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Abstract

This dissertation focuses on the measurement of productivity at the firm level and the implication of firm-level heterogeneous productivity in industrial organization and international trade. Chapter 1 studies the interaction between firm productivity and importing decision and quantify the static and dynamic gains from importing intermediate inputs. Chapter 2 develops a new way to estimate the production function consistently when some of the input prices are missing. Chapter 1 and Chapter 2 are based on the Hicks-Neutral technology assumption. Chapter 3 studies the biased technology change over time and biased technology dispersion across firms.

Chapter 1: Static and Dynamic Gains from Importing Intermediate Inputs: Theory and Evidence

This paper constructs a dynamic structural model to characterize firms' decisions to buy imported inputs or rely exclusively on domestically-supplied inputs and quantifies their effects on firm value and productivity. The model provides a unified framework to analyze the determinants of firms' import decisions and to empirically decompose the gains from importing into a static effect and a dynamic effect. Empirical results using Colombian plant-level data show that more productive plants tend to import intermediate inputs and that the total gain from importing is large. The decomposition shows importing is important mostly because it dynamically generates higher future productivity growth.

Chapter 2: Production Function Estimation with Unobserved Input Price Dispersion

We propose a method to consistently estimate production functions when intermediate inputs are not observed in the presence of input price dispersion. The traditional approach to dealing with unobserved input quantities—using deflated expenditure as a proxy—requires strong assumptions for consistency. In particular, we show that the traditional approach tends to underestimate the elasticity of substitution and bias estimates of the distribution parameters. Our approach applies to a general class of production functions with a mild identification restriction. As a demonstration, we apply our approach to the CES production function. A Monte Carlo experiment illustrates that the omitted price bias is significant in the traditional approach, while our method consistently recovers the production function parameters. We apply our method to a firm-level data set from Colombian manufacturing industries. The empirical results are consistent with the predictions that the use of expenditure as a proxy for quantities biases the elasticity of substitution downward. Moreover, using our preferred method, we provide evidence of significant input price dispersion and even wider productivity dispersion than is estimated using traditional methods.

Chapter 3: Biased Technology and Contribution of Technological Change to Economic Growth: Firm-Level Evidence

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.

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All errors are my own responsibility.

Chapter 1

Static and Dynamic Gains from Importing Intermediate Inputs: Theory and Evidence

1.1 Introduction

[1]Empirical literature has documented a strong and positive correlation between productivity and importing. Using cross-country macro data, literature found that countries more actively participating in importing have higher productivity levels and productivity growth rates (Coe and Helpman, 1995; Coe, Helpman, and Hoffmaister, 1997; Keller, 2004; Acharya and Keller, 2009). Recent firm/plant-level evidence found a positive correlation between importing and productivity (Halpern, Koren, and Szeidl, 2009; Blalock and Veloso, 2007; Amiti and Konings, 2007; Kasahara and Rodrigue, 2008; Vogel and Wagner, 2010).

A natural question to ask is: how do we explain this observed positive correlation theoretically? In general, there are two possible answers. First, the productivity difference between importers and non-importers may be due to self selection of firms to import intermediate inputs, i.e. more productive firms are more likely to import. Second, importing may have a positive impact on productivity changes.

[1]The author is grateful to Jonathan Eaton, Paul Grieco, Kala Krishna, Mark Roberts, James Tybout, Stephen Yeaple and all participants in the IO reading group at the Pennsylvania State University for many insightful comments. All errors are the author's own responsibility.

In either case, we would observe a positive correlation between importing and productivity. Empirical literature remains silent on how to explain this positive correlation.[2] The major reason is that there is not a unified framework to separate the selection into importing from the causal effect of importing on productivity. The first objective of this paper is to construct a unified framework which allows me to analyze the selection and effect of importing simultaneously. In the model, firms endogenously choose whether to import inputs or not, which in turn have an impact on their profit and productivity. I estimate the firms' policy function of importing and the endogenous productivity evolution process, which is affected by the importing decision, simultaneously in a integrated dynamic model. I then compute the gains from importing by conducting counterfactual analysis. This procedure allows me to disentangle the selection and effect of importing. I find that more productive and larger firms are more likely to import and productivity gains from importing are large.

The second objective of this paper is to explore the sources of gains from importing. I decompose the gains from importing into a static effect and a dynamic effect. The static effect represents the gains from importing during the period of importing. It corresponds to the *"Quality and Variety Assumption"* commonly used in the literature (Ethier, 1982; Romer, 1990; Grossman and Helpman, 1991). It mainly arises from two sources: (1) an input quality effect–the imported inputs may have better quality, which can immediately increase the firm's productivity; (2) an input variety effect–the imported inputs increase the variety of inputs, which may immediately help increase productivity.

The dynamic effect represents the dynamic impact of current importing experience on firms' future productivity and profit. This could happen even when the firm discontinues importing in the future. The dynamic effect can be caused by several different channels. For example, importing firms usually receive technical support from their foreign suppliers, which directly increases their productivity. Importing firms also have more exposure to foreign knowledge and technology.

[2] Vogel and Wagner (2010) is an exception. They tries to find evidence for both self selection and the effect of importing. Using German Turnover Tax Statistics Panel, they found that firms with higher productivity are more likely to import; however they found no clear evidence of a positive impact of importing on productivity, which is contrary to the findings in other existing listrature.

This exposure can directly increase firm productivity, or help the firm to reduce the cost of innovation and/or increase its chances of succeeding in R&D, leading to more R&D investment and a higher productivity growth rate. Another possible channel for the dynamic effect is through an indirect network effect of importing. Importing helps importers to establish a larger foreign business network, which in turn helps them to increase export. The expansion of the market increases the return to R&D and thus enhances the productivity growth rate[3].

To achieve these objectives, this paper constructs a dynamic structural model to characterize firms' decisions to import intermediate inputs or to rely exclusively on domestically-supplied inputs, and to quantify both the static and dynamic effects of importing on firm-level productivity. In the model, firm productivity evolves endogenously. The productivity, along with other factors, determines firms' importing decisions, which in turn has a dynamic effect on the future productivity of the importing firms. The model provides an approach to simulating the long-term impact of import expansion on firm productivity. As part of the model I estimate the dynamic decision rule for the plant's optimal importing decisions which depends on the expected future profits and the current fixed or sunk costs of importing.

I estimate the dynamic model structurally using a plant-level data set from Colombia. I find that more productive firms are more likely to import and that the gains from importing are large. The counterfactual analysis shows that the total gains from importing are mainly due to the dynamic effect, which increases firm value by enhancing future productivity. This means that importing is important mostly because it generates higher productivity growth in the long run. Meanwhile, the static effect has a positive and significant effect on firm value. As the static effect mainly constitutes the quality and variety effects, this finding provides some evidence on the *"Quality and Variety Assumption"* mentioned above, which are commonly assumed in the literature. The parametrization of the model further allows me to compute the quality effect and the (potential) variety effect separately. The empirical results show that the static effect is mainly due to the variety effect in all industries examined. These findings have important policy implications. For

[3]To study the indirect network effect of importing, a complete model including import, export and R&D decisions is called for.

example, they imply that, when evaluating an importing policy, government needs to carefully evaluate the long-term gains from importing against the short-term cost.

The last, yet very important, question is: why should the effect of exposure to trade through importing differ from that of exporting? The reason is that importing directly affects the production process and potentially has a substantial impact on the productivity of importers. In contrast, exporting only affects production indirectly through learning-by-exporting and changing demand. Therefore, importing affects firm productivity through a more direct way which is different from exporting. This means that we should not ignore it when evaluating trade policy and industrial development. Since importing is usually positively correlated with exporting, to identify the effect of importing, I control for exporting in the empirical exercise. To make sure that my estimate of the gains from importing is not due to exporting, I also conduct robustness checks by performing the same exercises on a subsample of firms which do not export. The subsample results are similar to what we find in the whole sample. This indicates that our results on the gains from importing are robust.

Several recent papers are closely related to my work. Kugler and Verhoogen (2009, 2012) emphasize the input quality effect of importing. They argue that the output quality could be improved by using imported inputs with higher quality, under the assumption that input quality and productivity are complementary to produce the output quality. Goldberg, Khandelwal, Pavcnik, and Topalova (2009, 2010), on the other hand, study how the increased availability of new input categories as a result of importing enhances the development of new products and thus increases the variety of final goods in India. Kasahara and Lapham (2012) investigate the aggregate productivity gains of importing via resource reallocation in an extended Melitz model (Melitz, 2003), while assuming that the productivity of each particular firm is fixed. In contrast, my paper studies how importing improves the productivity and firm value of importing firms. These three lines of research emphasize different, but equally important, aspects of production. Another new feature of this paper is that I stress the dynamic effect of importing and quantify the the gains from dynamic effect and static effect separately. My paper in several ways improves the work of Kasahara and Rodrigue (2008) and Ge, Lai, and Zhu (2011), which estimate the effect of importing on firm productivity. First, my paper further considers firms' optimal importing decision, which affects the estimated total gains from importing. Second, my paper incorporates both the static *"Quality and Variety Effects"* and the dynamic productivity effect of importing in one unified framework, so I can evaluate the relative importance of different sources of gains from importing in terms of increased firm profit. Moreover, the structural model in my paper allows me to use counterfactual analysis to evaluate the effects of different policy changes on firms' profitability and importing dynamics.

The remainder of this paper is organized as follows. Section 1.2 describes some basic facts in the Colombian data, which forms the basis for the theoretical model. Section 3.3 establishes a simple theoretical model to characterize firms' dynamic importing decisions. Section 1.4 describes the empirical model and estimation strategy. Section 1.5 reports the estimation results, and section 1.6 performs robustness checks for the estimation results. Section 1.7 discusses the self selection of firms in importing, and section 1.8 performs counterfactuals to decompose gains from importing. Section 2.7 concludes.

1.2 Basic Facts in Colombian Data

I start with a brief introduction to the data. The data set is from the Colombian manufacturing census from 1977 to 1989, which was collected by the Departamento Administrativo Nacional de Estadistica (DANE)[4]. The census covers all plants in the manufacturing sector for 1977-1982, and all plants with ten or more employees after 1982. It contains detailed information about plants' usage of domestic input, imported input, output, and many other plant characteristics (e.g. age, ownership). For a detailed introduction to the data set, refer to Roberts, Tybout, and Mundial (1996) and Roberts and Tybout (1997).

I use the data from six Colombian industries that differ in their importing patterns and technologies: basic industrial chemicals, pharmaceuticals, plastic products, leather shoes, printing and publishing, and clothing. The industry choice

[4]In the estimation I drop observations for 1990 and 1991 because the industry code changed since 1990 and I did not find a good link between the old and new industry codes.

reflects several considerations. First, all six industries are important industries for the Colombian economy, with the number of observations in each of these industries large enough to do empirical investigation industry by industry. Second, since we are going to investigate the effect of importing, I choose industries with different ratios of imported to domestic inputs. Third, with the interest of looking at the plants' self selection into the importing market and the effect of importing, I would like to have industries with different levels of technology. There are 25,051 observations for all six industries in total, with the number varying from 934 to 11,316 for each industry.

I start with a brief description of several stylized facts observed in the data, which are the basis for the theoretical model in the following section.

Fact one: within each industry some plants purchase imported inputs while others do not.

When looking at the plant-level importing status, we can see that, within each industry, some plants purchase imported inputs while others do not. Table 1.1 shows the number and percentage of plants for each industry which ever imported inputs during the years 1977-1989. I report the total number of plants ever observed in the data in column 3, the number of plants importing at least once during the data period in column 4, and the percentage of importers in column 5. Note that each plant is counted only once, even if it is observed or imported in multiple years. About 18.9% of all the plants had importing experience in the six industries during the sample years, while the percentage varies significantly across industries, from 4.6% in clothing industry to as high as 77.2% in pharmaceuticals. Moreover, the last column reports the value share of the imported material in total material used. On average, about 28% of materials used in the six industries are imported. This indicates that import should not be ignored in analyzing firm behavior. This observation raises the question: why do some plants purchase imported inputs while others in the same industry do not? This cannot be explained by the classic comparative advantage. Instead, plant-level heterogeneity must be introduced to account for the within-industry importing diversity.

Fact two: turnover in importing status.

If we look further into the data, we can see that each year some plants begin and some plants stop importing intermediate inputs. Table 1.2 shows the turnover of importing status for all six industries in question. In this table, I do not count the firms that import at year t, but exit (stop operation) at year $t+1$. The second to the last columns show the number of importers, the number of incumbent importers, the number of new importers, and the number of importers which quit importing at the end of the year, respectively. In 1978, for example, among the 324 importers, 297 were incumbent importers and 27 were new importers. At the end of 1978, 39 importers stopped importing. In the whole sample, about 9.86% of the importers annually were new to importing intermediate inputs, while about 12.63% stopped importing intermediate inputs at the end of the year. The significant turnover raises the second question: what are the determinants of the switch in the importing status? Again, plant-level heterogeneity within one industry must be introduced to account for this switch. To account for the turnover, we need to consider further heterogeneity within importing plants and non-importing plants, in addition to the heterogeneity between importing and non-importing plants.

Fact three: strong persistence in plants' importing status over time. Table 1.3 shows the transition probability of plants' importing status over time. During the sample years, on average, about 87% of plants which imported at t continue importing at $t+1$ and about 98% of plants which did not import at t stay non-importing at date $t+1$. An interesting question is: what are the sources of the persistence?

Andersson, Lööf, and Johansson (2008) point out that importing is associated with fixed costs that are sunk, as the import agreement is preceded by a search process for potential foreign suppliers, inspection of goods, negotiation, contract formulation etc. Castellani, Serti, and Tomasi (2010) argue in a similar way, adding that there are sunk costs of importing due to the learning and acquisition of customs procedures.[5] All of these papers emphasize the importance of a sunk startup cost of importing. With the existence of sunk startup costs, the importing status yesterday will affect the plant's choice today because it determines whether the plant needs to pay sunk startup costs. If a plant was importing yesterday, then it is more likely that it will stay in the market since it does not need to pay the sunk entry cost, unlike plants not importing yesterday. Thus the existence

[5] Alessandria and Choi (2007) and Aw, Roberts, and Xu (2011) similarly emphasized the importance of sunk cost and fixed cost for export.

of sunk startup costs of importing may be a good explanation for the persistence of importing status and will, therefore, be one of the key factors affecting plants' decisions on whether to import intermediate inputs in my model. Consequently, the model provides a way to empirically estimate the sunk costs, which naturally provides a way to justify or falsify the sunk cost argument.

Fact four: importers have higher value added per worker than non-importers.

Table 1.4 reports the mean value added per worker for each of the six industries, as well as for the whole sample. It is obvious that importers have much higher value added per worker compared to non-importers. These results hold true for the whole sample, as well as for individual industries.

Since high value added per worker generally means higher productivity, the observations in Table 1.4 suggest that importers are likely more productive than non-importers. This is consistent with the documented positive relationship between importing behavior and productivity in the literature. From the data pattern, however, we cannot tell which way the causality goes. That is, we don't know whether this profitability difference is because more productive plants tend to import intermediate inputs, or because importing helps increase productivity. Thus, a complete structural model is needed to tackle the cause and effect of importing.

The model is directly based on the stylized facts observed in the data. The bottom line is that the model needs to be able to explain these facts well. In particular, I model the turnover and persistence of importing status by fixed and sunk costs of importing randomly drawn from two different distributions. A current importer needs to pay a fixed cost to continue importing and a current non-importer needs to pay a sunk cost to start importing. The draw of sunk and fixed costs governs the turnover and persistence of importing status. The model also constructs a productivity measure for each plant. This allows us to compare the productivity of importers with that of non-importers and to characterize the endogenous productivity evolution path.

1.3 The Model

In this section, I introduce a dynamic model to characterize plants' decisions to import intermediate inputs or rely solely on domestically-supplied inputs[6], following the model developed by Aw, Roberts and Xu (2011), which was initially used to analyze firms' dynamic exporting decisions. An important feature of this model is that it considers both the determinants and effects of importing simultaneously. A new feature of the model in this paper is that it explicitly disentangles the static effect and the dynamic productivity effect of importing within one unified framework. The static effect can be further explained by an input quality effect and an input variety effect. These features allow us to investigate and quantify different sources of gains from importing.

1.3.1 Timing

Plants face monopolistic competition from other plants in the same industry, and the objective of each plant is to maximize its discounted value of lifetime profits. The timing of the information flow and decisions is as follows:

1. At the beginning of each date, each plant observes its own capital stock (K_{jt}), productivity shock (ω_{jt}) and its importing status for the current date (d_{jt}), as well as the aggregate demand and production shifter, γ_t. These variables are summarized in $s_{jt} = \{K_{jt}, \omega_{jt}, d_{jt}, \gamma_t\}$ which represents plant j'sstate at date t.

2. Each plant chooses the amount of labor, domestic input, and imported input to maximize its period profit. Then production and sales occur.

3. Each plant then observes the realization of its own sunk cost and fixed cost.

4. Plants decide whether to import intermediate inputs next period based on the realization of sunk and fixed costs. If a plant decides to import next period, it pays the fixed cost if it is importing this period, or the sunk cost if it is not importing this period.

5. Plants choose investment.

6. All state variables are updated and the next period begins.

[6]The data do not link plants common to a firm, so we treat the plant as the decision-making unit. This is potentially problematic because, among multi-plant firms, plant-level imports may partly respond to characteristics of other production units. However, the vast majority of Colombian firms operate a single plant.

1.3.2 Technology and Demand

The production function is Cobb-Douglas, with a nested CES function to produce the intermediate input using domestic and imported material inputs. The nested CES function characterizes the static effect of importing through quality effect and variety effect. A nice feature of this parametrization is that the input quality effect and the (potential) input variety effect are explicitly represented by parameters in the production function.

$$\begin{aligned} Q_{jt} &= \exp(\omega_{jt} + \xi_{jt}) \left[L_{jt}^{\alpha_l} M_{jt}^{\alpha_m} K_{jt}^{\alpha_k} \right] \\ \text{with } M_{jt} &= \left[M_{jdt}^{\frac{\theta-1}{\theta}} + (A M_{jft})^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} \end{aligned}$$

where ω_{jt} is the productivity observed by plant j itself and ξ_{jt} represents the i.i.d productivity shock or measurement error. L_{jt} and K_{jt} are labor and capital of plant j at date t. M_{jdt} and M_{jft} are domestic and imported inputs used to produce the intermediate input M_{jt}. θ is the corresponding elasticity of substitution of domestic and imported inputs. In some sense, θ represents the input variety effect of imported products because it governs how easily the two inputs can be substituted in production. When θ is large, the two inputs are more substitutable, meaning that the input variety effect of the imported inputs is small. A represents the input quality effect of the imported inputs relative to domestic inputs, whose quality coefficient is normalized to one. When $A = 1$, imported inputs have no quality advantage over domestic inputs; when $A > 1$, imported inputs have relative quality advantage over domestic inputs; when $A < 1$, imported inputs have relative quality disadvantage.[7]

If plant j is an importer of intermediate inputs, then the logarithm production function is

$$\ln Q_{jt} = \alpha_l \ln L_{jt} + \alpha_m \frac{\theta}{\theta - 1} \ln \left[M_{jdt}^{\frac{\theta-1}{\theta}} + (A M_{jft})^{\frac{\theta-1}{\theta}} \right] + \alpha_k \ln K_{jt} + \omega_{jt} + \xi_{jt} \quad (1.1)$$

[7] To identify the quality parameter, A, ideally I need the physical quantity of domestic and imported inputs, M_{jdt} and M_{jft}. However, in most cases researchers only have the value of inputs instead of physical quantity of inputs, as in this paper. In this case, the quality parameter (A) contains both the real quality effect and the price difference between domestic and imported inputs, $A = \frac{p_d}{p_f} \cdot$ (real quality effect parameter). To separate the real quality effect from the price difference, we need additional information on prices of the imported and domestic inputs.

If plant j is not an importer, then the logarithm production function takes the more familiar form

$$\ln Q_{jt} = \alpha_l \ln L_{jt} + \alpha_m \ln M_{jdt} + \alpha_k \ln K_{jt} + \omega_{jt} + \xi_{jt} \tag{1.2}$$

Demand is assumed to be the classic Dixit-Stiglitz type:

$$Q^D_{jt} = \left(\frac{I_t}{P_t}\right)\left(\frac{P_{jt}}{P_t}\right)^{\eta} \equiv \Phi_t P^{\eta}_{jt}$$

where η is the demand elasticity, which is assumed to be the same across products within one industry. P_{jt} is plant j's price and P_t is the industry price index. I_t is the market size of this industry. $\Phi_t \equiv \frac{I_t}{P_t^{1+\eta}}$ is the common demand shifter for all plants.

1.3.3 Plants' Static Decision

Plants produce differentiated products and face monopolistic competition in the output market. Based on the timing described above, labor, domestic and imported inputs are static variables and they depend on the beginning-of-date state $s_{jt} = \{K_{jt}, \omega_{jt}, d_{jt}, \gamma_t\}$. A plant's static optimization problem is to choose these static inputs to maximize its own period profit.

When $d_{jt} = 1$, plant j has access to the import market in the current period with no additional cost. Observing the input prices and the demand status, plant j's static problem is to choose the static inputs (L_{jt}, M_{jtd} and M_{jtf}) and output price to maximize its period profit. Specifically, plant needs to choose static inputs (L_{jt}, M_{jtd} and M_{jtf}) to minimize the cost of producing any amount of output; then, facing the plant level demand, the plant sets output price to maximize its period profit. Similarly, when $d_{jt} = 0$, the plant has no access to the import market at date t; it chooses labor and domestic inputs to minimize the cost of producing any amount of output, and then chooses output price to maximize its period profit.

From plants' period profit maximization, we can derive the revenue function as a function of productivity, capital stock, current importing status and a time dummy D_t, which captures the demand shifter and input prices. Put in logarithm form,

$$\ln R_{jt} = \gamma_t D_t + r_k \ln K_{jt} + r_\omega \omega_{jt} + r_d d_{jt} \tag{1.3}$$

with coefficients being $r_k = \frac{\alpha_k}{\frac{\eta}{(1+\eta)} - (\alpha_l + \alpha_m)}$, $r_d = \left[\frac{\alpha_m/(\theta-1)}{\frac{\eta}{(\eta+1)} - (\alpha_l+\alpha_m)}\right] \ln \left[1 + \left(A\frac{P_{dt}}{P_{ft}}\right)^{\theta-1}\right]$ and $r_\omega = \frac{(\alpha_l+\alpha_m)}{\frac{\eta}{(\eta+1)} - (\alpha_l+\alpha_m)}$. This equation shows that importing directly impacts the current revenue. The strength of the impact is r_d, which is a function of A and θ. This implies that the effect of importing on revenue depends on the strength of the input quality effect (A) and input variety effect (θ) of imported inputs.

Under the demand and production assumptions above, total variable cost is a fixed share of revenue

$$C_{jt} = \frac{1+\eta}{\eta} (\alpha_l + \alpha_m) R_{jt} \tag{1.4}$$

The corresponding profit is a fixed share of the revenue

$$\pi_{jt} = \left[1 - \frac{1+\eta}{\eta} (\alpha_l + \alpha_m)\right] R_{jt} \tag{1.5}$$

Note that equations (1.4) and (1.5) are generalizations of equations (6) and (7) in Aw, Roberts and Xu (2011), in which the marginal cost is assumed to be constant ($\alpha_l + \alpha_m = 1$). In their paper, the demand elasticity can be directly estimated from data on total variable cost and revenue. In this paper, if $\alpha_l + \alpha_m$ are known, then the demand elasticity η can also be estimated similarly from data on revenue and total variable cost.[8]

1.3.4 Dynamic Choice of Importing Status

Observing sunk and fixed costs, each plant's dynamic optimization problem is to decide whether or not to import materials in order to maximize its own continuation value. The main considerations of plants in terms of importing participation are gains from importing, the fixed cost of continued importing and the sunk startup costs of importing. Previous importing status is relevant because first-time importers need to pay the sunk cost (C^s_{jt}) and continuing importers instead pay the fixed cost (C^f_{jt}) to import. The sunk cost may be much higher than the fixed cost. Assume that the sunk cost and fixed cost are i.i.d draws from two different

[8]Refer to a separate online appendix for details about deriving equations (1.3), (1.4) and (1.5).

distributions, $C^s_{jt} \sim F^s$ and $C^f_{jt} \sim F^f$. They provide exogenous shocks to the firm decision.

The productivity (ω_{jt}) follows a first order Markov process

$$\begin{aligned} \text{Productivity} \quad : \quad & \omega_{jt} = E\left(\omega_{jt} \mid \omega_{jt-1}, d_{jt-1}\right) + \varepsilon_{jt} \\ = \quad & g\left(\omega_{jt-1}, d_{jt-1}\right) + \varepsilon_{jt}, \text{with iid } \varepsilon_{jt} \sim N(0, \sigma^2_\varepsilon) \end{aligned} \tag{1.6}$$

where the innovation of the Markov process ε_{jt} is drawn from a normal distribution with mean 0 and variance σ^2_ε. The new feature in this paper is that historical importing experience d_{jt-1} affects future productivity evolution process. If a firm was an importer at date t-1, its productivity will be enhanced due to the importing experience. This embodies the idea that importing intermediate inputs has a dynamic effect on productivity. Since the importing decisions are endogenous, this setup implies that productivity is endogenous.

Capital stock (K_{jt}) equals the current investment (i_{jt-1}) plus last period capital stock after depreciation: $K_{jt} = (1-\rho_k)K_{jt-1} + i_{jt-1}$, where ρ_k is the depreciation rate. Assume all distributions and the evolution of the dynamic variables are common information. Plant j's valuation before it observes the current date fixed cost and sunk cost is

$$V(s_{jt}) = \int\int \left[\pi_(s_{jt}) + \max_{d_{jt+1}} \left\{V^1(s_{jt}) - d_{jt}C^f_{jt} - (1-d_{jt})\,C^s_{jt}, V^0(s_{jt})\right\}\right] dF^s\, dF^f \tag{1.7}$$

where $V^1(s_{jt})$ and $V^0(s_{jt})$ are discounted choice specific continuation values of importing and not importing respectively, assuming that each plant always chooses optimal investment associated with its importing status. d_{jt} is a discrete 0/1 variable identifying firm j's importing status at date t. Importing decision is dynamic through two channels: productivity channel and cost channel[9]. On one hand, current importing decision affects future productivity. On the other hand, current importing status determines what costs, sunk or fixed, the firm pay to import in the next period. If the firm imported at date t, then it will pay a fixed cost C^f_{jt} to continue importing at date $t+1$. If the firm did not import at date t, then it will

[9]Ramanarayanan (2011, 2013) also writes a model of firms' importing decision which depends on productivity and other factors and use the model to study the gains from import in the latter. In their model,firms' choose importing decision to maximize static profit.

pay a sunk cost C^s_{jt} (very likely higher than fixed cost) to start importing.

Note that the value of investment is subsumed in the choice-specific value functions $V^1(s_{jt})$ and $V^0(s_{jt})$. To be more precise the choice specific value functions could be written as

$$\begin{aligned} V^1(s_{jt}) &= \delta E_t V(s_{jt+1} \mid s_{it}, d_{jt+1} = 1) \\ V^0(s_{jt}) &= \delta E_t V(s_{jt+1} \mid s_{it}, d_{jt+1} = 0) \end{aligned}$$

The expectation is taken over the stochastic evolution process of ω_{jt}, and the uncertainty of the demand shifter and input prices (γ_t). More specifically, by expressing expectation in integral form, the choice-specific value functions are written as:

$$V^1(s_{jt}) = \delta \max_{I_{jt}} \int \int V(s_{jt+1}, d_{jt+1} = 1) dF\left(\omega_{jt+1} \mid \omega_{jt}, d_{jt}\right) dF\left(\gamma_{t+1} \mid \gamma_t\right) \quad (1.8)$$

$$V^0(s_{jt}) = \delta \max_{I_{jt}} \int \int V(s_{jt+1}, d_{jt+1} = 0) dF\left(\omega_{jt+1} \mid \omega_{jt}, d_{jt}\right) dF\left(\gamma_{t+1} \mid \gamma_t\right) \quad (1.9)$$

Equations (1.8) and (1.9) give the optimal investment decision rule, $I_{jt} = I_t(\omega_{jt}, k_{jt}, d_{jt+1})$, which is a function of productivity, capital and future importing status. Equations (1.7), (1.8) and (1.9) together fully characterize plants' importing decisions under each state s_{jt} and can be used to evaluate the payoff to plants for each choice under each state.

1.4 Estimation Strategy

I observe in the data the value of domestic material, imported material, a 0/1 importing indicator[10], capital, investment, number of employees, wage expenditure, revenue and other plant characteristics (e.g. age and ownership). The parameters to be estimated include: $\alpha_l, \alpha_m, \alpha_k, \eta, A, \theta; g\left(\cdot,\cdot\right), \sigma^2_\varepsilon; F^s, F^f$. The parameters of major interest in this paper are the input quality effect parameter A, the input variety effect parameter θ, the productivity evolution process $g\left(\cdot,\cdot\right)$, and the distributions of sunk cost and fixed cost (F^s and F^f). A and θ represent the static productivity effect of importing due to input quality effect and input variety effect.

[10]The importing indicator equals 1 if the imported material is positive. It is zero otherwise.

$g(\cdot,\cdot)$ helps quantify the dynamic productivity effect associated with importing.

The intuition for identification is straightforward. The demand and production parameters, as well as the parameters governing the productivity evolution process, can be identified from plants' static decisions. Specifically, information from plants exclusively using domestic inputs can help identify the share parameters $\alpha_l, \alpha_m, \alpha_k$ in the production function and the parameters associated with ω_{jt-1} in the productivity evolution process $g(\cdot,\cdot)$. On the other hand, usage of imported and domestic materials from importing plants provides additional information to help identify the quality parameter A, the elasticity of substitution θ, and the parameters associated with d_{jt-1} in the productivity evolution process $g(\cdot,\cdot)$. Usage of imported and domestic materials from importing plants also provides information about the share parameters $\alpha_l, \alpha_m, \alpha_k$ and $g(\cdot,\cdot)$, which can be used to improve the estimation efficiency.

Given the estimates for α_l and α_m, the demand elasticity can be identified from the cost and revenue information. Finally, the distributions of sunk cost and fixed cost can be identified from plants' dynamic decisions on whether or not to import intermediate inputs. Specifically, the entry decisions of current non-importers provides direct information to identify the sunk cost distribution, and the exit decisions of current importers provides direct information to identify the fixed cost distribution.

The estimation algorithm is a three-stage procedure, combining the insights of Olley and Pakes (1996) and Das, Roberts, and Tybout (2007).

Stage one: estimate production parameters $\alpha_l, \alpha_m, \alpha_k, A, \theta$, using data on labor, capital, domestic and imported inputs and investment.

Stage two: given the estimates of α_l and α_m, the demand elasticity is estimated from equation (1.4), using variable cost and revenue data. Then the profit functions can be derived from the estimate of the revenue function from equations (3) and (5).

Stage three: the sunk and fixed costs parameters are estimated from plants' decisions on whether to import intermediate inputs. More precisely, the cost parameters can be identified from the conditional choice probabilities (CCP) of that plants begin or stop importing intermediate inputs.

1.4.1 Production Parameters: $\alpha_l, \alpha_m, \alpha_k, A, \theta,\ g, \sigma_\varepsilon^2$

In order to increase estimator efficiency, I make use of the data on all plants (both importers and non-importers) to estimate the production parameters, although the identification of $\alpha_l, \alpha_m, \alpha_k$ does not rely on information about importers. Denoting $x = \ln X$ and making use of the importing status dummy d_{jt} for firm j at date t, equation (1.1) and (1.2) can be rewritten in one equation as:

$$q_{jt} = \alpha_l l_{jt} + \alpha_m \frac{\theta}{\theta - 1} \ln \left[M_{jdt}^{\frac{\theta-1}{\theta}} + (AM_{jft})^{\frac{\theta-1}{\theta}} d_{jt} \right] + \alpha_k k_{jt} + \omega_{jt} + \xi_{jt} \tag{1.10}$$

This equation allows us to use input and output data for all plants to estimate the production parameters. $\omega_{jt} + \xi_{jt}$ constitutes the plant-level productivity, where only ω_{jt} is observed by the plant (but not by researchers), and ξ_{jt} is not observed by the plant or researchers. Under the timing assumption above, d_{jt} is uncorrelated with ξ_{jt} because the i.i.d productivity shock ξ_{jt} happens after the choice of d_{jt}. However, it is a well known fact that the direct OLS estimator from the above equation is subject to an endogeneity problem because the labor and material inputs choices are dependent on ω_{jt}. In addition, the importing status d_{jt} is also correlated with ω_{jt} because productivity is a Markov process. This correlation further aggravates the endogeneity problem.

To ensure a consistent estimator, the above endogeneity problem must first be resolved. In general, plants' investment contains information about the unobserved productivity ω_{jt}. Under the timing assumption in this paper, investment is a function of current capital stock, productivity, and the chosen importing status for the future, i.e. $i_{jt} = i_t(\omega_{jt}, k_{jt}, d_{jt+1})$. We can utilize the insights of Olley and Pakes (1996) to recover the unobserved productivity ω_{jt} from investment, $\omega_{jt} = \omega_t(i_{jt}, k_{jt}, d_{jt+1})$, under the usual monotonicity assumption.[11]

$$\begin{aligned} q_{jt} &= \alpha_l l_{jt} + \frac{\alpha_m \theta}{\theta - 1} \ln \left[M_{jdt}^{\frac{\theta-1}{\theta}} + (AM_{jft})^{\frac{\theta-1}{\theta}} d_{jt} \right] + \alpha_k k_{jt} + \omega_t(i_{jt}, k_{jt}, d_{jt+1}) + \xi_{jt} \\ &= \alpha_l l_{jt} + \alpha_m \frac{\theta}{\theta - 1} \ln \left[M_{jdt}^{\frac{\theta-1}{\theta}} + (AM_{jft})^{\frac{\theta-1}{\theta}} d_{jt} \right] + \phi(i_{jt}, k_{jt}, d_{jt+1}) + \xi_{jt} \end{aligned} \tag{1.11}$$

[11] To recover w_{jt} by inverting investment function, a critical condition is that investment is strictly increasing in productivity, which is a popular assumption in the literature. Intuitively, investment should (at least weakly) increase in productivity. However, a sound econometric test of the validity of the assumption is still called for.

where $\phi(i_{jt}, k_{jt}, d_{jt+1})$ captures the combined effect of capital and observed productivity on production. The static input shares $\widehat{\alpha_l}$ and $\widehat{\alpha_m}$, the quality parameter $\widehat{A}$,the variety parameter $\widehat{\theta}$, and the $\phi(\cdot)$ function can be estimated from equation (1.11) semiparametrically. This estimation is consistent since $l_{jt}, M_{jdt}, M_{jft}, i_{jt}, k_{jt}$ and d_{jt+1} are all uncorrelated with ξ_{jt}. In this paper, $\phi(i_{jt}, k_{jt}, d_{jt+1})$ is parameterized as a cubic function. Denote $\widehat{\phi}_{jt}$ as the fitted value for $\phi(i_{jt}, k_{jt}, d_{jt+1})$; then productivity can be expressed as $\omega_{jt} = \widehat{\phi}_{jt} - \alpha_k k_{jt}$. Substituting ω_{jt} in the production function with $\omega_{jt} = g\left(\omega_{jt-1}, d_{jt-1}\right) + \varepsilon_{jt}$ and replacing ω_{jt-1} with $\omega_{jt-1} = \widehat{\phi}_{jt-1} - \alpha_k k_{jt-1}$ yield an estimation equation:

$$\widehat{\phi}_{jt} = \alpha_k k_{jt} + g\left(\widehat{\phi}_{jt-1} - \alpha_k k_{jt-1}, d_{jt-1}\right) + \varepsilon_{jt} + \xi_{jt} \tag{1.12}$$

This equation can be estimated semi-parametrically. The parameter α_k and the $g(\cdot,\cdot)$ function can be retrieved from data on $\widehat{\phi}_{jt}, \widehat{\phi}_{jt-1}, k_{jt-1}$, and d_{jt-1}. In this paper, the $g(\cdot,\cdot)$ function is parameterized simply by $g(\omega_{jt-1}, d_{jt-1}) = g_0 + g_\omega \omega_{jt-1} + g_d d_{jt-1}$. g_ω represents the marginal effect of current productivity on future productivity, and g_d represents the dynamic effect of importing on productivity associated with importing. We are especially interested in g_d and we expect it to be positive based on our model.

Based on the estimate of α_k, we can construct a pseudo sample of productivity for each plant each year

$$\widehat{\omega_{jt}} = \widehat{\phi}_{jt} - \widehat{\alpha_k} k_{jt} \tag{1.13}$$

1.4.2 Stage Two: Demand Elasticity η and Profit Function

Under the structural assumptions of the production function and the demand function, we can characterize plants' revenue function and profit function using the structural parameters. Plants' static decisions lead to a simple relationship between the total variable cost and the revenue, as shown in equation (1.4). The total variable cost is defined as the total expenditure on domestic inputs, imported inputs and labor and is observed in the data. By introducing the usual optimization error and measurement error, equation (1.4) can be written in the following estimable form:

$$C_{jt} = \frac{1+\eta}{\eta}\left(\alpha_l + \alpha_m\right) R_{jt} + \zeta_{jt} \tag{1.14}$$

The error term ζ_{jt} is assumed to be i.i.d across plants and across time. As in Das, Roberts and Tybout (2007) and Aw, Roberts and Xu (2010), we can estimate the demand elasticity η from equation (1.14), given that α_l and α_m have been estimated above.

Construct the profit function. With all the production parameters and demand parameters on hand, we can compute r_k, r_w, and r_d in equation (1.3). To derive the revenue function, we still need to estimate the coefficients of the time dummies.

Denote $\widetilde{r}_{jt} = \log(R_{jt}) - (r_w\widehat{\omega_{jt}} + r_k k_{jt} + r_d d_{jt})$. The coefficients of time dummies can be estimated from the following equation:

$$\widetilde{r}_{jt} = \gamma_t D_t + e_{jt} \tag{1.15}$$

where the error term e_{jt} comes from an i.i.d measurement error or any form of optimization error which affects plant revenue.

The revenue function is then $R_{jt} = \exp(\gamma_t D_t + r_k k_{jt} + r_w \omega_{jt} + r_d d_{jt})$. The profit, as a fixed share of the revenue function from equation (1.5), is a function of $(\gamma_t, w_{jt}, k_{jt}, d_{jt})$,

$$\pi_{jt} = \left[1 - \frac{1+\eta}{\eta}(\alpha_1 + \alpha_2)\right] \exp\left(\ \gamma_t D_t + r_k k_{jt} + r_w \omega_{jt} + r_d d_{jt}\ \right) \tag{1.16}$$

where all unknown parameters are replaced with their estimates. This profit function is useful when computing the value functions of plants in the next subsection.

1.4.3 Sunk/Fixed Cost Parameters

The distributions of sunk cost and fixed cost, in principle, can be identified from plants' dynamic discrete decisions of importing status. A Maximum Likelihood Estimator (MLE) is constructed for estimating the distribution of both sunk and fixed costs in this section. As I am using a short panel data, it is hard to estimate the evolution process of the macroeconomic environment dummy, γ_t. In the dynamic estimation I treat the γ_t as constant over time. This treatment is supported by the fact that the estimated magnitude of γ_t is quite small compared to the other terms in the revenue function in equation (1.3).

The conditional probability of observing a data point with $d_{jt+1} = 1$, given state $s_{jt} = \{\omega_{jt}, k_{jt}, d_{jt}, \gamma_t\}$ is

$$\begin{aligned} L_{jt}^{1} &= \Pr\{d_{jt+1} = 1 \mid s_{jt}\} \\ &= \Pr\left\{d_{jt}C_{jt}^{f} + (1 - d_{jt})\, C_{jt}^{s} \leq V^{1}(s_{jt}) - V^{0}(s_{jt}) \mid s_{jt}\right\} \end{aligned} \tag{1.17}$$

The conditional probability of observing a data point with $d_{jt+1} = 0$ is $1 - L_{jt}^{1}$. The probability of observing importing status d_{jt+1} is

$$L_{jt} = d_{jt+1}L_{jt}^{1} + (1 - d_{jt+1})(1 - L_{jt}^{1})$$

Under the i.i.d assumption on fixed and sunk costs of importing, the probability of observing a specific importing history of plant j is

$$L_j = \prod_{t=1:T} L_{jt} \tag{1.18}$$

The probability of observing the importing status of all plants in the data set is

$$L = \prod_{j=1:N} L_j = \prod_{j=1:N}\prod_{t=1:T} L_{jt} \tag{1.19}$$

Given the shape of the sunk and fixed cost distributions, parameters in F^s and F^f could be estimated by MLE. In this paper, I assume that sunk costs and fixed costs are i.i.d drawn from two different exponential distributions, $C_{jt}^{s}\,\tilde{}\,\exp(cs)$ and $C_{jt}^{f}\,\tilde{}\,\exp(cf)$[12]. Then the distribution parameters (cs, cf) can be estimated by MLE. The major problem associated with this estimation is that $V^{1}(s_{jt})$ and $V^{0}(s_{jt})$ need to be constructed for each parameter evaluated from the plants' dynamic optimization problem. The computational algorithm to solve for $V^{1}(s_{jt})$ and $V^{0}(s_{jt})$ is in the A.

[12]The lognormal distribution is used to check the robustness of the distributional assumption. The results are consistent with that derived in this paper, showing that the distributional assumption on the sunk and fixed cost are not substantial.

1.5 Estimation Results

In this section, I will first report and briefly discuss the estimation results of the empirical model from the plant-level Colombian data. I use the unbalanced panel data to structurally estimate the dynamic model. I drop the first year for new firms and the last year for exiting firms to ensure that for each observation the plant state s_{jt} and the lagged and leading variables, in particular importing status d_{jt-1} and d_{jt+1}, are fully observed.[13] I then use the unbalanced data to estimate the dynamic model of importing decisions as well as the productivity evolution process. As Olley and Pakes (1996) point out, using unbalanced data can significantly reduce the problem of selection bias.

1.5.1 Production and Productivity Evolution

Table 1.5 reports the estimation results from equation (1.11) in stage one, estimated using nonlinear least square (NLLS). In this regression, I also added plant age and ownership to control for plant-specific characteristics. Age is the number of years in operation and ownership is a dummy variable which equals 1 if the plant is a public corporation and 0 otherwise.

In Table 1.5, α_l and α_m represent the labor share and material share in the production function, respectively. The magnitude for all parameters are reasonable. We are particularly interested in the quality parameter (A) and elasticity of substitution (θ). It is interesting that the estimated input quality parameter A is very close to 1. In four out of the six industries, the input quality parameter A is not statistically different from 1; in printing and publishing industry, A is statistically smaller than 1. This means that the imported intermediate inputs have a very small quality advantage or even a quality disadvantage over domestic inputs in these five industries. In the plastics industry, A is larger than 1 statistically, indicating that imported intermediate inputs have quality advantage in this industry. However, we must be cautious about interpreting this result. As we estimate the model using the value of imported and domestic inputs, the estimat-

[13]As this paper shut down entry/exit in order to focus on the importing decisions, this is a simple way to play around the first-year/last-year problem. An alternative way of dealing with this problem is to explicitly consider entry/exit in the model.

ed quality parameter (A) contains both the real input quality effect and the price difference between domestic and imported inputs. Because the prices for imported inputs are usually higher than those of domestic inputs for developing countries like Colombia, $A < 1$ implies that the imported inputs have a quality disadvantage over domestic inputs after taking the price difference into consideration. $A = 1$ implies that imported inputs have no quality advantage over domestic inputs after considering the price difference[14]. To separate the real input quality effect from the price difference, we need additional information on prices of both imported and domestic inputs. Unfortunately, these data are not available in the Colombian data; therefore, in the paper, the parameter A is interpreted as containing both the input input quality effect and the price difference between imported and domestic inputs.

Another interesting finding is that the elasticity of substitution θ between the imported and domestic inputs is significantly higher than one, but still not very large. This implies that the input variety effect of imported inputs does exist, which is consistent with the argument in Goldberg, Khandelwal, Pavcnik, and Topalova (2009, 2010). The estimates of A and θ together imply that when the input quality effect is small or even negative, plants may still want to import inputs in order to take advantage of the the input variety effect, along with other possible gains. I will elaborate on this point in more detail in the subsequent sections.

The estimates of capital elasticity and the productivity evolution process are recorded in Table 1.6. The estimation is based on equation (1.12). I estimate both the base model and an extension in which I control for exporting in the productivity evolution process. The results are reported respectively in panels A and B in Table 1.6. α_k is the capital elasticity and the g parameters characterize the productivity evolution process. g_w is the effect of today's productivity (w_{jt}) on tomorrow's productivity (w_{jt+1}). g_d measures the dynamic effect of importing status on future productivity. I also control for the export level in panel B, as captured by g_e. The parameter σ_w is the standard deviation of the productivity shock, which is assumed to be normally distributed $N(0, \sigma_w^2)$ in the estimation.

Both regressions yield consistent qualitative results: importing has a positive

[14]This probably suggests that price, in some sense, is a good proxy for inputs quality, as argued in Kugler and Verhoogen (2012).

and statistically significant effect on productivity evolution. If a plant imports today, its future productivity will be improved significantly. Also, the estimation results from the two cases both show that productivity is persistent. If a plant is productive today, it is very likely that tomorrow it will continue to be productive. However, the magnitudes of estimates are slightly different from each other in the base model and extended model. In the base model, the coefficient of the importing dummy ranges from 0.0050 in clothing industry to 0.0568 in printing and publishing industry. In contrast, in the extended model when exporting is controlled for, this coefficient ranges from 0.0026 in clothing industry to 0.0277 in printing and publishing industry. The reason is that there might be a correlation between importing and exporting. The estimated effect of importing would have picked up the effect of exporting if exporting is not controlled for in the base model.

Because our purpose is to identify the gains from importing, I will rely on the results from panel B to compute the dynamic effect of importing. After controlling for exporting, g_d ranges from 0.0026 in clothing industry to 0.0277 in printing and publishing industry, contributing to 0.16% (clothing) to 2.92% (printing and publishing) of the productivity growth rate annually.

I also ran two regressions to check the robustness of dynamic productivity effect of importing. In the first regression, I also control for firm age and ownership in the above regression. The estimated g_d is almost the same as that derived in Panel B in Table 1.6. In the second regression, I check whether the effect of importing on productivity is robust to different measure of import. I use import share instead of importing dummy to measure the effect of importing on productivity. I still get positive and significant effect of importing on producitivity. These results will be provided upon request and will be included in the online appendix. These observations confirm the conjecture in the model section that importing has a positive dynamic effect on productivity. We will compute the gains of firm value from this dynamic effect in section 8.

1.5.2 Demand and Revenue Function

Under the structural assumptions of production and demand, plants' revenue and profit functions can be constructed structurally. The revenue function parameters calculated from equation (1.3) and the demand parameters estimated from equation (1.14) are reported in panel A and panel C, respectively, in Table 1.7.[15] I also compute the implied revenue elasticities with respect to productivity, capital and importing participation, as reported in panel B in Table 1.7.

The estimated demand elasticity is significantly larger than 1. This is reasonable because the market power in the monopolistic competition market allows plants to charge a markup price. r_ω measures the effect of productivity on revenue and is positive. In the basic industrial chemicals industry, for example, $r_\omega = 0.7920$ means that a 1% increase in productivity increases revenue by about 2.53%. r_k is the revenue elasticity of capital stock. Other things equal, $r_k = 0.1286$ in the basic industrial chemicals industry means that a 1% increase in capital stock increases revenue by about 0.1286%. The most interesting finding here is the positive effect of importing on revenue, $r_d > 0$. The use of imported inputs immediately increases current period revenue. Because the quality and input variety effects are static, this finding implies that the total quality and input variety effect is positive. We will further explore this point using a counterfactual analysis in the subsequent section. The estimates for r_d imply that importing can increase revenue by about 0.74% to 40.52%[16] for the six industries under investigation.

1.5.3 Fixed and Sunk Cost

As noted above, the distribution parameters of the fixed and sunk costs can be estimated with Maximum Likelihood, using plants' dynamic decisions on whether or not to import inputs.

1.5.3.1 Distribution of the Sunk and Fixed Costs

In the estimation, to limit the range of the parameters more efficiently, we redefine $\lambda_s = \log(cs), \lambda_f = \log(cf)$ and estimate the parameters λ_s and λ_s in the program. The sunk and fixed cost distributional parameters, cs and cf, can be retrieved from λ_s and λ_s in a straightforward way.

[15] The constant r_0 is the average of time dummies estimated in equation (1.15). I do this in order to simplify the dynamic estimation.

[16] Current importing status d_{jt} increases revenue by $\exp(r_d) - 1$.

The estimation results for λ_s and λ_f are reported in Table 1.8. The estimates are all statistically significant. I also report the mean of the fixed cost and sunk cost in the second half of Table 8. Two observations are worthy of specific discussion. First, the estimated sunk cost is always larger than the fixed cost in all of the industries estimated. In all six industries, the estimated mean of sunk cost is over 15 times as large as that of the fixed cost. The second interesting result is that both the fixed cost and the sunk cost are very large. The mean of the sunk cost goes from about 15 to over 350 million Colombian Pesos. This accounts for about 8.78%-63.70% of the annual average profits in these industries. At the same time, the mean fixed cost ranges from 0.3616 to 4.1853 million Colombian Pesos, accounting for a low 5.30% of plants' annual profits in the pharmaceuticals industry to as high as 21.73% of annual profits in the plastics industry. The significant magnitude means that sunk and fixed costs are not negligible in terms of plants' import participation decisions.

The fact that the sunk cost is much larger than the fixed cost is consistent with our model conjecture that sunk cost is a critical factor that generates the observed persistence of plants' importing status. If a firm is importing today, to continue importing it only needs to pay a fixed cost, which is on average much smaller than the sunk cost. This explains why compared to non-importers, importers today are more likely to import tomorrow. Also, the large sunk costs prevent non-importers from starting to import. Only those non-importers who have a very small draw of the sunk cost start importing. This explains that why only a few non-importers start importing at each period.

There are several possible reasons for the high estimated sunk costs. As Andersson, Lööf, and Johansson (2008) point out, importing is associated with fixed costs that are sunk, because import agreement is preceded by a search process for potential foreign suppliers, inspection of goods, testing whether the good matches current production streamline, negotiation, contract formulation etc. These costs may be very high. Also, first time importers need to spend both human and monetary resources to learn customs procedures. This again increases the sunk cost.

As for the fixed cost, continuing importers do not need to pay costs to master the customs procedures, and they have more experience in importing. So we can expect that fixed cost will be much lower than sunk cost. However, fixed costs could still be very high due to several reasons. First, plants need to maintain the business relationship via different forms, which may be costly. Second, although first-time importers have inspected the goods, they still need to inspect goods each time they continue importing to make sure that the international exporters deliver the appropriate materials. Third, because shipping is more costly and risky in international trade, plants need to spend extra money to buy shipping and delivery insurance. Moreover, trade friction is common and frequent in international trade and importers are usually the side that suffers to losses. In these cases, they need to spend time and resources on, for example, filing lawsuits in order to fight for their rights. These costs may be very high.

In addition, there were substantial trade barriers that significantly affected importing during the data period in Colombia, which drove up the sunk and fixed importing costs. As documented by Roberts and Tybout (1996), although Colombia had quite an open trade policy in the 1970s, it totally reversed its trade policy to slow import liberalization starting in 1981. In 1981, only 36% of commodities could be freely imported, compared to 69% in 1980 before the policy change. The number of commodities subject to quantitative restrictions continued to rise through 1984. By that time, only 0.5% of all products were classified in the free import category, 83% required licenses, and 16.5% were completely prohibited. As a result of these import restrictions, plants who wanted to import needed to spend extra time and resources (both monetary and non-monetary) to lobby importing licenses. Because of the quota, bribery was very common, which may have greatly increased both the sunk and fixed costs of importing. All of the quota-induced costs related to importing are picked up by the fixed/sunk costs estimated in the model and can contribute to the large estimated sunk/fixed costs.

1.6 Robustness Check

Our goal is to accurately measure the effects of importing intermediate materials on productivity and firm value. As such, it is important to have confidence that the estimation results from the model are robust and not sensitive to particular underlying assumptions in the model. In particular, we need to make sure that the estimated effect of importing is not actually the effect of exporting, considering the possible correlation between the two activities. To remove the impact of exporting on the estimation results, I estimate the model for non-exporters only and compare the results with those from the whole sample. As the firm value is defined as the discounted present value of the future profit flow, in order to check the effect of importing on firm value, it is enough to check the effect of importing on revenue and productivity.

Tables 1.13 to 1.15 show that the non-exporter subsample yields qualitatively similar results as those from the whole sample: importing has a positive impact on productivity, with the coefficient of the importing dummy having a value between 0.0042 to 0.0322. Importing also has a positive impact on revenue, with the coefficient having a value between 0.1146 to 0.4012. The estimated elasticity of substitution between imported and domestic intermediate inputs in the subsample has a similar magnitude to that of the whole sample. The estimated quality parameter also indicates that the quality effect is trivial, as the quality parameters are not significantly different from 1 in the subsample in all six industries. This is consistent with what we find in the whole sample. These results show that the estimated effect of importing on revenue and productivity is robust and that the estimated effect of importing is actually not the effect of exporting.

1.7 Self Selection

Given the estimated model of import choice, we can describe the threshold costs involved when plants choose to import. Specifically we can find the threshold cost involved in current non-importers' decision to start importing and the threshold cost involved in current importers' decision to stop importing. From the dynamic model developed above, a plant (non-importer) in state $s_{jt} = (w_{jt}, k_{jt}, d_{jt} = 0)$ chooses to start importing if and only if its draw of sunk cost is smaller than the expected gain associated with importing

$$C_{jt}^{s} \leq V^{1}(s_{jt,} d_{jt} = 0) - V^{0}(s_{jt,} d_{jt} = 0) \tag{1.20}$$

where $V^1(s_{jt})$ and $V^0(s_{jt})$, as functions of $s_{jt,}$ are choice-specific value functions with $V^1(s_{jt}) = V(s_{jt}, d_{jt+1} = 1)$ and $V^0(s_{jt}) = V(s_{jt}, d_{jt+1} = 0)$. This condition determines the threshold cost for current non-importers' decision of whether or not to start importing. Similarly, a current importer in state $s_{jt} = (\omega_{jt}, k_{jt}, d_{jt} = 1)$ chooses to stop importing if and only if its draw of fixed cost is larger than the expected gain from continuing to import:

$$C_{jt}^f \geqslant V^1(s_{jt,}d_{jt} = 1) - V^0(s_{jt,}d_{jt} = 1) \tag{1.21}$$

This condition determines the threshold cost involved in current importers' decision of whether or not to stop importing. Recall that $V^1(s_{jt}) = V(s_{jt}, d_{jt+1} = 1)$ and $V^0(s_{jt}) = V(s_{jt}, d_{jt+1} = 0)$. Combining both $V^1(s_{jt})$ and $V^0(s_{jt})$ into one function yields $V(s_{jt}, d_{jt+1})$. As $V(s_{jt}, d_{jt+1})$ has been computed in stage 3 for each point (s_{jt}, d_{jt+1}) in the data, we can run a regression to smooth it. The regression results give a parametric form of the threshold costs which can be used to analyze plants' importing decisions.[17]

Figure 1.1 and Figure 1.2 report the threshold costs and productivity of importing for the basic industrial chemical industry as an example.[18] The threshold costs are determined by equations (1.20) and (1.21). Figure 1.1 shows the thresholds of productivity and sunk cost involved in current non-importers' decision of whether or not to start importing, for three different capital levels. The horizontal axis represents the productivity and the vertical axis represents the sunk cost in millions of 1977 Colombian Pesos. The solid line, the dashed line and the dot-dashed line each represent the thresholds when capital is chosen to be the median, the 75th quantile and the 25th quantile in the industry respectively. For a given capital level, firms below the associated threshold line have higher productivity/lower draw of sunk cost and will start importing. Firms above the threshold have lower productivity/higher draw of sunk cost and will not start importing. Take the solid line for example, firms in the shaded area do not importing and firms in the unshaded area start importing. The positive slope of the threshold implies that, all other things equal, as non-importers become more productive, they are more likely to start importing intermediate inputs. It clearly shows the self-selection of

[17]See B for the detail.

[18]Refer to B for more detail.

firms to importing inputs: firms that are more productive and that draws lower sunk costs are more likely to starting importing.

Figure 1.1 also shows that, given productivity, larger firms are more likely to import intermediate inputs. As capital increases from the 25th quantile to the median to the 75th quantile, the threshold involved in the decision to start importing shifts up in Figure 1.1. This means plants are more likely to start importing when they are larger in terms of capital level.

Similarly, Figure 1.2 shows the thresholds of productivity and fixed cost of stopping importing or not for current importers, for three different capital levels. The solid line, the dashed line and the dot-dashed line each represent the thresholds when capital is the median, the 75th quantile and the 25th quantile in the industry respectively. Considering the hypothetical importers with the median industry capital, for example, if its combination of productivity and fixed cost falls in the shaded area, it will stop importing. Otherwise, it continues importing. As the threshold has a upward slope, more productive firms are more likely to continue importing, all other things equal. Figure 1.2 also shows that larger importers are more likely to continue importing intermediate inputs. As capital increases from the 25th quantile to the median to the 75th quantile, the thresholds of fixed cost and productivity involved in the decision to continue importing shifts up. This implies that, all other things equal, larger importers (measured by capital level) are more likely to continue importing. The finding in figure to clearly shows that firms that are larger and more productive are more likely to continue importing.

The same results are also found in the other industries in our investigation. I omit the results in the interest of space. In general, self selection of plants into the importing market is clear: current non-importers are more likely to start importing if they are larger, more productive, and/or have drawn a low sunk costs of importing; current importers are also more likely to continue importing if they are larger, more productive and/or have drawn a low fixed cost.

1.8 Gains from Importing Intermediate Inputs

In this section, I will quantify the gains to plants from importing intermediate inputs and decompose them into a static effect and a dynamic effect.

1.8.1 Gains from Importing

The total gain to plants from importing inputs is defined as the net gain of plant value from importing, which equals the plant's value when it has access to the foreign import market minus the value of the same plant in an autarky economy. An autarky refers to an economy in which none of the plants have access to a foreign market. The autarky plant value can be easily derived by solving the following standard investment model

$$\begin{aligned} V(\omega_{jt}, K_{jt}) &= \pi^0_{(s_{jt})} + \delta \max_{i_{jt}} E_{\omega_{jt+1}} V(\omega_{jt+1}, K_{jt+1}) \\ s.t.\;\; K_{jt+1} &= i_{jt} + (1-\rho_k) K_{jt-1} \\ \omega_{jt} &= E\left(\omega_{jt} \mid \omega_{jt-1}, d_{jt-1} = 0\right) + \varepsilon_{jt} \end{aligned} \tag{1.22}$$

It is straightforward that the solution to the autarky model is equivalent to our full model with infinite fixed and sunk costs for importing. Using this idea, we can easily calculate the autarky plant value from our full model by letting the sunk and fixed costs be infinite. Total gains from importing intermediate inputs can be calculated as

$$\text{Total gain} = V(s_{jt}) - V(\omega_{jt}, K_{jt}) \tag{1.23}$$

To illustrate the gains from importing, I compute the plant values in the autarky economy and the full model for an average plant. The average plant is defined as a hypothetical plant whose capital and productivity level equals the mean of the industry's. Table 1.9 reports the gain to plants from importing inputs for all six industries, with the state variables (ω_{jt}, k_{jt}) chosen to be the industry means for each industry. I compute the loss of firm value if a firm is prohibited from importing. Table 9 shows that the total gains from importing inputs to the plant are substantial, accounting for $0.87\% - 22.28\%$ of plant value. The result also shows that gains from importing in more technologically advanced industries, the pharmaceuticals industry for example, are relatively larger. At the same time, in traditional industries like the clothing industry, the gains from importing inputs are very small. This is reasonable since, intuitively, firms in traditional industries cannot learn much from abroad, while firms in more technologically advanced industries can learn more from abroad.

1.8.2 Static and Dynamic Gains from Importing

In this subsection, I decompose the importing gains into the static effect and the dynamic effect, by simulating several modified versions of the full model.

When there is no dynamic effect of importing, $g_d = 0$. We can solve the full dynamic model under the restriction $g_d = 0$ to derive a new plant value, $V(s_{jt} \mid g_d = 0)$, which does not contain the dynamic effect. I define the gains from dynamic effect as the difference between the firm value in the full model and $V(s_{jt} \mid g_d = 0)$. Then the dynamic effect of importing can be computed as:

$$\text{Dynamic Effect} = V(s_{jt}) - V(s_{jt} \mid g_d = 0) \tag{1.24}$$

I define the static effect as the difference between the value of a firm when it has access to importing but has no dynamic effect ($V(s_{jt} \mid g_d = 0)$) and the firm value in the autarky economy ($V(\omega_{jt}, K_{jt})$):

$$\text{Static Effect} = V(s_{jt} \mid g_d = 0) - V(\omega_{jt}, K_{jt}) \tag{1.25}$$

I compute the value of $V(s_{jt} \mid g_d = 0)$ by computing the full model under the restriction $V(s_{jt} \mid g_d = 0)$.[19] Then I compute the dynamic effect and static effect using equations (1.24) and (1.25). By definition, the sum of dynamic effect and static effect equals the total gains from importing.

Table 1.10 reports the static gains and dynamic gains from importing for average plants of each industry, which are defined as a hypothetical plant whose capital and productivity level equals the mean of the industry's. I find that the dynamic effect is large, accounting for over 86% of the total gains in all six industries. This implies that importing is important mostly because it generates higher productivity growth in the long run. This is consistent with the findings in Table 1.6. In the productivity evolution process, importing experience has a positive and significant impact on future productivity. This result indicates that when considering gains from importing, we have to pay special attention to the associated dynamic effect.

The the static effect is always positive in all industries, accounting for 0.74% -

[19]Note that the autarky value $V(\omega_{jt}, K_{jt})$ is already derived when calculating the total gains from importing in the previous subsection.

13.96% of the total gains from importing in the six industries. This positive static effect, which mainly constitutes the input quality and variety effects, provides some evidence for the popularly used *"Quality and Variety Assumption"* of importing in the literature. However, the comparison of the magnitudes of the dynamic effect and static effect suggests that the quality and variety effects of importing, although positive, are not the major sources of gains from importing; it is the dynamic productivity effect which makes importing so profitable.

The static effect contains the input quality effect and input variety effect. A nice feature of the model parametrization is that it provides a way to evaluate the input quality effect. I define the input quality effect as the difference between $V(s_{jt})$ in the full model and $V(s_{jt} \mid A = 1)$, which is the firm value when the quality effect is shut down. I compute $V(s_{jt} \mid A = 1)$ by solving the full model with under the restriction $A = 1$. Then the input quality effect of importing is computed as:

$$\text{Input Quality Effect} = V(s_{jt}) - V(s_{jt} \mid A = 1) \tag{1.26}$$

The residual, defined as:

$$\text{Residual} = \text{Static Effect} - \text{Input Quality Effect} \tag{1.27}$$

contains the input variety effect, along with the computational errors. I call this residual, although not very rigorously, input variety effect in the rest of this paper.

Table 1.11 reports the components of static effect for average plants, which are similarly defined as hypothetical plants with their capital and productivity equal their industry median. The first column of results represents the static effect measured by firm value, and the third and fifth columns represent the that of quality effect and variety effect. The second, fourth, and sixth columns represent the corresponding share of each effect in the total gains from importing. Two interesting results are worth noting. First, the input quality effect, in general, is small or even negative. In the basic industrial chemicals industry, the plastics industry and the the leather shoes industry, input quality effects are positive, ranging from 0.02% of the total importing gains in the basic industrial chemicals industry to 1.34% in the plastics industry. However, they are, in general, fairly small. In the other three industries, the input quality effects are negative, which is consistent with the estimate $A < 1$ in Table 1.5 for these industries. Note that the parameter A captures both the real quality advantage of imported inputs and the domestic-to-imported input price ratio. $A > 1$ but close to one means either (1) the real quality effect is small, or (2) the real quality effect of imported inputs is large, but the price of imported inputs is too high which offset its quality advantage[20]. This result implies that importers do not gain much from better quality of imported inputs if they take into consideration the price difference of imported and domestic inputs.[21] Second, the input variety effect is substantial in all six industries, ranging from 1.66% in the plastics industry to 15.56% in the printing and publishing industry. This finding implies that importing firms do benefit substantially from more variety of inputs due to importing.

Our estimation results have important implications for trade policy, especially for developing countries. As we know, the technology used in developing countries is relatively old and inefficient. However, they usually halt participation in international trade activity. The large gain from importing intermediate inputs suggests that the developing countries may benefit from opening their markets to more active importing.

Also, as the cost/risk of a policy change is usually short-term, the government faces an intertemporal trade-off between the long-term gain and short-term risk/cost of a trade policy change. The decomposition results show that the static gain from importing is small but the dynamic gain is large. This suggests that even when the static gain from importing (through input quality effect and input variety effect) is smaller than the risk/cost of trade, the government may still find it beneficial to encourage importing if the dynamic gain is large enough because importing can improve future productivity in the long run.

[20] If price data on both imported and domestic inputs are available, the approach in this paper can easily separate the real quality effect from the relative price effect.

[21] If indeed there is significant real quality difference between domestic and imported inputs, our result of a "close-to-one" parameter A potentially supports the assumption in Kugler and Verhoogen (2009, 2012) that price is a good proxy for quality.

1.9 Conclusion

This paper constructs a dynamic structural model to characterize firms' decisions on whether to import intermediate inputs or rely exclusively on domestically-supplied inputs and to quantify the gains from importing on firm level profit and productivity. The model allows me to decompose the gains from importing into two components: a static effect and a dynamic effect.

Empirical results from Colombian plant-level data show that self selection into importing intermediate inputs is important. That is, more productive and larger plants tend to import intermediate inputs from abroad. The empirical results also show that gains to plants from importing inputs is substantial, accounting for about $0.87\% - 22.28\%$ of plants' continuation value in the six industries in examination.

A more interesting finding is that the dynamic effect is the most important source of gain from importing intermediate inputs. It accounts for about 90% of the total gains from importing. This implies that importing intermediate inputs is important mainly because it can endogenously improve the importers' future productivity in the long term endogenously. According to the estimates, the dynamic effect increases the importers' annual productivity growth by 1.47% on average. These findings have important policy implications. For example, they imply that when evaluating an import policy, the government should carefully evaluate the long-term gain from importing against the short-term cost.

As the static effect mainly constitutes the input quality and variety effect of importing, the positive static effect of importing is consistent with the popularly accepted "Quality and Input Variety Effect Assumption". However, the static effect is fairly small and is mainly due to the input variety effect. The input quality effect combined with the price difference, on the other hand, is trivial or even negative.

There are also some interesting topics for future research. First, in this paper, I consider the endogenous choice of importing but keep the export counterpart as an exogenous control, in order to focus on the import side. Considering the correlation between export (demand side) and import (production side), it is a good idea to incorporate both of them in the model and study their endogenous interaction with one another and their effect on productivity dynamics and industrial structure. This will give a more complete description of the dynamics of plants' importing and exporting decisions. Another interesting topic is the relationship between importing (and exporting) and R&D. With R&D data, we can explicitly investigate the channels through which imports and exports improve productivity. I leave these topics for future research.

Appendices

A Algorithm to Evaluate $V^1(s_{jt})$ and $V^0(s_{jt})$

All the static parameters have been estimated from stage 1 and stage 2. Therefore the only parameters to be estimated in this stage are the parameters in the distribution of fixed and sunk costs.

1. Pick a parameter set $\Gamma^1 \in \Gamma$, where Γ is the parameter space. In this paper, $\Gamma^1 = (\lambda_s, \lambda_f)$.

2. Discretize the state space S into S' with N grid points, pick one grid state $s \in S'$;

3. Given Γ^1 and s, compute the value function $V(s)$ defined in equation (1.7);

The algorithm to compute $V(s)$ for given Γ^1 and s:

3.1: Pick an starting value function $V_0(s)$, for all $s \in S'$;

3.2: Compute the choice-specific value function $V^1(s_{jt})$ and $V^0(s_{jt})$ from equations (1.8), and (1.9), where $F\left(w_{jt+1} \mid w_{jt,}d_{jt}\right)$ is derived from the productivity evolution process, and γ_{jt} is assumed to be constant over time since the panel is short;

3.3: Use $\pi_{(s_{jt})}$, $V^1(s_{jt})$ and $V^0(s_{jt})$ to update the value function to $V_0(s)$;

Iterate until $\mid V_{i+1}(s) - V_i(s) \mid$ is small enough. This finishes computing the value function at state s. Other states could be derived similarly via loop, or vectorization.

4. With the value function and the assumption on the distribution of C^f_{jt} and C^s_{jt} in hand, we can write the likelihood functions: $L_{jt}(\Gamma^1), L_j(\Gamma^1), L(\Gamma^1)$

5. Search over all the points in the parameter space Γ (or use other optimization algorithms), and pick $\gamma^* = \arg\max_{\gamma\in\Gamma} L(\gamma)$ as the estimates of the dynamic parameters.

B Self Selection: A Numerical Example

In this appendix, I perform a numerical example to illustrate firms' self selection into importing intermediate inputs. In particular, I want to answer the question: are more or less productive firms more likely to import? I simplify the analysis by parameterizing the value function.

Assume $V(s_{jt}, d_{jt+1})$ takes the following flexible form,

$$\begin{aligned} V(s_{jt}, d_{jt+1}) \quad = \quad & a_0 + a_{w1}\omega_{jt} + a^2_{\omega 2}\omega^2_{jt} + a_{w3}\omega^3_{jt} + a_{k1}k_{jt} + a_{k2}k^2_{jt} + a_{k3}k^3_{jt} \quad (28) \\ & + a_d d_{jt} + a_{\omega kdd'}\omega_{jt}k_{jt}d_{jt} + a_{d'}d_{jt+1} + a_{\omega kd'}\omega_{jt}k_{jt}d_{jt+1} \\ & + a_{\omega kdd'}\omega_{jt}k_{jt}d_{jt}d_{jt+1} \end{aligned}$$

Then the difference in the firm value for the firm to import and not to import is

$$\Delta V = V^1(s_{jt}) - V^0(s_{jt}) = a_{d'} + a_{\omega kd'}\omega_{jt}k_{jt} + a_{\omega kdd'}\omega_{jt}k_{jt}d_{jt}$$

The linearity of ΔV in $\omega_{jt}k_{jt}$ in this example depends on the functional form of $V(s \mid d')$, but the main results remain valid if I use other more flexible functional forms.

Running a regression using equation (28) generates the summary statistics of $V(s_{jt}, d_{jt+1})$, which are reported in Table 1.12. The estimates of the choice specific value function gives the value difference of the importer and non-importer in next period. In the basic industrial chemicals industry, for example, the difference of the choice-specific value function is

$$\Delta V = V^1(s_{jt}) - V^0(s_{jt}) = (-1.6707 + 0.1837\omega_{jt}k_{jt} - 0.0055\omega_{jt}k_{jt}d_{jt}) \cdot 10^6$$

It is clear that for this specific industry, current importing experience tends to decrease the potential gain of importing (coefficient on $\omega_{jt}k_{jt}d_{jt}$ is negative). This is because the first-time importers can sometimes acquire one-time benefits, which may allow first-time importers to gain more than existing importers. However, we cannot interpret this result as a common result for all industries. Current importing status may well increase ΔV, the additional gain of importers over non-importers, because current importing experience can increase future productivity via the dynamic productivity effect of importing ($g_d > 0$). The net effect of current importing status d_{jt} on ΔV equals the difference between the dynamic productivity effect and the first-time-importer benefit. When the former is bigger than the latter, the coefficient on d_{jt} could be positive. The estimation results show that the first-time-importer benefit dominates, and current importing experience tends to decrease the potential gain from importing in all the six industries. The magnitude of the effect of d_{jt} on ΔV is quite small in all the six industries.

Besides the point made above, I am particularly interested in the effect of current productivity on plants' choice of importing status. To see this, take the derivative of ΔV with respect to productivity (ω_{jt})

$$\frac{d\Delta V}{d\left(\omega_{jt}\right)} = (0.1837 - 0.0055k_{jt}d_{jt}) \cdot 10^6 > 0$$

So the value of importing relative to non-importing is always increasing in productivity. This result justifies the significant self selection of plants into the importing market: more productive plants and more capital-abundant plants are more likely to import inputs. I elaborate on this point in a bit more detail in Figure 1.1 and figure 1.2.

In Figure 1.1, the thresholds of plants' decisions to starting importing inputs are determined by the function $CS = -1.6707 + 0.1837\omega_{jt}k_{jt}$. Plants (current non-importers) with sunk cost and productivity below the solid line would like to start importing, while plants above the curve would not. The positive slope of the solid line implies that more productive plants are more likely to start importing inputs, showing a clear self selection pattern into importing market.

Similarly, Figure 1.2 shows plants' exit decisions from the importing market. The thresholds of plants' decisions to stop importing inputs are defined by the function $CF = -1.6707 + 0.1782\omega_{jt}k_{jt}$. Importers with productivity and fixed cost below the red curve would continue importing, while those above the solid line would stop importing. The positive slope of the solid line implies that more productive importers are more likely to continue importing inputs, clearly showing a self selection for firms to continue importing. That is, more productive importers tend into continued importing.

C Robustness Check

This appendix contains the estimation results for the robustness check in Section 6. They are estimated from a subsample of the data set which only contains non-exporting firms.

Table 1.1. Number and Percentage of Importers: 1977-1989

SIC	Industry	Num Plants	Num Importers	%Importers	%Imported[1]
3511	Basic Ind Chemicals	164	80	0.4878	0.1804
3522	Pharmaceuticals	232	179	0.7716	0.6216
3560	Plastics	747	291	0.3896	0.2788
3240	Leather Shoes	769	81	0.1053	0.0631
3420	Printing&Publishing	933	278	0.2980	0.3739
3220	Clothing	2613	121	0.0463	0.0410
	All six Industries	5458	1030	0.1887	0.2842

[1] "% imported" is defined as the value share of the imported material in the total value of material used.

Table 1.2. Number of Plants that Begin and Stop Importing Materials

Year	Total Importer	Old Importer	New Importer	Stopped [1]
1977	341	-	-	63
1978	324	297	27	39
1979	332	294	38	45
1980	358	303	55	40
1981	369	328	41	57
1982	332	290	42	47
1983	329	296	33	50
1984	305	283	22	36
1985	313	282	31	36
1986	313	291	22	31
1987	314	291	23	28
1988	312	283	29	26
1989	315	292	23	-

[1] Firms which exit (stop operation) at the end date is excluded.

Table 1.3. Transition Probability of Importing S-tatus

Probability	Import at t+1	Not Import at t+1
Import at t	0.8737	0.1263
Not Import at t	0.0247	0.9753

Table 1.4. Mean of Value Added Per Worker: Importers and Non-importers (1,000 Colombia Peso, 1977)

SIC	Industry	Non-importers	Importers	All firms
3511	Basic Ind Chemicals	333.47	442.22	380.29
3522	Pharmaceuticals	86.25	210.10	174.46
3560	Plastics	88.81	142.21	107.55
3240	Leather Shoes	84.41	113.07	86.65
3420	Printing&Publishing	77.87	126.03	89.57
3220	Clothing	91.67	99.61	91.87
	All six Industries	115.37	177.30	126.01

Table 1.5. Parameters of Static Inputs in the Production Function (NLLS)

Industry	Chemicals	Pharmaceuticals	Plastics	Shoes	Print&Pub	Clothing [1]
α_ℓ	0.4260	0.3466	0.3034	0.4736	0.4956	0.5510
	(0.0024)	(0.0026)	(0.0013)	(0.0012)	(0.0006)	(0.0003)
α_m	0.3420	0.5774	0.6253	0.4015	0.4283	0.3666
	(0.0011)	(0.0019)	(0.0006)	(0.0006)	(0.0003)	(0.0001)
A	1.0006	0.9255	1.0903	1.0001	0.9317	0.9995
	(0.4611)	(0.0828)	(0.0233)	(0.5430)	(0.0359)	(0.1013)
θ	5.0069	9.6690	21.5337	2.7108	22.3194	9.2140
	(0.1287)	(0.0897)	(0.0577)	(0.3821)	(0.0479)	(0.5232)
age	0.0469	0.0361	0.0294	0.0077	-0.0415	0.0129
	(0.0031)	(0.0018)	(0.0010)	(0.0010)	(0.0003)	(0.0003)
ownership	0.1514	0.0582	0.0133	0.1222	0.1507	0.1301
	(0.0083)	(0.0081)	(0.0045)	(0.0257)	(0.0024)	(0.0061)

[1] The standard errors are in the parentheses.

Table 1.7. Demand Elasticity and Constructed Revenue Function

Industry	Chemicals	Pharmac.	Plastics	Shoes	Print&Pub	Clothing
	Revenue Fun					
r	0.7920	1.7661	2.0021	1.8300	1.6968	1.8764
r_k	0.1286	0.1382	0.1157	0.1785	0.1673	0.1113
r_d	0.0611	0.0526	0.1268	0.3402	0.0074	0.0630
r_0	12.9609	12.9649	12.1032	10.0024	11.7837	11.1879
	Revenue Elast[2]					
productivity	2.5328	2.2258	3.2128	3.6272	1.8669	3.4363
capital	0.1286	0.1382	0.1157	0.1785	0.1673	0.1113
importing	0.0630	0.0540	0.1352	0.4052	0.0074	0.0651
	Demand Elast					
η^1	-2.3554	-3.2365	-3.5475	-3.8308	-3.1350	-3.4588
	(0.0127)	(0.0064)	(0.0024)	(0.0033)	(0.0029)	(0.0022)

[1] The revenue parameters are constructed from parameters estimated in stage 1. Therefore I do not report the standard deviations for revenue parameters in this table.

[2] The revenue elasticities are computed using the estimated primitives. (1) Revenue elasticity of productivity = $[\exp(0.01 * \textit{productivity} * r) - 1] * 100$. Productivity is the industry mean. (2) Revenue elasticity of capital = r_k. (3) The third row in Panel B represents the percentage gain of revenue when a plant imports. It is defined as $\exp(r_d) - 1$. Strictly speaking, it is not a concept of elasticity.

[3] Standard deviations for demand elasticity are in parentheses.

Table 1.6. Parameters in Productivity Evolution and Capital Share (NLLS)

Industry	Chemicals	Pharmaceuticals	Plastics	Shoes	Print&Pub	Clothing [1]
	Panel A:[2]					
α_k	0.1111	0.0992	0.0586	0.0917	0.1083	0.0580
	(0.0065)	(0.0027)	(0.0013)	(0.0023)	(0.0002)	(0.0005)
g_0	0.3954	0.1282	0.2527	0.4600	0.6003	0.3501
	(0.5068)	(0.4933)	(0.4217)	(1.0083)	(0.0302)	(0.2000)
g_ω	0.9032	0.9224	0.8421	0.7259	0.3906	0.7753
	(0.0324)	(0.1773)	(0.1754)	(0.2895)	(0.0153)	(0.0719)
g_d	0.0148	0.0092	0.0122	0.0213	0.0568	0.0050
	(0.0061)	(0.0067)	(0.0036)	(0.0141)	(0.0012)	(0.0047)
σ_ω	0.0762	0.0310	0.0329	0.0397	0.0682	0.0329
	Panel B:[3]					
α_k	0.1247	0.0723	0.0537	0.0854	0.0911	0.0545
	(0.0096)	(0.0036)	(0.0014)	(0.0020)	(0.0002)	(0.0007)
g_0	0.5583	0.2743	0.3085	0.5481	0.6390	0.4593
	(0.9385)	(0.9876)	(0.5828)	(0.9686)	(0.0320)	(0.3650)
g_ω	0.8240	0.7719	0.7919	0.6954	0.3154	0.7202
	(0.1169)	(0.5460)	(0.2666)	(0.2548)	(0.0128)	(0.1111)
g_d	0.0150	0.0213	0.0115	0.0205	0.0277	0.0026
	(0.0072)	(0.0128)	(0.0035)	(0.0157)	(0.0012)	(0.0070)
g_e	0.0172	-0.0005	0.0066	0.0262	0.0036	0.0012
	(0.0085)	(0.0001)	(0.0040)	(0.0115)	(0.0000)	(0.0000)
σ_ω	0.0994	0.0621	0.0402	0.0588	0.1307	0.0472

[1] The standard errors are in the parentheses.
[2] Panel A: Baseline Model.
[3] Panel B: Control for Export .

Table 1.8. Distribution of Sunk and Fixed Cost (MLE)

Industry	Chemicals	Pharmac.	Plastics	Shoes	Print&Pub	Clothing[1]
λ_s	17.1686	17.2725	18.5566	19.6835	16.5361	18.4536
	(0.2410)	(0.2619)	(0.1917)	(0.3880)	(0.1455)	(0.1956)
λ_f	14.4476	14.1224	15.0534	15.2471	12.7986	13.4990
	(0.0599)	(0.0596)	(0.0324)	(0.0628)	(0.0237)	(0.1022)
obj.fun	111.4271	109.0949	217.7079	66.2439	517.4818	125.6917
	Unconditional	mean costs				
Sunk cost	28.5916	31.7218	114.5543	353.5311	15.1900	103.3471
Fixed cost	1.8816	1.3592	3.4482	4.1853	0.3617	0.7287

[1] Standard deviations are in parentheses.

Table 1.9. Total Gains From Importing (in millions of 1977 Pesos)

Industry	$V_(s_(jt))$	$V_(\omega_(jt), k_(jt))$	Total Gain	Pctg Gain [1]
Basic Ind Chemicals	423.1123	361.8917	61.2206	14.47%
Pharmaceuticals	471.2608	366.2508	105.0101	22.28%
Plastics	327.7048	274.4459	53.2589	16.25%
Leather Shoes	94.6134	88.7746	5.8388	6.17%
Printing&Publishing	96.1717	91.8480	4.3237	4.50%
Clothing	91.1762	90.3861	0.7900	0.87%

[1] "Pctg Gain" refers to the percentage gain from importing.

Table 1.10. Dynamic and Static Effects from Importing (in millions of 1977 Pesos)

Industry	Dynamic Effect		Static Effect		Total Gain
	Value	Pctg[1]	Value	Pctg	
Chemicals	58.9987	96.37%	61.2299	3.63%	61.2206
Pharmaceuticals	102.8105	97.91%	2.1996	2.09%	105.0101
Plastics	51.6595	97.00%	1.5993	3.00%	53.2589
Leather Shoes	5.0599	86.66%	0.7789	13.34%	5.8388
Printing&Publishing	4.2915	99.26%	0.0322	0.74%	4.3237
Clothing	0.6800	86.07%	0.1101	13.93%	0.7900

[1] "Pctg" refers to percentage, and is defined as the share of gain from each effect in the total gain from importing.

Table 1.11. Components of Static Effect (in millions of 1977 Pesos)

Industry	Static Effect		Quality Effect		Variety Effect	
	Value	Pctg[1]	Value	Pctg	Value	Pctg
Basic Ind Chemicals	61.2299	3.63%	0.0093	0.02%	61.2205	3.61%
Pharmaceuticals	2.1996	2.09%	-3.2854	-3.13%	5.4849	5.22%
Plastics	1.5993	3.00%	0.7149	1.34%	0.8844	1.66%
Leather Shoes	0.7789	13.34%	0.0003	0.10%	0.7785	13.33%
Printing&Publishing	0.0322	0.74%	-0.6404	-14.81%	0.6726	15.56%
Clothing	0.1101	13.93%	-0.0008	-0.10%	0.1108	14.03%

[1] "Pctg" refers to percentage, and defined as the share of gain from each effect in the total gain from importing.

Table 1.12. Smooth Regression of Choice-Specific Value Function V($d'|s$): million

Industry	Chemicals	Pharmac.	Plastics	Shoes	Print&Pub	Clothing [1]
constant	646.6014	65.0779	1374.1488	-13.4515	-61.8935	90.4614
	(166.1887)	(39.8616)	(415.6380)	(163.0621)	(2.4290)	(43.2060)
ω	-859.4062	-424.2931	-2491.2518	-312.3677	-2.1521	-152.5948
	(158.4182)	(96.6087)	(707.7880)	(252.5648)	(6.6079)	(72.4795)
ω^2	294.3644	432.9022	1427.1816	155.7440	2.9648	82.3847
	(50.3537)	(77.7823)	(400.9077)	(130.0813)	(6.1753)	(40.4049)
ω^3	-31.8498	-132.4977	-254.5626	-24.3710	-0.5258	-12.6093
	(5.3132)	(20.7937)	(75.4108)	(22.2649)	(1.8851)	(7.4771)
k	55.7485	42.6903	25.5109	63.3869	22.3460	6.0324
	(3.2190)	(0.3200)	(5.0015)	(1.3622)	(0.1783)	(0.4941)
k^2	-4.0012	-3.3426	-2.0908	-5.6228	-1.9800	-0.2827
	(0.2158)	(0.0251)	(0.3395)	(0.1046)	(0.0134)	(0.0387)
k^3	0.1642	0.1842	0.1126	0.1907	0.0817	0.0218
	(0.0047)	(0.0006)	(0.0075)	(0.0026)	(0.0003)	(0.0010)
ωkd	0.0744	0.0682	0.2639	0.0414	0.0281	0.0347
	(0.0185)	(0.0094)	(0.0668)	(0.0189)	(0.0059)	(0.0082)
d	-3.4144	-1.0454	-6.6947	-1.0198	-0.3816	-0.7716
	(0.8876)	(0.1546)	(1.7855)	(0.4907)	(0.0895)	(0.1949)
d’	-9.2566	-6.4835	-38.8292	-19.5905	-1.6707	-1.5471
	(0.8876)	(0.1546)	(1.7855)	(0.4907)	(0.0895)	(0.1949)
$\omega kd'$	0.2776	0.6978	2.1410	1.0238	0.1837	0.0961
	(0.0185)	(0.0094)	(0.0668)	(0.0189)	(0.0059)	(0.0082)
$\omega kdd'$	-0.0062	-0.0092	-0.0261	-0.0043	-0.0055	-0.0041
	(0.0076)	(0.0049)	(0.0298)	(0.0087)	(0.0037)	(0.0040)

[1] The standard errors are in the parentheses.

Table 1.13. Robustness Check: Parameters of Static Inputs in Production Function (NonExporters)

Industry	Chemicals	Pharmac.	Plastics	Shoes	Print&Pub	Clothing [1]
α_l	0.3508	0.3414	0.2913	0.4973	0.4801	0.5635
	(0.0032)	(0.0030)	(0.0013)	(0.0011)	(0.0006)	(0.0002)
α_m	0.3846	0.5839	0.6235	0.3567	0.4374	0.3569
	(0.0014)	(0.0021)	(0.0006)	(0.0006)	(0.0003)	(0.0001)
A	0.9696	0.9706	0.9828	0.9964	0.9997	0.9994
	(0.4694)	(0.0911)	(0.0270)	(0.2164)	(0.0406)	(6.2074)
θ	4.4014	24.9377	18.5874	1.7724	35.7143	5.9312
	(0.0811)	(0.0856)	(0.0384)	(0.1674)	(0.0482)	(0.6933)
age	0.0606	0.0113	0.0330	-0.0002	-0.0267	0.0055
	(0.0032)	(0.0018)	(0.0010)	(0.0009)	(0.0003)	(0.0002)
ownership	0.1926	0.0487	0.0479	0.1081	0.1248	0.1340
	(0.0103)	(0.0098)	(0.0066)	(0.0587)	(0.0029)	(0.0092)

[1] The standard errors are in the parentheses.

Table 1.14. Robustness Check: Parameters in Productivity Evolution and Capital Share for Non-Exporters

Industry	Chemicals	Pharmac.	Plastics	Shoes	Print&Pub	Clothing [1]
α_k	0.1424	0.0662	0.0444	0.0933	0.0928	0.0540
	(0.0097)	(0.0031)	(0.0015)	(0.0016)	(0.0002)	(0.0006)
g_0	0.2452	0.2115	0.3137	0.7894	0.6763	0.3520
	(1.2080)	(0.7623)	(0.7764)	(1.1252)	(0.0451)	(0.2156)
g_ω	0.9355	0.8772	0.8075	0.6348	0.4224	0.7889
	(0.0857)	(0.2622)	(0.3062)	(0.2023)	(0.0192)	(0.0670)
g_d	0.0052	0.0097	0.0042	0.0262	0.0322	0.0042
	(0.0101)	(0.0099)	(0.0025)	(0.0152)	(0.0013)	(0.0080)
σ_ω	0.0052	0.0410	0.0225	0.0425	0.0664	0.0349

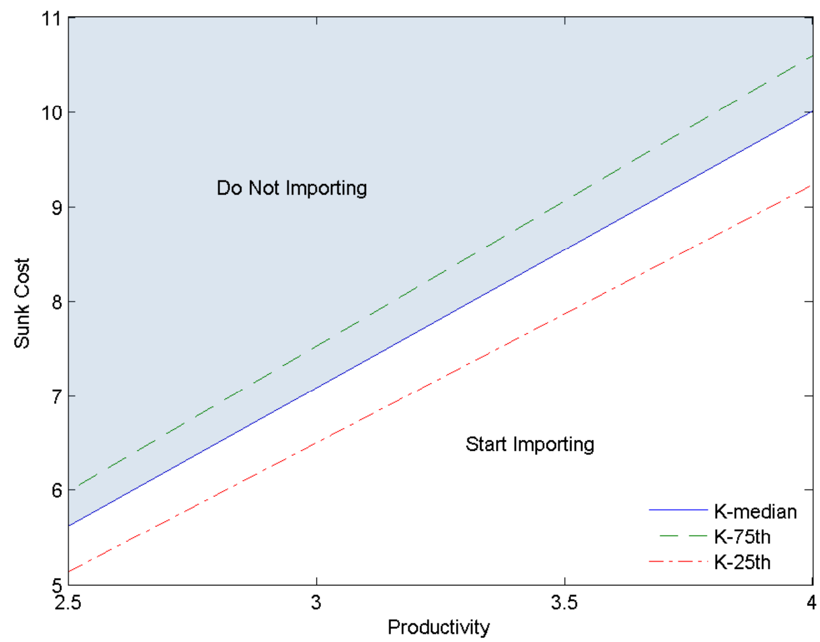
[1] The standard errors are in the parentheses.

Table 1.15. Robustness Check: Constructed Revenue Function and Demand Elasticity for Non-Exporters

Industry	Chemicals	Pharmac.	Plastics	Shoes	Print&Pub	Clothing
	Revenue Fun[1]					
r_ω	0.8389	1.7225	3.2131	3.8280	1.1466	2.4272
r_k	0.1290	0.0454	0.1246	2.0700	0.0157	0.1908
r_d	0.1406	0.1236	0.1558	0.4012	0.1146	0.1274
	Revenue Elast[2]					
productivity	2.6847	2.1703	5.2061	7.7379	1.2578	4.4673
capital	0.1290	0.0454	0.1246	2.0700	0.0157	0.1908
importing	0.1510	0.1316	0.1686	0.4936	0.1214	0.1359
	Demand Elast					
η [3]	-2.6336	-3.1627	-6.0130	-13.9710	-2.3932	-4.3375
	(0.0108)	(0.0087)	(0.0030)	(0.0036)	(0.0031)	(0.0017)

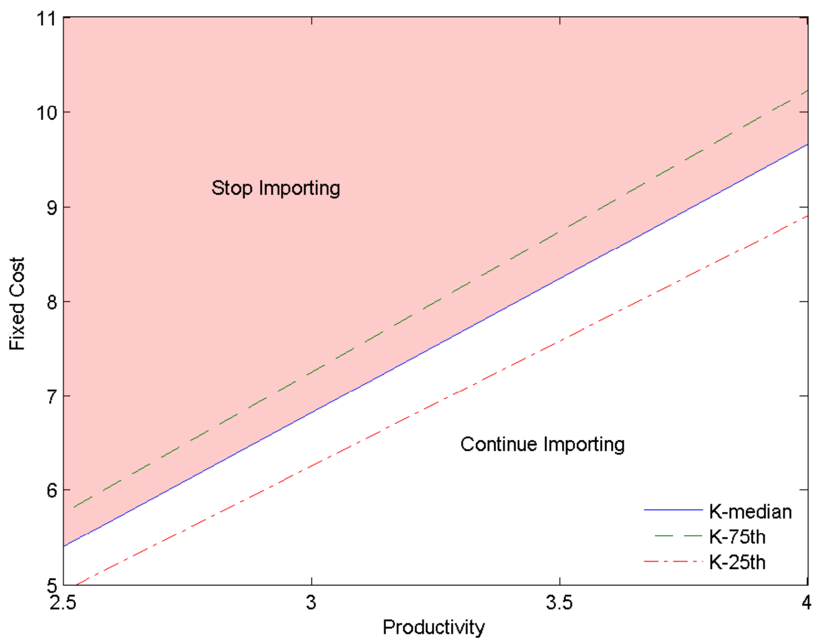
[1] The revenue parameters are constructed from parameters estimated in stage 1. Therefore I do not report the standard deviations for revenue parameters in this table.
[2] The revenue elasticities are computed using the estimated primitives. (1) Revenue elasticity of productivity = $[\exp(0.01 * productivity * r) - 1] * 100$. Productivity is the industry mean. (2) Revenue elasticity of capital = r_k. (3) The third row in Panel B represents the percentage gain of revenue when a plant imports. It is defined as $\exp(r_d) - 1$. Strictly speaking, it is not a concept of elasticity.
[3] Standard deviations for demand elasticity are in parentheses.

Figure 1.1. Thresholds for Current Non-Importing Firms to Start Importing: Sunk Costs, Productivity, and Firm Size



Notes: The solid line represents the threshold of starting importing for a current non-importing firm, which has a median industry capital. Given the capital, firms with a combination of productivity and sunk costs above this line (in the shaded area) do not start importing and firms below this line (in the unshaded area) start importing. The upward slope of the threshold line suggests that as productivity goes up, firms are more likely to start importing. The dashed line and the dot-dashed line represent the thresholds of starting importing for two hypothetical firms, which are assumed to have the 75th and the 25th quantile of industry capital stock, respectively. The comparison of the three thresholds implies that larger firms (measured by capital stock) are more likely to start importing, all other things equal.

Figure 1.2. Thresholds for Current Importing Firms to Stop Importing: Fixed Costs, Productivity, and Firm Size



Note: The solid line represents the threshold of stopping importing for a current importer, which has a median industry capital. Firms with a combination of productivity and fixed costs above this line (in the shaded area) stop importing. Firms below this line (in the unshaded area) continue importing. The upward slope of the threshold suggests that as productivity goes up, current importers are more likely to continue importing. The dashed line and the dot-dashed line represent the thresholds of stopping importing for two hypothetical firms, which are assumed to have the 75th and 25th quantile of industry capital stock, respectively. The comparison of the three thresholds shows that larger importers (measured by capital stock) are more likely to continue importing, all other things equal.

Chapter 2

Production Function Estimation with Unobserved Input Price Dispersion

2.1 Introduction

[1] In applications of production function estimation, many datasets do not contain a specific accounting of intermediate input prices and quantities, but instead provide only information on the total expenditure on material inputs. This presents a challenge for consistent estimation when input prices are not homogeneous across firms. To address this issue, many previous studies assume inputs are purchased from a single, perfectly competitive market, which implies that input prices are constant across firms. This assumption facilitates the use of input expenditures as a proxy for quantities (e.g., Levinsohn and Petrin, 2003). However, if this assumption does not hold—for example, if transport costs create price heterogeneity across geography—then the traditional proxy-based estimator is inconsistent. The logic of the inconsistency is straightforward: input price heterogeneity will be observed by firms who respond to price differences both by substituting across inputs and adjusting their total output, causing an endogeneity problem that cannot be controlled for using a Hicks-neutral structural error term. Even in a narrowly defined industry, perfect competition in input markets is not likely to hold, so the proxy approach is clearly not ideal. Fortunately, variation in labor input together with labor and materials expenditures, which are readily available in many data sets, contains useful information on the intermediate input price variation across firms. By utilizing this variation within a structural model, we introduce a method to consistently estimate firms' production function in the presence of unobserved

[1] Joint work of Paul L. E. Grieco, Shengyu Li, and Hongsong Zhang. The authors are grateful to Robert Porter, Mark Roberts, David Rivers, and Jim Tybout for very helpful comments and to Mark Roberts and Jim Tybout for providing the data for this project. All errors are the authors' own responsibility.

intermediate input price heterogeneity. Our method significantly relaxes the assumptions needed to estimate production functions when information on the prices and quantities of intermediate inputs is not available.

The omitted price problem for production function estimation was first recognized by Marschak and Andrews (1944). They proposed the use of expenditures and revenues as proxies for input and output quantities under the assumption that prices were homogeneous across firms. In practice, the literature has documented significant dispersions in both input and output prices across firms and over time (Dunne and Roberts, 1992; Roberts and Supina, 1996, 2000; Beaulieu and Mattey, 1999; Bils and Klenow, 2004; Ornaghi, 2006; Foster, Haltiwanger, and Syverson, 2008; Kugler and Verhoogen, 2012). Klette and Grillches (1996) show the consequence of ignoring the output price dispersion is a downward bias in the scale estimate of production function.[2] The effect of input price dispersion is slightly more complicated. Using a unique data set containing both inputs price and quantity data, Ornaghi (2006) documents input price bias under the Cobb-Douglas production function. In Section 2.2, we discuss how input price dispersion also biases both the output elasticity and substitution parameters in more general specifications.[3]

A typical data set for production function estimation contains firm-level revenue, intermediate (i.e., material) expenditure, total wage expenditure, capital stock, investment, and additional wage rate/labor quantity. However, quantities and prices for intermediate input are typically not available. The basic idea of our approach is to exploit the first order conditions of firms' profit maximization to impute the unobserved physical quantities of inputs from their expenditures. We then use this recovered physical quantity of intermediate inputs to replace the physical quantity of inputs in the estimation. This procedure helps solve the omitted intermediate input price bias. In addition, our method recovers the underlying input price distribution, which is an important source of heterogeneity across firms. Accounting for input price heterogeneity can give rise to richer explanations of firm policies. For example, firms' exit decisions are often modeled as a cutoff in firm productivity levels, input price heterogeneity would imply that less productive firms may remain in the market if they have access to lower input prices.

The idea of exploiting the first order condition of profit maximization is also employed in Katayama, Lu, and Tybout (2009), Gandhi, Navarro, and Rivers (2011) and Zhang (2012). In contrast to earlier work, which has focused on two-stage

[2]Klette and Grillches (1996) provide a structural approach for controlling for output price variation, we incorporate their approach into our model which additionally controls for input price variation.

[3]Ornaghi (2006) considers the Cobb-Douglas specification of the production function, where the elasticity of substitution is assumed to be fixed at one and leaves how price dispersion may bias the elasticity of substitution unexplored. Section 2.2 shows how input price dispersion also biases substitution parameters in more flexible production function specifications, which we confirm in our Monte Carlo study.

techniques and relies on the first-stage regression to recover the non-structural errors, Zhang (2012) and this paper use the first order conditions as constraints to control for structural errors directly. This approach has two key advantages. First, since productivity is directly recovered through the firm's optimization conditions, our approach controls for endogenous choices of inputs without imposing stark timing assumptions on the productivity process. Second, it is simple to implement. In our case, for the CES production function, it amounts to a single non-linear least squares regression. In general, estimation requires solving a single constrained optimization problem.

In addition to controlling for input price bias, we also address the output price bias by incorporating a model of product demand to account for unobserved output prices (Klette and Grillches, 1996). Consequently, our procedure is consistent in the presence of unobserved variation in both input and output prices.

Our approach applies to a very general set of production function parameterizations. It requires mild restrictions on the production function for identification. We introduce our approach with general production function form and establish the identification conditions. The identification condition is satisfied in many production functions we usually use, such as constant elasticity of substitution (CES) or translog, but not Cobb-Douglas. This is because a key source of variation, the expenditure ratio between inputs, is assumed to be fixed under the Cobb-Douglas specification. In fact, we show that within the more flexible CES production function family, the identification condition is always satisfied except when the elasticity of substitution is one (the special case of Cobb-Douglas).

We demonstrate our approach using the CES production function specification, and evaluate our approach by carrying out a Monte Carlo experiment that compares it's performance to the traditional estimator and an "oracle" estimator that observes input prices and quantities directly. The results show that our approach recovers the true parameters very well. In contrast, the traditional approach causes systematic biases in the parameter estimates. In particular, the elasticity of substitution is underestimated in the traditional approach as predicted, and the distribution parameters are also biased. This bias could mislead researchers attempting to make policy recommendations. For example, in a trade policy setting, this bias could result in erroneous counterfactual estimates of demand and supply changes of *all* inputs and outputs due to a proposed changes to tariff rates on imported intermediate inputs.

We apply our approach to a plant-level data set from Colombian manufacturing industries and compare our results with that derived from the traditional estimator. The results are consistent with that predicted in the Monte Carlo experiments. That is, compared with our method, the elasticity of substitution from the traditional approach is consistently lower. Moreover, the distribution parameter estimates of the traditional method differ significantly from those of our method. Finally, our results indicate significant input price dispersion in all industries, providing further indication of the importance of controlling for unobserved price heterogeneity.

This paper is organized as follows. Section 2.2 reviews the omitted input and output price biases in detail. Section 2.3 introduces a model with unobserved price heterogeneity, discusses identification, and outlines our procedure to consistently estimate the model. Section 2.4 provides an example using the CES specification for the production function. Section 2.5 presents Monte Carlo experiments that evaluate the performance of our estimator and confirm the biases in traditional methods when unobserved price heterogeneity is present. We apply our method to a dataset on Colombian manufacturing in Section 2.6, and again compare it's results with other estimators which are commonly used. We conclude in Section 2.7.

2.2 Omitted Price Biases

In ideal cases where physical quantities of input and output are available, they can be used directly in the estimation of production functions (Eslava, Haltiwanger, Kugler, and Kugler, 2004; Ornaghi, 2006; Grieco and McDevitt, 2012). However, many datasets contain information on the total expenditure on intermediate inputs but not a specific accounting of their prices and quantities. In this case, the traditional approach is to use the deflated value (by industry-level price indices) of inputs and output (De Loecker, 2011) as proxy of physical quantities. This procedure implicitly requires that firms are operating in perfectly competitive input markets so that all firms in the industry face the same prices. However, markets are more likely to be imperfectly competitive and are characterized by heterogenous features. For example, transportation costs may create input price differences between firms based on geography. Firm-level input and output prices vary across firms and over time, which impact the firm-level input choice. Consequently, the traditional approach will induce biases in the estimation (Klette and Grillches, 1996; Van Beveren, 2010).

Consider a production function in logarithm form $q_{jt} = f(x_{jt}, \theta_0)$, where q_{jt} is the log firm-level physical quantity of output produced by a vector of log physical input x_{jt}, and θ_0 is the parameter of interest. For commonly available firm-level production data sets, q_{jt} and x_{jt} are not available. Instead, we observe the (deflated) revenue $r_{jt} = q_{jt} + p^q_{jt}$ and (deflated) input expenditures $v_{jt} = x_{jt} + p^x_{jt}$, where p^q_{jt} and p^x_{jt} are the firm-level output and input prices which are deflated by industry-level price index. In the traditional estimation, q_{jt} and x_{jt} are often substituted by r_{jt} and v_{jt}. Thus, while the true model is,

$$r_{jt} = f(v_{jt} - p^x_{jt}, \theta_0) + p^q_{jt} + \epsilon_{jt},$$

the estimated model is,

$$r_{jt} = f(v_{jt}, \hat{\theta}) + u_{jt},$$

where ϵ_{jt} are i.i.d measurement errors, and u_{jt} contains both the measurement error ϵ_{jt} and the omitted terms p^q_{jt} and p^x_{jt}. Note that if input and output prices vary across firms, and input x_{jt} is chosen after these prices are observed, then the input expenditure v_{jt} is correlated with both input and output prices. Ignoring this when estimating $\hat{\theta}$ introduces biases, so $\hat{\theta}$ will not be a consistent estimator of θ_0. We now provide two specific examples to illustrate the effect of unobserved price dispersion.

Example 2.1:[4] Consider the Cobb-Douglas production function,

$$q_{jt} = \beta_0 + \beta_l \ell_{jt} + \beta_m m_{jt} + \epsilon_{jt},$$

where lower case letters represent the logarithm value and for simplicity ϵ_{jt} is the iid measurement error.[5] In commonly available data sets, where q_{jt} and m_{jt} are not available, revenue $r_{jt} = q_{jt} + p^q_{jt}$ and material expenditure $v^m_{jt} = m_{jt} + p^m_{jt}$ are used as proxy. Thus, the model is estimated via,

$$r_{jt} = \beta_0 + \beta_\ell \ell_{jt} + \beta_m v^m_{jt} + \overbrace{p^q_{jt} - \beta_m p^m_{jt} + \epsilon_{jt}}^{u_{jt}},$$

where $u_{jt} = p^q_{jt} - \beta_m p^m_{jt} + \epsilon_{jt}$ is the error term. The endogeneity problem arises since $E(v^m_{jt} u_{jt}) \neq 0$. For simplicity, suppose β_ℓ is known, then the estimated coefficient for material is given by,[6]

$$\text{plim } \hat{\beta}_m = \beta_m + \frac{cov(v^m, p^q - \beta_m p^m)}{var(v^m)} = \beta_m + \frac{cov(v^m, p^q)}{var(v^m)} - \beta_m \frac{cov(v^m, p^m)}{var(v^m)}.$$

The estimate is inconsistent if the last two additional terms are non-zero. Note that input expenditures and output price are usually negatively related,[7] we expect $\frac{cov(v^m, p^q)}{var(v^m)} < 0$. Similarly, if the relation between materials price and materials expenditure is positive, then $\frac{cov(v^m, p^m)}{var(v^m)} > 0$. In this case, we have $\hat{\beta}_m < \beta_m$. So the material coefficients will be underestimated if quantities of material and output are substituted by deflated values. However, in the case that material expenditure and material price are negatively related, so $\frac{cov(v^m, p^m)}{var(v^m)} < 0$, the direction of the bias is ambiguous. In both cases, input price bias is present as long as material choice depends on the omitted material price. ■

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[4] Ornaghi (2006) shows a similar example.

[5] Here we disregard the presence of unobserved productivity difference between firms for clarity. Our model in section 3 will account for the unobserved productivity.

[6] If β_ℓ is not known and β_ℓ and β_m are estimated jointly, then $\hat{\beta}_\ell$ will also be biased.

[7] Klette and Griliches (1996) lists cases where this is true.

Example 2.2: For the case of CES production function, ignoring input price heterogeneity can bias the elasticity of substitution between inputs. To see this, consider the CES production function (without capital for simplicity),

$$Q_{jt} = F(M_{jt}, L_{jt}) = [\alpha M_{jt}^{\gamma} + (1-\alpha) L_{jt}^{\gamma}]^{\frac{1}{\gamma}},$$

where $\gamma = \frac{\sigma - 1}{\sigma}$, and σ is the constant elasticity of substitution which is defined as

$$\sigma = -\frac{\partial \ln(M/L)}{\partial \ln(F_M/F_L)},$$

where F_M and F_L are the marginal output of material and labor. If (deflated) expenditures (denoted as $E_M = P_M M$ and $E_L = P_L L$) are used instead of firm-level quantities, then the estimated model is

$$Q_{jt} = \hat{F}(E_{M_{jt}}, E_{L_{jt}}) = [\hat{\alpha} E_{M_{jt}}^{\hat{\gamma}} + (1-\hat{\alpha}) E_{L_{jt}}^{\hat{\gamma}}]^{\frac{1}{\hat{\gamma}}},$$

where $\hat{\gamma} = \frac{\hat{\sigma} - 1}{\hat{\sigma}}$. In particular, the elasticity of substitution $\hat{\sigma}$ is measured between labor expenditure and material expenditure which is different from the original definition:

$$\begin{aligned}
\hat{\sigma} &= -\frac{\partial \ln(E_M/E_L)}{\partial \ln(\hat{F}_{E_M}/\hat{F}_{E_L})} = -\frac{\partial \ln(E_M/E_L)}{\partial \ln(F_M/F_L)} \times \frac{\partial \ln(F_M/F_L)}{\partial \ln(\hat{F}_{E_M}/\hat{F}_{E_L})} \\
&= \left(-\frac{\partial \ln(M/L)}{\partial \ln(F_M/F_L)} - \frac{\partial \ln(P_M/P_L)}{\partial \ln(F_M/F_L)}\right) \times \frac{\partial \ln(F_M/F_L)}{\partial \ln(\hat{F}_{E_M}/\hat{F}_{E_L})} \\
&= (\sigma - 1) \times \frac{\partial \ln(F_M/F_L)}{\partial \ln(\hat{F}_{E_M}/\hat{F}_{E_L})}
\end{aligned}$$

The last equation holds because $\sigma = -\frac{\partial \ln(M/L)}{\partial \ln(F_M/F_L)}$ by definition and $\frac{\partial \ln(P_M/P_L)}{\partial \ln(F_M/F_L)} = 1$ if the firm chooses M and L to minimize its variable cost. This equation shows that the bias comes from two sources. The first source is that the elasticity of substitution is evaluated using (E_M, E_L) instead of (M, L). That is,

$$\frac{\partial \ln(E_M/E_L)}{\partial \ln(F_M/F_L)} \neq \frac{\partial \ln(M/L)}{\partial \ln(F_M/F_L)}.$$

The second source is that the estimated production function itself is biased from the true production function due to the use of (E_M, E_L) instead of (M, L) in estimation, i.e.,

$$\frac{\partial \ln(F_M/F_L)}{\partial \ln(\hat{F}_{E_M}/\hat{F}_{E_L})} \neq 1.$$

If $\frac{\partial \ln(F_M/F_L)}{\partial \ln(\hat{F}_{E_M}/\hat{F}_{E_L})}$ is less than 1, then the elasticity of substitution is underestimated ($\hat{\sigma} < \sigma$). The intuition is that because of cost minimization, the physical input ratio will change in a direction against the change in input price ratio. As a result, the change in the input expenditure ratio E_M/E_L is offset partially by the change in P_M/P_L. For example, suppose there is an increase in material price, so P_M/P_L rises. With cost minimization, the physical input M will be partially substituted by labor, thus M/L drops. However, the percentage dropped in the expenditure ratio E_M/E_L is less than that in M/L, because $E_M/E_L = (P_M/P_L) \cdot (M/L)$ and P_M/P_L rose. Therefore,

$$\hat{\sigma} = -\frac{\partial \ln(E_M/E_L)}{\partial \ln(\hat{F}_{E_M}/\hat{F}_{E_L})} = (\sigma - 1) \times \frac{\partial \ln(F_M/F_L)}{\partial \ln(\hat{F}_{E_M}/\hat{F}_{E_L})} < (\sigma - 1) < \sigma,$$

the estimated elasticity of substitution from value data on inputs is smaller than the true elasticity of substitution. As a result, the estimated elasticity of substitution will be biased if values are used as proxy of quantities. Note that this also implies the distribution parameter (α) is also biased. ■

These examples have shown that when firms face heterogeneous input prices, traditional production function estimates that rely on materials expenditure to proxy for the quantity of materials are inconsistent. The bias can affect estimates of both output elasticity and the elasticity of substitution between inputs. It is easy to see how this inconsistency could lead to misleading counterfactual analysis to policy questions of interest. For example, consider a proposed tariff increase on some intermediate input: researchers who estimate the production function while failing to account for input price heterogeneity would mis-predict both the change in firm output and the degree of substitution from the imported input to other inputs resulting from the tariff. In the rest of the paper, we propose and demonstrate a structural approach which uses information on the relative expenditure on inputs to control for unobserved input price and consistently estimate the production function.

2.3 Estimation with Unobserved Price Dispersion

In this section, we introduce a simple model of firms' decision-making in a standard monopolistically competitive output market. The goal is to find an approach to estimating the production function when we have the commonly available data on output value, all inputs values, and the wage rate and labor quantity.[8] Our approach corrects the biases caused by omitted intermediate input price dispersion. Instead of substituting quantities by deflated values, our approach exploits the first

[8]Our model can be extended to deal with the case when the wage rate and labor quantity are not separately observed.

order conditions implied by profit maximization to impute unavailable physical quantities of intermediate inputs from expenditures.

2.3.1 The Model

This section presents our approach for general forms of production and demand function and outlines our approach for consistent estimation. In the next sections, we will use CES production function to demonstrate our method.

Suppose at each period t, each firm j produces a single product using labor (L_{jt}), intermediate material (M_{jt}), and capital (K_{jt}) from the production function,

$$Q_{jt} = \exp(\omega_{jt})F(L_{jt}, M_{jt}, K_{jt}; \theta).$$

where Q_{jt} is the output, ω_{jt} is a Hicks-neutral productivity shock observed by the firm (but not by researchers), and θ is the set of parameters in the production function. The inverse demand function is,

$$P_{jt} = P_t(Q_{jt}; \eta),$$

where P_{jt} is the output price and η is the set of parameters in the demand function. The inverse demand function $P_t(\cdot, \cdot)$ is continuous and decreasing in its first coordinate. We allow the demand to be different over time. We make the following assumptions on the model:

Assumption 1 (Smooth Production Function)**.** *Production function $F(\cdot)$ is known up to a finite dimensional parameter θ, strictly increasing in inputs, and continuously differentiable up to second order.*

Assumption 2 (Exogenous Input Prices)**.** *Firms are price takers in input markets. Suppliers use linear pricing, but input prices are allowed to be different across firms and over time.*

Assumption 3 (Profit Maximization)**.** *After observing their productivity draw, ω_{jt}, firms optimally choose labor and material inputs to maximize the profit in each period. The firm's capital stock for period t is chosen prior to the revelation of ω_{jt}.*

Several points are worth highlighting. As in Olley and Pakes (1996) and Levinsohn and Petrin (2003), capital is pre-fixed in the short run while both labor and material inputs are flexibly chosen at the beginning of each period. However, in contrast to the previous literature, these choices depend on idiosyncratic input prices. This is an additional source of firm heterogeneity along with the well-known Hicks-neutral technology shifter, ω_{jt}. The assumption that firms are price takers does not preclude firms being offered different prices on the basis of their size (i.e., capital stock), productivity, or negotiating ability, but does assume that firms do not receive "quantity discounts," which would endogenously affect purchasing decisions. As shown in the previous section, ignoring the variation in input prices and using the deflated input expenditures as proxies of physical inputs will introduce a bias into the estimation. To control for price and productivity differences across firms, we use an explicit model of profit maximization to construct estimation equations only involving commonly available value data.

While, relative to Olley and Pakes (1996), we strengthen some assumptions by requiring profit maximization, we are able to relax others. Because we use the first order conditions to recover the unobserved productivity, ω_{jt}, we will not need to use a "proxy" (such as investment) to recover it. Indeed, investment will not be used in our procedure at all, so there is no need for an invertability condition on the investment function. Instead, materials quantities and productivity will be jointly recovered from the two first order conditions. Moreover, we do not need to make assumptions regarding the law of motion of productivity or capital.[9]

2.3.2 Recovering the Unobserved Input Prices

We assume the econometrician observes revenue $R_{jt} = P_{jt}Q_{jt}$, inputs expenditure $E_{Mjt} = P_{M_{jt}}M_{jt}$, wage rate $P_{L_{jt}}$, number of workers or number of working hours L_{jt}, and capital stock K_{jt}. But they do not observe the material inputs prices or quantities ($P_{M_{jt}}$ and M_{jt}) or output prices and quantities (P_{jt} and Q_{jt}). In this section we develop an approach to identifying the production function using these commonly available data.

At the beginning of each period, after observing capital stock, K_{jt}, productivity shock, ω_{jt} and idiosyncratic input prices $P_{L_{jt}}$ and $P_{M_{jt}}$, firm j chooses its own labor and materials inputs to maximize its period profit. The firm's static decision problem can be formally written as:

$$\begin{aligned}&\max_{L_{jt}, M_{jt}} P_t(Q_{jt})Q_{jt} - P_{Ljt}L_{jt} - P_{Mjt}M_{jt}\\ &\text{s.t. } Q_{jt} = \exp(\omega_{jt})F(L_{jt}, M_{jt}, K_{jt}; \theta).\end{aligned}$$

The corresponding first order conditions are,

$$\begin{aligned}\exp(\omega_{jt})F_{L_{jt}}\left[P_t(Q_{jt}) + Q_{jt}\frac{\partial P_t(Q_{jt})}{\partial Q_{jt}}\right] &= P_{L_{jt}}, \qquad (2.1)\\ \exp(\omega_{jt})F_{M_{jt}}\left[P_t(Q_{jt}) + Q_{jt}\frac{\partial P_t(Q_{jt})}{\partial Q_{jt}}\right] &= P_{M_{jt}}.\end{aligned}$$

[9] Of course, additional assumptions on the productivity process may provide an additional source of variation which will be useful in identifying more general specifications of the production function.

Dividing the two first order conditions, multiplying both sides by $\frac{L_{jt}}{M_{jt}}$, and rearranging yields,

$$\frac{F_{L_{jt}} L_{jt}}{F_{M_{jt}} M_{jt}} - \frac{E_{L_{jt}}}{E_{M_{jt}}} = 0, \tag{2.2}$$

where $F_{L_{jt}}$ and $F_{M_{jt}}$ are the partial derivatives of F with respective to labor and material, and $E_{L_{jt}} = P_{L_{jt}} L_{jt}$ and $E_{M_{jt}} = P_{M_{jt}} M_{jt}$ are expenditures on labor and material, which are observed in the data.

Equation (2.2) is the key to our approach. It relates labor and the intermediate input, given that they are optimally chosen to maximize the profits. The following proposition gives conditions under which we are able to impute M_{jt} from the observed data.

Proposition 1 (Identification Condition)**.** *Define,*

$$z(M_{jt}, L_{jt}, K_{jt}, E_{Mjt}, E_{Ljt}; \theta) = \frac{F_{L_{jt}} L_{jt}}{F_{M_{jt}} M_{jt}} - \frac{E_{L_{jt}}}{E_{M_{jt}}}.$$

Suppose assumptions 1-3 are satisfied and we observe a random sample of $(L_{jt}, K_{jt}, E_{Mjt}, E_{Ljt})$, *where for all* $\theta \in \Theta$, $\frac{\partial z}{\partial M_{jt}} \neq 0$. *Then there exists a function* $M^*(L_{jt}, K_{jt}, E_{Mjt}, E_{Ljt}; \theta)$, *such that,*

$$z(M^*(L_{jt}, K_{jt}, E_{Mjt}, E_{Ljt}; \theta), L_{jt}, K_{jt}, E_{Mjt}, E_{Ljt}; \theta) = 0.$$

The proof for this proposition is an application of the implicit function theorem and is provided in A. The identification problem is essentially about whether we can separate M_{jt} and $P_{M_{jt}}$ from what we can observe, i.e., $E_{M_{jt}} = P_{Mjt} M_{jt}$. The condition that $\frac{\partial z}{\partial M_{jt}} \neq 0$ for all $\theta \in \Theta$ has intuitive economic meaning. It implies that we observe firms optimally reacting to changes in input prices (P_M and P_L) by adjusting their expenditures on intermediate inputs (M_{jt}) and labor (L_{jt}) and the intermediate-labor output elasticity ratio. In other words, $\frac{\partial z}{\partial M_{jt}} \neq 0$ implies that the elasticity of substitution between materials and labor (σ) is not always one. To see why, suppose $\sigma = 1$. By definition, $\sigma = -\frac{\partial \ln(L_{jt}/M_{jt})}{\partial \ln(F_{L_{jt}}/F_{M_{jt}})} = 1$. This implies that $\frac{F_{L_{jt}} L_{jt}}{F_{M_{jt}} M_{jt}}$ is a constant and $\frac{\partial z}{\partial M_{jt}} = 0$.

Once we recover $M^*(K_{jt}, L_{jt}, E_{Mjt}, E_{Ljt}; \theta)$, we can replace the unobserved intermediate inputs M_{jt} by it in the first order condition to back out ω_{jt}. In turn, we can substitute M^* and ω_{jt} into the estimation equation, where the only remaining unknown is the exogenous error term, so the model can be estimated via nonlinear least squares.

The following two examples illustrate Proposition 1. In the first example, we show that the identification condition is *not* satisfied for the Cobb-Douglas specification. This is because, as is well-known, the Cobb-Douglas production function assumes that expenditure shares are constant within the data, eliminating the source of variation we need to identify the model with unobserved input prices. In Example 3.2, we show that for the more general CES production function, we can impute materials quantities as long as the elasticity of substitution is not 1 (the Cobb-Douglass case). We are able to test for this restriction by observing whether the expenditure shares are constant across firms in the data.

Examle 3.1 (Cobb-Douglas Production Function)

For Cobb-Douglas production function

$$Q_{jt} = \exp(\omega_{jt})F(L_{jt}, M_{jt}, K_{jt}) = \exp(\omega_{jt})L_{jt}^{\alpha_L} M_{jt}^{\alpha_M} K_{jt}^{\alpha_K},$$

it is straightforward to show that,

$$\begin{aligned} z(M_{jt}, L_{jt}, K_{jt}, E_{Mjt}, E_{Ljt}; \theta) &= \frac{F_{L_{jt}} L_{jt}}{F_{M_{jt}} M_{jt}} - \frac{E_{L_{jt}}}{E_{M_{jt}}} \\ &= \frac{\alpha_L K_{jt}^{\alpha_K} L_{jt}^{\alpha_L - 1} M_{jt}^{\alpha_M} L_{jt}}{\alpha_M K_{jt}^{\alpha_K} L_{jt}^{\alpha_L} M_{jt}^{\alpha_M - 1} M_{jt}} - \frac{E_{L_{jt}}}{E_{M_{jt}}} \\ &= \frac{\alpha_L}{\alpha_M} - \frac{E_{L_{jt}}}{E_{M_{jt}}} \end{aligned}$$

Since $\frac{\partial z}{\partial M_{jt}} = 0$, we cannot recover the unobserved material from equation (2.2). The intuition is that, because the elasticity of substitution is fixed at one, when the relative inputs price $(\frac{P_L}{P_M})$ changes firms always choose labor and material such that the percentage increase (or decrease) of the labor-material ratio $(\frac{L}{M})$ equals the percentage decrease (or increase) of relative price $(\frac{P_L}{P_M})$. As a result, the expenditure ratio $\frac{E_{L_{jt}}}{E_{M_{jt}}}$ remains constant $(\frac{\alpha_L}{\alpha_M})$. In this case, we cannot separate the price and quantity of materials from the information on expenditure ratio $\frac{E_{L_{jt}}}{E_{M_{jt}}}$. ■

Of course, because we observe the expenditure ratio between materials and labor in the data, it is easy to verify that it is not constant across all firms. As long as there is variation, it is reasonable to specify a production function that allows the ratio to vary and use this variation to impute materials prices and quantities.

Examle 3.2 (CES Production Function)

For CES production function

$$Q_{jt} = \exp(\omega_{jt})F(L_{jt}, M_{jt}, K_{jt}) = \exp(\omega_{jt})[\alpha_L L_{jt}^{\gamma} + \alpha_M M_{jt}^{\gamma} + \alpha_K K_{jt}^{\gamma}]^{\frac{1}{\gamma}},$$

where $\gamma = \frac{\sigma - 1}{\sigma}$ and σ is the elasticity of substitution, we can show that,

$$z(M_{jt}, L_{jt}, K_{jt}, E_{Mjt}, E_{Ljt}, \theta)$$

$$
\begin{aligned}
&= \frac{F_{L_{jt}} L_{jt}}{F_{M_{jt}} M_{jt}} - \frac{E_{L_{jt}}}{E_{M_{jt}}} \\
&= \frac{\exp(\omega_{jt})[\alpha_L L_{jt}^{\gamma} + \alpha_M M_{jt}^{\gamma} + \alpha_K K_{jt}^{\gamma}]^{\frac{1}{\gamma}-1} \alpha_L L_{jt}^{\gamma-1} L_{jt}}{\exp(\omega_{jt})[\alpha_L L_{jt}^{\gamma} + \alpha_M M_{jt}^{\gamma} + \alpha_K K_{jt}^{\gamma}]^{\frac{1}{\gamma}-1} \alpha_M M_{jt}^{\gamma-1} M_{jt}} - \frac{E_{L_{jt}}}{E_{M_{jt}}} \\
&= \frac{\alpha_L L_{jt}^{\gamma}}{\alpha_M M_{jt}^{\gamma}} - \frac{E_{L_{jt}}}{E_{M_{jt}}}
\end{aligned}
$$

When $\gamma \neq 0$ (i.e., $\sigma \neq 1$), we can show that,[10]

$$
\frac{\partial z}{\partial M_{jt}} = -\gamma \frac{\alpha_L L_{jt}^{\gamma}}{\alpha_M M_{jt}^{\gamma+1}} \neq 0,
$$

and we can recover the unobserved material from equation (2.2). In this special case, equation (2.2) has a closed-form solution,

$$
M^*(L_{jt}, K_{jt}, E_{Mjt}, E_{Ljt}; \theta) = \left(\frac{\alpha_L}{\alpha_M} \frac{E_{M_{jt}}}{E_{L_{jt}}} \right)^{\frac{1}{\gamma}} L_{jt}.
$$

Intuitively, it is possible to infer information about material quantity M_{jt} from the inputs expenditure ratio $\frac{E_{M_{jt}}}{E_{L_{jt}}}$. This feature, together with the definition $E_{Mjt} = P_{Mjt} M_{jt}$ help us separate the quantity M_{jt} and material price P_{Mjt} from each other. ■

2.3.3 Estimation Equation

We now turn to estimation of the parameters of the production function, θ, and the inverse demand function, η, using commonly available data on output value, all input values, and the wage rate. If the identification condition is satisfied, that the intermediate input quantity can be uniquely imputed as

$$
M_{jt}^* = M^*(K_{jt}, L_{jt}, E_{Mjt}, E_{Ljt}, \theta), \tag{2.3}
$$

Once the quantity of material M_{jt} is recovered, we can plug M_{jt}^* back into either of the first order conditions and recover the unobserved productivity,

$$
\omega_{jt}^* = \omega^*(K_{jt}, L_{jt}, E_{Mjt}, E_{Ljt}, M_{jt}^*; \theta). \tag{2.4}
$$

Different from Olley and Pakes (1996), here we recover the unobserved pro-

[10]When $\gamma = 0$ (i.e., $\sigma = 1$), the CES function is equivalent to the Cobb-Douglas case (Example 3.1) and we cannot recover the unobserved materials from equation (2.2). This case must be excluded from the parameter set Θ.

ductivity parameterically from the firm's first order conditions.[11] There are at least two advantages of this method. First, the estimation does not require the investment data. Moreover, there is no need to rely on invertibility of the investment policy function, which may be problematic when adjustment costs generate lumpiness in the optimal investment policy Second, we do not require the Markov assumption on the productivity evolution process to control for endogeneity. We can, of course, use this method to estimate the productivity evolution after recovering the production function.

Since output quantities are not directly observed, we follow Klette and Grillches (1996) and use the revenue function as the estimating equation. The revenue function is

$$R_{jt} = \exp(u_{jt}) P_t \left(Q_{jt}; \eta\right) Q_{jt} \tag{2.5}$$

where R_{jt} is the observed revenue of the firm, $Q_{jt} = e^{\omega^*_{jt}} F(K_{jt}, L_{jt}, M^*_{jt}; \theta)$ is the predicted quantity of physical output based on observed inputs and the model parameters (θ, η), and u_{jt} is a revenue error term which incorporates measurement error as well as demand and productivity shocks that are unanticipated by the firm and are assumed to be iid across firms and over time. Taking logarithm of revenue function yields,

$$\ln R_{jt} = \ln P_t \left(e^{\omega^*_{jt}} F(K_{jt}, L_{jt}, M^*_{jt}; \theta); \eta\right) + \ln \left[e^{\omega^*_{jt}} F(K_{jt}, L_{jt}, M^*_{jt}; \theta)\right] + u_{jt} \tag{2.6}$$

In this equation, the unobserved productivity and material quantity, ω^*_{jt} and M^*_{jt}, are recovered as functions of observed variables as in equations (2.3) and (2.4). The only remaining unobservable, u_{jt}, is unknown to the firm and uncorrelated with the observed inputs. Therefore, we can consistently estimate (2.6) via non-linear least squares. In some specifications, some parameters in θ may be not identified due to the structure of the production function. However, additional restrictions are often available to provide full identification of θ. In the next section we provide an example using the CES production function in which we derive identifying restrictions from first order conditions. Restrictions making use of timing assumptions, as in Doraszelski and Jaumandreu (2012) may also be useful.

2.4 Implementation of the Approach in CES

While our procedure is applicable to a wide class of production functions, we now offer a concrete example based on the well-known CES specification. The CES production function is particularly well-suited to our approach as it permits closed form solutions for M^* and ω^*, and we use it in our Monte Carlo experiments and empirical applications below.

[11] Zhang (2012) uses a similar approach to allow for biased technical change in the production function.

2.4.1 Production and Demand

We consider a CES production function with an elasticity of substitution σ.[12] It has been commonly recognized that the CES production function needs to be normalized to give meaningful identification of its parameters. A branch of the literature has analyzed the importance and the method of normalization, for example, de La Grandville (1989), Klump and de La Grandville (2000), Klump and Preissler (2000), de La Grandville and Solow (2006), and Leon-Ledesma, M-cAdam, and Willman (2010). We follow this literature and normalize the CES production function according to the geometric mean. Specifically, let the baseline point for our normalization be the geometric mean of $(Q_{jt}, L_{jt}, M_{jt}, K_{jt})$, denot-ed as $\overline{Z} = (\overline{Q}, \overline{L}, \overline{M}, \overline{K})$ where $\overline{X} = \sqrt[n]{X_1 X_2 \cdots X_n}$.[13] Then the CES production function can be written as,

$$Q_{jt} = e^{\omega_{jt}} \overline{Q} \left[\alpha_L \left(\frac{L_{jt}}{\overline{L}} \right)^{\gamma} + \alpha_M \left(\frac{M_{jt}}{\overline{M}} \right)^{\gamma} + \alpha_K \left(\frac{K_{jt}}{\overline{K}} \right)^{\gamma} \right]^{\frac{1}{\gamma}}, \tag{2.7}$$

where $\gamma = \frac{\sigma - 1}{\sigma}$ and $\alpha_L, \alpha_M, \alpha_K$ are the distribution parameters, which sum to 1,

$$\alpha_L + \alpha_M + \alpha_K = 1. \tag{2.8}$$

The normalization has three advantages for our purposes. First, it scales the level of inputs according to an industry average, eliminating the effect of units on inputs and outputs. Second, the geometric mean ($\overline{Z}$) is observable in the data set, which can be used to construct an additional restriction to identify parameters. Third it gives the distribution parameters a precise interpretation. Specifically, they are the marginal return to inputs (in normalized units) at the baseline point.[14]

Since we observe revenues rather than output directly, we follow Klette and Grillches (1996) and also specify a classic Dixit-Stiglitz demand function,

$$\frac{Q_{jt}}{Q_t} = \left(\frac{P_{jt}}{P_t} \right)^{\eta}, \tag{2.9}$$

[12] We follow the literature in assuming constant returns to scale in this specification. This assumption can be relaxed by adding a scale parameter. This does not affect the estimation procedure but make the scale parameter and demand elasticity not separately identified. However, if Markov process of productivity is assumed, then one can easily (using Equation (39) in Appendix D) separately identify these two parameters using the variation in industrial-level output and prices.

[13] In principle, any point $Z_0 = (L_0, M_0, K_0, Q_0)$ (which satisfies normalization conditions, i.e., Equation (27)-(29) in Appendix B) can be chosen as the baseline point, for example a default choice could be $(1, \ldots, 1)$. The entire CES production function is identified up to the knowledge of the baseline point. Specifically, the CES function can be identified when such Z_0 is observed, while the baseline point is not necessary to be Z_0. In our setting we choose the baseline point as the geometric mean $\overline{Z}$, which is observable in our data set.

[14] Note that the normalized input of the baseline point is simply $(1, 1, 1)$.

where Q_t and P_t are industry-level output quantity and price in period t, and η is the demand elasticity.

As discussed earlier, the CES production function satisfies the identification condition if $\sigma \neq 1$ (i.e., $\gamma \neq 0$). All other market and firm behavior assumptions are the same as in the general model. As such, firms face monopolistic competition. At the beginning of each period, after observing their own state, they choose labor and material to maximize their short term profit.

2.4.2 Estimation Procedure

Given our specification for the production function (2.7) and demand function (2.9), we follow our proposed procedure from the previous section to derive the estimating revenue equation,[15]

$$\ln R_{jt} = \ln \frac{\eta}{1+\eta} + \ln \left[E_{M_{jt}} + E_{L_{jt}} \left(1 + \tau \left(\frac{K_{jt}/\overline{K}}{L_{jt}/\overline{L}} \right)^{\gamma} \right) \right] + u_{jt}, \tag{2.10}$$

where $\tau = \alpha_K/\alpha_L$.[16]

This estimating equation directly identifies η and γ. Additionally, it permits us to recover τ, a ratio of two of the three distribution parameters.[17] Denote these estimates as $\hat{\eta}$, $\hat{\gamma}$ and $\hat{\tau}$ respectively. With the estimate of τ in hand, we can recover the distribution parameters by making use of two additional restrictions. The first is simply the adding up constraint (2.8), the second is implied by the first order conditions of profit maximization. To see this, note that the first order conditions for each firm j at period t are

$$\lambda \overline{\alpha}_L e^{\omega_{jt}} \overline{Q} \left[\alpha_L \left(\frac{L_{jt}}{\overline{L}} \right)^{\gamma} + \alpha_M \left(\frac{M_{jt}}{\overline{M}} \right)^{\gamma} + \alpha_K \left(\frac{K_{jt}}{\overline{K}} \right)^{\gamma} \right]^{\frac{1}{\gamma}} \left(\frac{L_{jt}}{\overline{L}} \right)^{\gamma-1} \frac{1}{\overline{L}} = P_{L_{jt}},$$

and

$$\lambda \overline{\alpha}_M e^{\omega_{jt}} \overline{Q} \left[\alpha_L \left(\frac{L_{jt}}{\overline{L}} \right)^{\gamma} + \alpha_M \left(\frac{M_{jt}}{\overline{M}} \right)^{\gamma} + \alpha_K \left(\frac{K_{jt}}{\overline{K}} \right)^{\gamma} \right]^{\frac{1}{\gamma}} \left(\frac{M_{jt}}{\overline{M}} \right)^{\gamma-1} \frac{1}{\overline{M}} = P_{M_{jt}},$$

where λ is the lagrangian multiplier. The ratio of the two equations yields,

$$\frac{\alpha_L (L_{jt}/\overline{L})^{\gamma}}{\alpha_M (M_{jt}/\overline{M})^{\gamma}} = \frac{P_{L_{jt}} L_{jt}}{P_{M_{jt}} M_{jt}} \equiv \frac{E_{L_{jt}}}{E_{M_{jt}}}. \tag{2.11}$$

This equation holds for each firm j at each period t. Taking the geometric

[15]See D for the complete derivation.

[16]See Appendix C for a detailed economic intepretation of τ.

[17]This is due to the substitution of our structural equation for the unobserved materials inputs.

mean of (2.11) across all observations, implies the following restriction on the distribution parameters,[18]

$$\frac{\alpha_M}{\alpha_L} = \frac{\overline{E}_M}{\overline{E}_L}. \tag{2.12}$$

Because expenditure on materials is observed in the data for all observations, so the right hand side of this restriction can be directly computed from the data.

Then, we combine (2.8), (2.12) and the estimate of τ to derive explicit formulas for the distribution parameter estimates in terms of observables and $\hat{\tau}$,

$$\begin{aligned} \hat{\alpha}_L &= \frac{\overline{E}_L}{\overline{E}_L + \overline{E}_M + \hat{\tau}\overline{E}_L} \\ \hat{\alpha}_M &= \frac{\overline{E}_M}{\overline{E}_L + \overline{E}_M + \hat{\tau}\overline{E}_L} \\ \hat{\alpha}_K &= 1 - \hat{\alpha}_L - \hat{\alpha}_M \end{aligned} \tag{2.13}$$

That is, once $\hat{\tau}$ is estimated using (2.10), the distribution parameters estimates $\hat{\alpha}_L$, $\hat{\alpha}_M$ and $\hat{\alpha}_K$ can be recovered by (2.13).

With all of the production function parameters estimated we can solve for each firms productivity level from (2.4), which is reduced to (39) in Appendix D. Thus, if we have a model for the productivity evolution process, it can be estimated directly from our firm-year productivity estimates. In the remainder of this paper, we will use the CES specification to demonstrate our approach in a Monte Carlo experiment and an empirical exercise.

2.5 Monte Carlo Experiment

In this section, we conduct Monte Carlo experiments to evaluate the performance of our method, and provide evidence for the bias caused by the omitted input price. To this end, we first describe the data generation process, then estimate the model in three different ways based on assumed data availability.

2.5.1 Data Generation

The Monte Carlo experiments consist of N replications of simulated data sets, given a set of true parameters of interest (η, σ, α_L, α_M and α_K). In each replication, there are J firm in production for T periods. We simulate a sequence of productivity for each firm (ω_{jt}) from an AR(1) process. We allow the firms capital stock to evolve based on an investment rule that depends on its productivity and capital stock. Finally, we allow input prices ($P_{L_{jt}}$ and $P_{M_{jt}}$) to vary across firms and over time. Table 1 lists the underlying parameters used to generate the data

[18] Recall that the geometric mean of a ratio is the ratio of geometric means.

set. Given these variables and industrial-level outputs and prices (Q_t and P_t), we derive a sequence of optimal choices of labor and material inputs (L_{jt} and M_{jt} with corresponding input expenditures $E_{L_{jt}}, E_{M_{jt}}$), the optimal output quantity (Q_{jt}) and price (P_{jt}) for firm j in each period t. In this way, we generate a data set of $\{\omega_{jt}, K_{jt}, I_{jt}, L_{jt}, M_{jt}, E_{L_{jt}}, E_{M_{jt}}, Q_{jt}, R_{jt}, Q_t, P_t\}$ for each firm j and period t. For all three estimators, we use the CES production function normalized by the geometric mean as discussed in Section 2.4. A full description of the data generating process is provided in E. All these variables are observable to firms, however, usually only a subset of them are available to researchers.

2.5.2 Our Method

We first estimate the model with our method. In this case, we assume the researcher observes $\{K_{jt}, L_{jt}, E_{L_{jt}}, E_{M_{jt}}, R_{jt}, Q_t, P_t\}$ for each firm and each period. The researcher is not required to observe firm's investment, material input quantity, physical outputs quantity or, of course, productivity. As described in the previous section, we exploit the first order conditions to impute firm-level material quantities from labor quantities and expenditures. This approach allows us to construct a nonlinear equation which is immune from firm-level unobserved heterogeneity and only involve data available to researchers. Specifically, we can estimate the model by the nonlinear regression (2.10). We will evaluate our method by comparing the estimates to the true values as well as to two alternative estimation methods which require additional data.

2.5.3 Traditional Method with Direct Proxy

In this section, we describe the traditional method of using expenditure as a direct proxy of unavailable quantities to verify the bias caused by the omitted input price. The method follows Olley and Pakes (1996) in using a control function approach to make use of data on investment to control for unobserved productivity. Traditionally, researchers have used deflated expenditure on materials inputs to proxy for intermediate input quantities when applying this and similar methods (e.g., Levinsohn and Petrin, 2003), and we follow that practice here. We will refer to this method as the "OP" procedure. In contrast with our own method, we assume the output quantities are observable by researchers. Hence there will be no output price bias and any resultant bias is caused by the substitution of physical material input by its deflated cost.

Specifically, researchers observe $\{K_{jt}, I_{jt}, L_{jt}, E_{L_{jt}}, E_{M_{jt}}, Q_{jt}\}$, and we can estimate parameters via (logarithm of) production function directly (with the well-known OP method):

$$\ln\left(\frac{Q_{jt}}{\overline{Q}}\right) = \left\{\omega_{jt} + \frac{1}{\gamma}\ln\left[\alpha_L\left(\frac{L_{jt}}{\overline{L}}\right)^{\gamma} + \alpha_M\left(\frac{E_{M_{jt}}}{\overline{E}_M}\right)^{\gamma} + \alpha_K\left(\frac{K_{jt}}{\overline{K}}\right)^{\gamma}\right]\right\} + u_{jt}, \tag{2.14}$$

where the error term u_{jt} accounts for measurement error of revenue and productivity shocks that are unanticipated by the firm.

Olley and Pakes (1996) assume that productivity follows a first order Markov process. Following our data generating process, we assume that productivity follows an AR(1) specification,

$$\omega_{jt+1} = g_0 + g_1\omega_{jt} + \epsilon_{jt+1}.$$

Since the true data generating process is in fact AR(1), this rules out specification error associated with productivity evolution, so the Monte Carlo focuses on the bias caused by dispersion in input prices. Within our DGP, the investment decision is a function of current capital stock and the unobservable heterogenous productivity and therefore, the OP method can approximate the productivity by a control function of investment and capital stock: $\omega_{jt} = \omega_t(I_{jt}, K_{jt})$. Substituting this into equation (2.14) obtains,

$$\ln\left(\frac{Q_{jt}}{\overline{Q}}\right) = \phi(L_{jt}, E_{M_{jt}}, K_{jt}, I_{jt}, \Phi_t) + u_{jt}, \tag{2.15}$$

where Φ_t represents time dummies to capture aggregate investment shifters. This equation can be estimated non-parametrically. This estimation is consistent since right-hand-side variables are all uncorrelated with u_{jt}. In this paper, we estimate ϕ using sieves method.[19] Denote $\hat{\phi}_{jt}$ as the fitted value of $\phi(L_{jt}, E_{M_{jt}}, K_{jt}, I_{jt}, \Phi_t)$. Then productivity can be expressed as

$$\omega_{jt} = \hat{\phi}_{jt} - \frac{1}{\gamma}\ln\left[\alpha_L\left(\frac{L_{jt}}{\overline{L}}\right)^{\gamma} + \alpha_M\left(\frac{E_{M_{jt}}}{\overline{E}_M}\right)^{\gamma} + \alpha_K\left(\frac{K_{jt}}{\overline{K}}\right)^{\gamma}\right]. \tag{2.16}$$

Substituting ω_{jt+1} and ω_{jt} into the evolution process of productivity, we obtain

$$\epsilon_{jt+1} = \omega_{jt+1} - (g_0 + g_1\omega_{jt}).$$

Note that ϵ_{jt+1} is uncorrelated with variables up to period t, so we can construct the set of moment conditions:

$$E(\epsilon_{jt+1}x_{jt+1}) = 0 \tag{2.17}$$

where $\epsilon_{jt+1}(\eta, \tau, \gamma, g_0, g_1) = \omega_{jt+1} - (g_0 + g_1\omega_{jt})$, and x_{jt+1} is a combination of

[19] In practice, we model $\phi(\cdot)$ with a cubic function with interactions.

variables that are uncorrelated with the innovation term in period $t+1$, e.g., $L_{jt}, E_{L_{jt}}, E_{M_{jt}}, K_{jt}, K_{jt+1}$.[20] With these moment conditions, we can employ the standard GMM to estimate the parameters.

2.5.4 Oracle-OP Procedure

Finally, we compare our method to a first-best case when input quantities are actually observed. We refer to this as the "Oracle-OP" case as it uses the Olley and Pakes (1996) inversion to recover productivity but uses the actual materials input quantities instead of a proxy. That is, we observe $\{K_{jt}, I_{jt}, L_{jt}, M_{jt}, E_{L_{jt}}, E_{M_{jt}}, Q_{jt}\}$ for each firm and each period. This enables us to estimate the production function in (2.14) directly. Specifically, capital stock and investment are used in the control function for the productivity as in Olley and Pakes (1996). Then the model is estimated by moment conditions constructed according to the evolution of productivity (2.17). In sum, the only difference of the oracle case and previous OP's procedure is that material quantity is not substituted by its proxy, since the true quantity is observable in this case. In comparison to our own method, this method requires that the researcher observes investment, output quantity, and materials input quantities.

2.5.5 Results

The results of the Monte Carlo experiments for three separate elasticities of substitution are presented in Table 2.2. For each method, the listed parameter represents the median estimate of the 1000 Monte Carlo replications with it's standard error in parenthesis. The square brackets contain the root mean squared error of the estimates. Across all specifications, our method recovers the parameters well. In contrast, the elasticity of substitution (σ) and α_K are severely underestimated by OP. These findings correspond to the biases documented in Section 2.2 due to input price dispersion. The results for the oracle method confirm that the bias is due to input price heterogeneity. Once true materials inputs are observed, the OP method performs well. Interestingly, it appears there is little loss in efficiency between the oracle-OP method and the method we propose, despite the fact that we do not use investment, output quantity, or input quantities. Of course, our method makes use of the additional structure implied by the firm's first order conditions, which are not used within the OP framework.

To further investigate the performance of the estimators, Figure 1 plots the density of $\hat{\sigma}$ for the three cases. The dashed line represents the true value of σ. Clearly, while our method generates estimates that are concentrated around the

[20] In Monte Carlo experiment, we choose
$$x_{jt+1} = \left(\frac{L_{jt}}{\bar{L}}, \frac{E_{L_{jt}}}{\bar{E}_L}, \frac{E_{M_{jt}}}{\bar{E}_M}, \frac{K_{jt}}{\bar{K}}, \frac{K_{jt+1}}{\bar{K}}, \left(\frac{L_{jt}}{\bar{L}}\right)^2, \left(\frac{E_{L_{jt}}}{\bar{E}_L}\right)^2, \left(\frac{E_{M_{jt}}}{\bar{E}_M}\right)^2, \left(\frac{K_{jt}}{\bar{K}}\right)^2, \left(\frac{K_{jt+1}}{\bar{K}}\right)^2\right).$$

true elasticity of substitution, the traditional way relying on value data would give biased estimates of σ. This bias is economically significant, implying an elasticity of substitution up to 20% lower than the true value. As expected, when we allow the researcher to observe input quantities directly, the oracle-OP method performs well. The validation of the expenditure proxy requires no heterogeneity in input prices across firms. When this is not the case, the unobserved input price dispersion will lead to the bias in the estimation. The advantage of our method is that it provides a consistent way of imputing unobservable input quantities from observable expenditures of both materials and labor, which is necessary to control for the input price dispersion.

In addition to controlling for input price dispersion, our method allows the research to actually recover the unobserved prices after the relevant parameters are estimated. In short, material quantities and prices can be imputed from Equation (38) (in Appendix C). Figure 2.2 presents the kernel density estimation of the imputed material prices from our method and compare it with the density estimated from the true material prices.[21] It shows that the imputed material price density matches the true density quite well.

2.6 Application: Colombian Data

To evaluate the performance of our estimator using real data, we apply our method to the Colombian manufacturing industries from 1981 to 1989, which was collected by the Departamento Administrativo Nacional de Estadistica (DANE). This dataset contains detailed information about firm-level revenue (R), labor and material input expenditure (E_L and E_M), capital stock (K), employment (L), investment (I), etc. However, firm-level price information about input and output is not available. For a detailed introduction to the data set, refer to Roberts and Tybout (1997).

This application serves two purposes. The first is to compare our results with those found using the traditional proxy method to account for unobserved materials inputs. The second is to illustrate additional information which can be recovered using our method, including the distribution of input prices and their relationship to productivity. Firstly, we estimate the model using our method. Second, for comparison, we estimate the production function using materials expenditure as a proxy for materials inputs as in Olley and Pakes (1996). To focus on the impact of input price heterogeneity, we control for output price bias by incorporating a demand function in this approach, as suggested in Klette and Grillches (1996). Thus, the only difference between the two estimators is in their treatment of input quantities. We refer to the second method as OP-KG in the text and tables. For both methods, we use the CES specification of the production function normalized

[21] We present the case for true $\sigma = 2.5$, but the results from other cases are very similar.

at the geometric mean as illustrated above.

Estimates for four large industries are displayed in Table 2.3: clothing, bakery products, printing and publishing, and metal furniture.[22] In all these industries, the elasticity of substitution is significantly lower in OP-KG method compared with the results from our method. This is consistent with both our intuition about the bias generated by unobserved price dispersion and the patten shown in the Monte Carlo experiments. Also, the elasticities of substitution are significantly greater than one in all industries in our method. This implies that production function is not likely Cobb-Douglas in these industries. The results support the conclusion that ignoring input price dispersion would lead to inconsistent estimate of elasticities of substitution.

Biased estimates of elasticity of substitution (σ) using the OP-KG method will contaminate estimates of τ and therefore also bias the distribution parameters. However, the direction of the bias is unclear. We find that our method produces estimates of α_K that are more than twice as large as that from OP-KG method for the grain mill, plastics, and pharmaceuticals industries. However our estimate of α_k is smaller for the less capital intensive clothing industry.

Another interesting finding is that there are substantial differences in productivity dispersion estimates between the two methods. Figure 4 shows the productivity distributions estimated using our method and OP-KG method, for each of the four industries. For all industries, the productivity distribution in OP-KG without controlling for the unobserved input price dispersion is more concentrated. This result suggests that omitting the unobserved price dispersion in tends to underestimate the the firm heterogeneity in productivity. One possible reason might be due to the positive correlation between input prices and productivity which we find below. Intuitively, positive correlation between the productivity and input prices could bias productivity estimates since a firm with low productivity tends to use low-price material. In OP-KG method, where all firms are assumed to have the same material price, the material quantity used by low-productivity firms is underestimated, resulting in overestimates of their productivity. Similarly, OP-KG would underestimate the productivity for high-productivity firms facing high prices. As a result, OP-KG by not controlling for the unobserved input price would underestimate the degree of firm heterogeneity in productivity. This finding is related to a large literature on heterogeneity of productivity among firms. Our finding indicates that the "true" productivity heterogeneity across firms may be even larger than previously estimated in the literature, which fails to controlling for the unobserved input price dispersion.

As in the Monte Carlo experiments, after estimating all relevant parameters, we can impute the material quantities and prices. Because these prices are recovered

[22] We have estimated the model for a wide variety of industries and found these results to be representative with respect to the performance of the estimators, additional results are available by request.

from the first order condition, they reflect quality-adjusted quantities and the imputed prices are purged of the effect of quality differences. In Figure 3 we present the kernel density estimations of imputed material prices (in logarithm) from our method for each of the four industries pooled across all years. In all industries, the distributions of input prices are quite spread out. Some firms acquire materials in a relatively low price while others pay much more. In summary, Figure 3 suggests that even after controlling for the quality difference, there is still large dispersion in the input prices.

While it is not assumed in our estimation, we would expect a significant amount of persistence in firm's input prices over time. We run a regression of logarithm of imputed material prices to estimate the persistence of the firm's input prices:

$$\log(\hat{P}_{M_{jt}}) = \rho_0 + \rho_1 \log(\hat{P}_{M_{jt-1}}) + \pi_{jt},$$

where π_{jt} is an iid shock. Table 2.4 shows the estimated persistence with standard error. In all four industries, there is quite high persistence with mean around 0.75, which is close to the persistence reported in Atalay (2012) in which firm-level input prices and quantities are available. Thus, firms that are able to secure low prices today are likely to be able to secure them again in the future.

We also find that the imputed input price is positively correlated with the recovered productivity, as is wage rate, as shown in Table 5. Both these results are consistent with many existing findings (e.g. Hummels and Klenow 2005, Schott 2004, Kugler and Verhoogen 2012). Kugler and Verhoogen (2012) emphasize the quality complementarity hypothesis—input quality and plant productivity are complementary in generating output quality—in explaining the positive correlation between input price and firm productivity. Because we recover the input prices using the marginal contribution of input in production, our recovered input price is quality-adjusted. Even so, we find positive correlation between input prices and productivity. This indicates that alternative factors, such as plant-specific demand shocks and market power in input sectors, as discussed in Kugler and Verhoogen (2011), may also contribute to the dispersion of input price dispersion within industries.

2.7 Conclusion

In this paper, we analyze the problem of unobserved input prices and quantities in the estimation of production functions. We provide a method to correct both omitted input and output price biases simultaneously. Instead of using the deflated values as proxies of quantities, we exploit the first order conditions of profit maximization and impute unobservable firm-level quantities of output and inputs from observable revenue and expenditures. This allows us to construct a nonlinear regression equation only involving value data on inputs and outputs.

We conduct Monte Carlo experiments to evaluate the performance of our estimation method. The results confirm that ignoring unobserved price dispersion biases in the estimation when deflated values are used as proxies of quantities. In contrast, our method recovers the true parameters very well. We further show that these differences matter in real data by applying the methods to a dataset on the Colombian manufacturing sector. The results are in line with theory and the Monte Carlo study. Specifically, the elasticity of substitution is significantly lower compared with our method when using the expenditure proxy. The results suggest that our method of imputing unobservable firm-level input quantities from observable expenditures is important to effectively control for input price dispersion and consistently estimate the production function and the degree of dispersion in productivity.

Appendices

A Proof of Proposition 1

Proposition 1: Suppose assumptions 1-3 are satisfied and we observe a random sample of $(K_{jt}, L_{jt}, E_{Mjt}, E_{Ljt})$, where for all $\theta \in \Theta$, $\frac{\partial z}{\partial M_{jt}} \neq 0$. Then there exists a function $M^*_{jt}(K_{jt}, L_{jt}, E_{Mjt}, E_{Ljt}, \theta)$, such that,

$$z(M^*_{jt}(K_{jt}, L_{jt}, E_{Mjt}, E_{Ljt}, \theta), K_{jt}, L_{jt}, E_{Mjt}, E_{Ljt}, \theta) = 0.$$

Proof: Under assumption 4, F is continuously differentiable up to the second order and $F_{M_{jt}} > 0$. This implies that $z(M_{jt}, K_{jt}, L_{jt}, E_{Mjt}, E_{Ljt}, \theta)$ is first order continuously differentiable. According to the implicit function theorem, $z(M_{jt}, K_{jt}, L_{jt}, E_{Mjt}, E_{Ljt}, \theta) = 0$ and $\frac{\partial z}{\partial M_{jt}} \neq 0$ for all all $\theta \in \Theta$ implies that there exist an open ball B_x of $\left(\widetilde{K_{jt}}, \widetilde{L_{jt}}, \widetilde{E_{Mjt}}, \widetilde{E_{Ljt}}\right)$ centered at $(K_{jt}, L_{jt}, E_{Mjt}, E_{Ljt})$ and an open ball B_M of $\widetilde{M_{jt}}$ centered at M_{jt}, such that

$$\begin{aligned} &\left\{\left(\left(\widetilde{K_{jt}}, \widetilde{L_{jt}}, \widetilde{E_{Mjt}}, \widetilde{E_{Ljt}}\right), \widetilde{M_{jt}}\right) \in B_x \times B_M : z\left(\left(\widetilde{K_{jt}}, \widetilde{L_{jt}}, \widetilde{E_{Mjt}}, \widetilde{E_{Ljt}}\right), \widetilde{M_{jt}}; \theta\right) = 0\right\} \\ = \; &\left\{\left(\left(\widetilde{K_{jt}}, \widetilde{L_{jt}}, \widetilde{E_{Mjt}}, \widetilde{E_{Ljt}}\right), M^*_{jt}(\left(\widetilde{K_{jt}}, \widetilde{L_{jt}}, \widetilde{E_{Mjt}}, \widetilde{E_{Ljt}}\right); \theta)\right) : \left(\widetilde{K_{jt}}, \widetilde{L_{jt}}, \widetilde{E_{Mjt}}, \widetilde{E_{Ljt}}\right) \in B_x\right\} \end{aligned}$$

Since the observed sample $(K_{jt}, L_{jt}, E_{Mjt}, E_{Ljt}) \in B_M$, let

$$(K_{jt}, L_{jt}, E_{Mjt}, E_{Ljt}) = \left(\widetilde{K_{jt}}, \widetilde{L_{jt}}, \widetilde{E_{Mjt}}, \widetilde{E_{Ljt}}\right),$$

we have

$$z(M_{jt}, K_{jt}, L_{jt}, E_{Mjt}, E_{Ljt}, \theta) = 0 \Leftrightarrow M_{jt} = M^*_{jt}(K_{jt}, L_{jt}, E_{Mjt}, E_{Ljt}, \theta)$$

which implies that $z(M^*_{jt}(K_{jt}, L_{jt}, E_{Mjt}, E_{Ljt}, \theta), K_{jt}, L_{jt}, E_{Mjt}, E_{Ljt}, \theta) = 0.\blacksquare$

B The Standard CES Normalization

The purpose of this appendix is to show how the CES function is normalized in the literature, which can be compared to our normalization in the following appendix.

B.1 Motivation of Normalization

It has been commonly recognized that the CES production function need to be normalized to give meaningful identification of its parameters. There is a branch of literature analyzing the importance and the method of normalization, which includes de La Grandville (1989), Klump and de La Grandville (2000), Klump and Preissler (2000), de La Grandville and Solow (2006), and Leon-Ledesma, McAdam and Willman (2010).

The current literature has illustrated the key motivation of the normalization in details for two-factor-input production function (see Brown and de Cani (1963), Klump and Preissler (2000) and Leon-Ledesma, McAdam and Willman (2010)). However, we will work with three-factor-input production function, $Q = F(L, M, K)$. It is defined as a linear homogeneous function in which the elasticity of substitution between any two factors is a constant. The idea and motivation of the standard normalization procedure can be easily extended to our case. To see this, let us follow the literature by stating the definition of elasticity of substitution σ:

$$\begin{cases} \dfrac{\partial \ln(M/L)}{\partial \ln(F_L/F_M)} = \sigma \\ \dfrac{\partial \ln(K/L)}{\partial \ln(F_L/F_K)} = \sigma \end{cases} \tag{18}$$

This definition provides us with a second-order partial differential equation system. Given the assumption of the linear homogenous function, the general solution of the equation system is given by,

$$Q = F(L, M, K) = \lambda_1[L^\gamma + \lambda_2 M^\gamma + \lambda_3 K^\gamma]^{\frac{1}{\gamma}}, \tag{19}$$

where $\gamma = \frac{\sigma-1}{\sigma}$, and λs are three arbitrary constants of integration emerging in the process of solving the differential equation system. One particular functional form used in the literature is obtained by taking $\tilde{\alpha}_L = \frac{1}{1+\lambda_2+\lambda_3}$, $\tilde{\alpha}_M = \frac{\lambda_2}{1+\lambda_2+\lambda_3}$, $\tilde{\alpha}_K = 1 - \tilde{\alpha}_L - \tilde{\alpha}_M$ and $C = \lambda_1(1 + \lambda_2 + \lambda_3)^{\frac{1}{\gamma}}$, thus

$$Q = F(L, M, K) = C[\tilde{\alpha}_L L^\gamma + \tilde{\alpha}_M M^\gamma + \tilde{\alpha}_K K^\gamma]^{\frac{1}{\gamma}}. \tag{20}$$

Here $\tilde{\alpha}_L$, $\tilde{\alpha}_M$ and $\tilde{\alpha}_K$ are referred as distribution parameters. However, one can obtain different function forms by taking different specifications for λs. Each of these forms is called a family of CES functions. Examples of different families include ones used in Pitchford (1960), Arrow et al. (1961), and David and van de Klundert (1965). Therefore, as shown in the literature, a common baseline point is needed to compare different families of CES functions whose members are distinguished only by different elasticities of substitution. To this end, one needs to fix baseline point for the level of production (Q_0), factor inputs (L_0, M_0, K_0), and the marginal rates of substitution (μ_{ML0}, μ_{KL0}), which are equal to the price ratios (P_{M_0}/P_{L_0}, P_{K_0}/P_{L_0}) because of the cost minimization.[23] For detailed motivation of normalization, refer to La Grandville (1989) and Leon-Ledesma, McAdam, and Willman (2010).

[23]Note that P_{K_0} is the user price of capital, which usually is not accurately measured. To this end, we will extend the normalization to cases where P_{K_0} is not available.

B.2 Standard Normalization Procedure

We follow de La Grandville (1989) and Leon-Ledesma, McAdam, and Willman (2010) to illustrate the normalization of a three-factor-input CES production function. Given the elasticity of substitution σ, for any baseline point of input and output $Z_0 = (L_0, M_0, K_0, Q_0, \mu_{ML0}, \mu_{KL0})$, there are four equations about four parameters that characterize one particular family of CES functions:

$$\tilde{\alpha}_L + \tilde{\alpha}_M + \tilde{\alpha}_K = 1, \tag{21}$$

$$\left(\frac{F_M}{F_L}\right)_0 = \frac{\tilde{\alpha}_M}{\tilde{\alpha}_L}\left(\frac{L_0}{M_0}\right)^{1-\gamma} = \mu_{ML0} \equiv \frac{P_{M_0}}{P_{L_0}}, \tag{22}$$

$$\left(\frac{F_K}{F_L}\right)_0 = \frac{\tilde{\alpha}_K}{\tilde{\alpha}_L}\left(\frac{L_0}{K_0}\right)^{1-\gamma} = \mu_{KL0} \equiv \frac{P_{K_0}}{P_{L_0}}, \tag{23}$$

$$Q_0 = C[\tilde{\alpha}_L L_0^{\gamma} + \tilde{\alpha}_M M_0^{\gamma} + \tilde{\alpha}_K K_0^{\gamma}]^{\frac{1}{\gamma}}. \tag{24}$$

The Equation (22) and (23) are implied by cost minimization. Note that the validation of Equation (23) implicitly assumes the optimal choice of capital stock in the short run. The last equation holds since Q_0 is the physical output produced by its corresponding factor inputs. De La Grandville (1989) provides a graphical representation of the normalization. He shows that, after normalization all CES functions in the same family share the common baseline point of tangency, although their elasticities of substitution are different. Therefore, the purpose of normalization is to compare different CES functions in a meaningful way: on the one hand, different families of CES functions can be characterized by different baseline points, on the other hand, the members of each family sharing common baseline point are distinguished only by different elasticities of substitution.

These four equations imply a solution of four parameters:

$$\tilde{\alpha}_L(\sigma, Z_0) = \frac{P_{L0} L_0^{\frac{1}{\sigma}}}{P_{M0} M_0^{\frac{1}{\sigma}} + P_{L0} L_0^{\frac{1}{\sigma}} + P_{K0} K_0^{\frac{1}{\sigma}}},$$

$$\tilde{\alpha}_M(\sigma, Z_0) = \frac{P_{M0} M_0^{\frac{1}{\sigma}}}{P_{M0} M_0^{\frac{1}{\sigma}} + P_{L0} L_0^{\frac{1}{\sigma}} + P_{K0} K_0^{\frac{1}{\sigma}}},$$

$$\tilde{\alpha}_K(\sigma, Z_0) = \frac{P_{K0} K_0^{\frac{1}{\sigma}}}{P_{M0} M_0^{\frac{1}{\sigma}} + P_{L0} L_0^{\frac{1}{\sigma}} + P_{K0} K_0^{\frac{1}{\sigma}}},$$

$$C(\sigma, Z_0) = Q_0 \left[\frac{P_{L0} L_0^{\frac{1}{\sigma}} + P_{M0} M_0^{\frac{1}{\sigma}} + P_{K0} K_0^{\frac{1}{\sigma}}}{P_{L0} L_0 + P_{M0} M_0 + P_{K0} K_0}\right]^{\frac{\sigma}{\sigma-1}}.$$

Note that given the elasticity of substitution, the value of parameters depend on the choice of baseline point Z_0. Hence, comparing any two CES functions is not informative unless they are specified with the same baseline point.

Substituting the value of these parameters into the original function, we obtain:

$$Q = C(\sigma, Z_0)[\tilde{\alpha}_L(\sigma, Z_0)L^\gamma + \tilde{\alpha}_M(\sigma, Z_0)M^\gamma + \tilde{\alpha}_K(\sigma, Z_0)K^\gamma]^{\frac{1}{\gamma}}.$$

After re-parameterizations, one particular family of CES production function with corresponding normalized parameters is given by

$$Q = Q_0\left[\alpha_{L0}\left(\frac{L}{L_0}\right)^\gamma + \alpha_{M0}\left(\frac{M}{M_0}\right)^\gamma + \alpha_{K0}\left(\frac{K}{K_0}\right)^\gamma\right]^{\frac{1}{\gamma}},$$

where:

$$\begin{cases} \alpha_{L0} = \dfrac{E_{L_0}}{E_{L_0} + E_{M_0} + E_{K_0}} \\ \alpha_{M0} = \dfrac{E_{M_0}}{E_{L_0} + E_{M_0} + E_{K_0}} \\ \alpha_{K0} = 1 - \alpha_{L0} - \alpha_{M0} \end{cases}$$

and $E_{L_0} = P_{L_0}L_0$, $E_{M_0} = P_{M_0}M_0$ and $E_{K_0} = P_{K_0}K_0$ are expenditures of labor, material and capital respectively[24]. Hence a normalized CES function is characterized by the baseline point Z_0 and elasticity of substitution σ: while each baseline point specifies a family of CES production functions, the members of each family sharing a common baseline values are distinguished only by different elasticities of substitution. The normalized distribution parameters now solely depend on the baseline point. Thus they can be prefixed before the estimation if normalization equations (22)-(23) hold (thus the normalization is valid).

C Our CES Normalization

In the standard normalization literature, capital is assumed to be a static input which is chosen optimally in each period. However, in practice, capital may be chosen dynamically. For this reason, we extend the standard normalization approach to allow that capital is not running at the cost-minimizing level in the short run.

Specifically, although capital could be optimally chosen in the long run, the user price of capital (P_K, if available) may not reflect the marginal cost of capital in the short run. To this end, we assume the choice of capital can deviate from the optimal value by certain magnitude of τ which is treated as a parameter to be estimated. This extension also allows for additional flexibility to deal with

[24]Note that the expenditure on capital E_{K_0} is different from the capital stock K_0. But they are related by $E_{K_0} = P_{K_0}K_0$, where P_{K_0} is the user price of capital stock.

situations when the user cost of capital service ($E_K = P_K K$) is not available.

We start from the original production function

$$Q = \exp(\omega)F(L, M, K) = \exp(\tilde{\omega})[\tilde{\alpha}_L L^\gamma + \tilde{\alpha}_M M^\gamma + \tilde{\alpha}_K K^\gamma]^{\frac{1}{\gamma}}, \tag{25}$$

where $\tilde{\omega}$ is the firm-level productivity.

As suggested by Leon-Ledesma, McAdam, and Willman (2010), the baseline point is chosen as the geometric sample mean:

$$\overline{Z} = (\overline{L}, \overline{M}, \overline{K}, \overline{Q}, \overline{\mu}_{ML}),$$

where $\overline{\mu}_{ML}$ is the average marginal rate of substitution between material and labor (i.e., $\overline{P}_M/\overline{P}_L$).

Note that the choice of the baseline value specifies a family of CES functions. Given the baseline value, the equations that characterize this family are:

$$\tilde{\alpha}_L + \tilde{\alpha}_M + \tilde{\alpha}_K = 1, \tag{26}$$

$$\left(\frac{F_M}{F_L}\right)_{\overline{Z}} = \frac{\tilde{\alpha}_M}{\tilde{\alpha}_L}\left(\frac{\overline{L}}{\overline{M}}\right)^{1-\gamma} = \overline{\mu}_{ML}, \tag{27}$$

$$\left(\frac{F_K}{F_L}\right)_{\overline{Z}} = \frac{\tilde{\alpha}_K}{\tilde{\alpha}_L}\left(\frac{\overline{L}}{\overline{K}}\right)^{1-\gamma} = \left(\tau\frac{\overline{E}_L}{\overline{E}_K}\right)\overline{\mu}_{KL} = \tau\frac{\overline{L}}{\overline{K}}, \tag{28}$$

$$\overline{Q} = e^{\overline{\omega}}[\tilde{\alpha}_L \overline{L}^\gamma + \tilde{\alpha}_M \overline{M}^\gamma + \tilde{\alpha}_K \overline{K}^\gamma]^{\frac{1}{\gamma}}, \tag{29}$$

where $\overline{\omega}$ is the "average" productivity associated with producing $\overline{Q}$ by $(\overline{L}, \overline{M}, \overline{K})$.

Here τ in equation (28) is introduced as an inefficiency parameter to measure the mean deviation of capital stock from its optimal level. This extension is important for multiple reasons compared with the standard normalization procedure. First, by introducing such an additional flexible parameter, we allow for the case when the capital stock is not optimally chosen in the short run (although it could be optimal in the long run). Specifically, when $\tau = \frac{\overline{E}_K}{\overline{E}_L}$, the marginal rate of substitution of labor and capital at the baseline point is equal to the price ratio, which implies the capital stock is indeed optimally chosen; when $\tau \neq \frac{\overline{E}_K}{\overline{E}_L}$, the actual capital deviates from the optimal amount. We will not specify the value of τ but leave it to be revealed by data as a parameter to estimate. Second, in our empirical application, such a flexible parameter enables us to deal with situations where the average "price" (or the user cost) of capital stock $\overline{P}_K$ (or $\overline{E}_K$) is not available or accurately measured. In other words, instead of assuming that $\overline{P}_K$ or $\overline{E}_K$ is known, we let it be absorbed in the parameter τ which can be estimated from data.

Given γ and τ, the distribution parameters implied by the equations (26), (27) and (28) are given by:

$$\begin{aligned}\tilde{\alpha}_L(\gamma,\tau) &= \frac{\frac{\overline{E}_L}{\overline{L}^\gamma}}{\frac{\overline{E}_L}{\overline{L}^\gamma} + \frac{\overline{E}_M}{\overline{M}^\gamma} + \tau\frac{\overline{E}_L}{\overline{K}^\gamma}} \\ \tilde{\alpha}_M(\gamma,\tau) &= \frac{\frac{\overline{E}_M}{\overline{M}^\gamma}}{\frac{\overline{E}_L}{\overline{L}^\gamma} + \frac{\overline{E}_M}{\overline{M}^\gamma} + \tau\frac{\overline{E}_L}{\overline{K}^\gamma}} \\ \tilde{\alpha}_K(\gamma,\tau) &= 1 - \tilde{\alpha}_L(\gamma,\tau) - \tilde{\alpha}_M(\gamma,\tau)\end{aligned} \tag{30}$$

As in the standard normalization procedure, we plug the distribution parameters into the original CES function to obtain the normalized CES function after re-parametrization:

$$Q = e^\omega \overline{Q}\left[\alpha_L\left(\frac{L}{\overline{L}}\right)^\gamma + \alpha_M\left(\frac{M}{\overline{M}}\right)^\gamma + \alpha_K\left(\frac{K}{\overline{K}}\right)^\gamma\right]^{\frac{1}{\gamma}},$$

where

$$\begin{aligned}\alpha_L &= \frac{\overline{E}_L}{\overline{E}_L + \overline{E}_M + \tau\overline{E}_L} \\ \alpha_M &= \frac{\overline{E}_M}{\overline{E}_L + \overline{E}_M + \tau\overline{E}_L}, \\ \alpha_K &= 1 - \alpha_L - \alpha_M\end{aligned} \tag{31}$$

and

$$\omega = \tilde{\omega} - \overline{\omega}. \tag{32}$$

Note that, these equations imply $\frac{\alpha_K}{\alpha_L} = \tau$, which is why we define the ratio of α_K and α_L as τ in Equation (2.10).

D CES Estimation Equation

In this appendix, we develop the estimation equation for normalized CES production function. Each firm j chooses labor and material quantities to maximize the profit in each period t, given its capital stock and productivity. The firm's static problem is:

$$\max_{L_{jt},M_{jt}} P_t(Q_{jt})Q_{jt} - P_{L_{jt}}L_{jt} - P_{M_{jt}}M_{jt}, \tag{33}$$

where

$$Q_{jt} = e^{\omega_{jt}}\overline{Q}\left[\alpha_L\left(\frac{L_{jt}}{\overline{L}}\right)^\gamma + \alpha_M\left(\frac{M_{jt}}{\overline{M}}\right)^\gamma + \alpha_K\left(\frac{K_{jt}}{\overline{K}}\right)^\gamma\right]^{\frac{1}{\gamma}},$$

and

$$\frac{Q_{jt}}{Q_t} = \left(\frac{P_{jt}}{P_t}\right)^{\eta}.$$

Note that L_{jt}, M_{jt} and Q_{jt} are physical quantities of labor and material input and output respectively. The first order conditions with respective to labor and material are

$$\frac{1+\eta}{\eta}\frac{\partial Q_{jt}}{\partial L_{jt}}\frac{Q_{jt}^{1/\eta}P_t}{Q_t^{1/\eta}} = P_{L_{jt}}, \tag{34}$$

$$\frac{1+\eta}{\eta}\frac{\partial Q_{jt}}{\partial M_{jt}}\frac{Q_{jt}^{1/\eta}P_t}{Q_t^{1/\eta}} = P_{M_{jt}}. \tag{35}$$

Note that $E_{L_{jt}} = P_{L_{jt}}L_{jt}$ and $E_{M_{jt}} = P_{M_{jt}}M_{jt}$, and plug the demand function into above equations we obtain:

$$\frac{1+\eta}{\eta}\frac{\partial Q_{jt}}{\partial L_{jt}}\frac{L_{jt}}{Q_{jt}} = \frac{E_{L_{jt}}}{R_{jt}}, \tag{36}$$

$$\frac{1+\eta}{\eta}\frac{\partial Q_{jt}}{\partial M_{jt}}\frac{M_{jt}}{Q_{jt}} = \frac{E_{M_{jt}}}{R_{jt}}, \tag{37}$$

where $R_{jt} = P_{jt}Q_{jt}$ is the revenue for firm j at period t.

Take the ratio with respective to both sides of the equations, and we can solve for material quantity:

$$\frac{M_{jt}}{\overline{M}} = \left[\frac{\alpha_L E_{M_{jt}}}{\alpha_M E_{L_{jt}}}\right]^{\frac{1}{\gamma}} \frac{L_{jt}}{\overline{L}}. \tag{38}$$

This implies that material quantity can be imputed from observables ($E_{L_{jt}}$, $E_{M_{jt}}$, and L_{jt}) up to unknown parameters. Substitute this M_{jt} in the first order condition for labor and solve for ω_{jt}, we have

$$\begin{aligned} e^{-\frac{1+\eta}{\eta}\omega_{jt}} &= \alpha_L \frac{1+\eta}{\eta}\frac{P_t}{Q_t^{1/\eta}}\left(\frac{L_{jt}}{\overline{L}}\right)^{\gamma}\frac{\overline{Q}^{\frac{1+\eta}{\eta}}}{E_{L_{jt}}} \\ &\cdot \left[\alpha_L\left(\frac{E_{L_{jt}}+E_{M_{jt}}}{E_{L_{jt}}}\right)\left(\frac{L_{jt}}{\overline{L}}\right)^{\gamma} + \alpha_K\left(\frac{K_{jt}}{\overline{K}}\right)^{\gamma}\right]^{\frac{1}{\gamma\eta}+\frac{1}{\gamma}-1} \end{aligned} \tag{39}$$

Note that the imputed ω_{jt} is also a function of observables.

Plug the imputed M_{jt} and ω_{jt} into the revenue equation:

$$R_{jt} = \exp(u_{jt})P_t(Q_{jt})Q_{jt}, \tag{40}$$

after some algebra we have,

$$\ln R_{jt} = \ln \frac{\eta}{1+\eta} + \ln \left[E_{M_{jt}} + E_{L_{jt}} \left(1 + \tau \left(\frac{K_{jt}/\overline{K}}{L_{jt}/\overline{L}} \right)^{\gamma} \right) \right] + u_{jt}, \quad (41)$$

where $\tau = \frac{\alpha_K}{\alpha_L}$ is the flexible parameter in the normalization of the CES family.

E Monte Carlo Description

In this appendix, we outline the data generating process for the Monte Carlo experiments. Specifically, the Monte Carlo experiments consist of N replications of simulated data sets, given a set of true parameters of interest (η, σ, $\tilde{\alpha}_L$, $\tilde{\alpha}_M$ and $\tilde{\alpha}_K$). In each replication, we simulate a sequence of productivity (ω_{jt}), idiosyncratic input prices ($P_{L_{jt}}$ and $P_{M_{jt}}$), and capital stock (K_{jt}) for each firm j over time. Given these variables and random shocks, we derive a sequence of optimal choices of labor and material inputs (L_{jt} and M_{jt}), the optimal output quantity (Q_{jt}) and price (P_{jt}) for firm j in each period t.

In each replication, there are J firm in production for T periods. The evolution process of productivity for each firm is assumed to be a first order Markov process:

$$\omega_{jt+1} = g_0 + g_1 \omega_{jt} + \varepsilon^{\omega}_{jt+1}, \quad (42)$$

where $\varepsilon^{\omega}_{jt+1}$ is the innovation shock realized in period $t+1$, which is assumed to be a normally distributed i.i.d. error term with zero mean and standard deviation $se(\varepsilon^{\omega})$. The initial productivity of each firm (ω_{j0}) is drawn from a normal distribution of mean ω_0 and standard deviation $se(\omega_0)$.

The investment rule and the capital evolution process are set as,

$$\log(I_{jt}) = \xi \omega_{jt} + (1-\xi)\log(K_{jt}), \quad (43)$$

$$K_{jt+1} = K_{jt} + I_{jt}, \quad (44)$$

where $\xi \in (0,1)$ is an arbitrary weight. The initial capital stock of each firm (K_{j0}) is drawn from a normal distribution of mean K_0 and standard variance $se(K_0)$.

The idiosyncratic labor and material input prices ($P_{L_{jt}}$ and $P_{M_{jt}}$) are generated as follows:

$$P_{L_{jt}} = \overline{P}_{L_t} e^{\varepsilon_t^{PL}}, \quad (45)$$

$$P_{M_{jt}} = \overline{P}_{M_t} e^{\varepsilon_t^{PM}}, \quad (46)$$

where $\overline{P}_{L_t}$ and $\overline{P}_{M_t}$ are the industrial-level labor and material prices in period t, which can be drawn from $N(\overline{P}_L, se(\overline{P}_L))$ and $N(\overline{P}_M, se(\overline{P}_M))$ independently, or set to 1 for simplicity as in our implementation. ε_t^{PL} and ε_t^{PM} are deviations from the industrial-level input prices, which are independently drawn from $N(0, se(\varepsilon_t^{PL}))$

and $N(0, se(\varepsilon_t^{PM}))$ respectively. Note that, the variation of input prices across firm for a given period is characterized by $se(\varepsilon_t^{PL})$ and $se(\varepsilon_t^{PM})$.

For the demand side, we assume the industrial-level output quantities are generated by,

$$Q_t = r^t Q_0 e^{\varepsilon_t^Q}, \tag{47}$$

where r is the growth rate of the industrial-level output quantity, Q_0 is the initial industrial-level output quantity, and $\varepsilon_t^Q \sim N(0, se(\varepsilon^Q))$ is an independent random shock. The industrial-level output prices are generated by,

$$P_t = Q_t^{1/\eta}, \tag{48}$$

where η is the demand elasticity.

Now we have simulated $\{\omega_{jt}, K_{jt}, I_{jt}, P_{L_{jt}}, P_{M_{jt}}, Q_t, P_t\}$ for each firm j and period t. Given these variables, we can derive the optimal labor and material input choices (L_{jt} and M_{jt}) and the corresponding output quantity (Q_{jt}) for each firm j and period t according to the first order conditions associated with the firm's static profit maximization problem. Specifically, the optimal labor input is derived as,

$$L_{jt} = \left(\frac{\tilde{\alpha}_M P_{L_{jt}}}{\tilde{\alpha}_L P_{M_{jt}}}\right)^{\frac{1}{\gamma-1}} M_{jt}, \tag{49}$$

where the material input M_{jt} is given by,

$$M_{jt} = \left[\frac{(e^{-\omega_{jt}} Q_{jt})^{\gamma} - \tilde{\alpha}_K K^{\gamma}}{\tilde{\alpha}_M + \tilde{\alpha}_L \left(\frac{\tilde{\alpha}_M P_{L_{jt}}}{\tilde{\alpha}_L P_{M_{jt}}}\right)^{\frac{\gamma}{1-\gamma}}}\right]^{\frac{1}{\gamma}}, \tag{50}$$

and Q_{jt} is the solution of the following equation:

$$\frac{\eta+1}{\eta}\left(\frac{P_t}{Q_t^{\frac{1}{\eta}}}\right) Q_{jt}^{\frac{1}{\eta}} = e^{-\omega_{jt}} \frac{\left[P_{M_{jt}} + P_{L_{jt}}\left(\frac{\tilde{\alpha}_M P_{L_{jt}}}{\tilde{\alpha}_L P_{M_{jt}}}\right)^{\frac{1}{\gamma-1}}\right]}{\left[\tilde{\alpha}_M + \tilde{\alpha}_L\left(\frac{\tilde{\alpha}_M P_{L_{jt}}}{\tilde{\alpha}_L P_{M_{jt}}}\right)^{\frac{\gamma}{1-\gamma}}\right]^{\frac{1}{\gamma}}} \left(1 - \tilde{\alpha}_K K^{\gamma} (e^{-\omega_{jt}} Q_{jt})^{-\gamma}\right)^{\frac{1}{\gamma}-1}. \tag{51}$$

Given the derived variables and underlying true parameters, equation (51) is only about Q_{jt}. It is easy to verify that equation (51) implies a unique solution for Q_{jt} since given $\eta < -1$, the left hand side is decreasing in Q_{jt} while the right hand side is increasing in Q_{jt}. Denote the solution of the equation as Q_{jt}^*. Once we obtain Q_{jt}^*, we can derive the corresponding L_{jt} and M_{jt} from equation (49) and equation (50). Hence, the expenditures of input are given by $E_{L_{jt}} = P_{L_{jt}} L_{jt}$

and $E_{M_{jt}} = P_{M_{jt}} M_{jt}$. The observed output with a measurement error is given by

$$Q_{jt} = Q^*_{jt} e^{\varepsilon^q_t}, \tag{52}$$

where $\varepsilon^q_t \sim N(0, se(\varepsilon^q))$ is the measurement error. At last, firm level output price P_{jt} is derived by equation

$$\frac{Q_{jt}}{Q_t} = \left(\frac{P_{jt}}{P_t}\right)^{\eta}, \tag{53}$$

and the firm-level revenue is obtained by

$$R_{jt} = P_{jt} Q_{jt}. \tag{54}$$

Hence, we have generated a data set of $\{\omega_{jt}, K_{jt}, I_{jt}, L_{jt}, M_{jt}, E_{L_{jt}}, E_{M_{jt}}, Q_{jt}, R_{jt}, Q_t, P_t\}$ for each firm j and period t.

Table 2.1. Monte Carlo Parameter Values

Parameters	Description	Value
η	Demand elasticity	-4
σ	Elasticity of substitution	0.8, 1.5, 2.5
$\tilde{\alpha}_L$[1]	Distribution parameter of labor	0.4
$\tilde{\alpha}_M$	Distribution parameter of material	0.4
$\tilde{\alpha}_K$	Distribution parameter of capital	0.2
g_0	Parameter in productivity evolution	0.2
g_1	Parameter in productivity evolution	0.95
$se(\varepsilon^{\omega})$	Standard error of productivity innovation	0.01
$se(\varepsilon^{PL})$	Standard error of labor price shock	0.2
$se(\varepsilon^{PM})$	Standard error of material price shock	0.2
$se(\varepsilon^{R})$	Standard error of unexpected productivity shock	0.01
T	Number of periods	10
J	Number of firms	100
N	Number of Monte Carlo replications	1000

[1] Note that $\tilde{\alpha}_L$, $\tilde{\alpha}_M$ and $\tilde{\alpha}_K$ are the original distribution parameters, which are the same across replications. The normalized distribution parameters α_L, α_M and α_K depend on the baseline point which may vary across replications. See Appendix C for the details.

Table 2.2. Monte Carlo experiment: Estimated results from three different methods[2]

	True	$\sigma = 0.8$			$\sigma = 1.5$			$\sigma = 2.5$		
		Us	OP	Oracle	Us	OP	Oracle	Us	OP	Oracle
$\hat{\eta}$	-4.00	-3.994	-	-	-3.999	-	-	-3.999	-	-
		(0.003)	-	-	(0.001)	-	-	(0.000)	-	-
		[0.146]	-	-	[0.049]	-	-	[0.015]	-	-
$\hat{\sigma}$		0.800	0.669	0.802	1.501	1.208	1.502	2.499	1.988	2.495
		(0.011)	(0.174)	(0.030)	(0.027)	(0.214)	(0.048)	(0.039)	(0.372)	(0.068)
		[0.011]	[0.146]	[0.013]	[0.029]	[0.299]	[0.025]	[0.043]	[0.516]	[0.037]
$\hat{\tilde{\alpha}}_L$[3]	0.40	0.400	0.483	0.400	0.400	0.478	0.400	0.400	0.459	0.401
		(0.007)	(0.007)	(0.007)	(0.004)	(0.005)	(0.005)	(0.002)	(0.010)	(0.003)
		[0.005]	[0.083]	[0.003]	[0.001]	[0.078]	[0.002]	[0.001]	[0.059]	[0.001]
$\hat{\tilde{\alpha}}_M$	0.40	0.400	0.484	0.400	0.400	0.479	0.400	0.400	0.460	0.400
		(0.007)	(0.007)	(0.007)	(0.004)	(0.005)	(0.005)	(0.002)	(0.011)	(0.003)
		[0.005]	[0.084]	[0.003]	[0.001]	[0.079]	[0.002]	[0.001]	[0.060]	[0.001]
$\hat{\tilde{\alpha}}_K$	0.20	0.200	0.033	0.199	0.200	0.043	0.201	0.200	0.082	0.199
		(0.014)	(0.015)	(0.013)	(0.009)	(0.009)	(0.009)	(0.003)	(0.021)	(0.005)
		[0.009]	[0.166]	[0.005]	[0.003]	[0.157]	[0.005]	[0.001]	[0.118]	[0.003]
$\hat{\tau}$[4]		0.325	0.030	0.326	0.209	0.057	0.209	0.174	0.074	0.173
		(0.028)	(0.002)	(0.001)	(0.009)	(0.003)	(0.001)	(0.003)	(0.005)	(0.001)
		[0.028]	[0.296]	[0.004]	[0.009]	[0.152]	[0.003]	[0.004]	[0.099]	[0.003]

[2] The table reports the medians of N replications of each case. The standard errors are included in the parentheses and root mean squared errors are in the square brackets.

[3] $\hat{\tilde{\alpha}}$'s are the estimates of the original distribution parameters (i.e., $\tilde{\alpha}$'s). See the footnote of the Table 2.7.

[4] $\hat{\tau}$ is endogenously implied by the choice of capital stock. True value of $\hat{\tau}$ for the three cases are 0.326, 0.209 and 0.173 respectively.

Figure 2.1. Monte Carlo experiments: true $\sigma = 0.8, 1.5, 2.5$

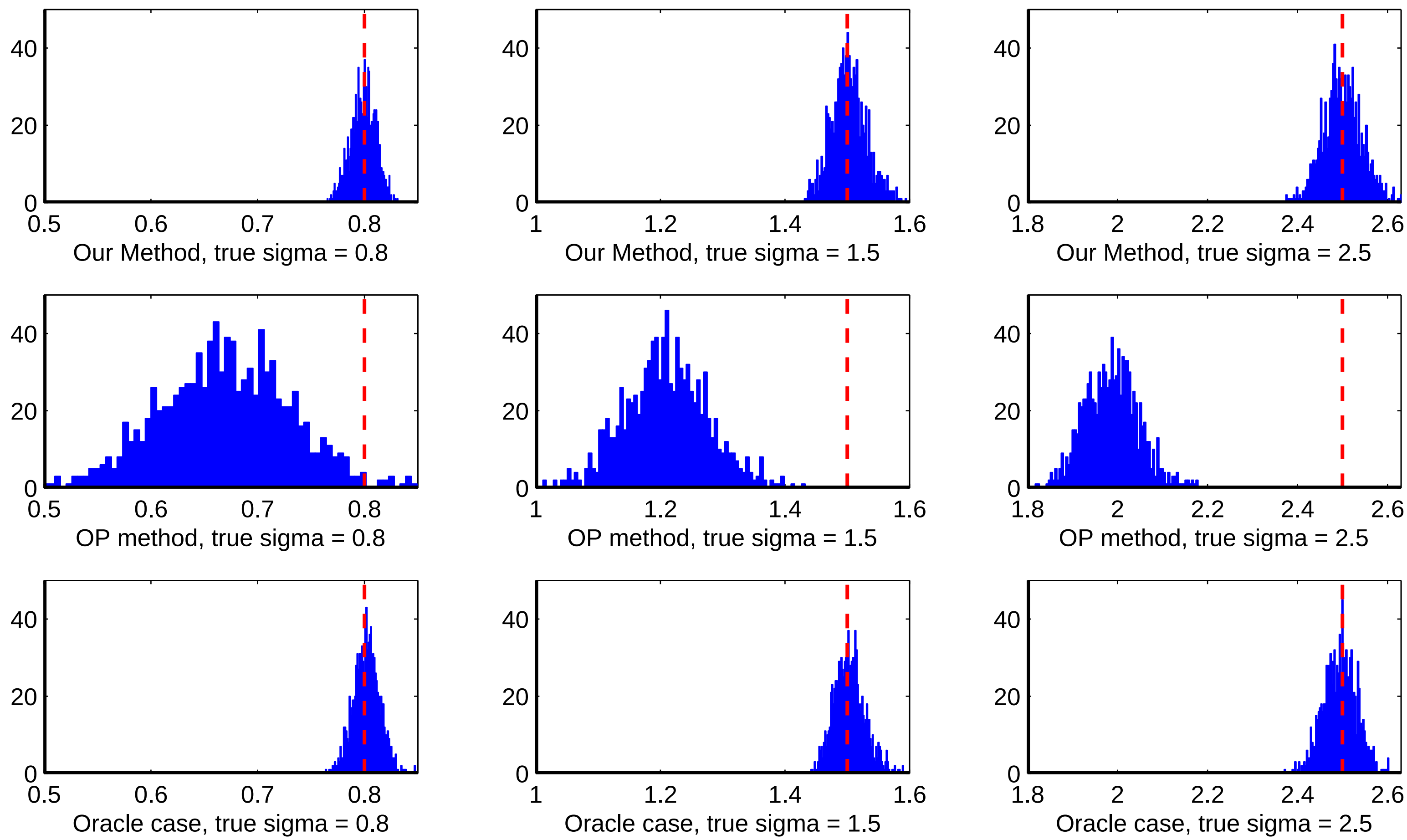


Figure 2.2. Kernel density estimation: imputed material prices v.s. true material prices

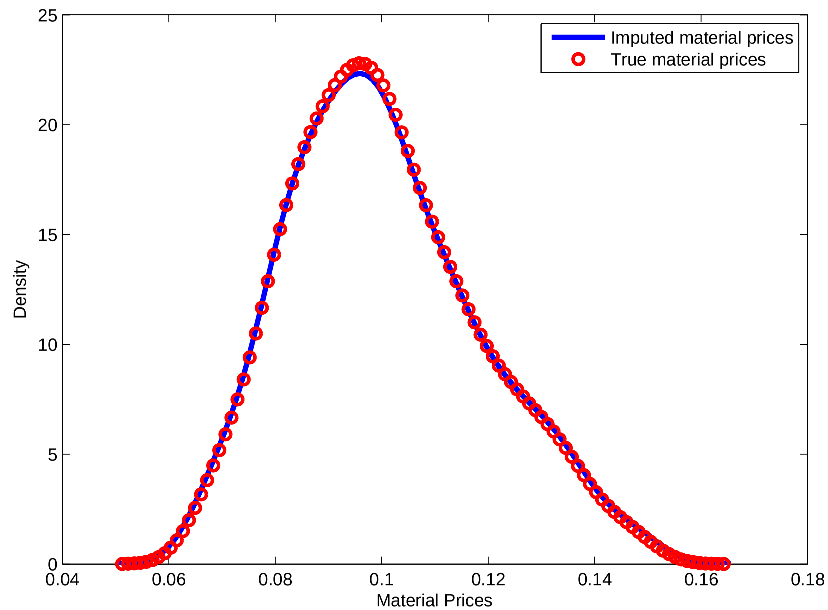


Table 2.3. Estimated results for Colombian industries

	Clothing		Bakery Products		Printing & Publishing		Metal Furniture	
	Us	OP-KG	Us	OP-KG	Us	OP-KG	Us	OP-KG
$\hat{\eta}$	-5.768	-8.465	-5.231	-5.253	-4.659	-12.161	-5.518	-6.947
	(0.121)	(1.544)	(0.188)	(0.417)	(0.236)	(5.434)	(0.433)	(2.686)
$\hat{\sigma}$	1.948	0.361	1.443	0.401	2.555	0.593	1.772	0.393
	(0.234)	(0.018)	(0.117)	(0.011)	(0.405)	(0.054)	(0.379)	(0.045)
$\hat{\alpha}_L$	0.361	0.371	0.244	0.251	0.372	0.381	0.300	0.304
	(0.002)	(0.001)	(0.002)	(0.000)	(0.005)	(0.004)	(0.005)	(0.005)
$\hat{\alpha}_M$	0.601	0.618	0.705	0.725	0.537	0.549	0.637	0.647
	(0.003)	(0.001)	(0.006)	(0.001)	(0.007)	(0.005)	(0.010)	(0.011)
$\hat{\alpha}_K$	0.038	0.011	0.050	0.025	0.091	0.070	0.064	0.049
	(0.004)	(0.002)	(0.007)	(0.002)	(0.013)	(0.009)	(0.015)	(0.016)
$\hat{\tau}$	0.106	0.030	0.207	0.098	0.245	0.183	0.213	0.160
	(0.012)	(0.005)	(0.032)	(0.008)	(0.037)	(0.025)	(0.055)	(0.054)
$\hat{g}_0$	0.008	0.101	0.039	0.148	-0.025	0.211	-0.033	0.219
	(0.010)	(0.011)	(0.015)	(0.011)	(0.015)	(0.039)	(0.024)	(0.072)
$\hat{g}_1$	0.695	0.972	0.822	0.955	0.906	0.950	0.824	0.877
	(0.014)	(0.010)	(0.012)	(0.005)	(0.019)	(0.014)	(0.026)	(0.026)
#Obs	5763		2269		2377		903	

Figure 2.3. Kernel density estimation of imputed material prices in logarithm

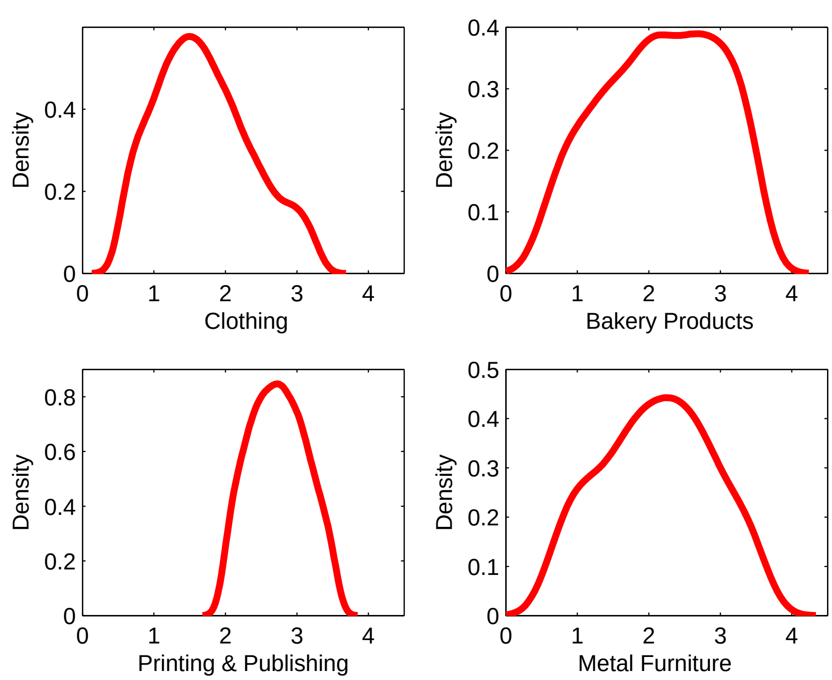


Table 2.4. Persistence of imputed material prices

	Persistence (ρ_1)	Standard Error
Clothing	0.77	0.20
Bakery Products	0.77	0.21
Printing & Publishing	0.82	0.18
Metal Furniture	0.68	0.19

Figure 2.4. Kernel density estimation of imputed productivity

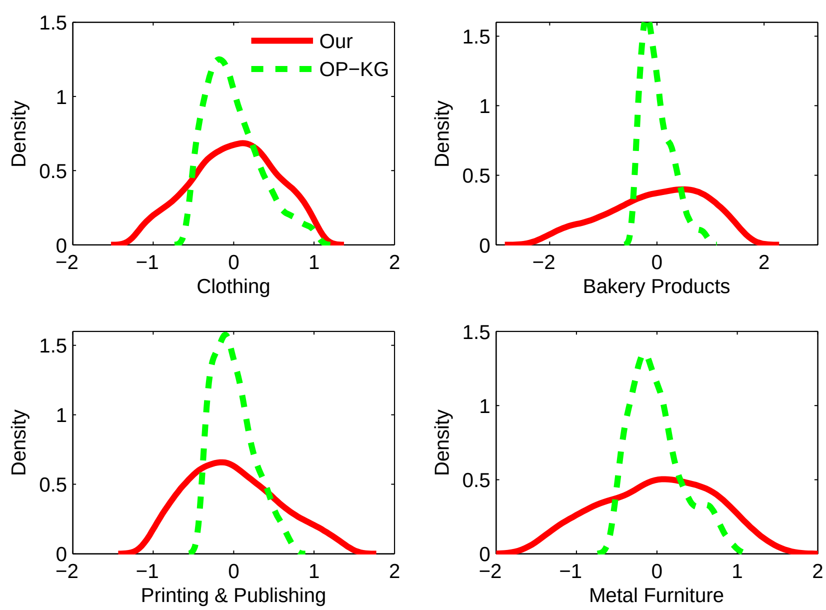


Table 2.5. Correlations between imputed productivity and input prices in logarithm

	$\text{corr}(\hat{\omega}, \log(\hat{P}_M))$	$\text{corr}(\hat{\omega}, \log(P_L))$	$\text{corr}(\log(\hat{P}_M), \log(P_L))$
Clothing	0.76	0.60	0.26
Bakery Products	0.93	0.58	0.40
Printing & Publishing	0.68	0.88	0.68
Metal Furniture	0.85	0.65	0.48

Chapter 3

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

3.1 Introduction

[1] 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.[2]

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.

[1]The author is grateful to Saroj Bhattarai, Johnathan Eaton, Edward Green, Paul Grieco, Mark Roberts, Spiro Stefanou, James Tybout, Neil Wallace and all participants in the IO workshop at the Pennsylvania State University for discussion and very helpful comments. All errors are the author's own responsibility.

[2]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.

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 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[3], which focuses on the country-level 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 3.2 introduces the

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

background and motivational facts. Section 3.3 introduces the model and estimation procedure for general (parametric) production functions. Section 3.4 and section 3.5 discuss the estimation procedure and empirical results from the translog production function. Section 3.6 provides a test against neutral technology. Sections 3.7 and 3.8 investigate the pattern of biased technological change and biased technological dispersion. Section 3.9 discusses the sources of growth in China and section 3.10 concludes.

3.2 The Background and Motivational Facts

3.2.1 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 Out-dated 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.

3.2.2 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 3.1 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[4]. 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 vehicle industry.

3.2.3 Motivational Facts

3.2.3.1 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 3.2. 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

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

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 3.2 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.

3.2.3.2 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 3.1 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 3.1 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, since 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 3.3 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.

3.3 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.

3.3.1 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*[5], 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 outputs 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.

3.3.2 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.

[5]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.

The second problem is related to the aforementioned Diamond's Impossibility Theorem (Diamond, McFadden, and Rodriguez, 1978), which says that under assumptions A1-A5[6], 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 economic 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

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

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.

3.3.3 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[7]. 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

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

The corresponding first order conditions are:

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

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

$$\begin{aligned} \exp(\upsilon_{jt}) L_{jt} \frac{F_2\left(\cdot\right)}{F\left(\cdot\right)} &= \frac{W_t L_{jt}}{P_t Y_{jt}} \\ M_{jt} \frac{F_3\left(\cdot\right)}{F\left(\cdot\right)} &= \frac{P_t^m M_{jt}}{P_t Y_{jt}} \end{aligned} \tag{3.1}$$

Denote S_{Ljt} and S_{Mjt} as the revenue share of labor and material, respectively,

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

observed in the data. S_{Ljt} and S_{Mjt} are written as

$$\begin{aligned} S_{Ljt} &= \frac{P_L L_{jt}}{P_{jt}Q_{jt}} = \frac{W_t L_{jt}}{P_t Y_{jt}\exp(\varepsilon_{jt})} \\ S_{Mjt} &= \frac{P_L L_{jt}}{P_{jt}Q_{jt}} = \frac{P_t^m M_{jt}}{P_t Y_{jt}\exp(\varepsilon_{jt})} \end{aligned} \tag{3.2}$$

By replacing $\frac{P_L L_{jt}}{P_{jt}Y_{jt}}$ and $\frac{P_M M_{jt}}{P_{jt}Y_{jt}}$ in equation (3.1) with the expressions in equation (3.2), we have

$$\begin{aligned} \exp(\upsilon_{jt})L_{jt}\frac{F_2\left(\exp(\omega_{jt})K_{jt}, \exp(\upsilon_{jt})L_{jt}, M_{jt}\right)}{F\left(\exp(\omega_{jt})K_{jt}, \exp(\upsilon_{jt})L_{jt}, M_{jt}\right)} &= S_{Ljt}\exp(\varepsilon_{jt}) \\ M_{jt}\frac{F_3\left(\exp(\omega_{jt})K_{jt}, \exp(\upsilon_{jt})L_{jt}, M_{jt}\right)}{F\left(\exp(\omega_{jt})K_{jt}, \exp(\upsilon_{jt})L_{jt}, M_{jt}\right)} &= S_{Mjt}\exp(\varepsilon_{jt}) \end{aligned} \tag{3.3}$$

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.

3.3.4 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 2 (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*

$$\frac{E^l_{jt\omega}}{E^m_{jt\omega}} \neq \frac{E^l_{jt\upsilon}}{E^m_{jt\upsilon}} \tag{3.4}$$

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

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

Proof. The proof is an application of the implicit function theorem. See the 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 (3.4).[8] 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.

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

The production function is $Y_{jt} = C\left[(A_{jt}K_{jt})^{\gamma} + (B_{jt}L_{jt})^{\gamma} + (M_{jt})^{\gamma}\right]^{\frac{s}{\gamma}}$, 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

$$\ln Q_{jt} = \left(\ln C + \frac{s}{\gamma}\ln s\right) - \frac{s}{\gamma}\ln S_{Mjt} + s\ln M_{jt} + (1 - \frac{s}{\gamma})\varepsilon_{jt} \qquad (3.5)$$

[8]Note that in this case, if we still distinguish capital-augmenting efficiency and labor-augmenting efficiency (although they are equal), condition (3.4) is still satisfied. But it is a waste of notation in this case.

■.

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.■

3.3.5 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

$$\begin{aligned} \omega^*_{jt} &= \omega\left(K_{jt}, L_{jt}, M_{jt}, S_{Ljt}, S_{Mjt}, \varepsilon_{jt}; \theta\right), \\ \upsilon^*_{jt} &= \upsilon\left(K_{jt}, L_{jt}, M_{jt}, S_{Ljt}, S_{Mjt}, \varepsilon_{jt}; \theta\right). \end{aligned} \tag{3.6}$$

Replacing ω_{jt} and υ_{jt} in the production function with equation (3.6) yields the estimation equation:

$$Y_{jt} = F\left(\exp(\omega^*_{jt})K_{jt}, \exp(\upsilon^*_{jt})L_{jt}, M_{jt}\right),$$

where ω^*_{jt} and υ^*_{jt} are defined in equation 3.6. 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:

$$\ln Q_{jt} = \ln F\left(\exp(\omega^*_{jt})K_{jt}, \exp(\upsilon^*_{jt})L_{jt}, M_{jt}\right) + \varepsilon_{jt} \tag{3.7}$$

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 (3.7) 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 (3.7) 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}.

3.4 Application 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

$$\begin{aligned} \ln Y_{jt} &= a_0 + a_k\left(\omega_{jt} + \ln K_{jt}\right) + a_l\left(\upsilon_{jt} + \ln L_{jt}\right) + a_m \ln M_{jt} \\ &+ \frac{1}{2}a_{kk}\left(\omega_{jt} + \ln K_{jt}\right)^2 + \frac{1}{2}a_{ll}\left(\upsilon_{jt} + \ln L_{jt}\right)^2 + \frac{1}{2}a_{mm}\left(\ln M_{jt}\right)^2 \\ &+ a_{kl}\left(\omega_{jt} + \ln K_{jt}\right)\left(\upsilon_{jt} + \ln L_{jt}\right) + a_{km}\left(\omega_{jt} + \ln K_{jt}\right)\ln M_{jt} \\ &+ a_{lm}\left(\upsilon_{jt} + \ln L_{jt}\right)\ln M_{jt} \end{aligned} \tag{3.8}$$

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:

$$\begin{aligned} W_t &= \frac{P_t Y_{jt}}{L_{jt}}\left[a_l + a_{ll}(\upsilon_{jt} + \ln L_{jt}) + a_{kl}(\omega_{jt} + \ln K_{jt}) + a_{lm}\ln M_{jt}\right] \\ P_t^m &= \frac{P_t Y_{jt}}{M_{jt}}\left[a_m + a_{mm}\ln M_{jt} + a_{km}(\omega_{jt} + \ln K_{jt}) + a_{lm}(\upsilon_{jt} + \ln L_{jt})\right] \end{aligned} \tag{3.9}$$

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}).[9]

[9] The investment decisions are not necessary for the identification of biased technology in this paper, but the additional moments associated with them can be used to improve the efficiency of the estimator.

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

$$S_{jt}^{l}\exp(\varepsilon_{jt}) \equiv \frac{W_t L_{jt}}{P_t Y_{jt}} = a_l + a_{ll}(\upsilon_{jt} + \ln L_{jt}) + a_{kl}(\omega_{jt} + \ln K_{jt}) + a_{lm}\ln M_{jt} \quad (3.10)$$

$$S_{jt}^{m}\exp(\varepsilon_{jt}) \equiv \frac{P_t^m M_{jt}}{P_t Y_{jt}} = a_m + a_{mm}\ln M_{jt} + a_{km}(\omega_{jt} + \ln K_{jt}) + a_{lm}(\upsilon_{jt} + \ln L_{jt})$$

which are functions of the unobserved capital efficiency and labor efficiency. This equation corresponds to equation (3.3) 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:

$$\begin{bmatrix} a_{kl} & a_{ll} \\ a_{km} & a_{lm} \end{bmatrix} \begin{bmatrix} \omega_{jt} \\ \upsilon_{jt} \end{bmatrix} = \begin{bmatrix} S_{jt}^{l}\exp(\varepsilon_{jt}) - (a_l + a_{ll}\ln L_{jt} + a_{kl}\ln K_{jt} + a_{lm}\ln M_{jt}) \\ S_{jt}^{m}\exp(\varepsilon_{jt}) - (a_m + a_{km}\ln K_{jt} + a_{lm}\ln L_{jt} + a_{mm}\ln M_{jt}) \end{bmatrix} \quad (3.11)$$

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:

$$\begin{bmatrix} \omega_{jt} \\ \upsilon_{jt} \end{bmatrix} = \begin{bmatrix} a_{kl} & a_{ll} \\ a_{km} & a_{lm} \end{bmatrix}^{-1} \cdot \begin{bmatrix} S_{jt}^{l}\exp(\varepsilon_{jt}) - (a_l + a_{ll}\ln L_{jt} + a_{kl}\ln K_{jt} + a_{lm}\ln M_{jt}) \\ S_{jt}^{m}\exp(\varepsilon_{jt}) - (a_m + a_{km}\ln K_{jt} + a_{lm}\ln L_{jt} + a_{mm}\ln M_{jt}) \end{bmatrix} \quad (3.12)$$

Given parameters and the data, the capital and labor efficiencies can be solved for from equation (3.12). Then by inserting the expressions in equation (3.12) into the original production function equation to substitute ω_{jt} and υ_{jt}, we have the estimation equation:

$$\begin{aligned} \ln Q_{jt} = {} & a_0 + a_k(\omega_{jt} + \ln K_{jt}) + a_l(\upsilon_{jt} + \ln L_{jt}) + a_m \ln M_{jt} \quad (3.13) \\ & + \frac{1}{2}a_{kk}(\omega_{jt} + \ln K_{jt})^2 + \frac{1}{2}a_{ll}(\upsilon_{jt} + \ln L_{jt})^2 + \frac{1}{2}a_{mm}(\ln M_{jt})^2 \\ & + a_{kl}(\omega_{jt} + \ln K_{jt})(\upsilon_{jt} + \ln L_{jt}) + a_{km}(\omega_{jt} + \ln K_{jt})\ln M_{jt} \\ & + a_{lm}(\upsilon_{jt} + \ln L_{jt})\ln M_{jt} + \varepsilon_{jt} \end{aligned}$$

where

$$\begin{bmatrix} \omega_{jt} \\ \upsilon_{jt} \end{bmatrix} = \begin{bmatrix} a_{kl} & a_{ll} \\ a_{km} & a_{lm} \end{bmatrix}^{-1} \cdot \begin{bmatrix} S^l_{jt}\exp(\varepsilon_{jt}) - (a_l + a_{ll}\ln L_{jt} + a_{kl}\ln K_{jt} + a_{lm}\ln M_{jt}) \\ S^m_{jt}\exp(\varepsilon_{jt}) - (a_m + a_{km}\ln K_{jt} + a_{lm}\ln L_{jt} + a_{mm}\ln M_{jt}) \end{bmatrix} \quad (3.14)$$

The non-structural error enters the estimation equation nonlinearly and is nonseparable from regressors. We can estimate equation (3.13) 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 (3.13) and (3.14). 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 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.

3.5 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 3.4 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 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 3.5. The mean output elasticity of labor and material are calculated from equation (3.10) 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 (3.10). The reported output elasticity and scale economies are specific to the production point observed in the data. Table 3.5 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.

3.5.1 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 C.

Table 3.6 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 3.2 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.[10]

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 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.

3.6 Tests of Biased Technology

We can recover the firm-time specific capital efficiency (ω_{jt}) and labor efficiency (υ_{jt}) from equation (3.14). 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.[11] 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.

3.6.1 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,

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

[10]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.

[11]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)

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} 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,

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

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.[12]

Table 3.8 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

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

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.

3.6.2 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 3.9. 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 TF-P) 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.

3.7 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 3.3 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 3.10. 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 3.3. The results are shown in table 3.11. 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.

3.8 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 3.12 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 3.2, 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 3.12. 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 3.13.

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.

3.9 Contribution of Biased Technology 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 E.

Table 3.14 and Table 3.15 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.

3.9.1 Continuing Firms

3.9.1.1 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 3.15 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 3.14, 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.

3.9.1.2 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 3.15, 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 3.12.

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.

3.9.2 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 3.16 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.

3.10 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.

Appendices

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 given point $(x,y) \in \left\{(x,y) : \left\|(x,y) - (x^{data}, y^{data})\right\| < \epsilon\right\}$,

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

This completes the proof of proposition 1. ■

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,

$\ln Q_{jt} = (a_k + a_{km}\ln M_{jt})(\omega_{jt}) + (a_l + a_{lm}\ln M_{jt})(\upsilon_{jt})$

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

where

$$\begin{aligned}\begin{bmatrix}\omega_{jt}\\ \upsilon_{jt}\end{bmatrix} &= \begin{bmatrix}a_{kl} & a_{ll}\\ a_{km} & a_{lm}\end{bmatrix}^{-1}\\ &\cdot\begin{bmatrix}S_{jt}^{l}\exp(\varepsilon_{jt})-\left(a_l+a_{ll}\ln L_{jt}+a_{kl}\ln K_{jt}+a_{lm}\ln M_{jt}\right)\\ S_{jt}^{m}\exp(\varepsilon_{jt})-\left(a_m+a_{km}\ln K_{jt}+a_{lm}\ln L_{jt}+a_{mm}\ln M_{jt}\right)\end{bmatrix}\end{aligned}\tag{15}$$

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

$$\begin{aligned}\frac{d\ln Q_{jt}}{d\varepsilon_{jt}}|_{\varepsilon_{jt}=0} &= 1+\left(a_k+a_{km}\ln M_{jt}\right)\left(D_{11}S_{jt}^{l}+D_{12}S_{jt}^{m}\right)\\ &+\left(a_l+a_{lm}\ln M_{jt}\right)\left(D_{21}S_{jt}^{l}+D_{22}S_{jt}^{m}\right)\\ &+\left[a_{kk}\left(\omega_{jt}|_{\varepsilon_{jt}=0}+\ln K_{jt}\right)+a_{kl}\left(\upsilon_{jt}|_{\varepsilon_{jt}=0}+\ln L_{jt}\right)\right]\left(D_{11}S_{jt}^{l}+D_{12}S_{jt}^{m}\right)\\ &+\left[a_{ll}\left(\upsilon_{jt}|_{\varepsilon_{jt}=0}+\ln L_{jt}\right)+a_{kl}\left(\omega_{jt}|_{\varepsilon_{jt}=0}+\ln K_{jt}\right)\right]\left(D_{21}S_{jt}^{l}+D_{22}S_{jt}^{m}\right)\end{aligned}\tag{16}$$

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

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

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 (16).

C Compute the Numerical Elasticity of Substitution

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

$$\begin{aligned}\ln Y_{jt} &= a_0 + a_k(\omega_{jt} + \ln K_{jt}) + a_l(\upsilon_{jt} + \ln L_{jt}) + a_m \ln M_{jt} \\ &+ \frac{1}{2}a_{kk}(\omega_{jt} + \ln K_{jt})^2 + \frac{1}{2}a_{ll}(\upsilon_{jt} + \ln L_{jt})^2 + \frac{1}{2}a_{mm}(\ln M_{jt})^2 \\ &+ a_{kl}(\omega_{jt} + \ln K_{jt})(\upsilon_{jt} + \ln L_{jt}) + a_{km}(\omega_{jt} + \ln K_{jt})\ln M_{jt} \\ &+ a_{lm}(\upsilon_{jt} + \ln L_{jt})\ln M_{jt}\end{aligned} \tag{17}$$

Marginal product of capital

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

Elasticity of substitution between labor and capital:

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

$$= \quad -\frac{(\frac{S^k_{jt}}{S^l_{jt}})\frac{L_{jt}}{K_{jt}}}{K/L}\left[\frac{d\left(\frac{S^k_{jt}}{S^l_{jt}}\frac{L_{jt}}{K_{jt}}\right)}{d\,(K/L)}\right]^{-1}$$

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.

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

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

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

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

D Test the Invertibility Condition

To derive the estimation equation (3.13), 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

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

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.

E Sources of Industrial Growth

The rate of output growth

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

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

where

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

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 $S_{jt}^k\frac{d\omega_{jt}}{dt}$ and $S_{jt}^l\frac{d\upsilon_{jt}}{dt}$, correspond to the contribution of productivity. It is a composite of two sources, the growth of capital efficiency ($S_{jt}^k\frac{d\omega_{jt}}{dt}$) and the growth of labor efficiency ($S_{jt}^l\frac{d\upsilon_{jt}}{dt}$). 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

$$\frac{\triangle Y_{jt}}{Y_{jt-1}} = S_{jt}^k\frac{\triangle K_{jt}}{K_{jt-1}}+S_{jt}^l\frac{\triangle L_{jt}}{L_{jt-1}}+S_{jt}^m\frac{\triangle M_{jt}}{M_{jt-1}}+S_{jt}^k\triangle\omega_{jt}+S_{jt}^l\triangle\upsilon_{jt}$$

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 3.1. 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 3.2. Industry Mean[1] of Capital-Labor Ratio and Input Price in China: 2000-2007

	2000	2001	2002	2003	2004	2005	2006	2007	growth
Clothing									
wage/int.[2]	206.22	191.37	222.81	228.84	213.69	229.24	260.35	253.56	22.96%
K/L	28.67	27.20	29.660	26.63	25.42	26.43	27.43	27.63	-3.64%
P.Board[3]									
wage/int.	169.18	171.73	203.46	200.47	190.07	201.40	210.49	217.00	28.26%
K/L	107.20	129.64	148.11	159.30	139.76	151.88	141.76	144.36	34.66%
Equipment									
wage/int.	243.47	257.56	351.92	395.58	360.56	407.14	416.80	367.46	50.93%
K/L	79.70	61.46	79.79	80.10	76.56	87.57	93.94	81.83	2.67%
M.Vehicle									
wage/int.	272.06	255.53	267.01	302.03	319.15	314.90	336.21	320.42	17.77%
K/L	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] "int." represents interest rate.
[3] "P.Board": paper and board making industry. "M.Vehicle": motor vehicle industry.

Table 3.3. 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 3.4. 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 3.5. 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 3.6. 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
PaperBoard	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
M.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 3.7. 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 3.8. 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 3.9. 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 3.10. 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 3.11. 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 3.12. 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	29.35	4.95	38.15	-4.38	49.44	-2.32	25.18	5.49
2002	30.76	0.70	26.64	-3.13	18.74	-0.18	37.76	-10.98
2003	29.98	8.25	22.83	1.14	34.28	-1.69	49.61	2.90
2004	19.51	11.21	24.37	1.21	57.21	-0.90	48.12	-13.65
2005	29.78	4.79	22.01	2.34	39.58	-2.49	1.37	5.04
2006	27.60	3.70	27.89	0.64	34.68	0.14	20.03	-2.40
Mean	23.85	4.80	23.13	-0.31	33.42	-1.06	25.62	-1.94

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

Table 3.13. R&D and the Evolution of Capital and Labor Efficiency

	Clothing		Paper&Board		Equipment		Motor Vehicle	
	Para	SE	Para	SE	Para	SE	Para	SE
<u>Capital E:</u>								
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)
<u>Labor E:</u>								
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)
<u>BTC:</u>								
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 3.14. 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 3.15. 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.

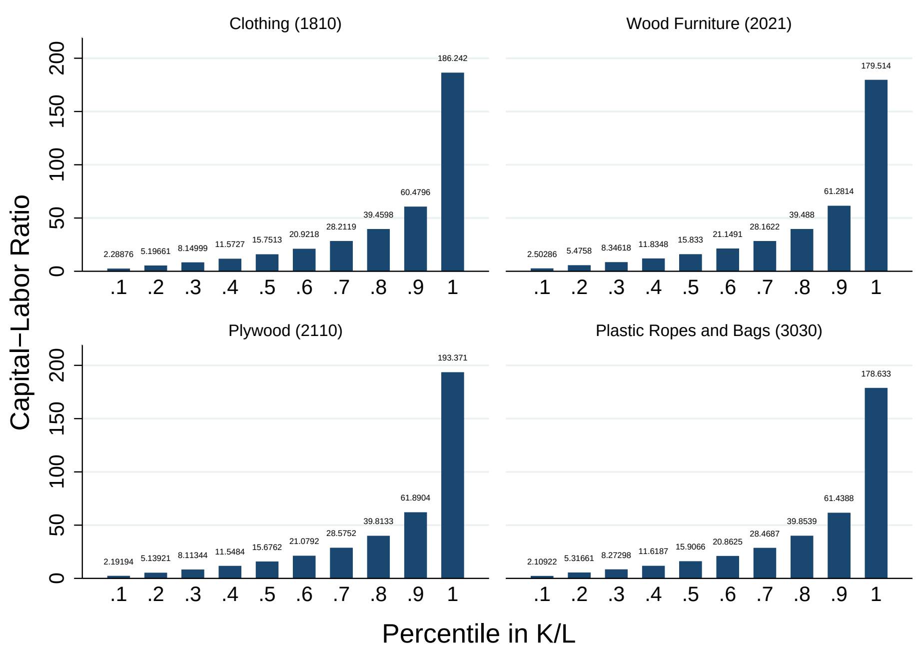
Table 3.16. Capital and Labor Efficiencies (KE and LE)for Entering, Exiting and Continuing Firms[1]

	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.

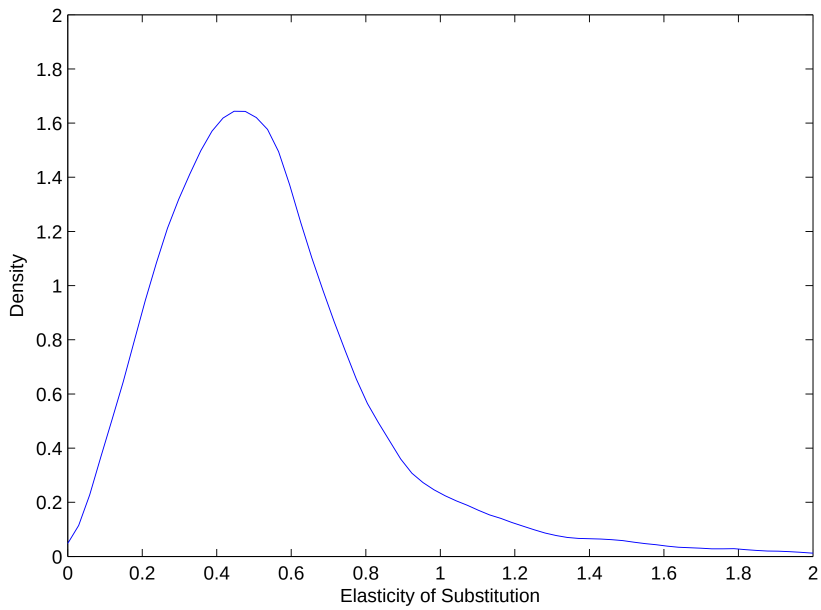
[2] Standard errors (SE) in parentheses.

Figure 3.1. Dispersion of Capital-Labor Ratio in 2007, by Industry)



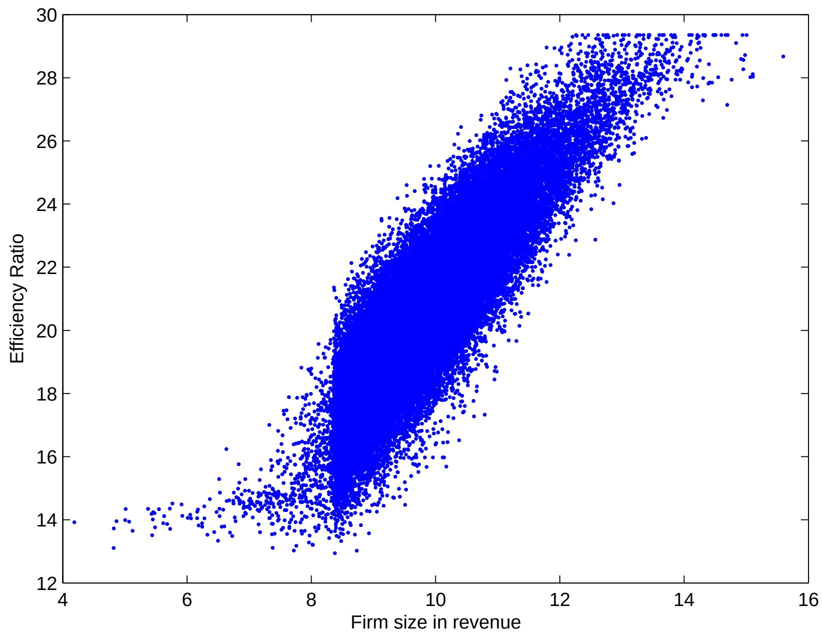
Notes: The figure shows the large dispersion of capital-labor ratio with each industry.

Figure 3.2. 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 3.3. 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.

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