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BIASED TECHNICAL CHANGE, SCALE, AND FACTOR SUBSTITUTION IN U.S. MANUFACTURING INDUSTRIES

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Although a realistic characterization of the production function is critical to macroeconomic analysis, estimating the function's characteristics is hampered by both data limitations and methodological difficulties. In this paper, I develop a new empirical strategy for estimating the CES production function with biased technical change. The proposed method extends the control function approach to the CES specification to address endogeneity concerns and is able to retrieve sector-specific and time-varying estimates of technical change. Using data from U.S. manufacturing industries, I find evidence that (i) the production technology exhibits nonincreasing returns to scale, (ii) the elasticity of substitution between capital and labor is below unity, and (iii) technical change is generally labor-augmenting along the balanced growth path.

Keywords: Elasticity of Substitution, Returns to Scale, Biased Technical Change, Control Function Approach

1. INTRODUCTION

The theory of production provides the basis for theoretical models that aim to understand macroeconomic phenomena. For instance, the elasticity of substitution is an important determinant of income inequality because it characterizes the link between capital accumulation and capital's share of income [Piketty (2014)]. The patterns of economic growth and technological development rely on assumptions about the nature of technical change [Grossman and Helpman (1991); Acemoglu (2002, 2003)] and the degree of returns to scale [Farmer and Guo (1994); Jones (2005)]. A realistic characterization of the underlying production technology is vital to ensure the soundness of macroeconomic models. Thus, the empirical analysis of production using disaggregated data can serve as a valuable source of information for establishing the framework for a theoretical analysis.

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Working with large disaggregated data sets, we can estimate the production function by exploring both time-series and cross-sectional information. However, it is challenging to address the endogeneity problem and simultaneously keep the empirical specification general enough to identify the parameters of interest. This paper addresses this problem by combining two strands of literature: the macroeconomic studies that focus on estimating the constant elasticity of substitution (CES) production function with biased technical change [Klump et al. (2007); León-Ledesma et al. (2010); Young (2013)] and the microeconometric methods that address the endogeneity problem using the control function approach [Olley and Pakes (1996); Levinsohn and Petrin (2003); Ackerberg et al. (2006)]. On one hand, following Olley and Pakes (1996), estimation of production functions at the micro-level is largely based on the Cobb–Douglas specification. The disadvantage is that this specification imposes a unitary elasticity of substitution. Thus, the improvement in technology does not produce a bias toward any of the factors (Hicks-neutral technical change). On the other hand, macroeconomic studies that use the more flexible CES specification with biased technical change do not provide a structural solution to the problem of endogeneity between inputs and technical change. This study fills that gap by proposing an extension of the Olley–Pakes method for the CES function with biased technical change.

Two empirical strategies are commonly used to estimate the CES function. The first approach is single equation estimation, which is based on either the first-order conditions of the producer's optimization problem [Antràs (2004); Karabarbounis and Neiman (2014)] or the production function [Kmenta (1967); Thursby and Lovell (1978)]. The second is the system approach, which jointly estimates the production function and first-order conditions [Klump et al. (2007); León-Ledesma et al. (2010, 2015)].[1] One limitation of these approaches is that the technical change terms are often modeled as the deterministic trend of a parametric function. However, the theory of induced innovation requires more general empirical specifications. The demand for innovation is generally motivated by profit opportunities and constrained by costs [Kennedy (1964); Samuelson (1965); Acemoglu (2002)]. Therefore, the intensity and direction of technical change depend on the environment in which firms operate and on their ability to realize changes, which implies, first, that the empirical specification should include both neutral and nonneutral technical change; second, and more important, that the productivity index that embodies technical change should be modeled as a stochastic variable that correlates with input decisions. The increasing availability of disaggregated panel data has made it possible to estimate such a model. Simultaneously, however, the estimation suffers from an endogeneity problem because productivity indices are unobserved. In addition, the nonlinearity of the CES function adds further complications to the empirical investigation.

In this paper, I propose a new estimation form for the CES function that incorporates both the production function and the first-order conditions [similar to León-Ledesma et al. (2010)], and I apply the control function method to correct for endogeneity bias. In so doing, this study illustrates that misspecification and the

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endogeneity problem can lead to substantial biases in the estimates of technology parameters [echoing that of León-Ledesma et al. (2015)]. Another key feature of this study is that the estimates of productivity indices are sector-specific and time-varying. In this regard, the paper is similar in spirit to Klump et al. (2008) and McAdam and Willman (2013), which employ time-varying measures of technical change to analyze the medium-run departures of the EU economy from the balanced growth path.

Using data from U.S. manufacturing industries over the period 1958–2005, this study provides sectoral estimates at the six-digit NAICS level. The estimates reveal that the elasticity of substitution between capital and labor is less than one and the technology exhibits nonincreasing returns to scale. Comparisons of different empirical models reveal two potential sources of bias. First, the Cobb–Douglas-based model overestimates returns to scale and underestimates Hicks-neutral productivity growth. Second, the endogeneity problem introduces upward bias into both returns to scale and the elasticity of substitution. Relying on the CES-based control function approach, an analysis of estimated productivity indices suggests that technical change is generally labor-augmenting, but capital-augmenting technical change occurs in some transitional stages.

The remainder of this paper is organized as follows. Section 2 outlines the CES production function with biased technical change. Section 3 examines the potential estimation bias under the Cobb–Douglas specification. Section 4 presents the control function approach and the procedure for estimating the CES production function. Section 5 summarizes and compares the estimation outcomes of different empirical models. Section 6 provides final remarks and potential avenues for future research.

2. ELASTICITY OF SUBSTITUTION, RETURNS TO SCALE, AND BIASED TECHNICAL CHANGE

I consider a neoclassical production function $F(.)$ with two factors, labor (L) and capital stock (K). The elasticity of substitution between capital and labor is defined by the percentage change in factor proportions due to a change in relative marginal products [Hicks (1932)]:

$$-\frac{d\log(K/L)}{d\log(F_K/F_L)} \geq 0, \tag{1}$$

where F_K and F_L denote $\partial F/\partial K$ and $\partial F/\partial L$, respectively. In this study, the specific functional form of production technology is the CES function [Arrow et al. (1961)]:

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

where the elasticity of substitution is represented by the parameter σ. The productive factors are gross complements in the sense of Acemoglu (2002) when $\sigma < 1$

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and gross substitutes when $\sigma > 1$. The CES production function reduces to the Cobb–Douglas function when $\sigma = 1$. For any given value of σ, the functional distribution of income is determined by $\alpha \in [0, 1]$. The parameter ρ represents the degree of returns to scale, i.e.,

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

The technology exhibits constant returns to scale when $\rho = 1$ and increasing (decreasing) returns to scale when $\rho > 1$ ($\rho < 1$).

The productivity index is added to the production function to capture technical progress. The most common specification is the Hicks-neutral technology, i.e., $A_h F(K, L)$, as imposed in the case of the Cobb–Douglas production function. If technical change is Harrod-neutral, the production function is $F(K, B_l L)$, where B_l denotes pure labor-augmenting productivity. Thus, an increase in productivity is equivalent to employing more labor. If technical change is Solow-neutral, the production function becomes $F(B_k K, L)$, where B_k denotes pure capital-augmenting productivity. A more general specification of technology is

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

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.[2]

I assume that firms maximize profit and set marginal products equal to input prices. Therefore, the first-order conditions of profit maximization 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 shows that the variation in the capital–labor ratio depends on factor-augmenting technical change (B) but not on Hicks-neutral technical change (A). As Acemoglu (2002) shows, if factors are complements in production ($\sigma < 1$), the relative capital-augmenting technical change is labor-biased. In contrast, when factors are substitutes ($\sigma > 1$), the relative capital-augmenting technical change becomes capital-biased. When $\sigma = 1$, the effect of biased technical change vanishes, and the factors ratio becomes proportional to w/r.

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3. EMPIRICAL IMPLICATIONS OF THE COBB–DOUGLAS SPECIFICATION

In this section, I examine the difference between the Cobb–Douglas and CES specifications in terms of estimation outcomes. Both specifications yield estimates of returns to scale and Hicks-neutral productivity. Now, suppose that the true data-generating process is characterized by a CES production function with biased technical change. The question I ask here is the following: If researchers nevertheless estimate a Cobb–Douglas function that imposes unitary elasticity and Hicks neutrality, how does the misspecification affect the estimated returns to scale and the estimated growth rate of Hicks-neutral productivity?

First, I focus on the estimation bias of returns to scale, and disregard productivity indices A and B in the discussion. The difference between the two empirical models in terms of Hicks-neutral productivity growth is described later in this section. The Kmenta (1967) approximation to (2) can be expressed as follows:

$$\log Y_{it} = \rho\alpha \log K_{it} + \rho(1-\alpha)\log L_{it} + \frac{1}{2}\rho\frac{\sigma-1}{\sigma}\alpha(1-\alpha)(\log K_{it}/L_{it})^2, \quad (7)$$

where $i = 1, \ldots, N$ indexes sectors and $t = 1, \ldots, T$ indexes time. The last term of (7) is neglected in the Cobb–Douglas specification (the omitted variable). I use $\hat{\beta}_k$ and $\hat{\beta}_l$ to denote the estimated coefficients of $\log K_{it}$ and $\log L_{it}$ under the Cobb–Douglas specification. Using the result of Theil (1957) regarding omitted variable bias, the expectations of these estimators can be expressed as

$$\mathrm{E}(\hat{\beta}_k) = \rho\alpha\left[1 + \frac{1}{2}\frac{\sigma-1}{\sigma}(1-\alpha)\hat{\pi}_k\right], \quad (8)$$

$$\mathrm{E}(\hat{\beta}_l) = \rho(1-\alpha)\left[1 + \frac{1}{2}\frac{\sigma-1}{\sigma}\alpha\hat{\pi}_l\right], \quad (9)$$

where $\hat{\pi}_k$ and $\hat{\pi}_l$ are the two estimates obtained from the regression of the omitted variable, $(\log K_{it}/L_{it})^2$, on the included variables, $\log K_{it}$ and $\log L_{it}$, respectively. Then, the estimate of returns to scale based on the Cobb–Douglas specification is

$$\mathrm{E}(\hat{\beta}_k + \hat{\beta}_l) = \rho\left[1 + \frac{1}{2}\frac{\sigma-1}{\sigma}\alpha(1-\alpha)(\hat{\pi}_k + \hat{\pi}_l)\right]. \quad (10)$$

Suppose that ρ is the true value of returns to scale; the reason that the Cobb–Douglas-based model may misestimate returns to scale is that the nonlinear component of the production function is neglected. Economically, this is because the elasticity of substitution between capital and labor is restricted to equal one in the Cobb–Douglas specification. Equation (10) indicates that this estimation bias depends on three factors: the elasticity of substitution, the distribution parameter, and $\hat{\pi}_k + \hat{\pi}_l$. Economic theory restricts the support of the distribution parameter, i.e., $\alpha \in [0, 1]$. Thus, the direction of the bias depends only on the sign of $\hat{\pi}_k + \hat{\pi}_l$

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TABLE 1. 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

and the elasticity of substitution. Table 1 summarizes the potential direction of estimation bias.

Next, I examine the difference between the Cobb–Douglas and CES specifications in terms of productivity estimates. One specific feature of this study is that I do not impose any parametric functional forms on productivity indices. I consider A and B as time-varying and sector-specific random variables that capture both macroeconomic shocks and sectoral deviations. The Kmenta approximation of (5) yields

$$\log Y_{it} = \log A_{it}^{\text{CES}} + \rho\alpha \log B_{it}^{\text{CES}} K_{it} + \rho(1-\alpha)\log L_{it} + \frac{1}{2}\rho\frac{\sigma-1}{\sigma}\alpha(1-\alpha)\left(\log B_{it}^{\text{CES}}\frac{K_{it}}{L_{it}}\right)^2. \quad (\mathbf{11})$$

In this discussion, I use $\log A_{it}^{\text{CES}}$ and $\log B_{it}^{\text{CES}}$ to denote productivity terms under the CES specification and $\log A_{it}^{\text{CD}}$ under the Cobb–Douglas specification. Given the true parameter values, the measurement of Hicks-neutral productivity based on the Cobb–Douglas specification is

$$\begin{aligned}\log A_{it}^{\text{CD}} &= \log Y_{it} - \rho\alpha \log K_{it} - \rho(1-\alpha)\log L_{it} \\ &= \log A_{it}^{\text{CES}} + \rho\alpha \log B_{it}^{\text{CES}} + \frac{1}{2}\rho\frac{\sigma-1}{\sigma}\alpha(1-\alpha)\left(\log B_{it}^{\text{CES}}\frac{K_{it}}{L_{it}}\right)^2.\end{aligned}$$

This equation demonstrates that the difference between $\log A_{it}^{\text{CD}}$ and $\log A_{it}^{\text{CES}}$ is a linear combination of two variables, $\log B_{it}^{\text{CES}}$ and $(\log B_{it}^{\text{CES}}\frac{K_{it}}{L_{it}})^2$, weighted by the following coefficients: $\rho\alpha$ and $\frac{1}{2}\rho\frac{\sigma-1}{\sigma}\alpha(1-\alpha)$.

Suppose that $\log A_{it}^{\text{CES}}$ is the true Hicks-neutral productivity index; then the Cobb–Douglas estimate, $\log A_{it}^{\text{CD}}$, is biased for two reasons. First, the Cobb–Douglas specification neglects nonneutral technical progress by imposing $\log B_{it}^{\text{CES}} = 0$. Second, it also neglects the nonlinear component of the production function, $\triangle(\log B_{it}^{\text{CES}}\frac{K_{it}}{L_{it}})^2$. The weighting coefficients regulate the impact of the two sources of bias. To illustrate the effect of this bias on productivity growth, I

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use the first-differenced equation

$$\triangle \log A_{it}^{\mathrm{CD}} = \triangle \log A_{it}^{\mathrm{CES}} + \rho\alpha \left[\triangle \log B_{it}^{\mathrm{CES}} + \frac{(1-\alpha)(\sigma-1)}{2\sigma} \triangle \left(\log B_{it}^{\mathrm{CES}} \frac{K_{it}}{L_{it}} \right)^2 \right]. \quad (12)$$

Given that $\alpha \in [0, 1]$ and $\rho > 0$, when capital and labor are gross substitutes ($\sigma > 1$), the coefficient $\frac{(1-\alpha)(\sigma-1)}{2\sigma}$ is positive. Thus, an increase (decrease) in both $\log B_{it}^{\mathrm{CES}}$ and $(\log B_{it}^{\mathrm{CES}} \frac{K_{it}}{L_{it}})^2$ leads to overestimation (underestimation) of productivity growth. The contribution to the bias from the Hicks-neutrality restriction is at least 50% more important than neglecting the nonlinear term.[3] When capital and labor are gross complements ($\sigma < 1$), the coefficient $\frac{(1-\alpha)(\sigma-1)}{2\sigma}$ is negative. Thus, increase (decrease) in both $\log B_{it}^{\mathrm{CES}}$ and $(\log B_{it}^{\mathrm{CES}} \frac{K_{it}}{L_{it}})^2$ have opposite effects on the bias. In this case, the direction of the bias is less clear and depends crucially on the value of σ. If $\sigma > \frac{1-\alpha}{3-\alpha}$, then the term $\triangle \log B_{it}^{\mathrm{CES}}$ plays a more important role in determining the direction of the bias.[4] Otherwise, $\triangle(\log B_{it}^{\mathrm{CES}} \frac{K_{it}}{L_{it}})^2$ becomes a more important determinant. Based on the estimates in the empirical application, Section 5.2 analyzes the tension between the two determinants of the bias.

There are two related studies that evaluate the estimation biases under the Cobb–Douglas specification, Dupuy (2006) and León-Ledesma et al. (2015). Following León-Ledesma et al. (2015), I use the Kmenta (1967) approximation method to derive analytical expressions for the bias. However, the consistency of these expressions relies on the accuracy of this particular approximation. Thus, the results in this section are simplified illustrations of the bias, which provide us guidance in comparing the Cobb–Douglas and the CES estimates. Given the limitation of analytical approximation, the empirical application in Section 5 examines more general cases by illustrating the bias numerically.

4. IDENTIFICATION AND ESTIMATION OF THE CONSTANT-ELASTICITY-OF-SUBSTITUTION PRODUCTION FUNCTION VIA THE CONTROL FUNCTION APPROACH

The assumption that data reflect the technology and optimizing behavior of producers implies that the underlying data-generating process can be represented by a set of equations, which includes the production function and first-order conditions. The first equation of the empirical model is the logarithmic transformation of (5), with an error term appended:

$$\log Y_{it} = \rho \log L_{it} + \frac{\rho\sigma}{\sigma-1} \log \left[\alpha \left(B_{it} \frac{K_{it}}{L_{it}} \right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha) \right] + \log A_{it} + \varepsilon_{it}. \quad (13)$$

The scalar disturbance term ε_{it} is an ex post shock, which is not anticipated by firms. Thus, ε_{it} does not affect the optimal choice of labor demand and

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capital–labor ratio. However, L_{it} and $\frac{K_{it}}{L_{it}}$ are correlated with unobserved productivity indices, A_{it} and B_{it}.

One difficulty of estimating (13) is caused by the nonlinearity of the functional form, where the unobserved variable B_{it} is not additively separable from regressors. These types of models have been studied by Imbens and Newey (2009) in a nonparametric framework. They provide various partial identification results for the structural equation via the control function approach (e.g., average derivatives, bounds for the quantile, and average structural functions). In the case of (13), however, these results are not sufficient for recovering the two technology parameters ρ and σ. Therefore, I propose an alternative estimation form combining (13) with the following optimality condition. Given the competitive factor market and profit maximization, the capital–labor income share can be expressed as

$$\frac{r_{it}K_{it}}{w_{it}L_{it}} = \left(\frac{\alpha}{1-\alpha}\right)\left(B_{it}\frac{K_{it}}{L_{it}}\right)^{\frac{\sigma-1}{\sigma}}. \tag{14}$$

I can obtain a substitute for the nonlinear component in (13) by adding one and multiplying $(1-\alpha)$ by both sides of (14):

$$\log(1-\alpha) + \log S_{it} = \log\left[\alpha\left(B_{it}\frac{K_{it}}{L_{it}}\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\right]. \tag{15}$$

The observed variable S_{it} is defined as $\frac{r_{it}K_{it}}{w_{it}L_{it}} + 1$. The regression model can be rewritten as

$$y_{it} = c + \rho l_{it} + \delta s_{it} + a_{it} + \varepsilon_{it}, \tag{16}$$

where the lower-case characters denote the logarithmic variables. The parameters c and δ are defined as $c \equiv \frac{\rho\sigma}{\sigma-1}\log(1-\alpha)$ and $\delta \equiv \frac{\rho\sigma}{\sigma-1}$.

Equation (16) is a log-linearized regression model that incorporates both the production function (13) and the first-order conditions (14). The second difficulty associated with this model is the endogeneity problem between the unobserved productivity shock a_{it} and regressors l_{it} and s_{it}. The most common solution to the endogeneity problem is the instrumental variables (IV) method. An asymptotically equivalent alternative is the control function approach. In this study, I use the latter approach because of the lack of valid instruments to control for productivity shocks.

4.1. The Control Function Approach

The control function approach was first developed and applied to correct for selection bias in binary response models [Heckman and Robb (1985)]. This method has been extended to the identification of a wide class of models in which the observed and unobserved explanatory variables are not independently distributed.[5] Olley and Pakes (1996) introduced the use of the control function approach for estimating a production function.

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The control function approach is a closely related alternative to the classical IV method. The key difference between the two estimation methods is how the exogenous variations embodied in the data are used. In the IV estimation, exogenous variations of instruments are used directly to construct moment conditions, whereas the underlying concept of the control function approach is to use the control variable to purge the dependence between the observed and unobserved explanatory variables. Formally, 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 conditional on v, i.e.,*

$$\mathrm{E}[u \mid x, v] = \mathrm{E}[u \mid v], \tag{17}$$

where x and u are not independently distributed.

As a concrete example, I consider a simple model to illustrate the control function approach. A linear regression model is defined as

$$y = \beta x + u,$$

with a reduced-form equation $x = g(z, v)$. The regressor, x, is correlated with the unobserved term, v. The exogenous variable, z, is uncorrelated with u and v. The objective is to estimate β. In this example, the endogeneity of x arises if and only if u is correlated with v. Thus, it can be shown that v is a valid control variable, which satisfies (17).[6] If this control variable is observable or estimable, a feasible estimation strategy is to use v as a proxy to replace u:

$$y = \beta x + m(v) + e,$$

where e is an exogenous error term and the function of v is viewed as an additional regressor.[7] Because x and v are uncorrelated with e, β and $m(.)$ can be estimated using the Robinson (1988) estimator. The identification condition of β is that x is not a deterministic function of v, which implies that there is at least one exogenous variable, z, in the reduced-form equation $g(.)$. Otherwise, the model is not identified because of a collinearity problem, i.e., $y = \beta g(v) + m(v) + e$. This identification condition is somewhat similar to the rank condition in classical IV estimations.

4.2. Estimation of the Constant-Elasticity-of-Substitution Production Function

The endogeneity problem in the model of interest (16), is caused by the correlation between an unobserved productivity shock, a_{it} (which corresponds to u in the previous example), and regressors, $x_{it} \equiv (l_{it}, s_{it})$. Before introducing the estimation procedure for the CES function, I briefly review the classic control

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function method under the Cobb–Douglas specification:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + a_{it} + \varepsilon_{it}, \tag{18}$$

where ε_{it} represents the exogenous shocks. The two seminal papers in this area, Olley and Pakes (1996) and Levinsohn and Petrin (2003), differ essentially in their choices of control variables. Olley and Pakes (1996) use investment flow as the control variable, whereas Levinsohn and Petrin (2003) use material demand. In both cases, the control variable is directly observed in the data set. The key assumption in these papers is that the chosen control variable is a function of productivity and capital stock, $v_{it} = f(a_{it}, k_{it})$, and $f(.)$ is monotonic in a_{it}. By inverting a_{it} out from $f(.)$, the productivity term a_{it} is expressed as a function of observed variables: $a_{it} = f^{-1}(v_{it}, k_{it})$. Then the parameter β_l is estimated in the first stage by replacing a_{it} in (18) with the inverse function. The parameter β_k is estimated in the second stage by assuming that productivity evolves as a first-order Markov chain.[8]

Based on the Cobb–Douglas specification, Olley and Pakes (1996) and Levinsohn and Petrin (2003) do not allow for nonneutral productivity in their models. The Hicks-neutral productivity index, a_{it}, is the only unobserved variable that is correlated with input variables. In the CES model, there is an additional source of endogeneity through $b_{it} \equiv \log B_{it}$, which correlates with x_{it}, a_{it}, and v_{it}. Therefore, I consider a more general equation in which both terms, a_{it} and b_{it}, are included, $v_{it} = f(a_{it}, b_{it}, k_{it})$. One technical difficulty of this generalization is that the inversion trick in the basic control function approach no longer works for a_{it}. The monotonicity of $f(.)$ in a_{it} is not sufficient for inversion, as the additional term, b_{it}, is also unobserved. Fortunately, using the capital–labor ratio equation, b_{it} can be expressed as a function of observed variables: l_{it}, k_{it}, and the input price ratio. Thus, I obtain the following relationship:

$$\mathrm{E}[a_{it} \mid l_{it}, k_{it}, v_{it}, r_{it}/w_{it}] = f^{-1}(l_{it}, k_{it}, v_{it}, r_{it}/w_{it}).$$

Plugging this function into (16) yields

$$\begin{aligned} y_{it} &= c + \rho l_{it} + \delta s_{it} + f^{-1}(l_{it}, k_{it}, v_{it}, r_{it}/w_{it}) + \varepsilon_{it} \\ &= \Phi(l_{it}, k_{it}, v_{it}, r_{it}/w_{it}) + \varepsilon_{it}. \end{aligned}$$

The parameters of interest, ρ and δ, are not directly identified from the nonparametric function. Thus, I follow Ackerberg et al. (2006) to estimate only the nonparametric function, Φ, in the first stage. This yields an expression of a_{it} netted out of ε_{it}, i.e., $\hat{a}_{it}(\rho, \delta) = \hat{\Phi} - \rho l_{it} - \delta s_{it}$. The parameters of interest are estimated in the second stage using a set of moment conditions.

In the second stage, at least two moment conditions are needed to estimate ρ and δ. To write these moment conditions, I impose the first-order Markov assumption

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on a_{it}, and I decompose the current value into

$$a_{it} = \mathrm{E}[a_{it} \mid a_{it-1}] + \xi_{it}.$$

ξ_{it} is the innovation shock, which represents an exogenous deviation of a_{it} from its expectation in period $t-1$. Thus, ξ_{it} is independent of all decisions made in period $t-1$. I assume that the decision regarding the current share of factor cost, s_{it}, is made in period $t-1$. This assumption can be justified by the fact that before production begins in period t, there are significant hiring costs and training time for new workers and a bargaining process between employers and employees. Therefore, the share of factor cost is a quasi-fixed variable, which yields the first moment condition $\mathrm{E}[\xi_{it} \cdot s_{it}] = 0$. The labor demand of the previous period yields the second moment condition $\mathrm{E}[\xi_{it} \cdot l_{it-1}] = 0$. In addition, a third moment condition that can be used in the estimation is $\mathrm{E}[\xi_{it} \cdot s_{it-1}] = 0$.

Given the first stage estimate of Φ and a set of candidate values for ρ and δ, an estimate of a_{it} can be expressed as follows: $\hat{a}_{it}(\rho, \delta) = \hat{\Phi} - \rho l_{it} - \delta s_{it}$. The innovation shock, ξ_{it}, can be written as $\hat{\xi}_{it}(\rho, \delta) = \hat{a}_{it}(\rho, \delta) - \mathrm{E}[\hat{a}_{it}(\rho, \delta) \mid \hat{a}_{it-1}(\rho, \delta)] = \hat{a}_{it}(\rho, \delta) - h[\hat{a}_{it-1}(\rho, \delta)]$, where $h(.)$ is a nonparametric function that characterizes the first-order Markov process. I can estimate ρ and δ by minimizing the sample analogues of the following moment conditions:

$$\mathrm{E}\begin{bmatrix} & s_{it} \\ \hat{\xi}_{it}(\rho, \delta) & s_{it-1} \\ & l_{it-1} \end{bmatrix} = 0.$$

Because there are more moment conditions than parameters of interest, I use the generalized method of moments (GMM) for estimation. Finally, the estimate of Hicks-neutral productivity is recovered up to a constant term (d) as

$$\hat{a}_{it} + d = y_{it} - \hat{\rho} l_{it} - \hat{\delta} s_{it}. \tag{19}$$

Given the implicit estimates of $\sigma = \frac{\rho}{\rho - \delta}$, the estimate of relative capital-augmenting productivity is computed up to a constant term (n) as

$$\hat{b}_{it} + n = \frac{1}{(\hat{\sigma} - 1)}(k_{it} - l_{it}) + \frac{\hat{\sigma}}{(1 - \hat{\sigma})} \log\left(\frac{w_{it}}{r_{it}}\right). \tag{20}$$

5. EMPIRICAL INVESTIGATION

The main source of information needed to conduct the econometric analysis comes from the NBER manufacturing industry database. The data set contains annual information on output, employment, payroll, investment, capital stock, and intermediate inputs together with price deflators from 462 industries during the period 1958–2005. Thus, this comprises a balanced panel of 22,176 observations. The construction of this database has been discussed in the technical report of Bartelsman and Gray (1996). A detailed description of additional data is reported

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TABLE 2. OLS and control function estimation of technology parameters

	OLS			Control function	
	Cobb–Douglas	CES	K/L ratio	Cobb–Douglas	CES
β_l	0.486			0.447	
	(0.004)			(0.023)	
β_k	0.521			0.540	
	(0.004)			(0.028)	
ρ	1.007	0.989		0.987	0.817
	(0.003)	(0.004)		(0.030)	(0.113)
δ		1.818			−0.856
		(0.022)			(0.242)
σ	1	2.193	1.610	1	0.512
		(0.030)	(0.011)		(0.099)

Notes: The standard errors of estimators in the parenthesis are obtained using a panel bootstrap of 300 replications.

in Appendix A. The NBER data set offers two advantages. First, it contains input prices that are essential for characterizing a producer's optimizing behavior. Second, the large number of sectoral observations guarantees precise estimates.

The estimates presented in the following subsections are sectoral estimates at the six-digit NAICS level. As the level of aggregation may affect estimation outcomes, it is more suitable to compare these results with those of micro and sectoral studies, such as Young (2013) and Oberfield and Raval (2014).[9] In this study, I primarily focus on the estimates obtained using the full sample. For a comparison, the sectoral subsample results are reported in Appendix C.

5.1. Estimates of Technology Parameters

Table 2 reports the results obtained from three different estimation forms: the classical Cobb–Douglas equation (18), the CES-based equation (16), and the log-linearized capital–labor ratio equation [the logarithmic transformation of (6) with an exogenous error term appended]:

$$\log\left(\frac{K_{it}}{L_{it}}\right) = \sigma \log\left(\frac{\alpha}{1-\alpha}\right) + \sigma \log\left(\frac{w_{it}}{r_{it}}\right) + (\sigma - 1) b_{it} + \varepsilon_{it}. \qquad (21)$$

Two estimation methods are considered: the control function approach as the benchmark estimator for addressing endogeneity problems and the OLS estimator to illustrate the potential estimation bias. First, I estimate the three equations using the OLS estimator, in which the correlation between regressors and unobserved productivity is neglected. Next, I estimate (16) and (18) using the control function approach. In the Cobb–Douglas case, I follow the Olley–Pakes estimation procedure, in which the investment flow is used as the control variable. In the CES case,

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I use the same control variable and follow the estimation procedure proposed in Section 4.2.

León-Ledesma et al. (2010) show that the normalized CES function can help identify the distribution parameter, α, and the constant term.[10] Unlike León-Ledesma et al. (2010), the two CES-based models (16) and (21) are not explicitly normalized because the main focus of this study is on the degree of returns to scale (ρ) and the elasticity of substitution (σ). The constant term and α are not separately identified in the empirical model and thus are not the parameters of interest. From an empirical perspective, however, different choices of explicit normalizing points may influence the estimation of ρ and σ. The question is the extent to which the normalization influences the results. In Appendix B, first, I demonstrate that the normalization does not affect the estimation of (21) because the normalizing points are absorbed by the constant term. Second, in the case of (16), the normalizing points cannot be linearly separated from the regressors. Thus, the estimation of (16) depends on the normalizing value of the capital–labor income ratio. Nevertheless, I empirically assess the impact of normalizing (16) on estimates of ρ and σ. The results suggest that different choices of normalizing points did not significantly alter the main findings. Therefore, in Table 2, I report only the estimation results without explicit normalization.

The preferred estimation model is the CES-based control function approach, in which the endogeneity of regressors is controlled for and the functional form is more flexible than in the Cobb–Douglas specification. The last column of Table 2 summarizes the estimation results for this model. The estimate of returns to scale (ρ) is 0.82 with a 95% confidence interval of [0.60, 1.04], which suggests that the technology exhibits nonincreasing returns to scale. The estimated elasticity of substitution (σ) equals 0.51 with a 95% confidence interval of [0.32, 0.71]. The estimate is significantly below one, thus suggesting that the two production factors are complements.[11]

A comparison of different estimation approaches reveals that both the endogeneity problem and the technology specification affect the estimates. First, the estimates of returns to scale in the Cobb–Douglas case are larger than those obtained with the CES model. Given that the estimate of σ is less than one and that $\hat{\pi}_k + \hat{\pi}_l = -1.77$, this finding is consistent with the remark in Section 3 that the estimation of ρ based on the Cobb–Douglas specification suffers from omitted variable bias; see Table 1.

Second, the endogeneity problem appears to lead to overestimated returns to scale and elasticity of substitution. Compared with the control function estimates, the OLS estimation of (16) yields higher returns to scale and a very high elasticity of substitution. The main explanation for the difference between the OLS and the control function estimates is that a_{it} is neglected in the OLS estimation. Thus, the OLS estimator suffers from endogeneity bias caused by a_{it}, which can also be viewed as omitted variable bias, where a_{it} is omitted. The direction of this bias depends on the correlation between the regressors and the omitted variable [Cameron and Trivedi (2005, p. 93)]. Using the estimates of a_{it} obtained in the

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control function approach, I find positive correlation coefficients between this productivity index and regressors: $\text{cor}(l_{it}, \hat{a}_{it}) = 0.06$ and $\text{cor}(s_{it}, \hat{a}_{it}) = 0.61$, which suggest that the OLS estimator overestimates ρ and δ, and this bias is especially severe for δ. The overestimation of δ leads to the overestimation of σ.

Third, the OLS estimate of the elasticity of substitution based on the capital–labor equation (21) is also greater than one. In this model, the unobserved productivity term, $(\sigma - 1)b_{it}$, is omitted in the OLS estimation. Therefore, the main estimation bias of σ is caused by the correlation between the regressor $\log(\frac{w_{it}}{r_{it}})$ and the omitted term $(\sigma - 1)b_{it}$. Using the estimates of b_{it}, I find a negative correlation: $\text{cor}[\log(\frac{w_{it}}{r_{it}}), \hat{b}_{it}] = -0.54$. The control function estimate of the elasticity of substitution is less than one, which implies that the correlation between the regressor and the omitted variable is positive. Therefore, the OLS estimator overestimates σ.

5.2. Estimates of Technical Change

Most previous studies measure technical change using aggregated time series, which only provide economywide estimates for a given period of time; see, for example, Table 1 in León-Ledesma et al. (2010, p. 1335). These approaches cannot inform us about the direction of technical change in transitional stages or the heterogeneity across sectors. In this study, using disaggregated panel data, the proposed method yields time-varying and sector-specific estimates of technical change. Formally, the estimated technology parameters obtained from the CES-based control function approach are used to recover the logarithmic productivity indices, as in (19) and (20). This yields relative measures of Hicks-neutral and factor-augmenting productivity for the 462 U.S. manufacturing sectors over the period 1958–2005.

Figure 1 depicts the evolution of the average productivity indexes $\log \hat{A}_{.t}^{\text{CES}}$ and $\log \hat{B}_{.t}^{\text{CES}}$, where $\log \hat{A}_{.t}^{\text{CES}} = 1/N \sum_i \log \hat{A}_{it}^{\text{CES}}$ and $\log \hat{B}_{.t}^{\text{CES}} = 1/N \sum_i \log \hat{B}_{it}^{\text{CES}}$. The estimates obtained from the Cobb–Douglas model are also depicted and denoted by $\log \hat{A}_{.t}^{\text{CD}}$.[12] The annual growth rate of productivity indexes is computed by first-differencing the estimated series, i.e., $\triangle \log \hat{A}_{it} = \log \hat{A}_{it} - \log \hat{A}_{it-1}$ and $\triangle \log \hat{B}_{it} = \log \hat{B}_{it} - \log \hat{B}_{it-1}$. Based on these estimates, I find that (i) the average Hicks-neutral productivity growth rate $(1/NT \sum \triangle \log \hat{A}_{it})$ is 0.97% with the Cobb–Douglas model and 3.06% with the CES model; (ii) the average factor-augmenting growth rate $(1/NT \sum \triangle \log \hat{B}_{it})$ is −5.30%, which suggests that labor-augmenting technical change is about 5.30% faster than capital-augmenting technical change.

Figure 1 invites at least three comments. First, there is a substantial difference between the Cobb–Douglas and CES estimates of Hicks-neutral productivity. The CES model yields higher average growth rates than those obtained in the Cobb–Douglas model. For instance, the left panel of Figure 1 shows that the Cobb–Douglas series has a significant downward trend in the 1970s. This observation appears to coincide with the so-called U.S. productivity slowdown [Jorgenson

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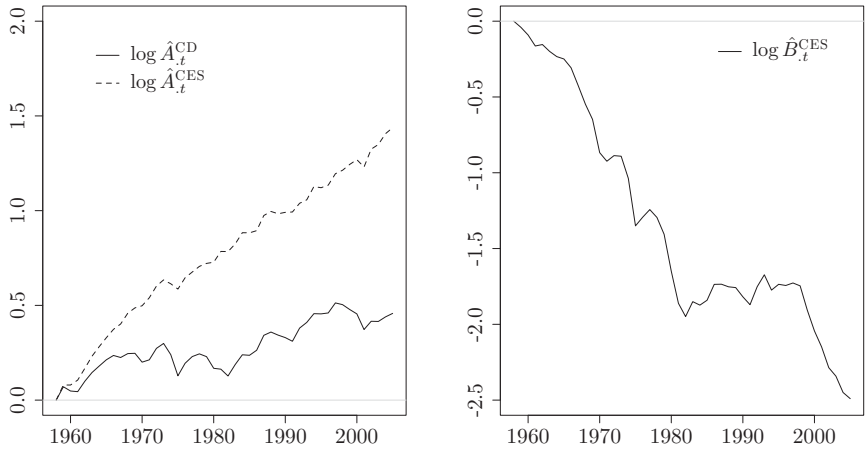


FIGURE 1. Evolution of average productivity indices. The series are normalized to zero at the base year 1959.

(2001)]. However, in the CES estimates, this productivity slowdown is much less pronounced. Second, the estimated factor-augmenting productivity has a downward trend, which suggests that technical change is generally directed toward labor-augmenting technical change. Given the estimated elasticity of substitution ($\hat{\sigma} = 0.51$), this finding is consistent with the theoretical prediction of Acemoglu (2003). When the elasticity of substitution is less than one, all firms have the incentive to pursue labor-augmenting innovation on the balanced growth path rather than capital-augmenting innovation. Third, the right panel of Figure 1 indicates a structural break in the 1980s for $\log \hat{B}_{.t}^{\mathrm{CES}}$—in which many of the sectors appear to experience a stronger capital-augmenting technical progress—thus deviating from the balanced growth path. This observation suggests that, although technical progress is likely to be labor-augmenting in the long run, it may be capital-augmenting along the transitional path. In the following paragraphs, I discuss these points in greater detail and analyze the reasons for these findings.

Figure 2 compares the Cobb–Douglas and the CES estimates for the Hicks-neutral productivity growth rate. The two series have similar dynamics and are highly correlated, i.e., $\mathrm{cor}(\triangle \log \hat{A}_{.t}^{\mathrm{CD}}, \triangle \log \hat{A}_{.t}^{\mathrm{CES}}) = 0.84$. In both series, we observe several periods for which Hicks-neutral productivity growth is substantially affected by negative shocks. The most notable shock is in the period 1970–1985, in which average annual growth is -0.79% according to the Cobb–Douglas estimate and 2.02% according to the CES estimate (compared with 0.97% and 3.06% in the full sample period, respectively). Figure 3 compares the estimates of annual productivity growth across sectors at the three-digit NAICS level. The lower panel indicates that the productivity slowdown of 1970–1985 did not affect all the sectors uniformly. For instance, both the Cobb–Douglas and the CES estimates suggest that the slowdown was particularly substantial in Sector 324 (petroleum and coal)

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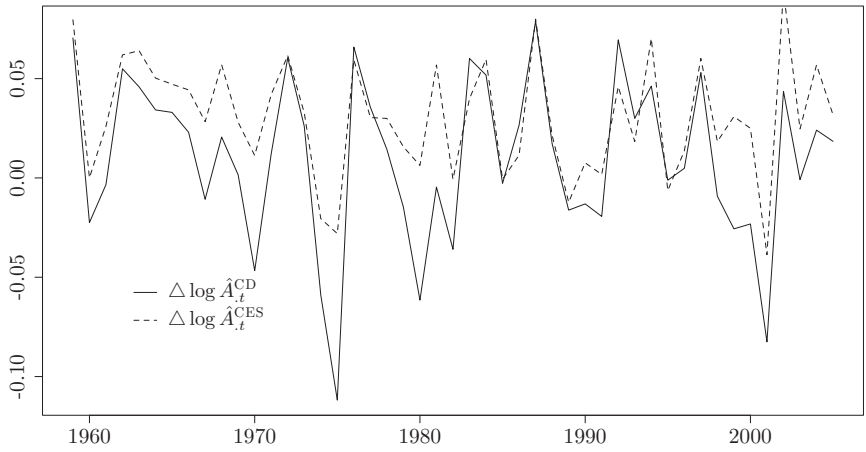


FIGURE 2. Comparison between $\triangle \log \hat{A}_{.t}^{CD}$ and $\triangle \log \hat{A}_{.t}^{CES}$.

but not in Sector 334 (computer and electronic products). This finding may be explained by the fact that the 1970s were a period of turmoil in the oil and energy markets and simultaneously marked the beginning of the ICT revolution.

The productivity slowdown is visible in both the Cobb–Douglas and the CES estimates, but it is significantly less severe when the CES model is used. For instance, the Cobb–Douglas estimates suggest that Hicks-neutral productivity in 1975 decreased by -11.18%, whereas the CES estimates suggest a much less significant change of -2.80%. Figure 3 provides another example: the Cobb–Douglas estimates indicate a productivity slowdown for Sector 312 (beverage and tobacco) during the period 1970–1985, but the CES estimates suggest an acceleration of productivity growth in this sector. The sharp difference between the two approaches can be explained by the decomposition of the productivity estimates in Section 3. Equation (12) indicates that the Cobb–Douglas estimates of Hicks-neutral productivity are biased for two reasons: the assumption of Hicks neutrality and the linear functional form. To determine the direction of this bias, I compute the average percentage changes of $\log \hat{B}_{it}^{CES}$ and of $(\log \hat{B}_{it}^{CES} \frac{K_{it}}{L_{it}})^2$, which are equal to -5.30% and -6.19%, respectively. As the estimated elasticity of substitution is less than one, the two variables affect the bias in opposite directions: $\triangle \log \hat{B}_{it}^{CES}$ causes a downward bias in the Cobb–Douglas estimates, whereas $\triangle (\log \hat{B}_{it}^{CES} \frac{K_{it}}{L_{it}})^2$ causes an upward bias. Because the distribution parameter, α, is not identified in this model, we cannot compute the exact magnitude of this bias. However, we know that $\triangle \log \hat{B}_{it}^{CES}$ is at least 52% more important in determining the direction of the bias than $\triangle (\log \hat{B}_{it}^{CES} \frac{K_{it}}{L_{it}})^2$.[13] Therefore, the analytical approximation of the bias is consistent with the numerical results, which suggests that the Cobb–Douglas model underestimates the Hicks-neutral productivity growth.[14]

Figure 4 depicts the average growth rates of factor-augmenting productivity across sectors at the three-digit NAICS level. In the full sample period

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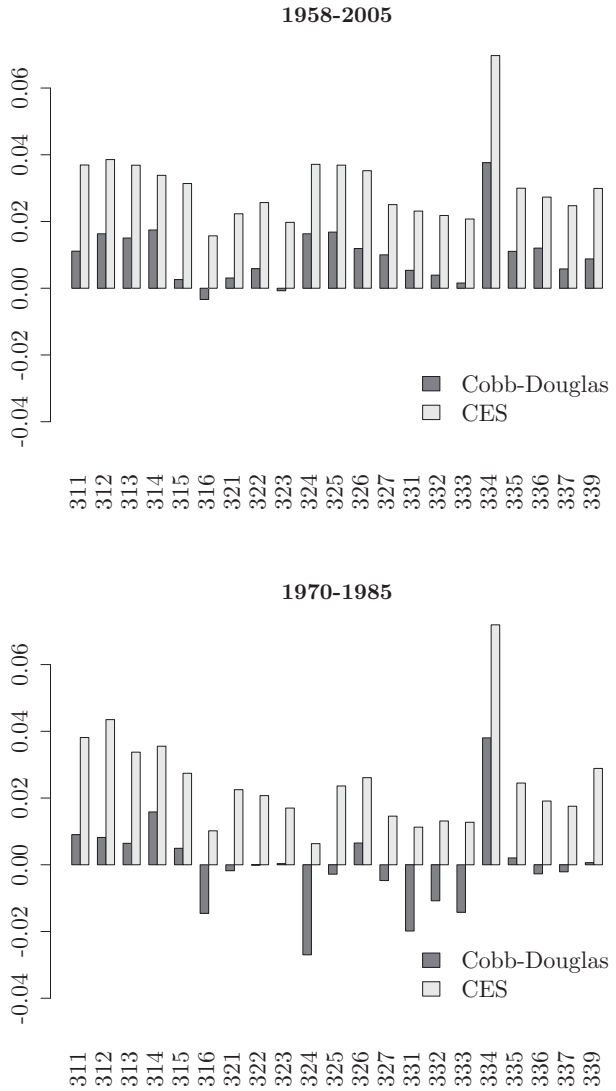


FIGURE 3. Sectoral growth rates of $\triangle \log \hat{A}_{it}^{\mathrm{CD}}$ and $\triangle \log \hat{A}_{it}^{\mathrm{CES}}$ at the three-digit NAICS level; the sectoral averages are obtained by averaging growth rates of productivity indices over the windows of observation and within the three-digit NAICS groups.

(1958–2005), $\triangle \log \hat{B}_{it}^{\mathrm{CES}}$ is generally negative, which implies that labor-augmenting productivity growth is faster than capital-augmenting productivity growth. In particular, Sectors 315 (apparel), 316 (leather and allied products), and 334 (computer and electronic products) are characterized by rapid labor-augmenting productivity growth. Acemoglu (2002, p. 792) proposes an

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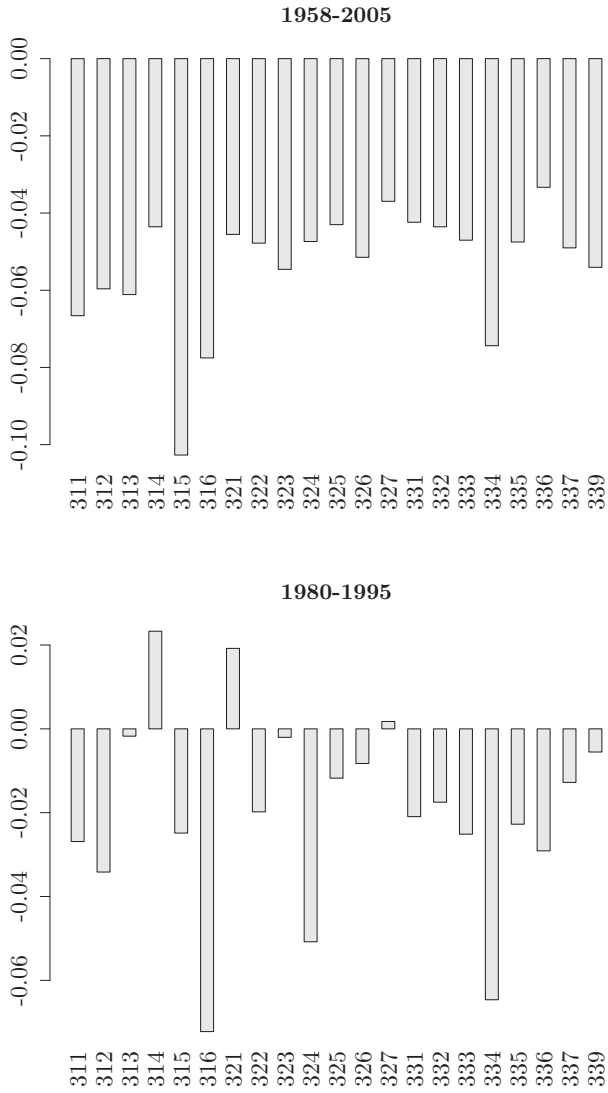


FIGURE 4. Sectoral growth rates of $\triangle \log \hat{B}_{it}^{\text{CES}}$ at the three-digit NAICS level.

endogenized technology demand model to analyze the forces that shape the direction of technical change and shows that the relative factor-augmenting technical change is determined by the elasticity of substitution (σ) and the relative factor supply ($\log \frac{K_{it}}{L_{it}}$). When the two factors are complements ($\sigma < 1$), an increase of $\log \frac{K_{it}}{L_{it}}$ decreases $\log B_{it}$. To elucidate the empirical evidence, I compute the correlation between $\triangle \log \frac{K_{it}}{L_{it}}$ and $\triangle \log \hat{B}_{it}$. The negative correlation coefficient,

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$\text{cor}(\triangle \log \frac{K_{it}}{L_{it}}, \triangle \log \hat{B}_{it}) = -0.92$, suggests that the accumulation of capital relative to labor directs technical change toward labor-augmenting. Given that the estimate of σ is less than one, this finding empirically supports the results in Acemoglu (2002).

The upper panel of Figure 4 indicates that technical progress is globally labor-augmenting in the period 1958–2005. However, technical change may become capital-augmenting in certain periods. For instance, the labor-augmenting productivity growth during the period 1980–1995 is weaker for most sectors, except for three cases: Sectors 316 (leather and allied products), 324 (petroleum and coal), and 334 (computer and electronic products). Compared with the full sample period (the average growth rate of $\triangle \log \hat{B}_{it}$ is -5.30%), a slowdown of the relative labor-augmenting productivity growth occurred during the period 1980–1995 (the average growth rate is -2.06%). Similarly to the previous paragraph, based on the results of Acemoglu (2002), this structural change can also be explained by examining the dynamics of relative factor supply. During the period 1958–2005, the average annual growth rate of $\log \frac{K_{it}}{L_{it}}$ is 3.48%. As the elasticity of substitution is below one, the deceleration of $\log \frac{K_{it}}{L_{it}}$ over the period 1980–1995 (with an annual growth rate of 2.51%) leads to a slowdown of labor-augmenting technical change. In some cases, this leads to the domination of capital-augmenting technical change and a departure from the balanced growth path (for example, Sector 314, textiles, and Sector 321, wood).

6. CONCLUSION

In this study, I develop a semiparametric approach to estimating the CES production function with biased technical change. This approach differs from the existing literature in two aspects. First, it employs the control function approach to estimate the CES production function with factor-augmenting technical change. Thus, it extends the classical microeconometric approaches that focus only on the Cobb–Douglas production function with Hicks-neutral technical change, i.e., Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2006). Second, the proposed method does not require functional restrictions on productivity indices and considers them as random variables. In this respect, it extends the previous macroeconometric studies, which include Antràs (2004), Klump et al. (2007), León-Ledesma et al. (2010), and Young (2013).

The empirical evidence presented in this paper indicates that production in U.S. manufacturing sectors is characterized by nonincreasing returns to scale and nonunitary substitution technology. Notably, the estimated elasticity of substitution between capital and labor is significantly below one. This result is critical for establishing the framework for a macroeconomic analysis. For instance, Piketty (2014) claims that capital's share rises with capital accumulation, which aggravates income inequality. However, the prediction of Piketty (2014) relies on the hypothesis that the elasticity of substitution is greater than one, whereas this

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empirical study suggests the contrary. In addition to the estimation of technology parameters, this paper also provides an empirical framework for testing theoretical predictions in the literature of biased technical change [Acemoglu (2002, 2003); Moro (2012); Li et al. (2015)]. The proposed method yields sector-specific and time-varying estimates of technical change. The estimation results suggest that technical change is generally labor-augmenting rather than capital-augmenting but that capital-augmenting technical change may become dominant along the transitional path.

Comparing different estimation approaches, this study identifies a series of potential biases in the estimation of production functions. The first source of bias is due to the assumption of Hicks neutrality and the linear functional form in the Cobb–Douglas specification, which may cause overestimation of returns to scale and underestimation of the Hicks-neutral productivity growth. In particular, the latter finding extends understanding of the U.S. productivity slowdown and is consistent with earlier research by Dupuy (2006) and León-Ledesma et al. (2015). The second source of estimation bias is the problem of endogenous regressors. The empirical results suggest that the endogeneity problem causes overestimation of returns to scale and the elasticity of substitution.

Two questions remain open for future research. First, in the current framework, both Hicks-neutral and factor-augmenting productivity are estimated relative to pure labor-augmenting productivity. Thus, an important question is whether pure capital-augmenting and labor-augmenting productivity can be separately identified in this framework. Second, this study primarily focuses on the CES production function with biased technical change. Another question is how to apply the control function approach to more flexible functional forms, such as the translog production function. Both questions require a reformulation of the control function approach and would be useful for deeper understanding of biased technical change.

NOTES

1. The Monte Carlo simulations in León-Ledesma et al. (2010) demonstrate that the system approach is able to provide more efficient estimates of technology parameters by exploring all the aspects of information incorporated into the data set.

2. One limitation of this empirical model, however, is that the pure Hicks-neutral and factor-augmenting productivity terms (A_h, B_k, and B_l) are not separately identified from (5). The estimates of productivity indices are relative to B_l.

3. In the case of $\sigma > 1$ and $\alpha \in [0, 1]$, the coefficient $\frac{(1-\alpha)(\sigma-1)}{2\sigma}$ is always below 0.5.

4. In the case of $\sigma < 1$ and $\alpha \in [0, 1]$, the absolute value $| \frac{(1-\alpha)(\sigma-1)}{2\sigma} | < 1$ implies that $\sigma > \frac{1-\alpha}{3-\alpha} \in [0, \frac{1}{3}]$. If $\sigma > 1/3$, we can safely say that $\log B_{it}^{\text{CES}}$ is the more important determinant of the bias.

5. For instance, the control function approach is used for triangular simultaneous equations models in Imbens and Newey (2009) and for treatment effect models in Heckman and Vytlacil (2007).

6. Replacing x with $g(z, v)$ yields $\mathrm{E}[u \mid x, v] = \mathrm{E}[u \mid g(z, v), v] = \mathrm{E}[u \mid z, v]$. Because z is uncorrelated with u and v, we can obtain $\mathrm{E}[u \mid z, v] = \mathrm{E}[u \mid v]$.

7. In this example, I present only the case in which the control variable is observed (and the instrument is missing). When the instrument is observed, instead, the control function approach can

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also be applied by taking the estimated conditional CDF of x given z as the control variable (Imbens and Newey, 2009).

8. More discussion of the identification condition and estimation procedure of the Cobb–Douglas function can be found in Ackerberg et al. (2006).

9. Solow (1964) suggests that the elasticity of substitution should be smaller for more narrowly defined industrial classifications. Basu and Fernald (1997) and Basu (2008) show that estimates of returns to scale also vary with the level of aggregation; in particular, the estimates seem smaller in disaggregated data. Young (2013) estimates the CES function using U.S. data at the two-digit SIC level. Oberfield and Raval (2014) provides plant-level estimates for the U.S. manufacturing sector.

10. The normalization is essentially an alternative representation of the CES production function in which the income parameter, α, and the constant have clear economic interpretations. Formally, the explicit normalization consists of fixing a set of benchmark values for level of output, inputs, and input prices; see León-Ledesma et al. (2010) and Klump et al. (2012).

11. The similar results documented in the literature include Young (2013), who finds that the elasticity of substitution at two-digit sectoral-level is likely to be below 0.6; and Oberfield and Raval (2014), who find that the average elasticity in 1987 is 0.5 at the plant level. Macro-level studies also suggest that the elasticity of substitution in the U.S. economy is likely to be between 0.4 and 0.6 [Chirinko (2008); León-Ledesma et al. (2015)].

12. In the Cobb–Douglas model, the estimates of $\log \hat{A}_{it}$ are computed as the usual Solow residuals: $\log \hat{A}_{it}^{\mathrm{CD}} = \log Y_{it} - \hat{\beta}_l \log L_{it} - \hat{\beta}_k \log K_{it}$.

13. Given that $\hat{\sigma} = 0.51$, if $\alpha \rightsquigarrow 0$, the coefficient $(1-\alpha)(\hat{\sigma}-1)/2\hat{\sigma} = -0.48$. Thus, equation (12) becomes $\triangle \log A_{it}^{\mathrm{CD}} = \triangle \log A_{it}^{\mathrm{CES}} + \rho\alpha[\triangle \log B_{it}^{\mathrm{CES}} - 0.48\triangle(\log B_{it}^{\mathrm{CES}} \frac{K_{it}}{L_{it}})^2]$. When $\alpha > 0$, the absolute value of $(1-\alpha)(\hat{\sigma}-1)/2\hat{\sigma}$ becomes even smaller.

14. Dupuy (2006) uses a different approach to study the consequences of neglecting nonneutral technical change in the production specification and the implications on the analysis of the U.S. productivity slowdown. He finds that "i) both neutral and non neutral technical change have occurred in the US in the period 1948–1999 and ii) 3/4 of the productivity slowdown observed in the 70s and 80s is due to a deceleration in the contribution of non neutral technical changes."

15. The database is accessible at www.nber.org/nberces/nbprod96.htm.

16. See the website www.census.gov/manufacturing/asm/index.html.

17. See the website www.bea.gov/national/nipaweb/Index.asp.

18. The ASM define fringe benefits as 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.

19. See the website www.census.gov/eos/www/naics/concordances/concordances.html.

20. The variation rate of fringe benefits in the period t of a six-digit sector is $F_{t-1}^{6-digit} \cdot (1 + F_t^{5-digit}/F_{t-1}^{5-digit})$, where F denotes the fringe benefits rate.

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APPENDIX A: PRESENTATION OF DATA SETS AND VARIABLES

The main source of information is the NBER-CES manufacturing industry databases.[15] These data essentially reflect the Annual Survey of Manufactures (ASM) conducted by the U.S. Census Bureau, which aggregates approximately 50,000 establishments to 473 six-digit NAICS manufacturing sector groups for the period 1958–2005.[16]

A.1. CONSTRUCTION OF CAPITAL PRICE

The NBER database provides the capital stock (K). The rental price of capital (P_K) can be computed using the investment price index (P_I). Consider the following formula: $P_{K,t} = P_{I,t}(1+\pi_t) - \mathrm{E}_t[(1-\tau_t)P_{I,t+1}]$, where π denotes the nominal interest rate. In this study, I use the 10-year U.S. treasury constant maturity rate from the Federal Reserve Bank of St. Louis. The parameter τ is the physical depreciation rate. The depreciation rate can be computed using the classical capital accumulation equation, $K_t = I_t + (1-\tau_t)K_{t-1}$, or set to be constant (in this paper, I use a constant rate of 8%). Assuming that there are no expectation errors on $P_{I,t+1}$, this formula can be simplified as $P_{K,t} = P_{I,t}(\tau + \pi_t)$.

A.2. CONSTRUCTION OF FRINGE BENEFITS

Neither the legally mandated payment (e.g., social security), nor the employer payment for other fringe benefits is included in the variable *payroll* in the NBER data set. Therefore, labor costs are systematically understated by this data set. To correct this bias, we must include fringe benefits. To this end, additional information is required, particularly the fringe benefit share, i.e., fringe benefits/total compensation. Two sources of information can be used, the 1992–2005 ASM tables and the National Income and Product Account (NIPA) tables from BEA. The NIPA tables (particularly Tables 6.2–6.3 and Tables 6.10–6.11) record the compensation of employees, wage and salary accruals, legally required social insurance, and pension and insurance funds from 1948 to 2010 for 21 two-digit

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SIC sector groups.[17] We can use these data to cover the period 1958–1991 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 1982–1992, we can find the value of fringe benefits recorded in the SIC classification system, whereas for the period 1997–2005, the data are collected in NAICS. The total fringe benefit is the employer's cost for legally required social insurance, employee pensions, and insurance funds.[18] 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 pensions, and insurance funds (the two methods yield 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 fringe benefits into the NBER database is that the data are recorded at different aggregation levels and in different industrial classification systems before 1997. We converted the two-digit SIC data (for the period 1958–1990) of NIPA tables and the four-digit SIC data (for the period 1991–1996) of ASM tables into NAICS data, according to the concordance proposed by the Census Bureau.[19]

A.3. SOURCES OF MISSING VALUES

The main source of missing values is that the data regarding fringe benefits from the NIPA tables are only available at the two-digit SIC level. Therefore, we assume that the fringe benefits are invariant across sectors within the two-digit SIC industry group. The second source of missing values is that some six-digit NAICS sectors are not recorded in the ASM tables for the period 2002–2005. In this case, we replace the missing values with the variation rate of corresponding five-digit NAICS sectors.[20] The third source of missing values is the concordance relationships between the four-digit SIC and six-digit NAICS classification systems. Some NAICS industry groups correspond to several SIC industry groups. Thus, the fringe benefits of the NAICS sector are computed as the average of the fringe benefits of its SIC counterparts. In some cases, the corresponding SIC groups are not manufacturing industries in the NAICS system. Consequently, their fringe benefits data are not available, and we simply disregard these nonmanufacturing SIC industry groups when computing average fringe benefits. Finally, we obtain a balanced panel data set that contains the output, adjusted labor costs, capital costs, and investment and material input costs with price deflators for 462 NAICS manufacturing industry groups over the period 1958–2005.

APPENDIX B: EMPIRICAL IMPLICATIONS OF THE NORMALIZED CES FUNCTION

From an empirical perspective, the difference in the choice of explicit normalizing points may influence the estimation results of ρ and σ. The impact of normalization on the estimation results depends on the chosen estimation form. To illustrate this point, I consider a normalized CES production function:

$$\log\left(\frac{Y_{it}}{Y_0}\right)=\rho\log\left(\frac{L_{it}}{L_0}\right)+\frac{\rho\sigma}{\sigma-1}\log\left[\alpha_0\left(\frac{B_{it}}{B_0}\frac{K_{it}/K_0}{L_{it}/L_0}\right)^{\frac{\sigma-1}{\sigma}}+(1-\alpha_0)\right]+\log\left(\frac{A_{it}}{A_0}\right)+\varepsilon_{it}.$$

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The normalized capital–labor ratio can be written as

$$\log\left(\frac{K_{it}/K_0}{L_{it}/L_0}\right)=\sigma\log\left(\frac{\alpha_0}{1-\alpha_0}\right)+\sigma\log\left(\frac{w_{it}/w_0}{r_{it}/r_0}\right)+(\sigma-1)\log\left(\frac{B_{it}}{B_0}\right)+\varepsilon_{it}.$$

Y_0, L_0, K_0, A_0, B_0, w_0, and r_0 denote the normalizing points; α_0 is the normalized distribution parameter, which can be interpreted as the capital income share evaluated at the normalizing points. ε_{it} is the exogenous error term in both specifications. We can rearrange both equations by collecting all the normalizing points in the linear terms:

$$\log Y_{it}=\underbrace{\log Y_0-\rho\log L_0-\log A_0}_{\text{constants}}+\rho\log\,(L_{it})$$
$$+\frac{\rho\sigma}{\sigma-1}\log\left[\alpha_0\left(\frac{B_{it}}{B_0}\frac{K_{it}/K_0}{L_{it}/L_0}\right)^{\frac{\sigma-1}{\sigma}}+(1-\alpha_0)\right]+\log A_{it}+\varepsilon_{it};$$

$$\log\left(\frac{K_{it}}{L_{it}}\right)=\underbrace{\log\left(\frac{K_0}{L_0}\right)-\sigma\log\left(\frac{w_0}{r_0}\right)-(\sigma-1)\log B_0+\sigma\log\left(\frac{\alpha_0}{1-\alpha_0}\right)}_{\text{constants}}$$
$$+\sigma\log\left(\frac{w_{it}}{r_{it}}\right)+(\sigma-1)\log B_{it}+\varepsilon_{it}.$$

All the normalizing points in the capital–labor ratio equation are collected in a constant term. Thus, the normalization does not affect the estimation of σ. In the case of the production function, because of the nonlinearity of the CES function, the normalizing points cannot be linearly separated from the regressors. Thus, the normalization may affect the estimation of ρ and σ based on the production function. To determine how it influences the estimation results of (16), I use the same substitute for the nonlinear function as in (15):

$$\log\left[\alpha_0\left(\frac{B_{it}}{B_0}\frac{K_{it}/K_0}{L_{it}/L_0}\right)^{\frac{\sigma-1}{\sigma}}+(1-\alpha_0)\right]$$
$$=\log(1-\alpha_0)+\log\left(\tfrac{w_0L_0}{r_0K_0}\right)+\underbrace{\log\left(\frac{r_{it}K_{it}}{w_{it}L_{it}}+\frac{r_0K_0}{w_0L_0}\right)}_{\log\tilde{S}_{it}}.$$

Thus,

$$\log Y_{it}=\log Y_0-\rho\log L_0-\log A_0+\tfrac{\rho\sigma}{\sigma-1}\log(1-\alpha_0)+\tfrac{\rho\sigma}{\sigma-1}\log\left(\tfrac{w_0L_0}{r_0K_0}\right)$$
$$+\rho\log\,(L_{it})+\frac{\rho\sigma}{\sigma-1}\log\left(\frac{r_{it}K_{it}}{w_{it}L_{it}}+\frac{r_0K_0}{w_0L_0}\right)+\log A_{it}+\varepsilon_{it}.$$

The differences between the explicit normalized and the nonnormalized CES function are found in the constant term and in the regressor $\log\tilde{S}_{it}=\log(\frac{r_{it}K_{it}}{w_{it}L_{it}}+\frac{r_0K_0}{w_0L_0})$. Empirically,

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only the difference in the regressor affects the estimation of ρ and σ. The nonnormalized model (16) with $\log S_{it} = \log(\frac{r_{it}K_{it}}{w_{it}L_{it}} + 1)$ is equivalent to the normalized model with a particular choice of normalizing point such that the benchmark value $\frac{r_0K_0}{w_0L_0} = 1$. To test the sensitivity of the estimates to different normalization points, I estimate the model with benchmark values: $\frac{r_0K_0}{w_0L_0} = 0.5$ and 1.5. When the benchmark value of capital–labor income share is 1.5, I obtain $\hat{\rho} = 0.88$ and $\hat{\sigma} = 0.52$. When the benchmark value is 0.5, $\hat{\rho} = 0.76$ and $\hat{\sigma} = 0.46$. Comparing the results reported in Table 2 with $\frac{r_0K_0}{w_0L_0} = 1$ ($\hat{\rho} = 0.82$ and $\hat{\sigma} = 0.51$) reveals that the estimates are not statistically different.

APPENDIX C: ESTIMATION WITH STRATIFIED SAMPLES

The estimates in Section 5 are obtained by assuming that all sectors have the same production technology. In Table 3, I report the subsample estimates. I stratify the full sample according to the three-digit NAICS sectoral classification and perform the regressions for each subsample. Chirinko (2008) notes that most macroeconomic studies focus on estimating the aggregate production function, whereas a technology parameter, such as σ, may differ across sectors. The exercise in this Appendix demonstrates that significant sectoral variations are present in all estimates of interest. However, the weighted average estimates of these parameters do not differ significantly from the corresponding aggregate estimates.

In Table C.1, 19 subgroups in the manufacturing industry are considered. I estimate the Cobb–Douglas and the CES model using the control function approach. The average growth rates of productivity are obtained by regressing $\log \hat{A}_{.t}$ and $\log \hat{B}_{.t}$ on a linear trend (denoted as g_A and g_B, respectively). In 12 sectors, the results are similar to the full sample estimation. Based on the CES estimation results, I find the following in these 12 cases: (i) the production technology exhibits nonincreasing returns to scale, and the Cobb–Douglas estimates of returns to scale are higher than the CES estimates; (ii) the estimated elasticities of substitution are less than one; (iii) the CES estimates of Hicks-neutral productivity growth are higher than those of the Cobb–Douglas model; and (iv) the estimates of g_B indicate that labor-augmenting productivity growth is faster than capital-augmenting productivity growth. In the remaining seven cases, however, the CES estimation does not produce consistent results. In particular, the estimates of σ are not significantly different from one. Therefore, the Cobb–Douglas specification cannot be rejected in these cases.

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TABLE C.1. Subsample estimation

			Cobb–Douglas				CES				
NAICS	Obs.	Weights	β_l	β_k	ρ	g_A	ρ	δ	σ	g_A	g_B
311*	2112	0.080	0.342	0.472	0.815	0.014	0.527	−1.031	0.662	0.036	−0.082
			(0.099)	(0.274)	(0.297)		(0.166)	(0.275)	(0.131)		
312	432	0.027	0.411	1.041	1.452	0.006	−0.222	−1.478	1.176	0.024	0.103
			(0.281)	(0.360)	(0.461)		(0.553)	(0.585)	(2.109)		
313–314	864	0.020	0.422	0.495	0.917	0.016	0.542	−0.237	0.304	0.028	−0.036
			(0.164)	(0.161)	(0.158)		(0.115)	(0.312)	(2.808)		
315	1104	0.025	0.369	0.497	0.867	0.005	0.501	−1.848	0.787	0.023	−0.173
			(0.087)	(0.208)	(0.214)		(0.346)	(1.640)	(1.643)		
316*	480	0.005	0.509	0.264	0.773	−0.001	0.748	−2.617	0.778	0.019	−0.165
			(0.056)	(0.201)	(0.211)		(0.236)	(0.866)	(0.171)		
321*	672	0.018	0.527	0.354	0.881	0.008	0.553	−1.219	0.688	0.022	−0.054
			(0.133)	(0.074)	(0.123)		(0.160)	(0.408)	(0.117)		
322*	960	0.037	0.465	0.088	0.553	0.017	0.709	−0.535	0.430	0.022	−0.040
			(0.082)	(0.293)	(0.312)		(0.112)	(0.267)	(0.159)		
323	576	0.027	0.602	0.450	1.052	0.003	0.926	−0.427	0.316	0.017	−0.034
			(0.115)	(0.191)	(0.180)		(0.396)	(0.838)	(0.814)		
324–325*	1872	0.123	0.583	0.471	1.054	0.014	0.725	−0.963	0.571	0.032	−0.047
			(0.079)	(0.060)	(0.065)		(0.108)	(0.200)	(0.081)		
326	768	0.033	0.454	0.542	0.996	0.012	0.491	−0.863	0.637	0.039	−0.054
			(0.141)	(0.118)	(0.068)		(1.559)	(2.282)	(0.307)		
327*	1152	0.029	0.425	0.538	0.963	0.008	0.831	−0.818	0.496	0.020	−0.030
			(0.058)	(0.117)	(0.120)		(0.127)	(0.186)	(0.086)		
331	1248	0.047	0.489	0.430	0.920	0.005	0.378	−1.004	0.726	0.016	−0.066
			(0.029)	(0.038)	(0.032)		(0.270)	(0.302)	(0.178)		
332*	2064	0.071	0.524	0.424	0.947	0.005	0.832	−0.624	0.428	0.018	−0.038
			(0.047)	(0.045)	(0.035)		(0.064)	(0.200)	(0.090)		
333*	2352	0.077	0.526	0.473	0.999	0.000	0.837	−0.698	0.455	0.016	−0.043
			(0.050)	(0.046)	(0.033)		(0.064)	(0.207)	(0.080)		
334	1344	0.079	0.064	0.831	0.895	0.026	−0.422	−5.771	1.079	0.097	0.224
			(0.288)	(0.201)	(0.212)		(0.516)	(2.100)	(0.106)		
335*	1056	0.033	0.451	0.587	1.038	0.008	0.580	−1.647	0.740	0.029	−0.075
			(0.077)	(0.068)	(0.075)		(0.132)	(0.421)	(0.100)		
336*	1440	0.124	0.583	0.568	1.151	0.006	0.903	−0.869	0.490	0.024	−0.040
			(0.059)	(0.071)	(0.078)		(0.143)	(0.385)	(0.132)		
337*	576	0.015	0.388	0.570	0.959	0.004	0.876	−1.196	0.577	0.022	−0.049
			(0.116)	(0.126)	(0.141)		(0.067)	(0.408)	(0.087)		
339*	1104	0.026	0.488	0.630	1.118	0.005	0.651	−1.205	0.649	0.026	−0.060
			(0.089)	(0.131)	(0.145)		(0.094)	(0.461)	(0.184)		
Mean	—	—	0.508	0.476	0.984	0.009	0.752	−0.924	0.542	0.025	−0.050

Notes: The sector groups with superscript * have significant CES estimates. The weights are computed as the value added of the group divided by the total sample value. The average of estimates is the mean of the 12 significant estimates, weighted by their share of value added.

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