY_{it}}$

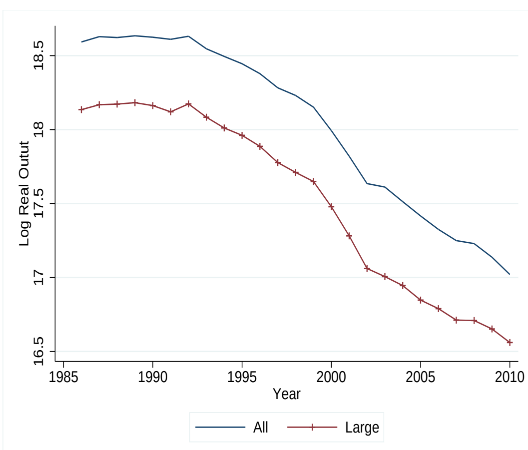
Notes. Corrugated board boxes.

Figure 4: Number of Plants Over Time

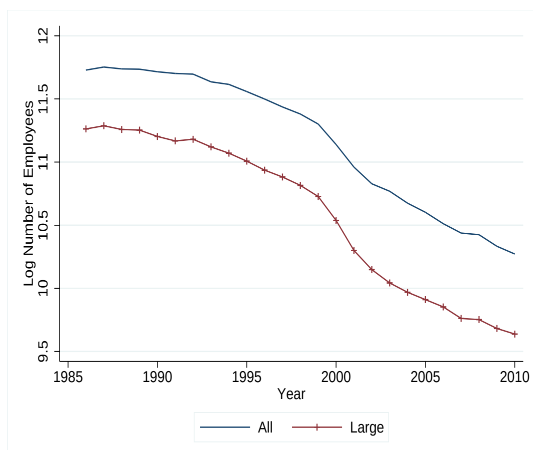


Notes. Knitted Garment. The line labelled 'All' uses the sample of all plants (reporting y_{it} at least) in the Knitted Garment industry, while 'Large' restricts the sample to the plants with 30+ employees and non-missing input/output/cost data.

Figure 5: Changes in Industry-level Output and Employment



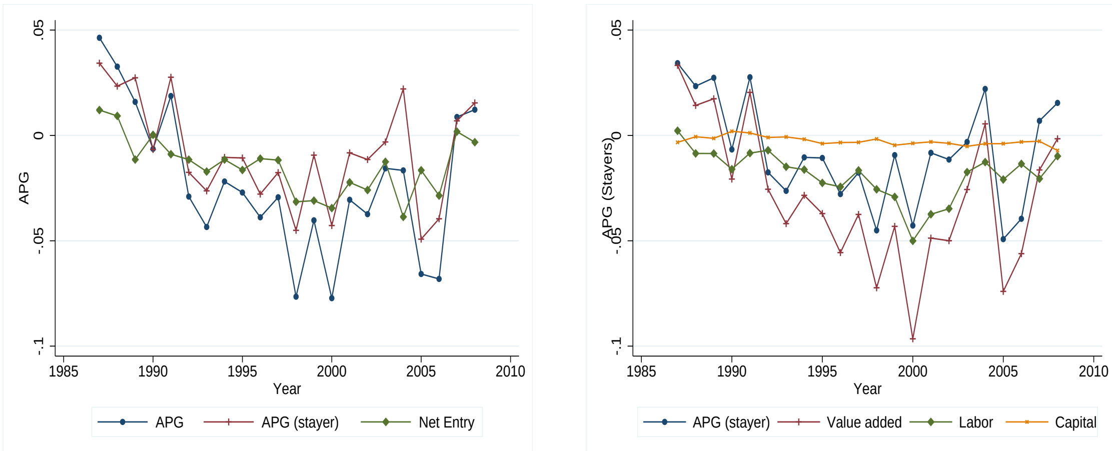
(a) Log Real Output



(b) Log Number of Employees

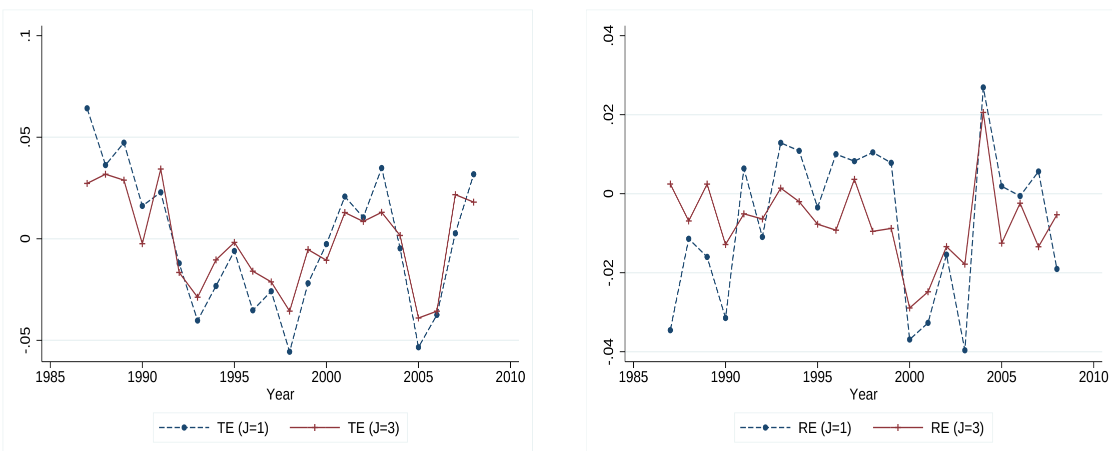
Notes. Knitted Garment. The line labelled 'All' uses the sample of all plants in the given industry, while 'Large' restricts the sample to the plants with 30+ employees and non-missing input/output/cost data.

Figure 6: APG and Its Components



Notes. Knitted Garment. The sample is restricted to the one used in the production function estimation.

Figure 7: PL Decomposition of APG



(a) Technical Efficiency

(b) Reallocation

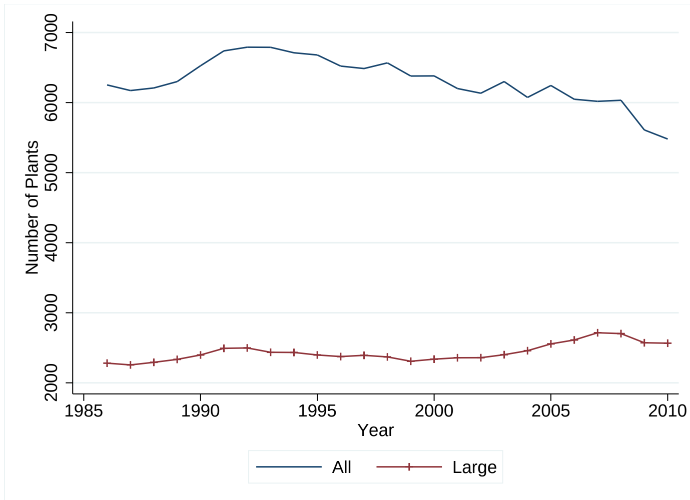
Notes. Knitted Garment. The sample is restricted to the one used in the production function estimation.

Figure 8: Reallocation Contribution by Input Factors

(a) Inermediate (b) Labor (c) Capital

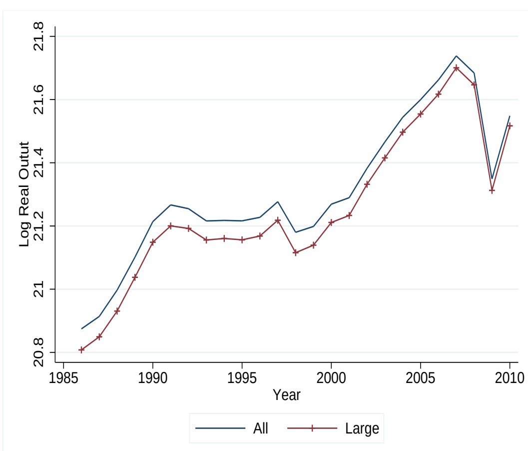
Notes. Knitted Garment. The sample is restricted to the one used in the production function estimation.

Figure 9: Number of Plants Over Time

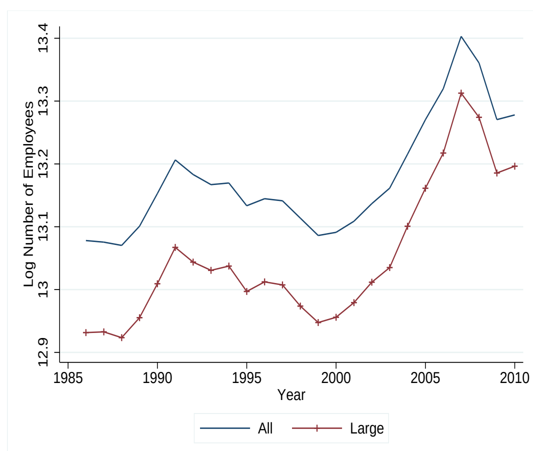


Notes. Motor vehicles parts and accessories. The line labelled 'All' uses the sample of all plants in the given industry, while 'Large' restricts the sample to the plants with 30+ employees and non-missing input/output/cost data.

Figure 10: Changes in Industry-level Output and Employment



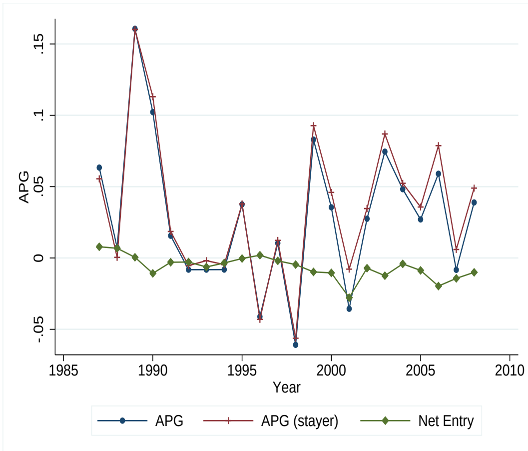
(a) Log Real Output

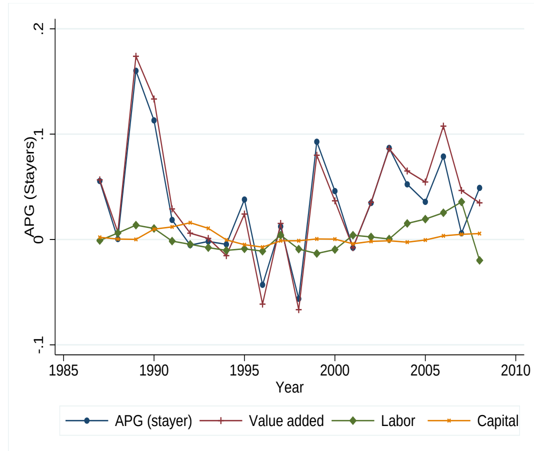


(b) Log Number of Employees

Notes. Motor vehicles parts and accessories. The line labelled 'All' uses the sample of all plants in the given industry, while 'Large' restricts the sample to the plants with 30+ employees and non-missing input/output/cost data.

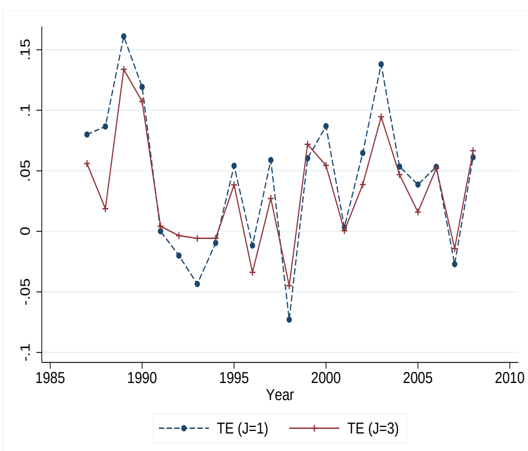
Figure 11: APG and Its Components



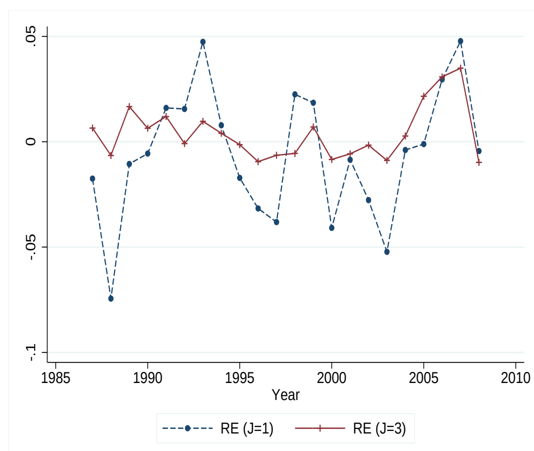


Notes. Motor vehicles parts and accessories. The sample is restricted to the one used in the production function estimation.

Figure 12: PL Decomposition of APG



(a) Technical Efficiency



(b) Reallocation

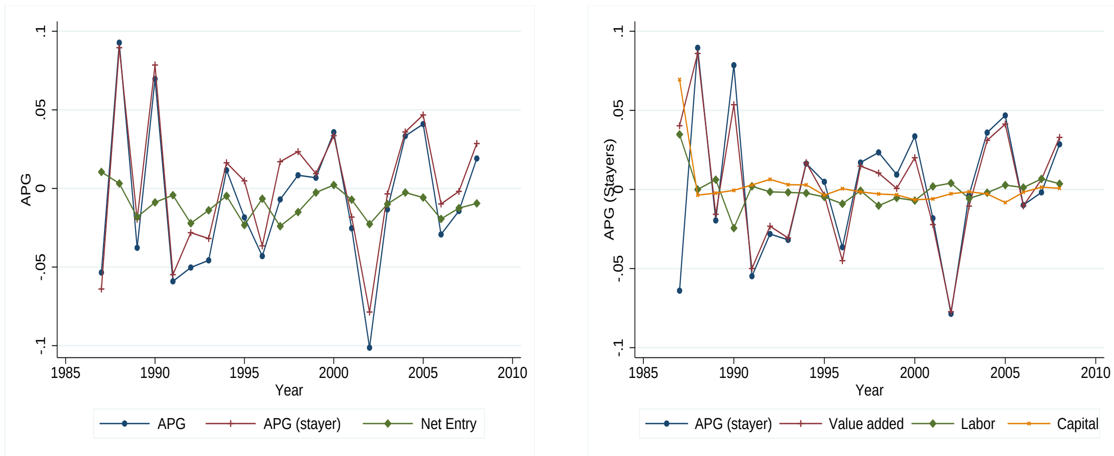
Notes. Motor vehicles parts and accessories. The sample is restricted to the one used in the production function estimation.

Figure 13: Reallocation Contribution by Input Factors

(a) Inermediate (b) Labor (c) Capital

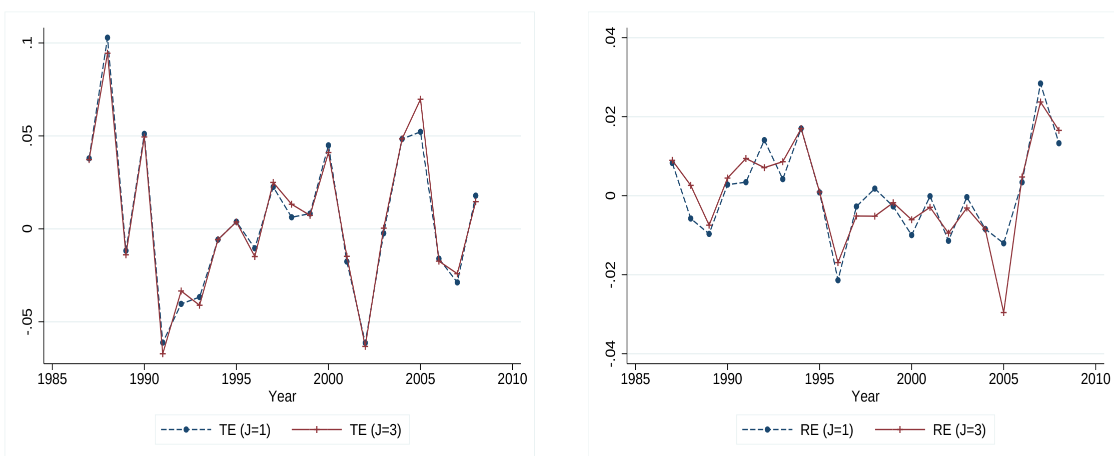
Notes. Motor vehicles parts and accessories. The sample is restricted to the one used in the production function estimation.

Figure 14: APG and Its Components



Notes. Corrugated board boxes. The sample is restricted to the one used in the production function estimation.

Figure 15: PL Decomposition of APG



(a) Technical Efficiency (b) Reallocation

Notes. Corrugated board boxes. The sample is restricted to the one used in the production function estimation.

Figure 16: Reallocation Contribution by Input Factors

(a) Inermediate (b) Labor (c) Capital

Notes. Corrugated board boxes. The sample is restricted to the one used in the production function estimation.

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