Biased Technology and Contribution of Technological Change to Economic Growth: Firm-Level Evidence*

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Abstract

The increasing mean wage-interest ratio and decreasing mean capital-labor ratio observed in some Chinese manufacturing industries suggest that technological change is factor-biased. In order to study the nature of technological change and its contribution to economic growth, this paper builds and estimates a structural model of firms' production decisions with biased technological change. This model allows me to identify and estimate the firm-time-specific factor-biased technology using micro data. The basic idea of the estimation is that the choice of inputs contains information about the unobserved productivities; therefore we can invert the inputs demand function to recover the unobserved productivities. I estimate the model from a firm-level data set of four Chinese Manufacturing industries. The empirical results provide firm-level evidence of biased technological change over time and biased technological dispersion across firms. The estimation results show that technological change contributes to the growth of gross output by 1.81%-3.10% annually and value added by 12.67%-21.16%, which is higher than the combined contribution of capital and labor. Capital efficiency grows much faster than labor efficiency in China, and the contribution of technological change to economic growth is mainly due to the change of capital efficiency. The results also show that large firms have a higher capital-labor efficiency ratio and that biased technological dispersion explains a large part of the dispersion of capital-labor ratio across firms.

Keywords: *Multidimensional Productivity, Technology Bias, Biased Technological Change, Biased Technological Dispersion*

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1 Introduction

During the last three decades, China maintained a high economic growth rate of over 8% per year (IMF, 2011), much higher than that in peer countries during the same period. One important question for China is: is this growth sustainable? If the growth is mainly driven by the increased inputs (especially labor), then the economic growth will stop when the inputs bonuses are exhausted. If the growth is mainly driven by technological change, the economic growth is sustainable. So it is very important to identify the sources of growth in China.[1]

Starting in 1999, Chinese government issued a technology-promoting policy to encourage firms to replace their aged technologies with new ones, through tax credits, loans and land rationing. This policy could potentially speed up the adoption of new technology by firms, meaning that technological change could be an important source of economic growth in China in 2000s. One goal of this paper is to evaluate the contribution of technological change to economic growth after the implementation of this policy.

In the mean time, firm-level data from Chinese manufacturing industries shows that in some industries the average wage-interest ratio increased sharply but the average capital-labor ratio decreased significantly, from 2000 to 2007. This suggests that a capital-saving technological change was ongoing in these industries during this period. In this circumstance, the model of Hicks neutral technology advancement misspecified the technology pattern in China and is likely to produce erroneous results regarding the contribution of technological change to economic growth. In this paper I introduce a factor-biased technology measure, which allows capital efficiency and labor efficiency to growth separately. This generalized framework also allows us to study how much the advancement of capital efficiency and labor efficiency, separately, contribute to the economic growth. The answer to these questions will provide some basis for growth policy.

This paper develops a new method to identify and estimate a firm-level multidimensional productivity measure with factor-biased technology using input-output data. This productivity measure accounts for separate capital-augmenting and labor-augmenting efficiency. The estimation is directly based on economic theory. The basic idea of the estimation is that the choice of (static) inputs contains information about unobserved

[1]Some literature documented that before 2000, input growth was the major sources of economic growth in China (Hu and Zheng, 2006; Easterly and Levine, 2001) under Hicks-Neutral technology assumption.

capital efficiency and labor efficiency. I thus can invert the input demand function to recover the unobserved capital efficiency and labor efficiency. I then substitute this recovered efficiencies for the structural productivity errors in the production function and solve the transmission bias. For clarity, I henceforth define the *"capital-labor efficiency ratio"* as the ratio of capital-augmenting efficiency to labor-augmenting efficiency; the *"biased technological change (BTC)"* as the change of the capital-labor efficiency ratio over time; the *"biased technological dispersion (BTD)"* as the cross-firm dispersion of the capital-labor efficiency ratio at a given time.

I estimate the model using a rich firm-level Chinese Manufacturing survey. I choose four industries with different technology level and capital intensities: Clothing, Industrial Paper & Paper Board Making, Production Equipments for Foods, Beverages and Tobacco, and Motor Vehicles. The estimation results first provide firm-level evidence of the existence on biased technological change at the firm level. The results show that capital efficiency grows much faster ($> 20\%$) than labor efficiency ($< 5\%$ and sometimes negative) during 2000-2007 in the four industries examined. When only continuing firms are considered, the capital efficiency change contributes to the annual industrial growth positively, by 1.60%, 1.74%, 3.29% and 2.64% respectively for the four industries. Labor efficiency contributes negatively in three out of the four industries, by 0.21%, -0.09%, -0.19% and -0.10% respectively for the four industries. The net entry and exit contributes to the industrial growth by 4.96%, -1.22%, -2.05%, and -1.05% for the four industries respectively. If I instead analyze the growth of value added, I find that technological change contributes to over one half of the growth of value added, which is higher than the combined contribution of increased capital and labor inputs. The contribution of technological change arises mainly from advancement of capital efficiency.

An advantage of the estimated firm-time-specific biased technology in my model is that we can evaluate the technology bias heterogeneity across firms. Results provide evidence of biased technological dispersion (BTD) across firms, which is new in the literature. Large firms on average have higher capital-labor efficiency ratio and the biased technological dispersion explains a large part of the dispersion of the capital-labor ratio across firms. The estimated firm-time-specific biased technology in my model extends the current literature on biased technological change[2], which focuses on the country-level

[2]For example,Brown and Cani (1963), David and Van de Klundert (1965), Wilkinson (1968), Sato (1970, 1980), Stevenson (1980), Panik (1976), Kalt (1978), Cowing and Stevenson (1981), Antras (2004),

or industry-level biased technological change. This result has important implications for the behavior and size distribution of firms, specifically entry/exit, inputs demand, and growth/contraction of firms.

The idea of exploiting the first order conditions of profit maximization in production estimation is also used in recent papers. Ackerberg, Caves, and Frazer (2006) point out the possibility of using the parametric first order condition of static inputs to control for transmission bias. Katayama, Lu, and Tybout (2009), Gandhi, Navarro, and Rivers (2011), Doraszelski and Jaumandreu (2012), and Grieco, Li, and Zhang (2013) also used the first order condition to assist in the production estimation. These studies focus on a two-stage estimation procedure and rely on a crucial assumption of Markov productivity to form the moment conditions to estimate the production parameters. In contrast, this paper directly recovers the unobserved multidimensional productivity from the first order condition and constructs the moment conditions directly using the non-structural errors in the production/revenue function. One advantage of this approach is that the estimation doesn't rely on the restrictive Markov process assumption on the productivity evolution process. As a result, cross section data is sufficient for the estimation. Another advantage is that it is straightforward and simple to implement. Additionally, this approach is directly based on the economic theory, profit maximization, and only requires mild assumptions for identification.

The use of first order conditions also provides a natural way to break Diamond's Impossibility Theorem (Diamond, McFadden, and Rodriguez, 1978), which states that the elasticity of substitution and biased technological change cannot be identified simultaneously from input-output data if no further restrictions are added. The reasoning behind this theorem is that both elasticity of substitution and capital-labor efficiency ratio affect the relative choice of inputs and we could not disentangle them from input-output data if no further conditions are added. The use of the first order conditions establishes a link between elasticity of substitution and biased technological change, leading to identification of both of them.

The remainder of the paper is organized as follows: Section 2 introduces the background and motivational facts. Section 3 introduces the model and estimation procedure for general (parametric) production functions. Section 4 and section 5 discuss the esti-

Klump, McAdam, and Willman (2007), Leon-Ledesma, McAdam, and Willman (2010).

mation procedure and empirical results from the translog production function. Section 6 provides a test against neutral technology. Sections 7 and 8 investigate the pattern of biased technological change and biased technological dispersion. Section 9 discusses the sources of growth in China and section 10 concludes.

2 The Background and Motivational Facts

2.1 Background: The Technology-Promoting Policy

In order to maintain a sustainable growth and prepare for the entrance into the World Trade Organization (WTO), the Chinese government issued a series of policies to encourage technological change after 1997. Two of these important policies are *"The guide to the Current Priority High-Tech Areas for Industrial Development"* and *"The list of Outdated Productivity, Production Process and Products to be Eliminated"*, both issued in 1999. These two policies encourage firms to update their technology, production processes and products. The former policy lists the technology, production process and products that firms are encouraged to develop, and the latter policy lists the ones that firms should eliminate. The encouraged technology, production processes and products use up-to-date technology and the discouraged ones use old technology. The government encouraged firms to update their technology through strong economic incentives such as tax credits, loan appraisals and land rationing. The government also implements a strict appraisal and evaluation procedure for firms to invest in new projects. New projects using the encouraged technologies would be easily approved by the Censoring Bureau, while new projects using old technologies would have more trouble getting approved.

"The Guide for Industrial Structure Change", issued in 2005, more clearly lists the encouraged, restricted and forbidden projects. To accompany these policies, the Ministry of Land and Resources issued two land-use restrictions, *"Projects Restricted from Using Land"* and *"Projects Forbidden from Using Land"*, to help implement technology-promoting policies. These policies together provide strong incentives for existing firms to update their technology, and for new firms to use new technology. This paper studies the pattern of technological change of Chinese firms under this background and its contribution to industrial growth.

2.2 Data

The data used in this paper is a rich, firm-level panel dataset from Chinese manufacturing industries, which was collected through annual surveys of manufacturing enterprises and maintained by the China National Bureau of Statistics. The number of firms increased from around 160,000 in 2000 to over 300,000 in 2007. The surveys covers two types of manufacturing firms: (1) state-owned enterprises (SOEs), and (2) non-SOEs whose annual sales are more than five million RMB (approximately 650,000 US dollar). The data set contains information on firm-level annual revenue, input expenditures, wage rate, detailed firm characteristics (e.g. age, ownership, location etc.), and nearly 100 financial variables. For a detailed description of the data set, refer to Feenstra, Li, and Yu (2011).

This paper uses data from four industries in China: Clothing, Industrial Paper & Paper Board Making (Paper&Board Making henceforth), Production Equipments for Foods, Beverages and Tobacco (Equipments henceforth), and motor vehicles. These industries varies in their technology level as well as capital-labor ratio. They play important roles in Chinese economy and differ significantly in their technology and capital-labor ratio. Clothing industry is a traditional industry in China and is highly labor intensive. The major machine used in this industry is a sewing machine; therefore, the productivity largely depends on the type of sewing machine used and how efficiently the workers are organized. The Paper & Board Making industry used poor technology with high pollution emissions in China before 2000, but faced pressure from the government to update its technology. The Equipments industry is in the middle of the four industries in terms of capital intensity. The Motor Vehicles industry is capital intensive and it uses mature technology in China.

Table 1 reports some basic features of the firms in these industries. The number of observations varies from 1,194 in the motor vehicles industry to over 50,000 in the clothing industry. The labor revenue share ranges from 3% in Motor Vehicles industry to 9% in Clothing industry[3]. At the same time, the capital-labor ratio ranges from 27.25 thousand RMB per worker in Clothing industry to 143.35 thousand RMB in Motor Vehicles industry. Among these industries, the Clothing industry is the most labor intensive, the Industrial Paper & Board Making and Motor Vehicle industries are the most capital intensive, and the Equipments industry in the middle. Additionally, firm size is the largest in the motor

[3]Note that we are using the gross production here. The material account for over 75% of the revenue.

vehicle industry.

2.3 Motivational Facts

2.3.1 Evolution: Capital-Labor Ratio and Inputs Prices

I compute the yearly mean of the capital-labor ratio and the wage-interest ratio for each industry in Table 2. All mean values are weighted by sales. According to the economic theory, an increase in the wage-interest rate ratio will drive up the capital-labor ratio, whatever the pattern of technological change. If the technological change is neutral, then the observed capital-labor ratio should rise. If there is a labor-saving technological change at the same time, the observed capital-labor ratio should rise even more. If the technological change is capital-saving, the observed capital-labor ratio can either go up or down, depending on which of the two forces (price change or technological change) is stronger. If the capital-saving technological change is not strong enough to offset the effect of an increased wage-interest ratio, the observed capital-labor ratio will still go up. If the capital-saving technological change is strong enough to offset the effect of an increased wage-interest ratio, the observed capital-labor ratio will go down.

Table 2 shows that during 2000 to 2007 when the wage-interest ratio in the Clothing and Motor Vehicles industries rose significantly by 22.96% and 17.77%, respectively, the capital-labor ratio decreased by 3.64% and 44.26%, respectively. This finding suggests that the Clothing and Motor Vehicle industries experienced strong capital-saving technical changes during this period..

In the other two industries, both the wage-interest rate ratio and the capital-labor ratio increased over the data period. This fact is consistent with either a neutral technological change, a labor-saving technological change, or a capital-saving technological change which is not strong enough to offset the effect of the increased wage-interest ratio. So, a quantitative analysis is needed to understand the pattern of technological change in these industries.

When there is a biased technological change, models that assume neutral technology misspecify the technological pattern and will lead to an inaccurate estimation of the contribution of technological change to industrial growth. In order to accurately evaluate the sources of growth in the Chinese economy, it is necessary to go beyond the neutral technology measure and consider the biased technological change. Moreover, it is also interesting to know the contribution of capital efficiency and labor efficiency to economic growth, which is something a neutral technology model can not address. This motivates the study of biased technological change in this paper.

2.3.2 Dispersion: Capital-Labor Ratio and Input Prices

Another stylized fact in the data is the high dispersion of the capital-labor ratio among firms. Figure 1 shows the dispersion of the capital-labor ratio for each industry in 2007. The firms in each industry are ordered and grouped into ten cohorts by capital-labor ratio. Each cohort represents 10% of the firms and is represented by a bar in the figure. The height of the bar represents the mean of the capital-labor ratio for that cohort. The capital-labor ratio differs significantly across firms within each industry. In the Clothing industry for example, the first 10% of firms have a mean of 2.07 thousand RMBs of capital per worker and the last 10% of firms have a mean of about 140 thousand RMBs of capital per worker (about 70 times larger). Generally, Figure 1 indicates that there is a significant dispersion of the capital-labor ratio among firms within each industry in 2007.

Input price dispersion caused by market friction provides one possible explanation for the dispersion of the capital-labor ratio (Spaliara, 2008). However, it is hard to explain the different capital-labor ratios for firms with similar input prices. One example is the dispersion of the capital-labor ratio across plants within the same firm. As Chew, Clark and Bresnahan (1989) point out, the input price difference cannot explain the capital intensity difference among plants producing the same products within the same firm, s-ince all plants within the same firm face more or less the same factor prices. Klump and de La Grandville (2000) provide another explanation based on elasticity of substitution. However, their estimator of elasticity of substitution is inconsistent if there is biased technological dispersion/change. The reason is that the elasticity of substitution is estimated based on the relative demand of capital and labor, which is affected by biased technology. If the technology is indeed biased but treated as neutral, the factor demand differentials among firms caused by biased technology will be mistakenly explained as being caused by different elasticity of substitution across firms.

Other factors such as ownership, firm size and macro economic environment also affect firms' capital-labor ratio. Table 3 reports the R-square for four regressions with the capital-labor ratio as the dependent variable and the variables listed above as regressors.

It shows how much of the dispersion of capital-labor ratio could be explained by these factors. The wage-interest rate ratio alone can explain 7.77%, 15.96%, 21.42% and 3.26% respectively, for the Clothing, Paper & Board Making, Equipments, and Motor Vehicles industries. Controlling for firm size, year dummy and ownership in addition increases the explanation power to 9.57%, 17.84%, 24.13% and 11.61%, respectively. This suggests that some important firm heterogeneities exist, which cause a large part of the unexplained dispersion of the capital-labor ratio.

The biased technological dispersion provides a candidate explanation of the observed dispersion of the capital-labor ratio. With biased technology, firms differ not only in the absolute level of productivity, but also in the relative efficiency of factors. The former determines the absolute level of inputs used, or the size of factor demand; the latter determines the relative amount of the input used, or the composition of factor demand. More specifically, the relative factor efficiency differentials among firms imply a different marginal product of factors among firms, which leads to different capital-labor ratios among firms even when their input prices are the same. This paper estimates the effect of biased technology on capital intensity based on a structural model which allows for a flexible factor elasticity of substitution and flexible biased technological change/dispersion across firms.

3 A Model for General Production Function

This section develops a model of firms' optimal choice of inputs to help identify the biased technological change/dispersion. The basic idea is that the optimal choice of inputs contains information about the unobserved productivity. Thus, we can recover the multidimensional productivity from the observed input choices to solve for the transmission bias. The first order conditions also establish a link between the elasticity of substitution and the efficiency ratio, which provides a natural way acound the Diamond's Impossibility Theorem (Diamond, McFadden, and Rodriguez, 1978) and leads to the identification of both technology bias and elasticity of substitution. This section introduces the model for the general (parametric) production function and establishes the conditions for identification. As an illustration I apply this method to the translog production function in the next section.

3.1 Production Function

I assume that technological change is purely factor-augmenting. In this case, improvement of factor efficiencies change the marginal products of different factors in different ways. I consider a production function with capital-augmenting and labor-augmenting technological change.

A1 (Factor-Augmenting): Technological change is capital and/or labor augmenting.

A firm's production function is parameterized up to finite parameters θ. Under assumption A1, the production function takes the general form

$$Y_{jt} = F\left(A_{jt}^{k} K_{jt}, A_{jt}^{l} L_{jt}, M_{jt}; \theta\right)$$

where A_{jt}^{k} is the capital-augmenting efficiency and A_{jt}^{l} is the labor-augmenting efficiency. The capital-labor efficiency ratio is $\frac{A_{jt}^{k}}{A_{jt}^{l}}$. It measures how much the technology is biased towards favoring capital (or labor). I define $(\omega_{jt}, \upsilon_{jt})$ as the logarithm of capital and labor efficiencies, where $\omega_{jt} = \ln A_{jt}^{k}$ and $\upsilon_{jt} = \ln A_{jt}^{l}$. From now on I will refer to $(\omega_{jt}, \upsilon_{jt})$ as the (log) capital efficiency and labor efficiency, and $\omega_{jt} - \upsilon_{jt}$ as the (log) capital-labor efficiency ratio. K_{jt}, L_{jt} and M_{jt} represent capital, labor and intermediate inputs respectively.

I further assume that the production function satisfies the following regularity conditions:

A2 (Differentiability): F(·,·,·) is twice continuously differentiable in all three of its arguments.

A3 (Positive marginal products): $F_1, F_2, F_3 > 0$.

A4 (Diminishing marginal product): $F_{ii} < 0$ and $F_{ij} > 0$, for all $i, j = 1, 2, 3$ and $i \neq j$.

I allow the technology to change in a very flexible way. Note that the production function need not to be *neoclassical*[4], as it is allowed to have retrogressive technological change. In fact, It is even not necessarily *classical* as it allows non-constant returns to scale.

A problem related to the productivity measure is that the quality of inputs and out-

[4] A production function with constant returns to scale is said to be *"classical"* if it is continuous and has positive marginal products and diminishing marginal rates of substitution. The production function is said to be *"neoclassical"* if it further satisfies the non-retrogression condition, which says technological change is always positive.

puts may be different across firms. Both the firm productivity and input quality affect the estimates of input efficiency. In particular, the estimated productivity measure will contain the effect of both the productivity of the technology used by the firm and the input quality difference. The price contains important information about the quality of goods. I follow Kugler and Verhoogen (2009, 2012) and use input (output) price as a measure of input (output) quality. Specifically, I assume that the dispersion of prices reflects the quality differences of inputs and outputs across firms, and that firms pay the same price for the quality-adjusted products. This also solves the problem of firms using different units to record their amount of inputs and outputs. By using the quality-adjusted inputs and outputs to replace (K_{jt}, L_{jt}, M_{jt}) and Y_{jt} in the production function, A^k_{jt} and A^l_{jt} is the labor efficiency and capital efficiency, net of the inputs quality difference. So A^k_{jt} and A^l_{jt} now measure the efficiencies brought on by firm technology, rather than input quality.

3.2 Non-Identification Result

Suppose that the data contains output value (Q_{jt}) and expenditures on capital, labor and material. Assume that the observed output is subject to an i.i.d measurement error, ε_{jt}. That is $Q_{jt} = Y_{jt} \exp(\varepsilon_{jt})$, where Y_{jt} is the firm's targeted output. We want to identify the unobserved input efficiency $(\omega_{jt}, \upsilon_{jt})$ and the production parameter θ from the observed data.

Under the above assumptions, so far the model is not identified due to the Diamond's Impossibility Theorem. One of the challenges is to overcome the transmission bias caused by the two dimensional unobserved capital efficiency and labor efficiency. The nonparametric control function approach based on investment (Olley and Pakes, 1996) is subject to the controversial invertibility problem, as well as the collinearity problem in their first stage estimation (even in their single unobservable case). These two problems become even worse in the case of multidimensional unobservables (Ackerberg, Caves, and Frazer, 2006). Even when the invertibility condition is established and the unobservables are nonparametrically recovered from observed variables, with multidimensional unobservables, we still cannot identify the model because we have multiple nonparametric functions to be estimated in a single equation.

The second problem is related to the aforementioned Diamond's Impossibility Theorem

(Diamond, McFadden, and Rodriguez, 1978), which says that under assumptions A1-A5[5], we cannot identify both the capital-labor efficiency ratio and the elasticity of substitution (implied by the production parameters) simultaneously. The reason is that both the capital-labor efficiency ratio and elasticity of substitution are free to change, and both affect the optimal choice of inputs. The impact of a change in the elasticity of substitution can make up for the effect of a change of technology ratio, and vice versa. As a result, more than one combination of elasticity of substitution (production parameters) and the technology ratio are consistent with the observed data. Therefore, the model is not identified.

There are many ways to add more moments to the data to identify the model. I briefly discuss three methods of doing this that seem likely to arise frequently in practice and play key roles in application.

The first possible source of identification is to add structure to the growth rate of capital and labor efficiencies. For example, as is often done in the literature we can assume that capital efficiency and labor efficiency grow non-retrogressively and that growth rates are functions of time t with finite parameters. This additional assumption on the growth trend of capital and labor efficiencies helps identify the model and leads to a very simple estimation procedure and an intuitive explanation of the parameters. As a result, it is widely used in the literature. However, we understand that this restriction is strong and questionable in practice, as capital and labor efficiencies do not necessarily grow at constant rate. Also, this restriction cannot be applied to cross-sectional data as we do not have an order of firms to define the growth rate.

The second possible source of identification is to use panel data. In the literature, only time series were used to identify the model. With panel data, if firms share common capital and labor efficiencies, the elasticity of substitution can be identified from the cross-sectional variation in the input usage. In particular, we can identify the elasticity of substitution from the cross-sectional variation in the input-output combination across firms and then identify the biased technological change from the time series. However, if we are not willing to assume that all firms share the same capital efficiency and labor efficiency, the panel data does not help for identification.

The third possible source of identification is to rely on the structure implied by eco-

[5] They assumed constant returns to scale and non-retrogressive technology change in addition.

nomic theory about firm's input choice to pin down the relationship between the elasticity of substitution and the efficiency ratio. A natural choice of this structure is the first order conditions for firms' static choice on labor and material. These first order conditions establish a link between the technology ratio and the elasticity of substitution implied by the production parameters. As a result, when there is a change in the efficiency ratio we cannot change the elasticity of substitution (or production parameters) arbitrarily to generate the observed data. This additional structure breaks overcomes the non-identification results summarized in Diamond, McFadden, and Rodriguez (1978). One obvious advantage of this method is that the additional structure has a solid theoretical ground and is naturally implied by the microeconomic theory on firms' objectives.

3.3 A Model of Optimal Input Choice

I utilize the first order conditions with respect to labor and material choice to help identify this model. Firms are price takers in both input and output markets[6]. They could face different input and output prices, which reflect the quality difference of inputs and output across firms. So the quality-adjusted price is the same for all firms at the same period. I assume that capital is fixed at the beginning of each period and that investment is chosen dynamically to maximize firm value. I also assume that firms know their own productivity level (capital efficiency and labor efficiency) before choosing labor and material.

A6 (Profit Maximization): Observing their own capital efficiency, labor efficiency and capital stock at the beginning of each period, firms choose labor and material statically to maximize their own period profit.

Denote P_t, W_t and P_t^m as the output price, wage rate and material price for quality-adjusted products. A firm's optimal static decision problem for labor and material is written as

$$\max_{L_{jt},M_{jt}} \left\{P_t F\left(\exp(\omega_{jt})K_{jt}, \exp(\upsilon_{jt})L_{jt}, M_{jt}\right) - W_t L_{jt} - P_t^m M_{jt}\right\}$$

[6]It is easy to extend this assumption to the case of monopolistic competition in the output market.

The corresponding first order conditions are:

$$\begin{aligned} \exp(\upsilon_{jt}) P_t F_2(\cdot) &= W_t \\ P_t F_3(\cdot) &= P_t^m \end{aligned}$$

where F_2 and F_3 are the partial derivative of F with respect to its second and third arguments respectively. Multiplying both sides of the first equation by $\frac{L_{jt}}{P_t Y_{jt}}$ and the second by $\frac{M_{jt}}{P_t Y_{jt}}$ and rearranging yields

$$\begin{aligned} \exp(\upsilon_{jt}) L_{jt} \frac{F_2(\cdot)}{F(\cdot)} &= \frac{W_t L_{jt}}{P_t Y_{jt}} \\ M_{jt} \frac{F_3(\cdot)}{F(\cdot)} &= \frac{P_t^m M_{jt}}{P_t Y_{jt}} \end{aligned} \tag{1}$$

Denote S_{Ljt} and S_{Mjt} as the revenue share of labor and material, respectively, observed in the data. S_{Ljt} and S_{Mjt} are written as

$$\begin{aligned} S_{Ljt} &= \frac{P_L L_{jt}}{P_{jt} Q_{jt}} = \frac{W_t L_{jt}}{P_t Y_{jt} \exp(\varepsilon_{jt})} \\ S_{Mjt} &= \frac{P_L L_{jt}}{P_{jt} Q_{jt}} = \frac{P_t^m M_{jt}}{P_t Y_{jt} \exp(\varepsilon_{jt})} \end{aligned} \tag{2}$$

By replacing $\frac{P_L L_{jt}}{P_{jt} Y_{jt}}$ and $\frac{P_M M_{jt}}{P_{jt} Y_{jt}}$ in equation (1) with the expressions in equation (2), we have

$$\begin{aligned} \exp(\upsilon_{jt}) L_{jt} \frac{F_2(\exp(\omega_{jt}) K_{jt}, \exp(\upsilon_{jt}) L_{jt}, M_{jt})}{F(\exp(\omega_{jt}) K_{jt}, \exp(\upsilon_{jt}) L_{jt}, M_{jt})} &= S_{Ljt} \exp(\varepsilon_{jt}) \\ M_{jt} \frac{F_3(\exp(\omega_{jt}) K_{jt}, \exp(\upsilon_{jt}) L_{jt}, M_{jt})}{F(\exp(\omega_{jt}) K_{jt}, \exp(\upsilon_{jt}) L_{jt}, M_{jt})} &= S_{Mjt} \exp(\varepsilon_{jt}) \end{aligned} \tag{3}$$

This two-equation system has two unobserved structural errors ω_{jt} and υ_{jt}. We can solve for ω_{jt} and υ_{jt} from this equation system, as functions of unobserved data, the non-structural errors ε_{jt}, and the the production parameters. The first order conditions also establish a link between the efficiency ratio and the elasticity of substitution (implied by production parameters). As discussed above, this linkage overcomes the Diamond's Impossibility Theorem (Diamond, McFadden, and Rodriguez, 1978) and leads to the identification of the technology ratio and elasticity of substitution from input and output data.

Note that the setup allows the capital and labor efficiencies to be flexible, but the "material efficiency" is assumed to be constant. The reason is that the most important aspect of productivity is how the firm organizes capital and labor for production. The materials will be used up and its efficiency change, if any, is small. The literature on biased technology also mainly focused on the capital and labor efficiencies. This paper follows the literature and focuses on the capital and labor efficiencies, while assuming that material efficiency is constant. This treatment greatly reduces the technical difficulties, and allows us to focus our attention on the dispersion and change of capital efficiency and labor efficiency, which are the most important components of the productivity.

If material efficiency is also of interest and is introduced in the model, the estimation strategy introduced later in this paper still applies. In this case, there are three unobserved productivity measures (capital efficiency, labor efficiency and material efficiency). The additional investment information can be utilized, in addition to the usual first order conditions associated with labor and material, to help recover the unobservables. Since the choice for investment is dynamic,, which usually makes it difficult or even impossible to have a closed form solution, the use of investment information adds some technical challenges to the method. This will be an interesting research topic.

3.4 Recovering the Unobserved Productivity

I want to estimate all parameters in the production function from the data on input and output. The basic idea is to recover the unobserved productivities from the first order conditions.

The additional structure implied by the first order conditions pins down the relationship between the efficiency ratio and elasticity of substitution. This restriction can help identify the model if we can recover the unobserved true productivity from the first order conditions uniquely. In the first order conditions, there are two independent equations and two unknowns. Generally we can solve for the unknowns.

Denote $f(x, y) = \begin{cases} \exp(\upsilon_{jt}) L_{jt} \frac{F_2(\cdot)}{F(\cdot)} - S_{Ljt} \exp(\varepsilon_{jt}) \\ M_{jt} \frac{F_3(\cdot)}{F(\cdot)} - S_{Mjt} \exp(\varepsilon_{jt}) \end{cases}$, where $x = (K_{jt}, L_{jt}, M_{jt}, S^L_{jt}, S^K_{jt}, \varepsilon_{jt})$ and $y = (\omega_{jt}, \upsilon_{jt})$. Denote the true values of capital efficiency and labor efficiency, which generate the data, as $y^{data} = (\omega^{data}_{jt}, \upsilon^{data}_{jt})$. Denote the observed data $(K_{jt}, L_{jt}, M_{jt}, S^L_{jt}, S^K_{jt})$ together with the true measurement error ε_{jt} as x^{data}. Then we have $f(x^{data}, y^{data}) = 0$.

Denote the output elasticity of labor and material as $E^l_{jt} = \frac{\partial \ln Q_{jt}}{\partial \ln L_{jt}}$ and $E^m_{jt} = \frac{\partial \ln Q_{jt}}{\partial \ln M_{jt}}$, and denote $E^i_{jtx} = \frac{\partial E^i_{jt}}{\partial x}$ as the derivative of output elasticity E^i_{jt} with respect to efficiency x, where where $i = l, m$ and $x = \omega, \upsilon$. Proposition 1 establishes the conditions under which we can invert the first order conditions to recover the unobserved productivities.

Proposition 1 (Invertibility Condition) *Suppose assumptions A1-A6 are satisfied and we observe a random sample of* $(K_{jt}, L_{jt}, M_{jt}, S^L_{jt}, S^K_{jt})$ *and denote* $x^{data} = (K_{jt}, L_{jt}, M_{jt}, S^L_{jt}, S^K_{jt}, \varepsilon_{jt})$ *If*

$$\frac{E^l_{jt\omega}}{E^m_{jt\omega}} \neq \frac{E^l_{jt\upsilon}}{E^m_{jt\upsilon}} \tag{4}$$

at the point (x^{data}, y^{data}), *then there exists an* $\epsilon > 0$ *and a two-dimensional function* $Z(\cdot;\theta) = \begin{pmatrix} \omega(\cdot;\theta) \\ \upsilon(\cdot;\theta) \end{pmatrix}$, *such that for any* $(x, y) \in \left\{(x,y) : \left\|(x,y) - (x^{data}, y^{data})\right\| < \epsilon\right\}$,

$$y = Z(x;\theta) = \begin{pmatrix} \omega(x;\theta) \\ \upsilon(x;\theta) \end{pmatrix}.$$

Proof. The proof is an application of the implicit function theorem. See the Appendix A for the detail of the proof. ■

The key condition for this invertibility condition to be satisfied is $\frac{E^l_{jt\omega}}{E^m_{jt\omega}} \neq \frac{E^l_{jt\upsilon}}{E^m_{jt\upsilon}}$. It says that the capital- and labor-augmenting efficiencies affect the output elasticity of inputs differently. The marginal labor-to-material output elasticity ratio with respect to capital efficiency does not equal that with respect to labor efficiency at the observed data point. Given this condition, the idea behind proposition 1 is straightforward. The output elasticity determines the revenue share of inputs. As ω_{jt} and υ_{jt} affect the output elasticity differently, we can infer ω_{jt} and υ_{jt} from the relative revenue share of labor and material, which are observed in the data.

What if $\omega_{jt} \equiv \upsilon_{jt}$? In this case, we do not have condition (4).[7] We do not rely on the relative revenue share of material and labor to recover ω_{jt} and υ_{jt}. In this case, we can directly solve for ω_{jt} (or υ_{jt}) from the absolute level of revenue share of material, or revenue share of labor. We can recover them from only one first order condition and leave the other as a restriction.

[7] Note that in this case, if we still distinguish capital-augmenting efficiency and labor-augmenting efficiency (although they are equal), condition (4) is still satisfied. But it is a waste of notation in this case.

The uniqueness condition depends on the parameters and there is no general result for uniqueness. But I will show that for CES and Translog production function the recovered $(\omega_{jt}, \upsilon_{jt})$ is unique.

Example 1: CES Production Function

CES production function is given by: $Y_{jt} = C\left[(A_{jt}K_{jt})^{\gamma} + (B_{jt}L_{jt})^{\gamma} + (M_{jt})^{\gamma}\right]^{\frac{s}{\gamma}}$, where $A_{jt} = \exp(\omega_{jt})$, $B_{jt} = \exp(\upsilon_{jt})$. $s > 0$ measures the scale economy in the production process.

I assume firms are price takers in both input and output markets. They face different input and output prices, which measures the quality of input and output. The first order conditions for CES are:

$$\begin{aligned}
\frac{sL^{\gamma}B_{jt}^{\gamma}}{\left[(A_{jt}K_{jt})^{\gamma} + (B_{jt}L_{jt})^{\gamma} + (M_{jt})^{\gamma}\right]} &= S_{Ljt}\exp(\varepsilon_{jt}) \\
\frac{sM^{\gamma}}{\left[(A_{jt}K_{jt})^{\gamma} + (B_{jt}L_{jt})^{\gamma} + (M_{jt})^{\gamma}\right]} &= S_{Mjt}\exp(\varepsilon_{jt})
\end{aligned}$$

Under the restriction that $s > 0$ and $\gamma \neq 0$ (Non Cobb-Douglas Production Function), we can solve for the closed form solutions to the capital efficiency and labor efficiency

$$\begin{aligned}
A_{jt} &= \left(\frac{s - S_{Ljt}\exp(\varepsilon_{jt}) - S_{Mjt}\exp(\varepsilon_{jt})}{S_{Mjt}\exp(\varepsilon_{jt})}\right)^{\frac{1}{\gamma}} \frac{M_{jt}}{K_{jt}} \\
B_{jt} &= \left(\frac{S_{Ljt}}{S_{Mjt}}\right)^{\frac{1}{\gamma}} \frac{M_{jt}}{L_{jt}}
\end{aligned}$$

Plugging them into the production function, taking the logarithm and adding i.i.d measurement error to the output yields the estimation equation

$$\ln Q_{jt} = \left(\ln C + \frac{s}{\gamma}\ln s\right) - \frac{s}{\gamma}\ln S_{Mjt} + s\ln M_{jt} + (1 - \frac{s}{\gamma})\varepsilon_{jt} \tag{5}$$

■.

Example 2: Translog Production Function

We will show that the translog production function also satisfies the invertibility condition under a mild restriction in the next section.■

3.5 Estimation Equation

Under assumption 1, we can recover the unobserved multidimensional productivities from the first order conditions with respect to labor and material as functions of capital, labor, material, labor share, material share and production parameters. Denote the solution as

$$\begin{aligned} \omega_{jt}^{*} &= \omega\left(K_{jt}, L_{jt}, M_{jt}, S_{Ljt}, S_{Mjt}, \varepsilon_{jt}; \theta\right), \\ \upsilon_{jt}^{*} &= \upsilon\left(K_{jt}, L_{jt}, M_{jt}, S_{Ljt}, S_{Mjt}, \varepsilon_{jt}; \theta\right). \end{aligned} \tag{6}$$

Replacing ω_{jt} and υ_{jt} in the production function with equation (6) yields the estimation equation:

$$Y_{jt} = F\left(\exp(\omega_{jt}^{*})K_{jt}, \exp(\upsilon_{jt}^{*})L_{jt}, M_{jt}\right),$$

where $\omega_{jt}^{*} = \omega(K_{jt}, L_{jt}, M_{jt},\ S_{Ljt}, S_{Mjt}, \varepsilon_{jt}; \theta)$ and $\upsilon_{jt}^{*} = \upsilon(K_{jt}, L_{jt}, M_{jt},\ S_{Ljt}, S_{Mjt}, \varepsilon_{jt}; \theta)$. Y_{jt} is the targeted output of the firm and is not observed by econometricians. Replacing it by the observed output (Q_{jt}) with measurement error yields the estimation equation:

$$\ln Q_{jt} = \ln F\left(\exp(\omega_{jt}^{*})K_{jt}, \exp(\upsilon_{jt}^{*})L_{jt}, M_{jt}\right) + \varepsilon_{jt} \tag{7}$$

This is a parametric equation, which is nonseparable in the error terms ε_{jt} because ω_{jt}^{*} and υ_{jt}^{*} also contain ε_{jt}. The identification condition requires that ε_{jt} is uniquely determined by equation (7) for any production parameter θ at any data point ($Q_{jt}, K_{jt}, L_{jt}, M_{jt}$, S_{Ljt}, S_{Mjt}). That is $\varepsilon_{jt} = \varepsilon(Q_{jt}, K_{jt}, L_{jt}, M_{jt},\ S_{Ljt}, S_{Mjt}; \theta)$. It is easy to show the existence of such a function under the same condition as in proposition 1. The above example shows that in CES ε_{jt} is uniquely determined in the production function. However, for general production functions the uniqueness of such a function depends on both the form of production function and the data point. For example, in translog production function the uniqueness of ε_{jt} depends on both the parameters and observed data points. This is a shortcoming of translog production function. Given that ε_{jt} can be uniquely determined by equation (7) as $\varepsilon_{jt} = \varepsilon(Q_{jt}, K_{jt}, L_{jt}, M_{jt},\ S_{Ljt}, S_{Mjt}; \theta)$, we can estimate the model with Nonlinear Least Square (NLLS) or General Mothod of Moments (GMM). The moment conditions are given as:

$$E\left[Z_{jt}'\varepsilon_{jt}\right] = 0$$

where ε_{jt} is the measurement error in output and Z_{jt} represents the set of instrument variables. In the estimation, I choose Z_{jt} to include all the first and second order terms of $\ln K_{jt},\ \ln L_{jt},\ \ln M_{jt}$, including all cross terms. We can also form additional moments using the fact that $S_{Ljt}\exp(\varepsilon_{jt}) = \frac{W_t L_{jt}}{P_{jt}Y_{jt}}$ and $S_{Mjt}\exp(\varepsilon_{jt}) = \frac{P_t^m M_{jt}}{P_{jt}Y_{jt}}$ are orthogonal with ε_{jt}.

4 Implementation in Translog Production Function

As a demonstration, in the rest of this paper I apply the approach to a transcendental logarithmic production function (translog). The advantage of the translog production function over other popularly used production functions (e.g. Cobb-Douglas and CES) is that it allows flexible output elasticity and elasticity of substitution, which can vary across firms and over time. I extend the standard translog production function to allow for dispersion of biased technology across firms and over time. This extended translog production function is

$$\begin{aligned} \ln Y_{jt} &= a_0 + a_k(\omega_{jt} + \ln K_{jt}) + a_l(\upsilon_{jt} + \ln L_{jt}) + a_m \ln M_{jt} \\ &+\frac{1}{2}a_{kk}(\omega_{jt} + \ln K_{jt})^2 + \frac{1}{2}a_{ll}(\upsilon_{jt} + \ln L_{jt})^2 + \frac{1}{2}a_{mm}(\ln M_{jt})^2 \\ &+a_{kl}(\omega_{jt} + \ln K_{jt})(\upsilon_{jt} + \ln L_{jt}) + a_{km}(\omega_{jt} + \ln K_{jt})\ln M_{jt} \\ &+a_{lm}(\upsilon_{jt} + \ln L_{jt})\ln M_{jt} \end{aligned} \tag{8}$$

I assume that firms are price-takers in both input and output markets. The corresponding first order conditions of the static choice of labor and material are:

$$\begin{aligned} W_t &= \frac{P_t Y_{jt}}{L_{jt}}\left[a_l + a_{ll}(\upsilon_{jt} + \ln L_{jt}) + a_{kl}(\omega_{jt} + \ln K_{jt}) + a_{lm}\ln M_{jt}\right] \\ P_t^m &= \frac{P_t Y_{jt}}{M_{jt}}\left[a_m + a_{mm}\ln M_{jt} + a_{km}(\omega_{jt} + \ln K_{jt}) + a_{lm}(\upsilon_{jt} + \ln L_{jt})\right] \end{aligned} \tag{9}$$

The optimal investments are determined as

$$V(S_{jt}) = \max_{i_{jt}, rd_{jt}} E\left\{\pi(K_{jt}, \omega_{jt}, \upsilon_{jt}) + \beta EV(S_{jt+1}) - C(rd_{jt-1}, rd_{jt}, \gamma_{jt}^{rd})\right\}$$

where the outer expectation is taken over the cost shocks to R&D (γ_{jt}^{rd}) and the inner expectation is taken over the productivity innovation (η_{wjt}, η_{vjt}).[8]

[8]The investment decisions are not necessary for the identification of biased technology in this paper,

The first order conditions imply that the capital share and labor share are:

$$
\begin{aligned}
S_{jt}^{l} \exp(\varepsilon_{jt}) &\equiv \frac{W_t L_{jt}}{P_t Y_{jt}} = a_l + a_{ll}(\upsilon_{jt} + \ln L_{jt}) + a_{kl}(\omega_{jt} + \ln K_{jt}) + a_{lm} \ln M_{jt} \qquad (10) \\
S_{jt}^{m} \exp(\varepsilon_{jt}) &\equiv \frac{P_t^m M_{jt}}{P_t Y_{jt}} = a_m + a_{mm} \ln M_{jt} + a_{km}(\omega_{jt} + \ln K_{jt}) + a_{lm}(\upsilon_{jt} + \ln L_{jt})
\end{aligned}
$$

which are functions of the unobserved capital efficiency and labor efficiency. This equation corresponds to equation (3) in section 3. In principle, the unobservables can be recovered from the capital and labor shares under regularity conditions. The above factor share equation system can be rearranged to derive:

$$
\begin{bmatrix} a_{kl} & a_{ll} \\ a_{km} & a_{lm} \end{bmatrix} \begin{bmatrix} \omega_{jt} \\ \upsilon_{jt} \end{bmatrix} = \begin{bmatrix} S_{jt}^{l} \exp(\varepsilon_{jt}) - (a_l + a_{ll} \ln L_{jt} + a_{kl} \ln K_{jt} + a_{lm} \ln M_{jt}) \\ S_{jt}^{m} \exp(\varepsilon_{jt}) - (a_m + a_{km} \ln K_{jt} + a_{lm} \ln L_{jt} + a_{mm} \ln M_{jt}) \end{bmatrix}
$$

Assumption (invertibility): $\det \begin{bmatrix} a_{kl} & a_{ll} \\ a_{km} & a_{lm} \end{bmatrix} \neq 0.$

The invertibility assumption requires that $a_{kl} a_{lm} \neq a_{km} a_{ll}$. This requirement is not strong, in general, and is satisfied except in very extreme cases. Moreover, this assumption does not place a significant restriction on the scale economies, elasticity of substitution, first order and second order conditions of the static optimization.

Under the invertibility assumption, the latent productivity variables can be recovered as:

$$
\begin{bmatrix} \omega_{jt} \\ \upsilon_{jt} \end{bmatrix} = \begin{bmatrix} a_{kl} & a_{ll} \\ a_{km} & a_{lm} \end{bmatrix}^{-1} \begin{bmatrix} S_{jt}^{l} \exp(\varepsilon_{jt}) - (a_l + a_{ll} \ln L_{jt} + a_{kl} \ln K_{jt} + a_{lm} \ln M_{jt}) \\ S_{jt}^{m} \exp(\varepsilon_{jt}) - (a_m + a_{km} \ln K_{jt} + a_{lm} \ln L_{jt} + a_{mm} \ln M_{jt}) \end{bmatrix} \qquad (11)
$$

Given parameters and the data, the capital and labor efficiencies can be solved for from equation (11). Then by inserting the expressions in equation (11) into the original

but the additional moments associated with them can be used to improve the efficiency of the estimator.

production function equation to substitute ω_{jt} and υ_{jt}, we have the estimation equation:

$$\begin{aligned} \ln Q_{jt} &= a_0 + a_k\left(\omega_{jt} + \ln K_{jt}\right) + a_l\left(\upsilon_{jt} + \ln L_{jt}\right) + a_m \ln M_{jt} \\ &+ \frac{1}{2}a_{kk}\left(\omega_{jt} + \ln K_{jt}\right)^2 + \frac{1}{2}a_{ll}\left(\upsilon_{jt} + \ln L_{jt}\right)^2 + \frac{1}{2}a_{mm}\left(\ln M_{jt}\right)^2 \\ &+ a_{kl}\left(\omega_{jt} + \ln K_{jt}\right)\left(\upsilon_{jt} + \ln L_{jt}\right) + a_{km}\left(\omega_{jt} + \ln K_{jt}\right)\ln M_{jt} \\ &+ a_{lm}\left(\upsilon_{jt} + \ln L_{jt}\right)\ln M_{jt} + \varepsilon_{jt} \end{aligned} \tag{12}$$

where

$$\begin{bmatrix} \omega_{jt} \\ \upsilon_{jt} \end{bmatrix} = \begin{bmatrix} a_{kl} & a_{ll} \\ a_{km} & a_{lm} \end{bmatrix}^{-1} \begin{bmatrix} S^l_{jt}\exp(\varepsilon_{jt}) - \left(a_l + a_{ll}\ln L_{jt} + a_{kl}\ln K_{jt} + a_{lm}\ln M_{jt}\right) \\ S^m_{jt}\exp(\varepsilon_{jt}) - \left(a_m + a_{km}\ln K_{jt} + a_{lm}\ln L_{jt} + a_{mm}\ln M_{jt}\right) \end{bmatrix} \tag{13}$$

The non-structural error enters the estimation equation nonlinearly and is nonseparable from regressors. We can estimate equation (12) using nonlinear least square (NLLS) or generalized method of moments (GMM). In this paper, I use GMM to estimate the parameters. I first solve for ε_{jt} from equation (12) and (13). Then I use ε_{jt} to form the moment conditions to estimate the parameters. The moment conditions used are: $E(\varepsilon_{jt}) = 0$ and ε_{jt} is orthogonal to $\ln K_{jt},\ \ln L_{jt},\ \ln M_{jt},\ (\ln K_{jt})^2,\ (\ln L_{jt})^2,\ (\ln M_{jt})^2,\ \ln K_{jt}\ln L_{jt}$, $\ln K_{jt}\ln M_{jt}$, and $\ln L_{jt}\ln M_{jt}$.

A technical problem is that there is no closed form solution to ε_{jt}. If we solve for ε_{jt} numerically, the estimation will be very slow because it involves solving for ε_{jt} from an equation for each data point during each iteration. To speed up the estimation, I use the first-order Taylor expansion around $\varepsilon_{jt} = 0$ to approximate ε_{jt}. I expect that $|\varepsilon_{jt}|$ is small, since ε_{jt} is the logarithm of the measurement error in the production function. In this case, the approximation of ε_{jt} based on the Taylor expansion is close to its true value. The technical details are reported in the Appendix B.

The advantages of this new method are multi-folded. Firstly, the invertibility condition can be easily tested. Secondly, in my new method, the parameters of static variables are identified although there are still collinearity, because I recover the unobserved productivity parametrically. This overcomes the collinearity problem and thus the nonidentification of the static parameters in the first stage of Olley and Pakes (1996) and Levinsohn and Petrin (2003). Another advantage of the new method is that the identification does not depend on any restrictive Markov process assumptions of productivity evolution. As a result, cross sectional data is sufficient for the estimation.

5 Empirical Results

I estimate the model for each of the four industries: Clothing, Industrial Paper and Paper Board Making, Production Equipments for Foods, Beverages and Tobaccos, and Motor Vehicles. Estimating separately allows industries to have different production functions and different patterns of technological dispersion and evolution. Table 4 reports the estimation results. The production parameters are statistically significant (except the constants). I test the invertibility condition for each of the industries based on the estimation results and it holds for all of them. The test details are reported in the Appendix D.

The economic meaning of the original parameters in the translog function is not very intuitive. I translate them into the output elasticity and scale economies, which are reported in Table 5. The mean output elasticity of labor and material are calculated from equation (10) and the capital elasticity from a similar equation:

$$\hat{S_{jt}^k} = a_k + a_{kk}(\omega_{jt} + \ln K_{jt}) + a_{kl}(\upsilon_{jt} + \ln L_{jt}) + a_{km} \ln M_{jt}.$$

In the translog production function, the output elasticity of input depends on both the production parameters and the point at which the production happens, as shown in equation (10). The reported output elasticity and scale economies are specific to the production point observed in the data. Table 5 shows that the estimated output elasticities of capital, labor and material are within reasonable range. In the Clothing and Equipment industries, the labor elasticity is relatively higher and the capital elasticity is relatively lower. In the Paper&Paper Board making and Motor Vehicles industries the labor elasticity is low and the capital elasticity is high. This is consistent with the fact that the former two industries are more labor intensive while the latter two are more capital intensive. All four industries show decreasing returns to scale at the production point observed in the data. However, firms may have increasing returns to scale before reaching the observed production point, as the returns to scale vary with the production point.

5.1 Elasticity of Substitution

There are two challenges in computing the elasticity of substitution for the translog production function. First, the translog production allows for a non-constant elasticity of substitution, which changes with the production points the firm chooses. Also, there is no closed form solution to the elasticity of substitution in the translog function. Therefore, I calculate a numerical elasticity of substitution for each observation instead. The technical details are reported in the Appendix C.

Table 6 reports the nine quantiles of the elasticity of substitution for each of the four industries. The medians of the elasticity of substitution are smaller than one, ranging from 0.1046 to 0.4932. These are smaller than the ones reported in the literature under constant elasticity of substitution assumption. One reason may be that the assumed neutral technology and the effect of biased technological dispersion/change on the input demand are captured by the estimated elasticity of substitution. Moreover, the results here also show that there is a significant dispersion in the elasticity of substitution even among firms within one industry. Taking the Clothing industry for example, the first quantile of the elasticity of substitution is 0.2162 and the ninth is 0.9090. Figure 2 shows a plot of the kernel density of elasticity of substitution for the Clothing industry as a example. It shows that the dispersion of elasticity in this industry is large. One explanation for the dispersion is that different sized firms differ in their ability to substitute labor for capital. In fact, I find a negative correlation between firm size (measured by sales) and the elasticity of substitution. This suggests that small firms can substitute labor and capital more easily than large firms.[9]

The smaller-than-one median elasticity of substitution has a important implication for the relationship between biased technological change and input demand. It implies that inputs are generally gross complements. When, for example, capital efficiency increases, the firm will use less capital and more labor as it cannot substitute capital for labor efficiently. Therefore, change in capital efficiency actually saves capital when the elasticity of substitution is smaller than one. This decreases the capital-labor ratio. To explain the opposite movements of the capital-labor ratio and the wage-interest ratio observed in

[9]This result is different from Klump and de La Grandville (2000), which found that larger firms have higher elasticity of substitution. The difference comes from the fact that they do not consider the dispersion of the capital-labor efficiency ratio across firms, which makes their estimates inconsistent in the context of biased technical dispersion.

some Chinese industries, we expect to see that capital efficiency grows faster than labor efficiency, which is a capital-saving technological change given that capital and labor are gross complements.

6 Tests of Biased Technology

We can recover the firm-time specific capital efficiency (ω_{jt}) and labor efficiency (υ_{jt}) from equation (13). In this subsection, I test the biased technology against the constant capital-labor efficiency ratio. The testing strategy is based on the testing statistics developed in Hadri (2000), which is a extension of Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests for panel data.[10] I test both the biased technological change over time and the biased technological dispersion across firms. This exercise provides evidence of biased technological change and biased technological dispersion at the firm level.

6.1 Test for Biased Technological Change

If the capital-labor efficiency ratio is constant, then the observed efficiency ratio, b_{jt}, is constant over time. By allowing shocks to b_{jt}, the efficiency ratio equals the sum of a constant and an i.i.d random shock, u_{jt}. That is,

$$b_{jt} = \alpha_j + u_{jt},$$

for all j. The test of neutral technology is equivalent to the test that the technology bias, b_{jt}, is level stationary over time. If there is biased technological change, then b_{jt} changes over time. We can set the model as:

$$b_{jt} = \alpha_{jt} + u_{jt},$$

where α_{jt} captures everything that affects the change of the capital-labor efficiency ratio. Let α_{jt} be a random walk process, $\alpha_{jt} = \alpha_{jt-1} + v_{jt}$, where v_{jt} is an i.i.d random shock with variance σ_v^2. If the technological change maintains a constant capital-labor ratio, then α_{jt}

[10]Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests are used for testing a null hypothesis that an observable time series is stationary around a deterministic trend. Such models were first proposed by Bhargava (1986). Kwiatkowski, Phillips, Schmidt, and Shin (1992) proposed a test of the null hypothesis that an observable series is trend stationary (stationary around a deterministic trend)

is a constant. This is equivalent to saying that $\sigma_v^2 = 0$. If the technological change is not neutral, α_{jt} changes over time and $\sigma_v^2 \neq 0$. The test hypothesis can be set as follows,

$$H_0 : \frac{\sigma_v^2}{\sigma_u^2} = 0 \text{ (constant capital-labor efficiency ratio)}$$
$$H_1 : \frac{\sigma_v^2}{\sigma_u^2} \neq 0 \text{ (biased technological change)}$$

Under the null hypothesis, $b_{jt} = \alpha_j + u_{jt}$. I estimate the equation under the null hypothesis and denote $\widehat{u_{jt}}$ as the regression residual. Denote

$$LM = \frac{\frac{1}{N}\sum_{j=1}^{N}\left(\frac{1}{T_j^2}\sum_{t=1}^{T_j}\widehat{S}_{jt}^2\right)}{\widehat{\sigma_u^2}}$$

where $\widehat{S}_{jt}$ is the partial sum of u_{jt}, $\widehat{S}_{jt} = \sum_{\tau=1}^{t}\widehat{u_{j\tau}}$; $\widehat{\sigma_u^2}$ is a consistent estimator of σ_u^2. Under the null hypothesis, $\widehat{\sigma_u^2} = \frac{1}{N}\sum_{j=1}^{N}\left(\frac{1}{T_j - 1}\sum_{t=1}^{T_j}\widehat{e}_{jt}^2\right)$. The test statistic is written as:

$$Z = \frac{\sqrt{N}\,(LM - \mu_W)}{\sigma_W}$$

where μ_W and σ_W, respectively, represent the mean and standard deviation of the random variable W, which is defined as the integration of a standard Brownian bridge over the interval $[0, 1]$. It is a standard result that $\mu_W = \frac{1}{6}$ and $\sigma_W = \frac{1}{\sqrt{45}}$. Hadri (2000) proved that under the null hypothesis, the statistic has asymptotic standard normal distribution.[11]

Table 8 reports the test results. For all four industries, the test statistic is much larger than the upper bound of the 1% confidence interval. We can safely reject the null hypothesis and conclude that capital efficiency and labor efficiency grow at different speeds. This test provides solid evidence of biased technological change in these industries during the data period. Given evidence of biased technological change in China, models of neutral technological change will misestimate the contribution of technological change to economic growth; therefore, a model with biased technological change is required. The individual contribution of capital efficiency and labor efficiency to the economic growth is also important from a policy point of view.

[11] See Hadri (2000) for more details if interested.

6.2 Test for Biased Technological Dispersion

The test for biased technological dispersion is similar to the test for biased technology. If the capital-labor efficiency ratio has no dispersion across firms, then the observed efficiency ratio, b_{jt}, is a constant across firms for any given period. That is, $b_{jt} = \alpha_t + u_{jt}$, for all t. The challenge of testing the biased technology is that there is no clear order of cross sectional firms. The testing strategy is to choose a way to order the cross sectional firms, and mimic the testing strategy discussed in the above subsection. The way of ordering is not important as long as it is not correlated with the u_{jt}, since b_{jt} will always be a constant plus an i.i.d random shock if there is no biased technological dispersion. In the test, I order firms randomly, which should be uncorrelated with u_{jt}.

The null hypothesis is that there is no dispersion of the capital-labor efficiency ratio across firms for any given period, and the alternative hypothesis is that there is biased technological dispersion. The results are reported in table 9. The test statistic is much larger than the upper bound of the 1% significance interval, indicating that I can safely reject the null hypothesis. This means that there is biased technological dispersion across firms.

The evidence of biased technological dispersion across firms has important implications for the sources of economic growth. In this case models of neutral technology ignore the firm heterogeneity in the capital-labor efficiency ratio, which leads to inconsistent estimation of firm productivity. This will lead to erroneous estimates of the contribution of technological change to economic growth. Moreover, firms with different capital-labor efficiency ratios differ in their relative demand of capital and labor. As the capital-labor efficiency ratio changes, capital and labor move across firms. This redistribution of inputs will also impact growth of economy.

The evidence of biased technological dispersion across firms also has important implications for may other fields. In Industrial Organization, it will affect the results related to the entry/exit and size distribution of firms. With biased technological dispersion, firms not only differ in their level of productivity, but also in their relative capital-labor efficiency ratio. Both of these affect the firm's behavior such as entry/exit decisions. For example, when there is an unexpected shock which increases the capital price significantly, the cost to firms with lower capital efficiency (who thus use more capital) will increase much more than for firms with higher capital efficiency. As a result, the former will shrink or even exit and the latter will grow, even if they have the same level of productivity (measured by TFP) before the shock. In international trade, the biased technological dispersion also has wide applications. For example, it will affect the production location choice of multinational firms. Firms with low labor efficiency (thus high labor demand) are more likely to establish their plants in labor abundant countries.

7 Biased Technological Dispersion

This section discusses the biased technological dispersion across firms and shows that this unobserved firm heterogeneity explains a large part of the dispersion of capital-labor ratios across firms. The next section discusses the biased technological change over time.

The efficiency ratio, as defined, is calculated as the difference between ω_{jt} and υ_{jt}. Figure 3 shows the relationship between the efficiency ratio and firm size. It is shown that large firms have a higher technology ratio. The correlation between the efficiency ratio and firm size ranges from 0.7768 to 0.9586 in the examined industries, as shown in table 10. This results implies that larger firms are using technologies which manage capital more efficiently relative to labor.

To explore how much the biased technological dispersion explains the dispersion of K/L, I run a regression of the capital-labor ratio on the efficiency ratio and all other factors considered in Table 3. The results are shown in table 11. It is shown that adding the technology ratio alone in the regression increases the explained variation of the capital-labor ratio significantly. In the Clothing industry, adding the technology bias increases the explained dispersion of the capital-labor ratio from 9.57% to 75.29%. The efficiency ratio alone explains 65.72% of the variation of the capital-labor ratio across firms, while the combined effect of the wage-interest rate ratio, firm size, ownership and year dummy accounts for less than 10%. In the other three industries, the technology ratio alone can explain the dispersion of the capital-labor ratio by 59.56%, 45.82% and 75.38% respectively.

The correlation between the technology ratio and the capital-labor ratio is significant and negative, as indicated by the negative coefficient on the technology ratio in the regression. This means that firms with a higher capital-labor efficiency ratio use less capital and more labor. This finding is consistent with the fact that capital and labor are gross complements (elasticity of substitution is smaller than one). This finding implies that firms which are eager to save capital try to increase capital efficiency, and firms which are eager to save labor try to increase labor efficiency. In the case of China, labor is abundant and capital is scarce. Firms face higher pressure to save capital. We expect that capital efficiency develops faster than labor efficiency.

The regression also shows that the wage-interest ratio and firm size both have a positive effect on capital-labor ratio. State owned firms have a higher capital labor ratio and FDI firms have a lower capital-labor ratio, compared to other non-SOE firms.

8 Biased Technological Change

This section investigates the feature of biased technological change. I compute the mean of capital efficiency and labor efficiency weighted by firm sales for each industry-year. Then the growth rate is computed as the percentage change in the mean efficiencies. Note that when computing the mean, both new firms and continuing firms are included, so the calculated efficiency growth rates involve the contribution of both continuing firms, entering firms and exiting firms.

Table 12 shows that the capital efficiency grew much faster than labor efficiency in all four industries. Capital efficiency grew at 23.13%-33.42% annually, while labor efficiency at -1.94%-4.80% annually in these industries. This is different from the findings in developed countries, which found that labor efficiency grows faster (Kalt, 1978; Cowing and Stevenson, 1981; Antras, 2004; Klump, McAdam, and Willman, 2007). One explanation for the difference is the different endowment structure in China and developed countries. China has abundant labor but scarce capital, so Chinese firms develop capital saving technology to maximize profit. In developed countries, capital is abundant and labor is scarce and expensive, so firms in these countries develop labor saving technology to maximize profit. As capital and labor are gross complements, a capital-saving technology requires that capital efficiency grows faster than labor efficiency. A labor-saving technology requires that labor efficiency grows faster than capital efficiency.

Another reason for the fast growth of capital efficiency and slow growth of labor efficiency is the technology-promoting policy, which provides strong incentives for firms to update their technology. However, in the policy documents, the advanced technologies are defined mainly by the equipment used. This says very little about the labor-augmenting technologies. This very likely has an impact on firms' technology choices.

Another explanation is that firms in China do not have incentive to develop labor saving technologies (by increasing labor efficiency) because China has an abundant labor supply. In contrast, firms in developed countries face high wages and, as a result, they try harder to improve labor efficiency to save labor.

As shown in Table 2, the capital-labor ratio decreases when the wage-interest rate ratio increased in clothing and motor vehicle industries from 2000 to 2007. This is counterintuitive. As labor becomes relatively more expensive, firms will use relatively more capital and less labor, all other things constant. As a result, the capital-labor ratio should increase. The biased technological change provides a candidate explanation for this abnormal observation. In these industries, the capital efficiency grows faster than labor efficiency during this period, as shown in table 12. As a reaction to this, firms chose to use relatively more labor than capital, because capital and labor are gross complements in these industries (the estimated elasticity of substitution is smaller than one). This drives down the capital-labor ratio.

Note the estimation does not rely on the restrictive assumptions about the productivity evolution process. As a post-regression check, I run some reduced form regressions to study the factors affecting the biased technological change. I am particularly interested in the effect of R&D on technological change and the persistence of capital and labor efficiencies. If R&D has an impact on the future capital-labor efficiency ratio, then firms can endogenously determine the direction of biased technological change by choosing the level of R&D. The persistence of capital and labor efficiencies are important, because they measure how much productivity firms can carry over to future production. If the efficiencies are persistent, firms will have a higher incentive to improve their productivity, because with persistent productivity they can benefit from this for multiple periods in the future once their productivity is improved today.

I regress capital and labor efficiencies on R&D, lagged capital efficiency, and lagged labor efficiency. I also control for ownership by adding dummy variables for SOE and FDI. The results are reported in table 13.

The first finding is that both capital efficiency and labor efficiency are very persistent. The persistence coefficient for capital efficiency is 0.8476 in the Clothing industry; 0.8834 in the Paper & Paper Board Making industry; 0.8839 in the Production Equipments industry; and 0.6925 in the Motor Vehicles industry. This indicates that firms can carry a large part of their capital efficiency to the next period. At the same time, labor efficiency has a positive impact on future capital efficiency in the first three industries and has no significant effect in the Motor Vehicle industry. Note that because ω_{jt} and υ_{jt} are the logarithms of the absolute capital efficiency and labor efficiency, the persistence parameters are actually the elasticities between the current productivity and future productivity. Taking the Clothing industry for example, the result says that an 1% increase in current capital efficiency increases future capital efficiency by 0.8476%. A 1% increase in current labor efficiency increases future capital efficiency by 0.1501%, much smaller than the effect of capital efficiency.

Labor efficiency is also persistent in these industries. The persistence parameters in the four industries are 0.6587, 0.8079, 0.7806 and 0.8884 respectively. This means that firms can carry over a large part of their labor efficiency to the future. A 1% increase in current labor efficiency will increase future labor efficiency by 0.6587%, 0.8079%, 0.7806% and 0.8884%, respectively. However, the current capital efficiency does not have a statistically significant effect on future labor efficiency, except in the Motor Vehicle industry. It is still unclear why this is the case, but it probably means that expertise in managing capital does not increase the expertise in managing labor in Chinese firms. The persistence of capital and labor efficiencies provide extra incentive for firms to invest in productivity improvement, because the improvement is carried over to future periods.

The second finding is that R&D has a positive impact on capital efficiency in all four industries. This suggests that firms can endogenously affect their capital efficiency through R&D investment. However, R&D has no statistically significant effect on the labor efficiency. This may be due to two reasons. First, the technology-promoting policies issued in 1999 and subsequent years defined the technologies by production equipment which determines the capital efficiency, but not labor efficiency. Firms receive economic incentives (such as tax credits, loan support and land rationing) only when they use the technologies defined in these policies. As a result, it is likely that the technological changes brought on by these policies are mainly focused on capital efficiency. Another possible reason is related to the accounting system. The investment in improving labor efficiency is not usually accounted in R&D. That's why the observed R&D has no significant effect on labor efficiency. In both cases, firms can choose their level and ratio of capital-labor efficiency by choosing investment in R&D (and other labor efficiency-related investments).

Ownership also has an impact on technology bias , which is consistent with the facts documented in China. Compared to non-SOE firms, SOEs have lower capital efficiency in all industries. SOEs also have lower labor efficiency in the Paper & Ppaper Board Making and Motor Vehicles industries. In the other two industries the SOEs have statistically indifferent labor efficiency compared to non-SOEs. FDI firms in these industries do not show a significant advantage in capital efficiency and labor efficiency, which is probably due to the fact that these industries are not high-tech industries and FDI firms do not have many technology advantages.

9 Contribution of Biased Technological Change to Economic Growth

The multidimensional productivity measure with biased technological change and biased technological dispersion allows us to answer some fundamental questions about economic growth in China. In particular, how much does technological change contribute to industrial growth? How much do capital efficiency and labor efficiency each contribute to the growth? And, is the growth in China sustainable? The answers to the first two questions shed some light on the sustainability of the growth in the Chinese economy. If the technological change contributes a lot to the industrial growth, we should be optimistic with the sustainability of the high growth rate in the Chinese economy. Otherwise, the economic growth may stagnate after the drainage of the input growth. The answer to the second question further lends some basis to the growth policies, by evaluating the relative importance of the capital efficiency change and labor efficiency change in the economic growth in China.

This section computes the sources of economic growth based on the estimates of biased technology. I decompose the growth rate of industrial output (gross output or value added) into several sources: capital, labor, material, capital efficiency, labor efficiency and entry/exit. Note that in this decomposition, the first five factors cover only effects from continuing firms. The net entry/exit effect contains the total effect from entering/exiting firms, which arises from the replacement of both technology and physical inputs by entering/exiting firms. I put the technical details of the decomposition in Appendix E.

Table 14 and Table 15 report the results for gross output and value added, respectively.

The growth rate in the four industries, as reported in the last column in these two tables, ranges in 13.03%-18.43% for gross output, and 23.74%-26.30% for value added. These growth rates are much higher than the average growth rate of the Chinese economy over these years, indicating that manufacturing sectors grow faster than the average economy. There was significant entry and exit in these industries during these years, in which entry and exit contributes to 4.96% of the growth in the Clothing industry. In the other three industries, entry/exit contributes negatively to the gross growth. Because the number of firms was increasing at in these industries, the negative contribution of entry/exit to growth implies that the entering firms are smaller than the exiting firms. To understand the sources of growth in China, in the rest of this section I will focus on the growth of value added, which is similar to the definition of gross domestic product (GDP). I will also use the results from gross output as a verification.

9.1 Continuing Firms

Total Contribution of technological change The first interesting finding is that technological change as a whole contributes in large to the growth of value added in all four industries. The sum of the second and third columns in table 15 represents the total contribution of technological change to the growth of value added. In the four industries, technological change increased the growth rate of value added by 12.67%-21.16%. That accounts for 52.70%, 63.61%, 63.46%, and 89.13% of the total growth of value added in these industries. In contrast, the increased usage of capital and labor, in total, increased the growth rate of value added by 7.5%-13.43%. The contribution of technological change is higher than that of increased usage of capital and labor.

The results from the gross output also show that technological change significantly contributes to the growth of gross output. As reported in table 14, technological change contributes to the growth of gross output by 1.37%-2.54% in the four industries. That is comparable to or even higher than the combined contribution of capital and labor, which ranges from 0.94%-2.28% in the four industries. This indicates that the growth of these industries will not stagnate if capital and labor stop growing, if the technological change can maintain its current rate.

Contribution of capital efficiency and labor efficiency The second finding is that the contribution of technological change to the economic growth is mainly due to capital efficiency change. In Table 15, capital efficiency change increased the growth rate of value added by 11.40%-22.28% in the four industries. In contrast, labor efficiency change contributed 1.27% to the growth in the Clothing industry and had a negative contribution to the growth of value added in the other three industries. Results from the gross output growth show similar results: capital efficiency change contributes to the output growth positively by 1.60% - 3.29% and labor efficiency change contributes negatively by -0.09%- -1.9% except in the Clothing industry (0.21%). This result is consistent with the finding that capital efficiency grows faster than labor efficiency, as shown in Table 12.

This finding has multiple implications to growth policy. On one hand, it reflects that the technology-promoting policies, that started at the end of the 1990s, mainly affected the capital efficiency. In those policies, the definition of new technologies focused on the equipment used but neglected the organization of workers. As a result, firms used more capital-biased technology. On the other hand, the finding also implies that labor efficiency change has great potential to help promote economic growth in the future. When the cheap labor from the agricultural sector is drained, policy makers will need to encourage the development of labor-saving technology in order to maintain the economic growth.

9.2 Entering and Exiting Firms

The net effect of entry and exit contributes in large to the output growth, from -0.99%-6.62%. This contribution is due to both the change in the usage of inputs and the difference in the technology used by the entering firms compared to exiting firms. Note that entry/exit contributes to the output growth through the replacement of both technology and physical inputs. This section shows the productivity features of entering and exiting firms.

Table 16 compares the efficiencies of entering, exiting and continuing firms. Compared to exiting firms, the entering firms have an advantage in at least one of the efficiencies. In clothing and motor vehicles, entering firms have higher capital efficiency, but slightly lower labor efficiency than exiting firms. In the Paper & Paper Board Making and Equipments industries, entering firms have both higher capital efficiency and labor efficiency. These results suggest that firm turnover plays an important role in technological change.

10 Concluding Remarks

This paper builds and estimates a structural model of firms' production decisions with different capital- and labor-augmenting efficiencies across firms. This setup allows for a factor-biased technological change over time and factor-biased technological dispersion across firms. I develop a new method to identify and estimate the biased technology from input-output data. The identification relies on the first order conditions of firms' optimal input choices to recover the unobserved productivities. The use of first order conditions also establishes a link between the biased technological change and the elasticity of substitution. This additional restriction overcomes the Diamond's Impossibility Theorem (Diamond, McFadden, and Rodriguez, 1978) and leads to the identification of both the biased technological change and the elasticity of substitution. This method can estimate the firm-level technology bias at any time.

The estimation results using a firm-level panel data set during 2000-2007 in China provide firm-level evidence of biased technological change over time and biased technological dispersion across firms. The results show that during 2000-2007, capital efficiency grew much faster than labor efficiency in China. The results also show that large firms manages capital more efficiently relative to labor, and the biased technological dispersion explains a large part of the dispersion of the capital-labor ratio among firms.

This model provides a method to explore some fundamental questions in economic growth, such as the contribution of technological change and, more specifically, the contribution of capital- and labor-augmenting efficiency changes to economic growth. These questions are especially important for China, which has maintained a high growth rate in the past three decades. In the application, I find that technological change contributes to over one half of the growth of value added. From 2000 to 2007, the value added grows at a rate of 23.74%-26.30% in the four industries, of which 12.67%-21.16% is explained by the technological change. This finding indicates that after the implementation of the technology-promoting policies since 1999, the technological change became the major source of growth in these industries. This finding sheds some positive light on the sustainability of the growth of the Chinese economy. Another important finding is that the high contribution of technological change is mainly due to capital efficiency change. The labor efficiency change has a relatively small and even negative contribution. This reflects the effect of the technology-promoting policy during the data period, which emphasizes the adoption of new production lines but ignores the labor efficiency change. It also suggests that Chinese firms can further explore their potential by improving their labor efficiency in the future.

The firm-level technology bias has potentially wide applications in many fields. It captures another layer of firm heterogeneity in productivity and emphasizes that the composition of input efficiencies is an important firm heterogeneity in addition to the productivity level. It predicts that firms with different compositions of capital efficiency and labor efficiency will react differently to the same economic shock even if they have the same measured neutral technology level. For example, subject to a negative capital price shock, firms with higher capital efficiency will expand their production and firms with lower capital efficiency will shrink even if they all have the same measured neutral technology before the shock. This is of vital importance when performing firm behavior analysis. In industrial organization, for example, the unobserved composition of technology is important in the study of entry/exit, growth/shrinkage and the size distribution of firms. In international trade, the composition of technology is important to understanding decisions of multinational firms (e.g. outsourcing decision and production location choice around the world). In policy analysis, the composition of technology is important in evaluating the effectiveness and fairness of a policy in public economics. For example, if some firms continuously use more capital relative to labor while others instead use more labor due to technology bias, a seemingly neutral policy, such as an investment tax rebate policy, may favor the more capital-intensive firms/industries.

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Appendices

Appendix A Proof of Proposition 1

By the definition of E^l and E^m, the function $f(x;y)$ is written as

$$f(x;y) = \begin{cases} E^l_{jt} - S_{Ljt}\exp(\varepsilon_{jt}), \\ E^m_{jt} - S_{Mjt}\exp(\varepsilon_{jt}). \end{cases}$$

The first order derivative of $f(x;y)$ with respect to y is

$$\frac{\partial f(x;y)}{\partial y} = \begin{matrix} E^l_{jt\omega} & E^l_{jt\upsilon} \\ E^m_{jt\omega} & E^m_{jt\upsilon} \end{matrix} .$$

Under the condition that given the production parameters $\frac{E^l_{jt\omega}}{E^m_{jt\omega}} \neq \frac{E^l_{jt\upsilon}}{E^m_{jt\upsilon}}$ at the data point (x^{data}, y^{data}), we have

$$\frac{\partial f(x;y)}{\partial y} \mid_{(x^{data},y^{data})} \neq 0.$$

Also, according to the first order conditions, we have

$$f(x;y) \mid_{(x^{data},y^{data})} = 0.$$

Then following the Implicit Function Theorem, there exists a $\epsilon > 0$ and a two-dimensional function $Z(\cdot;\theta) = \begin{pmatrix} \omega(\cdot;\theta) \\ \upsilon(\cdot;\theta) \end{pmatrix}$, such that for any $(x,y) \in \left\{(x,y) : \left\|(x,y) - (x^{data}, y^{data})\right\| < \epsilon\right\}$,

$$y = Z(x;\theta) = \begin{pmatrix} \omega(x;\theta) \\ \upsilon(x;\theta) \end{pmatrix}.$$

This completes the proof of proposition 1. ■

Appendix B Taylor Expansion to Speed Up the Program

This appendix shows how to solve for ε_{jt} from the estimation equation using Taylor expansion in order to speed up the estimation. The solved ε_{jt} then is used to form the moment conditions in the estimation. As $|\varepsilon_{jt}|$ is small, since ε_{jt} is the logarithm of the measurement error in the production function, the approximation of ε_{jt} based on Taylor expansion is close to its true value. This approximation avoids solving equations for ε_{jt} at each data point for each iteration and can significantly speed up the program.

The estimation equation is written as,

$\ln Q_{jt} = (a_k + a_{km}\ln M_{jt})(\omega_{jt}) + (a_l + a_{lm}\ln M_{jt})(\upsilon_{jt})$
$+\frac{1}{2}a_{kk}(\omega_{jt} + \ln K_{jt})^2 + \frac{1}{2}a_{ll}(\upsilon_{jt} + \ln L_{jt})^2 + a_{kl}(\omega_{jt} + \ln K_{jt})(\upsilon_{jt} + \ln L_{jt})$
$+a_0+(a_k + a_{km}\ln M_{jt})(\ln K_{jt})+(a_l + a_{lm}\ln M_{jt})(\ln L_{jt})+\frac{1}{2}a_{mm}(\ln M_{jt})^2+a_m \ln M_{jt}+\varepsilon_{jt}$

where

$$\begin{bmatrix} \omega_{jt} \\ \upsilon_{jt} \end{bmatrix} = \begin{bmatrix} a_{kl} & a_{ll} \\ a_{km} & a_{lm} \end{bmatrix}^{-1} \begin{bmatrix} S_{jt}^{l} \exp(\varepsilon_{jt}) - (a_l + a_{ll} \ln L_{jt} + a_{kl} \ln K_{jt} + a_{lm} \ln M_{jt}) \\ S_{jt}^{m} \exp(\varepsilon_{jt}) - (a_m + a_{km} \ln K_{jt} + a_{lm} \ln L_{jt} + a_{mm} \ln M_{jt}) \end{bmatrix}$$

Denote $D = \begin{bmatrix} a_{kl} & a_{ll} \\ a_{km} & a_{lm} \end{bmatrix}^{-1}$ and D_{mn} as the element of matrix D in row m and column n. The derivative of $\ln Q_{jt}$ with respect to ε_{jt} evaluated at $\varepsilon_{jt} = 0$ is

$$\begin{aligned} \frac{d \ln Q_{jt}}{d\varepsilon_{jt}}|_{\varepsilon_{jt}=0} &= (a_k + a_{km} \ln M_{jt}) \left(D_{11} S_{jt}^{l} + D_{12} S_{jt}^{m}\right) + (a_l + a_{lm} \ln M_{jt}) \left(D_{21} S_{jt}^{l} + D_{22} S_{jt}^{m}\right) \quad (14) \\ &+ \left[a_{kk} \left(\omega_{jt}|_{\varepsilon_{jt}=0} + \ln K_{jt}\right) + a_{kl} \left(\upsilon_{jt}|_{\varepsilon_{jt}=0} + \ln L_{jt}\right)\right] \left(D_{11} S_{jt}^{l} + D_{12} S_{jt}^{m}\right) \\ &+ \left[a_{ll} \left(\upsilon_{jt}|_{\varepsilon_{jt}=0} + \ln L_{jt}\right) + a_{kl} \left(\omega_{jt}|_{\varepsilon_{jt}=0} + \ln K_{jt}\right)\right] \left(D_{21} S_{jt}^{l} + D_{22} S_{jt}^{m}\right) + 1 \end{aligned}$$

Taking the first order expansion of the function $\ln Q_{jt}$ at point $\varepsilon_{jt} = 0$, we have

$$\begin{aligned} \ln Q_{jt} &= \ln Q_{jt}|_{\varepsilon_{jt}=0} + \frac{d \ln Q_{jt}}{d\varepsilon_{jt}}|_{\varepsilon_{jt}=0} (\varepsilon_{jt} - 0) + o(\varepsilon_{jt}) \\ \ln Q_{jt} &= \ln Q_{jt}|_{\varepsilon_{jt}=0} + \frac{d \ln Q_{jt}}{d\varepsilon_{jt}}|_{\varepsilon_{jt}=0} (\varepsilon_{jt} - 0) + o(\varepsilon_{jt}) \end{aligned}$$

Assume that for given data, $\left|\frac{d \ln Q_{jt}}{d\varepsilon_{jt}}\right|$ is bounded from zero for any parameter at $\varepsilon_{jt} = 0$, so we have

$$\begin{aligned} \varepsilon_{jt} &= \left[\ln Q_{jt} - \ln Q_{jt}|_{\varepsilon_{jt}=0} - o(\varepsilon_{jt})\right] / \frac{d \ln Q_{jt}}{d\varepsilon_{jt}}|_{\varepsilon_{jt}=0} \\ &\approx \left[\ln Q_{jt} - \ln Q_{jt}|_{\varepsilon_{jt}=0}\right] / \frac{d \ln Q_{jt}}{d\varepsilon_{jt}}|_{\varepsilon_{jt}=0} \end{aligned}$$

where $\ln Q_{jt}|_{\varepsilon_{jt}=0}$ is the value of $\ln Q_{jt}$ evaluated at $\varepsilon_{jt} = 0$, and $\frac{d \ln Q_{jt}}{d\varepsilon_{jt}}|_{\varepsilon_{jt}=0}$ is given in equation (14).

Appendix C Compute the Numerical Elasticity of Substitution

This appendix calculates the numerical elasticity of substitution for the translog production function.

$$\begin{aligned} \ln Y_{jt} &= a_0 + a_k (\omega_{jt} + \ln K_{jt}) + a_l (\upsilon_{jt} + \ln L_{jt}) + a_m \ln M_{jt} \quad (15) \\ &+ \frac{1}{2} a_{kk} (\omega_{jt} + \ln K_{jt})^2 + \frac{1}{2} a_{ll} (\upsilon_{jt} + \ln L_{jt})^2 + \frac{1}{2} a_{mm} (\ln M_{jt})^2 \\ &+ a_{kl} (\omega_{jt} + \ln K_{jt}) (\upsilon_{jt} + \ln L_{jt}) + a_{km} (\omega_{jt} + \ln K_{jt}) \ln M_{jt} \\ &+ a_{lm} (\upsilon_{jt} + \ln L_{jt}) \ln M_{jt} \end{aligned}$$

Marginal product of capital

$$
\begin{aligned}
F_K &= \frac{a_k}{K_{jt}} + \frac{a_{kk}\left(\omega_{jt}+\ln K_{jt}\right)}{K_{jt}} + \frac{a_{kl}\left(\upsilon_{jt}+\ln L_{jt}\right)}{K_{jt}} + \frac{a_{km}\ln M_{jt}}{K_{jt}} \\
F_L &= \frac{a_l}{L_{jt}} + \frac{a_{ll}\left(\upsilon_{jt}+\ln L_{jt}\right)}{L_{jt}} + \frac{a_{kl}\left(\omega_{jt}+\ln K_{jt}\right)}{L_{jt}} + \frac{a_{lm}\ln M_{jt}}{L_{jt}} \\
F_M &= \frac{a_m}{M_{jt}} + \frac{a_{mm}\ln M_{jt}}{M_{jt}} + \frac{a_{km}\left(\omega_{jt}+\ln K_{jt}\right)}{M_{jt}} + \frac{a_{lm}\left(\upsilon_{jt}+\ln L_{jt}\right)}{M_{jt}} \\
\frac{F_K}{F_L} &= \frac{\frac{a_k}{K_{jt}} + \frac{a_{kk}(\omega_{jt}+\ln K_{jt})}{K_{jt}} + \frac{a_{kl}(\upsilon_{jt}+\ln L_{jt})}{K_{jt}} + \frac{a_{km}\ln M_{jt}}{K_{jt}}}{\frac{a_l}{L_{jt}} + \frac{a_{ll}(\upsilon_{jt}+\ln L_{jt})}{L_{jt}} + \frac{a_{kl}(\omega_{jt}+\ln K_{jt})}{L_{jt}} + \frac{a_{lm}\ln M_{jt}}{L_{jt}}} \\
&= \frac{a_k + a_{kk}\left(\omega_{jt}+\ln K_{jt}\right) + a_{kl}\left(\upsilon_{jt}+\ln L_{jt}\right) + a_{km}\ln M_{jt}}{a_l + a_{ll}\left(\upsilon_{jt}+\ln L_{jt}\right) + a_{kl}\left(\omega_{jt}+\ln K_{jt}\right) + a_{lm}\ln M_{jt}}\frac{L_{jt}}{K_{jt}}
\end{aligned}
$$

Elasticity of substitution between labor and capital:

$$
\begin{aligned}
\sigma_{KL} &= -\frac{d\ln(K/L)}{d\ln(F_K/F_L)} \\
&= -\frac{d\ln(K/L)}{d\ln\left[\left(\frac{a_k+a_{kk}(\omega_{jt}+\ln K_{jt})+a_{kl}(\upsilon_{jt}+\ln L_{jt})+a_{km}\ln M_{jt}}{a_l+a_{ll}(\upsilon_{jt}+\ln L_{jt})+a_{kl}(\omega_{jt}+\ln K_{jt})+a_{lm}\ln M_{jt}}\right)\frac{L_{jt}}{K_{jt}}\right]} \\
&= -\frac{\left(\frac{a_k+a_{kk}(\omega_{jt}+\ln K_{jt})+a_{kl}(\upsilon_{jt}+\ln L_{jt})+a_{km}\ln M_{jt}}{a_l+a_{ll}(\upsilon_{jt}+\ln L_{jt})+a_{kl}(\omega_{jt}+\ln K_{jt})+a_{lm}\ln M_{jt}}\right)\frac{L_{jt}}{K_{jt}}}{d\left[\left(\frac{a_k+a_{kk}(\omega_{jt}+\ln K_{jt})+a_{kl}(\upsilon_{jt}+\ln L_{jt})+a_{km}\ln M_{jt}}{a_l+a_{ll}(\upsilon_{jt}+\ln L_{jt})+a_{kl}(\omega_{jt}+\ln K_{jt})+a_{lm}\ln M_{jt}}\right)\frac{L_{jt}}{K_{jt}}\right]}\frac{d\left(K/L\right)}{K/L} \\
&= -\frac{\frac{\left(\frac{a_k+a_{kk}\left(\omega_{jt}+\ln K_{jt}\right)+a_{kl}\left(\upsilon_{jt}+\ln L_{jt}\right)+a_{km}\ln M_{jt}}{a_l+a_{ll}\left(\upsilon_{jt}+\ln L_{jt}\right)+a_{kl}\left(\omega_{jt}+\ln K_{jt}\right)+a_{lm}\ln M_{jt}}\right)\frac{L_{jt}}{K_{jt}}}{K/L}}{\frac{d\left[\frac{a_k+a_{kk}\left(\omega_{jt}+\ln K_{jt}\right)+a_{kl}\left(\upsilon_{jt}+\ln L_{jt}\right)+a_{km}\ln M_{jt}}{a_l+a_{ll}\left(\upsilon_{jt}+\ln L_{jt}\right)+a_{kl}\left(\omega_{jt}+\ln K_{jt}\right)+a_{lm}\ln M_{jt}}\frac{L_{jt}}{K_{jt}}\right]}{d(K/L)}} \\
&= -\frac{\left(\frac{S^k_{jt}}{S^l_{jt}}\right)\frac{L_{jt}}{K_{jt}}}{K/L}\left[\frac{d\left(\frac{S^k_{jt}}{S^l_{jt}}\frac{L_{jt}}{K_{jt}}\right)}{d\left(K/L\right)}\right]^{-1}
\end{aligned}
$$

There is no closed-form solution. I instead compute the numerical approximation. The procedure is: (1) Keep L_{jt} constant and increase K_{jt} by 1%; (2) compute the change of $\ln(K_{jt}/L_{jt})$ and $ln(F_K/F_L)$ numerically; (3) use the formula to compute the approximation of the elasticity of substitution.

$$
\widehat{\sigma_{KL}} = -\left(\frac{\left[\frac{S^k_{jt}}{S^l_{jt}}\frac{L_{jt}}{K_{jt}}\right]_K - \left[\frac{S^k_{jt}}{S^l_{jt}}\frac{L_{jt}}{K_{jt}}\right]_{K-1\%K}}{(K/L)_K-(K/L)_{K-1\%K}}\right)^{-1}\frac{\left(\frac{S^k_{jt}}{S^l_{jt}}\right)\frac{L_{jt}}{K_{jt}}}{K/L} = -\left(\frac{(K/L)_K-(K/L)_{K-1\%K}}{\left[\frac{S^k_{jt}}{S^l_{jt}}\frac{L_{jt}}{K_{jt}}\right]_K - \left[\frac{S^k_{jt}}{S^l_{jt}}\frac{L_{jt}}{K_{jt}}\right]_{K-1\%K}}\right)\frac{\left(\frac{S^k_{jt}}{S^l_{jt}}\right)\frac{L_{jt}}{K_{jt}}}{K/L}
$$

$$
= -\left(\frac{0.01(K/L)}{\left[\frac{S^k_{jt}}{S^l_{jt}}\frac{L_{jt}}{K_{jt}}\right]_K - \left[\frac{S^k_{jt}}{S^l_{jt}}\frac{L_{jt}}{K_{jt}}\right]_{K-1\%K}}\right)\frac{\left(\frac{S^k_{jt}}{S^l_{jt}}\right)\frac{L_{jt}}{K_{jt}}}{K/L} = -\left(\frac{0.01}{\left[\frac{S^k_{jt}}{S^l_{jt}}\right]_K - \left[\frac{S^k_{jt}}{S^l_{jt}}\right]_{K-1\%K}\frac{1}{0.99}}\right)\frac{\left(\frac{S^k_{jt}}{S^l_{jt}}\right)}{1}
$$

$$= -\left(\frac{0.01*0.99}{\left[\frac{S^k_{jt}}{S^l_{jt}}\right]_K - \left[\frac{S^k_{jt}}{S^l_{jt}}\right]_{K-1\%K}}\right)\frac{(\frac{S^k_{jt}}{S^l_{jt}})}{1}.$$

Appendix D Test the Invertibility Condition

To derive the estimation equation (12), I assume that the invertibility condition is satisfied (Assumption 8). This means that the estimator is valid under this restriction $a_{kl}a_{lm} - a_{km}a_{ll} \neq 0$. In this appendix I describe the details to test this restriction. The test is based on Wald statistics. The null and alternative hypothesis are

$$\begin{aligned} H_0 &: a_{kl}a_{lm} - a_{km}a_{ll} = 0 \text{ (Invertibility condition is violated)} \\ H_1 &: a_{kl}a_{lm} - a_{km}a_{ll} \neq 0 \text{ (Invertibility condition is satisfied)} \end{aligned}$$

The test results are reported in table 7. It shows that H_0 is strongly rejected in all industries. This indicates that the invertilibity condition generally is valid.

Appendix E Sources of Industrial Growth

The rate of output growth

$$\begin{aligned} &\tfrac{d\ln Y_{jt}}{dt} = a_k\left(\tfrac{d\omega_{jt}}{dt} + \tfrac{d\ln K_{jt}}{dt}\right) + a_l\left(\tfrac{d\upsilon_{jt}}{dt} + \tfrac{d\ln L_{jt}}{dt}\right) + a_m\tfrac{d\ln M_{jt}}{dt} \\ &+a_{kk}\left(\omega_{jt} + \ln K_{jt}\right)\left(\tfrac{d\omega_{jt}}{dt} + \tfrac{d\ln K_{jt}}{dt}\right) + a_{ll}\left(\upsilon_{jt} + \ln L_{jt}\right)\left(\tfrac{d\upsilon_{jt}}{dt} + \tfrac{d\ln L_{jt}}{dt}\right) + a_{mm}\ln M_{jt}\tfrac{d\ln M_{jt}}{dt} \\ &+a_{kl}\left(\omega_{jt} + \ln K_{jt}\right)\left(\tfrac{d\upsilon_{jt}}{dt} + \tfrac{d\ln L_{jt}}{dt}\right) + a_{kl}\left(\upsilon_{jt} + \ln L_{jt}\right)\left(\tfrac{d\omega_{jt}}{dt} + \tfrac{d\ln K_{jt}}{dt}\right) + a_{km}\ln M_{jt}\left(\tfrac{d\omega_{jt}}{dt} + \tfrac{d\ln K_{jt}}{dt}\right) \\ &+a_{km}\left(\omega_{jt} + \ln K_{jt}\right)\tfrac{d\ln M_{jt}}{dt} + a_{lm}\ln M_{jt}\left(\tfrac{d\upsilon_{jt}}{dt} + \tfrac{d\ln L_{jt}}{dt}\right) + a_{lm}\left(\upsilon_{jt} + \ln L_{jt}\right)\tfrac{d\ln M_{jt}}{dt} \end{aligned}$$

$$\begin{aligned} \frac{d\ln Y_{jt}}{dt} &= \left(\frac{d\omega_{jt}}{dt} + \frac{d\ln K_{jt}}{dt}\right)\left[a_k + a_{kk}\left(\omega_{jt} + \ln K_{jt}\right) + a_{kl}\left(\upsilon_{jt} + \ln L_{jt}\right) + a_{km}\ln M_{jt}\right] \\ &\quad + \left(\frac{d\upsilon_{jt}}{dt} + \frac{d\ln L_{jt}}{dt}\right)\left[a_l + a_{ll}\left(\upsilon_{jt} + \ln L_{jt}\right) + a_{kl}\left(\omega_{jt} + \ln K_{jt}\right) + a_{lm}\ln M_{jt}\right] \\ &\quad + \frac{d\ln M_{jt}}{dt}\left[a_m + a_{mm}\ln M_{jt} + a_{km}\left(\omega_{jt} + \ln K_{jt}\right) + a_{lm}\left(\upsilon_{jt} + \ln L_{jt}\right)\right] \\ &= S^k_{jt}\frac{d\omega_{jt}}{dt} + S^k_{jt}\frac{d\ln K_{jt}}{dt} + S^l_{jt}\frac{d\upsilon_{jt}}{dt} + S^l_{jt}\frac{d\ln L_{jt}}{dt} + S^m_{jt}\frac{d\ln M_{jt}}{dt} \\ &= S^k_{jt}\frac{d\ln K_{jt}}{dt} + S^l_{jt}\frac{d\ln L_{jt}}{dt} + S^m_{jt}\frac{d\ln M_{jt}}{dt} + S^k_{jt}\frac{d\omega_{jt}}{dt} + S^l_{jt}\frac{d\upsilon_{jt}}{dt} \end{aligned}$$

where

$$\begin{aligned} S^k_{jt} &\triangleq \left[a_k + a_{kk}\left(\omega_{jt} + \ln K_{jt}\right) + a_{kl}\left(\upsilon_{jt} + \ln L_{jt}\right) + a_{km}\ln M_{jt}\right], \\ S^l_{jt} &\triangleq \left[a_l + a_{ll}\left(\upsilon_{jt} + \ln L_{jt}\right) + a_{kl}\left(\omega_{jt} + \ln K_{jt}\right) + a_{lm}\ln M_{jt}\right], \\ S^m_{jt} &\triangleq \left[a_m + a_{mm}\ln M_{jt} + a_{km}\left(\omega_{jt} + \ln K_{jt}\right) + a_{lm}\left(\upsilon_{jt} + \ln L_{jt}\right)\right]. \end{aligned}$$

The growth of output can be accounted for by five sources. The first three sources are due to the growth of physical inputs (capital, labor and material), which correspond to the first three terms in the equation. The last two sources, captured by $S^k_{jt}\frac{d\omega_{jt}}{dt}$ and $S^l_{jt}\frac{d\upsilon_{jt}}{dt}$, correspond to the contribution of productivity. It is a composite of two sources, the growth of capital efficiency ($S^k_{jt}\frac{d\omega_{jt}}{dt}$) and the growth of labor efficiency ($S^l_{jt}\frac{d\upsilon_{jt}}{dt}$). This is a new term compared to the traditional neutral technology measure, which measures only the level of productivity change. Instead, out new measure allows us to attribute the change of productivity to the change of capital efficiency and labor efficiency.

In discrete time

$$\frac{\triangle Y_{jt}}{Y_{jt-1}} = S^k_{jt}\frac{\triangle K_{jt}}{K_{jt-1}} + S^l_{jt}\frac{\triangle L_{jt}}{L_{jt-1}} + S^m_{jt}\frac{\triangle M_{jt}}{M_{jt-1}} + S^k_{jt}\triangle\omega_{jt} + S^l_{jt}\triangle\upsilon_{jt}$$

where $\triangle X_{jt}$ is defined as $\triangle X_{jt} = X_{jt} - X_{jt-1}$.

Industrial Growth with Entry and Exit

The aggregate output for each industry at time t and $t-1$ is defined as $Y_t = \sum_{j\in J_t} Y_{jt}$ and $Y_{t-1} = \sum_{j\in J_{t-1}} Y_{jt-1}$ respectively. J_t and J_{t-1} are the sets of firms in the industry at time t and $t-1$. Define $C_t = J_t \cap J_{t-1}$, $N_t = J_t/J_{t-1}$ and $X_t = J_{t-1}/J_t$. Then C_t represents the set of continuing firms, N_t the set of new entrants, and X_t the set of exiters. The growth of the aggregate output in the industry is written as

$$\begin{aligned}
\frac{Y_t - Y_{t-1}}{Y_{t-1}} &= \frac{1}{Y_{t-1}}\left[\sum_{j\in C_t}(Y_{jt} - Y_{jt-1}) + \sum_{j\in N_t} Y_{jt} - \sum_{j\in X_t} Y_{jt-1}\right] \\
&= \sum_{j\in C_t}\frac{(Y_{jt} - Y_{jt-1})}{Y_{t-1}} + \sum_{j\in N_t}\frac{Y_{jt}}{Y_{t-1}} - \sum_{j\in X_t}\frac{Y_{jt-1}}{Y_{t-1}} \\
&= \sum_{j\in C_t}\frac{Y_{jt-1}}{Y_{t-1}}\frac{(Y_{jt} - Y_{jt-1})}{Y_{jt-1}} + \sum_{j\in N_t}\frac{Y_{jt}}{Y_{t-1}} - \sum_{j\in X_t}\frac{Y_{jt-1}}{Y_{t-1}} \\
&= \sum_{j\in C_t} S_{jt-1}\left[S^k_{jt}\frac{\triangle K_{jt}}{K_{jt-1}} + S^l_{jt}\frac{\triangle L_{jt}}{L_{jt-1}} + S^m_{jt}\frac{\triangle M_{jt}}{M_{jt-1}} + S^k_{jt}\triangle\omega_{jt} + S^l_{jt}\triangle\upsilon_{jt}\right] \\
&\quad + \sum_{j\in N_t}\frac{Y_{jt}}{Y_{t-1}} - \sum_{j\in X_t}\frac{Y_{jt-1}}{Y_{t-1}} \\
&= \sum_{j\in C_t} S_{jt-1}S^k_{jt}\frac{\triangle K_{jt}}{K_{jt-1}} + \sum_{j\in C_t} S_{jt-1}S^l_{jt}\frac{\triangle L_{jt}}{L_{jt-1}} + \sum_{j\in C_t} S^m_{jt}\frac{\triangle M_{jt}}{M_{jt-1}} \quad \text{(Physical Input)} \\
&\quad + \sum_{j\in C_t} S_{jt-1}S^k_{jt}\triangle\omega_{jt} + \sum_{j\in C_t} S_{jt-1}S^l_{jt}\triangle\upsilon_{jt} \quad \text{(Productivity)} \\
&\quad + \sum_{j\in N_t}\frac{Y_{jt}}{Y_{t-1}} - \sum_{j\in X_t}\frac{Y_{jt-1}}{Y_{t-1}} \quad \text{(Net Entry/Exit)}
\end{aligned}$$

where S_{jt-1} is the share of firm j in the aggregate industrial output at date t, $S_{jt-1} = \frac{Y_{jt-1}}{Y_{t-1}}$. There are three sources of the growth of aggregate industrial output. The first source is the accumulation of physical inputs. The increased usage of capital, labor and material contributes to the growth of industrial output, as shown in the first line of the last equality.

The second source is due to the growth of productivity. The growth of capital efficiency and/or labor efficiency contributes to the growth of industrial output, as shown in the second line of the last equality. Note that this measure allows the capital efficiency and labor efficiency to grow in an uneven way. That is, technological change could be biased.

The last source is the net entry and exit effect. Entering firms contribute to increase the industrial output and the exiting firms contribute to decrease the industrial output. The net effect is captured by the third line of the last equality. The total effect is the sum of the three sources.

Table 1: Summary Statistics of Key Variables (Industry Mean)[1]

Industry	#Firms	Age	R[2]	K	L	LSH	Wage	R/L	K/L
Clothing	50,180	87	38,825	6,280	284.98	0.09	14.95	136.24	27.25
Paper&Board	14,065	129	58,515	27,536	252.42	0.05	12.69	231.82	143.35
Equipment	1,388	149	42,251	12,038	187.62	0.08	23.73	225.20	82.90
Motor Vehicle	1,194	82	301,847	55,854	532.58	0.03	19.67	566.77	114.77

[1] All values in 1,000 RMB. Age in months.

[2] R: revenue. K: capital. L: number of workers. LSH: labor share in revenue. Wage: wage rate. R/L: revenue per worker. K/L: capital-labor ratio.

Table 2: Industry Mean[1] of Capital-Labor Ratio and Inputs Prices in China: 2000-2007

	2000	2001	2002	2003	2004	2005	2006	2007	growth
Clothing									
Wage/Interest	206.22	191.37	222.81	228.84	213.69	229.24	260.35	253.56	22.96%
Capital/Labor	28.67	27.20	29.660	26.63	25.42	26.43	27.43	27.63	-3.64%
Paper&Board									
Wage/Interest	169.18	171.73	203.46	200.47	190.07	201.40	210.49	217.00	28.26%
Capital/Labor	107.20	129.64	148.11	159.30	139.76	151.88	141.76	144.36	34.66%
Equipment[2]									
Wage/Interest	243.47	257.56	351.92	395.58	360.56	407.14	416.80	367.46	50.93%
Capital/Labor	79.70	61.46	79.79	80.10	76.56	87.57	93.94	81.83	2.67%
Motor Vehicle									
Wage/Interest	272.06	255.53	267.01	302.03	319.15	314.90	336.21	320.42	17.77%
Capital/Labor	168.20	170.53	143.24	118.96	101.94	105.53	104.41	93.75	-44.26%

[1] Weighted mean by revenue share.

[2] Equipment refers to Foods, Beverages and Tobacco Production Equipment industry.

Table 3: Explanation Power of Inputs Prices and Other Factors

Factors	Rsquare(1)[1]	Rsquare(2)	Rsquare(3)	Rsquare(4)
Clothing	0.0777	0.0820	0.0926	0.0957
Paper&Board	0.1596	0.1635	0.1773	0.1784
Equipment	0.2142	0.2254	0.2404	0.2413
Motor Vehicle	0.0326	0.0574	0.0622	0.1161

[1] Dependent variable is the capital-labor ratio. Regressors differs from regressions from (1)to (4). The regressors in each regression: (1) wage-interest rate ratio; (2) add control for firm size measured by sales; (3) add control for year; (4) add control for ownership.

Table 4: Estimation Result of Production Function

	Clothing		Paper & Board		Equipment		Motor Vehicle	
	para	SE	para	SE	para	SE	para	SE
a_k	0.0393	(0.0336)[1]	0.0884	(0.0060)	0.1402	(0.0014)	0.1080	(0.0819)
a_l	0.5272	(0.1360)	0.3527	(0.0405)	0.5009	(0.0094)	0.1553	(0.0979)
a_m	0.3593	(0.0219)	0.5202	(0.0410)	0.3524	(0.0027)	0.6963	(0.0373)
a_{kk}	-0.0301	(0.0004)	-0.0062	(0.0000)	-0.0152	(0.0000)	0.0001	(0.0039)
a_{ll}	-0.1178	(0.0121)	-0.2176	(0.0391)	-1.5105	(0.0023)	-0.2396	(0.0534)
a_{mm}	0.1530	(0.0263)	-0.0633	(0.0025)	0.2510	(0.0001)	-0.2652	(0.0353)
a_{kl}	0.1171	(0.0011)	0.1061	(0.0026)	0.2552	(0.0000)	0.2552	(0.0158)
a_{km}	0.0189	(0.0015)	0.0216	(0.0001)	-0.0569	(0.0000)	0.0617	(0.0063)
a_{lm}	-0.2982	(0.0043)	-0.4102	(0.0332)	-0.1790	(0.0000)	-0.5947	(0.0636)
a_0	1.7012	(0.3914)	1.3191	(0.4027)	1.0480	(0.0146)	1.0166	(0.7686)
#obs	50,022		13,958		1,374		1,185	

[1] Standard deviation in parentheses.

Table 5: Output Elasticity and Scale Economics

Industry	Labor	Material	Capital	Scale
Clothing (1810)	0.0937	0.7414	0.0725	0.9076
Paper&Board(2221)	0.0453	0.7640	0.0763	0.8856
Equipment(3631)	0.0835	0.7251	0.0779	0.8865
Motor Vehicle (3731)	0.0285	0.8036	0.1061	0.9382

Table 6: Distribution of Elasticity of Substitution (Quantile)

Industry	.1	.2	.3	.4	.5	.6	.7	.8	.9 [1]
Clothing	0.2162	0.3009	0.3707	0.4331	0.4932	0.5556	0.6270	0.7262	0.9090
Paper&Board	0.1779	0.2442	0.2990	0.3515	0.4093	0.4796	0.5682	0.6933	0.9033
Equipment	0.0763	0.1228	0.1607	0.2072	0.2515	0.3007	0.3652	0.4389	0.5631
Motor Vehicle	0.0321	0.0491	0.0674	0.0852	0.1064	0.1310	0.1631	0.2056	0.2914

[1] They represent different quantiles.

Table 7: Wald Test of Invertibility Condition[1]

Industry	Statistic	5% significance level		2.5% significance level	
		Critical	Decision	Critical	Decision
Clothing	2.55E-10	0.0040	Reject H0	0.0010	Reject H0
Paper&Board	3.23E-06	0.0040	Reject H0	0.0010	Reject H0
Equipment	1.70E-04	0.0040	Reject H0	0.0010	Reject H0
Motor Vehicle	2.33E-04	0.0040	Reject H0	0.0010	Reject H0

[1] H0: invertibility condition is violated. H1: Invertibility condition is satisfied.

Table 8: Test against Neutral Technology Change[1]

Industry	Statistic	5% significance level		1% significance level	
		Lower[2]	Upper	Lower	Upper
Clothing	2.44E+06	-1.96	1.96	-2.5758	2.5758
Paper&Board	1.52E+06	-1.96	1.96	-2.5758	2.5758
Equipment	5.50E+05	-1.96	1.96	-2.5758	2.5758
Motor Vehicle	3.69E+05	-1.96	1.96	-2.5758	2.5758

[1] H0: Neutral technology change. H1: Biased technology change.

[2] Lower and upper represent lower bound and upper bound, respectively.

Table 9: Test against Neutral Technology Dispersion[1]

Industry	Statistic	5% significance level		1% significance level	
		Lower Bd	Upper Bd	Lower Bd	Upper Bd
Clothing	1.19E+19	-1.96	1.96	-2.5758	2.5758
Paper&Board	1.04E+16	-1.96	1.96	-2.5758	2.5758
Equipment	3.18E+11	-1.96	1.96	-2.5758	2.5758
Motor Vehicle	1.37E+11	-1.96	1.96	-2.5758	2.5758

[1] H0: Neutral technology dispersion. H1: Biased technology dispersion.

Table 10: Correlation Between Technology Bias (TB) and Firm Size[1]

Industry	Clothing	Paper&Board	Equipment	Motor Vehicle
Corr(TB,firmsize)	0.7768	0.9586	0.9533	0.8161

[1] Technology Bias (TB) is the ratio of capital efficiency to labor efficiency. Firm size is defined as sales.

Table 11: Explanation Power of Inputs Prices and Other Factors[1]

Factors	Rsquare(1)	Rsquare(2)	Rsquare(3)	Rsquare(4)	Rsquare(5)
Clothing	0.0777	0.0820	0.0926	0.0957	0.7529
Paper&Board	0.1596	0.1635	0.1773	0.1784	0.7740
Equipment	0.2142	0.2254	0.2404	0.2413	0.6995
Motor Vehicle	0.0326	0.0574	0.0622	0.1161	0.8699

[1] Dependent variable is the capital-labor ratio. Regressors differs from regression from (1) to (5). The regressors in each regression: (1) wage-interest rate ratio; (2) add control for firm size measured by sales; (3) add control for year; (4) add control for ownership; (5) add the technology bias measure.

Table 12: Growth Rate (%) of Capital Efficiency (KE) and Labor Efficiency (LE)[1]

Year	Clothing		Paper&Board		Equipment		Motor Vehicle	
	KE	LE	KE	LE	KE	LE	KE	LE
2001	29.3500	4.9500	38.1500	-4.3800	49.4400	-2.3200	25.1800	5.4900
2002	30.7600	0.7000	26.6400	-3.1300	18.7400	-0.1800	37.7600	-10.9800
2003	29.9800	8.2500	22.8300	1.1400	34.2800	-1.6900	49.6100	2.9000
2004	19.5100	11.2100	24.3700	1.2100	57.2100	-0.9000	48.1200	-13.6500
2005	29.7800	4.7900	22.0100	2.3400	39.5800	-2.4900	1.3700	5.0400
2006	27.6000	3.7000	27.8900	0.6400	34.6800	0.1400	20.0300	-2.4000
Mean	23.8500	4.8000	23.1300	-0.3100	33.4200	-1.0600	25.6200	-1.9400

[1] Unbalanced panel. So the result Includes contribution of both continuing and entering/exitting firms.

Table 13: R&D and the Evolution of Capital and Labor Efficiency

	Clothing		Paper&Board		Equipment		Motor Vehicle	
	Para	SE	Para	SE	Para	SE	Para	SE
Capital E:								
R&D	0.1856	(0.0448)[1]	0.0538	(0.0655)	0.1229	(0.0169)	0.5844	(0.1884)
lag_{KE}	0.8476	(0.0055)	0.8834	(0.0116)	0.8839	(0.0353)	0.6925	(0.0480)
lag_{LE}	0.1501	(0.0182)	-0.0905	(0.0225)	-0.0984	(0.0792)	-0.0847	(0.0923)
SOE	-0.1986	(0.0695)	-0.2655	(0.0725)	-0.4791	(0.2641)	-0.4982	(0.3992)
FDI	-0.0016	(0.0197)	-0.0094	(0.0678)	0.0408	(0.1795)	0.1286	(0.2738)
contant	2.2930	(0.0734)	1.4348	(0.1405)	1.8680	(0.5125)	2.0616	(0.5205)
Labor E:								
R&D	-0.0071	(0.0169)	-0.0690	(0.0322)	-0.0402	(0.0684)	-0.0693	(0.0754)
lag_{KE}	-0.0010	(0.0021)	-0.0774	(0.0057)	-0.0733	(0.0143)	0.0044	(0.0192)
lag_{LE}	0.6587	(0.0069)	0.8079	(0.0111)	0.7806	(0.0321)	0.8884	(0.0369)
SOE	0.0165	(0.0262)	-0.0645	(0.0356)	0.0234	(0.1071)	-0.2251	(0.1597)
FDI	-0.0704	(0.0075)	-0.0631	(0.0333)	-0.0268	(0.0728)	-0.1123	(0.1096)
contant	-0.4450	(0.0277)	-0.5016	(0.0690)	-0.5184	(0.2078)	-0.7860	(0.2083)
BTC:								
R&D	0.1927	(0.0487)	0.1229	(0.0838)	0.1631	(0.2051)	0.6536	(0.2256)
$lag_K E$	0.8486	(0.0060)	0.9609	(0.0149)	0.9572	(0.0429)	0.6881	(0.0575)
$lag_L E$	-0.5086	(0.0198)	-0.8984	(0.0288)	-0.8790	(0.0963)	-0.9730	(0.1105)
SOE	-0.2151	(0.0755)	-0.2010	(0.0928)	-0.5025	(0.3211)	-0.2732	(0.4781)
FDI	0.0688	(0.0215)	0.0537	(0.0867)	0.0676	(0.2183)	0.2409	(0.3279)
contant	2.7379	(0.0798)	1.9364	(0.1798)	2.3864	(0.6231)	2.8476	(0.6233)

[1] The standard errors are in the parentheses.

Table 14: Sources of Aggregate Growth of Gross Output(%): 2001-2006

	Capital Efficiency	Labor Efficiency	Capital Input	Labor Input	Material Input	Entry /Exit	Growth[1] Rate
Clothing:							
2001	1.50	0.22	0.81	1.19	6.83	4.33	14.88
2002	1.72	-0.07	1.17	1.46	10.16	2.56	17.01
2003	1.65	0.33	0.77	1.10	9.85	8.15	21.86
2004	1.06	0.33	0.18	0.67	6.15	5.02	13.41
2005	1.92	0.27	0.24	1.38	12.58	3.81	20.21
2006	1.73	0.18	0.44	1.63	10.21	5.89	20.08
Mean	1.60	0.21	0.60	1.24	9.30	4.96	17.91
Paper&Board:							
2001	2.45	-0.23	1.28	0.51	11.47	-1.68	13.79
2002	1.76	-0.24	3.82	1.04	20.01	-12.09	14.30
2003	1.78	0.01	2.46	0.43	15.69	9.95	30.32
2004	1.37	0.04	1.17	0.33	22.52	-13.55	11.88
2005	1.39	-0.02	0.38	0.39	10.57	7.52	20.23
2006	1.70	-0.11	1.44	0.42	11.01	2.51	16.96
Mean	1.74	-0.09	1.76	0.52	15.21	-1.22	17.92
Equipment:							
2001	3.60	-0.44	0.04	2.03	17.75	-14.96	8.03
2002	1.48	0.49	0.67	0.33	19.02	-4.96	17.03
2003	2.50	-0.55	1.51	1.59	13.62	5.88	24.55
2004	5.85	-0.20	-0.11	1.00	16.73	2.75	26.01
2005	3.05	-0.15	0.23	0.66	16.22	-4.66	15.35
2006	3.24	-0.31	0.23	1.01	11.82	3.63	19.61
Mean	3.29	-0.19	0.43	1.10	15.86	-2.05	18.43
Motor Vehicle:							
2001	1.60	0.19	0.13	0.00	8.70	-15.13	-4.51
2002	4.08	-0.22	1.87	0.51	11.70	-5.52	12.42
2003	4.32	-0.21	-0.56	0.22	12.23	5.05	21.05
2004	4.09	-0.44	0.33	0.60	18.90	-1.15	22.33
2005	-0.18	0.14	1.59	0.20	1.77	3.66	7.18
2006	1.93	-0.08	0.49	0.25	10.35	6.77	19.72
Mean	2.64	-0.10	0.64	0.30	10.61	-1.05	13.03

[1] "Growth rate" refers to the growth rate of deflated output value.

Table 15: Sources of Aggregate Growth of Value Added (%): 2001-2006

	Capital Efficiency	Labor Efficiency	Capital Inputs	Labor Inputs	Entry /Exit	Growth[1] Rate
Clothing:						
2001	11.70	1.23	5.27	6.95	-7.78	17.37
2002	13.05	-0.53	7.34	8.24	-13.61	14.49
2003	12.29	2.12	4.75	5.46	10.40	35.03
2004	7.28	2.21	1.79	2.77	11.26	25.31
2005	12.55	1.48	2.14	7.06	3.46	26.69
2006	11.53	1.09	3.22	7.83	1.68	25.34
Mean	11.40	1.27	4.08	6.38	0.90	24.04
Paper&Board:						
2001	22.36	-1.99	0.33	3.51	-28.05	6.16
2002	15.10	-2.13	16.95	5.48	-7.08	28.33
2003	14.10	-0.13	12.43	2.16	12.34	40.91
2004	14.03	-0.33	7.87	2.95	-20.93	3.59
2005	13.42	-0.03	5.43	2.10	19.66	40.58
2006	17.49	-1.02	8.27	3.13	-4.65	23.22
Mean	16.08	-0.94	10.21	3.22	-4.78	23.80
Equipment:						
2001	22.06	-4.27	2.25	11.20	10.78	42.03
2002	7.89	0.79	4.71	3.51	-0.61	16.30
2003	13.18	-2.55	8.48	8.42	17.23	44.77
2004	27.25	-2.37	1.05	6.73	-12.77	19.90
2005	22.06	-1.32	3.48	5.65	2.06	31.93
2006	18.33	-0.91	3.24	5.35	-23.15	2.86
Mean	18.46	-1.77	3.87	6.81	-1.08	26.30
Motor Vehicle:						
2001	21.29	0.89	3.00	0.12	-52.06	-26.76
2002	31.98	-1.84	12.39	3.79	3.07	49.39
2003	33.12	-2.22	-3.58	1.33	16.72	45.37
2004	33.55	-3.85	5.27	3.70	-23.14	15.53
2005	1.72	1.23	13.37	1.06	12.50	26.43
2006	15.49	-0.90	2.82	1.80	13.30	32.51
Mean	22.28	-1.12	5.54	1.97	-4.93	23.74

[1] "Growth rate" refers to the growth rate of deflated value added.

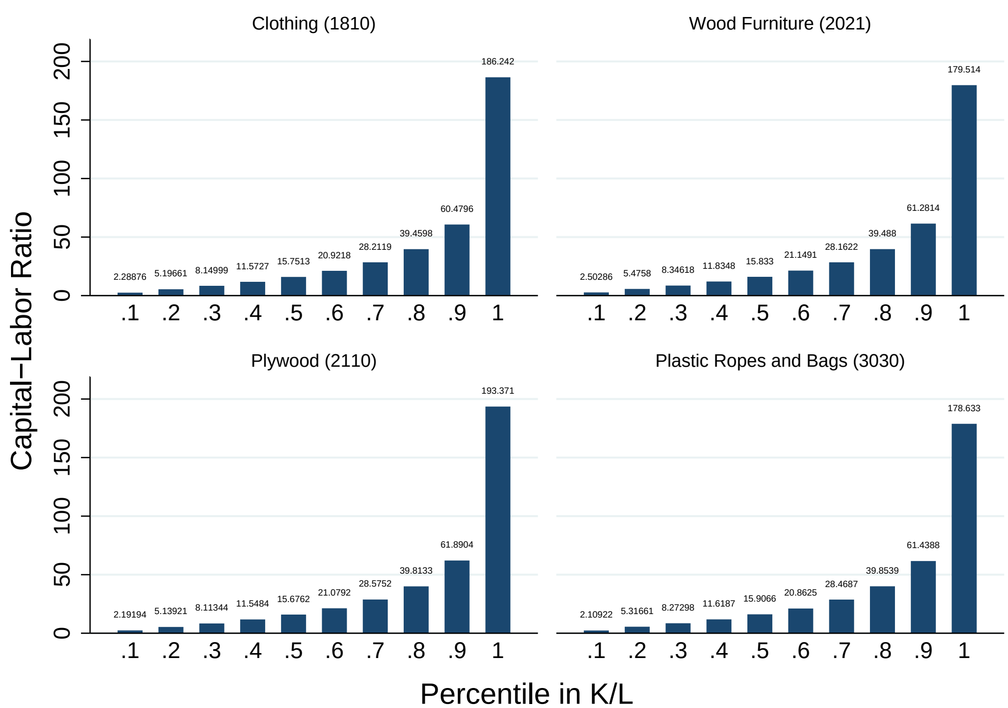
Table 16: Capital and Labor Efficiencies (KE and LE)for Entering, Exiting and Continuing Firms[1]

	Entering	Exiting	Continuing	Entering	Exiting	Continuing
	Clothing:			Equipment:		
KE	18.6178	18.3428	19.6618	25.8614	25.7389	27.4545
SE	(2.4051)[2]	(2.4326)	(2.4551)	(3.3686)	(3.2723)	(3.5105)
LE	-2.2297	-2.1358	-2.4554	-7.3170	-7.4331	-7.9434
SE	(0.6023)	(0.6188)	(0.5603)	(1.0032)	(1.0624)	(1.1085)
	Paper&Board:			Motor Vehicle:		
KE	16.7768	16.6605	18.0933	13.6393	12.7998	14.9539
SE	(2.7150)	(2.6688)	(2.9092)	(2.0935)	(2.0125)	(1.8309)
KE	-3.7738	-3.9903	-4.4054	-10.3969	-10.1211	-12.0527
SE	(0.8282)	(0.8775)	(1.0230)	(1.6310)	(1.3649)	(1.8341)

[1] Because this dataset only covers all SOE's and private firms above some scale, the entry and exit here does not mean the birth and death of firms. Instead they are defined as entering and exiting the dataset we have.

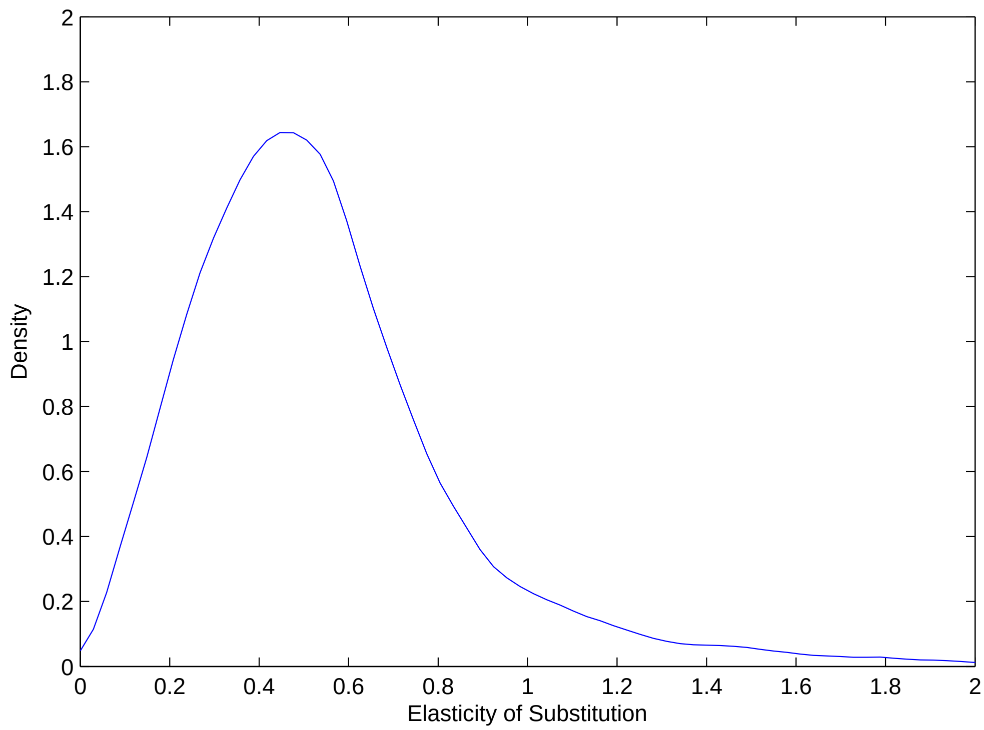
[2] Standard errors (SE) in parentheses.

Figure 1: Dispersion of Capital-Labor Ratio in 2007, by Industry)



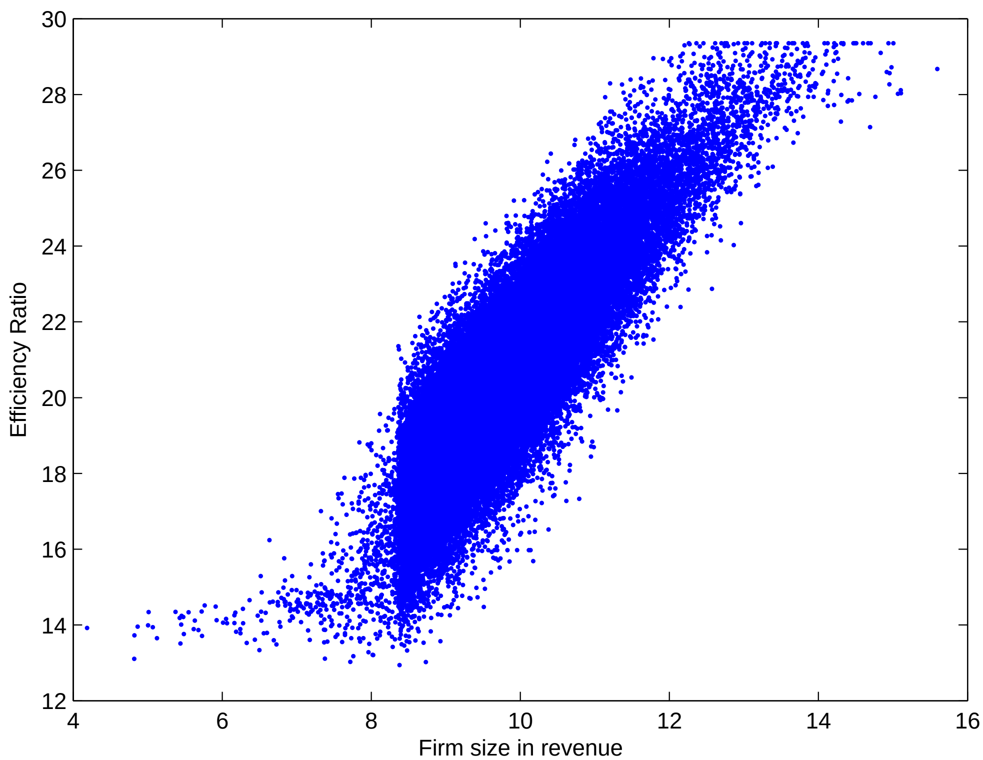
Notes: The figure shows the large dispersion of capital-labor ratio with each industry.

Figure 2: Distribution of Elasticity of Substitution (Clothing)



Notes: The figure shows that the estimated elasticity of substitution is significantly different from one. It also shows large dispersion of elasticity of substitution among firms within one industry.

Figure 3: Biased Technology Dispersion (BTD) and Firm Size (Clothing)



Notes: Firm size is measured as annual revenue. This figure shows that larger firms on average have higher ratio of capital efficiency to labor efficiency.