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DE LISBOA

Technological Change, Efficiency and Energy

Hou Zheng

PhD in Economics

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January 2021

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Abstract for Dissertation for PhD in Economics

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Economic performance is closely related with energy consumption, the major part of which still comes from non-renewable sources. While endeavoring to promote renewable energy, policy makers are interested in technological change that also increases energy efficiency. However, both growth models of directed technological change and microeconomic theories regarding innovation suggest that technological change is not necessarily biased towards energy, which calls for the support of empirical evidence. Previous studies on the topic mostly focus on a certain country/region using data at province/sector level. My dissertation applies Stochastic Frontier Analysis (SFA) as its main econometrical method and investigates the situation of technological progress involving energy as input and output. The findings may serve as reference for policy considerations related to innovation, energy pricing, firm operation, etc. Macro-level findings show that technological change is biased towards energy; micro-level findings show that technological change is biased the most towards labor; technological change has favored fuel over electricity in general. We infer that the market size effect is likely to overwhelm others in deciding the direction of technological change. Thus, policy should include tools in addition to energy prices in inducing technological change. We conclude that productive technical efficiency is positively affected by higher capital input relative to labor input, as well as higher average hourly wage and lower average working hours. Evidence also suggests that the liberalization in the Portuguese electricity market starting from the 2000s was successful in the sense that there is a trend of improvement in technical efficiency through time.

Keywords: energy; non-renewable resource; economic growth; Stochastic Frontier Analysis; directed technological change; technical efficiency.

Resumo de Dissertação de Doutorado em Economia

Mudança Tecnológica, Eficiência e Energia

Hou Zheng

Orientadores: Prof. Catarina Roseta Palma, Prof. Joaquim J.S. Ramalho

O desempenho econômico está intimamente relacionado ao consumo de energia, a maior parte da qual ainda vem de fontes não renováveis. Ao mesmo tempo que se esforçam para promover a energia renovável, os formuladores de políticas estão interessados em mudanças tecnológicas que também aumentem a eficiência energética. No entanto, tanto os modelos de crescimento da mudança tecnológica direcionada quanto as teorias microeconômicas sobre a inovação sugerem que a mudança tecnológica não é necessariamente enviesada para a energia, o que exige o apoio de evidências empíricas. Estudos anteriores sobre o tópico focam principalmente em um determinado país / região usando dados em nível de província / setor. Minha dissertação aplica a Stochastic Frontier Analysis (SFA) como seu principal método econométrico e investiga a situação do progresso tecnológico envolvendo energia como entrada e saída. As descobertas podem servir como referência para considerações de política relacionadas à inovação, preços de energia, operação de empresas, etc. As descobertas de nível macro mostram que a mudança tecnológica é tendenciosa para a energia; descobertas em nível micro mostram que a mudança tecnológica é mais tendenciosa para o trabalho; a mudança tecnológica tem favorecido o combustível em relação à eletricidade em geral. Inferimos que o efeito do tamanho do mercado provavelmente sobrecarregará os outros na decisão da direção da mudança tecnológica. Assim, a política deve incluir ferramentas além dos preços da energia na indução de mudanças tecnológicas. Concluímos que a eficiência técnica produtiva é positivamente afetada por maior entrada de capital em relação à entrada de trabalho, bem como maior salário-hora médio e menor média de horas de trabalho. Evidências também sugerem que a liberalização do mercado elétrico português a partir dos anos 2000 foi bem-sucedida no sentido de que há uma tendência de melhoria da eficiência técnica ao longo do tempo.

Palavras-chave: energia; recurso não renovável; crescimento econômico; Stochastic Frontier Analysis; mudança tecnológica dirigida; eficiência técnica.

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Technological Change, Efficiency and Energy

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1 General Introduction

Technological advances regarding energy have always attracted the attention of governments and firms, considering the growing dependence of contemporary economies on energy use. Evidence shows the causality from energy consumption to economic growth (Mozumder and Marathe, 2007); and there have been summaries on the literature regarding the nexus between energy consumption and growth, e.g. Payne (2010). Specifically, research supposes bi-directional causality between the two in the long run. For Portugal, the country that we focus on in the present research, empirical evidence on the relationship between energy consumption and growth was provided by Shahbaz et al. (2011) and Fuinhas and Marques (2012). Empirical evidences support the connection between economic growth, energy consumption and CO_2 emission for Indonesia (Shahbaz et al., 2013), China (Wang et al., 2016) and a number of other countries (Alam et al., 2016). A more thorough review of studies on the relationship between economic growth and energy is done by Wang et al. (2018).

Due to concerns on the sustainability of energy use and its environmental impacts, government policy often attempts to augment the cost of using energy by agents, in order to control energy consumption. Although individual firms may enjoy favorable returns from investment in energy-saving equipments (Train and Ignelzi, 1987), such reduction of energy inputs in general undermines economic output. Pereira and Pereira (2010) suggest that, in Portugal, for every ton of oil equivalent (toe) that is permanently reduced in aggregate energy consumption, aggregate output drops €6340. On the other hand, the environmental degradation, caused by the use of energy and subsequent CO_2 emissions, is unlikely to be solved automatically by economic growth (Özokcu and Özdemir, 2017). The reconciliation between economic growth, energy consumption and environmental impact relies on appropriate technological development.

Growth theory considers technological progress as the key to sustain economic growth with limited resources (e.g. Grimaud and Rougé, 2003). By applying new technologies that utilize inputs more efficiently in production, the restrictions on the use of energy input can be overcome. According to the classical microeconomic theory of induced innovation (Hicks, 1932), along with empirical evidence on price-motivated innovation (Popp, 2002), in response to increased energy prices, as well as energy policies, one might expect the adoption of new technologies by firms so that energy efficiency is improved.

Nevertheless, because of knowledge spill-over which is not fully internalized, firms may under-invest in R&D (Grubb and Ulph, 2002); moreover, policies may not be optimal in promoting energy-efficient technology development (Yang, 2006). It is also believed that the economic opportunity to improve energy efficiency is not fully seized by firms (Harris et al., 2000); and that not only R&D, but also deployment matters in the adoption of new technologies (Sagar and van der Zwaan, 2006). Many firms are constrained by financial barriers or lack of skills and information, so that the potential to improve energy efficiency is largely untapped (Kalantzis and Revoltella, 2019). In addition, the existence of alternative investment opportunities and the incomplete depreciation of capital stock can be causes for underinvestment in energy-saving technologies (De Groot et al., 2001). It is then difficult to predict whether and to what extent firm level technological change with respect to energy has taken place without exact empirical evidence.

Technological change over time in an economy consists of the change in total factor productivity and the bias of the technological change towards input factors (Diamond, 1965). In growth models of directed technological change, the direction of change depends on market size effect, price effect and various economic parameters (Acemoglu, 2002, 2010). Considering the aforementioned factors, how does technological change involving energy take place? What role does energy play in production, compared with other main input factors, namely capital and labor?

The utilization of energy should transition from non-renewable to renewable sources in the next few decades, due to concerns about the climate change effects of the former. Worldwide, consumption of both non-renewables and renewables has been growing rapidly, with the share of renewables in electricity production rising from 19.75% in 1990 to 26.62% in 2019; meanwhile, the share in Portugal witnessed greater change between 19.83% in 1992 and 61.37% in 2014 (Enerdata, 2020). Inducing technological change regarding renewable energy is an indispensable part in promoting this source, thereby mitigating climate change and pursuing more sustainable economic growth. Investigation on directed technological change between non-renewable and renewable energy is helpful in evaluating whether policies have been effective in reaching such target. Portugal, with its great effort and achievement in promoting renewable energy, can provide valuable lessons.

Empirical methods for assessing the direction of technological change evolved from measures such as cost shares and energy to GNP ratio (Hogan and Jorgenson, 1991) to estimation of CES production functions ((Kemfert and Welsch, 2000; Klump et al., 2007, among others), but Stochastic Frontier Analysis has gained the preference of researchers in recent years (e.g. Shao et al., 2016; Wesseh and Lin, 2016). Literature on Stochastic Frontier Analysis applied to the topic of technological change mostly focuses on sector level (Shao et al., 2016; Yang et al., 2018, among others). Our study applies SFA to country-level and firm-level data for a complete assessment on the direction of technological change at different levels.

The study of my dissertation is meaningful in several aspects. First, it provides empirical support to growth theory with directed technological change. It helps identify which effect prevails in determining the direction of technological change: the market size effect, the price effect, or any other effect? Second, it serves as a reference on the effectiveness of current energy policies related to technological development, and therefore advises those policies. Third, as abovementioned, the study also reveals some features for economic development, which can also be helpful in policy making.

The rest of this dissertation consists of three sections. In the second section, we select annual macro panel data from 1991 to 2014 for 16 developing and developed countries considering their GDP and geological diversity. We estimate a trans-log production function with half-normally distributed inefficiency term and calculate output elasticities and factor bias indices, among other indicators. Findings show that despite various patterns between different groups of countries, technological change is generally biased towards energy. In particular, there is strong evidence obtained by bootstrap that technological change favors energy more than labor. This is in line with the theoretical expectation that technological change ought to be biased towards the non-renewable input rather than the renewable ones. The content of this section results in a research paper that has been published on *Environment and Development Economics*.

In order to investigate directed technological change at the micro level, the third section applies stochastic frontier analysis to firm data for 32 economic subsectors, with respect to output produced with four inputs: capital, labor, electricity and fuel. Subsectors demonstrate different levels of technical inefficiency, which could be induced by capital deepening and higher share of financial income in total revenue. Output elasticity of labor is generally high among the subsectors, emphasizing labor as the main driver for economic growth. Output elasticity of capital is low overall, although a few subsectors enjoy better marginal returns. In most subsectors, technological change is biased the most towards labor; between electricity and fuel, technological change has favored fuel in more cases. We infer that the market size effect is likely to overwhelm others in deciding the direction of technological change. Thus, policy should include tools in addition to the energy price in inducing technological change. Carbon pricing could be an option for this purpose. The research paper corresponding to this section is submitted to *Energy Economics* and is currently under revision for resubmission.

In the estimation of empirical models in the third section, some economic subsectors didn't fit the model very well, the electricity sector being a case in point. This gave rise to the study of the fourth section, which analyzes the impact of operational factors on the technical efficiency of firms in the Portuguese electricity sector. Recently, technical efficiency and its determinants in the electricity sector have aroused the interest of researchers. A number of studies apply Stochastic Frontier Analysis to the subsector of transmission and distribution (T&D) of electricity, while less attention is paid to electricity generation. In the fourth section, we estimate Stochastic Frontier models for production, distance and cost functions using firm data in the Portuguese electricity sector. It includes the subsectors of electricity generation from thermal, hydraulic and other renewable sources, as well as T&D, in order to evaluate the impact of operational factors on technical efficiency. Among the factors considered in the study, we find that productive technical efficiency is positively affected by higher capital input relative to labor input, as well as higher average hourly wage and lower average working hours. Evidence also suggests that the liberalization in the Portuguese electricity market starting from the 2000s was successful in the sense that there is a trend of improvement in productive technical efficiency through time. The study in this section is a complement to that in the third section, and could be a reference for improving technical efficiency of firms in the electricity sector. The research paper corresponding to this section is submitted to the *Energy Journal*.

The three sections together form a complete picture of the role of energy in modern economy in relation to technological change. Empirical analyses are done with respect to macro and micro level in order to evaluate the direction of technological change involving energy in production; evolution of technical efficiency and its administrative determinants are evaluated for the Portuguese electricity sector. We then conclude with the fifth section.

2 Country-Level Study on the Direction of Technological Change

2.1 Introduction

Energy is, to the modern economy, what blood is to the body. In the past few decades, in spite of major investments in renewable energy sources, fossil fuels still constitute approximately 80% of the world's energy production[1]. One may naturally be concerned about how economic development can be guaranteed while energy, as a key input, seems unlikely to be free from the peril of depletion, given the current technology on its extraction and generation. 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 are aware of this, the implementation of policies is never a simple procedure, and it is important to assess 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, macro-level evidence is still rare; in this section, we illustrate the situation of directed technological change in the world's main economies.

Agents make R&D decisions in a market with imperfect competition, incomplete information, government regulations, externalities in knowledge spillovers and other frictions; it is difficult to determine from a theoretical perspective how, if at all, technological change is biased. Theoretically, technological change might be expected to show a bias towards the non-renewable input(s) rather than the renewable one(s), as the former gets depleted over time. Nevertheless, despite accumulated empirical effort at industry level, country-level evidence is still insufficient. An empirical study on country-level directed technological change might improve our understanding of general production patterns in the comtemporary world. Moreover, since many decisions are made by agents in technical R&D; this analysis might 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

[1]Source: IEA World Energy Balances 2019, https://www.iea.org/data-and-statistics

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 Stochastic Frontier Analysis (SFA) to be more appropriate for our research purpose, as it allows the estimation of indicators that provide a more comprehensive idea on the situation of technological change, including technical inefficiency, output elasticities and total factor productivity growth rate. In this section we apply SFA 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 how technological change has been biased in 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 provides us with an idea of the role played by technological change in macro level production; it also reveals 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 inputs, 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 SFA studies, we obtain confidence intervals and levels of statistical significance for the abovementioned indicators, in order to acquire a more rigorous result. Boostrap results show strong evidence of consistency among countries, in the sense that technological change favors energy more than labor. Such finding supports the hypothesis that technological change is more likely to be biased to the non-renewable input rather than the renewable.

The rest of this section is organized as follows. We review the literature on our topic in Subsection 2.2. In Subsection 2.3 we address the methodology and data. Subsection 2.4 presents the empirical results, along with related interpretation and discussion.

2.2 Literature Review

The reliance of economic activities on natural resources, a significant 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 focused 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 exhaustible resources. These early studies share one feature: they all believe technological change should play a relevant role in such progress.

Some economists seek solutions other than technological change. Groth and Schou (2002, 2007) deem increasing returns to capital as the drive for growth; however, as we are going to show in our results, general production activities are 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 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 conclusions, including Smulders and De Nooij (2003), Di Maria and Valente (2008), André and Smulders (2014).

Governments concerned with the scarcity of fossil-fuel energy and its environmental consequences have proposed policies like environmental taxes, aimed at limiting the use of fossil fuels. According to the belief of induced innovation by Hicks (1932), with the price incentives created by such policies, technological change ought to 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 socially optimal as knowledge spillovers are not fully internalized (Grubb and Ulph, 2002). Therefore, both taxation and research subsidies play a role in optimal policy making, as suggested by Jaffe et al. (2005), Grimaud et al. (2011), Acemoglu et al. (2012).

The 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, 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 et al. (2000), among others, the technological change of an economy over time consists of two aspects: the change in total factor productivity and the bias of technological change towards input factors. Acemoglu (2002, 2007) leaves unanswered whether the result would still be the same if technological change consists of these two aspects.

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 direction of technological changes. Comparative to our topic, Acemoglu (2010) discusses whether labor scarcity encourages technological advances, with the answer depending on the economic environment (functional 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 inputs. 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 research 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. Simple 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 as well.

Stochastic Frontier Analysis was first introduced by Aigner et al. (1977) and Meeusen and Van den Broeck (1977). Along the years this method was 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 it was, at first, used to discuss the inefficiency in production and its determinants. Although more often applied in micro-level studies, SFA 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, SFA has been applied in 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 us 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 set 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 regarding energy; analysis from a broader perspective is needed to assess how macro-level technological change has been unfurling in the global context.

One of our study's contributions is its empirical analysis of country-level production in a worldwide perspective, with capital, labor and energy as inputs. Besides this general contribution on the way 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 a reference for policy making.

2.3 Methodology and Data

2.3.1 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. The authors 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 emissions are, as a matter of fact, an output resulting from production and the distance function is the most proper functional form to describe such a process, as in Duman and Kasman (2018). In the macro context, since there isn't a global carbon emissions market where carbon emissions would incur comparable costs, we opt not to take it as an input.

Thus 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

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

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 also done by 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 $\sigma^2 = \sigma_U^2 + \sigma_V^2$[2]; 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 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)[3], the growth rate of the TFP can be

[2] 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.

[3] Interested readers may refer to Kumbhakar et al. (2000) for a more complete derivation

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 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:

of the following equations.

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

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.

2.3.2 Data

We collect annual data from 1991 to 2014 for 16 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, all chosen for their weight in terms of real GDP in the world; we also selected countries in 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[4] 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[5]. Throughout the sample period or for most of it, 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[6].

[4] According to World Economic Situation and Prospects 2018 (Economic Analysis & Policy Division, the United Nations, 2017), Russia is among the economies in transition, and is not considered as a developed country.

[5] 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.

[6] Source: Global Energy Statistical Yearbook 2018.

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

Y - real GDP collected from the database of the Federal Reserve[7], 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[8]) 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[9]. The descriptive statistics of the data are shown in Table 1.

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

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

[9] 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.

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

2.4 Results and Discussion

2.4.1 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).

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

The results of the tests are shown in Table 2.

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.

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).

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.

2.4.2 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 Appendices A and B. 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.

Among the three input factors in our model, the output elasticity for labor is

Table 4: Output elasticities of input factors and total factor productivity growth rate: average of the 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.

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.

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 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 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 produc-

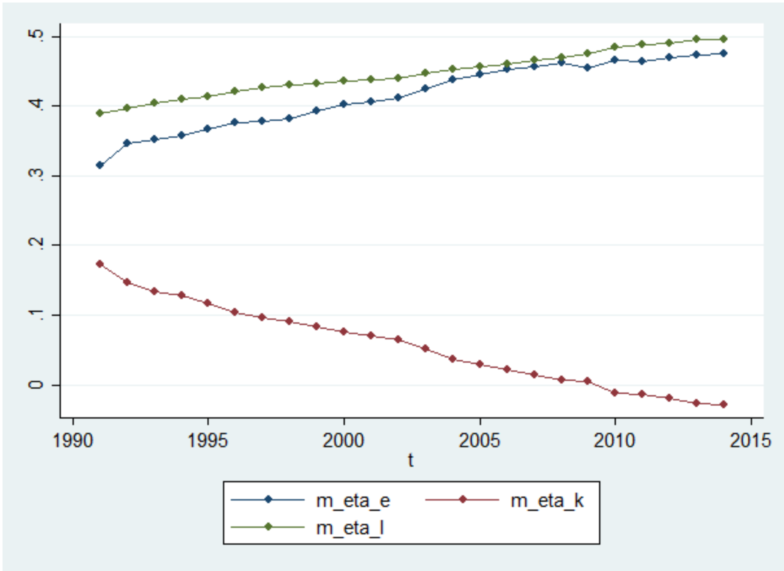

Figure 1: Average output elasticity for the 16 countries

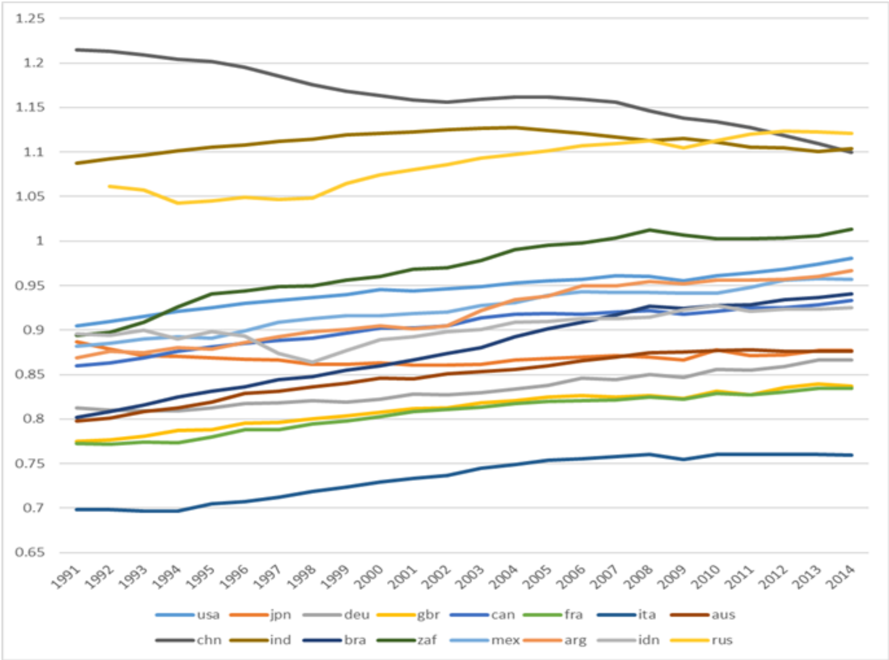

Figure 2: Returns to scale of the 16 countries, 1991-2014

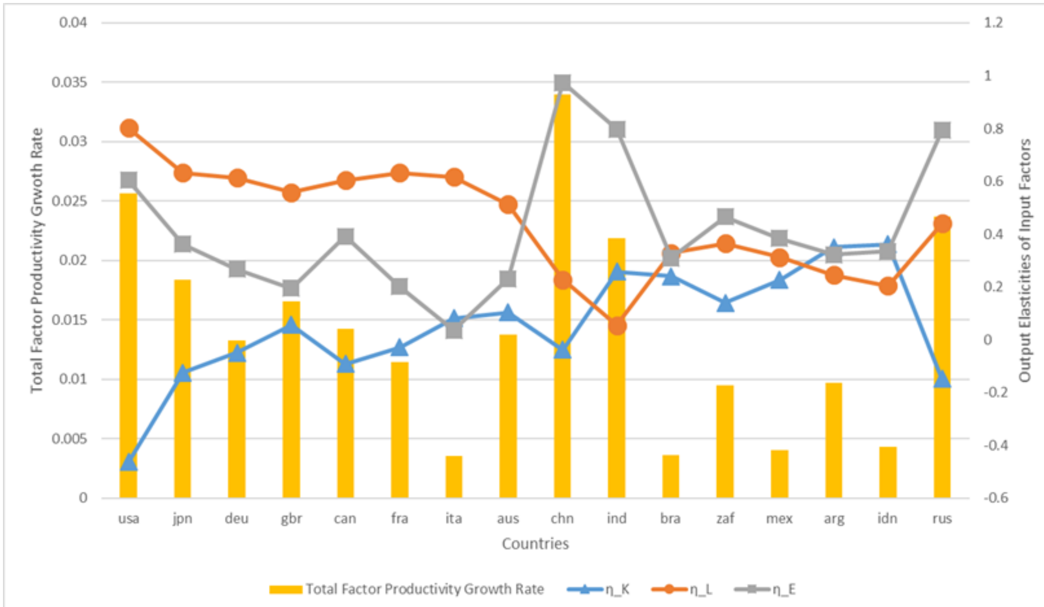

Figure 3: Average Total Factor Productivity Growth Rate and Output Elasticities of Various Inputs for the 16 Countries in the Sample

tivity 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 economic 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., 2020), negative output elasticity is not rare in firm-level observations. Meanwhile, we try to explain such phenomenon with the following possible reasons[10].

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 are 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: increases in capital stock are partly due to rising real estate prices, which have no effect on production.

4. Preference for domestic investment: some agents prefer to invest their money in domestic markets, 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 has 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.

2.4.3 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

[10] 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.

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 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 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 bias indices for each single observation in our study, our results indicate 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.

Table 5: Annual average factor bias index of the 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: 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.

While, 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 room 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 importing 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 nationally; on the other hand, facing comparatively lower levels of education, a more direct way to improve output could be better utilization of energy input.

Now we see that technological change is biased the most to energy, both for the average of the 16 countries and for most countries in the sample individually. 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 findings support the hypothesis that technological change is more likely to favor the non-renewable input rather than the renewable. However, the main determinant for the biasedness of technological change remains dubious. Is it market size, or price incentives, 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 such questions, we need not only more empirical evidence, but theoretical support as well.

3 Firm-Level Study on the Direction of Technological Change

3.1 Introduction and Literature Review

When talking about energy efficiency, people can refer to two different concepts. Energy efficiency can be the ratio of actual output to total potential output allowed by the production technology involving energy inputs (Boyd and Lee, 2019). In the context of directed technological change, energy efficiency often means the marginal product of energy input, which can be raised if technological change is biased towards energy. The Stochastic Frontier Analysis allows us to investigate both terms, while we care more about the latter as the main objective of our study.

The topic of how to sustain economic growth with limited resource stocks initiated from Hotelling (1931), and caught the attention of economic researchers in the 1970s (Anderson, 1972; Dasgupta and Heal, 1974; Solow, 1974; Stiglitz, 1974; Hartwick, 1977, among others). Technological progress is agreed by many theoretical studies to be the key for long-term growth with non-renewable resources (Grimaud and Rougé, 2003; Smulders and De Nooij, 2003; Di Maria and Valente, 2008; André and Smulders, 2014, among others).

The modern economy relies greatly on energy inputs, a large part of which are and will remain non-renewable for long. According to the International Energy Agency (IEA) (2020), with currently stated policy, global energy demand for renewables will increase by 864 Mtoe while that for non-renewables will also increase by 453 Mtoe[11] by 2030, which is not a remarkable part relative to the current total energy demand[12]. With the purpose of augmenting technological change on this input, policies often focus on energy price following the belief, originating from Hicks (1932), that innovation can be induced by prices. Nevertheless, as discussed in the first section, there are various factors affecting the adoption and deployment of technological change. The growth model of Acemoglu (2002) suggests that the direction of technological change depends on price effect and market size effect, which counteract each other. The conditions for predicting the direction of technological change vary with the economic environment (Acemoglu, 2010); specifically, technological change can be biased

[11] The global demand for gas will increase by 475 Mtoe, 349 Mtoe for oil and −271 Mtoe for coal.

[12] Total energy consumption of the world reached 14378 Mtoe in 2019, according to Enerdata (2020).

towards the clean (renewable) or the dirty (non-renewable) input. Therefore, empirical proof is necessary to answer such a question.

Attempts to assess the direction of technological change involving energy have been made by a number of researchers using different empirical methods. Preliminary measures such as ratio of energy input to GDP/GNP and cost shares of inputs are quite insufficient in considering the complexity of directed technological change (Hogan and Jorgenson, 1991; Sanstad et al., 2006). Some studies focus on the substitutability between factors, e.g. Kim and Heo (2013) conclude, through the estimation of a cost function and deriving elasticity of substitution, that technological change is biased towards energy rather than capital. CES production functions, often in nested structures, are more frequently applied for estimating elasticity of substitution between input factors (Kemfert and Welsch, 2000; Klump et al., 2007; Su et al., 2012; Dissou et al., 2014), but dealing with more than three inputs can be arduous. A recent practice is Zha et al. (2018) who conclude that capital better substitutes energy in China's industrial sector and technological change is biased more towards energy. VES and CEED production functions are also complements for such purpose (Dong et al., 2013). Elasticities of substitution provides information on whether inputs are substitutes or complements, but are not enough to measure directed technological change.

Stochastic Frontier Analysis has long been applied in energy economics. Among the main approaches, the distance function approach and the production function approach are those more commonly adopted. The distance function approach is preferable when researchers are more interested in technical efficiency, and it allows more than one type of output, desirable or undesirable, resulting from the production process. Duman and Kasman (2018) investigate production efficiency with GDP and CO_2 emission as two outputs produced with capital, labor and energy; Boyd and Lee (2019) analyze the efficiency in the utilization of electricity and fuel in five metal-based manufacturing industries in the US; Liu et al. (2019) study whether the technical efficiency of grid utilities in China is affected by environmental heterogeneity. The production function approach is more commonly applied in research on directed technological change. It not only enables the estimation of output elasticities of input factors and the biasedness of directed technological change, but also allows the derivation of growth indicators, e.g. the growth rate of total factor productivity, returns to scale, among others. Wesseh and Lin (2016) analyze the effectiveness in the use of renewable and non-renewable energy in African countries. Using data for 32 industrial subsectors in Shanghai, 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. Their result shows that energy is favored the most by technological change in general. With data for 36 industrial subsectors of China, Yang et al. (2018) suggest that technological change is biased towards fossil energy rather than non-fossil energy. Cheng et al. (2019), using province data of China, show that technological change is biased the most towards capital, and more to fossil energy than non-fossil energy. These findings do not necessarily contradict each other, but they highlight the relevance of investigating the direction of technological change at firm level, since the result can vary at different levels.

This type of research relies on the availability of data. For example, the data in Boyd and Lee (2019) is quinquennial from the Census of Manufacturing and Economic Census of the US. When we look at recent studies based on the production function approach, they provide valuable insight on directed technological change regarding energy at industry level. Notwithstanding, it is a bit disturbing to assume a common production function for every industrial subsector in the sample. In Shao et al. (2016) and Yang et al. (2018), an identical translog production function is estimated for all the industrial subsectors in their samples. It is justifiable to assume one production function for various countries at macro level, considering that the leading technology of the world is given and there is a catch-up effect; but it might not be true that different industries share a common production process. Of course, if only industry-level data is at hand, this is a necessary approach; but findings made with industry-level data are not quite sufficient in supporting theories on firm-level technological improvement. Besides, it is debatable whether industrial-level data truly represent the "micro level". A SFA with firm-level data can overcome this imperfection.

Thanks to the BPLim database[13], produced by the Microdata Research Laboratory of the Bank of Portugal, which includes data on capital, labor and energy inputs of firms in Portugal, we are able to analyze directed technological change from the perspective of firms, critical agents of production for modern economies. We estimate specific production functions for different industrial subsectors, thus providing rare empirical evidence for theories on firm-level technological progress.

In our study on macro-level directed technological change (Hou et al., 2020),

[13] Website: https://bplim.bportugal.pt/

the SFA is applied to the data of 16 developing and developed countries. We find that for most countries and for the average of the sample, technological change is biased most towards energy; the results demonstrate different patterns in economic growth for different groups of countries. The present analysis shall be helpful to support and explain some of our previous findings, for example, regarding the low output elasticity of capital.

Our study with firm data has two main advantages. First, the mechanism of technological change is different between sector and firm levels. Rigorously speaking, sector-level data is closer to macro data than micro; firm data does a better job in providing micro-level insight. Second, with sector-level panel data, an identical production function is estimated for all sectors, while we are able to estimate one corresponding production function for each subsector with firm data. This leads to more convincing results since differences in production process can be large between sectors. We select data for electricity and fuel inputs from the database: these are two energy forms playing different roles in production, and can be associated with renewable and non-renewable energy, respectively. We estimate a translog production function with capital, labor, electricity and fuel as input factors. We derive indicators for the two components of technological change: the growth rates of total factor productivity, and the factor-biased technological change.

The results of our study demonstrate the necessity of mitigating technical inefficiency, as it is significant in some economic subsectors. For this purpose, policies could encourage employment and regulate financial activities, since capital deepening and financial income exert positive marginal effect on technical inefficiency. Output elasticity of labor is generally high among the subsectors, emphasizing labor as the main driver for economic growth. Output elasticity of capital is low overall, although a few subsectors enjoy better marginal returns. In most subsectors, technological change is biased the most towards labor; between electricity and fuel, technological change has favored fuel in more cases. Such finding, along with our previous study (Hou et al., 2020), could be evidence implying that technological change is biased towards the non-renewable input rather than the renewable. Moreover, by referring to energy consumption and energy price, we infer that market size effect is more likely to overwhelm price effect, so energy price alone may not be an optimal policy tool for inducing technological change. Nonetheless, reducing the relative price of renewable energy may be a solution, which justifies carbon pricing.

Generally, the findings provide empirical evidence for growth theory with directed technological change, and also advise policy making related to energy efficiency and economic growth. From a practical perspective, our research provides information on the development of the selected Portuguese economic subsectors, and may instruct industry-level policy decisions in Portugal.

In the rest of this section, Subsection 3.2 describes the methodology and data to be applied in our research and Subsection 3.3 presents the empirical results and the corresponding discussion.

3.2 Methodology and Data

3.2.1 Estimation of the stochastic frontier production function and decomposition of productivity change

Generally, SFA studies consider several functional forms depending on their purposes. The distance function deals with multiple outputs and is usually applied to assess the determinants of technical inefficiency (Boyd and Lee, 2019; Liu et al., 2019). The cost function focuses on firms' ability to optimize their costs. Nevertheless, cost efficiency is not equivalent to production efficiency and the cost function doesn't provide direct information on directed technological change. The production function facilitates the analysis of directed technological change by allowing the calculation of output elasticities, factor bias indices, among other indicators.

The decomposition of productivity change into efficiency change, technical change and scale effects is commonly considered in the application of stochastic frontier analysis, e.g. Kumbhakar et al. (2000); Heshmati and Kumbhakar (2011).

As in Heshmati and Kumbhakar (2011), Shao et al. (2016), Wesseh and Lin (2016) and Yang et al. (2018), a translog production function is built in the form of second-order Taylor approximation. It is a locally flexible functional form and allows variable substitution elasticities, thereby serving the purpose of calculating the biased technological change.

The theoretical derivation for the equations used in the calculation of the indicators for technological change follows Kumbhakar et al. (2000). Suppose the production function is

$$y_{it} = f(x_{it}, t) \exp(-u_{it}), \tag{15}$$

where i represents a country, t represents the number of the time period and

$u \geq 0$ denotes output-oriented technical inefficiency. Technical change is defined as

$$TC_{it} = \frac{\partial \ln f(x_{it}, t)}{\partial t}. \tag{16}$$

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

$$\frac{\partial \ln y_{it}}{\partial t} = TC_{it} + TEC_{it}, \tag{17}$$

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

$$\dot{TFP} = \dot{y} - \sum_j S_j^a \dot{x}_j, \tag{18}$$

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

$$\begin{aligned} \dot{TFP} &= TC - \frac{\partial u}{\partial t} + \sum_j \left(\frac{f_j x_j}{f} - S_j^a\right)\dot{x}_j \\ &= (RTS - 1)\sum_j \lambda_j \dot{x}_j + TC + TEC + \sum_j (\lambda_j - S_j^a)\dot{x}_j, \end{aligned} \tag{19}$$

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, $f(x, t)$; $\lambda_j = (f_j x_j / \sum_k f_k x_k) = \eta_j / RTS$; and 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.

Considering capital, labor, electricity and fuel as inputs, we estimate the following production function for each chosen economic subsector:

$$
\begin{aligned}
\ln Y_{it} &= \beta_0 + \mathbf{d}'\boldsymbol{\alpha} + \beta_1 t + \frac{1}{2}\beta_2 t^2 \\
&+\beta_3 \ln K_{it} + \beta_4 \ln L_{it} + \beta_5 \ln E_{it} + \beta_6 \ln F_{it} \\
&+\beta_7 t \ln K_{it} + \beta_8 t \ln L_{it} + \beta_9 t \ln E_{it} + \beta_{10} t \ln F_{it} \\
&+\frac{1}{2}\beta_{11}(\ln K_{it} \ln L_{it}) + \frac{1}{2}\beta_{12}(\ln K_{it} \ln E_{it}) + \frac{1}{2}\beta_{13}(\ln K_{it} \ln F_{it}) \\
&+\frac{1}{2}\beta_{14}(\ln L_{it} \ln E_{it}) + \frac{1}{2}\beta_{15}(\ln L_{it} \ln F_{it}) + \frac{1}{2}\beta_{16}(\ln E_{it} \ln F_{it}) \\
&+\frac{1}{2}\beta_{17}(\ln K_{it})^2 + \frac{1}{2}\beta_{18}(\ln L_{it})^2 + \frac{1}{2}\beta_{19}(\ln E_{it})^2 + \frac{1}{2}\beta_{20}(\ln F_{it})^2 \\
&+V_{it} - U_{it},
\end{aligned}
$$

which is in the form of second-order Taylor approximation. Or, in order to facilitate our empirical estimation, the production function is equivalent to:

$$
\begin{aligned}
\ln Y_{it} &= \beta_0 + \mathbf{d}'\boldsymbol{\alpha} + \beta_t t + \beta_{tt} t^2 \\
&+\beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_E \ln E_{it} + \beta_F \ln F_{it} \\
&+\beta_{tK} t \ln K_{it} + \beta_{tL} t \ln L_{it} + \beta_{tE} t \ln E_{it} + \beta_{tF} t \ln F_{it} \\
&+\beta_{KL}(\ln K_{it} \ln L_{it}) + \beta_{KE}(\ln K_{it} \ln E_{it}) + \beta_{KF}(\ln K_{it} \ln F_{it}) \\
&+\beta_{LE}(\ln L_{it} \ln E_{it}) + \beta_{LF}(\ln L_{it} \ln F_{it}) + \beta_{EF}(\ln E_{it} \ln F_{it}) \\
&+\beta_{KK}(\ln K_{it})^2 + \beta_{LL}(\ln L_{it})^2 + \beta_{EE}(\ln E_{it})^2 + \beta_{FF}(\ln F_{it})^2 \\
&+V_{it} - U_{it}, \qquad (20)
\end{aligned}
$$

$$
U_{it} \sim N^+(0, \sigma^2_{Uit}), \qquad (21)
$$

$$
V_{it} \sim N(0, \sigma^2_V), \qquad (22)
$$

$$
\sigma^2_{Uit} = \exp(\mathbf{Z}'_{it}\boldsymbol{\delta}), \qquad (23)
$$

$$
\sigma^2_V = \exp(w_V), \qquad (24)
$$

where Y represents total output, K, L, E, F denote capital, labor, electricity and fuel as inputs, 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 $\sigma^2 = \sigma_U^2 + \sigma_V^2$. $\mathbf{d}$ is a vector of dummy variables that account for the firm size (micro, small, medium and large) and $\boldsymbol{\alpha}$ is the corresponding parameter vector; only 3 dummies are needed to avoid multi-collinearity. A parameter $\gamma = \sigma_U^2/(\sigma_U^2+\sigma_V^2)(0 \leq \gamma \leq 1)$ stands for the share in the compounded residual variance derived from technical inefficiency.

We assume that the variance of the inefficiency term, σ_U^2, depends on exogenous parameters. $\mathbf{Z}$ is a vector of variables including a constant of 1, and $\boldsymbol{\delta}$ is the corresponding parameter vector. Since the inefficiency term is assumed to be half-normally distributed, its variance also affects the expected mean: given that the distribution is truncated at 0, the expected mean increases as there is greater variance. Shao et al. (2016) and Yang et al. (2018) assume that the mean of the inefficiency term depends on exogenous factors; we believe that our assumption could produce more informative results for a large sample. If the coefficient on a certain factor is positive, it implies that such factor exerts a positive marginal effect on technical inefficiency (or a negative marginal effect on technical efficiency), and vice versa.

The translog production function above is estimated with the maximum likelihood method (ML); the one-step estimation method for exogenous effects on inefficiency was first introduced by Kumbhakar et al. (1991) and Reifschneider and Stevenson (1991).

Once we have estimated the production function (6), we can calculate the indicators for technological change following Kumbhakar et al. (2000), as well as the practice of Shao et al. (2016) and Yang et al. (2018). The growth rate of the TFP can be decomposed as

$$T\dot{F}P_{it} = TP_{it} + TEC_{it} + SEC_{it}. \tag{25}$$

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

$$TP_{it} = \frac{\partial \ln Y_{it}}{\partial t} = \beta_t + 2\beta_{tt}t + \beta_{tK}\ln K_{it} + \beta_{tL}\ln L_{it} + \beta_{tE}\ln E_{it} + \beta_{tF}\ln F_{it}, \tag{26}$$

where $\beta_t + 2\beta_{tt}t$ reflects the pure technological change of the subsector allowed by the frontier technology; $\beta_{tK}\ln K_{it} + \beta_{tL}\ln L_{it} + \beta_{tE}\ln E_{it} + \beta_{tF}\ln F_{it}$ is a measure for the non-neutral technological change of heterogeneous firms, which can result from a "learning-by-doing" effect that differs from firm to firm.

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

$$TEC_{it} = \frac{TE_{it}}{TE_{i,t-1}} - 1, \tag{27}$$

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:

$$SEC_{it} = (RTS_{it} - 1) \sum_j \frac{\eta_{jit}}{RTS_{it}} \dot{X}_{jit}, \tag{28}$$

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

$$\eta_{Kit} = \frac{\partial \ln Y_{it}}{\partial \ln K_{it}} = \beta_K + \beta_{tK} t + \beta_{KL} \ln L_{it} + \beta_{KE} \ln E_{it} + \beta_{KF} \ln F_{it} + 2\beta_{KK} \ln K_{it}; \tag{29}$$

$$\eta_{Lit} = \frac{\partial \ln Y_{it}}{\partial \ln L_{it}} = \beta_L + \beta_{tL} t + \beta_{KL} \ln K_{it} + \beta_{LE} \ln E_{it} + \beta_{LF} \ln F_{it} + 2\beta_{LL} \ln L_{it}; \tag{30}$$

$$\eta_{Eit} = \frac{\partial \ln Y_{it}}{\partial \ln E_{it}} = \beta_E + \beta_{tE} t + \beta_{KE} \ln K_{it} + \beta_{LE} \ln L_{it} + \beta_{EF} \ln F_{it} + 2\beta_{EE} \ln E_{it}; \tag{31}$$

$$\eta_{Fit} = \frac{\partial \ln Y_{it}}{\partial \ln F_{it}} = \beta_F + \beta_{tF} t + \beta_{KF} \ln K_{it} + \beta_{LF} \ln L_{it} + \beta_{EF} \ln E_{it} + 2\beta_{FF} \ln F_{it}. \tag{32}$$

An indicator for the biasedness of technological change, first proposed by Diamond (1965), and used by Shao et al. (2016) and Yang et al. (2018), the biased technological change index $Bias_{sj}$ can be used to estimate the relative biased degree of technological change to each input:

$$Bias_{sj} = \frac{\partial (f_s / f_j)}{\partial t} / \frac{f_s}{f_j} = \frac{\beta_{ts}}{\eta_s} - \frac{\beta_{tj}}{\eta_j}, \tag{33}$$

where s and j represent different inputs and f_s or f_j is the derivative of the function f with respect to s or j. This formula is applied to each observation i, t. $Bias_{sj} > 0$ 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 $Bias_{sj} = 0$, technological change in production is Hicks neutral.

The methodology described above is independently applied to each selected economic subsector. As there may exist large differences in the nature of production activities of each subsector, we consider it appropriate to estimate a production function for each subsector, as it provides more robust and credible information regarding the technological change in each subsector. As will be shown, the estimation results for subsectors do present considerable differences.

Some studies, e.g. Wang et al. (2018), also compute the elasticity of substitution between input factors. Elasticity of substitution allows us to evaluate the possibility of substituting one input factor with another and serves as a reference for policy making. Nevertheless, the results in Wang et al. (2018), as well as the results that we obtain, indicate that the elasticity of substitution derived with such method manifests great volatility and is not a good indicator. Therefore, we opt not to present the results for elasticity of substitution.

3.2.2 Data

For macro-level empirical studies, the perpetual inventory method is widely applied in order to proxy national (or sectoral) capital stocks (Berlemann and Wesselhoft, 2014). A formal application of the perpetual inventory method requires information on investment flows, asset service life, retirement distribution depreciation function, etc. (Dey-Chowdhury, 2008). The application of the perpetual inventory method is simplified in most SFA studies, for instance, Shao et al. (2016) take an initial capital stock and a depreciation rate to calculate the capital stock in the following years. This method is particularly useful when direct measurement of capital stock is difficult (Dey-Chowdhury, 2008). The data in the BPLim database, including the data on tangible fixed capital, are mostly based on information reported through Portuguese national accounting systems, e.g. Informação Empresarial Simplificada (IES, Simplified Corporate Information). We think it could work as more exact annual data on capital stock.

The BPLIM database provides annual firm-level data for Portuguese firms in all economic subsectors. We estimate the stochastic frontier translog production function using annual data from 2010 to 2016, namely the following variables:

Y – Output: measured by non-financial revenue;

K – Capital stock: measured by tangible fixed capital;

L - Labor input: measured by total hours worked, which, as we evaluate, better measures the amount of labor input than the number of employees;

E – Electricity input: measured by expenditure on electricity;

F – Fuel input: measured by expenditure on fuel.

Energy input is commonly measured in energy unit; however, given the nature of the data, we measure electricity and fuel input by the expenditure on them. Such measures are acceptable considering the steady and moderate changes in energy tariffs in Portugal in recent years[14]; on the other hand, since firms are sensitive to cost-benefit relations in investment decisions, indicators estimated from such measure, e.g. output elasticities, provide a good representation on the firms' incentives.

We consider the following three factors that affect technical inefficiency: capital deepening (CD), energy consumption structure (ES), and share of financial income (FI). Next we introduce the proxies for these factors and the justification for selecting them.

1. Capital deepening (CD), measured by the ratio of capital stock and labor input. According to Shao et al. (2016) and Wang et al. (2018), capital deepening has a significant effect on technical efficiency. However, the signs of the coefficients on this term are not the same in the two abovementioned studies. We shall examine whether, at firm level, its effect on technical efficiency is positive or negative.

2. Energy consumption structure (ES). As suggested by Fan et al. (2015), energy consumption structure has an important influence on the environmental productivity. It is measured by the share of coal consumption in total energy consumption in Shao et al. (2016); and by the share of fossil energy consumption in the total industrial energy consumption in Wang et al. (2018). We measure it by the share of electricity input in total energy input (electricity and fuel).

3. Share of financial income in total revenue (FI): as suggested by Barradas (2017), among others, financialization may be detrimental to the real economy. We expect to find evidence that a higher share of financial income might positively affect technical inefficiency in production.

[14] For detailed information one may refer to: https://www.erse.pt/atividade/regulacao/regulacao/

We only consider firms with data on Y for all 7 years of the sample. The subsectors are divided according to NACE Rev. 2 of EuroStat. Table 7 summarizes the classification of the subsectors and the number of observations used by the program in the estimation. Some subsectors are not considered in our study, mainly for one or more of the following reasons:

1. The output of the subsector cannot be measured well by revenue, e.g. P - education; M02 - scientific research and development.

2. There are too few effective observations of the subsector, so that it is impossible to estimate the model, e.g. C04 - manufacture of coke, and refined petroleum products.

3. The subsectors in which economic activities are difficult to describe as "production", e.g. K - financial and insurance activities; L - real estate activities.

4. Specification tests show that the model does not describe the data of the subsector very well, e.g. D - electricity, gas, steam and air-conditioning supply; J02 - telecommunications, etc.

3.3 Results and Discussion

3.3.1 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 and factor bias index, among other indexes.

To examine whether the specification of the production function is valid and effective, we apply the following specification tests to each estimation process for the subsectors:

(1) Whether the stochastic frontier production model is effective: $H_0 : \sigma_U^2 = 0$. If we fail to reject the null hypothesis, it means that technical inefficiency is not statistically significant for the subsector; hence, it is unnecessary to estimate the effect of exogenous factors on the distribution of the inefficiency term. In this case, in order to acquire more accurate results, we then re-estimate the model for the subsector taking the simpler assumption:

$$U_{it} \sim N^{+}(0, \sigma_U^2), \tag{34}$$

which keeps the basic assumption on residuals in the Stochastic Frontier

Table 7: Summary of the subsectors in the study

Subsector	Activities	Obs.
A01	Crop and animal production, hunting and related service activities	22,610
A02	Forestry and logging	1,806
A03	Fishing and aquaculture	1,050
B	Mining and quarrying	2,279
C01	Manufacture of food products, beverages and tobacco products	21,658
C02	Manufacture of textiles, apparel, leather and related products	25,354
C03	Manufacture of wood and paper products, and printing	15,990
C05	Manufacture of chemicals and chemical products	2,033
C06	Manufacture of pharmaceuticals, medicinal chemical and botanical products	304
C07	Manufacture of rubber and plastics products, and other non-metallic mineral products	12,749
C08	Manufacture of basic metals and fabricated metal products, except machinery and equipment	23,556
C09	Manufacture of computer, electronic and optical products	489
C10	Manufacture of electrical equipment	1,638
C11	Manufacture of machinery and equipment not elsewhere classified	4,009
C12	Manufacture of transport equipment	2,027
C13	Manufacture of furniture	6,934
C14	Other manufacturing	3,815
C15	Repair and installation of machinery and equipment	4,210
E01	Water collection, treatment and supply	387
E02	Sewerage	88
E03	Waste management and remediation	1,666
F	Construction	51,852
G01	Wholesale and retail trade and repair of motor vehicles and motorcycles	37,765
G02	Wholesale trade, except of motor vehicles and motorcycles	77,290
G03	Retail trade, except of motor vehicles and motorcycles	106,420
H01	Land transport and transport via pipelines	12,684
H02	Water transport	300
H04	Warehousing and support activities for transportation	4,477
I01	Accommodation	11,075
I02	Food and beverage service activities	55,177
J01	Publishing, audiovisual and broadcasting activities	4,199
J03	IT and other information services	6,475

Model unviolated.

(2) Specification test of the production function form of the stochastic frontier model: $H_0 : \beta_t = \beta_{tt} = \beta_{tK} = \beta_{tL} = \beta_{tE} = \beta_{tF} = \beta_{KL} = \beta_{KE} = \beta_{KF} = \beta_{LE} = \beta_{LF} = \beta_{EF} = \beta_{KK} = \beta_{LL} = \beta_{EE} = \beta_{FF} = 0$. 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: $H_0 : \beta_t = \beta_{tt} = \beta_{tK} = \beta_{tL} = \beta_{tE} = \beta_{tF} = 0$. If the null hypothesis is not rejected, the production function does not vary through time, hence the technological progress in the frontier production function does not exist.

(4) If technological progress does exist, it is also necessary to test whether the technological progress is neutral or not: $H_0 : \beta_{tK} = \beta_{tL} = \beta_{tE} = \beta_{tF} = 0$. If the null hypothesis is not rejected, it implies that the technological progress of the subsector is neutral.

The generalized likelihood statistic $LR = -2\ln[L(H_0)/L(H_1)]$ is used for testing the hypotheses, where $L(H_0)$ and $L(H_1)$ are the log likelihood function values of the null hypothesis and the alternative hypothesis, and $LR \sim \chi^2(n)$, n being the number of restrictions. The threshold values are according to Kodde and Palm (1986). Results of the tests are shown in Appendix C.

Among the 32 subsectors analyzed, in 6 of them (C08 - C12, J01), the null hypotheses $\sigma_U^2 = 0$ are not rejected. In 8 of the subsectors (A02, C05, C06, C09, E01, E03, H02, H04), we fail to reject the null hypotheses for test (3) and test (4). Nonetheless, the data of most subsectors fits our model quite well. As all null hypotheses are rejected for test (2), we can still use the results to compute the indicators with the methodology in the last section. But for the subsectors which fail to reject the null hypotheses for test (3) and (4), discretion is needed in interpreting the results regarding technological change.

The estimated results of the translog production functions for each subsector are presented in Table 8. For each selected subsector, most coefficients are statistically significant; almost all firm size dummies are statistically significant; and all the models are jointly statistically significant. In general, the translog production function is a proper form to be applied to the stochastic frontier analysis.

The effects of the determinants for technical inefficiency in each subsector are also shown in Table 8 (whenever the technical inefficiency term is statistically significant). A positive coefficient implies that the explanatory variable has a positive effect on the variance of the inefficiency term, hence it leads to a

Table 8: Estimated results for Portuguese economic subsectors
(Table 8 at the end of the file due to its size)

higher mean and uncertainty of technical inefficiency. Among the 26 subsectors where there exists statistically significant technical inefficiency, taking 0.05 as a threshold, the marginal effect of capital deepening is statistically significant for 13 subsectors, and is positive for 12 of them. Energy consumption structure (or cost share of electricity in total cost on energy) is statistically significant for 23 subsectors, in 12 of which the marginal effect being positive while in 11 subsectors being negative. In 12 subsectors, the share of financial income has a statistically significant and positive marginal effect on technical inefficiency.

From our estimated result, roughly speaking, firms in the agricultural sector and low-tech manufacturing subsectors are more prone to technical efficiency losses imposed by the three factors considered in this study. Firms in higher-technology manufacturing subsectors, however, are less likely to be affected by these factors, especially capital deepening (CD). This reflects that high-tech manufacturers are more effective in adopting new technologies; in particular, they are able to make better use of capital so that its amount doesn't affect technical efficiency. Meanwhile, higher share of electricity in energy input helps eliminate technical inefficiency in high-tech manufacturing subsectors; this is also the case for sector I (accommodation and food service activities). Sector E (water supply, sewerage, waste management and remediation) appears to be exempted from the impact of the three factors; considering the low TFP growth rate in subsectors E01 and E03 (see subsection 4.2), this might be explained by the sluggishness of technological development in this sector. The mean of FI is very low (almost 0%) in sector H (transportation and storage), and not surprisingly, its impact on technical inefficiency is statistically insignificant.

In a considerable number of subsectors, the signs of coefficients for capital deepening and the share of financial income are positive, implying that they could induce technical inefficiency. When labor input is insufficient compared with fixed capital, it might create technical inefficiency in production, which emphasizes the importance of labor input. Evidence also supports the hypothesis that over-financialization causes technical inefficiency. It is very likely that energy consumption structure affects technical inefficiency, but it is difficult to determine the direction of its effect based on current evidence. Our finding may suggest that policies encouraging employment can be desirable, especially

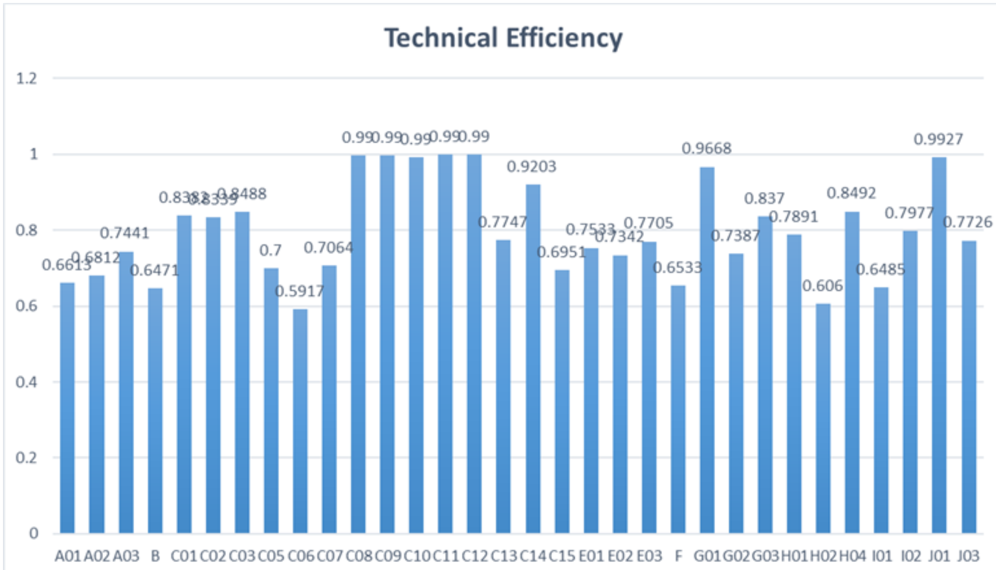

Figure 4: Mean Estimated Technical Efficiency of the Analyzed Subsectors

for agricultural and low-tech manufacturing subsectors, so that technical inefficiency can be mitigated; also, the policy maker might want to regulate financial activities so as to guarantee a healthy development of the real economy.

It is also possible to estimate the values of the inefficiency measure from $E(U_{it}|\epsilon_{it})$ evaluated at $\hat{\epsilon}_{it}$, and the efficiency index from $E(\exp(-U_{it})|\epsilon_{it})$ evaluated at $\hat{\epsilon}_{it}$, where $\epsilon_{it} \equiv V_{it} - U_{it}$. The approximation $1 - e^u \approx u$ is close when u is small (Kumbhakar et al., 2015); however, there may be obvious discrepancy between the sum of the two indices and 1 when the mean of inefficiency measure is larger. Figure 4 demonstrates the mean of estimated efficiency level in each analyzed subsector.

Taking A01 for an example, the estimated efficiency of 0.6613 indicates that firms in this subsector on average produce approximately 66.13% of the potential output given the current technological level, while the rest of potential output is lost due to technical inefficiency. In C08 - C12 and J01, technical inefficiency is statistically insignificant, hence the efficiency index is close to 1. In other subsectors, there exist large differences among the levels of efficiency, which range from 0.5917 to 0.9668. In A01, B, C06, F, H02, I01, efficiency level is lower than 0.67; in other words, over one third of potential output is lost due to technical inefficiency. Although some explanations can be posited for the low efficiency[15], there is much potential for better economic performance by improving technical efficiency in these subsectors. In C14 and G01, efficiency is over 0.9, in addition to the subsectors where no inefficiency is detected. Although our analysis helps to identify some parameters shared by all firms that affect technical inefficiency, there may still remain some industry-specific factors that make a difference, and it will be valuable information for policy making should they be found.

3.3.2 Output elasticities and the total factor productivity growth rate

Equations (25) $-$ (32) are used in the calculation of output elasticities of each input factor, along with technological progress (TP), technical efficiency change (TEC), scale efficiency change (SEC) and the growth rate of total factor productivity ($TFPGR$). Table 9 summarizes the results for output elasticities of each analyzed subsector.

Some irregular and volatile values, e.g. in E01 and E02 may be due to too few observations (387 observations for output elasticities in E01 and 88 for E02) so that abnormal values for particular firms may largely affect the average. The average output elasticities of each input change in different directions in different subsectors; moreover, the change in output elasticities is not always monotonic. Looking at the initial and terminal values (values in 2010 and 2016), the output elasticity of capital is increasing in A01-03, C01-02, C06, C12, E01, H02 and H04; remaining at an approximate level in C15; and decreasing in the other subsectors. The output elasticity of labor is decreasing in A01, C06, C09, C12, C14-15 and H02, and increasing in the other subsectors. The output elasticity of electricity is increasing in A03, B, C03, C05, C12, C14, E01-03, H02 and J01; remaining at an approximate level in C08, G03 and I01; and decreasing in the other subsectors. The output elasticity of fuel is increasing in A01-02, B, C05, C09-10, C13, C15, E02, F, I02 and J01-02; remaining at an approximate level in G01, G03 and H01; and decreasing in the other subsectors.

The changes in the output elasticities provide an intuitive idea of the direction of technological change; in the next step we shall calculate the bias index as a more solid evidence. From what we can observe from the output elasticities,

[15] For instance, for I01 - Accommodation, part of inefficiency might result from different price patterns of various classes of hotels, hostels, local accommodations, etc.

Table 9: Average output elasticities of input factors of Portuguese economic subsectors

Subsector	η_K	η_L	η_E	η_F
A01	.096/.108/.123	.354/.346/.350	.332/.325/.322	.194/.213/.208
A02	.099/.105/.103	.233/.240/.276	.156/.120/.100	.333/.360/.346
A03	.042/.053/.053	.290/.287/.303	.187/.190/.215	.389/.354/.302
B	.210/.173/.140	.371/.390/.424	.123/.173/.212	.188/.219/.242
C01	.204/.212/.224	.233/.236/.252	.340/.329/.314	.193/.195/.184
C02	.165/.170/.174	.406/.412/.425	.159/.150/.149	.360/.354/.349
C03	.127/.108/.088	.489/.529/.587	.073/.078/.087	.321/.320/.307
C05	.197/.180/.165	.421/.417/.441	.301/.325/.345	.053/.067/.069
C06	$-.066/.003/.163$	.345/.242/.265	$-.045/-.022/-.154$	.649/.647/.591
C07	.120/.113/.107	.513/.542/.585	.224/.223/.216	.197/.187/.175
C08	.145/.129/.115	.501/.542/.596	.084/.082/.083	.262/.260/.246
C09	$.023/.004/-.009$	.798/.790/.790	.025/.021/.012	.221/.275/.327
C10	.092/.092/.085	.737/.745/.771	.101/.067/.034	.177/.220/.257
C11	.101/.098/.097	.644/.674/.727	.140/.116/.087	.244/.243/.231
C12	.048/.060/.074	.755/.714/.686	.098/.114/.128	.147/.140/.128
C13	.121/.103/.086	.561/.602/.659	.099/.089/.079	.271/.285/.289
C14	.094/.081/.068	.669/.648/.643	.077/.111/.145	.259/.261/.250
C15	.071/.072/.072	.567/.553/.558	$-.028/-.049/-.065$	.530/.556/.562
E01	$-.04/-.04/-.04$	1.04/1.07/1.18	.060/.105/.099	$-.002/-.122/-.250$
E02	.187/.125/.043	$-1.22/-.85/-.60$	$.003/-.027/.052$	.604/.635/.608
E03	.244/.184/.124	.150/.176/.231	.138/.152/.165	.334/.339/.322
F	.066/.060/.055	.401/.432/.476	.331/.302/.275	.096/.113/.120
G01	.083/.080/.079	.422/.464/.513	$.028/.005/-.012$	.415/.421/.414
G02	.082/.076/.071	.435/.444/.464	.163/.160/.157	.196/.212/.215
G03	.068/.059/.049	.672/.690/.720	.248/.249/.248	.162/.165/.161
H01	.124/.102/.087	.404/.421/.469	.165/.147/.145	.312/.340/.313
H02	.013/.031/.043	.346/.228/.094	.359/.390/.452	$-.016/-.088/-.180$
H04	.041/.053/.066	.389/.393/.404	.286/.277/.261	$.006/-.019/-.034$
I01	.071/.063/.054	.446/.458/.476	.366/.365/.366	.115/.110/.099
I02	.053/.052/.051	.529/.568/.618	.291/.276/.263	.098/.106/.106
J01	.073/.062/.054	.521/.547/.588	.025/.035/.043	.365/.376/.371
J03	.084/.059/.037	.577/.637/.693	.203/.179/.160	.174/.178/.176

Note: $\cdot/\cdot/\cdot$ represents value in 2010/mean value/value in 2016.

we can say that the output elasticity of labor is increasing in most subsectors, while the output elasticities of the other inputs are decreasing in more subsectors. This suggests that technological change may have favored labor rather than the other input factors, so that labor is playing a role more and more important in contemporary production activities. It furthermore implies that industrial transformation is still ongoing from capital-intensive towards labor-intensive.

From the perspective of mean levels of output elasticities, it is also true that labor is generally more productive compared with other input factors. In 24 of the 32 subsectors, the mean output elasticity of labor is the highest among the four inputs, indicating labor as the main driver of economic growth. We may infer that the government's effort in promoting education, both academic and professional, could be helpful in improving long-term economic performance. Comparatively, the mean output elasticity of capital is the lowest among the four inputs in 15 of the 32 subsectors (of electricity, in 11, and of fuel, in 5). The overall level of output elasticity of capital is quite low, even for the subsectors where (from an intuitive point of view) the operation relies heavily on capital, e.g. I01 - Accommodation. Only in a few subsectors is the mean output elasticity of capital higher than 0.1. Such finding is pretty much different from the province-level result of China (Cheng et al., 2019), where capital enjoys the highest output elasticity among the main inputs. This implies different patterns or different phases of economic growth of developed and developing countries.

On one hand, low output elasticity of capital may help explain the phenomenon of liquidity trap in European countries: when the returns to investment are sufficiently low, monetary policies are no longer effective in stimulating the economy. On the other hand, this should be the result of capital flows among subsectors: in a capital market without transaction costs or entry barriers, investors shall adjust their investment until the returns for investment are equal in all subsectors. Should investors properly perceive the returns to capital in different subsectors, investing in subsectors like B, C01, C02 and C05 might be more profitable; however, such information is not easily accessed by investors, which prevents them from making perfect decisions. It may be of the government's interest to conduct investment to those subsectors so as to promote economic performance.

In addition, negative values frequently appear in firm-level observations. For output elasticities of other inputs, negative values are also commonly present. In theory, rational agents should stop investing in a type of input if the output elasticity of such input is negative. Nonetheless, there may exist several

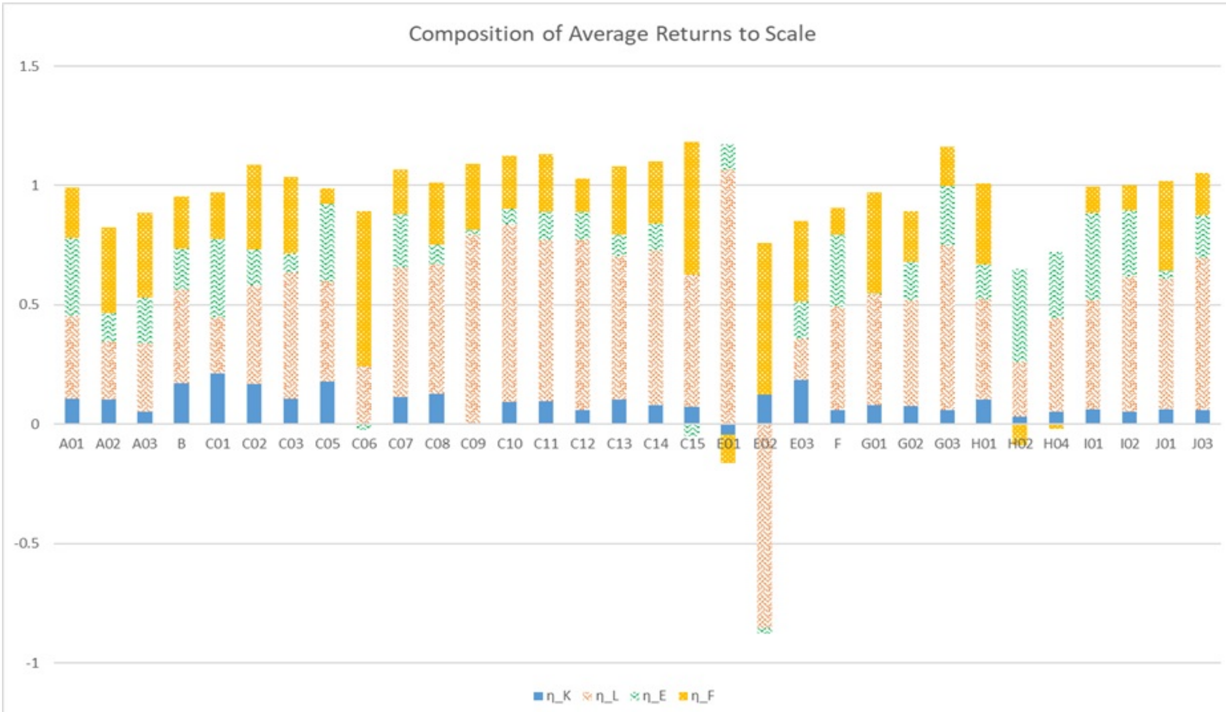

Figure 5: Composition of Average Returns to Scale in the 32 Subsectors

reasons. Agents may face limitations in deciding the amount of each input, for instance, some certain input, like capital, is necessary for maintaining the whole production process and allowing the use of other inputs. Or agents may have imperfect information or limited rationality, which prevents them from making ideal decisions. Such finding may as well help explain the negative values in the estimated output elasticity of capital in our previous study (Hou et al., 2020).

In terms of policy considerations, different mean output elasticities of electricity help justify price discrimination in electricity or fuel tariffs with respect to firms in different economic subsectors, targeted at policy goals such as mitigating carbon emission. For subsectors with lower mean output elasticity of electricity, for instance, an elevated electricity price may appear to be a bad idea as it would dampen production activities in such subsectors.

Figure 5 shows the average returns to scale and their composition in each subsector.

In sectors A, B, E, F, G and H, average returns to scale are often below

1. Investment in these sectors are justified even if there are diseconomies of scale, since they provide goods or services that are essential for the functioning of the economy and society: agriculture, mining and quarrying, infrastructure services, construction, transportation, etc. In most manufacturing subsectors, average returns to scale is above 1. It means that there is still potential for economic growth in these subsectors. One interesting feature can be observed from the figure: average returns to scale are often greater than 1 where average output elasticity of labor is high. Although the intention of our study is to investigate the role of energy in economic growth with directed technological change, once more the importance of labor is emphasized.

Table 10 shows the technological progress (TP), technical efficiency change (TEC), scale efficiency change (SEC) and the growth rate of total factor productivity ($TFPGR$) of the analyzed subsectors. Note that among these indicators, TP is calculated for all 7 years, while the other indicators are calculated for 6 years, so the mean values of the first three indicators do not add up to the mean of $TFPGR$.

A few strange values in TFPGR are due to irregular changes in technical efficiency in the corresponding subsectors (if we look at equation (13), it is easy to see that if the technical efficiency of a firm is extremely small in one period and increases to a normal level in the next, the value of TEC can become very large). We can observe that both technological progress (TP) and technical efficiency change (TEC) contribute to the growth in total factor productivity, while there is very little scale efficiency change (SEC) during the time period of our sample. In addition to what can be inferred from Table 10, in most subsectors, TFP growth rate is improving along the years, which indicates that the Portuguese economy is gaining momentum. Suggestion for policy is that, in order to maintain the tendency in the growth of TFP, eliminating technical inefficiency is almost as important as promoting technological progress, and is worth more attention of the policy maker.

Figure 6 illustrates the mean of the total factor productivity growth rate and output elasticities of the four input factors for the analyzed subsectors. The TFP growth rates of several subsectors are omitted because of irregular values, which result from TEC, as mentioned above. Except for a few subsectors which suffer from negative TFP growth, TFP is growing at moderate speeds in most economic subsectors in the sample. In some subsectors, annual TFP growth rate is over 5%, which indicates these subsectors as the source of momentum of economic growth. On the other hand, there are a number of subsectors

Table 10: Mean total factor productivity growth rate and its composition in Portuguese economic subsectors

Subsector	TP	TEC	SEC	$TFPGR$
A01	.023	.021	$-.0005$	.054
A02	..014	.019	$-.007$	.026
A03	.040	.067	$-.019$	.106
B	$-.025$	.057	$-.00003$	.039
C01	.004	.074	$-.0002$	.083
C02	.014	.007	.003	.025
C03	.011	.006	$-.002$	.023
C05	$-.003$	$-.007$	$-.002$	$-.009$
C06	$-.010$	.053	.001	.055
C07	.005	.972	$-.00005$	.987
C08	.008	$-1.22e-07$	.0008	.018
C09	$-.014$	$1.10e-07$	.002	.005
C10	$-.008$	$-1.10e-06$	.002	.004
C11	.009	$-1.07e-08$	.002	.017
C12	.011	$-1.67e-08$	$-.013$	.008
C13	.029	.0003	.001	.042
C14	.0004	.002	.001	.016
C15	.022	.056	.002	.090
E01	$-.007$	.008	.001	$-.0001$
E02	$-.028$	.084	.174	.249
E03	$-.016$	.004	$-.008$	$-.018$
F	$-.017$	.969	$-.002$	.972
G01	.013	.010	$-.003$	.039
G02	.005	.009	$-.006$	.016
G03	.003	$-.001$	.0005	.011
H01	.014	.398	.002	.419
H02	.018	1.083	1.130	2.231
H04	$-.006$	$-.0005$	$-.021$	$-.028$
I01	.024	.032	$-.001$	.069
I02	$-.005$	.001	$-.002$	.015
J01	$-.004$	$-1.05e-06$	.0005	.011
J03	$-.002$	$-.001$	.002	.007

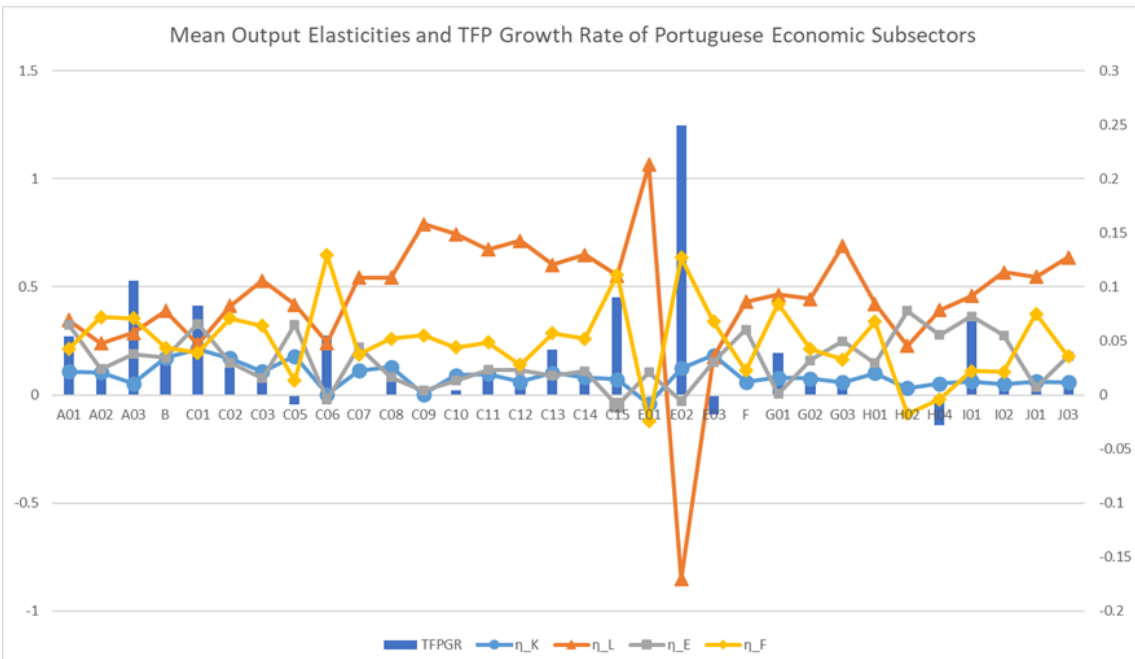

Figure 6: Mean Output Elasticities and TFP Growth Rate of Portuguese Economic Subsectors

where TFP growth rate is only slightly above zero, which may help explain the sluggishness in the economic growth of Portugal in recent years.

3.3.3 Directed technological change

We calculate the factor bias indices using equation (33) as reference for the direction of technological change. Table 11 depicts the average factor bias indices of each analyzed subsector, as well as the corresponding bias order determined by the factor bias indices.

There exists a great variety among bias orders of technological change across different Portuguese economic subsectors. Despite seeming randomness of bias orders at first sight, some general patterns can be observed.

First, technological change is biased the most towards labor in 15 of the 32 subsectors. This once more proves the importance of labor in firm-level production (in Portugal). It is interesting to compare this result with those for other countries. Yang et al. (2018) finds that in China's industrial sector, technological change is biased the most towards fossil energy in general; Cheng et al. (2019) finds that technological change is biased the most towards capital in China's provinces. This may imply a difference in the direction of technological change in developing and developed countries. Furthermore, it is a sign that labor is the main sustainer for economic development in developed countries, while developing countries rely more on capital and energy. This finding is in line with the macro-level result of Hou et al. (2020).

Second, the bias order is the lowest for electricity in 14 subsectors (in 8 for capital, in 5 for labor and fuel), and the second lowest in 8 subsectors, showing that technological change is deviating away from electricity. This is similar to the result for China (Yang et al., 2018).

Third, between electricity and fuel, technological change is biased more towards fuel rather than electricity in 20 of the 32 subsectors. In 10 of the 14 manufacturing subsectors in our analysis, technological change is also biased more towards fuel than electricity. Fuel is in the first two factors of the bias order in 19 subsectors, therefore we can infer that technological change has favored fuel energy in general.

As has been mentioned, electricity production in Portugal is going through a transition into renewables. Meanwhile, fuel energy, mostly non-renewable, is not very likely to become replaced by other energy forms in the near future. Therefore, in the case of Portugal, it is natural that technological change is

Table 11: Factor bias indices of technological change in Portuguese economic subsectors

Subsector	Bias K-L	Bias K-E	Bias K-F	Bias L-E	Bias L-F	Bias E-F	Bias order
A01	.045	.037	.026	−.008	−.019	−.011	$L < E < F < K$
A02	−.035	.079	−.010	.113	.025	−.089	$E < K < F < L$
A03	.031	.005	−.022	−.027	−.053	−.026	$L < E < K < F$
B	−.102	−.127	−.137	−.025	−.035	−.010	$K < L < E < F$
C01	−.020	.060	.026	.080	.046	−.034	$E < F < K < L$
C02	.022	.167	.006	.145	−.017	−.162	$E < L < F < K$
C03	−.112	.086	−.083	.198	.029	−.169	$E < K < F < L$
C05	−.054	−.060	.043	−.007	.096	.103	$F < K < L < E$
C06	−.303	−.767	−.215	−.463	.089	.552	$K < F < L < E$
C07	.025	.116	.057	.091	.032	−.060	$E < F < L < K$
C08	−.089	.002	−.062	.090	.026	−.064	$E < K < F < L$
C09	.076	.052	−.230	−.025	−.307	−.282	$L < E < K < F$
C10	−.038	.065	.037	.103	.075	−.028	$E < F < K < L$
C11	−.039	.093	−.014	.131	.025	−.106	$E < K < F < L$
C12	.169	.009	.150	−.161	−.019	.142	$L < F < E < K$
C13	−.112	.049	−.096	.161	.015	−.145	$E < K < F < L$
C14	−.075	−.914	−.098	−.839	−.023	.816	$K < L < F < E$
C15	.009	−.119	−.022	−.128	−.031	.097	$L < K < F < E$
E01	−.012	−.145	.035	−.133	.047	.180	$F < K < L < E$
E02	.118	.171	.302	.053	.184	.131	$F < E < L < K$
E03	−.247	−.233	−.220	.014	.028	.014	$K < F < E < L$
F	−.070	−.004	−.072	.066	−.002	−.068	$K < E < L < F$
G01	−.060	1.431	−.042	1.491	.018	−1.472	$E < K < F < L$
G02	−.025	.001	−.043	.026	−.018	−.044	$E < K < L < F$
G03	−.052	−.037	−.046	.015	.006	−.009	$K < E < F < L$
H01	−.061	.005	.150	.067	.211	.144	$F < E < K < L$
H02	−.563	−.509	−.363	.054	.201	.147	$K < F < E < L$
H04	−.006	.106	.265	.113	.272	.159	$F < E < K < L$
I01	−.019	.031	.007	.050	.026	−.024	$E < F < K < L$
I02	−.038	.029	−.019	.066	.019	−.047	$E < K < F < L$
J01	−.033	−.062	−.036	−.029	−.003	.026	$K < L < F < E$
J03	.006	.046	.001	.040	−.006	−.045	$E < L < F < K$

biased towards fuel rather than electricity, which is getting closer and closer to a renewable energy form. Yang et al. (2018), Cheng et al. (2019) also show that technological change is biased more towards fossil energy than non-fossil energy in China's industrial subsectors and provinces. Such finding can be explained by the motivation to increase the efficiency of the input with a limited stock. Previous studies (e.g. Shao et al., 2016; Hou et al., 2020) suggest that technological change is biased more towards energy, a great part of which is non-renewable, than two forms of renewable inputs, capital or labor. With the support of previous studies, we may consider our empirical finding as evidence that technological change is more likely to be biased towards the non-renewable input than the renewable input(s).

Fourth, what may arouse some surprise is that in the three transportation subsectors, H01, H02 and H04, where activities strongly rely on the use of fuel and expenses on fuel are generally much higher than those on electricity, technological change is biased more towards electricity instead of fuel. If we compare such phenomenon with the finding that capital is not so often favored by technological change, we may speculate that, if in an economic subsector, a certain input factor is essential for the maintenance of the production process[16], agents appear to be less likely to develop and adopt technologies that allow to utilize such input more efficiently. However, for the all 32 subsectors, we don't discover sufficient support for this hypothesis. Further research will be helpful in verifying this pattern.

Fifth, during the sample period, international crude oil price decreased significantly (e.g. Brent crude oil prices[17]). As a result, fuel prices (except natural gas) also fell in Portugal[18]. Meanwhile, natural gas and electricity prices in Portugal increased[19]. As we find in this study, directed technological change is biased towards fuel rather than electricity in most economic subsectors of Portugal. This may imply that price effect is not the driving force for directed technological change. On the other hand, during this time, total fuel consumption in Portugal slightly increased (to be specific, the increase is mainly in crude oil consumption) while consumption of electricity decreased in some of

[16] In this case, a low substitution elasticity of such input may be expected. Unfortunately, as has been addressed, it isn't quite practical to calculate the substitution elasticities in our present study.

[17] Source: BP Statistical Review of World Energy, https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html

[18] Source: https://www.mylpg.eu/stations/portugal/prices/

[19] Source: https://www.erse.pt/atividade/regulacao/regulacao/

the years[20]. This may imply that market size effect prevailed in deciding the direction of technological change; but the change in the amount of inputs seems too small to explain all this. Alternatively, forward-looking agents may take into account the scarcity of fuel resource so that it is favored by technological change even if its price is temporarily falling.

Sixth, although with a large number of firms in an economic subsector, the general bias indices are stable facing the influence of a small number of firms, the values of bias indices of individual firms demonstrate a certain degree of randomness, which could be determined by firm-level heterogeneity. In other words, in contrast to assumptions in sector-level studies, the direction of technological change may not be uniform in the same subsector, and there might be factors other than market size effect and price effect affecting such direction. Further study may reveal more details on this topic.

The direction of technological change has important impacts in various perspectives, including sustainable economic growth, cleaner production and mitigation of climate change, among others. From the perspective of a balanced energy structure and cleaner production, it might be desirable for technological change to be biased towards electricity. Chen et al. (2019) suggest that in the optimal path, technological change should be biased the most towards labor, and more to non-fossil energy than fossil energy. It may be difficult for the policy maker to resist the temptation to intervene the process of directed technological change by adjusting energy price or introducing subsidies, hoping to alter the relative price and the relative quantity of demand (Yang et al., 2018). However, such policy may not do a good job encouraging firms to develop or adopt technologies favoring a certain input factor. First, according to the results of our study, the market size effect is likely to overwhelm the price effect. In addition, as we find, there may be other factors affecting firms' decision on the direction of technological change. In Portugal, technological change was biased away from electricity while the electricity price increased. Second, simply raising electricity price may hinder production activities, especially in the subsectors where output elasticity of electricity is already low. Instead of inducing technological change through higher electricity price, a lower electricity price relative to fuel may be helpful in the sense that the relative consumption of electricity increases and hence amplifies market size effect. Carbon pricing would increase the relative prices of fuels while stimulating the use of renewable sources in

[20] Source: https://yearbook.enerdata.net/

electricity generation. Nevertheless, besides technological change, many issues are to be considered in electricity pricing. Policies could also directly target the development and adoption of energy-efficient technologies, e.g. providing more accessible energy audit services to firms (Kalantzis and Revoltella, 2019).

4 Firm Technical Efficiency in the Portuguese Electricity Sector

4.1 Introduction

For decades economists have been concerned with efficiency issues in electricity generation. Early studies mainly look at the consequence of regulatory policies. Christensen and Greene (1976, 1978) estimate translog cost functions in order to investigate the cost efficiency and scale economies in electricity generation of the U.S., where the electric power industry was going through a process of reorganization. The authors provide an economic evaluation of the impact of coordination of electricity generation on efficiency. Later on, new econometric methods were applied to evaluate the efficiency in electricity generation. Upon the data used by Christensen and Greene (1976), Greene (1990) applies a gamma-distributed stochastic frontier model. Some more recent research also considers CO_2 emission efficiency in electricity generation (Zhang et al., 2013).

Various methods are proposed for measuring efficiency in production and specifically, in electricity. For instance, Diewart and Nakamura (1999) propose the *best practice efficiency measure* based on Farrell (1957). Jamasb and Pollitt (2001) review the most commonly used benchmarking methods for electricity: Data Envelopment Analysis (DEA), Corrected Ordinary Least Squares (COLS) and Stochastic Frontier Analysis (SFA), as well as their main applications up to that time. Examples of DEA include Yang and Pollitt (2009), who analyze the performance of 221 Chinese coal-fired power plants during 2002, and Welch and Barnum (2009), who analyze both environmental and cost efficiency in electricity generation.

The stochastic frontier method makes distributional assumptions on the noise and inefficiency components (Kumbhakar and Tsionas, 2008), and allows the estimation of the impact of independent variables on the mean and variance of technical inefficiency. Regarding electricity generation, Lai and Kumbhakar (2018) demonstrate a homoscedastic four-component stochastic frontier (H4CSF) model and relate technical inefficiency of production to the age and capacity of a coal-fired power plant. However, besides its contribution to econometric methods, the article does not provide much policy insight.

Recently, some studies have been applying Stochastic Frontier Analysis to address efficiency issues in electricity. Growitsch et al. (2012), Kumbhakar et al. (2015) and Kumbhakar and Lien (2017) examine technical efficiency in Norwegian electricity distribution, and Liu et al. (2019) study whether environmental heterogeneity affects the technical efficiency of Chinese grid utilities. While a number of studies focus on technical efficiency and its determinants (especially those related to the environment) in electricity distribution, comparatively less attention is paid to power generation. In the latter, institutional structure (operation and management features associated with the power plants' ownership) can be the main source of inefficiency in electricity generation (Khanna and Zilberman, 1999). When it comes to the issue of electricity generation, therefore, it seems more appropriate to investigate the effect imposed by institutional and operational features upon efficiency.

In the present research we apply Stochastic Frontier Analysis to firm-level data for electricity subsectors (including electricity generation from different sources, transmission and distribution) in Portugal in order to study the evolution of technical efficiency along the years. We try to estimate the effects of operational factors of firms, such as factors related with the firms' financial activities and utilization of labor, on their technical inefficiency. Research involving environmental factors, e.g. Liu et al. (2019), serves more as reference for performance-based subsidizing policies; our findings provide valuable insight on how to improve firm performance from the perspective of industrial organization. Compared with environmental factors, it is more practical to affect operational features through policies and managing techniques, and thus raise the efficiency in electricity subsectors.

The liberalization of the Portuguese electricity market began in the 2000s. This process consisted of the privatization of state-owned entities, legal unbundling of the electric transmission network, promoting competition and switching opportunities in electricity markets, integration into the Iberian market, phasing-out of regulated tariffs, among others (Ghazvini et al., 2019). Such a reform could be expected to improve efficiency in the electricity sector (Jamasb, 2006). Empirical efforts are made to prove that this is the true for the Portuguese case, e.g. Barros (2008) finds that DEA suggests improvement in the technical efficiency of hydroelectric plants in Portugal between 2000 and 2004. Technical efficiency is also considered as an indicator of the effectiveness of regulatory regimes in the Norwegian electricity sector (Senyonga and Bergland, 2018). Nevertheless, it was in 2006 that the new legislation defined the regime for electricity generation in Portugal. Despite the liberalization process, most electricity generation still enjoys state guaranteed prices and is still a long way from a competitive market (Amorim et al., 2013). Therefore, we need an updated and thorough examination on the evolution of technical efficiency in electricity generation. The data in the present study covers the years from 2006 to 2016, a period in which the new electricity framework had just come into force. This is ideal for the investigation of the impact of liberalization in the Portuguese electricity sector.

Depending on the functional form, among all, several approaches are frequently applied in SFA: the production function approach, the distance function approach, the cost function approach and the profit function approach. Each of them focuses on a particular aspect of the production process and requires different types of data. Considering the data that we have access to, we estimate different models using the first three approaches so as to obtain a comprehensive understanding on the evolvement of technical efficiency in the Portuguese electricity sector.

The empirical results suggest that from 2006 to 2016, productive technical efficiency improves through time, although such improvement seems slow and the mean level of technical efficiency is only about 50% to 60%. On the other hand, there is little evidence that cost efficiency also improves through time. All the factors representing operational heterogeneity are found to be statistically significant in some specifications. In particular, higher capital input relative to labor input, higher average hourly wage and lower average working hours improve productive technical efficiency. This might serve as a reference for policy consideration or firm management.

In the rest of this section, Section 4.2 describes the methodology and data utilized in our empirical analysis; in Section 4.4 we present the empirical results and corresponding discussion.

4.2 Methodology and Data

In Stochastic Frontier Analysis, different approaches can serve research purposes while requiring data on different types of variables. The production function approach is very commonly applied in assessing technical efficiency, as well as issues regarding directed technological change (Yang et al., 2018; Hou et al., 2020). The distance function approach can be used to evaluate the efficiency in utilizing inputs to reach more than one type of output, which is often exogenous (Liu et al., 2019). The cost function approach assumes cost minimization as the goal. Other frontiers are also useful in addressing issues in energy economics. For instance, the energy demand frontier, where the dependent variable is assumed as the minimum energy use to produce an energy service (Zhang and Adom, 2018); Bayesian frontier model can also be used to assess efficiency issues (Makieła and Osiewalski, 2018). Applying various approaches provides a more comprehensive evaluation on the technical efficiency of the electricity generating subsectors. Considering the availability of data and suitability of the models to our purpose, we apply the production function approach, the distance function approach and the cost function approach and compare the results regarding the results on the determinants of technical inefficiency and its time trend.

4.2.1 The production function approach

For firms in the subsectors of electricity generation, we estimate the translog production function in the form of second-order Taylor approximation:

$$\begin{aligned} \ln y_{it} \quad = \quad & \beta_0 + \sum_{j=1}^{J} \phi_j d_j + \beta_1 t + \frac{1}{2}\beta_2 t^2 + \beta_3 \ln K_{it} + \beta_4 \ln L_{it} + \beta_5 t \ln K_{it} + \beta_6 t \ln L_{it} \\ & + \frac{1}{2}\beta_7 (\ln K_{it})^2 + \frac{1}{2}\beta_8 (\ln L_{it})^2 + \frac{1}{2}\beta_9 \ln K_{it} \ln L_{it} + v_{it} - u_{it}, \qquad (35) \end{aligned}$$

$$v_{it} \sim N(0, \sigma_v^2),$$

where K represents capital input and L stands for labor input; subscripts i, t denote the firm and time period; v_{it} is the normally distributed error term and u_{it} is the inefficiency term. d_j represents four dummies for the electricity subsectors: production of electricity from hydropower; from thermal power plants; from wind, geothermal, solar and other sources (although not fully accurate, for simplicity we designate it as the subsector of other renewables); and transmission and distribution of electricity[21]. The technical efficiency level can be calculated by $TE_{it} = \exp(-u_{it})$.

The production function allows us to calculate the output elasticities of each input for each observation as:

$$\eta_{Kit} = \frac{\partial \ln y_{it}}{\partial \ln K_{it}} = \beta_3 + \beta_5 t + \beta_7 \ln K_{it} + \frac{1}{2}\beta_9 \ln L_{it}, \qquad (36)$$

[21] To avoid multicollinearity, the number of dummies should be one less than the total number of subsectors. $\sum_{j=1} d_j = 0$ corresponds to the subsector of "electricity trade", where there are very few observations.

$$\eta_{Lit} = \frac{\partial \ln y_{it}}{\partial \ln L_{it}} = \beta_4 + \beta_6 t + \beta_8 \ln L_{it} + \frac{1}{2}\beta_9 \ln K_{it}, \tag{37}$$

which can be used as a reference for deciding which input is more effective in promoting production.

Different assumptions can be made on the distribution of the inefficiency term u_{it}. In order to study the effects of operational factors on efficiency, we estimate the model using the following assumption:

$$u_{it} \sim N^{+}(\mu, \sigma_{uit}^2), \tag{38}$$

$$\mu = \mathbf{W}_{it}' \mathbf{\Omega} \tag{39}$$

$$\sigma_{uit}^2 = \exp(\mathbf{Z}_{it}' \boldsymbol{\delta}), \tag{40}$$

where $\mathbf{W}$ and $\mathbf{Z}$ are vectors of variables including a constant of 1, while $\mathbf{\Omega}$ and $\boldsymbol{\delta}$ are the corresponding parameter vectors.

Moreover, we also estimate another model in order to verify if there exists a time trend for technical inefficiency change. Time-varying inefficiency models are applied by Kumbhakar (1990), Battese and Coelli (1992), Lee and Schmidt (1993) and Kumbhakar and Wang (2005), among others. Following the Time-Varying Inefficiency Model (TVIM) of Kumbhakar (1990), we adopt the assumption:

$$u_{it} = G(t) u_i, \tag{41}$$

$$u_i \sim N^{+}(\mu, \sigma_u^2), \tag{42}$$

$$G(t) = [1 + \exp(\gamma_1 t + \gamma_2 t^2)]^{-1}. \tag{43}$$

A positive coefficient on t or t^2 implies that technical efficiency is improved through time.

4.2.2 The distance function approach

The production function approach is output-oriented, in the sense that it seeks to maximize the output level with certain input combinations. Commonly, an input-oriented distance function is considered in similar studies, as the output shall be seen as exogenous (Kumbhakar et al., 2015); in our case, it is also reasonable to apply an input-oriented distance function if we consider electricity demand as exogenous. The distance function can be defined as

$$D(\mathbf{x}, \mathbf{y}) = \max_{\lambda}\{\lambda | (\mathbf{x}/\lambda) \in V(\mathbf{y}), \lambda \geq 1\}, \tag{44}$$

where the input set $V(\mathbf{y})$ represents all input vectors $\mathbf{x}$ that can produce the output vector $\mathbf{y}$, and λ measures the maximum amount by which an input vector can be radially contracted while the output vector remains constant. Then the technical efficiency of a firm is

$$TE(\mathbf{x}, \mathbf{y}) = 1/D(\mathbf{x}, \mathbf{y}). \tag{45}$$

Specifically, for M outputs and K inputs, a translog distance function can be defined as

$$\begin{aligned} \ln D_{it} \quad = \quad & \beta_0 + \sum_{j=1}^{J} \phi_j d_j + \sum_{m=1}^{M} \alpha_m \ln y_{mit} + \frac{1}{2} \sum_{m=1}^{M} \sum_{n=1}^{M} \alpha_{mn} \ln y_{mit} \ln y_{nit} \\ & + \sum_{k=1}^{K} \beta_k \ln x_{kit} + \frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \ln x_{kit} \ln x_{lit} + \sum_{k=1}^{K} \sum_{m=1}^{M} \gamma_{km} \ln x_{kit} \ln y_{mit} \\ & + \omega_1 t + \frac{1}{2} \omega_2 t^2 + \sum_{m=1}^{M} \theta_m t \ln y_{mit} + \sum_{k=1}^{K} \rho_k t \ln x_{kit} + v_{it}, \end{aligned} \tag{46}$$

where subscripts i, t denote the firm and time period; d_j represents dummies for the electricity subsectors; v_{it} is the normally distributed error term. Symmetric restrictions require that $\alpha_{mn} = \alpha_{nm}$ and $\beta_{kl} = \beta_{lk}$. The distance function is homogeneous of degree one, which requires the following constraints to be imposed on the coefficients:

$$\begin{aligned} \sum_{k=1}^{K} \beta_k \quad &= \quad 1, \sum_{l=1}^{K} \beta_{kl} = 0, k = 1, 2, \cdots, K; \\ \sum_{k=1}^{K} \gamma_{km} \quad &= \quad \sum_{k=1}^{K} \rho_k = 0, m = 1, 2, \cdots, M. \end{aligned} \tag{47}$$

By normalizing all the inputs in the distance funcion by an input x_{Kit}, we get

$$-\ln x_{Kit} = f(\ln x^*_{kit}, \ln y_{mit}, t) + v_{it} - u_{it}, \tag{48}$$

$$v_{it} \sim N(0, \sigma_v^2),$$

$$\sigma_v^2 = \exp(w_v),$$

where $f(\cdot)$ is the translog input function form, and $x^*_{kit} = x_{kit}/x_{Kit}$, $u_{it} \equiv \ln D_t$ is a half normally distributed non-negative inefficiency term. Therefore we get an equation that can be estimated.

Considering y_1 and y_2 as outputs and K (capital) and L (labor) as inputs, with some manipulation, we can normalize the translog distance function by K_{it} so that it becomes

$$\begin{aligned}
-\ln K_{it} \quad = \quad & \beta_0 + \sum_{j=1}^{J} \phi_j R_j + \alpha_1 \ln y_{1it} + \alpha_2 \ln y_{2it} + \beta_L \ln L^*_{it} \\
& + \frac{1}{2}\alpha_{12} \ln y_{1it} \ln y_{2it} + \frac{1}{2}\alpha_{11} (\ln y_{1it})^2 + \frac{1}{2}\alpha_{22} (\ln y_{2it})^2 + \frac{1}{2}\beta_{LL} (\ln L^*_{it})^2 \\
& + \gamma_{L1} \ln L^*_{it} \ln y_{1it} + \gamma_{L2} \ln L^*_{it} \ln y_{2it} + \theta_1 t \ln y_{1it} + \theta_2 t \ln y_{2it} + \rho_L t \ln L^*_{it} \\
& + \delta_1 t + \frac{1}{2}\delta_2 t^2 + v_{it} - u_{it}, \qquad (49)
\end{aligned}$$

where $L^*_{it} = \frac{L_{it}}{K_{it}}$. As described in the previous subsection, according to (38) - (43), we estimate several models with different assumptions regarding the distribution of the technical inefficiency term.

4.2.3 The cost function approach

The cost function approach assumes that the agents take cost minimization as their aim; alternatively, the target can also be minimizing other indicators like pollutant emissions (Kang, 2018). Then input-oriented cost efficiency can be evaluated using SFA. This approach allows the evaluation of cost efficiency in reaching an exogenous output target, therefore could provide information on how well Portuguese electricity firms optimize their cost while meeting the electricity demand of the economy. Following Kumbhakar et al. (2015), the cost minimization problem for producer i under input-oriented technical efficiency specification is

$$\min \mathbf{w}'\mathbf{x} \text{ s.t. } y = f(\mathbf{x}e^{-\eta}), \tag{50}$$

$$\text{F.O.C.: } \frac{f_j(\mathbf{x}e^{-\eta})}{f_1(\mathbf{x}e^{-\eta})} = \frac{w_j}{w_1}, j = 2, \cdots, J, \tag{51}$$

where $\mathbf{x}$ and $\mathbf{w}$ are vectors of inputs and their prices, $\eta \geq 0$ is the input-oriented technical inefficiency that measures the percentage by which all the inputs are overused in producing output y. The cost function can be therefore defined as

$$C^*(\mathbf{w}, y) = \sum_j \mathbf{w}_j x_j e^{-\eta}, \tag{52}$$

which is the frontier cost function that gives the minimum cost given input prices $\mathbf{w}$ and the observed output level y. On the other hand, the actual cost can be written as

$$C^a = \sum_j w_j x_j = C^*(\mathbf{w}, y) \exp(\eta), \tag{53}$$

and therefore, we have

$$\ln C^a = \ln C^*(\mathbf{w}, y) + \eta. \tag{54}$$

The relationship implies that log actual cost is increased by η, i.e. all the inputs are overused by η. The efficiency index of a producer is then

$$\exp(-\eta) = \frac{C^*}{C^a}.$$

Specifically, we assume that the cost function takes a translog form:

$$
\begin{aligned}
\ln C^a_{it} &= \ln C^*(\mathbf{w}_{it}, y_{it}) + v_{it} + \eta_{it} \\
&= \beta_0 + \sum_{j=1}^{J} \phi_j d_j + \sum_j \beta_j \ln w_{jit} + \sum_j \beta_{tj} t \ln w_{jit} + \beta_y \ln y_{it} + \beta_{ty} t \ln y_{it} \\
&\quad + \frac{1}{2} \sum_j \sum_k \beta_{jk} \ln w_{jit} \ln w_{kit} + \frac{1}{2} \beta_{yy} (\ln y_{it})^2 + \sum_j \beta_{jy} \ln w_{jit} \ln y_{it} \\
&\quad + \sum_j \beta_{tj} t \ln w_{jit} + \beta_{ty} t \ln y_{it} + \beta_t t + \beta_{tt} t^2 + v_{it} + \eta_{it}, \qquad (55)
\end{aligned}
$$

$$v_{it} \sim N(0, \sigma_v^2),$$

where d_j represent dummies for the electricity subsectors, v_{it} is the normally distributed error term and $\beta_{jk} = \beta_{kj}$ as required by symmetry. The cost function is homogeneous of degree one in the input prices, which imposes the following parameter restrictions:

$$\sum_j \beta_j = 1, \sum_j \beta_{jk} = 0 \forall k, \sum_j \beta_{jy} = 0, \sum_j \beta_{tj} = 0. \qquad (56)$$

Taking these restrictions into account, with K and L representing capital and labor as two inputs, after substitution and manipulation, we normalize the cost function by w_{Kit} as

$$
\begin{aligned}
\ln(\frac{C^a_{it}}{w_{Kit}}) &= \beta_0 + \sum_{j=1}^{J} \phi_j d_j + \beta_y \ln y_{it} + \beta_{ty} t \ln y_{it} + \beta_L \ln(\frac{w_{Lit}}{w_{Kit}}) + \beta_{tL} t \ln(\frac{w_{Lit}}{w_{Kit}}) + \frac{1}{2} \beta_{yy} (\ln y_{it})^2 \\
&\quad + \frac{1}{2} \beta_{LL} (\frac{w_{Lit}}{w_{Kit}})^2 + \beta_{Ly} \ln(\frac{w_{Lit}}{w_{Kit}}) \ln y_{it} + \beta_t t + \frac{1}{2} \beta_{tt} t^2 + v_{it} + \eta_{it}, \qquad (57)
\end{aligned}
$$

As in other approaches, we make assumptions on the distribution of the inefficiency term η_{it}, which are similar to the assumptions defined by (38) - (43).

4.2.4 Data

We estimate the empirical models with annual data from 2006 to 2016 for firms in the subsectors of electricity generation, which is part of the BPLIM database[22]

[22] Website: https://bplim.bportugal.pt/

of the Bank of Portugal.

For production activities in the sample, we consider the following inputs:

K - Capital stock, measured by tangible fixed capital in euros;

L - Labor input, measured by total hours worked by paid employees.

Based on the variables listed in the BPLim database, we might consider the following variables:

Output level y is measured by non-financial revenue (in euros) in the production function approach and the cost function approach. For the distance function approach, we consider the following outputs:

y_1 - Total sales in the internal market (in euros);

y_2 - Total sales in the EU market (in euros).

In order to be able to take the natural logarithm, a constant 1 is added to each observation of y_2, so that when the original observation equals zero we have the natural logarithm being 0.

In the cost function approach, we use the following proxies for input prices:

w_K - for the proxy for the price of capital, we use the return of financial investment as the opportunity cost of capital, which is obtained by the ratio of financial income to financial investment.

w_L - the price of labor is measured by average hourly wage in euros, which is obtained by the ratio of total payment of wages to the total hours worked by paid employees.

The actual cost of each firm is calculated by

$$C_{it}^{a} = K_{it}w_{Kit} + C_{Lit},$$

where C_{Lit} is the total payment of wages.

We consider the following explanatory determinants of technical inefficiency:

Age (LAGE): the natural logarithm of the age of the firm until 2016; the impact of firm age on technical inefficiency is studied by Lai and Kumbhakar (2018).

Capital deepening (CD): measured by the ratio of capital to labor; too much capital relative to labor input may cause inefficiency (Shao et al., 2016; Yang et al., 2018).

Financial income (FIC): measured by the ratio of financial income to total revenue. Previous evidence shows that over-involvement in financial activities can be detrimental to real production (Hou et al., 2020).

Financial investment (FIV): ratio of financial investment to total non-current assets. This is also a measure for the degree of involvement in financial activities of a firm.

Operating subsidies (SSD): measured by the ratio of operating subsidies to total revenue; high subsidies may undermine efficiency. There has been the evidence that production subsidies can stimulate substantial managerial inefficiencies of biogas plants (Eder and Mahlberg, 2018).

Average working hours (AVHR): measured by the natural logarithm of average hours worked per paid employee; working too much time may increase inefficiency.

Average wage (AVWG): obtained by taking the natural logarithm of the ratio of total payment of wages to the total hours worked by paid employees; a higher wage is expected to improve efficiency.

Different specifications are estimated to evaluate the effects of these factors upon the mean and variance of technical inefficiency.

Table 12 summarizes the descriptive statistics of the data used in our study. As the panel is not balanced, the observations actually utilized in each empirical model may vary. The variables are in their original values although logarithms are used in the estimation.

Notice that although the mean of w_K may seem a bit larger than expected, it is due to some abnormal observations with extremely large financial returns. If we calculate the ratio of mean financial return to the mean of financial income to mean financial investment in the Portuguese electricity sector, the value fluctuates around 10% per year.

4.3 Empirical results and discussion

4.3.1 The production function approach

We estimate several models of production function for Portuguese firms in the electricity sector. The results are presented in Table 13. Among the models with inefficiency term depending on the explanatory variables, we choose to present the results of Model 1 and Model 2 in the table, as other specifications produce similar results. In each model, all the seven explanatory variables appear only once in either the mean equation or the variance equation; variables related with similar issues appear in the same equation, e.g. FIC and FIV, $AVHR$ and $AVWG$. The models are chosen in the same way for the other two approaches.

Most coefficients in the production function are statistically significant, showing that the translog form is a proper specification. Most coefficients for the

Table 12: Descriptive statics of the variables used in the Portuguese electricity sector

Variable	Obs.	Mean	Std. Dev.	Min	Max
Output variables					
y	7,383	$2.74e+07$	$2.70e+08$	-110765.5	$6.48e+09$
y_1	7,383	$2.07e+07$	$2.17e+08$	0	$5.86e+09$
y_2	7,383	1214844	$2.32e+07$	0	$1.15e+09$
Input variables					
K	7,383	$1.97e+07$	$2.11e+08$	0	$5.12e+09$
L	5,832	26511.06	301535.9	0	7560803
Cost variable					
C^a	1,542	$4.20e+08$	$1.14e+10$	0	$4.36e+11$
Input price variables					
w_K	1,542	27.07281	379.4113	0	12539.5
w_L	2,142	10.47935	12.54542	0	174.8294
Determinants of technical inefficiency					
Age	7,377	13.80371	12.04432	0	101
CD	1,933	12.20962	3.140485	1.446775	19.88779
FIC	5,558	.0923781	.2638705	0	1
FIV	6,152	.1019698	.2748856	$-.0959321$	1
SSD	5,558	.0036099	.0454418	0	1
$AVHR$	2,129	1667.959	482.6395	1	3757.733
$AVWG$	2,142	10.47935	12.54542	0	174.8294

dummy variables are statistically significant, indicating differences between the production technologies of electricity subsectors. Nonetheless, in the first two models, there is statistical significance for only a few coefficients related with t, which implies that there is very little technological progress that improves the productivity of the electricity sector in the sample period. While technological progress pushes the production frontier upwards, higher technical efficiency is also important in the sense that it moves the actual output closer to the frontier. In this case, it is extremely important that firms reach higher technical efficiency levels so as to make better use of the current technology.

Regarding the technical inefficiency term, the results also demonstrate statistical significance for most coefficients in all the estimated models. We can infer that firm-level technical inefficiency in the Portuguese electricity sector is indeed affected by these operational factors. Yet, the signs of the coefficients are not all as expected. There are negative signs for the coefficients on $LAGE$, which means that firms of greater age are technically more efficient on average. This is probably the result of learning-by-doing and refined managing techniques. The coefficients for CD (capital deepening) are negative when it appears in the mean or variance equation in the first two models: higher capital input relative to labor input has a negative effect on the mean and variance of technical inefficiency. Such result is different from that in studies using data for other sectors (Shao et al., 2016; Hou et al., 2020). This is probably because of different patterns of production in different economic sectors: some sectors are labor-intensive while others, including the Portuguese electricity sector, are capital-intensive. The result on the effect of financial activities is somehow counter-intuitive: while the coefficients for FIC are positive, which represents positive effect on the mean and variance of technical inefficiency; the coefficients of FIV are negative. In other words, if a firm has a high ratio of financial income relative to its total revenue, it is likely to be technically inefficient, but if it has a high ratio of financial investment relative to its total non-current asset, its technical efficiency is likely to be low. Further study may be needed for a better explanation. The coefficient for SSD is positive in Models 1 and 2, implying that operating subsidy might be detrimental to technical efficiency. The coefficients on $AVHR$ and $AVWG$ are all negative; considering levels of statistical significance, it can be inferred that higher average hourly wage contributes to a higher mean technical efficiency.

Figure 7 is obtained from Model 1 and depicts the evolution of mean technical efficiency in the Portuguese electricity sector and its main subsectors (genera-

Table 13: Estimated results for production frontier functions of Portuguese electricity firms

Variable	Coefficient		
	Model 1	Model 2	TVIM
Frontier			
$\ln K$	$-.236^{**}(.116)$	$-.976^{***}(.183)$	$.124(.124)$
$\ln L$	$.374^{**}(.176)$	$1.11^{***}(.219)$	$-.151(.183)$
$(\ln K)^2$	$.044^{***}(.004)$	$.082^{***}(.008)$	$.016^{***}(.005)$
$(\ln L)^2$	$.068^{***}(.010)$	$.077^{***}(.010)$	$.097^{***}(.012)$
$\ln K \ln L$	$-.077^{***}(.009)$	$-.129^{***}(.015)$	$-.046^{***}(.011)$
$t \ln K$	$.008^{*}(.004)$	$.002(.005)$	$.020^{***}(.004)$
$t \ln L$	$-.017^{**}(.007)$	$-.012(.007)$	$-.041^{***}(.007)$
t	$.080(.092)$	$.122(.094)$	$-.099(.235)$
t^2	$.001(.004)$	$.001 - 1.92(.004)$	$-.009(.016)$
d_{hyd}	$-3.37^{***}(.286)$	$-3.47^{***}(.258)$	$-.723^{*}(.405)$
d_{thm}	$-2.63^{***}(.280)$	$-2.72^{***}(.250)$	$-.472(.394)$
d_{rnw}	$-3.50^{***}(.288)$	$-3.57^{***}(.268)$	$-.864^{**}(.397)$
d_{tnd}	$-3.33^{***}(.304)$	$-3.52^{***}(.272)$	$-1.16^{*}(.630)$
Intercept	$13.4^{***}(1.28)$	$15.7^{***}(1.42)$	$17.6^{***}(3.31)$
Inefficiency term: mean			
$LAGE$	$-11.1^{***}(3.01)$	$-1.92^{***}(.336)$	
CD		$-1.16^{***}(.112)$	
FIC	$34.4^{***}(8.67)$		
FIV	$-22.5^{***}(6.17)$		
SSD	$19.2^{***}(7.11)$		
$AVHR$		$-.561(.356)$	
$AVWG$		$-1.27^{***}(.206)$	
Intercept	$6.03^{**}(2.62)$	$23.3^{***}(2.91)$	$9.67^{***}(3.08)$
Inefficiency term: variance			
CD	$-.103^{***}(.018)$		
FIC		$2.64^{***}(.306)$	
FIV		$-2.02^{***}(.363)$	
SSD		$1.88^{***}(.666)$	
$AVHR$	$-.440^{***}(.097)$		
$AVWG$	$-.392^{***}(.050)$		
Intercept	$8.61^{***}(.751)$	$1.88^{***}(.160)$	$2.04^{***}(.130)$
Inefficiency term: time variance			
t			$.079^{**}(.038)$
t^2			$.001(.004)$

Note: standard errors are in parentheses;
*/**/*** stands for statistical significance at 10%/5%/1% level.

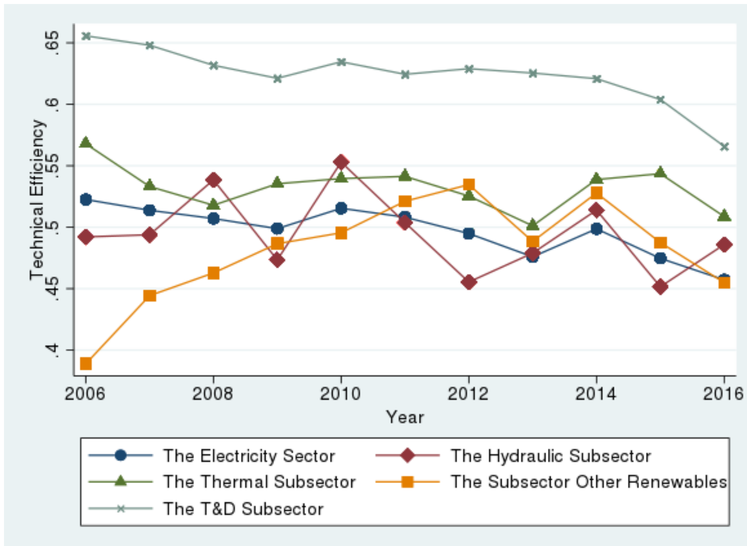

Figure 7: Annual mean technical efficiency level of the Portuguese electricity sector and its main subsectors, 2006-2016, obtained from estimation of production function

tion from hydropower, thermal, other renewable sources and transmission and distribution of electricity) from 2006 to 2016. Overall, technical efficiency in the hydro and thermal subsectors stays closer to the mean of the electricity sector, while the T&D subsector enjoys a higher mean technical efficiency level. It is difficult to judge whether technical efficiency has improved through time, as the curves are far from monotonic; nevertheless, in the Time-Varying Inefficiency Model, the coefficient on t is positive and statistically significant at 5% level, which could be evidence of improvement of technical efficiency through time in the sample period. Meanwhile, technical efficiency in the subsector of other renewables seems to have improved and that in T&D decreased through the years.

4.3.2 The distance function approach

The estimated results for the distance function models are presented in Table 14. Due to the complexity and nonlinearity of the models, the models estimated by each approach can be slightly different from those in the other two approaches for convergence reasons.

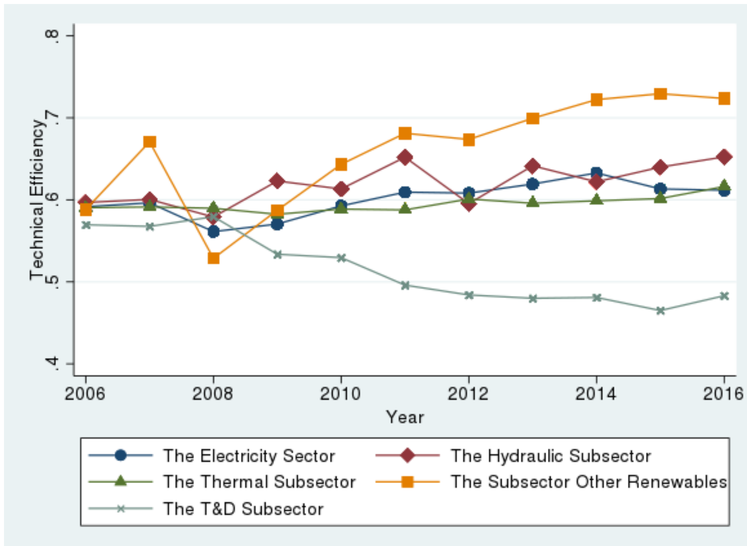

Figure 8: Annual mean technical efficiency level of the Portuguese electricity sector and its main subsectors, 2006-2016, obtained from estimation of distance function

Most coefficients in the distance function are statistically significant, meaning that models are very well specified. Capital deepening has a negative effect on the variance of the inefficiency term; technical inefficiency is also related with average working hours and average hourly wage. Not surprisingly, the coefficient on $AVWG$ is statistically significant and negative in the mean equation, i.e. higher average hourly wage helps eliminate technical efficiency. Higher average working hours increases technical inefficiency in both its mean and variance. There is the possibility of bilateral causality; nevertheless, the result implies that keeping moderate average working hours may improve technical efficiency. This finding helps complete our whole picture. On the other hand, we find no evidence that technical efficiency is affected by the share of operating subsidies in total revenue.

In the Time-Varying Inefficiency Model, both coefficients on t and t^2 are statistically significant, indicating the existence of a time trend in the evolution of technical inefficiency. The coefficient on t is .096 while that on t^2 is $-.008$, which means that the improvement in technical efficiency is slowed down through time.

Figure 8, which is obtained from Model 1, shows the evolution of mean technical efficiency in the Portuguese electricity sector and its main subsectors

Table 14: Estimated results for distance frontier functions of Portuguese electricity firms

Variable	Coefficient		
	Model 1	Model 2	TVIM
Frontier			
$\ln L^*$	$.793^{***}(.091)$	$.921^{***}(.078)$	$.794^{***}(.050)$
$\ln y_1$	$.631^{***}(.119)$	$1.04^{***}(.094)$	$.445^{***}(.072)$
$\ln y_2$	$-.128^{**}(.055)$	$-.206^{***}(.053)$	$-.039(.031)$
$(\ln L^*)^2$	$.059^{***}(.007)$	$.047^{***}(.004)$	$.034^{***}(.002)$
$(\ln y_1)^2$	$-.032^{***}(.005)$	$-.051^{***}(.004)$	$-.025^{***}(.003)$
$\ln y_1 \ln y_2$	$-.006(.005)$	$.003(.004)$	$.004(.003)$
$(\ln y_2)^2$	$.023^{***}(.004)$	$.020^{***}(.003)$	$.002(.002)$
$\ln L^* \ln y_1$	$.043^{***}(.006)$	$.021^{***}(.006)$	$.023^{***}(.004)$
$\ln L^* \ln y_2$	$.005(.004)$	$.010^{***}(.004)$	$.005^{**}(.003)$
$t \ln y_1$	$.014^{***}(.005)$	$.011^{**}(.004)$	$.002(.002)$
$t \ln y_2$	$-.020^{***}(.003)$	$-.018^{***}(.003)$	$-.007^{***}(.001)$
$t \ln L^*$	$-.001(.005)$	$-.002(.004)$	$-.017^{***}(.002)$
t	$-.170^{**}(.075)$	$-.168^{**}(.072)$	$.334^{***}(.093)$
t^2	$-.0002(.0036)$	$.003(.003)$	$-.037^{***}(.008)$
d_{hyd}	$-.517^{***}(.191)$	$-.691^{***}(.185)$	$-.489^{**}(.245)$
d_{thm}	$-.400^{**}(.193)$	$-.733^{***}(.179)$	$-.642^{***}(.243)$
d_{rnw}	$-.692^{***}(.198)$	$-1.00^{***}(.188)$	$-.454^{*}(.249)$
d_{tnd}	$-1.11^{***}(.216)$	$-1.21^{***}(.208)$	$-1.54^{***}(.357)$
Intercept	$-10.1^{***}(.775)$	$-6.57^{***}(1.79)$	$-6.79^{***}(.844)$
Inefficiency term: mean			
$LAGE$	$.288^{**}(.131)$	$.209^{***}(.059)$	
FIC	$1.41^{**}(.638)$		
FIV	$-1.29^{**}(.522)$		
SSD	$-19.2(14.0)$		
$AVHR$		$.414^{***}(.080)$	
$AVWG$		$-.155^{***}(.049)$	
Intercept	$-.718(.449)$	$2.86(1.78)$	$3.28^{***}(.631)$
Inefficiency term: variance			
CD	$-.274^{**}(.113)$	$-.267^{***}(.058)$	
FIC		$-1.29(1.35)$	
FIV		$2.60^{***}(.453)$	
SSD		$-17.7(13.9)$	
$AVHR$	$1.77^{***}(.415)$		
$AVWG$	$.282(.200)$		
Intercept	$-11.0^{***}(3.02)$	$2.20^{***}(.555)$	$-.289^{**}(.127)$
Inefficiency term: time variance			
t			$.096^{***}(.017)$
t^2			$-.008^{***}(.002)$

Note: standard errors are in parentheses;
*/**/*** stands for statistical significance at 10%/5%/1% level.

in the sample period. As in the production function approach, mean technical efficiency in the hydro and thermal subsectors is closer to that in the electricity sector; mean technical efficiency in the subsector of other renewables and T&D diverge from the mean of the sector. The greatest difference from the production function approach is in the level of technical efficiency of the T&D subsector, which is possibly due to the measure of output: in the distance approach it is measured by total sales in internal and EU markets. The performance of T&D firms may be more sensitive to long distance required by international electricity transmission. Nevertheless, the general tendency is similar to the result in the production function approach. Technical efficiency in the subsector of other renewables appears to have increased along the sample years, while that in the T&D subsector has decreased.

4.3.3 The cost function approach

Table 15 summarizes the estimated results for the cost function models.

Most coefficients are statistically significant. It is worth noticing the subtle difference between technical efficiency in production and cost efficiency. Technical efficiency in production is a measure of a firm's ability to reach the potential output level allowed by the technology using a certain set of inputs. Cost efficiency, on the other hand, reflects a firm's ability to optimize its cost in realizing an output goal. It is therefore quite natural that operational factors have different impacts in terms of efficiency. In the estimated results for cost function models, generally, CD exerts positive effects on the mean and variance of technical inefficiency. This implies that firms with larger capital stock (relative to labor input) are likely to be affected in their cost efficiency. While this result is different to that of the production function approach, it has to be noticed that cost efficiency is not exactly identical to productive efficiency. There is potential explanation for this result: it may be due to the input prices considered in the cost functions (which are absent in the other approaches). According to our data, from 2006 to 2016, mean hourly wage in the Portuguese electricity sector grew from 8.27 euros to 10.24 euros; there is also fluctuation in the returns to investment in our data. Regarding the price of fuel, which is not accounted by our models for consistency (as the importance of fuel is mainly reflected in the thermal subsector), there also exist large fluctuations. Between 2006 and 2016, the annual average Northwest Europe marker price for coal ranges between 56.79 and 147.67 USD/ton; Heren NBP index for natural gas fluctuates

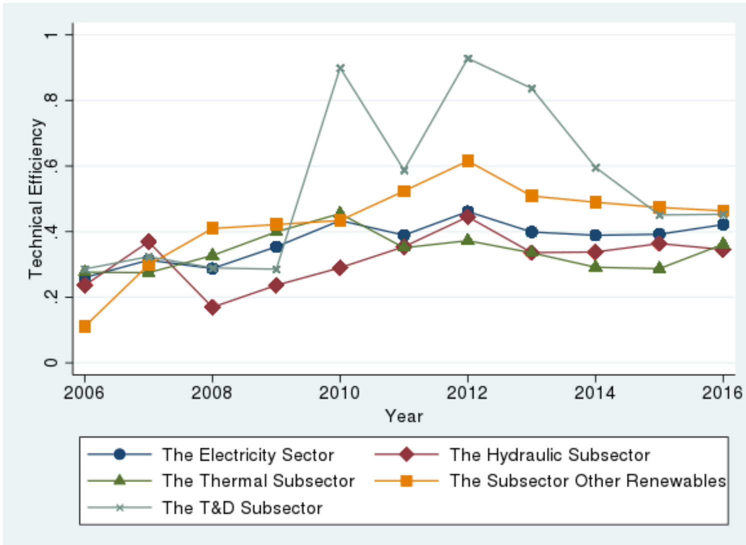

Figure 9: Annual mean technical efficiency level of the Portuguese electricity sector and its main subsectors, 2006-2016, obtained from estimation of cost function

between 4.69 and 10.79 USD per million Btu[23]. Notwithstanding, since firms in the Portuguese electricity sector face similar economic environments in the same year, our result is still meaningful. In both terms of mean and variance, FIC has positive effects and FIV has negative effects on technical inefficiency, which is in line with the production function models. From the perspective of cost efficiency, however, it is difficult to judge the effect of $LAGE$, and there is little evidence of impact by SSD, $AVHR$ and $AVWG$ upon technical inefficiency.

In the TVIM, both coefficients on t and t^2 are statistically insignificant. Thus, evidence doesn't support improvement through time in cost efficiency of the Portuguese electricity sector from 2006 to 2016.

Figure 9 depicts the annual mean cost efficiency in the Portuguese electricity sector and its main subsectors according to Model 1. In some years, the efficiency level of the T&D subsector is higher, but in general, mean technical efficiency in other subsectors stays quite close to the mean of the sector. It is worth highlighting that cost efficiency is also increasing in the subsector of other renewables, a result that is common to all approaches.

[23] Source: https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html

Table 15: Estimated results for cost frontier functions of Portuguese electricity firms

Variable	Coefficient		
	Model 1	Model 2	TVIM
Frontier			
$\ln W$	$.930^{***}(.128)$	$.876^{***}(.157)$	$1.08^{***}(.105)$
$(\ln W)^2$	$.032^{***}(.003)$	$.033^{***}(.003)$	$.026^{***}(.002)$
$\ln y$	$-.039(.154)$	$.116(.176)$	$.009(.096)$
$(\ln y)^2$	$.027^{***}(.004)$	$.023^{***}(.005)$	$.021^{***}(.004)$
$\ln W \ln y$	$-.046^{***}(.008)$	$-.042^{***}(.010)$	$-.052^{***}(.007)$
$t \ln W$	$.003(.005)$	$.003(.007)$	$-.002(.005)$
$t \ln y$	$-.012^{*}(.007)$	$-.023^{***}(.008)$	$.001(.006)$
t	$.175(.127)$	$.303^{**}(.152)$	$-.015(.175)$
t^2	$-.001(.006)$	$.001(.007)$	$-.001(.012)$
d_{hyd}	$.494(.394)$	$.595^{*}(.324)$	$.886(.692)$
d_{thm}	$.622(.389)$	$.499(.319)$	$1.15^{*}(.683)$
d_{rnw}	$.676^{*}(.394)$	$.502(.332)$	$1.43^{**}(.703)$
d_{tnd}	$1.38^{***}(.416)$	$.926^{**}(.399)$	$2.20^{**}(.927)$
Intercept	$5.94^{***}(1.62)$	$5.21^{***}(1.80)$	$11.0^{***}(1.30)$
Inefficiency term: mean			
$LAGE$		$.566^{**}(.278)$	
CD	$.320^{***}(.034)$		
FIC	$2.40^{***}(.579)$		
FIV	$-3.59^{***}(.547)$		
$AVHR$		$-.080(.284)$	
$AVWG$		$.034(.112)$	
Intercept	$-1.80^{***}(.502)$	$-1.37(1.78)$	$3.63^{***}(.814)$
Inefficiency term: variance			
$LAGE$	$-1.39^{**}(.606)$		
CD		$.395^{***}(.080)$	
FIC		$3.96^{***}(1.04)$	
FIV		$-6.96^{***}(1.30)$	
SSD	$11.9(19.1)$	$-13.8(18.6)$	
$AVHR$	$-1.29^{**}(.526)$		
$AVWG$	$.007(.479)$		
Intercept	$10.9^{***}(3.81)$	$-3.94^{***}(1.17)$	$1.19^{***}(.280)$
Inefficiency term: time variance			
t			$-.006(.074)$
t^2			$-.001(.006)$

Note: $\ln W = \ln(w_L/w_K)$; standard errors are in parentheses; */**/*** stands for statistical significance at 10%/5%/1% level.

4.3.4 General Comments

Generalizing the results of the three approaches, higher capital input relative to labor leads to higher technical efficiency in terms of production, but lower efficiency in cost terms. Both production function and cost function models provide evidence of the firms' involvement in financial activities affecting technical efficiency. The share of financial income in total revenue decreases technical efficiency, while the ratio of financial investment to capital stock increases it. Evidence from the production function approach indicates that firms with longer history tend to enjoy higher technical efficiency and operating subsidies may undermine technical efficiency, but this finding is not confirmed by evidence from other approaches. Average working hours per employee and average hourly wage affect productive efficiency rather than cost efficiency. To be specific, higher hourly wage and moderate average working hours are likely to improve technical efficiency.

When it comes to the question of whether there is a trend of improving technical efficiency through time, the answer is yes in terms of production, although the improvement may have slowed down; meanwhile, there is no evidence for improvement in terms of cost efficiency. This is probably due to the fluctuation in input prices, e.g. average hourly wage.

The liberalization of the Portuguese electricity market was successful in the sense that productive efficiency has improved. Nonetheless, as various factors affect technical efficiency, it is not enough to ride the trend. Firms in the electricity sector should also pay attention to operational issues in order to improve efficiency. From the figures representing mean technical efficiency levels in the electricity subsectors, technical efficiency in other renewables consistently increases through time. Due to concerns on energy security and environmental impacts, Portugal made great efforts in promoting electricity generation from renewable sources in the last few decades, leading to a boom in this type of generation (Netto, 2013). Our finding implies that firms in the subsector are becoming experienced at generating electricity from renewable sources so that they are making better use of the technology.

In the results obtained by all three approaches, although there exist differences between the subsectors, the mean technical efficiency level of the Portuguese electricity sector ranges around 50% to 60% overall. Such a result suggests that there is still potential for improving technical efficiency. The findings in our research indicate that firms in the electricity sector ought to increase

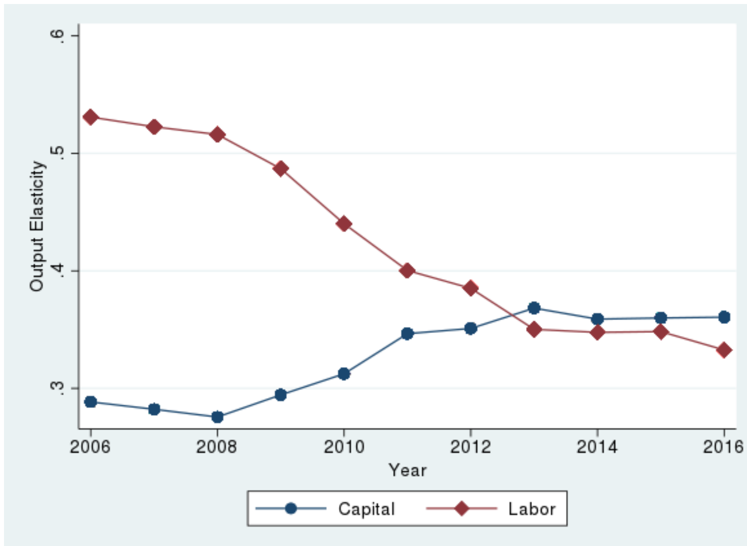

Figure 10: Annual mean output elasticities of capital and labor in the Portuguese electricity sector, 2006-2016, derived from Model 1, the production function approach

capital input rather than labor input. This is supported by Figure 10, which shows the annual mean output elasticities of capital and labor calculated according to equations (36) and (37). The figure shows that the output elasticity of capital increases through time while that of labor decreases, implying that it is optimal for Portuguese electricity firms to increase capital input (especially in the form of equipments instead of real estate) and not labor. Meanwhile, increasing hourly wage and keeping working hours at a moderate level is also helpful in improving technical efficiency.

Operating subsidies, at best, do not help improve technical efficiency, and even undermine efficiency in terms of production. This is in line with the finding by Eder and Mahlberg (2018). The reason might be that subsidies undermine the motivation of improving efficiency. There has been the debate regarding whether the benefit of subsidies overwhelms their cost. Although subsidies are designed to promote the development of renewable energy, removing the subsidy scheme may imply net present value gains (Johansson and Kriström, 2019). In addition, there is the hazard of managers of electricity companies improperly profitting from subsidies, as highlighted in a recent case of one of the major companies in the Portuguese electricity sector[24]. However, we leave the question of whether subsidies to electricity firms are still a worthwhile policy endeavour, since there are other impacts of these subsidies.

[24] For more information the reader may refer to: https://www.jornaldenegocios.pt/empresas/energia/detalhe/mexia-e-manso-neto-vao-ser-acusados-de-corrupcao-ativa-no-caso-edp, or: https://visao.sapo.pt/atualidade/2020-06-02-caso-edp-antonio-mexia-e-suspeito-de-quatro-crimes-de-corrupcao-ativa-e-um-de-participacao-economica-em-negocio/

5 Conclusion

In the Stochastic Frontier empirial research that consists of three parts, we investigate the direction of technological change at country and firm level, as well as the change and operational determinants of firm-level technical efficiency in the Portuguese electricity sector. While each part makes its own policy implication according to its empirical finding, they together form a complete picture on technological change and technical efficiency in production involving energy as input and output.

In Section 2 we apply 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 SFA studies, 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 prices or 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.

Nonetheless, we find that the average production of all sample countries demonstrates decreasing returns to scale. 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 this section is to analyze 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 satisfying. However, it still leaves some difficult questions to be answered. For countries with the same bias orders, is there any common pattern? What determines the direction of technological change? Part of these questions can be answered to some extent by our study of Section 3, while the rest remains to be explored.

In micro-level production activities involving energy inputs, how does directed technological change take place? The answer to this question has many implications on policies regarding energy efficiency, energy price and technological innovation. While a number of previous studies investigate this issue with sector data, evidence from firm level is lacking. The study of Section 3 applies stochastic frontier analysis to panel data for Portuguese firms, with respect to output produced from four input factors: capital, labor, electricity and fuel. For each of the 32 economic subsectors in our analysis, we estimate a translog production function with an error term and a technical inefficiency term, which is affected by three factors: capital deepening, energy consumption structure and share of financial income.

Results demonstrate the common existence of technical inefficiency in Portuguese economic subsectors; in some subsectors, over one third of potential output is lost due to technical inefficiency. In a considerable number of subsectors, capital deepening and share of financial income exert positive marginal effects on technical inefficiency. Energy consumption structure also has significant effects on technical inefficiency in most subsectors; however, from current evidence, it is difficult to determine the direction of its effect. Roughly, unlike higher-tech manufacturing subsectors, agricultural and low-tech manufacturing subsectors are more likely to be affected by the abovementioned factors.

According to our estimation, the average output elasticity of labor is increasing in most subsectors, while that of other inputs is decreasing more often. The mean level of output elasticity of labor is the highest among the four inputs in 24 of the 32 subsectors, revealing the importance of labor in production activities and in economic growth. In contrast, the overall level of mean output elasticity of capital is quite low (below 0.1 in most subsectors); negative values appear in individual observations at a considerable frequency. This phenomenon implies the agents' limited ability in making optimal investment decisions, possibly because of the need to maintain operation, or other factors. Different mean levels of output elasticity of capital also suggest the possibility of ameliorating economic structure by inducing investment in certain economic subsectors. Compared with empirical results on Chinese provinces, where output elasticities of capital are higher, this shows the difference in the driver for economic growth in developing and developed countries, in line with previous macro-level studies.

Regarding the direction of technological change, among a number of findings and interpretations, there are three points that we would like to highlight:

1. In most Portuguese economic subsectors, technological change is biased the most towards labor.

2. Between the two energy forms considered in our study, technological change is biased more towards fuel rather than electricity.

3. Considering data on energy consumption and price in the same period in Portugal, market size effect is likely to overwhelm price effect in deciding the direction of technological change, while there may be other firm level determinants, which remain to be identified in future studies.

Based on our findings regarding technical inefficiency, output elasticities, TFP growth and direction of technological change, we may advise policy making in a few aspects:

1. Optimal policies for sustaining economic growth should involve promoting education and eliminating technical inefficiency, since it is difficult to achieve a sudden increase in TFP growth.

2. Higher electricity price may not be the best tool to direct technological change towards electricity. As an alternative, relatively lower electricity price may help reach this goal through market size effect. Carbon pricing is an option for this purpose. Meanwhile, policies should pursue the development and adoption of technologies that improve energy efficiency, for example, more accessible energy audits for firms.

3. While regulating financial activities may help eliminate technical inefficiency, it is necessary to encourage employment in agricultural and low-tech subsectors.

Our study serves as a good firm-level supplement to empirical studies regarding directed technological change. Firm data allows us to estimate each economic subsector's own production function, which distinguishes among subsectors regarding the patterns in production activities. We obtain clues on how firms make decisions on investment and adoption of technologies. Our findings support the growth theory of directed technological change while providing insights for policy making.

Nonetheless, the study leaves some issues unattended. The analysis is performed for 32 economic subsectors in Portugal, and thus does not take full advantage of the dimension of the database. An analysis with respect to a single subsector could reveal more details, e.g. firm-level determinants for the direction of technological change, the distribution of some parameters or their evolution with time.

In Section 4 we apply Stochastic Frontier Analysis to annual firm-level data in the Portuguese electricity sector. In order to obtain a comprehensive understanding on the evolution of technical efficiency in the Portuguese electricity sector, we estimate frontier models in three different functional forms: production function, distance function and cost function. Specifically, we are interested in two issues: whether technical efficiency depends on operational heterogeneity and whether it improves through time in the sample period, which covers the process of liberalization in the Portuguese electricity market.

Regarding the first question, we find that all the selected factors have statistically significant impact on the firms' technical efficiency in at least some of the empirical models. Among all, higher capital input relative to labor, higher average hourly wage and lower average working hours are found to be likely to improve technical efficiency in production. On the second question, the answer is that technical efficiency in production does improve through time, but such improvement may have slowed down gradually. Specially, observing the figures for annual mean technical efficiency of the subsectors, we discover that technical efficiency improves in the subsector of renewables except hydro. This signals success of Portugal's effort in promoting electricity generation from renewable sources.

The reform in the electricity sector promoted the general evolution in productive efficiency. Notwithstanding, the trend is likely to fade away over time; it is equally important to implement specific policies targeted at improving technical efficiency. Our findings imply that in order to improve technical efficiency, policy making or firm management should aim at promoting investment in equipment, raising average hourly wage and controlling working time of the employees. Findings from the production function approach raise the doubt on whether operating subsidies are desirable from the perspective of technical efficiency.

Our analysis still leaves room for discussion. What is the mechanism of a firm's involvement in financial activities affecting technical inefficiency? Among the electricity subsectors, why do some enjoy higher mean technical efficiency than others? These questions might be worthy of further investigation.

In the coming years a significant energy transition must be accomplished throughout the world, as current trends are not enough to mitigate climate change nor prevent potential catastrophic impacts in the coming century. It is therefore important for all countries to improve their use of energy. I hope my work contributes to this significant challenge of humanity. Meanwhile, my dissertation also contributes to the realization of some of the Sustainable Development Goals proposed by the 2030 Agenda of the UN (2015), i.e., Goal 7, affordable, reliable, sustainable and modern energy for all; Goal 8, sustained, inclusive and sustainable economic growth; Goal 9, infrastructure, inclusive and sustainable industrialization and innovation. After all, I hope my study could help modern society get better adapted to the challenges brought by the current limitation in resources, economic development and technologies.

Appendices

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)

Appendix C: Results of specification tests for Section 3

The following table presents the LR statics for the specification tests, as well as whether the null hypothesis is rejected or not. Critical values are according to Kodde and Palm (1986).

***: Rejection of the null hypothesis at 0.01 level.

**: Rejection of the null hypothesis at 0.05 level.

*: Rejection of the null hypothesis at 0.10 level.

The subscripts "A01" and so on correspond to the estimated result for each subsector. The number in the parentheses correspond to the following hypotheses:

$H_{XX(1)}$ - $H_0 : \sigma_U^2 = 0$;

$H_{XX(2)}$ - $H_0 : \beta_t = \beta_{tt} = \beta_{tK} = \beta_{tL} = \beta_{tE} = \beta_{tF} = \beta_{KL} = \beta_{KE} = \beta_{KF} = \beta_{LE} = \beta_{LF} = \beta_{EF} = \beta_{KK} = \beta_{LL} = \beta_{EE} = \beta_{FF} = 0$;

$H_{XX(3)}$ - $H_0 : \beta_t = \beta_{tt} = \beta_{tK} = \beta_{tL} = \beta_{tE} = \beta_{tF} = 0$;

$H_{XX(4)}$ - $H_0 : \beta_{tK} = \beta_{tL} = \beta_{tE} = \beta_{tF} = 0$.

Results for specification tests - I

Hypothesis	LR statistic	Hypothesis	LR statistic	Hypothesis	LR statistic
$H_{A01(1)}$	1070.64***	$H_{C05(1)}$	119.90***	$H_{C12(1)}$	$-6.551e-07$
$H_{A01(2)}$	2684.73***	$H_{C05(2)}$	245.57***	$H_{C12(2)}$	377.55***
$H_{A01(3)}$	164.75***	$H_{C05(3)}$	3.72	$H_{C12(3)}$	11.37*
$H_{A01(4)}$	19.82***	$H_{C05(4)}$	3.09	$H_{C12(4)}$	3.98
$H_{A02(1)}$	62.69***	$H_{C06(1)}$	64.24***	$H_{C13(1)}$	38.75***
$H_{A02(2)}$	155.32***	$H_{C06(2)}$	128.33***	$H_{C13(2)}$	1466.44***
$H_{A02(3)}$	6.74	$H_{C06(3)}$	6.88	$H_{C13(3)}$	175.59***
$H_{A02(4)}$	3.88	$H_{C06(4)}$	5.85	$H_{C13(4)}$	37.88***
$H_{A03(1)}$	85.46***	$H_{C07(1)}$	346.65***	$H_{C14(1)}$	3.53**
$H_{A03(2)}$	369.07***	$H_{C07(2)}$	2041.85***	$H_{C14(2)}$	659.57***
$H_{A03(3)}$	52.00***	$H_{C07(3)}$	71.25***	$H_{C14(3)}$	19.44***
$H_{A03(4)}$	1.84	$H_{C07(4)}$	24.36***	$H_{C14(4)}$	3.48
$H_{B(1)}$	280.02***	$H_{C08(1)}$	$-.00015$	$H_{C15(1)}$	475.09***
$H_{B(2)}$	377.52***	$H_{C08(2)}$	4046.96***	$H_{C15(2)}$	516.67***
$H_{B(3)}$	33.92***	$H_{C08(3)}$	167.42***	$H_{C15(3)}$	34.39***
$H_{B(4)}$	20.17***	$H_{C08(4)}$	70.01***	$H_{C15(4)}$	6.53
$H_{C01(1)}$	315.77***	$H_{C09(1)}$	$-6.737e-06$	$H_{E01(1)}$	7.11***
$H_{C01(2)}$	3328.76***	$H_{C09(2)}$	71.31***	$H_{E01(2)}$	85.16***
$H_{C01(3)}$	45.18***	$H_{C09(3)}$	8.22	$H_{E01(3)}$	4.42
$H_{C01(4)}$	21.89***	$H_{C09(4)}$	3.63	$H_{E01(4)}$	4.38
$H_{C02(1)}$	159.21***	$H_{C10(1)}$	$-.000088$	$H_{E02(1)}$	28.66***
$H_{C02(2)}$	2476.41***	$H_{C10(2)}$	337.20***	$H_{E02(2)}$	91.28***
$H_{C02(3)}$	63.06***	$H_{C10(3)}$	12.55*	$H_{E02(3)}$	18.24***
$H_{C02(4)}$	15.35***	$H_{C10(4)}$	7.46	$H_{E02(4)}$	14.49***
$H_{C03(1)}$	51.89***	$H_{C11(1)}$	$-2.413e-07$	$H_{E03(1)}$	4.15**
$H_{C03(2)}$	1426.36***	$H_{C11(2)}$	587.64***	$H_{E03(2)}$	380.97***
$H_{C03(3)}$	97.44***	$H_{C11(3)}$	18.20***	$H_{E03(3)}$	9.85
$H_{C03(4)}$	44.99***	$H_{C11(4)}$	7.17	$H_{E03(4)}$	7.07

Results for specification tests - II

Hypothesis	LR statistic	Hypothesis	LR statistic	Hypothesis	LR statistic
$H_{F(1)}$	3924.63^{***}	$H_{H01(1)}$	1748.28^{***}	$H_{I02(1)}$	237.35^{***}
$H_{F(2)}$	5018.50^{***}	$H_{H01(2)}$	3946.07^{***}	$H_{I02(2)}$	6693.96^{***}
$H_{F(3)}$	773.47^{***}	$H_{H01(3)}$	102.78^{***}	$H_{I02(3)}$	1324.39^{***}
$H_{F(4)}$	175.72^{***}	$H_{H01(4)}$	35.40^{***}	$H_{I02(4)}$	242.49^{***}
$H_{G01(1)}$	618.85^{***}	$H_{H02(1)}$	53.47^{***}	$H_{J01(1)}$	$-.00016$
$H_{G01(2)}$	3538.68^{***}	$H_{H02(2)}$	103.56^{***}	$H_{J01(2)}$	695.50^{***}
$H_{G01(3)}$	326.60^{***}	$H_{H02(3)}$	6.29	$H_{J01(3)}$	21.93^{***}
$H_{G01(4)}$	43.06^{***}	$H_{H02(4)}$	5.85	$H_{J01(4)}$	8.77^{*}
$H_{G02(1)}$	912.75^{***}	$H_{H04(1)}$	73.75^{***}	$H_{J03(1)}$	65.31^{***}
$H_{G02(2)}$	4660.14^{***}	$H_{H04(2)}$	274.45^{***}	$H_{J03(2)}$	619.47^{***}
$H_{G02(3)}$	121.59^{***}	$H_{H04(3)}$	3.35	$H_{J03(3)}$	33.24^{***}
$H_{G02(4)}$	31.48^{***}	$H_{H04(4)}$	2.81	$H_{J03(4)}$	22.53^{***}
$H_{G03(1)}$	463.51^{***}	$H_{I01(1)}$	584.31^{***}		
$H_{G03(2)}$	8522.94^{***}	$H_{I01(2)}$	1747.48^{***}		
$H_{G03(3)}$	224.42^{***}	$H_{I01(3)}$	182.99^{***}		
$H_{G03(4)}$	38.45^{***}	$H_{I01(4)}$	10.54^{**}		

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Table 8 - Estimated results of production functions for Portuguese economic subsectors																
Subsector	A01	A02	A03	B	C01	C02	C03	C05	C06	C07	C08	C09	C10	C11	C12	C13
Coefficients																
Constant	4.949***(.321)	9.023***(1.296)	8.241***(1.092)	7.134***(.953)	3.665***(.254)	3.941***(.261)	5.025***(.285)	2.847***(.889)	5.509*(3.157)	3.409***(.301)	3.874***(.233)	1.840(1.467)	5.509***(.940)	4.555***(.818)	4.80***(.988)	4.241***(.380)
t	-.102***(.024)	-.011(.093)	-.039(.080)	-.241***(.071)	-.062***(.020)	-.014(.019)	-.142***(.023)	-.072(.072)	-.228(.153)	-.121***(.025)	-.131***(.016)	-.203*(.117)	-.142*(.073)	-.068*(.040)	-.015(.066)	-.175***(.029)
t^2	.010***(.001)	.001(.005)	.018***(.004)	.006(.004)	.006*** (.001)	.002(.001)	.008***(.001)	.003(.004)	.011(.010)	.011***(.002)	.009***(.001)	.016**(.008)	.010**(.005)	.006**(.002)	.010**(.004)	.012***(.002)
lnK	.145***(.030)	-.113(.097)	-.031(.107)	.042(.078)	-.229***(.024)	-.158***(.024)	-.089***(.028)	-.165*(.090)	-.926***(.317)	-.179***(.030)	-.085***(.019)	.128(.132)	.184**(.085)	-.024(.051)	-.057(.083)	-.035(.031)
lnL	.289***(.050)	.471**(.197)	-.152(.168)	.029(.157)	.664***(.042)	-.136***(.039)	-.103*(.054)	.260*(.138)	-.821(.584)	.371***(.050)	.413***(.037)	.346(.260)	.070(.175)	-.101(.118)	-.189(.144)	.151**(.065)
lnE	.093**(.036)	-.070(.130)	.139*(.083)	-.146(.097)	.198***(.034)	.560***(.035)	.341***(.043)	.607***(.104)	1.439***(.449)	.335***(.041)	.140***(.026)	.329(.231)	-.339**(.145)	.263***(.087)	.461***(.137)	.425***(.055)
lnF	.188***(.037)	-.228(.141)	.178*(.099)	.396***(.080)	.382***(.024)	.729***(.029)	.640***(.035)	.718***(.123)	1.768***(.276)	.557***(.029)	.502***(.024)	.612***(.148)	.587***(.109)	.623***(.071)	.596***(.077)	.333***(.042)
$t * lnK$	.005***(.002)	-.0005(.005)	.002(.005)	-.010**(.005)	.005***(.001)	.003*(.001)	-.007***(.002)	-.006(.005)	.041**(.017)	-.002(.002)	-.006***(.001)	-.004(.011)	-.002(.005)	-.001(.003)	.008(.005)	-.006***(.002)
$t * lnL$	.0004(.0028)	.009(.011)	-.003(.009)	.011(.009)	.006*(.003)	.001(.002)	.019***(.004)	.004(.011)	-.012(.028)	.016***(.004)	.016***(.002)	-.008(.017)	.006(.014)	.014**(.006)	-.011(.011)	.020***(.005)
$t * lnE$	-.006***(.002)	-.010(.007)	-.003(.004)	.010* (.005)	-.010***(.002)	-.007***(.002)	-.004(.003)	.003(.006)	-.028(.024)	-.009***(.003)	-.002(.002)	-.002(.014)	-.014(.009)	-.011**(.005)	-.003(.010)	-.008**(.004)
$t * lnF$	.005**(.002)	.001(.007)	-.004(.006)	.010**(.004)	-.0006(.0016)	.005**(.002)	.002(.002)	.006(.006)	-.001(.014)	.0001(.002)	.001(.002)	.023*(.012)	.015**(.008)	-.001(.005)	.0003(.006)	.006**(.003)
$lnK * lnL$	-.011***(.004)	.010(.015)	-.015(.012)	.024**(.010)	.0007(.0035)	-.002(.003)	.006(.004)	.0007(.013)	.234***(.081)	-.001(.004)	-.011***(.003)	-.011(.021)	-.077***(.015)	-.007(.008)	.036***(.013)	-.007*(.004)
$lnK * lnE$	-.005**(.002)	.001(.009)	.007(.007)	-.018**(.007)	-.008***(.003)	-.026***(.003)	.010***(.003)	.005(.008)	-.219***(.042)	.011***(.003)	.025***(.002)	-.042**(.018)	.040***(.010)	.006(.006)	-.066***(.010)	.012***(.004)
$lnK * lnF$	-.011***(.003)	.025**(.010)	.035***(.009)	-.017***(.006)	-.005***(.002)	.042***(.003)	.002(.003)	-.004(.010)	-.104***(.034)	.007**(.003)	-.004*(.002)	.027*(.016)	.013(.009)	-.005(.005)	.001(.008)	-.0004(.003)
$lnL * lnE$	-.022***(.004)	.032**(.016)	.036***(.010)	-.049***(.010)	-.087***(.005)	.006(.005)	-.070***(.006)	-.069***(.015)	-.298***(.084)	-.105***(.006)	-.034***(.004)	.014(.036)	-.015(.024)	-.050***(.012)	-.045**(.020)	-.073***(.008)
$lnL * lnF$	-.043***(.005)	-.105***(.015)	-.050***(.011)	-.059***(.011)	-.061***(.004)	-.044***(.004)	-.062***(.006)	-.083***(.020)	-.243***(.050)	-.035***(.005)	-.088***(.004)	-.137***(.038)	-.079***(.023)	-.080***(.013)	-.047***(.013)	-.044***(.007)
$lnE * lnF$	-.057***(.003)	-.032***(.010)	-.074***(.008)	.0004(.006)	-.014***(.003)	-.131***(.004)	-.065***(.005)	-.030***(.011)	.016(.050)	-.054***(.004)	-.030***(.003)	-.017(.031)	-.056***(.016)	-.008(.011)	-.032**(.013)	-.056***(.006)
$(lnK)^2$	.008***(.0008)	-.005***(.002)	-.008**(.004)	.011***(.002)	.023***(.001)	.010***(.001)	.003***(.001)	.014***(.003)	.055***(.018)	.006***(.001)	.008***(.001)	.006(.005)	.010***(.003)	.009***(.002)	.013***(.003)	.006***(.001)
$(lnL)^2$	.043***(.002)	.022***(.007)	.046***(.007)	.056***(.007)	.046***(.003)	.043***(.002)	.085***(.004)	.078***(.012)	.156***(.029)	.073***(.003)	.064***(.002)	.082***(.022)	.119***(.014)	.099***(.005)	.064***(.006)	.075***(.003)
$(lnE)^2$	.061***(.002)	.016**(.006)	.029***(.003)	.050***(.005)	.067***(.002)	.054***(.002)	.050***(.003)	.033***(.006)	.230***(.045)	.069***(.003)	.015***(.002)	.012(.019)	.037***(.008)	.023***(.006)	.066***(.011)	.043***(.004)
$(lnF)^2$	.056***(.002)	.074***(.007)	.036***(.006)	.027***(.003)	.034***(.001)	.044***(.002)	.046***(.002)	.026***(.005)	.142***(.019)	.022***(.002)	.051***(.002)	.046***(.015)	.039***(.007)	.030***(.005)	.018***(.005)	.050***(.003)
(Firm size dummies omitted.)																
Technical inefficiency equation																
Constant	-1.903*** (.100)	-1.714***(.247)	-2.329***(.267)	-.611***(.134)	-3.764***(.341)	-.533***(.136)	-1.006***(.206)	-2.58***(.454)	2.167***(.353)	-1.018***(.109)						-1.639***(.195)
CD	7.8e-06*** (2.3e-06)	-.0007*(.0003)	.00007(.00012)	-1.56e-06 (2.81e-06)	.00005*** (7.82e-06)	.00002*** (5.64e-06)	.00009***(.00002)	-.003(.002)	-.0001(.0009)	-1.24e-06 (2.37e-06)						-.00002(.00004)
ES	2.002***(.131)	2.617***(.375)	2.975***(.364)	-.854**(.339)	1.484***(.346)	-4.474***(.300)	-4.582***(.570)	2.99*** (.525)	-4.51***(.792)	-.752***(.185)						-.848**(.339)
FI	4.457***(.400)	2.336***(.813)	3.447(19.628)	5.491***(1.012)	31.404***(4.522)	21.125***(6.22)	8.714**(3.617)	-14.87(16.44)	-24.66*(14.8)	11.072***(1.384)						-155.81*(87.48)
Related statics																
Log likelihood	-24556.381	-2022.1859	-690.89744	-2363.1578	-20946.385	-24650.458	-14388.606	-1974.2583	-286.60584	-11857.388	-18270.291	-461.87897	-1593.28	-3084.9688	-2010.0671	-4886.4818
LR static	51267.74	3585.93	5898.33	8871.36	139391.13	123652.44	95002.03	13968.20	3258.86	89819.33	161082.97	6508.94	13989.21	30936.10	21534.49	47068.80
Note: Standard errors in parentheses; */**/*** represent statistical significance at 0.10/0.05/0.01 level.																

Table 8 (continued) - Estimated results of production functions for Portuguese economic subsectors																
Subsector	C14	C15	E01	E02	E03	F	G01	G02	G03	H01	H02	H04	I01	I02	J01	J03
Coefficients																
Constant	-.250(.646)	1.739***(.603)	-.777(2.477)	3.591(4.418)	-.556(1.275)	6.172***(.172)	7.126***(.250)	-.978***(.172)	3.204***(.130)	2.073***(.240)	-11.63***(4.12)	.367(.741)	3.838***(.275)	5.927***(.149)	3.641***(.632)	3.789***(.403)
t	-.103**(.048)	-.052(.045)	.153(.123)	-.441*(.241)	.062(.091)	-.256***(.015)	-.205***(.020)	-.105***(.014)	-.099***(.011)	-.059***(.019)	.495*(.261)	-.013(.067)	-.072***(.022)	-.260***(.011)	-.210***(.050)	-.109***(.033)
t^2	.012***(.003)	.010***(.003)	-.002(.007)	.017(.012)	.002(.006)	.022***(.001)	.018***(.001)	.008***(.001)	.008***(.001)	.006***(.001)	.003(.013)	-.001(.004)	.015***(.002)	.019***(.001)	.012***(.003)	.007***(.002)
lnK	-.001(.060)	-.049(.054)	.406***(.137)	-.166(.303)	-.201*(.116)	.105***(.014)	-.014(.022)	.271***(.015)	.114***(.012)	.303***(.025)	-1.049***(.325)	.110*(.061)	.054**(.021)	.028**(.012)	-.045(.051)	.118***(.035)
lnL	.667***(.125)	.716***(.097)	.341(.650)	2.853**(1.129)	1.307***(.257)	.077***(.029)	.147***(.045)	1.018***(.031)	.137***(.024)	.763***(.047)	4.215***(.936)	.878***(.122)	.581***(.050)	.014(.026)	.407***(.094)	.452***(.076)
lnE	.666***(.098)	.014(.080)	-.560**(.265)	1.640***(.493)	.055(.127)	.349***(.021)	-.160***(.042)	.431***(.022)	.533***(.018)	.295***(.026)	.790**(.342)	.782***(.094)	-.069(.052)	.291***(.025)	.348***(.066)	.358***(.048)
lnF	.576***(.077)	.674***(.082)	1.665***(.312)	-2.287**(.967)	.867***(.123)	.281***(.023)	.353***(.031)	.665***(.023)	.433***(.016)	-.075**(.033)	.944**(.368)	.458***(.088)	.367***(.027)	.214***(.015)	.415***(.064)	.137***(.050)
$t * lnK$	-.004(.003)	-.0001(.003)	.0002(.006)	-.036**(.014)	-.016**(.007)	-.002**(.001)	-.0007(.001)	-.002**(.001)	-.003***(.001)	-.006***(.002)	.009(.014)	.005(.004)	-.003*(.002)	-.0002(.0006)	-.002(.003)	-.007***(.002)
$t * lnL$	-.005(.007)	-.005(.006)	.013(.024)	.094**(.041)	.011(.012)	.013***(.002)	.014***(.003)	.003(.002)	.008***(.002)	.005*(.003)	-.050*(.030)	.006(.009)	.007**(.004)	.019***(.001)	.008(.007)	.015***(.004)
$t * lnE$	.008(.006)	-.007(.005)	.010(.008)	.016(.015)	.002(.007)	-.012***(.001)	-.012***(.003)	-.002*(.001)	-.001(.001)	-.006***(.002)	.002(.019)	-.004(.006)	-.005(.003)	-.009***(.002)	.003(.005)	-.008**(.004)
$t * lnF$	.005(.005)	.011**(.005)	-.038*(.023)	-.045**(.019)	-.001(.007)	.006***(.002)	.005***(.002)	.006***(.002)	.001(.001)	.007***(.002)	-.014(.020)	-.008(.006)	-.001(.002)	.002***(.001)	.005(.005)	.005(.003)
$lnK * lnL$	-.009(.009)	-.028***(.008)	.031(.037)	-.009(.079)	-.040**(.016)	-.007***(.002)	-.008**(.003)	-.030***(.002)	-.010***(.002)	-.035***(.004)	-.006(.036)	-.015*(.009)	-.041***(.004)	-.008***(.002)	-.007(.007)	-.021***(.005)
$lnK * lnE$	-.005(.007)	.018***(.006)	-.013(.010)	-.036(.025)	-.030***(.007)	-.002(.001)	.003(.003)	-.0004(.0016)	-.008***(.001)	.002(.002)	.010(.019)	-.020***(.006)	.005(.003)	-.001(.002)	-.004(.005)	-.001(.004)
$lnK * lnF$	.010*(.005)	.021***(.005)	-.035(.027)	.061*(.036)	.011(.008)	-.007***(.002)	-.004**(.002)	-.009***(.002)	.004***(.001)	-.016***(.003)	.034(.021)	.010(.006)	.001(.002)	.007***(.001)	-.010**(.004)	.001(.004)
$lnL * lnE$	-.069***(.014)	-.016(.012)	-.133***(.048)	.195***(.048)	.025*(.015)	-.026***(.003)	-.026***(.006)	-.050***(.003)	-.062***(.003)	.037***(.004)	.019(.048)	-.091***(.011)	-.112***(.006)	-.090***(.003)	-.058***(.010)	-.080***(.007)
$lnL * lnF$	-.097***(.013)	-.165***(.011)	-.243***(.078)	.333**(.147)	-.174***(.013)	-.053***(.003)	-.055***(.004)	-.112***(.003)	-.074***(.002)	-.193***(.005)	-.091(.072)	-.036***(.011)	-.026***(.005)	-.018***(.002)	-.127***(.009)	-.060***(.007)
$lnE * lnF$	-.047***(.012)	-.028**(.011)	.168***(.044)	-.231***(.065)	-.001(.008)	-.059***(.003)	-.088***(.004)	-.016***(.003)	-.013***(.002)	-.081***(.003)	-.144***(.037)	.027***(.007)	-.039***(.005)	-.041***(.002)	.010(.007)	-.007(.006)
$(lnK)^2$	.007***(.002)	.003**(.001)	-.010*(.006)	.012(.016)	.039***(.005)	.005***(.0004)	.009***(.001)	.008***(.0005)	.004***(.0003)	.014***(.001)	.029***(.008)	.006**(.002)	.014***(.001)	.003***(.0003)	.014***(.002)	.008***(.002)
$(lnL)^2$	.076***(.004)	.092***(.006)	.195***(.069)	-.447***(.109)	.044**(.019)	.055***(.002)	.054***(.002)	.061***(.002)	.093***(.001)	.103***(.003)	-.153**(.065)	.038***(.007)	.085***(.004)	.081***(.002)	.090***(.006)	.075***(.006)
$(lnE)^2$	.031***(.007)	.012*(.006)	.021**(.010)	-.049***(.014)	.012***(.004)	.059***(.001)	.073***(.004)	.023***(.001)	.030***(.001)	.030***(.002)	.050***(.015)	.023***(.004)	.095***(.004)	.066***(.002)	.011**(.005)	.046***(.003)
$(lnF)^2$	.051***(.006)	.077***(.006)	-.014(.026)	.064***(.024)	.054***(.006)	.044***(.002)	.080***(.002)	.043***(.001)	.029***(.001)	.130***(.003)	.026(.031)	-.023***(.004)	.022***(.002)	.023***(.001)	.070***(.004)	.038***(.003)
(Firm size dummies omitted.)																
Technical inefficiency equation																
Constant	-3.133**(1.346)	.217*(.112)	-.674(.577)	.541(.487)	-1.753***(.615)	-1.66***(.037)	1.645***(.101)	-2.53***(.097)	-3.52***(.229)	-2.78***(.080)	-.979**(.409)	-5.49***(.826)	-.315***(.096)	-1.74***(.126)		-2.470***(.265)
CD	-.0001(.0005)	.00014**(.00006)	-.003(.002)	.002(.003)	.0001(.0001)	1.88e-06 (1.84e-06)	.0002*** (.00003)	.00001*** (2.73e-06)	.00005*** (.00001)	.0002*** (.00002)	-.007***(.003)	2.10e-07 (4.38e-07)	.00001*** (2.16e-06)	.0002*** (.00003)		.003***(.001)
ES	-3.247(3.528)	-6.463***(.977)	-1.821*(.965)	-5.46**(2.41)	-.975(1.189)	3.590***(.065)	-48.5***(2.48)	2.969***(.121)	1.243***(.289)	6.466***(.144)	5.174***(.800)	5.795***(.844)	-.843***(.129)	-.860***(.172)		.950**(.393)
FI	-311.920(300.417)	1.582(4.273)	-.415(16.184)	-6.94(42.39)	-27.62(24.62)	3.448***(.307)	-27.16(46.40)	6.821***(.819)	6.899***(.532)	3.868(4.390)	-407.5(552.9)	-2.444(2.948)	4.011***(.902)	5.097(6.435)		14.367***(3.833)
Related statics																
Log likelihood	-3676.842	-4090.3423	-239.00118	-43.054255	-1965.4822	-56975.833	-44367.584	-95239.532	-115933.34	-9210.7156	-363.66027	-6462.9175	-9673.6369	-35971.325	-4845.2941	-6199.1981
LR static	16049.77	18704.65	3189.46	1168.47	5614.01	151473.53	100097.74	198784.55	268514.76	119768.57	1165.15	10140.69	73996.67	234357.95	17377.21	38960.07
Note: Standard errors in parentheses; */**/*** represent statistical significance at 0.10/0.05/0.01 level.																