Bureau d'économie théorique et appliquée (BETA)
UMR 7522

Documents de travail

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Auteurs

Xi Chen

Document de Travail n° 2012 - 20

Novembre 2012

Faculté des sciences économiques et de gestion
Pôle européen de gestion et d'économie (PEGE)
61 avenue de la Forêt Noire
F-67085 Strasbourg Cedex

Secétariat du BETA
Géraldine Manderscheidt
Tél. : (33) 03 68 85 20 69
Fax : (33) 03 68 85 20 70
g.manderscheidt@unistra.fr
www.beta-umr7522.fr

Estimation of the CES Production Function with Biased Technical Change: A Control Function Approach

Xi CHEN*

November 14, 2012

Abstract

In this paper, I extend the Olley-Pakes (1996) estimation method to the CES production function with biased technical change. The new semi-parametric approach allows consistent estimation of the degree of returns to scale, the elasticity of substitution, and the bias in technical change. Identification of these parameters is achieved under the assumption that the data generating process reflects not only technologies but also optimizing behavior of producers. Using data from U.S. manufacturing industries over the period 1958-2005, I find strong evidence that industries are characterized by a production technology with the elasticity of substitution below one and with significant biased technical progress.

JEL: C14, C23, O30, D24

Keywords: *Semi-parametric estimation, Panel data analysis, Returns to scale, Elasticity of substitution, Factor-augmenting technical change, Industry-level studies.*

*Xi Chen (xichen@unistra.fr), BETA, University of Strasbourg. Address: PEGE-BETA, 61 Av de la Forêt Noire, 67085 Strasbourg, France.

1 Introduction

The seminal paper of Olley and Pakes (1996) introduced a structural semi-parametric method, the so-called control function approach, to deal with the endogeneity problem encountered in estimating production functions. This class of estimation techniques has been applied in a large number of recent empirical studies.[1] Following Olley and Pakes (1996), recent developments have exclusively focused on the Cobb-Douglas specification, for example, Levinsohn and Petrin (2003), Ackerberg et al (2006), Wooldridge (2009), and De Loecker (2011).[2] The Cobb-Douglas specification, however, is an extreme restrictive assumption that ignores key features of the economy, in particular, the non-neutrality of productivity improvements (biased technical change).

In general, the neutrality restriction can be relaxed by considering a class of production functions where technical change is non-separable from the productive factor. In particular the non-linearity of CES specifications allows us to study biased technical change. But at the same time the non-linearity together with unobserved technical change increases the difficulties in estimating parameters. In this paper, I investigate how a CES production function with biased technical change and non-constant returns to scale can be consistently estimated.

Three approaches were used in the literature for estimating a CES production function. The most common estimation method uses the first order conditions of profit maximization. Based on first order conditions, Berndt (1976) provided estimates of the elasticity of substitution which are close to unity. Antràs (2004) showed that Berndt's results are biased toward the Cobb-Douglas specification, because his estimates suffer from spurious regression bias. The second approach uses the Kmenta (1964) approximation to transform the nonlinear CES function into a linear-in-parameter equation in order to facilitate estimation (for example, Thursby and Lovell, 1978). The third one consists of estimating jointly the first order conditions and production function in a system. The origin of this idea can be traced back to the paper of Nerlove (1967) and a recent application is Klump et al (2007). Chirinko (2008) provides a survey of the recent literature and shows that the elasticity of substitution lies in the range of 0.4 to 0.6. for U.S. economy. However, all these estimation methods have their limits and are not suitable for the purpose of this study. The first order conditions approach is based

[1]Empirical studies using the Olley-Pakes control function approach include, for example, Javorcik (2004), Konings and Vandenbussche (2008), and De Loecker (2011).

[2]The interested reader is referred to Ackerberg, Benkard, Berry, Pakes (2007) and Van Beveren (2010).

on optimizing behavior of producers only, while the Kmenta approximation is based on the production function that captures only technology. Based on different aspects of production analysis, the regression models produce divergent results and contribute to the lack of consensus on the value of the substitution elasticity. Compared to single equation approaches, the system estimation is able to provide more efficient estimates of technology parameters by using both aspects of information (production function and first order conditions), see Leon-Ledsma et al (2010). However, the estimation strategies used in this literature does not follow the recent developments of techniques that address the input simultaneity bias.

Firm's input decisions are typically related to productivity. Therefore, the Ordinary Least Squares (OLS) estimation suffers from the simultaneity bias. The traditional estimation methods that control the simultaneity bias, include the Instrumental Variables (IV), the fixed effect (Mundlak, 1961) and the dynamic panel (Arellano and Bond, 1991), however are not able to provide satisfactory results in the case of production function estimation, see Van Beveren (2010). Olley and Pakes (1996) have developed an alternative empirical strategy to overcome endogeneity problems. In this paper, I combine two strands of literature: the one that focus on estimating the CES production function by using traditional methods (for example, Berndt, 1976, Antràs, 2004, Klump et al, 2007 and Leon-Ledsma et al, 2010) and the one that deals with endogeneity problems by using the semi-parametric estimation method with a Cobb-Douglas specification (for example, Olley and Pakes, 1996, Levinsohn and Petrin, 2003 and De Loecker, 2011). I contribute to the literature by proposing an extension of the Olley-Pakes method for the CES production function with biased technical change, which allows consistent estimation of the degree of returns to scale, the elasticity of substitution, and the bias in technical change. Both information on technology (characterized by production function) and optimizing behavior of producers (characterized by first order conditions) are used to achieve identification.

This study differs from the existing literature in several ways. First, I generalize beyond the Cobb-Douglas specification to a more flexible CES production function with Hicks-neutral and factor-augmenting productivity shocks. I propose a semi-parametric estimation method that is able to deal with the endogeneity bias caused by the two unobserved productivity shocks. Second, since I have long time series for many sectors, I estimate the model for different periods and for different sectoral groups in order to understand the technology evolution and the intra-industrial distortion. Using data from U.S. manufacturing industries over the period 1958-2005, it transpires that within the class of CES production functions the unitary elasticity of substitution restriction is rejected. I provide estimates of sectors-level returns to scale and elasticity of substitution, which are 0.95 and 0.63, respectively. The estimation results show that the Cobb-Douglas-based estimator generally overestimates the degree of returns to scale. I also find that the degree of returns to scale is diminishing over time and differs across sectors. By using the estimated elasticity of substitution, I recover the growth rate of relative biased technical change.

The remainder of this paper is organized as follows: I first present the CES production function with biased technical change and some implications in Section 2. In Section 3, I discuss the control function approach, the identification conditions and the estimation procedures. Empirical results and robustness checks are given and analyzed in Section 4. Section 5 concludes.

2 The CES production function with biased technical change

Before going into the formal econometric analysis, I frame the problems and give the precise definition of notions discussed above. Firstly, I focus on the CES functional specification, then introduce the technical change terms.

2.1 The CES specification

Consider a production function $F(.)$ of two factors, labor (L) and capital stock (K) with the value-added output, Y. The elasticity of substitution σ between capital and labor is defined by the percentage change in factor proportions due to a change in the relative marginal products, see Hicks (1932):

$$\sigma \equiv -\frac{\mathrm{dlog}(K/L)}{\mathrm{dlog}(F_K/F_L)} \geq 0, \tag{1}$$

where F_K and F_L denote $\partial F/\partial K$ and $\partial F/\partial L$, respectively. Given this definition, Arrow et al (1961) derived an aggregate production technology with Constant Elasticity of Substitution (CES):

$$Y = F(K, L) = C[\alpha K^{\frac{\sigma-1}{\sigma}} + (1-\alpha)L^{\frac{\sigma-1}{\sigma}}]^{\frac{\rho\sigma}{\sigma-1}}, \tag{2}$$

where C is the constant term. Factors are gross complements in production when $\sigma < 1$ and substitutes when $\sigma > 1$. The CES production becomes Cobb-Douglas when $\sigma = 1$. This function is homogeneous of degree ρ in K and L. For any given value of σ, the functional distribution of income is determined by $\alpha \in (0, 1)$. This distribution parameter also depends on the units in which capital and labor are measured and on an arbitrary normalization point. Klump et al (2011) emphasized the importance of normalizing the CES function, when it comes to identifying the two terms, C and α. Without normalization, the two parameters (C and α) could be any arbitrary point. Here, I focus only on identifying the parameters σ and ρ.

Given the two factors CES production function above, the parameter ρ only represents the degree of returns to scale in capital and labor, i.e.,

$$\rho \equiv \frac{\partial \text{log} Y}{\partial \text{log} L} + \frac{\partial \text{log} Y}{\partial \text{log} K}. \tag{3}$$

When capital and labor are increased, if output increases in the same proportion, i.e., $\rho = 1$, then the technology exhibits constant returns to scale. If output increases less than proportionately, i.e., $\rho < 1$, the technology exhibits decreasing returns to scale. If output increases more than proportionately, i.e., $\rho > 1$, the technology exhibits increasing returns to scale. We also need to be aware of the degree of aggregation under study. Basu and Fernald (1997) and Basu (2008) showed that the estimate of returns to scale varies with the aggregation level, in particular it seems to be smaller in disaggregated data. The estimation results presented in Section 4 are obtained from U.S. manufacturing data at the six-digit NAICS level.

2.2 Factors-augmenting technical change

Technical change can enter the production function in different ways. The most common choice is the Hicks-neutral technology, i.e., $A_h F(K, L)$, as in the case of Cobb-Douglas production function. Hicks-neutrality implies that technical change does not affect the balance between labor and capital demand. Other economic neutrality conditions are Harrod- and Solow-neutrality assumptions. If technical change is Harrod-neutral, the production function becomes $F(K, B_l L)$, where B_l is the labor-augmenting productivity, an increase in productivity is equivalent to having more labor. If technical change is Solow-neutral, i.e., $F(B_k K, L)$, where B_k is the capital-augmenting productivity, an increase in productivity is equivalent to saving capital. In this paper, I relax these neutrality assumptions by considering the following CES production function:

$$Y = A_h F(B_h K, B_l L) = A_h[\alpha(B_k K)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(B_l L)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma\rho}{\sigma-1}}. \tag{4}$$

We can also rewrite this production function as:

$$Y = A[\alpha(BK)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)L^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma\rho}{\sigma-1}}, \tag{5}$$

where $A \equiv A_h/B_l^{\rho}$ is the relative Hicks-neutral productivity, and $B \equiv B_k/B_l$ is the relative capital-augmenting productivity.

Given a basic assumption that firms minimize costs, firms set marginal products equal to input prices. The first order conditions of the CES production function under cost minimization problem imply that:

$$\frac{K}{L} = \left(\frac{\alpha}{1-\alpha}\right)^{\sigma} \left(\frac{w}{r}\right)^{\sigma} B^{\sigma-1}, \tag{6}$$

where w and r denote the wage and the rental capital price, respectively. This equation illustrates that the capital-labor ratio depends on the biased technical change but not on the neutral technical change. If factors are complements in production ($\sigma < 1$), firms reduce their capital-labor ratio when they face an increase in relative capital-augmenting productivity. If factors are substitutes ($\sigma > 1$), firms raise their capital-labor ratio. When $\sigma = 1$ (Cobb-Douglas specification), the effect of biased technical change vanishes and the factors ratio becomes proportional to w/r.

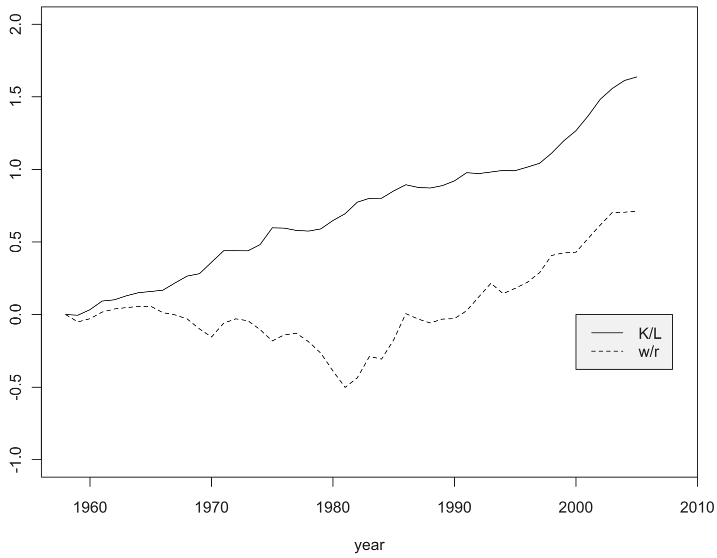

Figure 1 - Average capital-labor ratio and factor price ratio for U.S. manufacturing industries in the period 1958-2005.

Given any value of the elasticity of substitution, the growth of the capital-labor ratio can be decomposed into two parts, the relative price effects and the biased technical change effects. Figure 1 shows the evolution of average capital-labor ratio for U.S. manufacturing industries in the period 1958-2005.[3] By examining this figure, we can expect that σ was significantly different from one in the period of the late 60s and early 80s. The next section presents the strategy for estimating the parameters of interest, ρ, σ and the growth rate of technical change by using the control function approach.

3 Identification and estimation via control functions

The assumption that data reflect technology and optimizing behavior of producers implies that the DGP can be represented by a set of equations, which includes the production function (technology) and the optimal input demand functions (optimization behavior). Both aspects of information are used for identification, in particular the two equations of our regression model are Equations (5) and (6).

$$\log Y_{it} = \rho \log L_{it} + \frac{\rho\sigma}{\sigma - 1} \log \left[\alpha (B_{it} \frac{K_{it}}{L_{it}})^{\frac{\sigma-1}{\sigma}} + (1-\alpha) \right] + \log A_{it} + \varepsilon_{it}, \tag{7}$$

[3]This series is obtained by averaging the 462 U.S. manufacturing industries.

Equation (7) is the logarithmic transformation of (5) with an error term appended; $i = 1, ..., N$ indexes sectors and $t = 1, ..., T$ indexes time. The parameters ρ and σ are our central parameters of interest. The scalar disturbance term ε_{it} is an *ex post* shock, which captures the exogenous shocks that are not anticipated by firms. Hence ε_{it} does not affect the optimal choice of labor demand and capital-labor ratio. The endogenous variables L_{it} (optimal labor demand) and $\frac{K_{it}}{L_{it}}$ (optimal capital-labor ratio) are partially determined by unobserved productivity shocks A_{it} and B_{it}. Similar models have been studied by Chesher (2003), Imbens (2007), Imbens and Newey (2009) in the nonparametric framework. Imbens and Newey (2009) provide various partial identification results for the structural equation via the control function approach (e.g. average derivatives, bounds for quantile and average structural function). However, these results are not sufficient for recovering the two technology parameters ρ and σ. The principal reason for the lack of point identification is that the unobserved variable B_{it} is not additively separable from the regressors in the production function. Therefore, in the following lines, I will linearize Equation (7) in order to obtain a more tangible form for the empirical investigation.

Firstly, I eliminate the constant term and the potential individual effect by first-differencing model (7):

$$\triangle \log Y_{it} = \rho \triangle \log L_{it} + \frac{\rho\sigma}{\sigma - 1} \log \left[\frac{\alpha(B_{it}\frac{K_{it}}{L_{it}})^{\frac{\sigma-1}{\sigma}} + (1-\alpha)}{\alpha(B_{it-1}\frac{K_{it-1}}{L_{it-1}})^{\frac{\sigma-1}{\sigma}} + (1-\alpha)} \right] + \triangle \log A_{it} + \triangle \varepsilon_{it}. \quad (8)$$

Consider the optimal capital-labor ratio equation:

$$\frac{K_{it}}{L_{it}} = \left(\frac{\alpha}{1-\alpha} \right)^{\sigma} \left(\frac{w_{it}}{r_{it}} \right)^{\sigma} B_{it}^{\sigma-1}, \quad (9)$$

where the input price ratio $\frac{w_{it}}{r_{it}}$ is observed and exogenous w.r.t. A_{it} and B_{it} (firms are assumed to be price-takers). We can use (9) to substitute the unobservable productivity shock B_{it} from Equation (8). Some algebraic manipulation yields:

$$\log(1-\alpha) + \log S_{it} = \log \underbrace{\left[\alpha(B_{it}\frac{K_{it}}{L_{it}})^{\frac{\sigma-1}{\sigma}} + (1-\alpha) \right]}_{S_{it}^*}, \quad (10)$$

where the observed variable S_{it} is defined as $\frac{r_{it}K_{it}}{w_{it}L_{it}} + 1$ and S_{it}^* denotes a latent variable. According to (10), one can replace the latent variable with the observed one, but as in practice the substitution of the latent variable is usually not perfect, I introduce a scalar measurement error term. This leads to a fully additive regression model:

$$\triangle \log Y_{it} = \rho \triangle \log L_{it} + \gamma \triangle \log S^{*}_{it} + \triangle a_{it} + \triangle \varepsilon_{it}; \tag{11}$$

$$\triangle \log S_{it} = \triangle \log S^{*}_{it} + \eta_{it}, \tag{12}$$

where $a_{it} \equiv \log A_{it}$, $\gamma \equiv \frac{\rho\sigma}{\sigma-1}$ and η_{it} is a classical (zero-mean and uncorrelated with $\triangle \log S^{*}_{it}$) measurement error term.

The model (11)-(12) can be viewed as an EIV (Error-in-Variable) model in which we are still facing two endogeneity problems. The first endogeneity problem is due to the Hick-neutral productivity shock that affects the optimal labor demand decision of firms, then the regressor $\triangle \log L_{it}$ is correlated with the unobserved term $\triangle a_{it}$. The second endogeneity problem is that the regressor $\triangle \log S_{it}$ is correlated with the measurement error η_{it}. There are different ways of estimating the parameters in linear regression models with endogenous regressors. 2SLS is one of the most common estimators in linear IV regressions. An asymptotically-equivalent alternative is the control function approach. In this paper, I use the latter approach because of the lack of valid instruments for controlling productivity shocks. The following sections discuss the control function approach, the identification conditions and the estimation procedures. I also compare the estimations based on different production function specifications (CES versus Cobb-Douglas).

3.1 The control function approach

The control function approach was first developed and applied to correct the selection bias of binary response models in Heckman and Robb (1985). This method has been extended for identification of a wide class of models where the explanatory observed variables and the explanatory unobserved variables are not independently distributed. For instance, it is used for triangular simultaneous equations models in Imbens and Newey (2009), for treatment effect models in Heckman and Vytlacil (2007) and for measurement error models in Hahn, Hu and Ridder (2008). The use of the control function approach for estimating a production function was introduced by Olley and Pakes (1996). The control function approach is a closely related alternative to the classical IV method. In 2SLS estimation, the exogenous variations of instruments are used directly for constructing moment conditions, while the idea of the control function approach is to use control variables (either observed or estimated) that purge the dependence between the observed and unobserved explanatory variables.

Formally, consider a general regression model, $y = f(x, u)$, where the regressor x is correlated with the error term u. Given the assumption that x and u are independent conditionally on a control variable v, Imbens and Newey (2009) give a set of the identification results for this nonlinear models with non-separable disturbances. The identification power of the control variable (v) can be illustrated by the following equation (Imbens and Newey, 2009, p1488). For any integrable function $\Lambda(y)$,

$$\begin{aligned} \mathrm{E}[\Lambda(y) \mid x, v] &= \int \Lambda(f(x,u))F_{u|x,v}du \\ &= \int \Lambda(f(x,u))F_{u|v}du = \mathrm{E}[\Lambda(y) \mid v], \end{aligned}$$

where $F_{u|.}$ is the conditional cumulative distribution function (CDF) of u. The identification comes from the fact that the unobserved variable u of the structural equation can be integrated out by conditioning on v. Since in this paper, we are dealing only with the linear regression model, a weaker assumption is sufficient: x and u are mean-independent conditionally on v, instead of the stochastic independence. For the rest of this paper, a valid control variable is defined as follows:

Definition

A valid control variable is any observable or estimable variable v such that x and u are mean-independent conditionally on v, i.e.,

$$\mathrm{E}[u \mid x, v] = \mathrm{E}[u \mid v], \tag{13}$$

where x and u are not independently distributed.

Now, as a concrete example consider a simple linear regression model:

$$y = \beta x + u, \tag{14}$$

with the reduced form equation of x:

$$x = g(z, v). \tag{15}$$

where the variable z is assumed to be a valid instrument that is highly correlated with x

and uncorrelated with u and v. The endogeneity of x arises if and only if u is correlated with v. I assume that v is observable or estimable and can be used as a proxy for u:

$$u = m(v) + e, \tag{16}$$

where $E[ve] = 0$. Plugging (16) into the linear regression model (14) gives:

$$y = \beta x + m(v) + e, \tag{17}$$

where the function of v is viewed as an additional regressor. It can be shown that v is a valid control variable, which satisfies (13), i.e., $\mathrm{E}[u \mid x, v] = \mathrm{E}[u \mid g(z, v), v] = \mathrm{E}[u \mid z, v] = \mathrm{E}[u \mid v]$. The identification of β is achieved in the model (17) if and only if x is not an deterministic function of v. Otherwise, there is a collinearity problem, i.e., $y = \beta g(v) + m(v) + e$. Thus, in this setup the identification requires the presence of at least one exogenous variable z in (15), which satisfies $\mathrm{E}[u \mid z, v] = \mathrm{E}[u \mid v]$. This is similar to the rank condition in the 2SLS estimation. Since x and v are uncorrelated with the error term e, the parameter β and the function $m(.)$ can be consistently estimated by Robinson's (1988) estimator. Compared to the 2SLS estimator, the main advantage of using the control function approach in linear regression models is that this estimation method can be implemented whether the instrument z is observed or unobserved.

When instrument z is not available in the data but several candidates of the control variable are observed (typical choices of the control variable for controlling productivity shocks, are the investment, Olley and Pakes, 1996 and the material demand, Levinsohn and Petrin, 2003), then the model (17) can be directly estimated. While when z is observed but v is unobserved, the control variable is estimated by using x and z in the first stage of the estimation. For instance, the estimated conditional CDF of x given z has been proved to be a valid control variable, see Imbens and Newey (2009).

3.2 Identification conditions

We return to our model of interest, the CES-based model (11)-(12). The two potential sources of bias are the endogeneity caused by the unobserved productivity shock, a_{it}, and by the measurement error, η_{it}. For controlling the first endogeneity problem (caused by the productivity shock), it seems hard to find a valid instrument but control variables are available. For controlling the second endogeneity problem (caused by the measurement error), valid instruments are available. Thus, the treatments of the two endogeneity problems are different. Now, I provide conditions that guarantee identification of our model.

Assumption 1 *For any observation (indexed by i and t), there is a variable V_{1it} such that the labor demand L_{it} can be written as:*

$$L_{it} = L(Z_{1it}, V_{1it}), \tag{18}$$

where a_{it} is mean-independent of Z_{1it} given V_{1it}.

Under Assumption 1 the dependence between regressors and the unobserved productivity shock a_{it} can be purged by conditioning on variable V_{1it}. The identification of the model (via control variable V_{1it}) is achieved as long as there is some exogenous variation in either L_{it} or V_{1it}. To see this point, note that:

$$\mathrm{E}[a_{it} \mid L_{it}, V_{1it}] = \mathrm{E}[a_{it} \mid L(Z_{it}, V_{1it}), V_{1it}] = \mathrm{E}[a_{it} \mid Z_{1it}, V_{1it}] = \mathrm{E}[a_{it} \mid V_{1it}], \tag{19}$$

where the last equality follows from the mean-independence condition. The choice of control variables depends essentially on whether it satisfies Assumption 1. Given an observed control variable V_{1it}, one can replace a_{it} with a nonparametric function of V_{1it}. In a similar way, the second endogeneity problem (caused by the measurement error, η_{it}) can be solved by using the next assumption:

Assumption 2 *For any observation, at least one valid instrument is available such that:*

$$\triangle \log S_{it} = h(Z_{2it}) + V_{2it}, \tag{20}$$

where η_{it} is mean-independent of Z_{2it} given V_{2it}.

The additivity restriction is imposed in (20) for simplifying the estimation procedure. Given the data at hand, V_{2it} is not observed. However, we can assume that the growth rate of $\frac{w_{it}}{r_{it}}$ or the lagged values of S_{it} are valid instruments (Z_{2it}) and estimate V_{2it} in the first-stage. The traditional approach in the linear EIV case is to estimate the model by using the 2SLS estimator. But the estimation procedure based on the control function approach is more convenient here. Under Assumption 2, the residuals V_{2it} is a valid control variable:

$$\mathrm{E}[\eta_{it} \mid \triangle\log S_{it}, V_{2it}] = \mathrm{E}[\eta_{it} \mid h(Z_{2it}) + V_{2it}, V_{2it}] = \mathrm{E}[\eta_{it} \mid Z_{2it}, V_{2it}] = \mathrm{E}[\eta_{it} \mid V_{2it}], \quad (21)$$

and by construction V_{2it} is a proxy for η_{it}, then the model (11)-(12) can be identified by inverting out η_{it}.

3.3 Estimation procedures

Now I describe the estimation procedure for the CES based model (11)-(12), which follows closely the previous identification discussion. I also review briefly the estimation strategy proposed by Olley and Pakes (1996) for the Cobb-Douglas model, which is included in our empirical studies for comparison.

The Cobb-Douglas based model (Olley and Pakes, 1996) The regression model based on the Cobb-Douglas production function is:

$$\triangle\log Y_{it} = \beta_l \triangle\log L_{it} + \beta_k \triangle\log K_{it} + \triangle a_{it} + \triangle\varepsilon_{it}. \quad (22)$$

Olley and Pakes (1996) assume that the investment function $I_t(.)$ is strictly monotonic in a_{it}, i.e.,

$$I_{it} = I_t(K_{it}, a_{it}). \quad (23)$$

Then (23) can be inverted to $a_{it} = I_t^{-1}(K_{it}, I_{it})$, where the variables K_{it} and I_{it} are used as control variables. Substituting this inverse function into the model (22), we have:

$$\triangle\log Y_{it} = \beta_l \triangle\log L_{it} + \Phi(K_{it}, I_{it}, K_{it-1}, I_{it-1}) + \triangle\varepsilon_{it}, \quad (24)$$

where $\Phi(K_{it}, I_{it}, K_{it-1}, I_{it-1}) = \beta_k \triangle\log K_{it} + I_t^{-1}(K_{it}, I_{it}) - I_{t-1}^{-1}(K_{it-1}, I_{it-1})$. Thus, we can estimate the parameter β_l and the nonparametric functions by applying Robinson's (1988) estimator on (24). Olley and Pakes (1996) assume that productivity a_{it} evolves exogenously as a first-order Markov process:

$$\begin{aligned} a_{it} &= E[a_{it} \mid information_{t-1}] + \xi_{it} \\ &= E[a_{it} \mid a_{it-1}] + \xi_{it}, \end{aligned}$$

where a firm's expectations about future productivity depend only on a_{it-1}, and ξ_{it} is the unexpected innovation in a_{it} that is orthogonal to the information set at $t-1$, i.e., $E[\xi_{it} \mid information_{t-1}] = 0$. Assuming a linear model $a_{it} = \tau + \rho a_{it-1} + \xi_{it}$, the implied innovation term is $\xi_{it} = a_{it} - \tau - \rho a_{it-1}$. Given the estimated coefficient $\hat{\beta}_l$ of the first-stage estimation, we can rewrite the unexpected innovation as a parametric function of observations:

$$\xi_{it}(\beta_k, \tau, \rho) = \log Y_{it} - \hat{\beta}_l \log L_{it} - \beta_k \log K_{it} - \tau - \rho(\log Y_{i-1} - \hat{\beta}_l \log L_{it-1} - \beta_k \log K_{it-1}).$$

Typically, the production timing assumption suggests that the period s capital demand (K_{is}) and the period $s-1$ labor demand (L_{is-1}), for $s \leq t$, are decided upon at $t-1$ or before, and are included in the information set at $t-1$. This assumption implies that both K_{is} and L_{is-1} must be uncorrelated with the unexpected innovation (ξ_{it}). In particular, I estimate the parameter β_k, τ and ρ by using GMM with the following instruments: the capital accumulation at t ($\triangle \log K_{it}$) and the lagged value of labor demand ($\log L_{it-1}$).[4] Given the estimates of β_l and β_k, the degree of returns to scale is computed as the sum of the two estimated parameters, $\hat{\rho}_{CD} = \hat{\beta}_l + \hat{\beta}_k$ under the Cobb-Douglas specification. The estimator $\hat{\rho}_{CD}$ is a sequential two-step estimator whose standard error is computed using the bootstrap.

The CES based model The treatment of the unobserved productivity a_{it} remains the same as in the Olley-Pakes estimation method, but the additional difficulty here is that the regressor $\triangle \log S_{it}$ is correlated with the measurement error η_{it}. Consider the model (11)-(12) where the term $\triangle a_{it}$ is substituted as before:

$$\triangle \log Y_{it} = \rho \triangle \log L_{it} + \gamma \triangle \log S_{it} - \gamma \eta_{it} + \varphi(K_{it}, I_{it}, K_{it-1}, I_{it-1}) + \triangle \varepsilon_{it}, \tag{25}$$

with $\varphi(K_{it}, I_{it}, K_{it-1}, I_{it-1}) = I_t^{-1}(K_{it}, I_{it}) - I_{t-1}^{-1}(K_{it-1}, I_{it-1})$. If the control variable is directly observed, the measurement error term η_{it} can be proxied by a nonparametric function, i.e., $E[\gamma \eta_{it} \mid V_{2it}] = \Gamma(V_{2it})$. However, the control variable V_{2it} is unobserved, then it has to be estimated first. Assume that the growth rate of input price ratio, i.e., $Z_{2it} = \frac{w_{it}}{r_{it}}$ is a valid instrument that satisfies Assumption 2. The preliminary estimated values of the control variable V_{2it} are obtained based on the kernel estimation:

[4] The starting values of GMM estimation is: $c = 0$, $\rho = 1$ and $\hat{\beta}_k^{ols}$ obtained by regressing $\triangle \hat{a}_{it} \equiv \triangle \log Y_{it} - \hat{\beta}_l \triangle \log L_{it} - \beta_k \triangle \log K_{it}$ on $\triangle \log K_{it}$.

$\hat{V}_{2it} = \triangle \log S_{it} - \hat{h}(Z_{2it})$. Since we cannot insert an estimated variable into a nonlinear function, we need to restrict the nonparametric function $\Gamma(.)$ to a linear parametric one, i.e., $E[\gamma\eta_{it} \mid V_{2it}] = -\theta V_{2it}$.

$$\triangle \log Y_{it} = \rho \triangle \log L_{it} + \gamma \triangle \log S_{it} + \theta \hat{V}_{2it} + \varphi(K_{it}, I_{it}, K_{it-1}, I_{it-1}) + \triangle \varepsilon_{it}. \tag{26}$$

Therefore, the parameter ρ, γ and θ can be consistently estimated by using the Robinson (1988) estimator. Since the first-stage estimation is nonparametric, the asymptotic variance matrix of the estimator depends on preliminary estimates and it is difficult to compute using general results for semi-parametric regression models. Thus, the corresponding standard errors are obtained using the bootstrap. Henceforth, the estimated elasticity of substitution is recovered as: $\hat{\sigma} = \frac{\hat{\gamma}}{\hat{\gamma}-\hat{\rho}}$.

3.4 Bias of the Cobb-Douglas specification

Now the question is, what differences should we expect in term of estimation outcomes between the Cobb-Douglas-based regression model and the CES-based regression model. Firstly, the Cobb-Douglas model sets the elasticity of substitution, σ, to one. Thus, if the economy was not characterized by the Cobb-Douglas technology, then we should find estimates of σ that significantly differ from one. Secondly, both models produce estimates of returns to scale, ρ. I will show in the following lines that the Cobb-Douglas specification may overestimates the returns to scale.

For the sake of clarity and convenience, I focus only on the bias of misspecification. Thus, the technical change terms, A_{it} and B_{it} are disregarded in this subsection. Consider the Kmenta approximation of (2):

$$\log Y_{it} = C + \rho\alpha \log K_{it} + \rho(1-\alpha)\log L_{it} + \frac{1}{2}\rho\frac{\sigma-1}{\sigma}\alpha(1-\alpha)(\log K_{it} - \log L_{it})^2, \tag{27}$$

where C is the constant term. The last term of the right hand side is ignored when one considers the Cobb-Douglas production function. The first-difference transformation yields:

$$\triangle \log Y_{it} = \rho\alpha \triangle \log K_{it} + \rho(1-\alpha)\triangle \log L_{it} \tag{28}$$

$$+\tfrac{1}{2}\rho\tfrac{\sigma-1}{\sigma}\alpha(1-\alpha)[(\log K_{it} - \log L_{it})^2 - (\log K_{it-1} - \log L_{it-1})^2].$$

If $\hat{\beta}_k$ and $\hat{\beta}_l$ are the estimated coefficients of $\triangle \log K$ and $\triangle \log L$ based on the Cobb-

Douglas specification. According to the well known results of Theil (1957), the expectations of these estimators are:

$$E(\hat{\beta}_k) = \rho\alpha + \frac{1}{2}\rho\frac{\sigma - 1}{\sigma}\alpha(1-\alpha)\hat{\pi}_k; \tag{29}$$

$$E(\hat{\beta}_l) = \rho(1-\alpha) + \frac{1}{2}\rho\frac{\sigma - 1}{\sigma}\alpha(1-\alpha)\hat{\pi}_l, \tag{30}$$

where $\hat{\pi}_k$ and $\hat{\pi}_l$ are the two estimates obtained from the regression of the omitted variable, $(\log K_{it} - \log L_{it})^2 - (\log K_{it-1} - \log L_{it-1})^2$, on the included variables, $\triangle \log K_{it}$ and $\triangle \log L_{it}$. Thus, the bias of the estimated returns to scale by using the Cobb-Douglas specification is:

$$E(\hat{\beta}_k + \hat{\beta}_l) - \rho = \frac{1}{2}\rho\frac{\sigma - 1}{\sigma}\alpha(1-\alpha)(\hat{\pi}_k + \hat{\pi}_l). \tag{31}$$

Given the parameter ρ is positive and $\alpha \in [0,1]$, the bias of estimated returns to scale based on the Cobb-Douglas specification are summarized in the following table.

Table 1 - The bias of estimated returns to scale based on the Cobb-Douglas specification

	$\hat{\pi}_k + \hat{\pi}_l < 0$	$\hat{\pi}_k + \hat{\pi}_l = 0$	$\hat{\pi}_k + \hat{\pi}_l > 0$
$\sigma < 1$	overestimation	unbiased	underestimation
$\sigma = 1$	unbiased	unbiased	unbiased
$\sigma > 1$	underestimation	unbiased	overestimation
$\sigma < 0$	underestimation	unbiased	overestimation

The case of negative elasticity $\sigma < 0$ is not allowed by economic theory, but due to estimation errors this case is empirically possible. Since the empirical results in this paper suggest that $\sigma < 1$ (see Section 4) and $\hat{\pi}_k + \hat{\pi}_l$ is generally negative, we can expect that the regression based on the Cobb-Douglas specification overestimates the degree of returns to scale. The estimation results in the next section will confirm this conclusion.

4 Empirical Investigation

The empirical investigation focuses on U.S. manufacturing industries at six-digit NAICS aggregation level. The information needed for conducting the econometric analysis comes from the NBER Manufacturing Industry database, which contains annual information on output, employment, payroll, investment, capital stock and other inputs cost together with prices deflators of 462 industries from 1958 to 2005. The construction of this database has been discussed in the technical report of Bartelsman and Gray (1996). The detailed description of this data set is reported in Appendix. Compared to firm-level data sets, the NBER data set offers some advantages. Firstly, it contains the price indexes that are the essential information for characterizing the optimizing behavior. Secondly, it allows us to avoid the multiple products problem of the firm-level data. Finally, at the six-digit NAICS aggregation level we still have a large number of sectors, which guarantees a good asymptotic approximation for cross-sectional regressions.

4.1 Estimation results

I start by reporting the estimates of returns to scale and elasticity of substitution for different windows of observation and for different sector groups. Then, given the estimates of technology parameters, I recover the Hicks-neutral and the factor-augmenting productivity and compute their annual growth rates.

Table 2 - Estimates of the full panel (1958-2005)

	Cobb-Douglas	CES
Labor (β_l)	0.907 (0.008)	-
Capital (β_k)	0.306 (0.016)	-
Returns to Scale (ρ)	1.213 (0.019)	0.954 (0.025)
Elasticity of Substitution (σ)	1	0.629 (0.009)
$\pi_k + \pi_l$	-0.524 (0.033)	

Table 2 summarizes the estimation results over the full panel as well as the estimated standard errors (obtained by using the bootstrap with 1000 replications). The second column reports the estimates of parameters β_l and β_k based on the Cobb-Douglas specification (following Olley and Pakes, 1996). The third column gives the estimation results for the CES model. The degree of returns to scale defined in (3) is computed as the sum of β_l and β_k in the Cobb-Douglas model, which is 1.213 with a 95% confidence interval [1.176, 1.250]. This result indicates that the industries were characterized by increasing returns to scale technology. The estimated degree of returns to scale obtained from the CES based model is 0.954 with a 95% confidence interval [0.906, 1.003], which suggests that the technology exhibits non-increasing returns to scale. The estimated elasticity of substitution is 0.629 with a 95% confidence interval [0.611, 0.647] that is far from covering one. In Section 3.4, I showed that the Cobb-Douglas based estimation of returns to scale suffers from an omitted variables bias when the elasticity of substitution differs from unity, see Table 1. The estimate of $\pi_k + \pi_l$ in Equation (31) is negative and significantly different from zero, which indicates that the Cobb-Douglas based regression overestimates the degree of returns to scale.

When T is large in the panel, one potential concern is the non-stationarity of the data. The first-difference transformation could stationarize series in the linear function, but not for nonlinear parts of the model. Therefore, given the non-stationarity the question we need to ask is whether the estimation results obtained by using the long panels are misleading? To answer this, I consider shorter panels, where $T = 3$ and compare the estimation results with previous findings. In this case, the estimation relies mainly upon the cross-sectional variation, thus the results are less affected by the problem of non-stationarity. The estimation results are reported in Table 3. The evolution of estimated returns to scale and elasticity of substitution with the 95% confidence intervals are depicted in Figures 2 and 3, respectively.

On the average, I find the similar estimation results as for the full panel case. The average estimates obtained from the CES based model suggest that the industries were characterized by a non-increasing returns to scale technology with the non-unitary elasticity of substitution, while the Cobb-Douglas based model predicts increasing returns to scale. The average estimated returns to scale obtained from the Cobb-Douglas specification and the CES specification are 1.164 and 0.819, respectively. The average estimated elasticity of substitution is 0.675.

Comparing the estimates of returns to scale obtained from the two models, we see that the Cobb-Douglas based regressions overestimate the degree of returns to scale in the majority of cases (14 out of 16 panels). Figures 2 and 3 show that the estimates of returns to scale are diminishing over time in both models, while the estimates of the elasticity of substitution are relatively stable. By regressing the estimates of returns to scale on a linear trend, I find that the decreasing rates are 3.4% (based on the CES specification) and 3.9% (based on the Cobb-Douglas specification) for each period of three years. This result may reflect the fact that the growth of U.S manufacturing industries was more and more driven by the technical change rather than the economies of scale.

From Figure 3, we can see that the confidence intervals of the estimated elasticity of substitution lay entirely below one for 8 out of 16 panels. In 3 out of 16 panels, the confidence intervals cover one, where we cannot conclude on the substitutability of production factors. The estimated elasticity of substitution should not be heeded in 5 cases, because their standard errors are very large. For the cases in which the estimated elasticity of substitution are significantly below unity, the estimates of $\pi_l + \pi_k$ predict correctly the bias of estimated returns to scale based on the Cobb-Douglas specification. For example, in the panel "64-65-66", the estimated $\pi_l + \pi_k$ is significantly negative and the Cobb-Douglas based regression overestimates the degree of returns to scale; in the panel "88-89-90", the estimated $\pi_l + \pi_k$ is not significantly different from zero and the two estimates of returns to scale are close.

The size of elasticity of substitution has important economic implications, for example σ is critical for determining the pattern of capital accumulation or the path of growth. Previous estimation procedures only produce the economy's aggregated estimates. The elasticity of substitution, however, may differ across sectors. Now I stratify the panel according to the sectoral classification (the 3-digit NAICS) and perform the regressions for each sub-group of manufacturing industry. The estimation results are reported in Table 4. Figures 4 and 5 depict the corresponding estimates with 95% confidence intervals for different sectors.

There are significant differences among the estimates of technology parameters across the sectors. The estimates of returns to scale lay in the range of 0.566 to 1.173 with the CES model, and the estimates of the elasticity of substitution lay in the range of 0.479 to 0.865. As for previous findings, the Cobb-Douglas based regressions overestimate the degree of returns to scale in the majority of sectors, expect for Sector 316 (Leather & allied prod) where the estimated returns to scale by considering the CES specification is higher. All estimates of the elasticity of substitution are significantly below one, which rejects once again the Cobb-Douglas specification. In 15 out of 20 cases, the estimates of $\pi_l + \pi_k$ are negative and significantly different from zero, which explain the overestimation of returns to scale by the Cobb-Douglas based regression. In other cases, the estimates of $\pi_l + \pi_k$ have relatively large estimated standard errors that we cannot conclude on the direction of the bias for the Cobb-Douglas based regression.

Table 3 - Estimates with the short panel of 3 periods

	Cobb-Douglas			CES		
Panels	β_l	β_k	$\beta_l + \beta_k$	ρ	σ	$\pi_k + \pi_l$
58-59-60	1.066 (0.032)	0.258 (0.076)	1.324 (0.087)	1.237 (0.064)	0.377 (3.790)	−0.959 (0.108)
61-62-63	1.019 (0.027)	0.623 (0.088)	1.642 (0.090)	1.060 (0.074)	0.847 (0.045)	−0.051 (0.137)
64-65-66	0.958 (0.033)	0.478 (0.151)	1.436 (0.144)	1.001 (0.073)	0.819 (0.041)	−0.245 (0.092)
67-68-69	0.981 (0.043)	0.383 (0.098)	1.364 (0.101)	1.107 (0.078)	0.861 (0.023)	−0.519 (0.125)
70-71-72	0.783 (0.029)	0.816 (0.112)	1.600 (0.115)	0.860 (0.127)	0.910 (0.075)	−0.236 (0.193)
73-74-75	0.972 (0.044)	−0.486 (0.148)	0.487 (0.156)	0.766 (0.076)	0.837 (0.035)	0.125 (0.172)
76-77-78	0.903 (0.037)	0.408 (0.128)	1.310 (0.126)	0.831 (0.094)	0.622 (0.193)	0.386 (0.147)
79-80-81	1.137 (0.051)	0.091 (0.096)	1.228 (0.112)	0.965 (0.103)	0.685 (0.078)	−0.652 (0.115)
82-83-84	0.971 (0.048)	0.394 (0.127)	1.365 (0.127)	0.551 (0.122)	0.691 (0.072)	−0.300 (0.134)
85-86-87	0.848 (0.040)	0.340 (0.132)	1.188 (0.133)	0.716 (0.126)	−0.266 (11.247)	−0.524 (0.183)
88-89-90	0.762 (0.049)	0.095 (0.117)	0.856 (0.122)	0.735 (0.136)	0.767 (0.067)	0.198 (0.142)
91-92-93	0.716 (0.037)	0.325 (0.148)	1.041 (0.151)	0.478 (0.089)	0.829 (0.449)	0.626 (0.124)
94-95-96	0.605 (0.053)	0.376 (0.197)	0.981 (0.207)	0.601 (0.186)	0.905 (0.234)	0.256 (0.133)
97-98-99	0.833 (0.053)	0.225 (0.100)	1.057 (0.142)	0.622 (0.148)	0.656 (0.092)	−0.461 (0.170)
00-01-02	0.803 (0.041)	0.121 (0.152)	0.924 (0.175)	1.045 (0.169)	0.812 (5.444)	0.169 (0.227)
03-04-05	0.580 (0.054)	0.251 (0.134)	0.831 (0.123)	0.532 (0.198)	0.451 (37.401)	−0.450 (0.131)
Mean	0.871	0.293	1.164	0.819	0.675	-

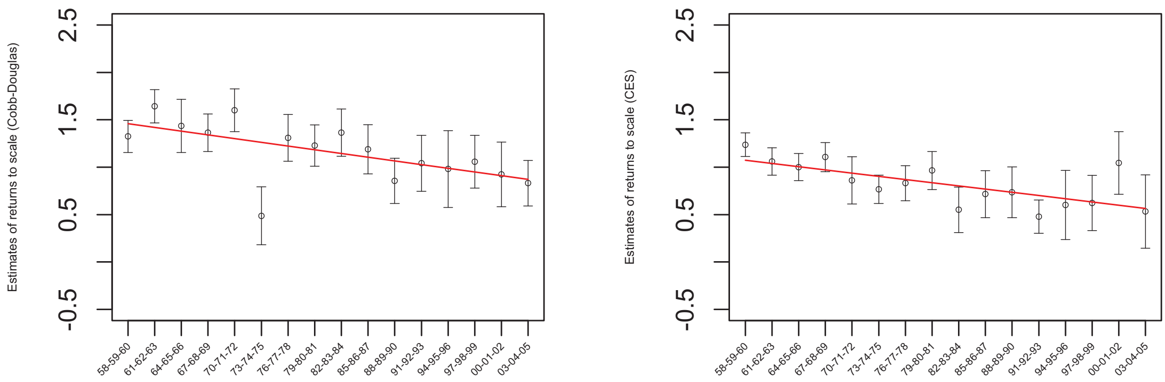

Figure 2 - Estimates of returns to scale with 95% confidence intervals, the sloping line represents the fitted line of the regression of estimates on a linear trend.

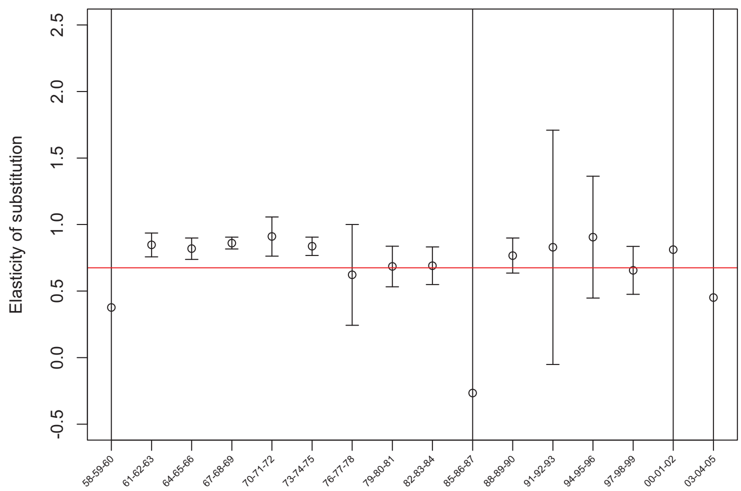

Figure 3 - Estimates of elasticity of substitution with 95% confidence intervals obtained from the CES-based model, the horizontal line represents the average value of estimates when the panels “59-59-60”, “64-65-66”, “67-68-69”, “00-01-02” and “03-04-05” are disregarded.

Table 4 - Estimates with sectoral stratification

		Cobb-Douglas			CES		
Sectors	$N \cdot T$	β_l	β_k	$\beta_l + \beta_k$	ρ	σ	$\pi_k + \pi_l$
Food mfg (311)	2112	0.809	0.384	1.242	0.767	0.546	−2.108
		(0.042)	(0.112)	(0.127)	(0.121)	(0.048)	(0.100)
Beverage & tobacco prod. (312)	432	0.768	0.191	1.035	0.785	0.557	−0.789
		(0.077)	(0.136)	(0.197)	(0.212)	(0.106)	(0.199)
Textile & mills (313&314)	864	0.820	0.241	1.129	0.566	0.709	−0.592
		(0.041)	(0.085)	(0.106)	(0.111)	(0.055)	(0.101)
Apparel (315)	1104	0.838	0.152	1.032	0.940	0.795	−2.847
		(0.031)	(0.066)	(0.088)	(0.111)	(0.082)	0.163)
Leather & allied prod.(316)	480	0.847	−0.147	0.713	0.715	0.865	−1.218
		(0.057)	(0.194)	(0.199)	(0.164)	(0.050)	(0.221)
Wood product mfg (321)	672	0.794	0.197	1.040	0.791	0.687	0.146
		(0.043)	(0.120)	(0.123)	(0.087)	(0.042)	(0.092)
Paper mfg (322)	960	0.742	0.240	1.051	0.579	0.642	−0.638
		(0.039)	(0.126)	(0.178)	(0.253)	(0.058)	(0.164)
Printing (323)	576	0.870	0.201	1.122	1.032	0.664	−0.862
		(0.024)	(0.108)	(0.127)	(0.110)	(0.034)	(0.106)
Petroleum & coal prod. (324)	240	0.890	0.294	1.230	1.089	0.677	0.160
		(0.125)	(0.212)	(0.279)	(0.358)	(0.118)	(0.305)
Chemical mfg (325)	1632	0.814	0.191	1.049	0.598	0.479	−0.422
		(0.041)	(0.145)	(0.151)	(0.097)	(0.074)	(0.096)
Plastics & rubber prod. (326)	768	0.967	0.377	1.143	0.806	0.562	−0.341
		(0.040)	(0.097)	(0.095)	(0.094)	(0.048)	(0.073)
Nonmetallic mineral prod.(327)	1152	0.952	0.002	1.019	0.994	0.568	0.099
		(0.029)	(0.071)	(0.077)	(0.065)	(0.029)	(0.084)
Primary metal mfg (331)	1248	0.966	0.032	1.044	0.961	0.627	−0.669
		(0.052)	(0.145)	(0.154)	(0.131)	(0.051)	(0.145)
Fabricated metal prod. (332)	2064	0.925	0.268	1.243	1.029	0.639	0.005
		(0.020)	(0.114)	(0.117)	(0.064)	(0.024)	(0.077)
Machinery (333)	2352	1.012	0.153	1.215	1.041	0.613	−0.548
		(0.025)	(0.136)	(0.138)	(0.075)	(0.049)	(0.070)
Computer & electro. prod. (334)	1344	0.867	0.679	1.592	1.173	0.479	−1.062
		(0.031)	(0.097)	(0.101)	(0.085)	(0.209)	(0.147)
Electrical equipment (335)	1056	0.906	0.204	1.157	0.694	0.680	−0.169
		(0.040)	(0.092)	(0.094)	(0.111)	(0.042)	(0.106)
Transportation equipment (336)	1440	1.160	0.031	1.235	0.991	0.669	−0.438
		(0.029)	(0.071)	(0.075)	(0.105)	(0.035)	(0.103)
Furniture & related prod.(337)	576	0.856	0.185	1.088	0.788	0.812	−0.344
		(0.042)	(0.125)	(0.148)	(0.167)	(0.054)	(0.105)
Miscellaneous (339)	1104	0.770	0.294	1.111	0.812	0.641	−0.740
		(0.031)	(0.101)	(0.112)	(0.160)	(0.083)	(0.086)

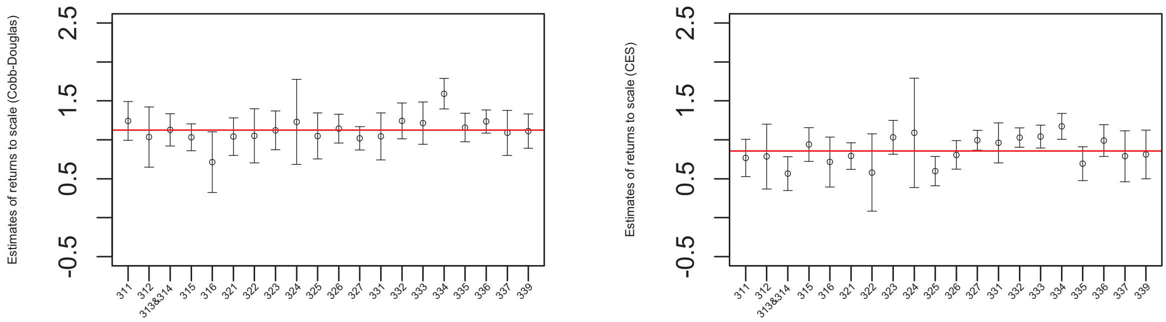

Figure 4 - Estimates of returns to scale with 95% confidence intervals for different sectors, the horizontal line represents the average value of estimates.

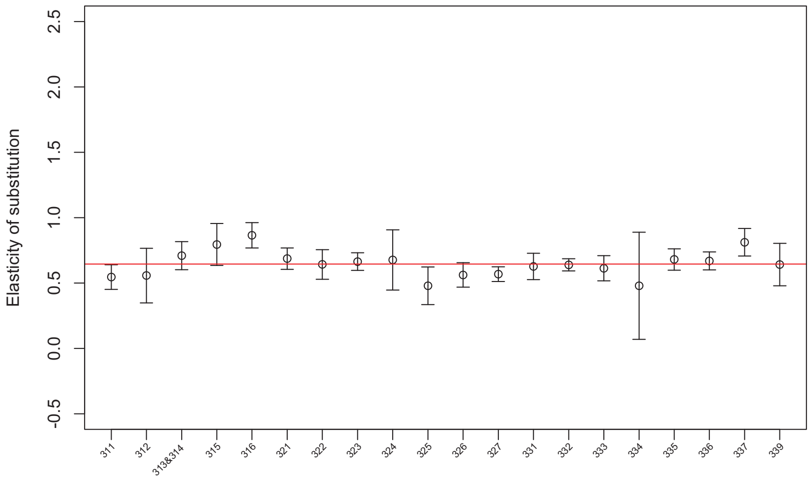

Figure 5 - Estimates of elasticity of substitution with 95% confidence intervals for different sectors, the horizontal line represents the average value of estimates.

4.2 Recovering the Hicks-neutral and factor-augmenting productivity

Given the estimates of technology parameters, I can now recover the relative Hicks-neutral and factor-augmenting productivity in logarithmic forms, $\log A_{it}$ and $\log B_{it}$, and then compute the corresponding growth rates. The term $\log A_{it}$ is defined as $\log A_{it} = \log A_{hit} - \rho \log B_{lit}$ and the term $\log B_{it}$ is defined as $\log B_{it} = \log B_{kit} - \log B_{lit}$, where A_h is the net Hicks-neutral productivity, B_l is the net labor-augmenting productivity and B_k is the net capital-augmenting productivity, see Equation (5). Since the net productivity terms cannot be identified separately, we only interpret the productivity measures in relative terms.

Given the estimates obtained from the CES based regression, the relative Hicks-neutral productivity $\log A_{it}$ is recovered by using Equation (7) as:

$$\log \hat{A}_{it} + c = \log Y_{it} - \hat{\rho} \log L_{it} - \hat{\gamma} \log S_{it}, \tag{32}$$

where $c = \gamma \log(1-\alpha)$. For the sake of comparison, we can also compute the Hicks-neutral productivity under the Cobb-Douglas model as:

$$\log \hat{A}_{it}^{CD} = \log Y_{it} - \hat{\beta}_l \log L_{it} - \hat{\beta}_k \log K_{it}. \tag{33}$$

Given the estimated elasticity of substitution, I can invert the capital-labor ratio equation (9) to obtain the expression of logarithmic relative factor-augmenting productivity:

$$\log \hat{B}_{it} + d = \frac{\hat{\sigma}}{\hat{\sigma}-1} \log \frac{r_{it}}{w_{it}} + \frac{1}{\hat{\sigma}-1} \log \frac{K_{it}}{L_{it}}, \tag{34}$$

where $d = \frac{\sigma}{\sigma-1} \log\left(\frac{\alpha}{1-\alpha}\right)$. As mentioned above the parameter α is not identified under our estimation procedure, but this is not a problem here, these constant terms do not affect the estimation of the growth rate.

Consider the estimates obtained from the full panel cases,[5] after averaging over sectors, I examine the time variation of the aggregated productivity growth rates:

$$\lambda_t^A \equiv N^{-1} \sum_i^N \triangle \log \hat{A}_{it} \quad \text{and } \lambda_t^B \equiv N^{-1} \sum_i^N \triangle \log \hat{B}_{it}.$$

[5] Under the CES specification, the estimates are: $\hat{\sigma} = 0.629$, $\hat{\rho} = 0.954$, $\hat{\gamma} = 1.617$ and $\hat{\theta} = -1.655$; under the Cobb-Douglas specification, the estimates are: $\hat{\beta}_l = 0.907$ and $\hat{\beta}_k = 0.306$

The following figure compares the estimation of the relative Hicks-neutral productivity growth, λ_t^A and of the relative labor-augmenting productivity growth, $-\lambda_t^B$ obtained from the CES based model for the period 1959-2005.

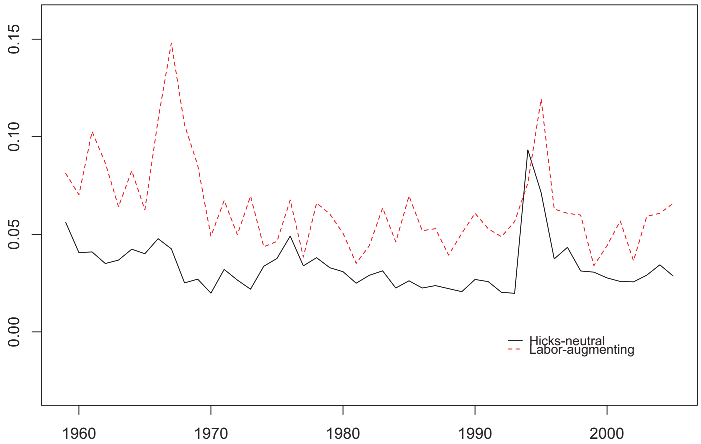

Figure 6 - Estimation of the relative Hicks-neutral and the relative labor-augmenting productivity growth rates (λ_t^A and $-\lambda_t^B$) for the period 1959-2005

Figure 6 shows that both time series are stationary and that the relative labor-augmenting productivity growth rates ($-\lambda_t^B$) is more volatile than the relative Hicks-neutral productivity growth rates (λ_t^A). The time series of the relative labor-augmenting productivity growth consists of two main spikes. The earlier spike was in 1967, and the second one has been in 1995 where a spike of λ_t^A appeared at the same period. The two series are positively correlated with a correlation coefficient of 0.486. Now, by averaging over sectors and periods, I compute the average (annual) productivity growth rates as:

$$\bar{\lambda}^A \equiv T^{-1}N^{-1}\sum_t^T\sum_i^N \triangle \log \hat{A}_{it} \quad \text{and } \bar{\lambda}^B \equiv T^{-1}N^{-1}\sum_t^T\sum_i^N \triangle \log \hat{B}_{it}.$$

I obtain an average Hicks-neutral productivity growth ($\bar{\lambda}^A$) of 3.37% based on the CES model (32), while under the Cobb-Douglas model (33) the average Hicks-neutral productivity growth is 1.89%. I find that labor-augmenting technical progress grew annually about 6.42% faster than capital-augmenting technical progress, i.e., $\bar{\lambda}^B = \bar{\lambda}^{Bk} - \bar{\lambda}^{Bl} = -6.42\%$, where $\bar{\lambda}^{Bk}$ denotes the net capital-augmenting productivity growth rate and $\bar{\lambda}^{Bl}$ denotes the net labor-augmenting productivity growth rate.[6] Our estimation of $\bar{\lambda}^B$

[6]Under the Cobb-Douglas specification, by construction, the net factor-augmenting productivity growth is restricted to zero, i.e., $\bar{\lambda}^{Bl} = \bar{\lambda}^{Bk} = 0$.

is larger than the one obtained by Antràs (2004), i.e., 3.15%. But both findings lead to the same conclusion that when the production technology is characterized by $\sigma < 1$, all firms have the incentive to pursue labor-augmenting innovations on the balanced growth path rather than capital-augmenting innovations (the theoretical justifications can be found in Acemoglu, 2003).

The previous estimation of productivity growth are obtained by assuming that all sectors have the same technology, which is characterized by the degree of returns to scale (ρ) and the elasticity of substitution (σ) under the CES specification. However, the results in Table 4 suggest that the production technology may differ across sectors. Table 5 summarizes the estimation of (relative) average productivity growth rates by taking into consideration the sectoral heterogeneity. Figure 7 displays the estimated values of average productivity growth rates for the 20 sectoral groups. In most cases, the estimates of $\bar{\lambda}^A$ lay in the range of 0.02 to 0.05; the estimates of $\bar{\lambda}^B$ are negative (labor-augmenting technical progress grew faster than capital-augmenting technical progress) and lay in the range of -0.04 to -0.10. There are 3 outliers , which are sectoral groups 315, 316 and 334. Despite the sectoral differences, the estimation results obtained by considering the sectoral heterogeneity are generally in line with the previous aggregated estimation results.

Table 5 - Estimates of average productivity growth rates with sectoral heterogeneity

Sectors	$N \cdot T$	ρ	σ	$\bar{\lambda}^A$	$\bar{\lambda}^B$
Food mfg (311)	2112	0.767	0.546	0.037	−0.071
Beverage & tobacco prod. (312)	432	0.785	0.557	0.039	−0.064
Textile & mills (313&314)	864	0.566	0.709	0.035	−0.083
Apparel (315)	1104	0.940	0.795	0.051	−0.223
Leather & allied prod.(316)	480	0.715	0.865	0.023	−0.242
Wood product mfg (321)	672	0.791	0.687	0.025	−0.064
Paper mfg (322)	960	0.579	0.642	0.026	−0.060
Printing (323)	576	1.032	0.664	0.023	−0.072
Petroleum & coal prod. (324)	240	1.089	0.677	0.045	−0.062
Chemical mfg (325)	1632	0.598	0.479	0.035	−0.042
Plastics & rubber prod. (326)	768	0.806	0.562	0.036	−0.056
Nonmetallic mineral prod.(327)	1152	0.994	0.568	0.028	−0.040
Primary metal mfg (331)	1248	0.961	0.627	0.027	−0.050
Fabricated metal prod. (332)	2064	1.029	0.639	0.024	−0.053
Machinery (333)	2352	1.041	0.613	0.023	−0.054
Computer & electro. prod. (334)	1344	1.173	0.479	0.070	−0.072
Electrical equipment (335)	1056	0.694	0.680	0.031	−0.063
Transportation equipment (336)	1440	0.991	0.669	0.028	−0.041
Furniture & related prod.(337)	576	0.788	0.812	0.030	−0.107
Miscellaneous (339)	1104	0.812	0.641	0.031	−0.066

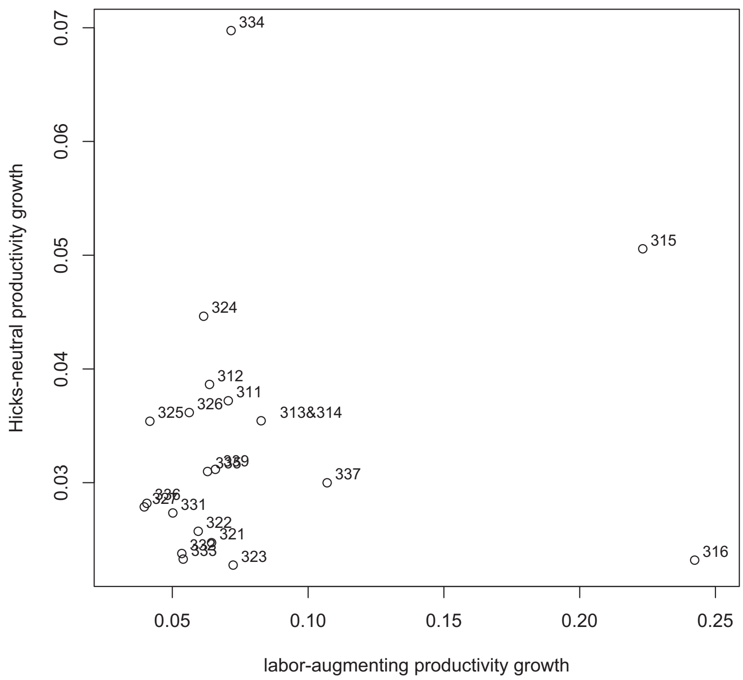

Figure 7 - Estimation of average productivity ($\bar{\lambda}^A$ and $-\bar{\lambda}^B$)

5 Conclusion

In this study, I introduced a new method of estimating a CES production function with biased technical change, which extends the work of Berndt (1976), Olley and Pakes (1996), Antràs (2004), Klump et al (2007) and Leon-Ledesma et al (2010). This approach is superior to its prior counterparts in three aspects. First, it employs a more flexible production function specification; second, it is able to deal with the endogeneity problem of input variables; third, the degree of returns to scale, the elasticity of substitution and the growth rate of biased technical change can be estimated simultaneously.

The new empirical evidences presented in this paper, show that the U.S manufacturing industries were characterized by decreasing returns to scale and non-unitary substitution elasticity (below one) technology; the bias in technical change is mainly labor-augmenting. Furthermore, the estimation results obtained by considering different windows of observation and stratified data sets, may throw some light on the questions such as the production technology evolution of last half century and the intra-industrial distortion in U.S manufacturing sectors.

Appendix: Presentation of Data set and Construction of Variables

Different sources of data

The main source of information comes from the NBER-CES Manufacturing Industry databases.[7] These data reflect essentially the Annual Survey of Manufactures (ASM) conducted by U.S. Census Bureau, which aggregates approximately 50,000 establishments to 473 six-digit NAICS manufacturing sector groups for the period 1958-2005.[8] The variables included in the database are output, employment (production/non-production), payroll, investment, capital stocks, materials and energy cost together with price deflators. The construction of this database has been discussed in the technical report of Bartelsman and Gray (1996). Malley and Muscatelli (1999) provided further detail on the definition of variables.

The variable *payroll* of the NBER data set does not include social security or other legally mandated payments, or employer payments for some fringe benefits. Therefore, the labor costs are systematically understated by this data set. In order to correct this bias, we need to include fringe benefits. To this end, additional information is required, especially the fringe benefits costs ratio, i.e, (fringe benefits/total compensation). Two sources of information can be used, i.e., the 1992-2005 ASM tables and the National Income and Product Account (NIPA) tables conducted by BEA.

The NIPA tables (especially Tables 6.2 - 6.3 and Tables 6.10 - 6.11), record the compensation of employees, wage and salary accruals, legally required social insurance, pension and insurance funds from 1948 to 2010 for 21 two-digit SIC sector groups.[9] We can use these data for covering the period of 1958 to 1991 by assuming homogeneity within sectors at the two-digit level. More disaggregated data (at four-digit SIC and six-digit NAICS level) are available in the ASM tables. For the period 1992 to 1996, we can find the value of fringe benefits recorded in SIC classification system, while for the period 1997 to 2005 the data are collected in NAICS.

Construction of capital price

The NBER database provides the total real capital stock (K), then we need to construct the rental price of capital (P_K) by using the investment price index (P_I). Consider the following formula: $P_{K,t} \equiv P_{I,t}(1+\pi_t) - \mathrm{E}_t[(1-\delta_t)P_{I,t+1}]$, where π denotes the nominal interest rate. In this study we use the 10-year U.S. treasury constant maturity rate, which comes from the

[7] The database is accessible on the website: www.nber.org/nberces/nbprod96.htm
[8] See the website: http://www.census.gov/manufacturing/asm/index.html
[9] See the website: http://www.bea.gov/national/nipaweb/Index.asp

Federal Reserve Bank of St. Louis. δ is the physical depreciation rate. The depreciation rate can be computed by using the classical capital accumulation equation, $K_t = I_t + (1 - \delta_t)K_{t-1}$ or set to be constant (in this paper we assume that $\delta = 8\%$). Assuming that there is no expectation errors on $P_{I,t+1}$, the above formula can be simplified as: $P_{K,t} \equiv P_{I,t}(\delta_t + \pi_t)$.

Construction of fringe benefits ratio

The total fringe benefits is the employer's costs for legally required social insurance, employee pension and insurance funds.[10] The fringe benefits can be computed in two manners: the difference between the total compensation and the payroll or the sum of costs for social insurance, employee pension and insurance funds (the two methods carry out the similar results in our data). Thus, the ratio of fringe benefits to total compensation is used to magnify the labor costs of the NBER database. The main difficulty of incorporating the fringe benefits into the NBER database is that the data are recorded at different aggregation level and in different industrial classification systems before 1997. We converted the 2-digit SIC data (for the period 1958-1990) of NIPA tables and the 4-digit SIC data (for the period 1991-1996) of ASM tables in to the NAICS data, according to the concordance proposed by Census Bureau.[11]

Sources of missing values The main source of missing values is that the data on fringe benefits from the NIPA tables is only available at the 2-digit SIC level. Therefore, we assume that the fringe benefits are invariant across sectors within the 2-digit SIC industry group. The second source is that some 6-digit NAICS sectors are missing in the ASM tables for the period of 2002 to 2005. In this case, we replace the missing values by the variation rate of corresponding 5-digit NAICS sectors.[12] The third source of missing values is due to the concordance relationships between the 4-digt SIC and 6-digit NAICS classification system. Some NAICS industry groups correspond to several SIC industry groups. Thus, the fringe benefits of NAICS sector is computed as the average of fringe benefits of its SIC counterparts. In some cases, the corresponding SIC groups are not manufacturing industries. Consequently, their fringe benefits data are not available and we simply disregard these non manufacturing SIC industry groups for computing the average of fringe benefits.

[10] The ASM define the fringe benefits as the expenditures for social security tax, unemployment tax, workmen's compensation insurance, state disability insurance pension plans, stock purchase plans, union-negotiated benefits, life insurance premiums, and insurance premiums on hospital and medical plans for employees.

[11] See the website: http://www.census.gov/eos/www/naics/concordances/concordances.html

[12] The variation rate of fringe benefits at period t of 6-digit sector $= F_{t-1}^{6-digit} \cdot (1 + \frac{F_t^{5-digit}}{F_{t-1}^{5-digit}})$, where F denotes the fringe benefits rate.

Finally, we obtain a balanced panel data set that contains the output, adjusted labor costs, capital cost, investment and material input costs with price deflators for 462 NAICS manufacturing industry groups over the period 1958-2005.

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