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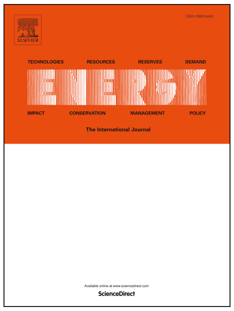

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Energy-biased Technical Change in the Chinese Industrial Sector with CES Production Functions

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Abstract

We develop a theoretical framework to study energy-biased technical change considering capital, labor and energy as inputs. The framework involves a first order condition estimation of elasticity and technical change parameters for a three factor-nested Constant Elasticity of Substitution (CES) function. Technical change parameters, elasticities and time derivatives of marginal products are combined to compute technical change bias. Conceptually, we introduce total bias in order to estimate the direction without requiring a direct comparison with another factor. For Chinese industries from 1990 to 2012, the optimal structure is capital and energy to be combined at the composite level and then with labor to form total output. Technical change is found to be unambiguously energy biased, it increases in every year, and the bias is predominately away from labor. The results show that Chinese industrialization was fuelled by fossil fuels and energy-intensive technologies. Nonetheless, the growth rate of energy-biased technical change decreased during the 2000s that may result from more energy efficient development.

Key words: Biased technological change; CES production function; Elasticity of substitution

1. Introduction

Hicks [1] ideologically introduced technical change bias considering only two factors, capital, and labor. It means technical change is biased towards a factor if it increases the marginal product of that factor more than the other factor. Since then, predominately two factors of production models have been adopted, mainly on capital relative to labor. The Hicks program of labor-saving bias has been the focus of controversies surrounding the direction of technical change [2]. For instance, according to Abramovitz [3], technology favored physical capital

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in the 19th century. While Sato [4] indicated that technological progress was labor-saving over the period 1909-1960. In a widely cited contribution, Acemoglu [5] suggested that when technical progress is asymptotically labor-augmenting, it may become capital-biased in transition to induce factor-saving innovations. Acemoglu [6] pointed out that in the late 18th and early 19th century technology favored low-skilled workers whereas more recently evidence seems to suggest a bias in favor of high-skilled workers. Similarly, Verschelde et al. [7] pointed towards low-skilled labor-saving technical change using firm level data from 1995-2011. From the previous research it has been found that Hicks neutrality is not supported by the data in any given sector. We should consider the technical change bias in the production function.

In order to estimate the technical change of three inputs, we would employ a nested CES function rather than a two-factor CES. Within the three factor-nested CES function, we could obtain technical change parameters and elasticity of substitution of inputs. We then combine the technical change parameters with time derivatives of the marginal products to derive relative bias. It is used to compare bias between any two inputs. However, relative technical change bias does not provide a single bias for a given factor. Consequently, we introduce the concept of total bias for any one of the factors of production. We put forward this definition to determine the biased technical change for various factors rather than two factors. This is to detect the bias of a specific factor in a muti-input production process.

The theoretical framework is used to understand the technical change bias in China. China has been one of the fastest growing economies over the last 30 years largely supported by energy consumption. Economic growth exceeded 10% annually from 2000 to 2011 [8] and it became the world's largest energy consumer [9]. Furthermore, China is the world’s leading energy-related CO_2 emitter [10]. As a result of the significant energy consumption, the economic growth and the CO_2 emissions, studying China’s energy-biased technical change has clear global implications. There is a case for directed policy intervention to limit the detriment to the environment. However, there is no study devoted on estimating China’s energy bias technical change. The empirical contribution of this paper is to estimate the relative bias, total bias, the change in bias over time. We provide a test for factor biases in manufacturing sectors with distinct characteristics without imposing a parametric specification of the production function.

The paper is structured as follows. The following section is literature review. The third section develops the nested CES production function, the derivation of the first order estimation of the technology and elasticity parameters. After which technical change relative bias and total bias are introduced. The fourth section presents the data and results. The final section discusses further research and concludes.

2. Literature Review

As a result of the pressing problems of energy security and climate change, energy seems to be an indispensable production factor under separability aspects in energy and climate modeling [11]. For example, in Fare [12]'s study for the relationship between environmental production functions and environmental directional distance functions, the inputs consist of the capital stock, the number of employees, and the heat content (in Btu) of the coal, oil, and natural gas consumed at the plant. In recent studies, Lin and Astagli [13] took consumption of petroleum and electricity coal consumption as well as capital formation and labor as inputs when they applies the translog production function to investigate technical change and energy substitution possibilities. For China, Xie and Hawkes [14] investigated the potential for inter-fuel substitution between coal, oil, natural gas and electricity in China's transport industry. Long et al [15] used the input matrix to include labor, capital, coal, electricity, and clinker to study the convergence analysis of eco-efficiency of China's cement manufacturers. To choose the optimal bundle among energy and non-energy inputs, Zha and Zhou [16] proposed to combine the translog cost function and CES function.

For the topic of bias of technical change, the limited number of empirical studies indicates that technical change can be either energy-using or energy-saving [17, 18]. Karanfil and Yeddir-Tamsamani [19] estimated a translog cost-share system investigating technical bias in the French economy. They pointed out that bias is sensitive to energy prices and their verdict is mixed. Vogel et al. [20] also used a translog cost-share system studying EU countries. They found a small energy bias. In fact, when technical change increases the productivity of inputs that are gross complements to energy, the demand of energy will increase, with negative effects on energy reduction and environment [21-23]. Therefore, whether technical change is energy biased depends on the elasticity of substitution between energy and non-energy inputs. Excluding biased technical change can bias estimates of substitution toward unity [24]. The deep interconnections between factor substitution and technical change are also emphasized in [25]. For energy specific factor, technical change bias can be used to promote energy efficiency and to design climate policy [26].

Despite the importance of elasticities and technical change bias in economics, and efforts devoted to their identification, there seems little empirical consensus on their value and nature [27]. Empirical research has been hampered by the difficulties in identifying at the elasticity of substitution as well as technical change for more than two-factor case [28]. However, the bias depends on the elasticity between energy and non-energy inputs, which cannot be easily considered together, like the mentioned translog cost function. These regressions therefore conflate the impact of the factor bias with the impact of factor substitution. The second drawback is that output elasticities, the basis of factor bias estimation, can be negative, which violates the warranted monotonicity property (i.e. strong or free disposability). This implies that more inputs cannot lead to less output and producing less output cannot lead to more input use [7]. Theoretically, CES is considered as the most viable estimation technique [29]. A major reason is that it is more structured and has a smaller number of parameters to estimate than the translog function [30]. The two standard approaches to estimating the parameters of CES functions are the linear Taylor-series approximation developed by [31] and the non-linear least squares estimation. However, the applicability of the so-called Kmenta approximation is limited as it cannot be used to linearise CES functions with more than two inputs. Specifically, the model would suffer from severe fitting errors [32]. Conversely, the estimation of the non-linear CES function frequently performs poorly [33].

3. Methodology

3.1 CES nested production function

The nested CES function is adopted to allow for the elasticity of substitution to differ between input pairs [34]. It allows identification of elasticities of substitution at the lower and the upper levels of the CES nesting and test the nature of technological change of all input factors. In order to determine the best fit for Chinese industry, three nested CES functions are considered. The three nested functions for capital (K), labor (L) and energy (E) are (KL)E, (KE)L and (EL)K which are specified below respectively[①]. For example, (KL)E signifies K and L to be combined at the composite level Z and then with E to form total output.

$$Y_t = \{\beta[\alpha(A_t K_t)^{-\rho_1} + (1-\alpha)(B_t L_t)^{-\rho_1}]^{\frac{\rho}{\rho_1}} + (1-\beta)(C_t E_t)^{-\rho}\}^{-\frac{1}{\rho}} \tag{1}$$

$$Y_t = \{\beta[\alpha(A_t K_t)^{-\rho_1} + (1-\alpha)(C_t E_t)^{-\rho_1}]^{\frac{\rho}{\rho_1}} + (1-\beta)(B_t L_t)^{-\rho}\}^{-\frac{1}{\rho}} \tag{2}$$

$$Y_t = \{\beta[\alpha(C_t E_t)^{-\rho_1} + (1-\alpha)(B_t L_t)^{-\rho_1}]^{\frac{\rho}{\rho_1}} + (1-\beta)(A_t K_t)^{-\rho}\}^{-\frac{1}{\rho}} \tag{3}$$

Y is the total output, *K*, *L* and *E* are the inputs of capital, labor, and energy respectively. *A*, *B* and *C* stand for capital, labor and energy augmenting technological progress, respectively. *t* is a time trend. The distribution parameter $\alpha \in (0,1)$ represents the contribution ratio of capital to output. $\beta \in (0,1)$ determines the importance of the factor in the production function. $\rho \in (-1,\infty)$ and $\rho_1 \in (-1,\infty)$ are the elasticities of substitution. When ρ=0, the CES production function reduces to the Cobb-Douglas production function. When $\rho \to -1$, it becomes the linear production function with perfect substitution. When $\rho \to \infty$, it becomes the Leontief function with zero elasticity of substitution.

[①] Due to data unavailability for materials in industry, it is not considered in the present paper. According to Frondel and Schmidt [29], the estimates are quite irrelevant whether or not a static translog study incorporates materials.

3.2 The estimation of the elasticity of substitution with biased technological change

Our estimation of the 2-level 3-input CES production function refers to [18]. We both use ratios of first-order conditions to estimate the parameters of three nested structures. However, he focused on the nested production structure. When we applied the method, we normalized CES production function, which has been emphasized on the parameters of aggregated CES production function [35]. Because due to the normalization of CES functions, all the parameters of the derived aggregate production function can be provided with sound interpretation [28, 36]. This normalization has been successfully applied in a series of theoretical papers investigating a wide variety of topics [37].

The technology change is usually simulated through factor-augmenting multipliers, here we suppose:

$$A_t = A_0 e^{\gamma(t-t_0)},\ B_t = B_0 e^{\mu(t-t_0)},\ C_t = C_0 e^{\nu(t-t_0)} \tag{4}$$

In this form, technical change is represented as a time-dependent multiplier on the production function. γ, μ, ν are the technological change parameters for capital, labor, and energy respectively. As we normalize to the base year, we determine a different estimation γ, μ, ν for each of the three nested CES functions. A_0, B_0, C_0 are technical change parameters at the base year. We assume technology is progressing and consequently these parameters are always positive. When they are normalized, their expressions would differ with the nested structures. For instance for (KL)E, A_0, B_0, C_0 are defined below:

$$A_0 = (\alpha_0)^{-1/\rho_1}(\beta_0)^{-1/\rho}\frac{Y_0}{K_0} \tag{5}$$

$$B_0 = (1-\beta_0)^{-1/\rho_1}\frac{Y_0}{L_0} \tag{6}$$

$$C_0 = (1-\alpha_0)^{-1/\rho_1}(\beta_0)^{-1/\rho}\frac{Y_0}{E_0} \tag{7}$$

There are two steps to estimating the CES function. In the first step, we estimate the optimal demand for K and L per unit of Z. The first order condition estimation starts with the production functions as follows:

$$Z_t = [\alpha(A_t K_t)^{-\rho_1} + (1-\alpha)(B_t L_t)^{-\rho_1}]^{-1/\rho_1} \tag{8}$$

In the second step, the value added Z and P_Z are used to estimate the optimal demand for E and Z per unit of Y. The demand of K, L and E under the optimal condition is then obtained.

$$Y_t = \{\beta Z_t^{-\rho} + (1-\beta)(C_t E_t)^{-\rho}\}^{-1/\rho} \tag{9}$$

Applying Shephard's lemma on the cost function $C(P_Z, P_E, \overline{Y})$, we derive following equations:

$$\ln(\frac{Z}{Y}) = \frac{1}{1+\rho}\ln\beta_0 + \frac{1}{1+\rho}\ln(\frac{P_Y}{P_Z}) \tag{10}$$

$$\ln(\frac{E}{Y}) = \frac{1}{1+\rho}\ln(1-\beta_0) - \frac{\rho}{1+\rho}c(t-t_0) + \frac{1}{1+\rho}\ln(\frac{P_Y}{P_E}) \tag{11}$$

By first order difference $\ln I_t - \ln I_{t-1} = i$, $\ln P_t^I - \ln P_{t-1}^I = p_I$, $I = K,L,E$; $\ln U_t - \ln U_{t-1} = u$ ($u = \gamma,\mu,\nu$, $U = A,B,C$), and $\sigma = \frac{1}{1+\rho}$, $\sigma_1 = \frac{1}{1+\rho_1}$, then:

$$e - y = (\sigma - 1)\nu + \sigma(p_Y - p_E) \tag{12}$$

$$z - y = \sigma(p_Y - p_Z) \tag{13}$$

Consequently, the following two equations can be derived from Eq. (8):

$$k - z = (\sigma_1 - 1)\gamma + \sigma_1(p_Z - p_K) \tag{14}$$

$$l - z = (\sigma_1 - 1)\mu + \sigma_1(p_Z - p_L) \tag{15}$$

As p_Z and z are intermediate variables and unable to be observed, they should be replaced. Thus we add $p_Z - p_Y$ to Eq. (13) and $p_K - p_Z$ to Eq. (14) respectively, then we get:

$$p_Y - p_Z = \frac{p_Z + z - (p_Y + y)}{\sigma - 1} \tag{16}$$

$$p_K + k - (p_Z + z) = (\sigma_1 - 1)\gamma + (\sigma_1 - 1)(p_Z - p_Y - (p_K - p_Y)) \tag{17}$$

Substituting Eq. (16) into Eq. (17) gives:

$$p_K + k - (p_Z + z) = (\sigma_1 - 1)\gamma + (\sigma_1 - 1)(\frac{p_Z + z - (p_Y + y)}{1-\sigma} - (p_K - p_Y)) \tag{18}$$

Suppose $p_I + i - (p_J + j) = \tilde{G}_{ij}$, $J = Z,Y$. $\tilde{G}_{ij}$ is the change in the share of I in the production J. Eq.(18) can be shown:

$$\tilde{G}_{KZ} = (\sigma_1 - 1)\gamma + \frac{\sigma_1 - 1}{1-\sigma}\tilde{G}_{ZY} + (1-\sigma_1)(p_K - p_Y) \tag{19}$$

Similarly, we can give the expression of $\tilde{G}_{LZ}$ as:

$$\tilde{G}_{LZ} = (\sigma_1 - 1)\mu + \frac{\sigma_1 - 1}{1-\sigma}\tilde{G}_{ZY} + (1-\sigma_1)(p_L - p_Y) \tag{20}$$

The first-order conditional estimation substitutes the change of the combination of the factors for the change of price and quantity of intermediate variables ($p_Z + z = d\ln(P_K K + P_L L)$). Thus $\tilde{G}_{KZ}$ and $\tilde{G}_{LZ}$ can be estimated. We are now to derive a system of three equations by equations (12), (13) and (20):

$$\begin{cases} e-y=(\sigma-1)\nu+\sigma(p_Y-p_E) \\ \tilde{G}_{KZ}=(\sigma_1-1)\gamma+\dfrac{\sigma_1-1}{1-\sigma}\tilde{G}_{ZY}+(1-\sigma_1)(p_K-p_Y) \\ \tilde{G}_{LZ}=(\sigma_1-1)\mu+\dfrac{\sigma_1-1}{1-\sigma}\tilde{G}_{ZY}+(1-\sigma_1)(p_L-p_Y) \end{cases} \tag{21}$$

The linear expression of Eq. (21) is:

$$\begin{cases} y_1=\alpha_1+\beta_1x_1 \\ y_2=\alpha_2+\beta_2x_{21}+\beta_3x_{22} \\ y_3=\alpha_3+\beta_2x_{21}+\beta_3x_{32} \end{cases} \tag{22}$$

Where $\alpha_1=(\sigma-1)\nu$, $\alpha_2=(\sigma_1-1)\gamma$, $\alpha_3=(\sigma_1-1)\mu$. $\beta_1=\sigma$, $\beta_2=\dfrac{\sigma_1-1}{1-\sigma}=\dfrac{\beta_3}{\beta_1-1}$. With the estimated linear equations, we could obtain $\hat{\alpha}_i$[②], $\hat{\beta}_i$, $i=1,2,3$[③]. Thus our estimates of elasticity are as follows:

$$\sigma=\hat{\beta}_1,\ \sigma_1=1-\hat{\beta}_3, \tag{23}$$

Here σ and σ_1 are supposed to be positive, which mean the inputs are substitutes. The estimated technical change of the three factors are:

$$\gamma=-\frac{\hat{\alpha}_2}{\hat{\beta}_3},\ \mu=-\frac{\hat{\alpha}_3}{\hat{\beta}_3},\ \nu=\frac{\hat{\alpha}_1}{\hat{\beta}_1-1} \tag{24}$$

For the (KE)L nested structures, technical change of the factors inputs can be estimated by a similar technique as above.

$$\gamma=-\frac{\hat{\alpha}_2}{\hat{\beta}_3},\ \mu=\frac{\hat{\alpha}_1}{\hat{\beta}_1-1},\ \nu=\frac{\hat{\alpha}_1}{\hat{\beta}_1-1} \tag{25}$$

And for (EL)K, the estimated technical change of three factors are

$$\gamma=\frac{\hat{\alpha}_1}{\hat{\beta}_1-1},\ \mu=-\frac{\hat{\alpha}_3}{\hat{\beta}_3},\ \nu=-\frac{\hat{\alpha}_2}{\hat{\beta}_3} \tag{26}$$

3.3 Relative bias and total bias of technical change

For the relative bias derivation, we first calculate the marginal products of *K*, *E*, *L* and determine the percentage change in marginal products over time. We then combine the percentage change in marginal products over time with the technical change parameters. This determines the biased technical change between two inputs (relative bias).

② Hat means estimated values.
③ The detailed calculation is given upon required.

To understand the derivation and the reasoning, the labor and capital case is now discussed. The ratio of the marginal products of capital and labor is provided below:

$$\frac{MP_K}{MP_L} = \frac{\alpha}{1-\alpha}(\frac{A}{B})^{\frac{\sigma-1}{\sigma}}(\frac{K}{L})^{-\frac{1}{\sigma}} \tag{27}$$

As pointed out by Acemoglu [38], whether technical change is capital or labor biased in the above equation depends on elasticity of substitution. When capital and labor are gross substitutes, capital-augmenting technical change is capital-biased. Conversely, when they are complements the converse applies. To estimate bias from the data, the percentage changes of A and B over time are estimated. Then the following equation to estimate bias is applied.

$$\begin{aligned} Bias_{KL} &= \hat{F}_K - \hat{F}_L = \frac{\partial F_K / \partial t}{F_K} - \frac{\partial F_L / \partial t}{F_L} = -\rho \frac{\partial A_t / \partial t}{A_t} - (-\rho \frac{\partial B_t / \partial t}{B_t}) \\ &= -\rho \hat{A}_t - (-\rho \hat{B}_t) = \frac{\sigma_{KL} - 1}{\sigma_{KL}}(\hat{A}_t - \hat{B}_t) \end{aligned} \tag{28}$$

Where F is marginal product of the factor. Eq. (28) applies to the two-factor case. As will be illustrated in the results section, the (KE)L nested function is the best fit for the data. Consequently, the equations will be derived from this nested structure. To introduce three factors, we first calculate the marginal products from the CES with nested (KE)L production structure:

$$F_{Kt} = \frac{\partial Y}{\partial K} = \alpha\beta \frac{Y^{1+\rho}}{K^{1+\rho_1}} A_t^{-\rho_1} [\alpha(A_t K)^{-\rho_1} + (1-\alpha)(B_t L)^{-\rho_1}]^{\frac{\rho}{\rho_1}-1} \tag{29}$$

$$F_{Et} = \frac{\partial Y}{\partial E} = (1-\alpha)\beta \frac{Y^{1+\rho}}{E^{1+\rho_1}} C_t^{-\rho_1} [\alpha(A_t K)^{-\rho_1} + (1-\alpha)(C_t E)^{-\rho_1}]^{\frac{\rho}{\rho_1}-1} \tag{30}$$

$$F_{Lt} = \frac{\partial Y}{\partial L} = (1-\beta)(\frac{Y}{L})^{1+\rho} B_t^{-\rho} \tag{31}$$

The change of marginal products are:

$$\hat{F}_{Kt} = \frac{\partial(F_K)/\partial t}{F_K} = -\rho_1 \hat{A}_t + (\rho_1 - \rho)\hat{A}_t \pi_t \tag{32}$$

$$\hat{F}_{Et} = \frac{\partial(F_E)/\partial t}{F_E} = -\rho_1 \hat{C}_t + (\rho_1 - \rho)\hat{C}_t (1-\pi_t) \tag{33}$$

$$\hat{F}_{Lt} = \frac{\partial(F_L)/\partial t}{F_L} = -\rho \hat{B}_t \tag{34}$$

Where $\pi_t = \frac{\alpha(A_t K_t)^{-\rho_1}}{\alpha(A_t K_t)^{-\rho_1} + (1-\alpha)(C_t E_t)^{-\rho_1}}$ can be treated as the contribution from capital in the aggregated value. Alternatively, (1-π_t) is the contribution from energy. In this model, the relative bias is able to vary over time. As can be seen in Eqs. (32)-(34), marginal products depends on the elasticity as well as the technical change derived from the estimated parameters in the nested structure. In the case of (KE)L nested function, $\rho = \frac{1}{\sigma_{KE} - 1}$, $\rho_1 = \frac{1}{\sigma_{(KE)L} - 1}$, $\sigma_1 = \frac{1}{1+\rho_1}$. *A*, *B* and *C* can be valued by γ, μ and ν. As a result, the following equations are to measure the relative bias between two inputs:

$$Bias_{KLt} = \hat{F}_{Kt} - \hat{F}_{Lt} = \frac{\sigma_{KE}-1}{\sigma_{KE}}(\gamma - \pi_t\gamma) + \frac{\sigma_{(KE)L}-1}{\sigma_{(KE)L}}(\pi_t\gamma - \mu) \tag{35}$$
$$= (\frac{\sigma_{KE}-1}{\sigma_{KE}}\gamma - \frac{\sigma_{(KE)L}-1}{\sigma_{(KE)L}}\mu) - (\frac{\sigma_{KE}-1}{\sigma_{KE}} - \frac{\sigma_{(KE)L}-1}{\sigma_{(KE)L}})\pi_t\gamma$$

$$Bias_{ELt} = \hat{F}_{Et} - \hat{F}_{Lt} = \frac{\sigma_{KE}-1}{\sigma_{KE}}(\nu - (1-\pi_t)\nu) + \frac{\sigma_{(KE)L}-1}{\sigma_{(KE)L}}((1-\pi_t)\nu - \mu) \tag{36}$$
$$= (\frac{\sigma_{KE}-1}{\sigma_{KE}}\nu - \frac{\sigma_{(KE)L}-1}{\sigma_{(KE)L}}\mu) - (\frac{\sigma_{KE}-1}{\sigma_{KE}} - \frac{\sigma_{(KE)L}-1}{\sigma_{(KE)L}})(1-\pi_t)\nu$$

$$Bias_{KEt} = \hat{F}_{Kt} - \hat{F}_{Et} = \frac{\sigma_{KE}-1}{\sigma_{KE}}(\gamma - \nu) + (\frac{\sigma_{(KE)L}-1}{\sigma_{(KE)L}} - \frac{\sigma_{KE}-1}{\sigma_{KE}})[\pi_t\gamma - (1-\pi_t)\nu] \tag{37}$$
$$= \frac{\sigma_{KE}-1}{\sigma_{KE}}(\gamma - \nu) - (\frac{\sigma_{KE}-1}{\sigma_{KE}} - \frac{\sigma_{(KE)L}-1}{\sigma_{(KE)L}})[\pi_t\gamma - (1-\pi_t)\nu]$$

The first term on the right of the above three equations is constant over time and the variation of the biased technical change depends on the second term. The relative bias can be positive or negative. For example, when $Bias_{KL}$ is positive, this implies technical change is capital biased. In contrast, when it is negative the converse applies. Although the above equations provide a useful measure of technical change bias between any two given factors, it has limitations for policy-makers. As policy makers need to know bias towards any given factor rather than just a relative measure. Thus, we provide all the possible conditions to determine the total bias for a factor, see Table 1 for (KE)L nested structure. The total bias is to measure the bias of each input factor and it can provide an indication on whether the bias is weakening or strengthening over the years. For example, capital can be biased under three possibilities. See the first condition in Table (1), when the relative bias is towards capital both for (KL) and (KE), technical change is biased toward two direction. Thus the total bias towards capital is the summation of $Bias_{KE}$ and $Bias_{KL}$. The second condition shows that when technical change is biased towards labor for (KL) but towards capital for (KE), it suggests that the absolute value of $Bias_{KE}$ is both larger than

$Bias_{KL}$ and $Bias_{KL.}$ Consequently, the total bias of capital is equal to $Bias_{KE}$. When technical change is biased towards capital for (KL), while towards energy for (KE) and towards labor for (EL), the absolute value of $Bias_{KL}$ is larger than $Bias_{LE}$ and $Bias_{KE.}$ The rules are similar to labor biased and energy biased, see detailed in Table 1.

INSERT TABLE 1 ABOUT HERE

4. Data and results

4.1 Data set

Our investigation focuses on the aggregated Chinese industrial sector spanning the period from 1990 to 2012. We exploit three datasets to determine the elasticity and technical change bias: (i) China Statistical Yearbook as published by China's National Bureau of Statistics [8]; (ii) China Energy Yearbook as published by China's National Bureau of Statistics [39]; (iii) China Labor Statistic Yearbook as published by China's National Bureau of Statistics [40].

The perpetual inventory method is used to estimate capital i.e. $K=K_{t-1}(1-\delta)+I_t$ [40]. I_t is the investment for year t. δ is depreciation which is the price of capital. This is determined by the 6-12 months official interest rates of loans to financial institutions. Capital in the base year (with t=1) is calculated by $K_0=I_0/(g+\delta)$. I_0 is Total Investment in Fixed Assets by region in 1985. g is the average growth rate of added value during the time series, δ is the depreciation rate which is 9.6 percent following [41]. To determine labor, we use the China Labor Statistic Yearbook. The wage of the base year is multiplied by the real wage index to determine wage for each year. As for energy use data, they are aggregated by various fossil fuels and measured in tonnes of coal equivalent. For the base year, coal price from the China Energy Databook v. 7.0 is adopted. Coal price in subsequent years is determined through the Coal Production Price Index (PPI) from the [8].

4.2 Simulating of KLE production function and elasticity of substitution

We use the first-order condition estimation to determine the parameters of three CES nested functions[④]. Five parameters are estimated (see Table 2) for each of the three nested CES functions.

INSERT TABLE 2 ABOUT HERE

KE(L) is preferred over (EL)K as it is statistically more significant. Furthermore, the (KL)E function is disregarded as the elasticity of substitution is negative and the technical change parameter for capital is insignificant. Thus, we conclude (KE)L is a better fit for the Chinese industrial sector than the other two nested functions. Given our choice of KE(L), this implies that capital and energy are best suited to be combined at a

④ We check the transformed data about the unit root test. The results show all the input and output factors are stable at the first order difference at least at 10% critical value.

composite level then with labor to form total output. Our nesting structure is aligned with Kemfert [42] study of the German aggregated industrial sector as an aggregate and Lv et al. [43] research of Chinese industry. For macroeconomics models application, (KE)L nested structure is also used in [44] (the GTAP–E model) and [45] (the GREEN model).

The positive value of σ implies that substitution between capital and energy is possible. Consequently, adopting more energy efficient or clean technologies will help Chinese industry to reduce energy intensity and raise the production efficiency of energy. High elasticities of aggregated KE and L (σ_1) indicate that it is likely that substitution will reduce labor employment in the industry of China.

4.3 Relative bias and total bias of technical change

Relative bias is calculated based on Eqs. (35)-(37). Total bias is obtained from the conditions in Table 1. The results illustrate that technical change is unambiguously energy biased relative to both labor and capital. This can be seen in Table 3. From the values in the table, we found TC is biased towards capital between capital and labor, while towards energy between energy and labor, capital and energy. Figure 1 shows the time path of total energy bias. The values of relative bias given in Table 3 satisfy $Bias_{KEt}<0$, $Bias_{ELt}>0$. Thus the total bias is $Bias_{Et} = abs(Bias_{KEt}) + abs(Bias_{ELt})$, see Figure. 1. It shows the time path of total energy bias, which has increased every year from 10.97 in 1990 to 11.70 in 2000. Its highest point is 12.33 in 2012, the last year of our analysis.

INSERT TABLE 3 ABOUT HERE

INSERT FIGURE 1 ABOUT HERE

The results make intuitive sense given the sector growth patterns in China. Over this period, China continued its industrialization. Industry as a proportion of GDP grew from 61.2% in 1992 to 72.8% in 2005. Although it then decreased, it still represents 47% of GDP in 2012 [8]. This industrialization was fueled vastly by coal accounting for two-thirds of China's primary energy consumption over the last 20 years [39]. Non fossil fuel use is very limited. For instance, in 2014 only 11.2% was renewable and hydroelectric. In contrast, 66% was coal, 17.1% was oil and 5.7% was natural gas ([8], 2015). Consequently, this means that our results are aligned with the energy consumption profile as outlined by research. Hitoshi [46] found for the Japanese industries, technical change was energy and labor-saving but not electricity-saving and it tends to be capital-using. For 25 European countries, Vogel, et al. [20] determined the technical change bias was labor-saving and energy-using for the manufacturing industries. However, they found a marginally significant small energy bias at the country level.

Chen and Yu [47] determined that for OCED and non-OCED countries progress is capital biased relative to energy. Nonetheless, the authors point to the rise of the oil price of 2000-2003 as a potential reason.

There are several reasons for this tendency of energy bias. The first explanation may be due to the low price of energy resulting from subsidies. Historically the Chinese government has regulated energy prices by providing fossil fuel subsidies [48]. For example, the fossil-fuel subsidy was 20.7 billion USD (Real 2013 USD). This represents 11 percent of the reference price [49]. Consequently, the real energy price in China has been lower than the global market price. After three decades of reforms, the government still influences the coal price through administrative persuasion to state-owned coal mines and allocation of transport capacity (Hang and Tu, 2007) [50]. In addition, electricity tariffs are currently regulated by the government [51]. Hence, it is difficult to determine whether allowing the market to be subject to price fluctuations in China would lead to energy-saving technology progress. Nonetheless, research in other areas of the world found that technical change bias towards energy has been sensitive to energy prices. The rate of energy-saving technical progress is higher during the periods of higher energy prices and lower during lower energy prices [19]. The second reason for the energy bias of technological change is the heavy physical investment with limited innovation. Jin and Zhang [52] found that during China's initial growth, small capital stock leads to incentives for capital accumulation rather than R & D innovation to improve energy use. The social planner only has an incentive to augment physical capital stock rather than undertake R&D investment for technological innovation, thus creating a non-innovation-led growth path. This non-innovation-led path gives rise to China's energy-intensive growth pattern. Specifically, there is little knowledge accumulation with no real energy-saving effect of technological progress. This leads to monotonic increases in fossil energy use by 3.9 folds during the sample period. We also feel that a reason may come from the rebound effect of energy efficiency. As highlighted by Sorrell [53], easier substitution between energy and other inputs leads to larger rebound. In China, in the past two decades, there has been significant improvement in energy efficiency in the industry. Nonetheless, energy consumption continues to increase, which implies that the potential energy savings by technical change are offset by the substitution effect and income effect. The rebound effect has been estimated at 53.2% during 1981-2009 for whole China [54] and 46.38% at the aggregated industry [55].

Although the growth rate of the energy bias fluctuated in the 1990's, there was no downward trend. Specifically, in 1990 the growth rate was 0.65%, and by 1999 it was back to that point. However, since then it has decreased significantly to a low of 0.35% growth in 2011. This decline coincided with the investment into renewables. It is important to recognize that investment in renewable resources such as wind and solar started in 2000 is to relieve shortages of energy. Policies like the Cleaner Production Law introduced in 2002 and the Medium (2005-2010) and Long-term Plan of Energy Conservation (2010-2020) are also outlined energy conservation aims and implementation plans for subsequent years. Thus, the renewable investment and environmental concerns in China reduced the growth rate of energy biased technical change.

In Fig. 1, the percentage contribution of the bias towards energy from labor is presented. The percentage contribution from labor increased consistently from 59.5% in 1990 to 65.3% in 2012. Conversely, the contribution from capital decreased from 40.5% in 1990 to 34.7% in 2012. These results align with the intricacies of the Chinese economy. Labor cost increased since 1990, whereas capital cost decreased [8].

5. Conclusion

Resulting from the need to consider energy as an input, we contribute by enhancing our framework to study the technical change of any number of factors at the sector level. Relative technical bias is to estimate the bias between two inputs whereas aggregated total bias is for three inputs. The multi-factor generalisation is derived from the elasticity of substitution and technical change of the factors. Empirically we applied the approach to a data set for Chinese industry over the 1990-2012 period.

For the entire Chinese industrial sector, capital and energy has a high elasticity of substitution. Thus, capital and energy is best suited to be nested at the composite level and then combined with labor to form total output. The results match the results of engineering studies which suggest a large potential for improving energy efficiency by substituting capital for energy. To reduce energy consumption, the alternative policy reforms should foster energy-saving technologies acquisition. It may be more expensive to innovate in clean technologies because of path-dependence in the direction of technical change [56]. In this case, the government should give subsidy or invest energy-saving technology.

With our estimation framework, we found technical change is strongly biased towards energy compared to labor and capital (relative bias). That means energy-augmenting technical change is smaller than that of either capital or labor. In addition, technical change is totally biased towards energy which increases over time. This bias is predominately away from labor. This indicates that energy has been used more intensively in production. Substitution towards energy may increase the energy value share brought by energy biased technical change. Although the bias increased, the growth rate has decreased in recent years. These insights should be taken into account by policy makers in order to devise legislation to reduce energy consumption. For instance, energy taxation or deregulation of electricity tariffs are potentially efficient economic instruments for energy conservation. And the relevant costs-benefit analysis are inevitably required, which are beyond the scope of our research.

Given these results, we would like to suggest some areas of further research. The purpose of the study was to estimate technological change bias for the entire industrial sector, without focusing on the elasticity and the bias for individual sectors. We found that for the entire industrial sector, technical change is energy biased. Nonetheless, technical change could be more and could be less energy biased in specific sectors and provinces. It is also possible that in some provinces and sectors, there may not even be an energy bias. In order to enable policy makers to devise sector-specific policies, further research at a sector level would be appropriate. Furthermore, in this empirical investigation, we can only access to high-quality data of the Chinese energy economy during the period of the research. To attain better statistic characteristics, we shall include more high-quality data from a extended period. The second extension would be to try to measure the effects of the government's recent environmental policies on the bias towards energy. Since 2000, China formulated new environmental laws and more recently voluntary agreements and emission trading. As we found that the growth rate of total energy biased technical change decreased, it is of interest to determine whether this is a direct result of China's environmental policies. A simple but important lesson that can be gathered from China's experience is the impact of policies. Policies such as subsidies are also applied in other countries, particularly in the developing world like India and Russia [57]. This may also be contributing to energy bias in these respective countries. Similarly, our method is applicable to determine bias in these countries if their own governments want to influence the direction of technical change.

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Appendix

Table 1 Full name of abbreviations

Abbreviation	full name
CES	Constant Elasticity of Substitution
MP	Marginal Product
(KE)L	(Capital-Energy) Labor
(EL)K	(Energy-Labor) Capital
Bias	Biased Technological Change

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Table 1
Total bias under (KE)L nested structure

Factor biased	Conditions	Total bias
Capital	$Bias_{KLt} > 0$, $Bias_{KEt} > 0$	$Bias_{Kt} = abs(Bias_{KEt}) + abs(Bias_{KLt})$
	$Bias_{ELt} > 0$, $Bias_{KLt} < 0$, $Bias_{KEt} > 0$ $abs(Bias_{KEt}) > abs(Bias_{LEt})$ and $abs(Bias_{KLt})$	$Bias_{Kt} = abs(Bias_{KEt})$
	$Bias_{KEt} < 0$, $Bias_{ELt} < 0$, $Bias_{KLt} > 0$ $abs(Bias_{KLt}) > abs(Bias_{LEt})$ and $abs(Bias_{KEt})$	$Bias_{Kt} = abs(Bias_{KLt})$
Labor	$Bias_{ELt} < 0$, $Bias_{KLt} < 0$	$Bias_{Lt} = abs(Bias_{ELt}) + abs(Bias_{KLt})$
	$Bias_{ELt} > 0$, $Bias_{KLt} < 0$, $Bias_{KEt} > 0$ $abs(Bias_{KLt}) > abs(Bias_{LEt})$ and $abs(Bias_{KEt})$	$Bias_{Lt} = abs(Bias_{KLt})$
	$Bias_{KEt} < 0$, $Bias_{ELt} < 0$, $Bias_{KLt} > 0$ $abs(Bias_{ELt}) > abs(Bias_{KEt})$ and $abs(Bias_{KLt})$	$Bias_{Lt} = abs(Bias_{ELt})$
Energy	$Bias_{KEt} < 0$, $Bias_{ELt} > 0$	$Bias_{Et} = abs(Bias_{KEt}) + abs(Bias_{ELt})$
	$Bias_{KEt} > 0$, $Bias_{ELt} > 0$, $Bias_{KLt} < 0$ $abs(Bias_{ELt}) > abs(Bias_{KEt})$ and $abs(Bias_{KLt})$	$Bias_{Et} = abs(Bias_{ELt})$
	$Bias_{KEt} < 0$, $Bias_{ELt} < 0$, $Bias_{KLt} > 0$ $abs(Bias_{KEt}) > abs(Bias_{LEt})$ and $abs(Bias_{KLt})$	$Bias_{Et} = abs(Bias_{KEt})$

Table 2

The elasticity and the change rates of technical change

Nested function	σ	σ_1	γ	μ	ν	Determinant residual covariance
(KL)E	-0.2769*	0.7750***	0.0641	0.1107**	0.0838***	1.70E-18
	(-1.6364)	(5.3965)	(-1.4412)	(-2.1494)	(-4.0382)	
(KE)L	0.0300***	0.7847***	0.1431***	0.1403***	-0.1288**	2.43E-08
	(-5.3152)	(4.4360)	(-3.1877)	(-4.7735)	(2.2718)	
(EL)K	0.0352***	0.8179***	0.0455**	-0.1170**	0.2477***	7.98E-18
	(-4.4178)	(4.2745)	(-2.1163)	(1.7656)	(-3.7253)	

*,**,*** significant at the 10%-level, 5%-level, 1%-level respectively. Figures in parentheses are the t-statistics.

Table 3

Bias of technical change between two inputs: relative bias

Year	$Bias_{KLt}$	$Bias_{ELt}$	$Bias_{KEt}$	Year	$Bias_{KLt}$	$Bias_{ELt}$	$Bias_{KEt}$
1990	2.0850	6.5298	-4.4448	2002	3.1544	7.4924	-4.3380
1991	2.1738	6.6097	-4.4360	2003	3.2088	7.5413	-4.3325
1992	2.2556	6.6834	-4.4278	2004	3.2493	7.5778	-4.3285
1993	2.3275	6.7481	-4.4206	2005	3.3096	7.6320	-4.3225
1994	2.4044	6.8173	-4.4129	2006	3.3759	7.6918	-4.3158
1995	2.4748	6.8807	-4.4059	2007	3.4448	7.7538	-4.3090
1996	2.5857	6.9805	-4.3948	2008	3.5186	7.8202	-4.3016
1997	2.7005	7.0838	-4.3833	2009	3.5884	7.8830	-4.2946
1998	2.8105	7.1828	-4.3723	2010	3.6603	7.9477	-4.2874
1999	2.9047	7.2676	-4.3629	2011	3.7137	7.9957	-4.2821
2000	2.9972	7.3508	-4.3537	2012	3.7844	8.0595	-4.2750
2001	3.0790	7.4245	-4.3455				

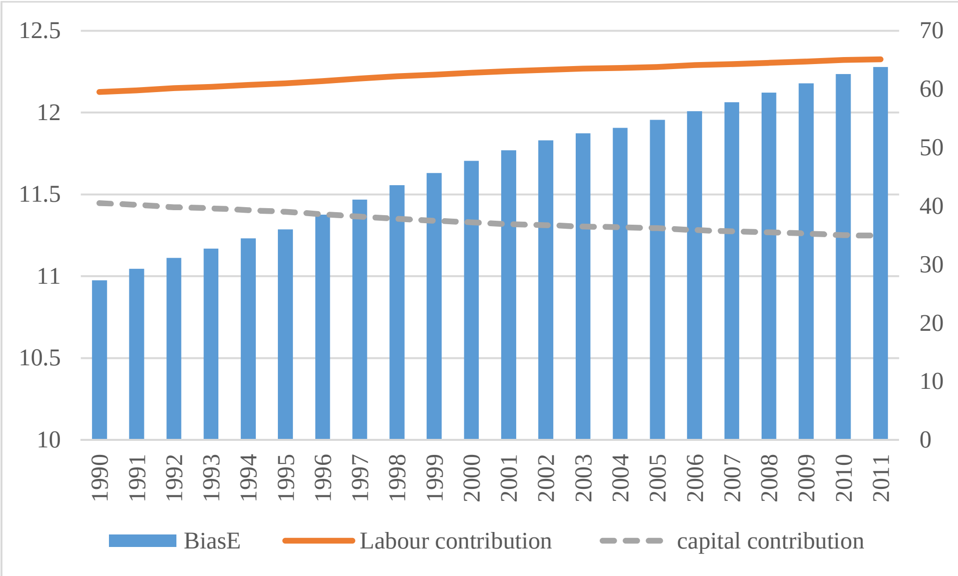

Fig. 1. Total energy bias and its decomposition (1990-2012)

- We outline a framework to estimate technical change, elasticity of substitution, and relative bias.
- A concept of total bias for three factors of production is introduced.
- Empirically we applied the approach to a data set for Chinese industry over the 1990-2012 period.

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