Directed Technological Change, Energy and More: A Modern Story

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Abstract

Reliance of modern economic activities on the use of energy and that the majority part of energy currently consumed is non-renewable provokes concerns on the more efficient utilization of energy input in general production. While theories expect directed technological change to be biased towards the non-renewable input, there is rare macro-level evidence that technological change is biased towards energy than other main inputs. To fill this blank, our paper applies the stochastic frontier analysis to country data regarding output produced with three inputs factors, capital, labor and energy, and estimate a series of indicators for technological change. The findings show that technological change is biased the most towards energy in general. Although different groups of countries exhibit various patterns in the results, strong evidence is in common that technological change favors energy more than labor. This is in line with theories in the sense that technological change is expected to be biased towards the non-renewable input rather than the renewable.

Keywords: directed technological change, energy, economic growth, stochastic frontier analysis.

JEL classification: O33, O44, Q32, Q43.

1 Introduction

Energy is, to the modern economy, what blood is to the body. In the past few decades, although fossil energy dependency has declined, it still constitutes a major part of the world's energy consumption[4]. One may naturally be concerned

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[4]From 1991 to 2017, the share of renewables in electricity production has increased from 19.66% to 24.80%, according to data of the Global Energy Statistical Yearbook 2018: https://yearbook.enerdata.net/.

about how economic development can be guaranteed while energy, as a key input, seems unlikely to be free from the imperil of depletion, given the current technology on the extraction and generation of energy. Theoretically, consensus has long been reached by economists that technological progress is the key to a sustainable economic growth that relies on the use of a limited stock of resources. Although policy makers shall be aware of this, the implementation of policies is never a simple procedure that can fully reach its goal, and we cannot be so sure whether technological change is biased towards energy rather than other input factors. Empirical work on the direction of technological change involving energy input has been arousing the interest of energy and environmental economists for years, including Karanfil and Yeddir-Tamsamani (2010), Shao et al. (2016), Zha et al. (2017), among others. However, evidence for the macro level is still rare; in this paper, we try to draw a picture on the situation of directed technological change of the world's main economies.

Agents make R&D decisions in a market with imperfect competition, incomplete information, government regulations, externality of knowledge spillover and other frictions; it is difficult to simply decide from a theoretical perspective how technological change is biased. Theoretically, it can be expected that technological change be biased towards the non-renewable input(s) rather than the renewable one(s). Nevertheless, despite accumulated empirical effort at industry level, evidence is still insufficient for judging at the country level whether technological change has been biased towards energy. An empirical study on the country level directed technological change might improve our understanding on the general production pattern of the comtemporary world and how decisions are made by agents in technological R&D; it shall also provide valuable information for policy making regarding innovations related with the efficiency of energy utilization.

Whether technological change is biased towards energy has been empirically examined at industry level. Zha et al. (2017) and Zha et al. (2018) estimate CES production function for Chinese industrial sectors; Karanfil and Yeddir-Tamsamani (2010) estimate a translog cost-share system for French economic sectors. The approaches in these studies enable the analysis of the biasedness of technological change; nonetheless, we find that the production function approach of the Stochastic Frontier Analysis is more appropriate for our research purpose, as it allows to estimate indicators that provide a more comprehensive idea on the situation of technological change, like technical inefficiency, output elasticities and total factor productivity growth rate. In this paper we apply the stochastic frontier analysis to country level data and estimate a translog production function with three main inputs, capital, labor and energy. We calculate the marginal products (output elasticities) for each input, as well as the factor bias index first proposed by Diamond (1965), so as to find out how technological change is biased in the recent decades. We also calculate the growth rates of total factor productivity, which indicate the general situation of technological development of each country.

The analysis shall give us an idea on the role played by technological change in macro level production; it shall also reveal some patterns in economic growth of developed and developing countries. Based on our sample, we are going to show that, on average, output elasticities of energy and labor are increasing, while the output elasticity of capital is decreasing, and has negative values for some countries. Among the three input factors, the output elasticity of labor is the highest for developed countries, and the output elasticity of energy is the highest or very close to the highest for developing countries. For the average of the sample, and also for most countries in the sample, technological change is biased the most towards energy. Moreover, there are significant differences in the patterns of output elasticities, total factor productivity growth rate and factor bias order for different (groups of) countries, which may provide insights for policy making.

In addition to the methodologies commonly applied in studies of Stochastic Frontier Analysis, we obtain confidence intervals and levels of statistical siginificance for the abovementioned indicators, in order to acquire a more rigorous result. According to results obtained from bootstrap, there is strong evidence for the consistency between countries, in the sense that technological change favors energy more than labor. Such finding could support the hypothesis that technological change is more likely to be biased to the non-renewable input rather than the renewable.

The rest of this paper is organized as follows. We review the literature on our topic in Section 2. In Section 3 we address the methodology and data. Section 4 presents the empirical results, along with related interpretation and discussion. Concluding remarks are made in Section 5.

2 Literature Review

The reliance of economic activities on resources, a great part of which is non-renewable, caught the attention of economists as early as Hotelling (1931), who proposes a basic model of the extraction of non-renewable resources, suggesting that perfect competition yields an extraction path, chosen by firms, identical to the social optimum. In the 1970s, a number of economists focus their attention on economic growth with non-renewable resources, including Anderson (1972), Dasgupta and Heal (1974), Solow (1974), Stiglitz (1974), Ingham and Simmons (1975), Hartwick (1977), Garg and Sweeney (1978), among others. It has been the world's concern, as well as many economists', how to sustain economic growth with exaustible resources. These studies share one feature in common: they all believe that technological change should play a relevant role in such progress.

Some economists seek solutions other than technological change. Groth and Schou (2002, 2007) suppose increasing returns to capital as the drive for growth; however, as we are going to show in our results, the general production activities of the world is more likely to exhibit decreasing returns to scale. Benchekroun and Withagen (2011) highlight the role of consumption (which hence affects investment); yet it seems less realistic for policies to target on consumption rather than technological progress. Most economists consider technological change as the key to long-run economic growth with limited resources: Grimaud and Rougé (2003) propose a Schumpeterian model of endogenous growth and show that economic growth can be sustained even with non-renewable resources, as long as an adequate level of technological change is guaranteed; a number of researchers share similar opinions, including Smulders and De Nooij (2003), Di Maria and Valente (2008), André and Smulders (2014).

Governments concerned with the scarcity of fossil energy and its environmental consequences propose policies like environmental taxes, aimed at limiting the use of fossil energy. According to the belief of induced innovation by Hicks (1932), with the price incentives created by these policies, technological change shall take place so that the efficiency of energy use is improved over time. There is also the prediction that technological change is biased to non-energy intensive products (Otto et al., 2007). Although there is evidence that innovation is motivated by price factors (Newell et al. 1999, Popp 2002, Linn 2008, Kumar and Managi, 2009), firms' investment in R&D may not be social optimal as the knowledge spillover is not fully internalized (Grubb and Ulph, 2002). Therefore, both taxation and research subsidy is important for optimal policy making, as suggested by Grimaud et al. (2011), Acemoglu et al. (2012).

Growth model of directed technological change proposed by Acemoglu (2002, 2007) indicates that technological progress is affected by two counteracting effects, the price effect and the market size effect. Specifically, when the menu of technological possibilities only allows for factor augmenting technologies, the induced technological change increases the relative marginal product of the factor becoming more abundant. On the other hand, as suggested by Hicks (1932), Diamond (1965), Kumbhakar (2000), among others, the technological change over time of an economy consists of two aspects: the change in total factor productivity and the bias of the technological change towards input factors. Acemoglu (2002, 2007) leaves unanswered whether the result would still be the same if technological change consists of two aspects as described above.

Empirical support is needed regarding the direction of technological change in the real world, as there are several factors undermining the reliability of the theoretical predictions. First, in most of the models regarding technological change and non-renewable resources, only two inputs are considered, with labor often being excluded. Second, the world is utilizing both renewable and non-renewable energy, so predictions considering non-renewable resources may not be accurate. Third, theoretical models differ from each other in their assumptions, and propose different conditions for the directions of technological changes. Comparative to our topic, Acemoglu (2010) discusses whether labor scarcity encourages technological advances, with the answer depending on the economic environment (function form). Similar reasoning also stands if we talk about energy in place of labor.

In the theoretical framework of Acemoglu (2002, 2007), the direction of technological change depends on the elasticity of substitution between input factors. However, it is difficult to draw an empirical answer by estimating the elasticity of substitution, especially when three input factors are involved. The actual threshold that decides the direction of technological change is unclear; and including three inputs in the estimation requires a nesting structure in the form $(K, L)E$, $(K, E)L$ or $(E, L)K$ (if we consider capital, labor and energy as inputs), as in the cases of Kemfert and Welsch (2000), Su et al. (2012) and Dissou et al. (2014). This complicates the analysis greatly, not to mention further researches that may include four or more inputs. This form also makes it difficult to compare the technological change augmented to each input factor.

Different empirical methods and measures have been applied to analyze the direction of technological change. Immature measures for technological progress regarding energy include the ratio of energy input to GDP/GNP and cost shares of inputs (Hogan and Jorgenson, 1991; Sanstad et al., 2006); the former does not allow us to compare the technological change augmented to different inputs, and the latter does not perfectly reflect the productivity change since a change in cost shares can result from multiple reasons.

Considering only two input factors, Klump et al. (2007) estimate a supply-side system of the U.S. economy from 1953 to 1998, and find that labor-augmenting technical progress is exponential, while the growth of capital-augmenting progress is hyperbolic or logarithmic. Dong et al. (2013) use inter-provincial panel data of China to find that technological change is biased towards capital rather than labor. By studying the substitutability between energy and capital in manufacturing sectors in 10 OECD countries, Kim and Heo (2013) conclude that the the adoption of energy-saving technologies has not been induced by increased energy prices. Yet the results of these studies are not fully convincing as they leave a major input factor unconsidered. A comprehensive empirical analysis on technological change regarding energy should at least take capital and labor into account.

The Stochastic Frontier Analysis is first introduced by Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977). Along the years this method is developed by a great number of subsequent studies, including Kumbhakar (1990), Kumbhakar et al. (2000), Wang (2002), Wang and Schmidt (2002), Greene (2005), Kumbhakar and Wang (2005), Chen et al. (2014), Parmeter and Kumbhakar (2014), among others. It assumes that the error term is composed by a noise term and an inefficiency term, and is at first used to discuss the inefficiency in production and its determinants. Although more often applied to micro-level studies, the Stochastic Frontier Analysis is also used for investigating macro-level production process, e.g. Heshmati et al. (2011) who use province level data of China; Kumbhakar and Wang (2005) assuming capital and labor as inputs.

In recent years, the Stochastic Frontier Analysis has been applied to energy economics to address the issue of directed technological change. Two approaches are more frequently applied: the distance function approach and the production function approach. The distance function approach allows to analyze the technical efficiency in a production procedure that involves multiple outputs; recent applications in energy economics include Boyd and Lee (2019), Liu et al. (2019), among others. The production function approach, on the other hand, facilitates the calculation of a series of indicators for technological change. Wesseh and Lin (2016) analyze the effectiveness in using renewable and non-renewable energy in African countries. Shao et al. (2016) study whether technological change has taken place in a way that alleviates the dependence of industrial production on CO_2 emissions in Shanghai. Yang et al. (2018) investigate whether technological change is biased towards fossil energy or non-fossil energy in China's industrial sector. Still, the literature lacks an idea on the whole picture of the world's directed technological change involving energy input; analysis from a more broad perspective is needed so that we could have the concept on how macro-level technological change has been going on in the global context.

One of our study's contributions is that, it empirically analyzes the country level production in a worldwide perspective, with capital, labor and energy as inputs. Besides the general information on directed technological change and the way how changes have been taking place in macro level production of the world (or at least of the sample countries), the methodology also allows the comparison of different patterns of development between countries. Findings can be considered as evidence that provides support to theoretical studies, as well as reference for policy making.

3 Methodology and Data

3.1 Stochastic frontier production function and estimation method

A method is proposed in studies of the stochastic frontier analysis, e.g. Kumbhakar et al. (2000), for decomposing productivity change into efficiency change, technical change and scale effects. They also provide examples of TFP (total factor productivity) change decomposition at the industry level. Shao et al. (2016) use panel data of 32 industrial sub-sectors in Shanghai over 1994–2011 to investigate and compare the degrees of technological change biased to four production factors, i.e., capital, labor, energy, and carbon emissions. The results show that in most sub-sectors, technological change was biased towards energy during the sample period. Nevertheless, the study adopts the production function approach with carbon emission as an input, which is a compromise to facilitate the analysis to the biasedness of technological change. Carbon emission is, as a matter of fact, an output resulting from the production and the distance function is the most proper functional form to describe such process, as in Duman and Kasman (2018). In the macro context, since there isn't a global carbon emission market where carbon emission incurs cost, we opt not to take it as an input.

With the above-mentioned consideration, we decide not to include carbon emission in our study as an input factor. We estimate a stochastic frontier model with three inputs: capital, labor and energy, and try to assess the direction of technological progress.

Referring to Kumbhakar et al. (2000), Heshmati and Kumbhakar (2011), Shao et al. (2016), suppose the production function is

$$y_{it} = f(x_{it}, t) \exp(-u_{it}), \tag{1}$$

where i represents a country, t represents the number of the time period, $u \geq 0$ denotes output-oriented technical inefficiency. Technical change is defined as

$$TC_{it} = \frac{\partial \ln f(x_{it}, t)}{\partial t}. \tag{2}$$

The overall productivity change is affected by both technical change and change in technical efficiency (TEC). Assuming input quantities fixed, we have

$$\frac{\partial \ln y_{it}}{\partial t} = TC_{it} + TEC_{it}, \tag{3}$$

where $TEC_{it} = -\frac{\partial u_{it}}{\partial t}$. When input quantities change, productivity change is measured by TFP (total factor productivity) change which is defined as

$$\dot{TFP} = \dot{y} - \sum_j S_j^a \dot{x}_j, \tag{4}$$

where $S_j^a = w_j x_j / \sum_k w_k x_k$, w_j being the price of input x_j. The dot denotes time growth rate. Differentiating (1) and using (4), we get

$$\begin{aligned} \dot{TFP} &= TC - \frac{\partial u}{\partial t} + \sum_j (\frac{f_j x_j}{f} - S_j^a)\dot{x}_j \\ &= (RTS - 1)\sum_j \lambda_j \dot{x}_j + TC + TEC + \sum_j (\lambda_j - S_j^a)\dot{x}_j, \end{aligned} \tag{5}$$

where $RTS = \sum_j \frac{\partial \ln y}{\partial \ln x_j} = \sum_j \frac{\partial \ln f(\cdot)}{\partial \ln x_j} = \sum_j f_j(\cdot)x_j/f(\cdot) \equiv \sum_j \eta_j$ is the measure of returns to scale; η_j are input elasticities defined at the production frontier, $f(x,t)$; $\lambda_j = (f_j x_j / \sum_k f_k x_k) = \eta_j / RTS$; f_j is the marginal product of input x_j. Therefore, TFP change is decomposed into scale components, technical change, technical efficiency change and price effects.

In previous empirical studies (Shao et al., 2016; Wesseh and Lin, 2016; Yang et al., 2018), a translog production function of a second-order Taylor approximation is generally adopted. It allows variable substitution elasticities and is very suitable for calculating the biased technological change. As proposed by Greene (2005) and is also the practice of Yang et al. (2018), we let the model account for fixed effects, which is represented by country dummies. Considering capital, labor and energy as inputs, we build the following translog production function:

$$\begin{aligned}\ln Y_{it} = {} & \beta_0 + \alpha_i D_i + \beta_t t + \beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_E \ln E_{it} \\ & + \beta_{tK} t \ln K_{it} + \beta_{tL} t \ln L_{it} + \beta_{tE} t \ln E_{it} \\ & + \beta_{KL}(\ln K_{it} \ln L_{it}) + \beta_{KE}(\ln K_{it} \ln E_{it}) + \beta_{LE}(\ln L_{it} \ln E_{it}) \\ & + \beta_{KK}(\ln K_{it})^2 + \beta_{LL}(\ln L_{it})^2 + \beta_{EE}(\ln E_{it})^2 \\ & + V_{it} - U_{it}, \end{aligned} \tag{6}$$

$$U_{it} \sim N^+(0, \sigma_U^2).$$

where Y represents the total output, K, L, E denote capital input, labor input and energy input, respectively; parameters β_x are to be estimated; V is the noise term while U is the technical inefficiency term, hence the compounded residual variance $\sigma^2 = \sigma_U^2 + \sigma_V^2$[5]; D_i represents country dummies and α_i are the corresponding coefficients. A parameter $\gamma = \sigma_U^2/(\sigma_U^2 + \sigma_V^2)(0 \leq \gamma \leq 1)$ represents the share in the compounded residual variance derived from technical inefficiency. As the assumption is made such that the error terms are not normally distributed and the conditional mean of the errors is different from zero, the basic assumption of the ordinary least square method is violated. Following Battese and Coelli (1995), Kumbhakar et al. (2015), we estimate the

[5] σ_U^2 and σ_V^2 are estimated as the following:

$$\sigma_U^2 = \exp(w_U),$$

$$\sigma_V^2 = \exp(w_V),$$

where w_U and w_V are unrestricted constant parameters.

function above with maximum likelihood method, where the likelihood function is expressed in terms of the variance parameters σ_U^2 and σ_V^2.

Referring to Kumbhakar et al. (2000)[6], the growth rate of the TFP can be decomposed as

$$\dot{TFP}_{it} = TP_{it} + TEC_{it} + SEC_{it}. \tag{7}$$

The first term, TP_{it}, denotes technological progress, which is defined as

$$TP_{it} = \frac{\partial \ln Y_{it}}{\partial t} = \beta_t + \beta_{tK} \ln K_{it} + \beta_{tL} \ln L_{it} + \beta_{tE} \ln E_{it}, \tag{8}$$

where β_t is the neutral technological change rate of the world, or our sample countries; $\beta_{tK} \ln K + \beta_{tL} \ln L + \beta_{tE} \ln E_{it}$ is the non-neutral technological change, which is heterogeneous across different countries.

The second term, TEC_{it}, denotes technical efficiency change over time:

$$TEC_{it} = \frac{TE_{it}}{TE_{i,t-1}} - 1, \tag{9}$$

where $TE_{it} = \exp(-U_{it})$.

The third term, SEC_{it}, denotes the scale efficiency change, which reflects the improvement of productivity benefiting from scale economy:

$$SEC_{it} = (RTS_{it} - 1) \sum_j \frac{\eta_{jit}}{RTS_{it}} \dot{X}_{jit}, \tag{10}$$

where $j = K, L, E$ denotes the input factor; $\dot{X}_{jit}$ is the growth rate of each input; η_{jit} is the output elasticity with respect to each input. The scale effect index is $RTS_{it} = \eta_{Kit} + \eta_{Lit} + \eta_{Eit}$, where the output elasticities of capital, labor and energy are calculated as the following:

$$\eta_{Kit} = \frac{\partial \ln Y_{it}}{\partial \ln K_{it}} = \beta_K + \beta_{tK} t + \beta_{KL} \ln L_{it} + \beta_{KE} \ln E_{it} + 2\beta_{KK} \ln K_{it}; \tag{11}$$

$$\eta_{Lit} = \frac{\partial \ln Y_{it}}{\partial \ln L_{it}} = \beta_L + \beta_{tL} t + \beta_{KL} \ln K_{it} + \beta_{LE} \ln E_{it} + 2\beta_{LL} \ln L_{it}; \tag{12}$$

$$\eta_{Eit} = \frac{\partial \ln Y_{it}}{\partial \ln E_{it}} = \beta_E + \beta_{tE} t + \beta_{KE} \ln K_{it} + \beta_{LE} \ln L_{it} + 2\beta_{EE} \ln E_{it}. \tag{13}$$

An indicator for the biasedness of technological change, according to Shao et

[6] Interested readers may refer to Kumbhakar et al. (2000) for a more complete derivation of the following equations.

al. (2016) and Yang et al. (2018), originating from Diamond (1965), the biased technological change index $Bias_{sj}$ can be used to estimate the relative biased degree of technological change to each input:

$$Bias_{sj} = \frac{\partial(f_s/f_j)}{\partial t} / \frac{f_s}{f_j} = \frac{\beta_{ts}}{\eta_s} - \frac{\beta_{tj}}{\eta_j}, \tag{14}$$

where s and j represent different inputs; f_s or f_j is the derivative of the function f with respect to s or j.

$Bias_{sj} > 0$ means that the marginal output growth rate of s caused by technological change is greater than that of j, indicating that technological change is biased to factor s; and vice versa. If $Bias_{sj} = 0$, it means that technological change in the production is Hicks neutral.

3.2 Data

We collect annual data from 1991 to 2014 for 16 main developing and developed countries located in different geographic areas of the world, namely the US, Japan, Germany, the UK, Canada, France, Italy, Australia, China, India, Brasil, South Africa, Mexico, Argentina, Indonesia and Russia. In selecting the countries to be included in our sample, we consider equal numbers of developed and developing countries with higher real GDP in the world; we also try to let the selected countries be distributed to different geographic areas (continents) of the world, in order to retain a certain degree of diversity.

There are 8 developing countries and 8 developed countries[7] in the sample. The US, Japan, Germany, the UK, Canada, France, Italy and Australia are among the 9 developed countries with the highest real GDP in the world (ranking according to the World Bank); Spain is in the 8th place and is substituted with Australia, in order to avoid excessive weight of European countries in the sample. Likewise, China, India, Brasil, South Africa, Mexico, Argentina, Indonesia and Russia are among the 11 developing countries with the highest real GDP in the world. The real GDP of these countries account for over 90% of the world's real GDP[8]. Throughout the sample period or for most time of it, the US, Japan, Germany, the UK, France, Italy, China, India and Brazil are energy

[7] According to World Economic Situation and Prospects 2018 published by the UN, Russia is among the economies in transition, and is not considered as a developed country.

[8] Calculated with data from the Federal Reserve and the World Bank (for the world's real GDP). For example, the real GDP of the 16 countries in 2014 adds up to $7.13 * 10^{13}$ 2009 dollars, the real GDP of the world in 2014 being $7.36 * 10^{13}$ 2010 dollars.

importers; Canada, Australia, South Africa, Mexico, Argentina, Indonesia and Russia are energy exporters[9].

For estimating the stochastic frontier translog production function, we collect the following data:

Y - real GDP collected from the database of the Federal Reserve[10], in constant 2011 USD.

K - capital stock collected from the database of the Federal Reserve, in constant 2011 USD.

L - working population collected from the database of the Federal Reserve. For some countries, direct data for the working population is not available, and we obtain such data from the employment to population ratio (15 - 64 years) and the population between 15 and 64 (collected from the database of the World Bank[11]) in these countries.

In accounting labor input, we choose to adopt working population as a proxy, instead of other proxies that account for human capital. Nevertheless, there are a number of different ways for estimating human capital (Stroombergen et al., 2002), and human capital measurement is context-specific (Baron, 2011), so it is difficult to determine a proper measure of human capital; in estimating human capital there may arise inaccuracies that will generate trouble for our empirical analysis. Besides, the output elasticity of labor that we calculate is by itself, to some degree, a measure of human capital.

E - total primary energy consumption in Mtoe (millions of tons of oil equivalent), from Global Energy Statistical Yearbook 2018.

Country data for the share of renewables in energy production is available; yet, we are lacking the information on the share of renewables in energy consumption, which stops us from treating renewable and non-renewable energy separately.

Following the true fixed effects model of Greene (2005), country dummies are included in the estimation to account for country level fixed effects. We drop the first country dummy in order to avoid multicollinearity, thus we have 15 dummies left.

Hypotheses of unit roots are rejected for most countries[12]. The descriptive

[9] Source: Global Energy Statistical Yearbook 2018.

[10] https://fred.stlouisfed.org/

[11] https://data.worldbank.org/

[12] The Levin-Lin-Chu test rejects null hypotheses for $\ln Y$, $\ln K$; the test rejects null hypothesis for $\ln L$ when the data for Russia is excluded since the test requires a strongly balanced panel; the test rejects null hypothesis for $\ln E$ when the data for China and India is excluded.

statistics of the data are shown in Table 1.

Table 1

Descriptive statistics of input and output data

Variables (unit)	Obs	Mean	Std. Dev.	Min	Max
Real GDP (millions of constant 2011 USD)	384	3088068	3474901	344670.5	$1.72e+07$
Capital stock (millions of constant 2011 USD)	384	$1.05e+07$	$1.10e+07$	948456.3	$6.76e+07$
Labor force (thousands of persons)	383	102013.6	165095.7	7585.462	673787.1
Total energy consumption (Mtoe)	384	474.906	613.2286	47.49662	3052.325

4 Results and Discussion

4.1 The production function

The first step of our empirical analysis is to estimate the translog production function (6). Along with the estimation process, several specification tests are implemented in order to make sure that the production function is well defined. Then, based on the estimated parameters, we derive the output elasticities, total factor productivity growth rate, factor bias index, among other indexes.

To examine whether the specification of the production function is valid and effective, the following specification tests are necessary:

(1) Whether the stochastic frontier production model is effective: $H_0 : \sigma_U^2 = 0$. If the null hypothesis is not rejected, it means that no technical inefficiency exists and that the stochastic frontier analysis is not needed.

(2) Specification test of the production function form of the stochastic frontier model: $H_0 : \beta_t = \beta_{tK} = \beta_{tL} = \beta_{tE} = \beta_{KL} = \beta_{KE} = \beta_{LE} = \beta_{KK} = \beta_{LL} = \beta_{EE} = 0$. If the null hypothesis is not rejected, it means that the production function should be Cobb–Douglas instead of the translog one.

(3) Whether there is technological progress in the frontier production function: $H_0 : \beta_t = \beta_{tK} = \beta_{tL} = \beta_{tE} = 0$. If the null hypothesis is not rejected, it would imply that the production function does not vary through time, hence the technological progress in the frontier production function does not exist. If technological progress does exist, it is also necessary to test whether the technological progress is neutral or not: $H_0 : \beta_{tK} = \beta_{tL} = \beta_{tE} = 0$.

(4) Whether there exist fixed effects across the 16 countries in the sample: $H_0 : \alpha_2 = \alpha_3 = \cdots = \alpha_{16} = 0$. Not rejecting the null hypothesis implies that there are no fixed effects.

We use the generalized likelihood statistic $LR = -2 \ln[L(H_0)/L(H_1)]$ to test the hypotheses, with $L(H_0)$ and $L(H_1)$ being the log likelihood function values of the null hypothesis and the alternative hypothesis. The threshold values are according to Kodde and Palm (1986).

The results of the tests are shown in Table 2.

Table 2

Results of specification tests of the production function

Null hypothesis	LR statistic	$\chi^2_{0.05}$
$\sigma_U^2 = 0$	36.27(rejection)	2.705
$\beta_t = \beta_{tK} = \beta_{tL} = \beta_{tE} = \beta_{KL} = \beta_{KE} = \beta_{LE} = \beta_{KK} = \beta_{LL} = \beta_{EE} = 0$	452.80(rejection)	17.67
$\beta_t = \beta_{tK} = \beta_{tL} = \beta_{tE} = 0$	222.86(rejection)	8.761
$\beta_{tK} = \beta_{tL} = \beta_{tE} = 0$	94.09(rejection)	7.045
$\alpha_2 = \alpha_3 = \cdots = \alpha_{16} = 0$	1447.92(rejection)	24.384

As we can see from the table, the null hypothesis of test (1) is rejected, meaning that there does exist technical inefficiency, and the assumption on residuals is valid. The null hypothesis of test (2) is rejected, so that the Cobb-Douglas production function is outperformed by the translog functional form which better describes the production process. The result of test (3) implies that technological progress exists in the sample countries' production and is not neutral.

The estimated results of the translog production function are shown in Table 3. Most parameters of the translog production function are statistically significant. Seeing from the maximum likelihood function value and the result of the LR test, the explanatory power of the model is quite convincing. We can calculate $\gamma = \sigma_U^2/(\sigma_U^2 + \sigma_V^2) = 0.9418$, which implies that the variation of the compounded residual is mainly caused by technical inefficiency. The stochastic frontier model better describes the production process of the sample countries than a model with classic assumptions on residuals.

Table 3

Estimated results of the translog production function

Variable	Coefficient	Variable	Coefficient
Constant	4.500(7.580)	t	.029(.029)
$\ln K$	.439(.847)	$\ln K \ln L$	$.185^{***}(.037)$
$\ln L$	$-.621(.783)$	$\ln K \ln E$	$-.328^{***}(.0564)$
$\ln E$	$2.181^{***}(.807)$	$\ln E \ln L$	$.149^{**}(.065)$
$t \ln K$	$-.003^{**}(.0016)$	$(\ln K)^2$	$-.015(.033)$
$t \ln L$	$-.002(.0018)$	$(\ln L)^2$	$-.125^{***}(.036)$
$t \ln E$	$.011^{***}(.001)$	$(\ln E)^2$	$.147^{***}(.056)$
(Country dummies ommited.)			
$\sigma_U^2 = .005^{***}(.0005837)$		$\sigma_V^2 = .0003^{***}(.0001)$	
Related tests			
Log likelihood	667.91086	LR test	194640.16

Note: Standard errors for coefficients are in parentheses.

*** Statistical significance at the 1% level.

** Statistical significance at the 5% level.

* Statistical significance at the 10% level.

Several equations alternative to (6) were considered in the estimation. For example, when we include one time dummy (the value being 1 for the years starting from 2008) or two time dummies (the value being 1 for the years starting from 1998 and 2008, respectively) to account for economic crises, there is very little difference in the estimated coefficients, as well as the results for other subsequently calculated indicators. When we include a dummy which takes the value as 1 for energy exporters instead of country dummies, although the average levels of the output elasticities are slightly different, their trends remain similar, while the values of the bias indices are more volatile and cannot provide information accurate enough for our analysis. Thus we decide to keep the empirical model in the form of equation (6).

4.2 Output elasticities and total factor productivity growth rate

We use the formulas (7) – (13) to calculate the output elasticities with respect to each input factor, as well as technological progress (TP), technical efficiency change (TEC), scale efficiency change (SEC) and the growth rate of total factor productivity ($TFPGR$). Table 4 shows the results for the average of the 16 countries in the sample. We obtain confidence intervals from 1000 bootstrap replications, which is shown in the Appendix. Levels of statistical significance are marked in Table 4.

The growth rate of total factor productivity of the sample countries had been rather steady around the average growth rate until early 2000s. Then the growth rate increases to a higher level for a few years, and suffers from a sudden fall in 2008 and 2009, possibly as a consequence of the financial crisis. A similar fluctuation also happend in 1998, possibly due to the financial crisis that took place in East Asia and Russia. The values of technical efficiency change (TEC) and scale efficiency change (SEC) fluctuate around zero, with their absolute values much smaller than those of technological progress (TP), which remains at a quite stable level. This indicates that the growth in total factor productivity of the sample countries mostly depends on technological progress instead of improvements in technical efficiency and scale efficiency.

Table 4

Output elasticities of input factors and total factor productivity growth rate: Average of the 16 countries

Year	K	L	E	TP	TEC	SEC	$TFPGR$
1991	.172*	.389***	.315***	.013***			
1992	.146*	.397***	.346***	.014***	.0054	−.0001	.018**
1993	.134*	.405***	.353***	.014***	−.0002	.0002	.014*
1994	.127*	.410***	.358***	.014***	.0026	−.0013	.015*
1995	.116	.415***	.367***	.014***	−.0079	−.0007	.006
1996	.103	.422***	.376***	.014***	−.0006	−.0014	.012**
1997	.097	.427***	.379***	.014***	.0072	−.0018	.020**
1998	.091	.431***	.383***	.014***	−.0117	−.0015	.001
1999	.083	.433***	.393***	.014***	−.0046	−.0007	.009
2000	.075	.436***	.402***	.014***	.0062	−.0012	.019**
2001	.070	.438***	.407***	.014***	−.0007	−.0004	.013
2002	.065	.441***	.413***	.014***	−.0045	.0002	.010
2003	.051	.447***	.425***	.015***	−.0001	.0005	.015
2004	.037	.453***	.438***	.015***	.0002	−.0001	.015**
2005	.029	.457***	.446***	.015***	.0051	.0001	.020**
2006	.021	.461***	.453***	.015***	.0083***	−.00004	.023***
2007	.014	.465***	.457***	.015***	.0094*	.0002	.025***
2008	.006	.470***	.462***	.015***	−.0078*	−.0003	.007
2009	.005	.475***	.456***	.015***	−.0174***	.0019	−.001
2010	−.011	.485***	.466***	.015***	.0102*	−.0001	.025***
2011	−.014	.488***	.465***	.015***	.0096**	.0011	.025***
2012	−.020	.491***	.469***	.015***	−.0025	−.00007	.012
2013	−.026	.495***	.473***	.014***	−.0002	−.0004	.014***
2014	−.029	.497***	.475***	.014***	−.0044	−.0001	.010
Annual Average	.056	.447***	.416***	.014***	.00006	−.00026	.014***

*/**/***: Statistical significance at 10%/5%/1% level, obtained from 1000 bootstrap replications.

Among the three input factors in our model, the output elasticity for labor is the highest, followed by energy, while the output elasticity of capital is the lowest among the three. This implies that in the contemporary world, the economy has already passed the phase when its growth is mainly driven by the accumulation of capital. Instead, labor is playing a central role in boosting production; the economy is also depending more and more on the use of energy.

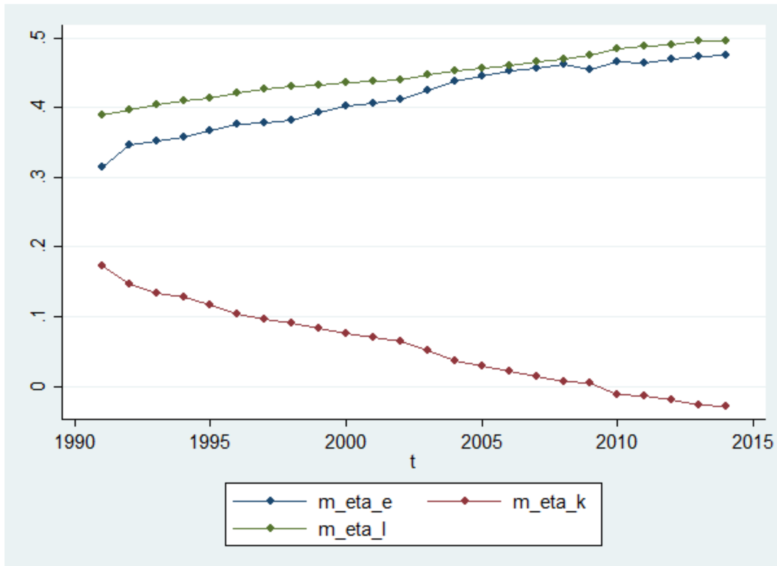

Figure 1: Average output elasticity for the sample countries

The values for the output elasticity of labor and energy are all statistically significant; the output elasticity of capital, for most time, is not statistically different from zero. Nonetheless, the standard errors of the output elasticity of the three inputs are similar, and for most time periods there is no intersection between the confidence intervals of the output elasticity of capital and that of other inputs. So there is little doubt that the output elasticity of capital is the lowest among the three inputs factors.

Figure 1 shows the average output elasticity for the sample countries along the years. Generally, the output elasticity of capital is decreasing, while that of labor and energy is increasing. In addition, the output elasticity of energy is increasing at such a high rate that its gap from the output elasticity of labor is diminishing. Although there is intersection in the confidence intervals of the output elasticity of labor and that of energy, if we look at Table 5, we can find that the bias index E-L is statistically significant and positive in most time periods, implying that technological change is indeed biased towards energy rather than labor.

Figure 2 shows the returns to scale (RTS) of the 16 countries from 1991 to 2014. The returns to scale (RTS) of the countries range between 0.70 to 1.22; from 1991 to 2014, the average returns to scale of the 8 developed coutries is

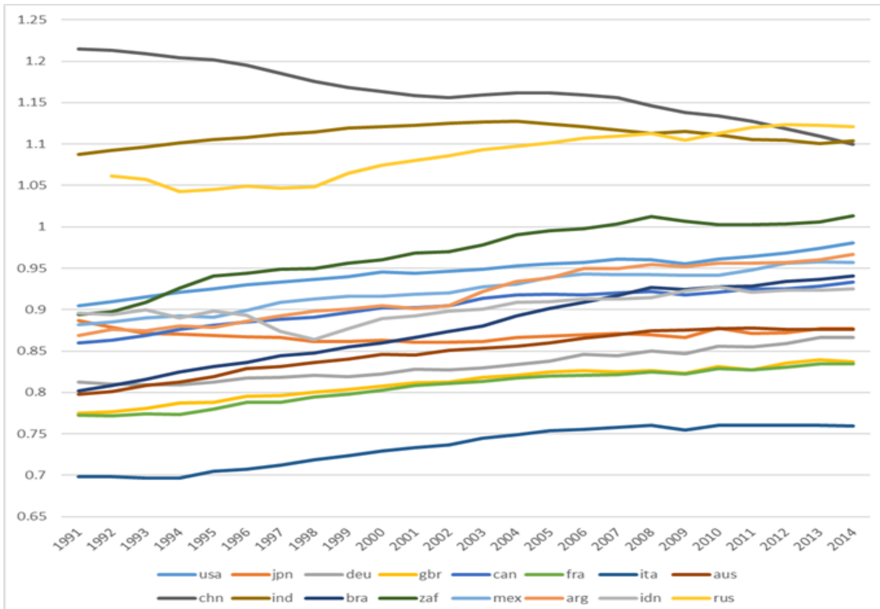

Figure 2: Returns to scale of the 16 countries, 1991-2014

0.843, while the average returns to scale of the 8 developing countries is 0.994, with the average of the 16 countries equal to 0.919. Developing countries have been generally enjoying higher returns to scale; China, India and Russia have average returns to scale greater than 1. The average of the sample countries, however, shows decreasing returns to scale, which is a phase that each country will finally come to when they become better developed. Among the 16 countries, China has the highest average returns to scale along the years. The average returns to scale of Italy is the lowest, significantly lower than the other countries. While China, Russia and India are all countries with immense populations and geographic areas, which may partly be the reason for their high returns to scale, it is still hard to explain the gap between the returns to scale of Italy and those of other countries.

Figure 3 illustrates the averages along the years of the total factor productivity growth rate and the output elasticities of the three input factors for each country in our sample. Among capital, labor and energy, the output elasticity of labor is the highest for developed countries, while in developing countries the output elasticity for energy is the highest, or very close to the highest (in the case of Brazil, Argentina and Indonesia). This reveals different patterns of eco-

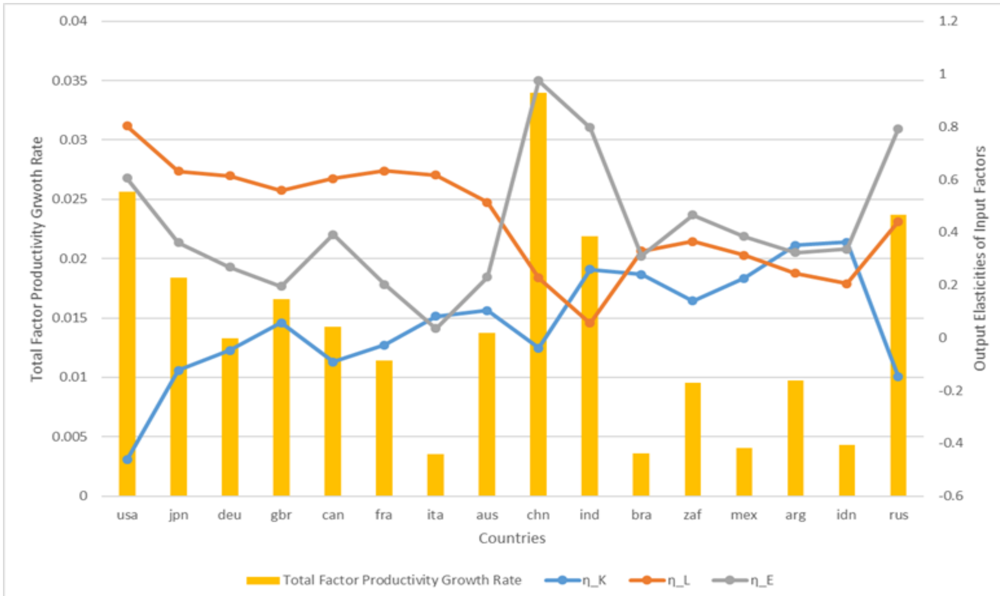

Figure 3: Average Total Factor Productivity Growth Rate and Output Elasticities of Various Inputs for the 16 Countries in the Sample

nomic growth in developed and developing coutries. For developed countries, labor plays more role as the drive for economic growth. The higher elasticities of labor in developed countries reflect higher levels of education; as a consequence, industries that require highly skilled workers (e.g. the IT sector, service sector and financial sector) are better developed. Developing countries, on the other hand, rely more on the use of energy to sustain their growth; there is great potential for them to boost their long-term economic growth by improving education levels.

It is worth noticing that for some observations, e.g. the U.S. and China, there are negative values for the output elasticity with respect to capital. The direct factor that leads to such phenomenon is the negative coefficient on the term $\ln K$, along with the large standard deviation in the data for capital. From a theoretical point of view, this is not quite feasible since rational agents will not invest if the output elasticity is negative. Nevertheless, in our micro level study (Hou et al., 2019), negative output elasticity is not rare in firm-level observations. Meanwhile, we try to explain such phenomenon with the following possible reasons[13].

1. Limited information: usually, agents do not mathematically calculate output elasticity; they usually increase all inputs simultaneously and observe an increase in production, so they keep investing in the same way.

2. Investment externalities: from the perspective of individual agents, they may be making optimal investment decisions, which is not necessarily also optimal for the whole economy at the macro level, as they don't take into account the externalities of their investment. A micro-level study might provide more information regarding this topic.

3. Real estate price: increase in capital stock is partly due to raise in the prices of real estate, which doesn't do any help in production.

4. Preference for domestic investment: some agents prefer to invest their money in domestic market, because of risk concerns or difficulties in investing their money abroad (where the output elasticity of capital is higher).

We can also observe significant differences between the growth rates of total factor productivity of different countries in the sample. The growth rates of the US, China and Russia are the highest, while the growth rates of Italy, Brazil and Mexico are the lowest. This reflects the progress each country have made in technological development. For countries like Italy, Brazil and Mexico, encouraging technological R&D and the adoption of new technologies might be a solution for ameliorating their economic performance.

4.3 Directed technological change

According to Equation (14), we calculate the factor bias index of technological change for the 16 countries in the sample. Table 5 shows the average factor bias index of the countries in the sample from 1991 to 2014, marked with levels of statistical significance obtained from 1000 bootstrap replications. We can observe that while some changes take place in the first half of the sample period, the values of the bias indices and the bias order is quite stable in the second half of the sample period. The main change is the bias order for capital: in the beginning it takes the first place in the bias order of technological change; but soon it loses the lead and moves to the second place; in the end, capital is the least favored by technological change among the three input factors. For most time periods, technological change is biased the most towards energy, which is

[13] In our case, negative values are detected only in the output elasticities of capital. In the cases where there are negative values in the ouput elasticities of other inputs, the above first and second factor might still serve as possible explanations.

what we are trying to find out by our research. Technological change is not biased to labor at first; from 2005 onwards, the bias order of labor exceeds that of capital. Throughout the sample period, the main trend for the bias order is $K < L < E$, and such order is likely to maintain in the near future.

In the modern world where technology is highly developed, technological progress usually takes place in a subtle manner. The absolute values of the bias indices are usually small, hence sometimes they may not be statistically significant. Nevertheless, in most time periods, the bias indices E-L are statistically significant, indicating that technological change is biased more towards energy than labor. The situation is similar in the bias indices for each country. Even though we cannot be fully confident in the other bias indices judging from the levels of statistical significance, if we relate the results in the bias indices with the trends in the change of output elasticities of the inputs, we can infer that the overall technological change of the sample countries is biased the most towards energy, followed by labor, and the least towards capital.

Table 5

Annual average factor bias index of the selected countries

Year	Bias K-L	Bias K-E	Bias E-L	Bias order
1991	.055**	.028	.027	$L < E < K$
1992	.022	.002	.020	$L < E < K$
1993	.022	−.016	.038	$L < K < E$
1994	.008	−.020	.028	$L < K < E$
1995	−.014	−.026	.012	$K < L < E$
1996	.031	.030	.001	$L < E < K$
1997	.090***	.123**	−.033	$E < L < K$
1998	.009	−.168***	.177***	$L < K < E$
1999	.044*	−.066*	.110***	$L < K < E$
2000	.021	−.051	.073***	$L < K < E$
2001	.013	−.052	.064***	$L < K < E$
2002	.005	−.052*	.057***	$L < K < E$
2003	.021	−.028	.049**	$L < K < E$
2004	.004	−.041	.045**	$L < K < E$
2005	−.001	−.043	.042**	$K < L < E$
2006	−.003	−.043	.041**	$K < L < E$
2007	−.003	−.043	.040*	$K < L < E$
2008	−.006	−.044	.039*	$K < L < E$
2009	−.002	−.043	.040*	$K < L < E$
2010	−.010	−.048*	.038**	$K < L < E$
2011	−.007	−.046	.038**	$K < L < E$
2012	−.009	−.047	.038**	$K < L < E$
2013	−.011	−.049	.038**	$K < L < E$
2014	−.011	−.050*	.038*	$K < L < E$

*/**/***: Statistical significance at 10%/5%/1% level, obtained from 1000 bootstrap replications.

Table 6 shows the average factor bias index in the period 1991-2014 for each country in the sample. The technological change bias order is $L < K < E$ for the US and China; $L < E < K$ for Japan, Germany, Canada, France and Russia; $K < L < E$ for the other countries in the sample. From an intuitive perspective, there are some patterns for countries that share the same bias order. Two major economies of the comtemporary world, the US and China, share the bias order $L < K < E$; countries with the bias order $L < E < K$ are well developed countries or former major economy of the world; and most developing countries have the bias order $K < L < E$.

In the bias orders of the 16 countries, one thing in common can be discovered: technological change is always biased more towards energy than labor. What makes the difference is the position of capital, or in other words, how much capital is favored by technological change. Though it may not be practical to present the bias indices for each single observation in our paper, from our result we can tell that in most countries, the bias index K-L and bias index K-E are decreasing, which can also be reflected in the change of values in Table 5. But the time when the sign of bias index changes (if it does) differs in each country, which leads to the difference in overall bias orders. It seems to be a sequential issue that affects the bias orders of the countries. Yet, on one hand, there may be further country-specific factors giving rise to such "sequential issue"; on the other hand, we cannot exclude the effect of other potential determinants on the bias orders. So there remains the space for discussion on the determinant(s) for the direction of technological change.

One may naturally wonder if there is a connection between the direction of technological change and the energy balance of trade. For all or most time periods, the US, Japan, Germany, the UK, France, Italy, China, India and Brazil are energy importers; Canada, Australia, South Africa, Mexico, Argentina, Indonesia and Russia are energy exporters. According to our finding, technological change is biased the most towards energy in the energy exporting countries except for Canada and Russia; meanwhile, there are energy importer countries where technological change is also biased the most towards energy. It is then quite difficult to conclude that the energy balance of trade determines the direction of technological change. One possible explanation could be that, on one hand, due to underdevelopment in industries, most of the developing countries are not able to consume the total amount of energy produced by themselves; on the other hand, facing comparatively lower level of education, the more direct way to improve output seem to be better utilization of energy input.

Table 6

Country average factor bias index

Country	Bias K-L	Bias K-E	Bias E-L	Bias order
The US	.011*	−.010	.021***	$L < K < E$
Japan	.047**	.013	.034***	$L < E < K$
Germany	.123***	.077*	.046***	$L < E < K$
The UK	−.071	−.134	.063***	$K < L < E$
Canada	.070***	.038*	.032***	$L < E < K$
France	.125***	.063	.062***	$L < E < K$
Italy	−.056*	−.173	.118	$K < L < E$
Australia	−.047*	−.104*	.057**	$K < L < E$
China	.010	−.011	.021*	$L < K < E$
India	−.0003	−.036	.036**	$K < L < E$
Brazil	−.014	−.061	.047	$K < L < E$
South Africa	−.032*	−.061**	.030**	$K < L < E$
Mexico	−.013	−.048*	.035***	$K < L < E$
Argentina	−.005	−.049	.044	$K < L < E$
Indonesia	−.002	−.046	.044	$K < L < E$
Russia	.031*	.013	.018**	$L < E < K$
Average	.011	−.033	.044	$L < K < E$

*/**/***: Statistical significance at 10%/5%/1% level, obtained from 1000 bootstrap replications.

Now we see that technological change is biased the most to energy among the three inputs, for the average of the 16 countries and for most countries in the sample. In particular, evidence is strong that technological change is biased more towards energy rather than labor. Labor, of course, can be considered as a renewable input; energy input is, at least partly, non-renewable. In such sense, our finding can be seen as supporting the hypothesis that technological change is more likely to favor the non-renewable input rather than the renewable. However, It still remains a doubt what is the main determinant for the biasedness of technological change. Is it the market size, or price incentive, or other factors that decide the direction of technological change? Do agents take into account the fact that some input is non-renewable when they make R&D decisions? To answer the questions above, probably we shall need not only more empirical evidence, but theoretical support as well.

5 Conclusion

In this paper we apply the Stochastic Frontier Analysis to data for 16 countries in order to assess the technological change in production at macro level with three input factors: capital, labor and energy. As has rarely been applied in studies of Stochastic Frontier Analysis, we use bootstrap to obtain confidence intervals and statistical significance levels, in order to have more rigorous and convincing results.

Our findings indicate that, in the sample countries between 1991 and 2014, on average, output elasticities of energy and labor are increasing; specifically, the output elasticity of energy grows at a higher rate so that it is catching up with the output elasticity of labor, which is supported by the statistically significant bias index between energy and labor. The output elasticity of capital is decreasing, and has negative values for some observations; yet agents keep investing in capital, possibly because of limited information, investment preference, real estate price and investment externalities. Among the three input factors, the output elasticity of labor is the highest for developed countries, and the output elasticity of energy is the highest or very close to the highest for developing countries. In addition, compared with developed countries, developing countries are more likely to enjoy higher returns to scale in production.

We find that the average production of the sample countries demonstrates decreasing returns to scale, while the returns to scale for developing countries are generally higher. Results also show a significant difference between the total factor productivity growth rates between the countries in the sample. For some countries, the advice on policy making might be to encourage technological progress, in order to sustain their economic growth.

By calculating the factor bias index, we find out that for the general trend of the 16 countries and for most countries in the sample, technological change is biased the most towards energy. Different countries demonstrate different technological change bias orders, but technological change commonly favors energy rather than labor. Such could be evidence that technological change is more likely to be biased towards the non-renewable input than the renewable.

The purpose of our study is to analyze the directed technological change in worldwide production activities; if, by any chance, it could provide a clue for studies in economic growth or other fields of macroeconomics, it would be of our great pleasure. Meanwhile, it still leaves some questions difficult to answer at this moment. For countries with the same bias orders, is there any pattern in common? What determines the direction of technological change? That's a topic open to future studies.

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Appendix

Appendix A

Output elasticities of input factors: Average of the 16 countries

95% bias-corrected confidence intervals in parentheses, from 1000 bootstrap replications.

Year	K	L	E
1991	.172(−.003/.335)	.389(.214/.579)	.315(.144/.490)
1992	.146(−.014/.315)	.397(.229/.589)	.346(.174/.530)
1993	.134(−.008/.328)	.405(.249/.595)	.353(.156/.529)
1994	.127(−.020/.304)	.410(.233/.606)	.358(.165/.545)
1995	.116(−.060/.305)	.415(.257/.613)	.367(.193/.554)
1996	.103(−.057/.279)	.422(.256/.610)	.376(.181/.551)
1997	.097(−.072/.264)	.427(.261/.595)	.379(.212/.559)
1998	.091(−.049/.256)	.431(.272/.600)	.383(.183/.554)
1999	.083(−.080/.248)	.433(.277/.622)	.393(.228/.572)
2000	.075(−.086/.239)	.436(.277/.591)	.402(.228/.579)
2001	.070(−.087/.242)	.438(.285/.623)	.407(.231/.584)
2002	.065(−.091/.237)	.441(.262/.601)	.413(.237/.588)
2003	.051(−.106/.224)	.447(.290/.622)	.425(.246/.591)
2004	.037(−.110/.220)	.453(.289/.623)	.438(.260/.596)
2005	.029(−.126/.205)	.457(.303/.625)	.446(.261/.614)
2006	.021(−.134/.175)	.461(.312/.633)	.453(.271/.614)
2007	.014(−.147/.176)	.465(.312/.646)	.457(.284/.624)
2008	.006(−.148/.169)	.470(.318/.646)	.462(.285/.637)
2009	.005(−.155/.155)	.475(.316/.642)	.456(.289/.612)
2010	−.011(−.162/.133)	.485(.348/.664)	.466(.254/.629)
2011	−.014(−.166/.166)	.488(.329/.658)	.465(.279/.627)
2012	−.020(−.179/.150)	.491(.341/.653)	.469(.274/.633)
2013	−.026(−.170/.150)	.495(.353/.662)	.473(.284/.636)
2014	−.029(−.185/.132)	.497(.340/.664)	.475(.309/.649)
Annual Average	.056(−.041/.189)	.447(.326/.574)	.416(.293/.526)

Appendix B

Total Factor Productivity Growth Rate and its components: Average of the 16 countries

95% confidence intervals in parentheses, from 1000 bootstrap replications.

Year	TP	TEC	SEC	$TFPGR$
1991	.013(.007/.018)			
1992	.014(.008/.019)	.0054(−.006/.030)	−.0001(−.004/.004)	.018(.002/.037)
1993	.014(.008/.019)	−.0002(−.016/.012)	.0002(−.003/.005)	.014(−.003/.025)
1994	.014(.008/.019)	.0026(−.012/.012)	−.0013(−.005/.003)	.015(−.001/.023)
1995	.014(.008/.019)	−.0079(−.025/.002)	−.0007(−.004/.005)	.006(−.013/.019)
1996	.014(.008/.019)	−.0006(−.015/.010)	−.0014(−.004/.002)	.012(.001/.023)
1997	.014(.008/.019)	.0072(−.003/.022)	−.0018(−.006/.001)	.020(.002/.035)
1998	.014(.009/.019)	−.0117(−.061/.004)	−.0015(−.005/.0007)	.001(−.059/.017)
1999	.014(.009/.019)	−.0046(−.015/.004)	−.0007(−.004/.003)	.009(−.009/.020)
2000	.014(.008/.019)	.0062(−.006/.019)	−.0012(−.004/.002)	.019(.003/.036)
2001	.014(.010/.019)	−.0007(−.012/.008)	−.0004(−.003/.003)	.013(−.004/.027)
2002	.014(.009/.019)	−.0045(−.043/.006)	.0002(−.002/.005)	.010(−.029/.024)
2003	.015(.009/.019)	−.0001(−.018/.016)	.0005(−.004/.007)	.015(−.005/.031)
2004	.015(.009/.019)	.0002(−.016/.011)	−.0001(−.005/.008)	.015(.002/.030)
2005	.015(.009/.019)	.0051(−.008/.023)	.0001(−.003/.005)	.020(.005/.035)
2006	.015(.010/.020)	.0083(.004/.016)	−.00004(−.004/.005)	.023(.013/.034)
2007	.015(.010/.020)	.0094(−.0003/.023)	.0002(−.003/.005)	.025(.014/.039)
2008	.015(.009/.020)	−.0078(−.019/.001)	−.0003(−.004/.003)	.007(−.008/.022)
2009	.015(.009/.019)	−.0174(−.037/ − .005)	.0019(−.003/.008)	−.001(−.022/.017)
2010	.015(.010/.020)	.0102(−.0009/.026)	−.0001(−.004/.006)	.025(.015/.040)
2011	.015(.009/.020)	.0096(.0002/.022)	.0011(−.002/.003)	.025(.015/.038)
2012	.015(.009/.020)	−.0025(−.013/.010)	−.00007(−.003/.002)	.012(−.002/.028)
2013	.014(.009/.020)	−.0002(−.009/.015)	−.0004(−.003/.002)	.014(.004/.034)
2014	.014(.009/.020)	−.0044(−.018/.008)	−.0001(−.004/.002)	.010(−.009/.025)
Annual Average	.014(.010/.017)	.00006(−.003/.003)	−.00026(−.002/.002)	.014(.009/.018)

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