

Does Directed Technological Change Favor Energy? Firm-level Evidence from Portugal

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Abstract

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. In order to investigate directed technological change at the micro level, this paper 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 order to induce technological change.

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

JEL classification: D24, L60, O13, O14, O33, Q40.

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1 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 this paper, 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). In this paper we apply Stochastic Frontier Analysis to firm-level data which comes from the Central Balance Sheet, BPLim database of the Bank of Portugal[4] for a number of economic subsectors.

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 induc-

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

ing 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.

The rest of this paper is organized as follows. Section 2 briefly reviews related literature on our topic. Section 3 describes the methodology and data to be applied in our research. Section 4 presents the empirical results and the corresponding discussion. Concluding remarks are made in Section 5.

2 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[5] by 2030, which is not a remarkable part relative to the

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

current total energy demand[6]. 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 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

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

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, 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), 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.

3 Methodology and Data

3.1 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

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

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

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

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

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

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

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

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

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

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

$$
\begin{aligned}
\ln Y_{it} \quad = \quad & \beta_0 + \mathbf{d}'\boldsymbol{\alpha} + \beta_t t + \beta_{tt} t^2 \\
& + \beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_E \ln E_{it} + \beta_F \ln F_{it} \\
& + \beta_{tK} t \ln K_{it} + \beta_{tL} t \ln L_{it} + \beta_{tE} t \ln E_{it} + \beta_{tF} t \ln F_{it} \\
& + \beta_{KL}(\ln K_{it} \ln L_{it}) + \beta_{KE}(\ln K_{it} \ln E_{it}) + \beta_{KF}(\ln K_{it} \ln F_{it}) \\
& + \beta_{LE}(\ln L_{it} \ln E_{it}) + \beta_{LF}(\ln L_{it} \ln F_{it}) + \beta_{EF}(\ln E_{it} \ln F_{it}) \\
& + \beta_{KK}(\ln K_{it})^2 + \beta_{LL}(\ln L_{it})^2 + \beta_{EE}(\ln E_{it})^2 + \beta_{FF}(\ln F_{it})^2 \\
& + V_{it} - U_{it}, \qquad (6)
\end{aligned}
$$

$$U_{it} \sim N^{+}(0, \sigma^2_{Uit}), \qquad (7)$$

$$V_{it} \sim N(0, \sigma^2_V), \qquad (8)$$

$$\sigma^2_{Uit} = \exp(\mathbf{Z}'_{it}\boldsymbol{\delta}), \qquad (9)$$

$$\sigma^2_V = \exp(w_V), \qquad (10)$$

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

$$\dot{TFP}_{it} = TP_{it} + TEC_{it} + SEC_{it}. \tag{11}$$

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

$$TP_{it} = \frac{\partial \ln Y_{it}}{\partial t} = \beta_t + 2\beta_{tt}t + \beta_{tK} \ln K_{it} + \beta_{tL} \ln L_{it} + \beta_{tE} \ln E_{it} + \beta_{tF} \ln F_{it}, \tag{12}$$

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:

$$TEC_{it} = \frac{TE_{it}}{TE_{i,t-1}} - 1, \tag{13}$$

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:

$$SEC_{it} = (RTS_{it} - 1) \sum_j \frac{\eta_{jit}}{RTS_{it}} \dot{X}_{jit}, \tag{14}$$

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:

$$\eta_{Kit} = \frac{\partial \ln Y_{it}}{\partial \ln K_{it}} = \beta_K + \beta_{tK} t + \beta_{KL} \ln L_{it} + \beta_{KE} \ln E_{it} + \beta_{KF} \ln F_{it} + 2\beta_{KK} \ln K_{it}; \tag{15}$$

$$\eta_{Lit} = \frac{\partial \ln Y_{it}}{\partial \ln L_{it}} = \beta_L + \beta_{tL} t + \beta_{KL} \ln K_{it} + \beta_{LE} \ln E_{it} + \beta_{LF} \ln F_{it} + 2\beta_{LL} \ln L_{it}; \tag{16}$$

$$\eta_{Eit} = \frac{\partial \ln Y_{it}}{\partial \ln E_{it}} = \beta_E + \beta_{tE} t + \beta_{KE} \ln K_{it} + \beta_{LE} \ln L_{it} + \beta_{EF} \ln F_{it} + 2\beta_{EE} \ln E_{it}; \tag{17}$$

$$\eta_{Fit} = \frac{\partial \ln Y_{it}}{\partial \ln F_{it}} = \beta_F + \beta_{tF} t + \beta_{KF} \ln K_{it} + \beta_{LF} \ln L_{it} + \beta_{EF} \ln E_{it} + 2\beta_{FF} \ln F_{it}. \tag{18}$$

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:

$$Bias_{sj} = \frac{\partial(f_s/f_j)}{\partial t} / \frac{f_s}{f_j} = \frac{\beta_{ts}}{\eta_s} - \frac{\beta_{tj}}{\eta_j}, \tag{19}$$

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 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[7]; 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

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

(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.

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 1 summarizes the classification of the subsectors and the number of observations used by the program in the estimation. Some subsectors are not considered or shown in our paper, 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.

(Table 1 about here)

4 Results and Discussion

4.1 The production function

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

$$U_{it} \sim N^{+}(0, \sigma_U^2), \tag{20}$$

which keeps the basic assumption on residuals in the Stochastic Frontier 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 the Appendix.

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 2. 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 2 (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 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.

(Table 2 about here)

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 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 1 demonstrates the mean of estimated efficiency level in each analyzed subsector.

(Figure 1 about here)

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[8], 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.

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

4.2 Output elasticities and the total factor productivity growth rate

Equations (11) – (18) 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 3 summarizes the results for output elasticities of each analyzed subsector.

(Table 3 about here)

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, 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 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 2 shows the average returns to scale and their composition in each subsector.

(Figure 2 about here)

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 4 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 $TFPGR$.

(Table 4 about here)

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 3, 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 3 about here)

Figure 3 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 where TFP growth rate is only slightly above zero, which may help explain the sluggishness in the economic growth of Portugal in recent years.

4.3 Directed technological change

We calculate the factor bias indices using equation (19) as reference for the direction of technological change. Table 5 depicts the average factor bias indices of each analyzed subsector, as well as the corresponding bias order determined by the factor bias indices.

(Table 5 about here)

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 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[9], 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[10]). As a result, fuel prices (except natural

[9] 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.

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

gas) also fell in Portugal[11]. Meanwhile, natural gas and electricity prices in Portugal increased[12]. 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 the years[13]. 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,

energy.html

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

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

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

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 elevating electricity price may hinder production activities, especially in the subsectors where output elasticity of electricity is already very low. Instead of inducing technological change through higher electricity price, a lower electricity price relative to fuel may be more helpful in the sense that the relative consumption of electricity increases and hence amplifies market size effect. Higher carbon pricing would increase the relative prices of fuels while stimulating the use of renewable sources in 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).

5 Conclusion

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. This paper 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.

This paper 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.

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Appendix: Results of specification tests

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 1

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

Table 3

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.

Table 4

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

Table 5

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	$E < L < F < K$

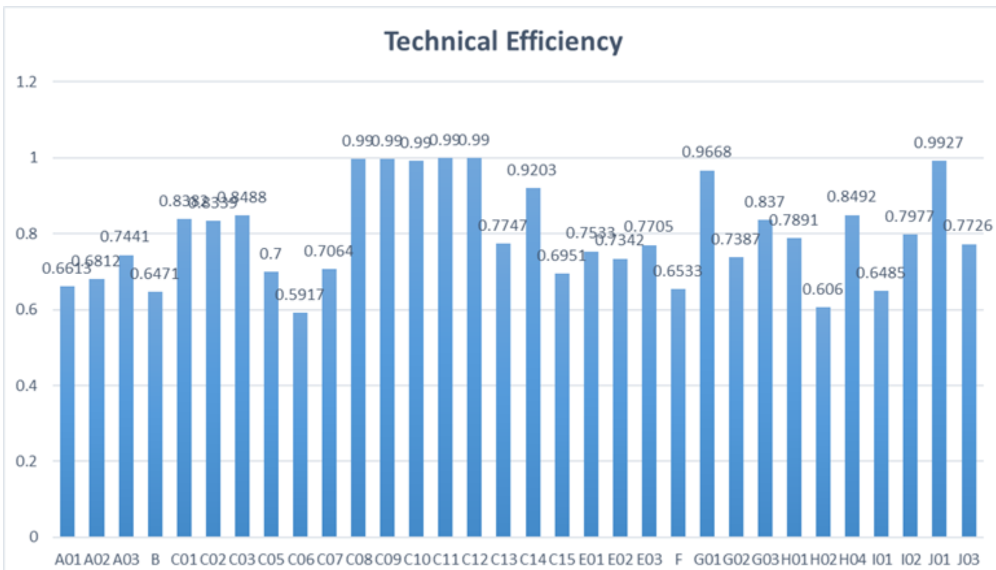

Figure 1: Mean Estimated Technical Efficiency of the Analyzed Subsectors

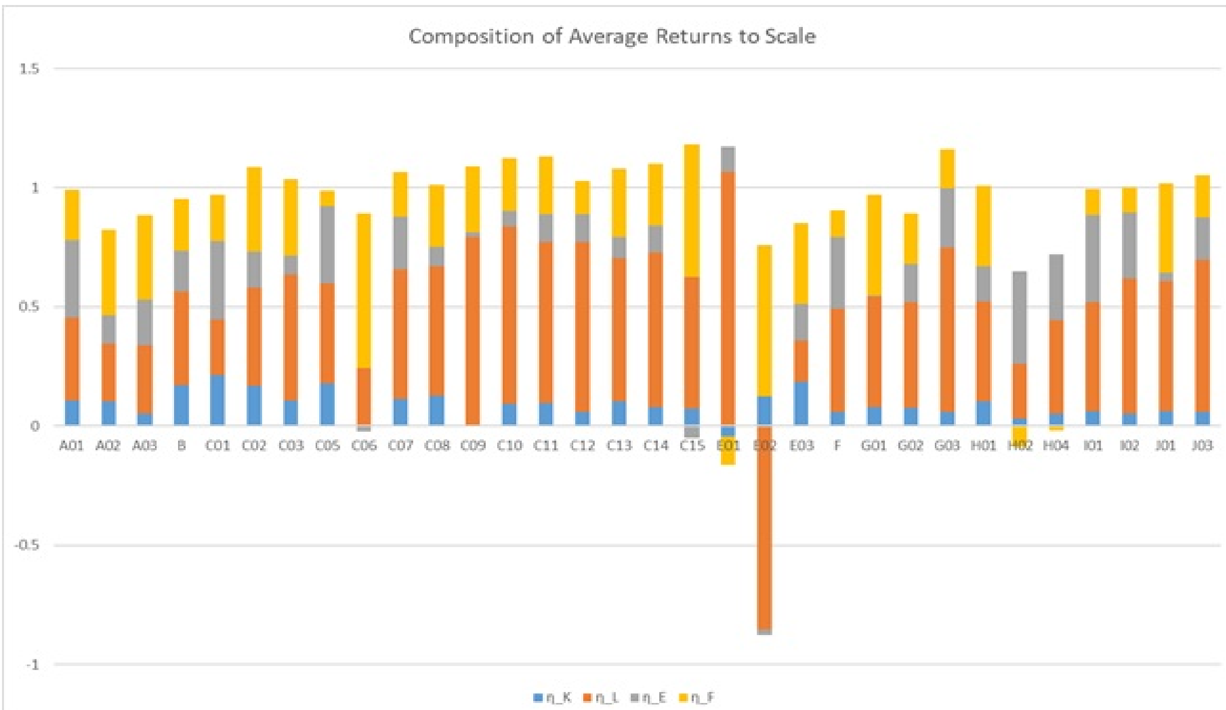

Figure 2: Composition of Average Returns to Scale in the 32 Subsectors

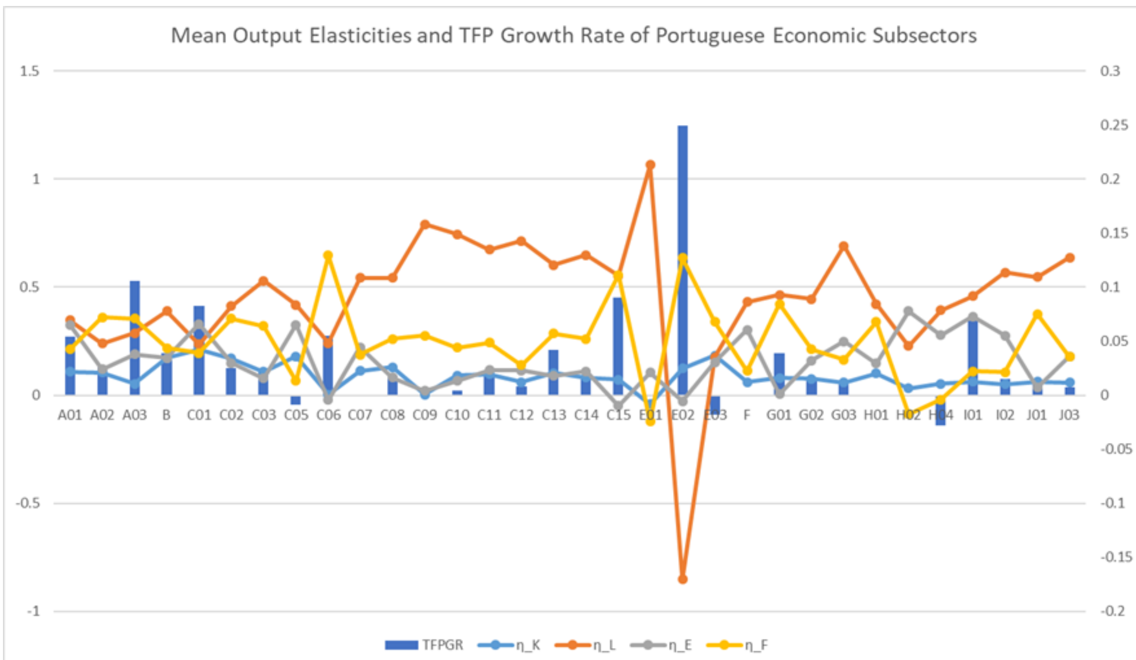

Figure 3: Mean Output Elasticities and TFP Growth Rate of Portuguese Economic Subsectors

Table 2 - 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 2 (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.

Response to Reviewers

The authors would like to thank the reviewers and the editors for their precious comments. Considering the above, we have made major changes in a few aspects in our revision, among other minor changes:

1. We have revised the introductory section so that the contribution and motivation of the paper is more clearly outlined;
2. The literature review is now more complete with supplement contents, as we describe in one of the responses;
3. More comparison is made with previous literature;
4. We try to dig deeper in the interpretation of estimated results and highlight a few findings and policy implications;
5. We changed the title to make it more appealing;
6. Other changes in response to the reviewers' comments, as described below.

Response to Reviewer #1

1. On page 16, the authors state that a low output elasticity of capital "may be the signal of approaching the steady state of economic growth while TFP growth is slow". The authors are advised to provide a detailed explanation of this sentence. Generally speaking, output elasticity only represents the contribution of this factor to output. It is not appropriate to discuss this calculation result using TFP. From the estimated results of this study, TFP has experienced great fluctuations.

Response:

We have reconsidered the interpretation to the low output elasticity of capital. Indeed, output elasticity does not necessarily imply the steady state. Now we interpret it as: low output elasticity of capital may help explain the phenomenon of liquidity trap in European countries: when the returns to investment is sufficiently low, monetary policies are no longer effective in stimulating the economy.

2. The estimation results of the translog production function in Table 2 attract my attention. In the technical inefficiency equation, the estimated results of CD, ES, and FI in different industries are quite different. The authors should provide sufficient explanation for these results according to differentiated production characteristics.

Response:

By comparing the estimated result on the inefficiency term and the characteristics of the subsectors, we observe the following pattern, which is now described in subsector subsection 4.1:

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.

3. On page 19, the authors present that "Our finding in this paper could be more persuasive since we are dealing with two forms, one renewable and one non-renewable, of energy. The authors should provide a detailed explanation for this conclusion. Because the above two articles (Yang et al., 2018; Hou et al., 2020) also use two forms of energy.

Response:

The former statement is a bit misleading. Now we explain it as: “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).”

4. The authors should recheck this manuscript more carefully. In particular, the authors need to pay attention to academic standardization and preciseness. Some simple spelling mistakes should be avoided. For instance, "dealling" appears on page 19. Besides, the use of subscripts is not uniform, like "βtKlnK+βtLlnL+βtElnEit+βtKlnFit" on page 9.

Response:

Thank you for pointing out. In the revised version we have re-checked the spelling and technical details.

5. On page 9, this study state that "βt+βttt" is the neutral technological change rate, while "βtKlnK+βtLlnL+βtElnE+βtKlnF" represents the non-neutral technological change. This statement seems to be inconsistent with the definition of biased technological progress, so the authors are suggested to revise this statement.

Response:

Indeed, the statement here is not exactly identical to the definition in theoretical models of directed technological change. It is a measure adapted to facilitate the empirical analysis. We now state it as:

βt+2βttt reflects the pure technological change of the subsector allowed by the frontier technology; βtKlnK+βtLlnL+βtElnE+βtKlnF βtFlnF 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.

There was a typo in the previous version: “βt+βttt” is now changed to “βt+2βttt”.

6. The authors employ capital stock to proxy capital input, which is measured by tangible fixed capital. But tangible fixed capital is misused. In most studies, the perpetual inventory method is used to calculate the capital stock.

Response:

As we now explain in subsection 3.2, for macro-level empirical studies, the perpetual inventory method is widely applied in order to proxy national (or sectionalsectoral) 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. The 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.

Response to Reviewer #2

1. The introduction is not properly motivated. The innovation and scientific contributions of the manuscript are not clearly outlined.

Response:

We have revised the introduction. More references are added to make the story more complete. There is also additional data to support our statement. Among other changes, we outline our contribution in the paragraph: "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."

In the introduction we also highlight additional findings and policy implications in the new version: "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."

2. The review of the relevant literature appears to be in-exhaustive.

Response:

In the revised version we amplify the literature review with respect to a few perspectives. Among other changes, regarding theoretical literature regarding the relation of technological change and economic growth with non-renewable resources:

“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).”

Regarding previous empirical studies using other approaches:

“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.”

References on SFA applications are also added, e.g. Liu et al. (2019), Cheng et al. (2019); additional data is used to make our statement stand out more clearly.

3. The justification of the applied method is not convincing. To say that the approach is 'widely used' does not suggest that it is appropriate for the problem at hand. Moreover, if conventional wisdom holds that directed technical change depends on price effect, then why use a production model that does not capture prices? Wouldn't a translog cost function be better than the translog production function?

Response:

As we explain in the new version and articulate a bit more here, 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 for technical inefficiency. The cost function focuses on the firms' ability of optimizing 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 on directed technological change by allowing the calculation of output elasticities, factor bias indices, among other indicators.

By estimating a cost function (not necessarily in SFA), we are able to derive elasticities of substitution (Kim and Heo, 2013). But elasticities of substitution only indicate substitutability or complementarity between factors and are not direct enough in measuring directed technological change.

In addition, the price effect in the model of directed technological change mainly refers to the price of final goods rather than factor prices. Thus, even if we consider the factor prices, we still fail to fully capture the price effect in the estimation.

In the new version, we relate the direction of technological change with energy prices and consumption in Portugal during the same period in order to discuss the impact of market size and price effects. We infer that market size effect is likely to prevail.

4. The results are not sufficiently compared to previous studies. Do they bring any new insights to the literature?

Response:

Relevant recent studies on directed technological change involving energy by application of SFA include Shao et al. (2016) using sector data of Shanghai, Yang et al. (2018) using sector data of China, Cheng et al. (2019) using province data of China and Hou et al. (2020) using macro data. We compare our results regarding output elasticities and the direction of technological change with the findings from the abovementioned studies. We now describe result of such comparison in the current version as follows (in subsections 4.2 and 4.3).

“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.”

“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).”

“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).”

“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."

5. Conclusions appear to be weak.

Response:

We have revised the concluding section. In particular, 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.

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Abstract

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. In order to investigate directed technological change at the micro level, this paper 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 order to induce technological change.

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

JEL classification: D24, L60, O13, O14, O33, Q40.

Table 2 - 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 2 (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.																

Figure 1 Click here to access/download;Figure(s);Efficiency.jpg

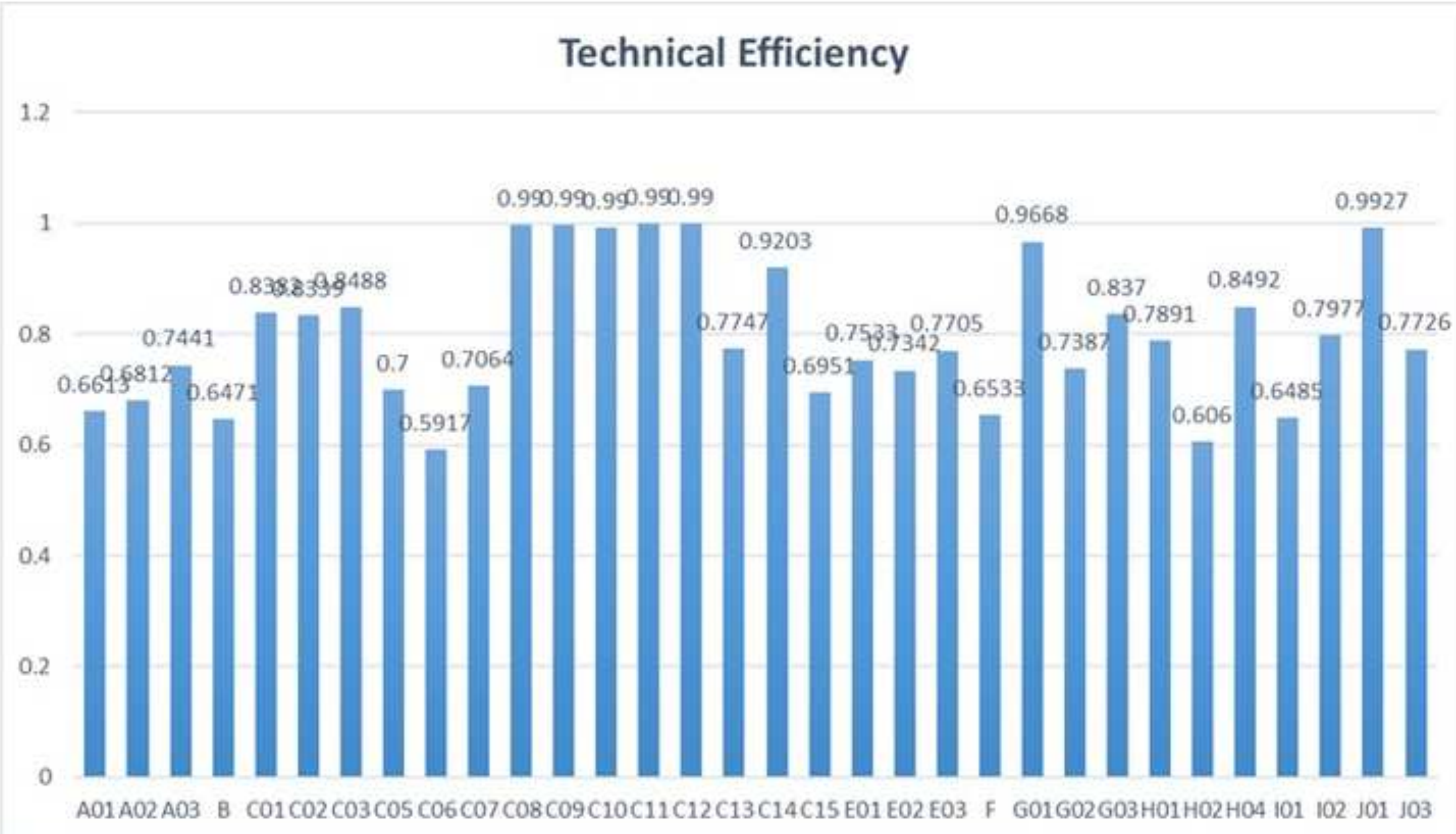
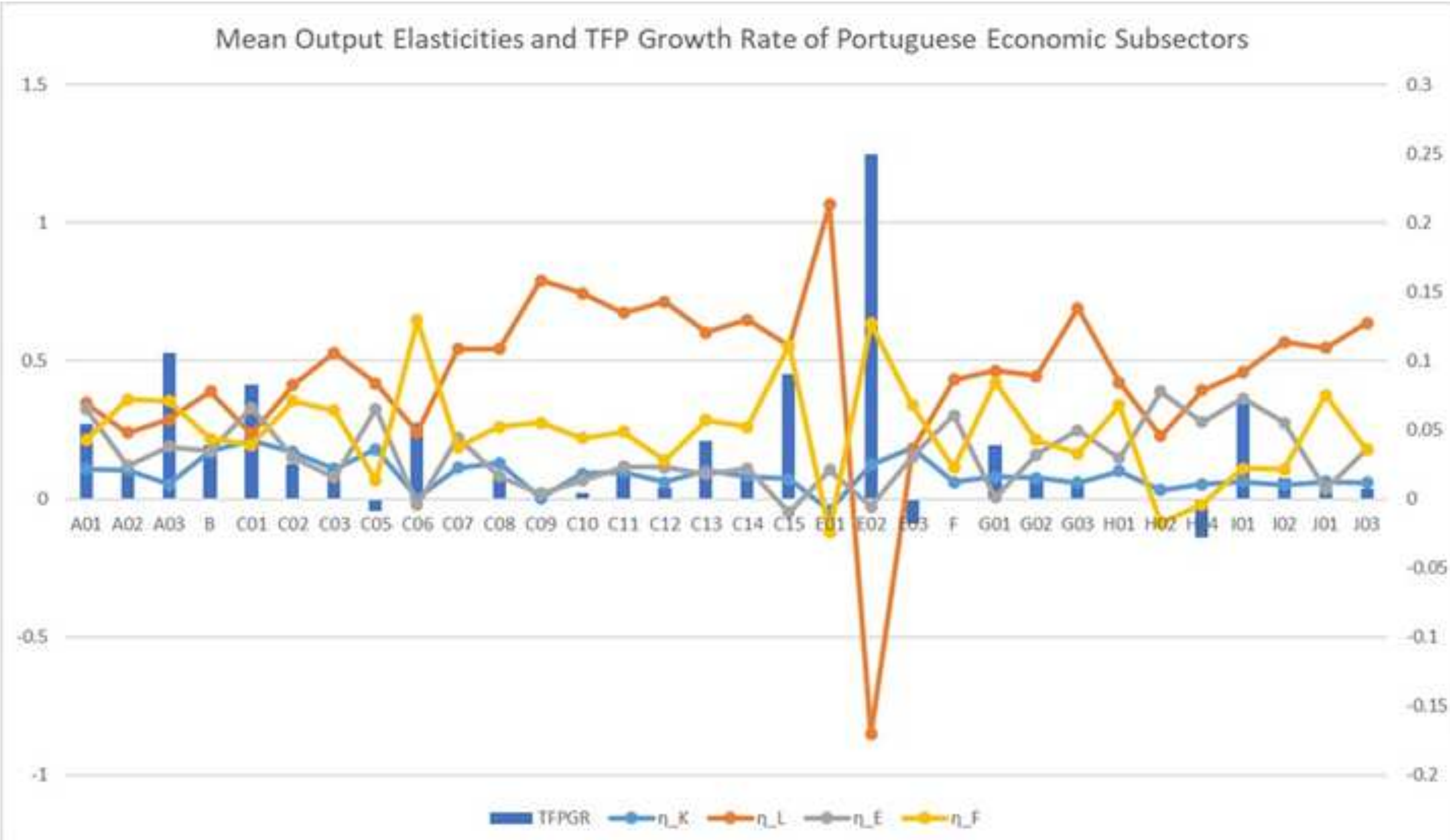


Figure 2

Click here to access/download;Figure(s);RTS.jpg

Figure 3

Click here to access/download;Figure(s);OutputElasticitiesTFPGR.jpg



Title page

Does Directed Technological Change Favor Energy? Firm-level Evidence from Portugal

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Research Highlights

- Among Portuguese firms, technological change is generally biased more towards fuel than electricity.
- Considering the case of Portugal, this implies that technological change favors non-renewable energy instead of renewables.
- Market size effect is likely to overwhelm price effect, so energy prices alone may not be an optimal policy tool to induce technological change.
- Labor is the main driver for economic growth, while returns to capital are low. Total factor productivity growth is moderate.
- There is much space for improving firm performance by eliminating technical inefficiency.

Credit Author Statement

Zheng Hou: writing – original draft; methodology; data curation; software; formal analysis.

Catarina Roseta-Palma: conceptualization; supervision; formal analysis; writing – review & editing.

Joaquim Ramalho: methodology; supervision; formal analysis; writing – review & editing.

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, en-ergy, eco-nomic growth, stochas-
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2020/texmf-
dist/fonts/type1/public/amsfonts/cm/cmr10.pfb><c:/TeXLive/2020/texmf
-dist/fonts/type1/public/amsfonts/cm/cmr12.pfb><c:/TeXLive/2020/texmf-
dist/font
s/type1/public/amsfonts/cm/cmr6.pfb><c:/TeXLive/2020/texmf-
dist/fonts/type1/pub
lic/amsfonts/cm/cmr7.pfb><c:/TeXLive/2020/texmf-
dist/fonts/type1/public/amsfont
s/cm/cmr8.pfb><c:/TeXLive/2020/texmf-
dist/fonts/type1/public/amsfonts/cm/cmsy10
.pfb><c:/TeXLive/2020/texmf-
dist/fonts/type1/public/amsfonts/cm/cmsy7.pfb><c:/T
eXLive/2020/texmf-
dist/fonts/type1/public/amsfonts/cm/cmsy8.pfb><c:/TeXLive/202
0/texmf-
dist/fonts/type1/public/amsfonts/cm/cmti10.pfb><c:/TeXLive/2020/texmf-d
ist/fonts/type1/public/eurosym/feymr10.pfb><c:/TeXLive/2020/texmf-
dist/fonts/ty
pe1/public/amsfonts/symbols/msbm10.pfb>
Output written on DraftV3b.pdf (41 pages, 300869 bytes).
PDF statistics:
 210 PDF objects out of 1000 (max. 8388607)
 147 compressed objects within 2 object streams
 0 named destinations out of 1000 (max. 500000)
 1 words of extra memory for PDF output out of 10000 (max. 10000000)
```