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# Can operational efficiency in the Portuguese electricity sector be improved? Yes, but...

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ABSTRACT

Efficiency has long been an issue of concern in the electricity sector. Most existing studies relate technical efficiency in electricity generation to policy factors while that in transmission and distribution is associated with environmental factors. Although firm operation is also a relevant perspective on this topic, its explicit impact upon technical efficiency has rarely been studied. In order to analyze the evolution and operational determinants of productive and cost efficiency in the Portuguese electricity sector (including generation from different sources, trade, transmission and distribution), this study estimates Stochastic Frontier models using firm-level panel data from 2006 to 2019, covering the period of liberalization of the Portuguese electricity market. The evidence indicates efficiency improvement through time, which is likely to slow down and needs to be consolidated. Results on the inefficiency determinants suggest that it is possible to improve productive technical efficiency by encouraging investment in fixed assets, higher average hourly wage and moderate average working hours. In addition, based on the results, we advocate deepening the integration of the Iberian electricity market and stimulating competition in the renewable energy sector.

## 1. Introduction

The performance of the electricity sector plays a crucial role in overall economic activity. In the 20th century, most countries built their electricity sectors around vertically integrated monopolies under government control, yet the importance of fostering efficiency became clear. Many countries undertook electricity market reforms to increase competition, unbundling generation, transmission and distribution as subsectors with different technical and economic characteristics. Such reforms are generally expected to improve technical efficiency (Barros, 2008; Ma and Zhao, 2015; Lundin, 2020; Bobde and Tanaka, 2020); however, this effect can be undermined by various factors arising from incomplete deregulation or other practical difficulties (Sun and Wu, 2020; Lee and Howard, 2021; Mirza et al., 2021). Portuguese electricity market liberalization has been ongoing for almost two decades, so empirical evidence on whether it has indeed improved efficiency overall could illustrate reform effectiveness. Furthermore, the subsector analysis can not only support policy considerations on efficiency improvements, consolidating the market reform, but also bring important implications for sustainable development, combating climate change and alleviating energy poverty (Dong et al., 2022; Shahzad et al., 2022).

For decades the energy sector has been concerned with efficiency issues. Early studies mainly look at the consequence of regulatory policies (e.g., Christensen and Greene, 1976, 1978). New econometric methods were applied to assess efficiency in electricity generation, e.g. Greene's (1990) application of a gamma-distributed Stochastic Frontier model to the data used in Christensen and Greene (1976). Later research also considers $CO_2$ emission efficiency in electricity generation (Zhang et al., 2013). On the other hand, transmission and distribution of electricity (T&D) has been the focus of recent efficiency analyses (Kumbhakar and Lien, 2017; Orea et al., 2018; Mydland et al., 2018; Liu et al., 2019; Kumbhakar et al., 2020; Soroush et al., 2021, among others). Efficiency issues have also aroused the interest of regulators in the energy sector (Gunn, 1997; ACER, 2016, 2021; European Commission et al., 2019; CEER, 2020a,b, among others).

Since the adoption and deployment of new technologies can be a difficult process, sometimes agents fail to reach the maximum output level that any particular technology would permit. Thus, when evaluating efficiency levels, technical efficiency is usually defined as the share of actual output in relation to the maximum output allowed by the current technology (Kumbhakar et al., 2000). In the energy sector, technical efficiency is sometimes referred to as operational efficiency (e.g., Ma and Zhao, 2015; Jaunky and Zhang, 2016), reflecting the fact that efficiency is affected by factors related with operation of firms/plants. However, while existing studies focus on the impact of environmental

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factors on technical efficiency in the energy sector (e.g., Growitsch et al., 2012; Karim and Pollitt, 2017; Liu et al., 2019), the impact of operational factors has rarely been discussed.

Both productive efficiency and cost savings are considered relevant when evaluating performance in the electricity sector (Lundin, 2020; Chu, 2021), and therefore either can be used to assess whether market reform is successful. As noted in the next section, various types of frontiers have been used for different purposes in energy economics studies. In the present research we apply Stochastic Frontier Analysis to firm-level panel data for electricity subsectors (including electricity generation from different sources; trade, transmission and distribution) in Portugal, in order to study the evolution of technical efficiency throughout the period corresponding to the liberalization of the Portuguese electricity market. We take advantage of the BPLIM database, which covers the years 2006–2019, to assess efficiency levels and identify whether the liberalization process allowed improvement in both productive and cost efficiency. To obtain a comprehensive understanding on the evolution of technical efficiency, we estimate models with production frontiers, distance frontiers and cost frontiers.

We also estimate the effects of operational factors of firms, such as financial activities and utilization of labor, on their technical inefficiency. Studies involving environmental factors (Growitsch et al., 2012; Karim and Pollitt, 2017; Liu et al., 2019) are more common as references for performance-based subsidy policies or adjustment of efficiency scores by regulators; our findings provide valuable insight on how to improve performance from the perspective of firm operation and management.

The empirical results demonstrate that there is room for improvement in technical efficiency in the Portuguese electricity sector. Nevertheless, it appears possible to improve technical efficiency from both macro and micro perspectives. From the macro perspective, we discover a time trend of growth in productive efficiency during the process of liberalization of the Portuguese electricity market. However, the trend is likely to slow down and last for a limited period. From the micro perspective, in firm management, there is the possibility of improving efficiency by taking into account operational factors. All the factors representing operational heterogeneity in our study are found to be statistically significant in some specifications. In particular, higher capital input relative to labor input, higher average hourly wage and moderate average working hours improve productive technical efficiency. Stemming from the results, we suggest deeper integration of the Iberian electricity market and stimulating competition in the renewable energy sector.

Our research contributes to the literature in several aspects. First, instead of environmental factors, we analyze the effect of factors related with firm operation, which could aid to improve management in electricity firms. Second, this study covers a large number of firms in the Portuguese electricity sector, including all its subsectors, with a time span covering 14 consecutive years after the liberalization began. This allows for a more comprehensive assessment of the effect of the market liberalization process. Third, with the available data we are able to analyze productive and cost efficiency, both of which are important aspects for the sector.

The rest of this paper is organized as follows. We review related literature within Section 2. In Section 3 we describe the methodology and data utilized in our empirical analysis. In Section 4 we present the empirical results and corresponding discussion. Concluding remarks are made in Section 5.

## 2. Literature review

Various methods are proposed for measuring efficiency in production and specifically, in electricity. For instance, Diewart and Nakamura (1999) propose the *best practice efficiency measure* based on Farrell (1957). Jamasb and Pollitt (2001) review the most commonly used benchmarking methods for electricity: Data Envelopment Analysis (DEA), Corrected Ordinary Least Squares (COLS) and Stochastic Frontier Analysis (SFA), as well as their main applications up to that time; recently, DEA and SFA are more often adopted in assessing technical efficiency. DEA does not rely on particular functional forms regarding input and output and allows the researcher to focus on efficiency issues (Ma and Zhao, 2015). Nonetheless, its estimation of efficiency is biased by construction since it does not account for statistical noise (Simar and Wilson, 1998, 2000). More robust estimators solve this problem to some extent, including the order-m estimator (Cazals et al., 2002), order-$\alpha$ quantile estimator (Aragon et al., 2005) and the two-stage bootstrap estimator (Simar and Wilson, 2007). Applications of DEA in energy economics include Yang and Pollitt (2009) on Chinese coal-fired power plants; Welch and Barnum (2009) on both environmental and cost efficiency in electricity generation in the U.S.; Jaunky and Zhang (2016) on Chinese provincial power sectors; Rødseth (2017) on the U.S. electricity sector; Bigerna et al. (2019, 2020, 2022) on the relationship between energy efficiency and environmental and market regulation; Gultom (2019) on efficiency in the U.S. electricity sector; Navarro-Chávez et al. (2020) on the Mexican electricity sector; Alizadeh et al. (2020) on the Iranian electricity sector; Jindal and Nilakantan (2021) on Indian coal-fired power plants; Vesterberg et al. (2021) on Swedish electricity distribution; Sánchez-Ortiz et al. (2021) on the Spanish electricity sector; and Nakaishi et al. (2021) on the environmental efficiency of Chinese coal-fired power plants, among others.

The Stochastic Frontier method assumes technical inefficiency which represents failure to achieve the output frontier given the inputs and current technology. Conventionally,[1] Stochastic Frontier methods make distributional assumptions on the noise and inefficiency components (Kumbhakar and Tsionas, 2008), and allows the estimation of the impact of independent variables on the mean and variance of technical inefficiency. Depending on the functional form assumed, SFA has been widely adopted in energy economics. With the production function approach, it can be used to assess directed technological change (Hou et al., 2020, 2021); or the profitability and, eventually, the viability of energy production options (Lee and Howard, 2021). Llorca et al. (2017) evaluate efficiency in the Latin-American transport sector with energy demand functions. Stochastic Frontier models provide the flexibility of being tailored to address a wide range of issues, and thus better serve more specific research questions.

Kumbhakar et al. (2020) examines cost efficiency of Norwegian electricity distribution firms, in a recent application of Stochastic Frontier Analysis to assess efficiency issues in the electricity sector. In addition to the former, studies on technical efficiency issues in Norwegian electricity distribution include Førsund and Hjalmarsson (2004), Growitsch et al. (2012), Kumbhakar et al. (2015a), Kumbhakar and Lien (2017), Orea et al. (2018), Mydland et al. (2018), among others. Soroush et al. (2021) study the impact of institutional quality on cost efficiency in Italian electricity distribution utilities. Regarding electricity generation, Lai and Kumbhakar (2018) demonstrate a homoscedastic four-component stochastic frontier (H4CSF) model and relate technical inefficiency of production to the age and capacity of a coal-fired power plant. Liu et al. (2019) study whether environmental heterogeneity affects the technical efficiency of Chinese grid utilities. Silva et al. (2019) apply a stochastic frontier approach with maximum entropy estimation to European electricity distribution companies. Peñasco et al. (2019) examine the effect of policy factors on efficiency of Spanish solar energy plants. While a number of studies focus on technical efficiency and its determinants in electricity distribution, comparatively less attention is paid to power generation. In the latter, institutional structure (operation and management features associated with the

[1] Some Stochastic Frontier methods do not rely on distributional assumptions for the noise or inefficiency components, e.g., Kumbhakar and Bernstein (2019); the use of nonlinear squares would also allow to avoid the use of distributional assumptions, see Belotti and Ferrara (2021) for a recent example.

power plants' ownership) can be the main source of inefficiency in electricity generation (Khanna and Zilberman, 1999). When it comes to the issue of electricity generation, therefore, it seems more appropriate to investigate the effect of operational features upon efficiency.

Literature on efficiency in the electricity sector has long paid attention to factors related to firm operation. Nerlove (1963) studies the returns to scale in the U.S. electricity industry; Christensen and Greene (1976, 1978)) analyze cost efficiency and scale economies in U.S. electricity generation; Knittel (2002) studies the impact of regulations on firm efficiency in the U.S. electricity industry; Rungsuriyawiboon and Stefanou (2007) focus on the use of inputs (fuel, labor & maintenance, capital) in fossil fuel fired steam electric utilities in the U.S.; Rødseth (2017) demonstrates the impact of environmental regulations on managerial allocative efficiency in the U.S. electricity sector; finally, Bernstein (2020) stresses the impact of regulations like the Cross-State Air Pollution Rule (CSAPR) on technical efficiency and returns to scale of U.S. natural gas fired power plants. Nevertheless, operational variables are rarely used as explanatory variables for technical inefficiency, which is a blank we try to fill with the current paper.

The liberalization of the Portuguese electricity market began in fits and starts in the 1980s. While some aspects of the reform are still ongoing, the market has moved much closer to full competition in electricity generation, supply and wholesale (Ferreira et al., 2007). The reform entered its final stage in 2006 (Amorim et al., 2013), with a process that consisted of the privatization of state-owned entities, the legal unbundling of the electric transmission network, the promotion of competition and switching opportunities for customers in electricity markets, the integration into the Iberian market and the phasing out of regulated tariffs, among others (Ghazvini et al., 2019). With these reforms in the market structure and tariff policy, the Portuguese regulator seeks higher efficiency in electrical networks, operational cost, resource allocation and continuous intraday trading (ERSE, 2021).

Generally, deregulation reforms are expected to improve efficiency in the electricity sector (Gunn, 1997; Jamasb, 2006; Wisuttisak, 2012; Jamasb et al., 2017). Regulatory frameworks could stimulate innovation and therefore improve efficiency in the energy sector (European Commission et al., 2019; CEER, 2020a,b; ACER, 2021). Evidence suggests that liberalizing policies can improve performance in the energy sector though various pathways: competition policy enforcement can exert a positive impact on productivity in the energy market (Duso et al., 2019); institutional reform and privatization have been associated with improvements in quality and efficiency in the Latin American Electricity Sector (Balza et al., 2013); deregulation provides incentives for agents to make careful investment decisions that are more consistent with the technological nature of (nuclear) power plants (Lei et al., 2017); regulatory independence improves electricity generation performance in India (Jindal and Nilakantan, 2022); privatization in the Swedish electricity distribution sector gave rise to efficiency gains (Lundin, 2020); electricity reform improved technical efficiency in Indian power distribution (Bobde and Tanaka, 2020); vertical separation of transmission network allows a more efficient allocation of resources and therefore cost savings (Chu, 2021); electricity price policies can affect the deployment of new technologies (Sinsel et al., 2020); technical efficiency was also considered an indicator of the effectiveness of regulatory regimes in the Norwegian electricity sector (Senyonga and Bergland, 2018); finally, the transition from a bilateral electricity market to a centralized auction market in Texas was found to help improve market efficiency and reduce cost (Brehm and Zhang, 2021).

Nevertheless, the Portuguese electricity market still faces a transition from state-guaranteed prices towards a competitive market (Amorim et al., 2013). In the pursuit for a sustainable transition, additional mechanisms await to be deployed, accounting for socio-technical development and energy justice (Sareen and Haarstad, 2018; Antunes et al., 2022); time is needed for the benefits of deregulation to be transferred to the market and end-users (Ghazvini et al., 2019). It is not uncommon for reforms to do an incomplete job in fixing the regulations that bring about inefficiency. Some examples: although the 2002 unbundling reform in the Chinese electricity sector contributed to efficiency improvement (Ma and Zhao, 2015), there are still regulations on price and quantity that affect the efficiency of power plants (Sun and Wu, 2020); the U.S. electricity market restructuring imposed a negative effect on technical efficiency of utilities (Gultom, 2019); Australian distributors operate below efficient levels even after the deregulation that has been ongoing since 1998 (Lee and Howard, 2021); finally, efficiency in Pakistan's electricity market still suffers from multiple practical difficulties after reform (Mirza et al., 2021). Meanwhile, in some cases, deregulation may bring about instability in electricity markets (Binder and Mjelde, 2017), or result in efficiency loss due to mandated divestiture of generation assets or higher upstream transaction costs (Leung et al., 2019); environmental regulations may also affect efficiency in the energy sector (Hu et al., 2023); market and/or environmental regulations could hinder production in the electricity sector (Bigerna et al., 2020, 2022).

Barros (2008) applies DEA to find improvement in the technical efficiency of hydroelectric plants in Portugal between 2000 and 2004. Nevertheless, it was only in 2006 that the new legislation defined the regime for electricity generation in the country. An updated and more thorough examination of the evolution of technical efficiency in electricity generation from both production and cost perspectives is therefore in order. The data in the present study covers the years from 2006 to 2019, a period in which the new electricity framework had come into force. The time span of the data ideally serves the purpose of investigating the efficiency impact of market liberalization. In order to comprehensively evaluate the evolution of technical efficiency, especially considering the importance of integration of Portuguese electricity market into the Iberian market, we estimate SFA models in three functional forms, as described in the following section.

## 3. Methodology and data

As a non-parametric approach, DEA is preferred by some researchers as it does not require a specific function form and thus provides more flexibility; however, when it comes to the relationship between efficiency and explanatory factors, a two-stage approach is usually adopted (e.g., Bigerna et al., 2019, 2020, 2022), where additional caution is needed in order to avoid biased estimations. In Stochastic Frontier Analysis, different approaches can serve research purposes while relying on different types of data and assumptions. The production function approach is applied in assessing technical efficiency in a common production process, as well as issues regarding directed technological change (Shao et al., 2016; Yang et al., 2018; Hou et al., 2020, 2021). The distance function approach can be used to evaluate the efficiency in utilizing inputs to reach more than one type of output, which is often exogenous (Liu et al., 2019) or includes undesirable output(s) (Tan et al., 2020; Jin et al., 2021). The cost function approach assumes minimization of cost (or pollutant, loss, etc.) as the goal (Kang, 2018; Soroush et al., 2021). Other types of frontiers can also be set up in order to address specific issues in energy economics, for instance: energy demand frontier (Zhang and Adom, 2018; Du et al., 2021), which can measure the energy saving efficiency in meeting residential or production energy demand; Bayesian frontier (Kleit and Terrell, 2001; Makieła and Osiewalski, 2018; Haider and Mishra, 2021), which requires prior information in the form of parameter distribution to be obtained from previous studies; spatial frontier (Orea et al., 2018), which includes a spatial structure in the error term, among others.

Applying various approaches provides a more comprehensive evaluation on the technical efficiency of the electricity generating subsectors. Considering the availability of data and suitability of the models to our purpose, we estimate three types of functions and compare the results regarding the evolution of technical efficiency in Portuguese electricity subsectors, as well as its determinants related with firm operation. The production function provides a basic overlook of productive efficiency.

The distance function separates the output into internal market income and EU market income and double checks whether results are robust taking into account complex pricing schemes in the international electricity market (especially the Iberian market[2]). According to our result, comparatively, the production function approach may underestimate the efficiency levels of the Portuguese electricity subsectors. Complementary to productive efficiency, the cost function examines cost efficiency of the electricity firms. As will be shown in this paper, subsectors with higher productive efficiency do not necessarily enjoy high cost efficiency. Although it is possible to estimate other functional forms, e.g. the revenue function, we choose to adopt these three forms as they can better represent the production and cost efficiency of the firms.[3]

### 3.1. The production function approach

The sample of Portuguese electricity firms is divided into four subsectors: production of electricity from hydropower; from thermal power plants; from wind, geothermal, solar and other sources (although not fully accurate, for simplicity we designate this subsector as other renewables); and transmission and distribution of electricity. We consider a translog production function in the form of a second-order Taylor approximation, which takes the general specification as follows:

$$\begin{aligned}\ln y_{it} = {} & \beta_0 + \sum_{j=1}^{J} \phi_j d_j + \beta_1 t + \frac{1}{2}\beta_2 t^2 + \beta_3 \ln K_{it} \\ & + \beta_4 \ln L_{it} + \beta_5 t \ln K_{it} + \beta_6 t \ln L_{it} \\ & + \frac{1}{2}\beta_7 (\ln K_{it})^2 + \frac{1}{2}\beta_8 (\ln L_{it})^2 + \frac{1}{2}\beta_9 \ln K_{it} \ln L_{it} \\ & + v_{it} - u_{it}; v_{it} \sim i.i.d.N(0, \sigma_v^2),\end{aligned} \tag{1}$$

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

where $K$ represents capital input and $L$ stands for labor input; subscripts $i$, $t$ denote the firm and time period; $v_{it}$ is the normally distributed error term and $u_{it}$ is the inefficiency term. $d_j$ is used in the truncated-normal models and the TVIM model (which will be explained below) and represents dummies for the electricity subsectors.[4] $\beta$, $\phi$ are unknown parameters to be estimated. The technical efficiency level can be calculated by $TE_{it} = \exp(-u_{it})$. The translog function can be considered as a representation of any functional form. The Cobb–Douglas function is a special case of the translog function; in the estimation we test the joint statistical significance of the terms except those constituting the Cobb–Douglas function (i.e., $\beta_0$, $\beta_3$, $\beta_4$), and the result justifies the use of the translog function.

Different assumptions can be made on the distribution of the inefficiency term $u_{it}$. A basic specification assumes that the inefficiency term is half-normally distributed.[5] Some recent Stochastic Frontier models assume persistent and transient components of technical inefficiency (Colombi, 2010; Chen et al., 2014; Kumbhakar et al., 2014; Filippini and Greene, 2016). These models improve upon previous ones by considering persistent inefficiency factors and acknowledging that firms may reduce short-term inefficiencies while retaining some long-term ones. We estimate the following model:

$$\begin{aligned}\ln y_{it} = {} & \beta_0 + \beta_1 t + \frac{1}{2}\beta_2 t^2 + \beta_3 \ln K_{it} + \beta_4 \ln L_{it} + \beta_5 t \ln K_{it} + \beta_6 t \ln L_{it} \\ & + \frac{1}{2}\beta_7 (\ln K_{it})^2 + \frac{1}{2}\beta_8 (\ln L_{it})^2 + \frac{1}{2}\beta_9 \ln K_{it} \ln L_{it} + \mu_i + v_{it} - \kappa_i - u_{it},\end{aligned} \tag{2}$$

where $\mu_i$ is the firm random effect, $v_{it}$ is the noise term, $\kappa_i$ is the persistent inefficiency and $u_{it}$ is the transient inefficiency. The model is estimated following Kumbhakar et al. (2014). The overall efficiency is calculated as OTE (overall technical efficiency) = PTE (persistent technical efficiency) * TTE (transient technical efficiency).

Considering the different technologies utilized in different forms of electricity generation, transmission and distribution, the KLH (Kumbhakar et al., 2014) models are estimated separately for each of the four Portuguese electricity subsectors: hydro; thermal; other renewables; trade, transmission and distribution of electricity (referred to as TTD hereafter for simplicity). For the TTD subsector, dummies are imposed for each of the subdivisions, i.e., transmission of electricity; distribution of electricity; trade of electricity.[6] In the estimation of the functional forms described in subsequent subsections, similar assumptions apply.

The production function allows us to calculate the output elasticity of each input using the estimated coefficients and the original data, following the equations below:

$$\eta_{Kit} = \frac{\partial \ln Y_{it}}{\partial \ln K_{it}} = \beta_3 + \beta_5 t + \beta_7 \ln K_{it} + \frac{1}{2}\beta_9 \ln L_{it}; \tag{3}$$

$$\eta_{Lit} = \frac{\partial \ln Y_{it}}{\partial \ln L_{it}} = \beta_4 + \beta_6 t + \beta_8 \ln L_{it} + \frac{1}{2}\beta_9 \ln K_{it}. \tag{4}$$

where $\eta_{Kit}$ and $\eta_{Lit}$ represent the output elasticity of capital and labor corresponding to each observation. Therefore returns to scale are given by:

$$RTS_{it} = \eta_{Kit} + \eta_{Lit}. \tag{5}$$

Following Kumbhakar et al. (2000) as well as other practices (Shao et al., 2016; Yang et al., 2018; Hou et al., 2021), the Scale Efficiency Change, which reflects the improvement of productivity benefiting from returns to scale, can be calculated as follows:

$$SEC_{it} = \frac{RTS_{it} - 1}{RTS_{it}} (\eta_{Kit} \Delta \ln K_{it} + \eta_{Lit} \Delta \ln L_{it}), \tag{6}$$

where $\Delta \ln K_{it}$ and $\Delta \ln L_{it}$ are the growth rates of capital and labor inputs. The output elasticities, RTS and eSEC are calculated based on the KLH models.

Then, in order to study the effects of operational factors on efficiency, we estimate the model using the assumption of truncated normal distribution:

$$u_{it} \sim i.i.d.N^{+}(\mu, \sigma_{uit}^2), \tag{7}$$

$$\mu = \mathbf{W}_{it}' \boldsymbol{\Omega} \tag{8}$$

$$\sigma_{uit}^2 = \exp(\mathbf{z}_{it}' \boldsymbol{\delta}), \tag{9}$$

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

In the literature, regulatory factors are often measured by indexes such as the PMR (Product Market Regulation) index and EPS (Environmental Policy Stringency) index (Bigerna et al., 2020, 2022). Nonetheless, these are country-specific indicators and cannot be used for firm-level study. As the sample covers the time period after the deregulation begins in the Portuguese electricity sector, the effect of the deregulation cannot be captured by a time dummy. Therefore, we estimate a model in order to verify if there exists a time trend for technical inefficiency change during the deregulation. Time-varying inefficiency models, which allow the estimation of the coefficient of time variables

[2] The Iberian Market for Electricity consists of organized markets or power exchanges, and non-organized markets where bilateral over-the-counter trading takes place with or without brokers (Ferreira et al., 2019).

[3] The revenue function would reflect efficiency resulting from marketing strategy, or similar factors, rather than productive efficiency.

[4] To avoid multicollinearity, the actual number of dummies should be one less than the total number of subsectors.

[5] $u_{it} \sim i.i.d.N^{+}(0, \sigma_u^2)$.

[6] We are unable to estimate models for each of sub-subsectors in the TTD subsector, as there are only 31 observations in the sub-subsector of electricity transmission, which is insufficient for the estimation.

on the inefficiency term, are applied by Kumbhakar (1990), Battese and Coelli (1992), Lee and Schmidt (1993) and Kumbhakar and Wang (2005), among others. Following the Time-Varying Inefficiency Model (TVIM) of Kumbhakar (1990), we adopt the assumption:

$$u_{it} = G(t)u_i, \tag{10}$$

$$u_i \sim i.i.d.N^{+}(\mu, \sigma_u^2), \tag{11}$$

$$G(t) = [1 + \exp(\gamma_1 t + \gamma_2 t^2)]^{-1}. \tag{12}$$

Taking the derivative of $G(t)$ with respect to $t$ using (12) yields $G'(t) = -[1 + \exp(\gamma_1 t + \gamma_2 t^2)]^{-2} \cdot \exp(\gamma_1 t + \gamma_2 t^2)(\gamma_1 + 2\gamma_2 t)$, so that $G'(t) \le 0$ when $\gamma_1 + 2\gamma_2 t \ge 0$, which corresponds to a decrease in $u_{it}$ and thus an increase in efficiency. A positive coefficient on $t$ and $t^2$ implies that technical efficiency improves through time. Different signs on their coefficients would imply U-shape or inverted U-shape evolution (with the turning point depending on the values of the coefficients). The same applies in interpreting the results of the distance function and cost function approaches.

### 3.2. The distance function approach

The production function approach is output-oriented, in the sense that it seeks to maximize the output level with certain input combinations. We adopt the distance function approach for a few reasons. First, it helps us to verify whether the results are sensitive to different markets, namely the internal market and the EU market, especially the Iberian market. Electricity exchange in a certain geographical area may help improve efficiency in the production, supply and consumption of electricity (Iskandarova et al., 2022). Second, as total non-financial revenue, which we use as a proxy for output in the production and cost function models, is not a perfect measure for the electricity sector, using different measures in the distance function models could provide extra robustness to our results. Third, as will be shown in the next section, the distance function proves to better fit some of our models, including the KLH model and truncated model. Given the complexity of the models and the numbers of variables, convergence problems may occur during the estimation process, which prevents us from putting all the variables in both mean and variance equations of the inefficiency term of the production function models. The distance function model allows us to evaluate the impact of the operational factors within a single model, which remediates the imperfection of the production function models.

Commonly, an input-oriented distance function is considered when the output can be seen as exogenous (Kumbhakar et al., 2015b); in our case, it is also reasonable to apply an input-oriented distance function if we consider electricity demand as exogenous. The distance function can be defined as

$$D(\mathbf{x}, \mathbf{y}) = \max_{\lambda}\{\lambda | (\mathbf{x}/\lambda) \in V(\mathbf{y}), \lambda \ge 1\}, \tag{13}$$

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

$$TE(\mathbf{x}, \mathbf{y}) = 1/D(\mathbf{x}, \mathbf{y}). \tag{14}$$

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

$$\begin{aligned} \ln D_{it} = \beta_0 &+ \sum_{j=1}^{J} \phi_j d_j + \sum_{m=1}^{M} \alpha_m \ln y_{mit} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln y_{mit} \ln y_{nit} \\ &+ \sum_{k=1}^{K} \beta_k \ln x_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \ln x_{kit} \ln x_{lit} + \sum_{k=1}^{K}\sum_{m=1}^{M} \gamma_{km} \ln x_{kit} \ln y_{mit} \\ &+ \omega_1 t + \frac{1}{2}\omega_2 t^2 + \sum_{m=1}^{M} \theta_m t \ln y_{mit} + \sum_{k=1}^{K} \rho_k t \ln x_{kit} + v_{it}, \end{aligned} \tag{15}$$

where subscripts $i$, $t$ denote the firm and time period; $d_j$ represents dummies for the electricity subsectors (used in the truncated-normal model and the TVIM model); $v_{it}$ is the normally distributed error term. $\alpha$, $\beta$, $\gamma$, $\phi$, $\theta$, $\omega$, $\rho$ are unknown parameters to be estimated. Symmetric restrictions require that $\alpha_{mn} = \alpha_{nm}$ and $\beta_{kl} = \beta_{lk}$. The distance function is homogeneous of degree one, which requires the following constraints to be imposed on the coefficients:

$$\begin{aligned} &\sum_{k=1}^{K} \beta_k = 1, \sum_{l=1}^{K} \beta_{kl} = 0, k = 1, 2, \ldots, K; \\ &\sum_{k=1}^{K} \gamma_{km} = \sum_{k=1}^{K} \rho_k = 0, m = 1, 2, \ldots, M. \end{aligned} \tag{16}$$

By normalizing all the inputs in the distance function by an input $x_{kit}$, we get

$$-\ln x_{kit} = f(\ln x_{kit}^{*}, \ln y_{mit}, t) + v_{it} - u_{it}; v_{it} \sim i.i.d.N(0, \sigma_v^2), \tag{17}$$

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

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

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

$$\begin{aligned} -\ln K_{it} = \beta_0 &+ \sum_{j=1}^{J} \phi_j d_j + \alpha_1 \ln y_{1it} + \alpha_2 \ln y_{2it} + \beta_L \ln L_{it}^{*} \\ &+ \frac{1}{2}\alpha_{12} \ln y_{1it} \ln y_{2it} + \frac{1}{2}\alpha_{11}(\ln y_{1it})^2 \\ &+ \frac{1}{2}\alpha_{22}(\ln y_{2it})^2 + \frac{1}{2}\beta_{LL}(\ln L_{it}^{*})^2 \\ &+ \gamma_{L1} \ln L_{it}^{*} \ln y_{1it} + \gamma_{L2} \ln L_{it}^{*} \ln y_{2it} + \theta_1 t \ln y_{1it} \\ &+ \theta_2 t \ln y_{2it} + \rho_L t \ln L_{it}^{*} \\ &+ \omega_1 t + \frac{1}{2}\omega_2 t^2 + v_{it} - u_{it}, \end{aligned} \tag{18}$$

where $L_{it}^{*} = \frac{L_{it}}{K_{it}}$. As described in the previous subsection, according to (2), (7) - (12), we estimate several models with different assumptions regarding the distribution of the technical inefficiency term.

### 3.3. The cost function approach

The cost function approach assumes that the agents take cost minimization as their aim. Then input-oriented cost efficiency can be evaluated using SFA. This approach allows the evaluation of cost efficiency in reaching an exogenous output target, thereby providing information on how well Portuguese electricity firms optimize their cost while meeting electricity demand. Following Kumbhakar et al. (2015a), the cost minimization problem for producer i under an input-oriented technical efficiency specification is

$$\min \mathbf{w}'\mathbf{x} \text{ s.t. } y = f(\mathbf{x}e^{-\eta}), \tag{19}$$

$$\text{F.O.C.:} \ \frac{f_j(\mathbf{x}e^{-\eta})}{f_1(\mathbf{x}e^{-\eta})} = \frac{w_j}{w_1}, j = 2, \ldots, J, \tag{20}$$

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

$$C^{*}(\mathbf{w}, y) = \sum_j \mathbf{w}_j x_j e^{-\eta}, \tag{21}$$

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

$$C^{a} = \sum_j w_j x_j = C^{*}(\mathbf{w}, y)\exp(\eta), \tag{22}$$

and therefore, we have

$$\ln C^a = \ln C^*(\mathbf{w}, y) + \eta. \tag{23}$$

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

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

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

$$\begin{aligned}
\ln C^a_{it} &= \ln C^*(\mathbf{w}_{it}, y_{it}) + v_{it} + \eta_{it} \\
&= \beta_0 + \sum_{j=1}^{J} \phi_j d_j + \sum_j \beta_j \ln w_{jit} + \sum_j \beta_{tj} t \ln w_{jit} + \beta_y \ln y_{it} + \beta_{ty} t \ln y_{it} \\
&+ \frac{1}{2}\sum_j \sum_k \beta_{jk} \ln w_{jit} \ln w_{kit} + \frac{1}{2}\beta_{yy}(\ln y_{it})^2 + \sum_j \beta_{jy} \ln w_{jit} \ln y_{it} \\
&+ \sum_j \beta_{tj} t \ln w_{jit} + \beta_{ty} t \ln y_{it} + \beta_t t + \beta_{tt} t^2 + v_{it} + \eta_{it}; v_{it} \sim i.i.d.N(0, \sigma_v^2),
\end{aligned} \tag{24}$$

where $d_j$ represent dummies for the electricity subsectors (used in the truncated-normal models and the TVIM model), $\beta$, $\phi$ are unknown parameters to be estimated, $v_{it}$ is the normally distributed error term. Some theoretical assumptions are necessary to facilitate the transformation of the cost function. Following Kumbhakar et al. (2015a), $\beta_{jk} = \beta_{kj}$ is required by symmetry. The cost function is homogeneous of degree one in the input prices, which imposes the following parameter restrictions:

$$\sum_j \beta_j = 1, \sum_j \beta_{jk} = 0 \forall k, \sum_j \beta_{jy} = 0, \sum_j \beta_{tj} = 0. \tag{25}$$

Once these constraints are substituted into the model, the homogeneity conditions are automatically satisfied. This procedure amounts to using one of the input prices to normalize cost and other input prices. With $K$ and $L$ representing capital and labor as two inputs, after substitution and manipulation, we normalize the cost function using $w_{Kit}$ as the normalizing price, obtaining

$$\begin{aligned}
\ln(\frac{C^a_{it}}{w_{Kit}}) &= \beta_0 + \sum_{j=1}^{J} \phi_j d_j + \beta_y \ln y_{it} + \beta_{ty} t \ln y_{it} \\
&+ \beta_L \ln(\frac{w_{Lit}}{w_{Kit}}) + \beta_{tL} t \ln(\frac{w_{Lit}}{w_{Kit}}) + \frac{1}{2}\beta_{yy}(\ln y_{it})^2 \\
&+ \frac{1}{2}\beta_{LL}(\frac{w_{Lit}}{w_{Kit}})^2 + \beta_{Ly} \ln(\frac{w_{Lit}}{w_{Kit}}) \ln y_{it} + \beta_t t + \frac{1}{2}\beta_{tt} t^2 + v_{it} + \eta_{it},
\end{aligned} \tag{26}$$

As in other approaches, we make assumptions on the distribution of the inefficiency term $\eta_{it}$, which are similar to the assumptions defined by equations (2), (7) - (12).

The results on the determinants of cost inefficiency should be interpreted with precaution due to potential endogeneity. Although attempts have been made to overcome the potential endogeneity problem caused by firm-level input variables and inefficiency explanatory variables (Karakaplan and Kutlu, 2017; Lai and Kumbhakar, 2018, 2019; Kutlu et al., 2020; Prokhorov et al., 2021), the methodology development is still in a phase of exploration and there is no widely accepted method that solves the problem (Amsler et al., 2017; Liu et al., 2019). In Stochastic Frontier models, the noise and inefficiency components are usually assumed to be uncorrelated with the inputs, but this assumption can be relaxed (Lai and Kumbhakar, 2019). For uniformity across the approaches, we keep the inefficiency explanatory variables in the cost function approach. Nevertheless, results from the KLH models and TVIMs should be free of concerns on potential endogeneity issue.

### 3.4. Data

We estimate the empirical models with annual panel data from 2006 to 2019 for firms in the Portuguese electricity subsectors, which is part of the BPLIM database[7] of the Bank of Portugal (Banco de Portugal). Firms are identified by anonymized tax/bank identification numbers and the data can only be accessed on BPLIM's dedicated servers. The data used in this study comes from the Central Balance Sheet, mostly based on information reported through Informação Empresarial Simplificada (IES, Simplified Corporate Information) and contains annual data.

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

- $K$ - Capital stock, measured by tangible fixed capital in euros;
- $L$ - Labor input, measured by total hours worked by paid employees.

In the production function approach and the cost function approach, output level $y$ is measured by non-financial revenue deflated by the electricity price for Type I industrial users of each year (Source: Direção-Geral de Energia e Geologia[8]). For the distance function approach, we consider the following outputs:

- $y_1$ - Total sales in the internal market, deflated with electricity price for Type I industrial users in Portugal;
- $y_2$ - Total sales in the EU market, deflated with electricity price for Type I industrial users in Spain. Given the geographical location of Portugal, the main destination of electricity export is Spain, while electricity trade with other European countries is limited by the interconnection capacity between Spain and France (Fortes et al., 2016).

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

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

- $w_K$ - for the proxy for the price of capital, we use the return of financial investment as the opportunity cost of capital, which is obtained by the ratio of financial income to financial investment.
- $w_L$ - the price of labor is measured by average hourly wage in euros, which is obtained by the ratio of total payment of wages to the total hours worked by paid employees.

The actual cost of each firm is calculated by

$$C^a_{it} = K_{it} w_{Kit} + C_{Lit}, \tag{27}$$

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

We consider the following explanatory determinants of technical inefficiency:

- Age (LAGE): the natural logarithm of the age of the firm until 2019; the impact of firm age on technical inefficiency is studied by Lai and Kumbhakar (2018).
- Capital deepening (CD): measured by the ratio of capital to labor; too much capital relative to labor input may cause inefficiency (Shao et al., 2016; Yang et al., 2018).
- Financial income (FIC): measured by the ratio of financial income to total revenue. On one hand, over-involvement in financial activities can undermine the firms' incentive for improving real production, as supported by previous empirical evidence (Hou et al., 2020); on the other hand, recent studies indicate that energy firms are exposed to financial risks (Si et al., 2021; Wu et al., 2021), which could bring about disturbance in their operation.

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

[8] https://www.dgeg.gov.pt/pt/estatistica/energia/precos-de-energia/precos-de-eletricidade-e-gas-natural/

- Financial investment (FIV): ratio of financial investment to total non-current assets. This is also a measure for the degree of involvement in financial activities of a firm.
- Operating subsidies (SSD): measured by the ratio of operating subsidies to total revenue; high subsidies may undermine efficiency. There has been the evidence that production subsidies can stimulate substantial managerial inefficiencies of biogas plants (Eder and Mahlberg, 2018).
- Average working hours (AVHR): measured by the natural logarithm of average hours worked per paid employee; working too much time may undermine technical efficiency. Abbas et al. (2022) suggest that firms can benefit from providing free time to employees for creative ideas and investing in R&D activities; Morikawa (2023) indicates negative relationship between working hours and economic productivity of firms.
- Average wage (AVWG): obtained by taking the natural logarithm of the ratio of total payment of wages to the total hours worked by paid employees; a higher wage is expected to improve efficiency.

Inefficiency explanatory variables are identical for the three functional forms so that the results are comparable across specifications. Although environmental and/or policy factors are also relevant to technical inefficiency, we do not incorporate them in this study for a couple of reasons. On one hand, the database is not constructed for the purpose of environmental analysis; it is therefore impractical to merge it with data from other sources. On the other hand, due to the high nonlinearity of the empirical models, an excessive number of explanatory variables for the inefficiency term will bring unnecessary difficulty to the estimation; since the impact of environmental factors on technical efficiency has been amply addressed in relevant literature (Growitsch et al., 2012; Karim and Pollitt, 2017; Liu et al., 2019, etc.), we choose to focus on operational factors.

Table 1 summarizes the descriptive statistics of the data used in our study. Descriptive statistics for each subsector are presented in Appendix A. As the panel is not balanced, the observations actually utilized in each empirical model may vary. The variables are in their original values although logarithms are used in the estimation. Additional statistics on quartile values, skewness and kurtosis of the variables used in the cost function approach are presented in Appendix B.

Notice that although the mean of $w_K$ may seem a bit larger than expected, it is due to some abnormal observations with extremely large financial returns.[9] If we calculate the ratio of mean financial return to the mean of financial income to mean financial investment in the Portuguese electricity sector, the value fluctuates around 10% per year.

## 4. Empirical results and discussion

In this section, we present the results of the models estimated following Section 3. For each functional form, we interpret the empirical results of the models from several aspects. First, using the results of the KLH models, we evaluate the overall efficiency levels, taking into account the persistent and transient inefficiency and their statistical significance. Then, we analyze whether and how explanatory variables exert impact on inefficiency, using results of the truncated normal models. Finally, we check if a time trend of efficiency change is supported by the TVIM.

**Table 1**
Descriptive statistics of the variables used in the analysis.
*Source:* Descriptive statistics for firms in the Portuguese electricity sector from the BPLIM database.

| Variable | Obs. | Mean | Std. Dev. | Unit |
|---|---|---|---|---|
| Output variables: | | | | |
| Production function: | | | | |
| $y$ | 10,111 | 1.23e+08 | 1.26e+09 | Kwh |
| Distance function: | | | | |
| $y_1$ | 10,111 | 9.97e+07 | 1.10e+09 | Kwh |
| $y_2$ | 10,111 | 6 424 417 | 1.31e+08 | Kwh |
| Input variables (production/distance function): | | | | |
| $K$ | 10,111 | 1.75e+07 | 1.96e+08 | Euro |
| $L$ | 8232 | 23 953.03 | 278 419.5 | Hour |
| Cost variable (cost function): | | | | |
| $C^a$ | 2269 | 3.61e+08 | 9.96e+09 | Euro |
| Input price variables (cost function): | | | | |
| $w_K$ | 2269 | 27.27801 | 485.9664 | Ratio |
| $w_L$ | 2810 | 10.81476 | 16.36633 | Euro/hour |
| Determinants of technical inefficiency (all functional forms): | | | | |
| Age | 9833 | 15.75897 | 12.25394 | Year |
| CD | 2516 | 12.10082 | 3.105545 | Ratio |
| FIC | 7447 | .0854397 | .2555958 | Ratio |
| FIV | 8297 | .109695 | .2830145 | Ratio |
| SSD | 7447 | .0038495 | .0494926 | Ratio |
| AVHR | 2797 | 1651.297 | 492.4247 | Hour |
| AVWG | 2810 | 10.81476 | 16.36633 | Euro/hour |

Note: Minimum/maximum values anonymized for confidentiality requirement of the database.

### 4.1. The production function approach

The results of KLH models for each subsector are presented in Table 2. Before further discussion, it should be clarified that the equations estimated in our models are the second-order Taylor approximations for the real functional forms, which are difficult to be determined or expressed explicitly. Therefore, the individual estimated coefficients should not be interpreted intuitively[10]; instead, we focus on the issue of technical efficiency.

All the KLH models presented are jointly statistically significant at 1% level. The signs and statistical significance of the coefficients for each model are similar compared to the models with half-normally distributed inefficiency terms (and everything else being identical). Transient technical inefficiency is statistically significant in all Portuguese electricity subsectors, while persistent inefficiency is statistically significant in the subsectors of hydro and other renewables.

Fig. 1 depicts the evolution of productive technical efficiency from 2006 to 2019 in the four Portuguese electricity subsectors (hydro; thermal; other renewables; trade, transmission and distribution of electricity).

Several intuitions can be gathered from the figure. First, productive technical efficiency is generally low among Portuguese electricity firms. The highest observation for mean technical efficiency is merely over 50%. This may be caused by the fact that some firms in the Portuguese electricity subsectors are much larger than the rest of the sample, as the mean level of persistent efficiency is quite low in some subsectors. On the other hand, results imply plenty of space for improvement in technical efficiency; taking into account the operational factors that we study may contribute to such improvement. Second, the thermal and TTD subsectors enjoys higher technical efficiency in general, while the subsectors of hydro and other renewables seem to suffer from lower technical efficiency. Given that Portugal has been developing electricity

[9] Although larger than usual, these values are not infeasible. We trust that they are true values since the data source is credible, and therefore should be maintained in order to avoid biased estimations. In practice, dropping observations with $w_K \geq 1$ provides similar results in terms of the signs of the coefficients and their statistical significances in KLH models and TVIMs, while causes convergence problems in truncated-normal models.

[10] Some indicators calculated using the data and the coefficients, however, can be informative, e.g., the output elasticities as previously mentioned.

**Table 2**
Estimated results for KLH production frontier functions of Portuguese electricity subsectors.
*Source:* Estimation of Stochastic Frontier models using Stata.

| Variable | Coefficient | | | |
|---|---|---|---|---|
| | Hydro | Thermal | Other renewables | TTD |
| Frontier | | | | |
| $lnK$ | −.153(.266) | .0005(.203) | −.218(.257) | 1.35***(.281) |
| $lnL$ | −.094(.277) | −.141(.340) | .778(.544) | .953*(.578) |
| $(lnK)^2$ | .019(.012) | .015**(.007) | .038***(.009) | .060***(.015) |
| $(lnL)^2$ | .056**(.024) | .097***(.021) | .011(.029) | .177***(.046) |
| $lnK * lnL$ | −.007(.026) | −.041**(.019) | −.039**(.020) | −.263***(.040) |
| $t * lnK$ | −.015*(.008) | .016***(.006) | .009*(.005) | .004(.010) |
| $t * lnL$ | −.033***(.011) | −.008(.008) | .009(.013) | −.030*(.018) |
| $t$ | .506***(.143) | −.149*(.088) | −.095(.145) | .018(.160) |
| $t^2$ | −.002(.004) | −.0002(.003) | −.002(.004) | .016***(.006) |
| Intercept | 10.5***(2.02) | 11.6*(2.14) | 6.99***(3.11) | −3.16(2.79) |
| Inefficiency terms | | | | |
| $\sigma_U^2$ | .394***(.115) | .315***(.089) | .421***(.095) | .466***(.176) |
| $\sigma_\kappa^2$ | 1.21***(.185) | −7.94(107) | 1.01***(.077) | −7.03(49.4) |
| Obs. | 543 | 737 | 818 | 351 |
| N. Groups | 87 | 114 | 165 | 59 |

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

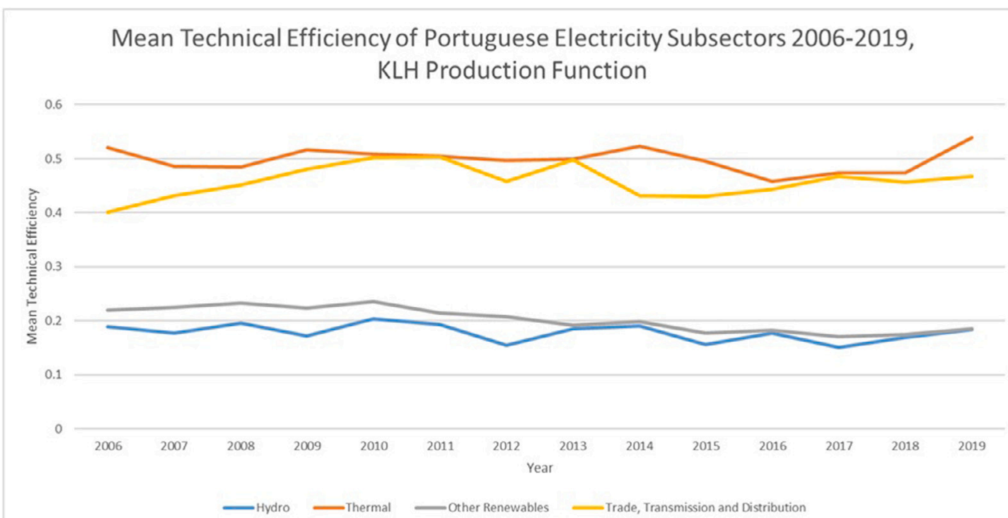


**Fig. 1.** Mean Technical Efficiency of Portuguese Electricity Subsectors 2006-2019, KLH Production Function.

generation from renewable sources,[11] efficiency issues in these subsectors certainly deserve more attention from regulators. Third, it is difficult to judge whether technical efficiency has improved through time, thus it is necessary to adopt the TVIM to disentangle the effect of a time trend.

Based on the KLH models, we calculate the Scale Efficiency Change according to equations (3) - (6). The mean Scale Efficiency Change of each subsector is shown in Fig. 2. In all the subsectors, mean SEC is positive in most years. This implies that during the market liberalization, the Portuguese electricity sector benefits from economies of scale, especially in the hydro and TTD subsectors. The sudden increase of SEC in the hydro subsector in 2019 is probably due to the change in electricity price which we adopt as deflator (from 0.2525 euro/kwh in 2018 to 0.1943 euro/kwh in 2019).

The results of truncated normal models and the TVIM are presented in Table 3. Given the large number of variables and complexity of the model, convergence problems may occur in the estimation.[12] Therefore, we estimate various truncated normal models and choose to present the results for two of them, while other specifications produce similar results for the signs and statistical significance levels of the inefficiency variables. In each truncated normal model we estimate, each of the seven explanatory variables appears at least once in either the mean equation or the variance equation; altogether in the two models, each explanatory variable appears at least once in both equations. The same applies to the truncated normal cost function models.

Most coefficients in the production function are statistically significant, while the coefficients of each model are also jointly statistically significant. All the coefficients for the dummy variables are statistically significant, indicating structural differences between the production technologies of electricity subsectors, which justifies our approach of

[11] According to Enerdata Global Energy Statistical Yearbook 2021 (https://yearbook.enerdata.net/renewables/renewable-in-electricity-production-share.html), in 2020, 59.7% of Portugal's electricity was generated from renewable sources.

[12] Potential causes may include limited variation or unbalanced panel.

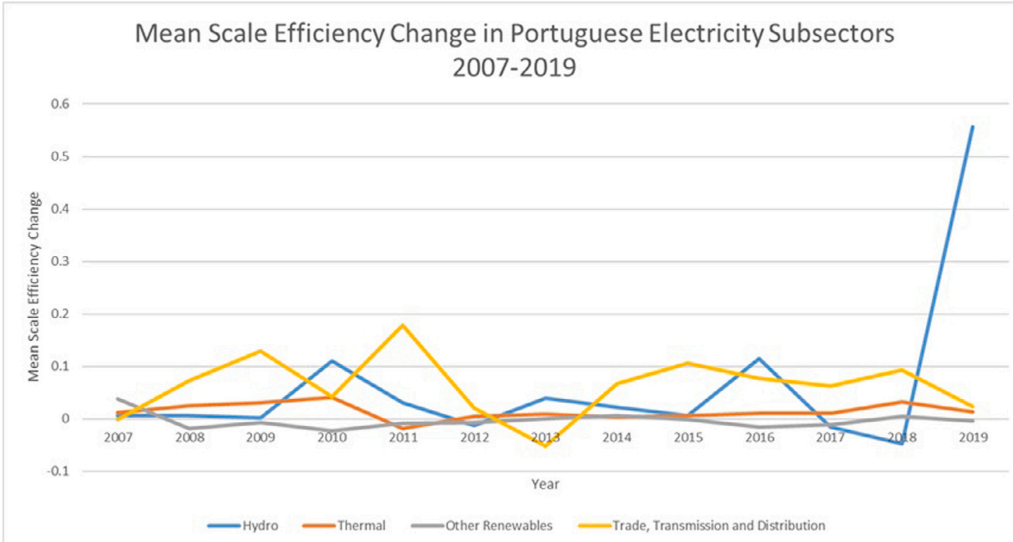


**Fig. 2.** Mean Scale Efficiency Change in Portuguese Electricity Subsectors 2007-2019, KLH Production Function.

estimating separate KLH models for each subsector, as well as the difference in these subsectors' mean technical efficiency levels. Nonetheless, in the first two models, there is statistical significance for only a part of the coefficients related with $t$ (mainly $t^2$). This is a signal that in the Portuguese electricity sector, technological progress through time contributed very little to the neutral improvement of productivity, except for the slight acceleration implied by the coefficients on $t^2$.

Regarding the technical inefficiency term, the results also demonstrate statistical significance for most coefficients in all the estimated models. We can infer that firm-level technical inefficiency in the Portuguese electricity sector is indeed affected by operational factors. Yet, the signs of the coefficients are not all as expected. The coefficient on $LAGE$ (log of firm age) in the variance equation is statistically significant and negative, which means that technical efficiency of firms with greater age is less variant; nonetheless, the coefficient of $LAGE$ in the mean equation lacks statistical significance. The coefficients for $CD$ (capital deepening) are negative when it appears in the mean or variance equation: higher capital input relative to labor input has a negative effect on the mean and pre-truncation variance of technical inefficiency. Such a result is different from studies for other sectors (Shao et al., 2016; Hou et al., 2020). This can be because of different patterns of production in different economic sectors: some sectors are labor-intensive while others, including the Portuguese electricity sector, are capital-intensive. Consequently, investing in equipment instead of recruiting more staff may improve efficiency in the Portuguese electricity sector. The result on the effect of financial activities is somehow counter-intuitive: while the coefficients for $FIC$ (financial income) are statistically significant and positive, which represents positive effect on the mean (pre-truncation) variance of technical inefficiency; the coefficient of $FIV$ (financial investment) in the variance equation is statistically significant and negative. We may try to understand this from two sides. Firms with higher technical efficiency may enjoy better financial positions and have extra money for financial investment. When they earn money from such investments, however, they may lose focus on operational efficiency. Therefore, firms are advised to resist the temptation of relying too much on financial activities instead of their core business. The coefficient for $SSD$ (operating subsidy) is statistically significant and positive in both mean and variance equations, implying that operating subsidy might be detrimental to technical efficiency. The coefficients on $AVHR$ (average working hours) and $AVWG$ (average wage) are all negative, with the coefficient for $AVHR$ in the mean equation lacking statistical significance. Such could be evidence that a higher average wage is helpful in stimulating the employees to improve technical efficiency.

In the TVIM, the coefficient on $t$ is statistically insignificant and that on $t^2$ is only statistically significant at 10% level. Therefore, there is insufficient proof that technical efficiency has improved through the sample period.

### 4.2. The distance function approach

All KLH distance function models presented in Table 4 are jointly statistically significant at 1% level. Transient technical inefficiency is only statistically significant in the subsector of other renewables; in other words, technical inefficiency is more attributable to persistent factors related to structural differences in each firm's unobservable inputs (including climate/geographical conditions for electricity generation from renewable sources, operational strategies, etc.).

Fig. 3 shows how technical efficiency changed in the four Portuguese electricity subsectors from 2006 to 2019 according to the KLH distance function models.

From the figure we can observe some differences from the production function results. Mean technical efficiency in the TTD subsector started from a very low level and increased through time. Yet irregularity may result from the electricity price deflators, which may not perfectly apply to the TTD subsector. Pricing schemes for electricity transmission and distribution can be different from those for electricity generation. From the results of the distance function approach, mean technical efficiency in the subsectors of hydro and other renewables is higher compared with the production function results. This implies that the production function approach may underestimate the efficiency levels in these two subsectors without separating the sales to internal and EU market. Electricity generated from renewable sources, in particular hydro power, can be prone to seasonal climate conditions which more frequently leads to power surplus that has to be traded across the border. The ongoing development in the Portuguese renewable energy sector calls for better integration of the Iberian market for efficiency gains and more flexible energy (especially electricity) trading.

When the difference in output measurement is taken into account and the higher efficiency level among the production and distance

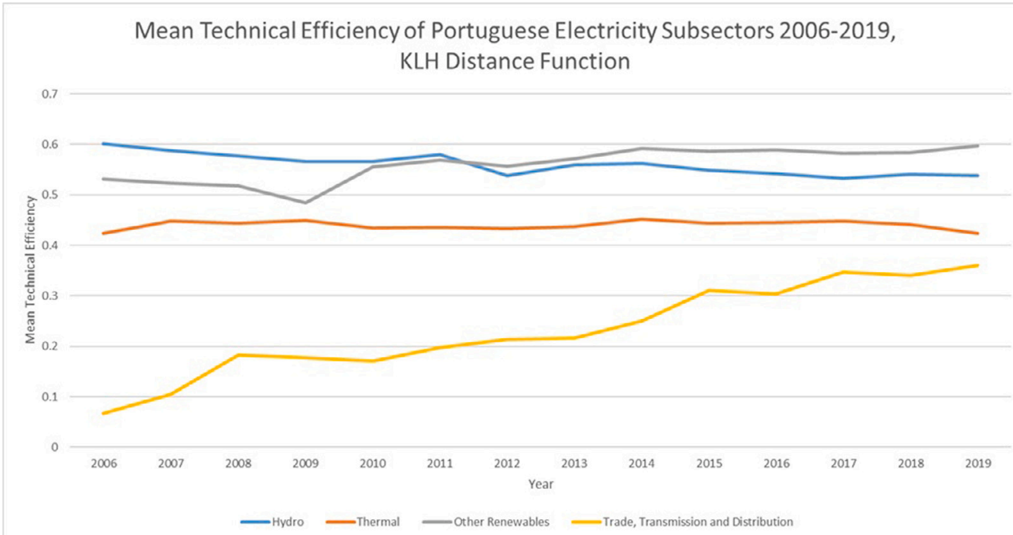


**Fig. 3.** Mean Technical Efficiency of Portuguese Electricity Subsectors 2006-2019, KLH Distance Function.

**Table 3**
Estimated results for truncated normal models and TVIM of production frontier functions of the Portuguese electricity sector.
*Source:* Estimation of Stochastic Frontier models using Stata.

| Variable | Coefficients | | |
|---|---|---|---|
| | Model 1 | Model 2 | TVIM |
| Frontier | | | |
| $lnK$ | −.448***(.147) | .054(.100) | .084(.117) |
| $lnL$ | 1.08***(.207) | .270(.171) | .211(.161) |
| $(lnK)^2$ | .053***(.007) | .041***(.004) | .023***(.004) |
| $(lnL)^2$ | .073***(.010) | .081***(.010) | .077***(.011) |
| $lnK * lnL$ | −.114***(.012) | −.094***(.008) | −.055***(.009) |
| $t * lnK$ | .006*(.003) | .001(.003) | .010***(.003) |
| $t * lnL$ | −.007(.005) | .003(.006) | −.021***(.005) |
| $t$ | −.089(.067) | −.133*(.069) | .079(.083) |
| $t^2$ | .005*(.002) | .006**(.002) | −.005(.004) |
| Intercept | 13.7***(1.22) | 11.7***(1.08) | 14.2***(1.13) |
| (Dummies omitted) | | | |
| Inefficiency term: mean | | | |
| LAGE | | −21.6(13.8) | |
| CD | −.473***(.075) | | |
| FIC | | 108*(64.4) | |
| FIV | | −63.7(38.9) | |
| SSD | | 69.3*(42.0) | |
| AVHR | −.079(.147) | | |
| AVWG | −.926***(.056) | | |
| Intercept | 10.6***(1.20) | −37.3(30.5) | |
| Inefficiency term: variance | | | |
| LAGE | −1.49***(.168) | | |
| CD | | −.057***(.017) | |
| FIC | 4.65***(.492) | | |
| FIV | −3.74***(.555) | | |
| SSD | 2.25**(.920) | | |
| AVHR | | −.498***(.079) | |
| AVWG | | −.387***(045) | |
| Intercept | 4.36***(.357) | 9.63***(.791) | 3.03***(.142) |
| Inefficiency term: time variance | | | |
| $t$ | | | .007(.018) |
| $t^2$ | | | −.002*(.001) |
| Obs. | 2050 | 2050 | 2449 |
| Log likelihood | −3893.1809 | −3908.1036 | −4538.9925 |

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

functions is considered for each subsector, mean efficiency levels range from 40% to 60% in general. This still implies very much space for efficiency improvement, which can start from operating factors of the firms.

The results of the truncated normal model and the TVIM model are summarized in Table 5. As it is possible to have all the explanatory factors for technical efficiency in both equations for the mean and variance of the inefficiency term, the result of this model will suffice for the truncated normal specification.

Most coefficients in the two models are statistically significant and all coefficients are jointly statistically significant in each model, meaning that they are very well specified. Consistent with results from the production function approach, capital deepening ($CD$) has a negative effect on both mean and pre-truncation variance of the inefficiency term. The coefficient of $LAGE$ is statistically significant in both mean and variance equations, with the sign in the mean equation being positive, indicating that firms with greater age are more likely to suffer from inefficiency. The coefficient of $FIV$ (financial investment) is not statistically significant in the mean equation and statistically significant only at 10% level in the variance equation. The coefficients of $FIC$ (financial income) are statistically significant, being positive in the mean equation. This confirms that higher financial income (relative to total revenue) may hinder the firms' incentive of improving technical efficiency. The mean of technical inefficiency is also positively related with higher average working hours. Generalizing all the models that we estimate (including those not presented in the table), higher average working hours increases technical inefficiency in both its mean and (pre-truncation) variance, while higher average wage reduces the mean of technical inefficiency in some specifications. There is the possibility of bilateral causality: lower efficiency requires more working time to reach the production goal; nevertheless, the result implies that keeping moderate average working hours may improve technical efficiency. Employees with more free time could provide creative ideas and invest in R&D activities (Abbas et al., 2022); on the contrary, working excessive hours can undermine their motivation and performance. The finding above helps complete our whole picture. Meanwhile, evidence from the distance function models does not support that technical efficiency is affected by the share of operating subsidies in total revenue.

A clear time trend can be intuitively observed for the TTD subsector in Figure 3. Moreover, in the Time-Varying Inefficiency Model,

**Table 4**
Estimated results for KLH distance frontier functions of Portuguese electricity subsectors.
*Source:* Estimation of Stochastic Frontier models using Stata.

| Variable | Coefficients | | | |
|---|---|---|---|---|
| | Hydro | Thermal | Other renewables | TTD |
| Frontier | | | | |
| $lnL^*$ | .678***(.122) | .587***(.110) | .844***(.104) | .549***(.185) |
| $lny_1$ | .369**(.146) | .575***(.158) | .149(.163) | .337*(.182) |
| $lny_2$ | −.125(.128) | .123**(.054) | −.687***(129) | −.089(.098) |
| $(lnL*)^2$ | .059***(.005) | .057***(.004) | .043***(.005) | .053***(.010) |
| $(lny_1)^2$ | −.016**(.006) | −.019***(.006) | −.016**(.007) | −.017***(.005) |
| $lny_1 * lny_2$ | .014(.011) | −.006(.004) | .029***(.007) | .004(.005) |
| $(lny_2)^2$ | −.010(.006) | −.001(.003) | .017***(.005) | .004(.003) |
| $lnL^* lny_1$ | .038**(.007) | .056***(.007) | .020**(.009) | .024**(.011) |
| $lnL^* lny_2$ | −.013*(.007) | −.001(.004) | −.009(.008) | .017***(.004) |
| $t * lny_1$ | −.003(.003) | .005(.003) | .005(.005) | −.003(.006) |
| $t * lny_2$ | −.008***(.002) | −.001(.002) | .013*(.007) | −.004(.003) |
| $t * lnL^*$ | −.020***(.003) | −.022***(.003) | −.006(.004) | −.010*(.006) |
| $t$ | −.034(.053) | −.168***(.055) | −.213***(.076) | −.037(.102) |
| $t^2$ | .0007(.001) | −.0008(.001) | .006**(.002) | .003(.003) |
| Intercept | −11.3***(.911) | −12.3***(1.16) | −7.02***(1.05) | −10.4***(1.62) |
| Inefficiency terms | | | | |
| $\sigma_U^2$ | −12.0(224) | −11.9(116) | −3.44***(.844) | −10.8(136) |
| $\sigma_\kappa^2$ | −.245(.302) | .599**(.281) | −1.00**(.443) | 1.83***(.103) |
| Obs. | 334 | 574 | 355 | 269 |
| N. Groups | 57 | 87 | 86 | 48 |

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

both coefficients on $t$ and $t^2$ are statistically significant, indicating the existence of a time trend in the evolution of technical inefficiency. The coefficient on $t$ is 0.066 while that on $t^2$ is −0.004, which means that the improvement in technical efficiency is slowed down through time. Moreover, assuming that the coefficients are accurate, we have $G'(t) \geq 0$ when $t \geq 8.25$, implying that the time trend for efficiency is no longer increasing after 2014. Therefore, even if there is an efficiency improvement through time during the electricity market liberalization, its effect is quite limited.

### 4.3. The cost function approach

The estimated results for the KLH cost function models of Portuguese electricity subsectors are presented in Table 6.

All KLH cost function models presented are jointly statistically significant at 1% level; the TTD subsector is the only one where transient inefficiency is statistically significant. The coefficients on variables related with $t$ are statistically significant mainly in the hydro and TTD subsectors, indicating that changes have taken place in the cost frontier of these subsectors.

Fig. 4 demonstrates the evolution of cost efficiency in the four Portuguese electricity subsectors from 2006 to 2019. The efficiency level in the subsector of other renewables seems very low. However, its mean transient efficiency is 99.42% and mean persistent efficiency is 41.44%, but the persistent inefficiency term is not statistically significant. Hence the actual efficiency level in the subsector of other renewables may be underestimated. In the TTD subsector, the transient inefficiency term is statistically significant, so the mean efficiency level between 60% and 80% is more credible.

Widespread cost inefficiency is evident only in the other renewables and TTD subsectors. During the sample period, firms in the hydro and thermal subsectors were more successful in their cost control.

The results of the truncated normal models and the TVIM model are presented in Table 7. Most coefficients in the models are statistically significant and in each model the coefficients demonstrate joint statistical significance. It is worth remembering the difference between technical efficiency in production and cost efficiency. The former is a measure of a firm's ability to reach the potential output level allowed by the technology using a certain set of inputs. Cost efficiency, on the other hand, reflects a firm's ability to optimize its cost in realizing an output goal. It is therefore natural that operational factors have different impacts. As in the estimated cost function results, generally, $CD$ (capital deepening) exerts positive effects on the mean and (pre-truncation) variance of technical inefficiency. This implies that firms with larger capital stock (relative to labor input) are likely to have lower cost efficiency, unlike the result from other functional forms[13] . From an operational perspective, this does not mean that firms in the Portuguese electricity sector have to face a trade-off between productive and cost efficiency; nonetheless, those with higher ratio of capital to labor should pay extra attention to cost control.

In both terms of mean and pre-truncation variance, $FIC$ (financial income) has positive effects and $FIV$ (financial investment) has negative effects on technical inefficiency, which is in line with the production function models. $LAGE$ (log of firm age) is statistically significant at 1% level in both mean and variance equations so that firms with longer history are likely to suffer from cost inefficiency. $AVHR$ (average working hours) and $AVWG$ (average wage) do not

[13] A potential cause for this phenomenon may be the input prices considered in the cost functions (which are absent in the other approaches). According to our data, from 2006 to 2019, mean hourly wage in the Portuguese electricity sector grew from 8.27 euros to 14.04 euros; there is also fluctuation in the returns to investment in our data. Regarding the price of fuel, which is not accounted by our models for consistency (as the importance of fuel is mainly reflected in the thermal subsector), there also exist large fluctuations. Between 2006 and 2019, the annual average Northwest Europe marker price for coal ranges between 56.79 and 147.67 USD/ton; Herein NBP index for natural gas fluctuates between 4.47 and 10.79 USD per million Btu (Source: https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html).

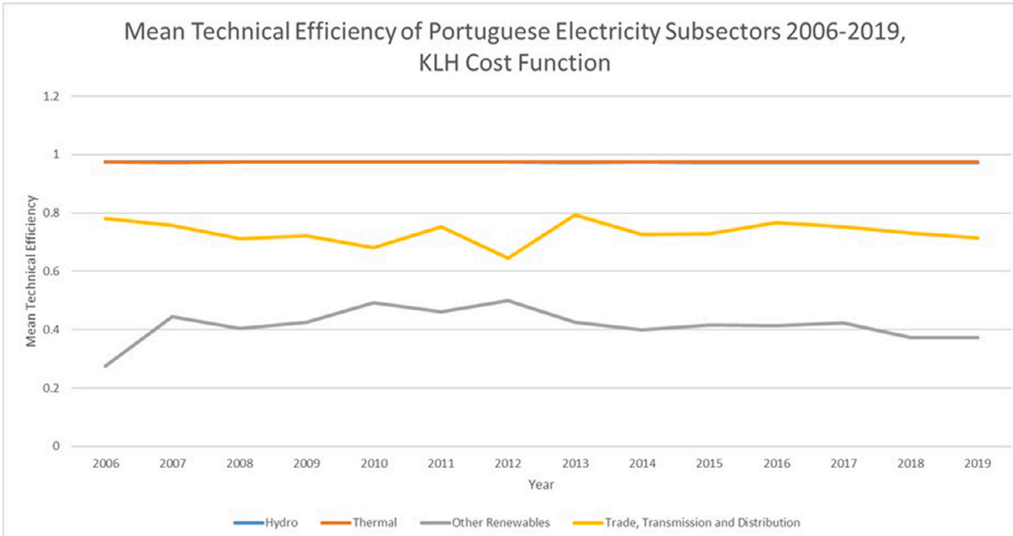


**Fig. 4.** Mean Technical Efficiency of Portuguese Electricity Subsectors 2006-2019, KLH Cost Function.

have statistical impact on the mean of cost inefficiency; there is also little evidence of impact by $SSD$ (operating subsidy).

In the TVIM, both coefficients on $t$ and $t^2$ are statistically insignificant. Thus, evidence does not support improvement through time in cost efficiency of the Portuguese electricity sector from 2006 to 2019. This is understandable given that cost inefficiency is not evident in the hydro and thermal subsectors.

### 4.4. General comments

We have analyzed the evolution of technical efficiency in the Portuguese electricity sector from 2006 to 2019 using Stochastic Frontier models for production, distance and cost functions. Each focuses on different aspects of the issue; nevertheless, generalizing the results of the three approaches, there are a few findings worth highlighting.

First of all, there is still much room for improvement in technical efficiency – particularly productive efficiency – in the Portuguese electricity sector. Generalizing results from the production function approach and the distance function approach, average technical efficiency for some subsectors fluctuates between 40% and 60%. This is lower than previous studies, in which the overall efficiency level in the T&D subsector ranges between 70% and 80% (Liu et al., 2019; Kumbhakar et al., 2020). Two perspectives can provide clues for technical efficiency improvements.

From the macro perspective, findings from the distance function TVIM indicate limited efficiency improvement through time, while there is no evidence for improvement in terms of cost efficiency. In terms of efficiency, the policy maker should not stay satisfied for several perspectives. First, the benefit from liberalization does not last long enough. Incomplete deregulation in the electricity sector may hinder efficiency improvement (Sun and Wu, 2020) and the Portuguese electricity market is far from competitive (Amorim et al., 2013). To consolidate the previous success, the regulator could consider further reforms to inject competition into the market. Second, productive efficiency does not necessarily translate into cost efficiency. Last but not the least, firm-level efficiency in the Portuguese electricity sector could be improved by targeting at operational issues.

In particular, from the micro perspective, firms could focus on operational factors. Higher capital input relative to labor leads to higher efficiency in terms of production, but lower efficiency in cost, indicating that firms should pay more attention to cost optimization. Both production function and cost function models provide evidence of the firms' involvement in financial activities affecting efficiency. Regulators may encourage firms to invest in fixed assets rather than financial activities through fiscal policies. Firms with longer histories are more prone to technical inefficiency; possible causes include structural frictions in management and inertia or conservatism that brings about difficulty in efficiency improvement. Moreover, higher hourly wage and moderate average working hours are likely to improve technical efficiency.

Operating subsidies, at best, do not help improve technical efficiency, and may even undermine efficiency in terms of production. This is in line with the finding by Eder and Mahlberg (2018). Wu et al. (2022) suggest that higher subsidy level imposes a crowding out effect on R&D efforts of new energy enterprises. There has been a debate on whether the benefit of subsidies overwhelms their cost. Although subsidies are designed to promote the development of renewable energy, they are unlikely to enhance welfare (Fischer et al., 2013); removing the subsidy scheme may imply net present value gains (Johansson and Kriström, 2019). Subsidies could also undermine the positive effect of technological innovation upon energy firms' environmental performance (Liang et al., 2022). In addition, there is the hazard of managers of electricity companies improperly profiting from subsidies, as highlighted in a case involving a major company in the Portuguese electricity sector.[14] However, subsidies may still be worthwhile policy endeavor, since they could be geared to other policy goals, such as carbon emissions removals.

Results from the production function and distance function approach demonstrate sensitivity to output measurement. By considering the cross-border sales of electricity (mostly in the Iberian market), we unveil higher productive efficiency in some subsectors and a time trend of efficiency improvement. It is evident that the Portuguese electricity

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

**Table 5**
Estimated results for truncated normal model and TVIM of distance frontier functions of the Portuguese electricity sector.
*Source:* Estimation of Stochastic Frontier models using Stata.

| Variable | Coefficients | |
|---|---|---|
| | Truncated normal model | TVIM |
| Frontier | | |
| $lnL^*$ | 1.84***(.297) | .783***(.053) |
| $lny_1$ | 1.06***(.088) | .395***(.077) |
| $lny_2$ | −.218***(.047) | .022(.033) |
| $(lnL*)^2$ | .038***(.003) | .035***(.002) |
| $(lny_1)^2$ | −.044***(.003) | −.019***(.003) |
| $lny_1 * lny_2$ | −.002(.004) | −.003(.002) |
| $(lny_2)^2$ | .018***(.003) | .004**(.002) |
| $lnL^* lny_1$ | .012**(.005) | .020***(.003) |
| $lnL^* lny_2$ | .003(.004) | −.002(.002) |
| $t * lny_1$ | .001(.003) | .002(.002) |
| $t * lny_2$ | −.008***(.002) | −.006***(.001) |
| $t * lnL^*$ | −.003(.003) | −.015***(.002) |
| $t$ | −.120**(.047) | .287(.304) |
| $t^2$ | .006***(.002) | −.022(.018) |
| Intercept | −.176(3.73) | −6.10(4.38) |
| (Dummies omitted) | | |
| Inefficiency term: mean | | |
| LAGE | .301***(.051) | |
| CD | −.907***(.293) | |
| FIC | .620**(.244) | |
| FIV | −.254(.159) | |
| SSD | .471(.583) | |
| AVHR | 1.59***(.296) | |
| AVWG | .040(.031) | |
| Intercept | 6.70*(3.74) | 4.47(4.31) |
| Inefficiency term: variance | | |
| LAGE | −.466***(.104) | |
| CD | −.183***(.028) | |
| FIC | −1.95**(.786) | |
| FIV | .539*(.304) | |
| SSD | −4.94(3.69) | |
| AVHR | .063(.209) | |
| AVWG | 1.37***(.137) | |
| Intercept | −.563(1.61) | −.177(.121) |
| Inefficiency term: time variance | | |
| $t$ | | .066***(.012) |
| $t^2$ | | −.004***(.0009) |
| Obs. | 1347 | 1532 |
| Log likelihood | −1688.557 | −1352.6572 |

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

sector benefits from the integration of the Iberian electricity market, which should be consolidated and deepened.

Another issue of concern is the efficiency in the subsectors of electricity generation from renewable sources. Results from the production function approach imply low efficiency for the hydro and other renewables subsectors; in particular, scale efficiency growth, as well as cost efficiency in the subsector of other renewables, is lower than for other subsectors. This does not fit the aims of EU's policy to promote the share of renewable energy (European Union, 2018). Given the notable share of renewable energy sources in total electricity consumption in Portugal, cost efficiency is an essential factor to guarantee the long-term sustainability and economic viability of renewable energy. Policy should consider stimulating competition within the renewable energy subsector(s), targeting cost efficiency and scale efficiency.

The electricity market is unique because electricity cannot be stored, necessitating continuous equilibrium between supply and demand. This characteristic may result in lower efficiency levels compared to other sectors, particularly when relying on intermittent renewable sources. Consequently, electricity generators behave intermittently; for instance, when there is wind, thermal generators are inactive, and vice versa. Strategies have been adopted to balance electricity supply and demand, e.g., time-based pricing; notwithstanding, the seasonality of renewable sources of electricity poses great challenges on the pursuit of efficiency in the energy transition. Therefore, efficiency in the electricity sector deserves continuous attention from policies in combating climate change and realizing the Sustainable Development Goals.

## 5. Conclusion and policy implications

The Portuguese electricity sector stepped into its final stage of market liberalization in 2006 (Amorim et al., 2013). Previous studies suggest that electricity market reforms could improve efficiency (Barros, 2008; Ma and Zhao, 2015; Lundin, 2020; Bobde and Tanaka, 2020) but in some cases this job may not be perfectly done as the reforms are hampered by incomplete deregulation and practical factors (Sun and Wu, 2020; Lee and Howard, 2021; Mirza et al., 2021). On the other hand, previous studies on technical efficiency in the electricity sector mostly focus on one of the subsectors and the impact of operational factors on efficiency has been less discussed compared to environmental factors (Growitsch et al., 2012; Karim and Pollitt, 2017; Liu et al., 2019). We apply Stochastic Frontier Analysis to annual firm-level data in the Portuguese electricity sector from 2006 to 2019 mainly to assess two aspects: whether productive and cost efficiency has improved after the market liberalization and whether efficiency in the electricity sector is affected by factors related to firm operation.

Evidence indicates limited efficiency improvement through time; there is little evidence that the reform also affects cost efficiency. This may result from an incomplete reform process: the market is still far from competitive, with the existence of state guaranteed prices and feed-in tariffs. The regulator may consider deepening the reform so that the previous success could be consolidated. A possible option is to encourage firms to invest in fixed assets rather than financial activities.

Specifically, based on our findings, we advocate deeper integration of the Iberian electricity market and stimulating competition, especially within the subsector of electricity generation from renewable sources (except hydro). While our data cover the period until 2019, policy has changed in the last few years, e.g., feed-in tariffs are being replaced by auctions; the deployment of smart grids and dynamic tariffs, etc.[15] Another starting point could be limiting the amount of subsidies, since findings from the production function approach raise doubts on whether operating subsidies are desirable from the perspective of technical efficiency.

From the perspective of firms in the electricity sector, it is equally important to implement specific strategies targeted at improving technical efficiency. In particular, our findings imply that firms could aim to promote investment in equipment; raise average hourly wage and control working time of the employees in order to grant stronger incentives to the pursuit of higher efficiency.

Moreover, given the reliance of economic development on the use of electricity and the global imperative to reduce carbon emissions, higher efficiency in the electricity sector must be sought if the UN Sustainable Development Goals[16] are to be achieved.

There are still a few imperfections in our study which we hope to overcome in future research. First, due to the nature of the database, the measures for output of the electricity sector are not ideal even though we have deflated them with electricity price.[17] Likewise, we are unable to incorporate environmental/policy factors as determinants

[15] See, for example, https://www.iea.org/reports/portugal-2021.

[16] To be specific, SDG 7, affordable, reliable and modern energy; SDG 8, sustained, inclusive and sustainable economic growth, full and productive employment and decent work; SDG 13, combat climate change and its impacts.

[17] As the database consists of data for firms in all Portuguese economic sectors, physical variables are not included in it the database. Deflating the revenues by electricity price is still imperfect, since different users face different tariffs and there exist different price schemes like feed-in tariffs, state

**Table 6**
Estimated results for KLH cost frontier functions of Portuguese electricity subsectors.
*Source:* Estimation of Stochastic Frontier models using Stata.

| Variable | Coefficients | | | |
|---|---|---|---|---|
| | Hydro | Thermal | Other renewables | TTD |
| Frontier | | | | |
| $lnW$ | 2.07***(.326) | 1.35***(.176) | .658***(.252) | .160(.225) |
| $(lnW)^2$ | .016(.010) | .033***(.002) | .043***(.005) | .026***(.004) |
| $lny$ | .446**(.221) | 1.70***(.466) | −.297(.295) | −.997**(.408) |
| $(lny)^2$ | .010(.007) | −.024*(.014) | .026**(.010) | .049***(.012) |
| $lnW * lny$ | −.102***(.019) | −.069***(.010) | −.038**(.015) | .001(.010) |
| $t * lnW$ | −.003(.011) | −.002(.004) | .003(.008) | .008(.008) |
| $t * lny$ | .034***(.010) | .005(.005) | .011(.012) | −.034***(.008) |
| $t$ | −.529***(.185) | .018(.100) | −.034(.213) | .577***(.177) |
| $t^2$ | −.002(.007) | −.008**(.003) | −.011*(.007) | −.004(.005) |
| Intercept | 3.10(2.26) | −8.27**(3.93) | 11.7***(2.73) | 16.2***(3.80) |
| Inefficiency terms | | | | |
| $\sigma_U^2$ | −9.12(155) | −10.8(228) | −9.87(234) | −1.81***(.627) |
| $\sigma_\kappa^2$ | −7.49(76.7) | −7.13(109) | .790(.555) | −8.13(649) |
| Obs. | 145 | 239 | 154 | 100 |
| N. Groups | 34 | 48 | 53 | 25 |

Note: $lnW = \ln(\frac{w_L}{w_K})$; standard errors are in parentheses.

* Stands for statistical significance at 10% level.

** Stands for statistical significance at 5% level.

*** Stands for statistical significance at 1% level.

**Table 7**
Estimated results for truncated normal models and TVIM of cost frontier functions of the Portuguese electricity sector.
*Source:* Estimation of Stochastic Frontier models using Stata.

| Variable | Coefficients | | |
|---|---|---|---|
| | Model 1 | Model 2 | TVIM |
| Frontier | | | |
| $lnW$ | .522***(.145) | .483***(.134) | 1.06***(.101) |
| $(lnW)^2$ | .028***(.003) | .034***(.003) | .031***(.002) |
| $lny$ | −.240(.166) | −.426**(.169) | −.126(.100) |
| $(lny)^2$ | .026***(.004) | .032***(.004) | .022***(.004) |
| $lnW * lny$ | −.016*(.008) | −.019**(.008) | −.048***(.006) |
| $t * lnW$ | .011**(.005) | .008**(.004) | −.005(.003) |
| $t * lny$ | −.018***(.006) | −.013**(.005) | .006(.004) |
| $t$ | .275**(.115) | .318***(.105) | .011(.162) |
| $t^2$ | −.003(.004) | −.008**(.004) | −.007(.008) |
| Intercept | 9.17***(1.81) | 5.34**(2.23) | 13.8***(1.73) |
| (Dummies omitted) | | | |
| Inefficiency term: mean | | | |
| LAGE | | .284***(.073) | |
| CD | | .263***(.026) | |
| FIC | | .607*(.315) | |
| FIV | | −1.07***(.246) | |
| SSD | | −3.37(4.33) | |
| AVHR | .103(.469) | | |
| AVWG | −.004(.122) | | |
| Intercept | −.890(3.49) | 2.41***(1.51) | 4.97***(1.40) |
| Inefficiency term: variance | | | |
| LAGE | .600***(.173) | | |
| CD | .504***(.071) | | |
| FIC | 2.66***(.918) | | |
| FIV | −6.05***(1.14) | | |
| SSD | −19.0(20.9) | | |
| AVHR | | −1.34***(.508) | |
| AVWG | | 2.03***(.525) | |
| Intercept | −7.16***(1.28) | 3.49***(3.45) | 1.16***(.236) |
| Inefficiency term: time variance | | | |
| $t$ | | | −.019(.055) |
| $t^2$ | | | .001(.004) |
| Obs. | 605 | 605 | 638 |
| Log likelihood | −1026.0033 | −974.4851 | −911.95986 |

Note: $lnW = \ln(\frac{w_L}{w_K})$; standard errors are in parentheses.

* Stands for statistical significance at 10% level.

** Stands for statistical significance at 5% level.

*** Stands for statistical significance at 1% level.

guaranteed prices or contract prices for business users (Amorim et al., 2013); these can remain constant for years.

for technical inefficiency. Second, applying more advanced Stochastic Frontier models could provide more consistent and accurate results, e.g., models that tackle potential endogeneity problems. As such, better data and econometrical models could provide a possible direction for future studies. Meanwhile some features uncovered in our study also provide hints for further exploration. Among the electricity subsectors, why do some enjoy higher mean technical efficiency than others? How exactly do operational factors affect technical inefficiency? Further research could try to answer these questions.

**List of acronyms**

ACER: European Union Agency for the Cooperation of Energy Regulators

CEER: Council of European Energy Regulators

COLS: Corrected Ordinary Least Squares

CSAPR: Cross-State Air Pollution Rule

DEA: Data Envelopment Analysis

EPS: Environmental Policy Stringency (index)

ERSE: Entidade Reguladora dos Serviços Energéticos (Regulatory Entity of Energetic Services)

H4CSF: homoscedastic four-component stochastic frontier

KLH: Kumbhakar et al. (2014)

OTE: overall technical efficiency

PMR: Product Market Regulation (index)

PTE: persistent technical efficiency

RTS: returns to scale

SFA: Stochastic Frontier Analysis

SEC: scale efficiency change

TTD: trade, transmission and distribution (of electricity)

TTE: transient technical efficiency

TVIM: Time-Varying Inefficiency Model

## CRediT authorship contribution statement

**Zheng Hou:** Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Catarina Roseta-Palma:** Writing – review & editing, Supervision, Formal analysis, Conceptualization. **Joaquim J.S. Ramalho:** Writing – review & editing, Supervision, Methodology, Formal analysis.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Zheng Hou reports financial support was provided by Fundação para a Ciência e a Tecnologia (Portugal). Catarina Roseta-Palma, Joaquim Ramalho reports financial support was provided by Fundação para a Ciência e a Tecnologia (Portugal). If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

The authors do not have permission to share data.

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## Appendix A

See Tables A.1–A.4.

## Appendix B

See Table B.1.

**Table A.1**
Descriptive statistics of the hydro subsector.
*Source:* Descriptive statistics for firms in the Portuguese electricity sector from the BPLIM database.

| Variable | Obs. | Mean | Std. Dev. | Unit |
|---|---|---|---|---|
| Output variables: | | | | |
| Production function: | | | | |
| $y$ | 1863 | 1.07e+08 | 1.13e+09 | Kwh |
| Distance function: | | | | |
| $y_1$ | 1863 | 6.74e+07 | 7.32e+08 | Kwh |
| $y_2$ | 1863 | 1.65e+07 | 2.31e+08 | Kwh |
| Input variables (production/distance function): | | | | |
| $K$ | 1863 | 6 055 749 | 3.92e+07 | Euro |
| $L$ | 1525 | 7394.07 | 56 522.1 | Hour |
| Cost variable (cost function): | | | | |
| $C^a$ | 496 | 1.19e+08 | 1.93e+09 | Euro |
| Input price variables (cost function): | | | | |
| $w_K$ | 496 | 2.594145 | 19.25219 | Ratio |
| $w_L$ | 607 | 9.321639 | 16.21654 | Euro/hour |
| Determinants of technical inefficiency (all functional forms): | | | | |
| Age | 1861 | 16.55508 | 13.31725 | Year |
| CD | 567 | 12.22927 | 2.779652 | Ratio |
| FIC | 1358 | .1108795 | .2829913 | Ratio |
| FIV | 1577 | .1398874 | .3075679 | Ratio |
| SSD | 1358 | .0022491 | .0395224 | Ratio |
| AVHR | 603 | 1686.642 | 511.7876 | Hour |
| AVWG | 607 | 9.321639 | 16.21654 | Euro/hour |

Note: Minimum/maximum values anonymized for confidentiality requirement of the database.

**Table A.2**
Descriptive statistics of the thermal subsector.
*Source:* Descriptive statistics for firms in the Portuguese electricity sector from the BPLIM database.

| Variable | Obs. | Mean | Std. Dev. | Unit |
|---|---|---|---|---|
| Output variables: | | | | |
| Production function: | | | | |
| $y$ | 2200 | 1.08e+08 | 6.97e+08 | Kwh |
| Distance function: | | | | |
| $y_1$ | 2200 | 8.90e+07 | 6.07e+08 | Kwh |
| $y_2$ | 2200 | 399 244.6 | 4 896 665 | Kwh |
| Input variables (production/distance function): | | | | |
| $K$ | 2200 | 3.94e+07 | 2.26e+08 | Euro |
| $L$ | 1816 | 43 230.29 | 241 015.3 | Hour |
| Cost variable (cost function): | | | | |
| $C^a$ | 566 | 3.48e+07 | 2.26e+08 | Euro |
| Input price variables (cost function): | | | | |
| $w_K$ | 566 | 50.3571 | 587.3607 | Ratio |
| $w_L$ | 812 | 12.82322 | 12.92574 | Euro/hour |
| Determinants of technical inefficiency (all functional forms): | | | | |
| Age | 2196 | 15.2796 | 9.658552 | Year |
| CD | 750 | 12.20229 | 2.730019 | Ratio |
| FIC | 1779 | .0722838 | .2316486 | Ratio |
| FIV | 1826 | .0876207 | .2439479 | Ratio |
| SSD | 1779 | .0047489 | .0481698 | Ratio |
| AVHR | 810 | 1710.787 | 453.4301 | Hour |
| AVWG | 812 | 12.82322 | 12.92574 | Euro/hour |

Note: Minimum/maximum values anonymized for confidentiality requirement of the database.

**Table A.3**
Descriptive statistics of the subsector of other renewables.
*Source:* Descriptive statistics for firms in the Portuguese electricity sector from the BPLIM database.

| Variable | Obs. | Mean | Std. Dev. | Unit |
|---|---|---|---|---|
| Output variables: | | | | |
| Production function: | | | | |
| $y$ | 5388 | 1.22e+07 | 3.72e+07 | Kwh |
| Distance function: | | | | |
| $y_1$ | 5388 | 8 179 360 | 2.99e+07 | Kwh |
| $y_2$ | 5388 | 17 301.29 | 631 488.6 | Kwh |
| Input variables (production/distance function): | | | | |
| $K$ | 5388 | 9 500 885 | 2.89e+07 | Euro |
| $L$ | 4263 | 1210.384 | 6142.572 | Hour |
| Cost variable (cost function): | | | | |
| $C^a$ | 992 | 2.91e+08 | 5.79e+09 | Euro |
| Input price variables (cost function): | | | | |
| $w_K$ | 992 | 30.18246 | 585.2606 | Ratio |
| $w_L$ | 962 | 9.456395 | 11.60023 | Euro/hour |
| Determinants of technical inefficiency (all functional forms): | | | | |
| Age | 5141 | 9.191208 | 5.899829 | Year |
| CD | 842 | 12.86092 | 3.435711 | Ratio |
| FIC | 3770 | .0892808 | .264399 | Ratio |
| FIV | 4401 | .1088209 | .2900235 | Ratio |
| SSD | 3770 | .0039548 | .0535065 | Ratio |
| AVHR | 958 | 1592.89 | 520.9343 | Hour |
| AVWG | 962 | 9.456395 | 11.60023 | Euro/hour |

Note: Minimum/maximum values anonymized for confidentiality requirement of the database.

**Table A.4**
Descriptive statistics of the TTD subsector.
*Source:* Descriptive statistics for firms in the Portuguese electricity sector from the BPLIM database.

| Variable | Obs. | Mean | Std. Dev. | Unit |
|---|---|---|---|---|
| Output variables: | | | | |
| Production function: | | | | |
| $y$ | 660 | 1.22e+09 | 4.22e+09 | Kwh |
| Distance function: | | | | |
| $y_1$ | 660 | 9.74e+08 | 3.87e+09 | Kwh |
| $y_2$ | 660 | 5.04e+07 | 3.29e+08 | Kwh |
| Input variables (production/distance function): | | | | |
| $K$ | 660 | 4.28e+07 | 3.93e+08 | Euro |
| $L$ | 628 | 162 801.5 | 903 811.5 | Hour |
| Cost variable (cost function): | | | | |
| $C^a$ | 215 | 2.09e+08 | 2.97e+10 | Euro |
| Input price variables (cost function): | | | | |
| $w_K$ | 215 | 10.06502 | 42.7616 | Ratio |
| $w_L$ | 429 | 12.17185 | 27,3877 | Euro/hour |
| Determinants of technical inefficiency (all functional forms): | | | | |
| Age | 635 | 21.80157 | 30.88298 | Year |
| CD | 357 | 9.890924 | 2.443717 | Ratio |
| FIC | 540 | .0379877 | .1751774 | Ratio |
| FIV | 493 | .102679 | .2641849 | Ratio |
| SSD | 540 | .0041765 | .0471529 | Ratio |
| AVHR | 426 | 1619.497 | 452.3095 | Hour |
| AVWG | 429 | 12.17185 | 27,3877 | Euro/hour |

Note: Minimum/maximum values anonymized for confidentiality requirement of the database.

**Table B.1**
Statistics on variables used in the cost function approach.

| Variable | 1st Quartile | Median | 3rd Quartile | Skewness | Kurtosis |
|---|---|---|---|---|---|
| $lny$ | 13.25495 | 15.32106 | 16.7461 | −1.656293 | 8.676622 |
| $lnC^a$ | 13.39565 | 14.98808 | 16.36901 | −.0173873 | 4.679085 |
| $w_K$ | 0 | .0002785 | .1655676 | 29.6292 | 973.915 |
| $w_L$ | 3.151875 | 7.459277 | 14.59747 | 14.4162 | 413.0098 |

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