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Efficiency and Environmental Factors in the US Electricity Transmission Industry

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Abstract : The electricity industry in most developed countries has been restructured over recent decades with the aim of improving both service quality and firms' performance. Regulated segments (e.g. transmission) still provide the infrastructure for the competitive segments and represent a notable amount of the total price paid by final customers. However there is a lack of empirical studies that analyze firms' performance in the electricity transmission sector. We conduct an empirical analysis of the US electricity transmission companies for the period 2001-2009. We use stochastic frontier models that allow us to identify determinants of firms' inefficiency and to control for weather conditions, potentially one of the most decisive uncontrollable factors in electricity transportation. Our results suggest that there is room for improvement in the performance of the US electricity transmission system. Regulators should also take into account that more adverse conditions generate higher levels of inefficiency and that achieving long-term efficiency improvements tends to deteriorate firms' short-term relative performance.

Keywords : electricity transmission, heteroscedastic stochastic cost frontiers, inefficiency determinants

JEL Classification JEL D22, L51, L94

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1. Introduction

The electricity industry in most developed countries has been restructured over recent decades with the aim of reducing costs, improving service quality and encouraging electricity utilities to perform efficiently. As a result, former state-owned utilities were privatized and electricity sectors were vertically separated into generation, transmission, distribution and commercialization, particularly in the Europe (see Jamasb and Pollitt, 2005). Whereas some of these segments such as generation and commercialization were opened to competition, other segments such as transmission and distribution are still regulated. In this sense, incentive-based regulation schemes have been recently implemented in several countries (e.g. UK, Norway) in order to encourage both transmission and distribution utilities to perform efficiently.

Joskow (2011) points out that for industries in which regulated segments provide the infrastructure platform upon which competitive segments rely, social welfare depends on firms' performance and reforms made in both regulated and competitive segments. Much of the research in the electricity industry has focused on competitive wholesale markets, although the regulated segments provide the infrastructure for the competitive segments and even though networks constitute a significant share of the final price paid by electricity consumers.[1] Even though electricity transmission is necessary for distribution and commercialization, there is a lack of empirical studies that analyze both the economic characteristics of the technology and firms' inefficiency in the electricity transmission.

Statistical benchmarking methods have been largely used in the electricity industry to determine the relative efficiency of individual firms' costs compared to their peers (see Brophy Haney and Pollitt, 2009, 2012). Obtaining reliable (and fair) measures of firms' inefficiency requires controlling for the different environmental conditions under which each firm operates. This is especially acute in benchmarking because of the financial implications that this analysis can have over the firms and their effect over the whole network.

One of the most decisive uncontrollable factors in electricity transportation (i.e. in transmission and distribution) is the weather conditions of the area in which the companies operate. Billinton and Wenyuan (1991), and Billinton and Acharya (2005) tried to explain changes in the probability of failure rate in the system using complex mathematical models. Generally speaking, they pointed out that most technical interruptions occur when weather is adverse and, in particular, extremely adverse. They also showed that assessing likely failure rates while ignoring weather tend to give too optimistic and erroneous predictions.

Regarding electricity transmission, Billinton and Wu (2001) pointed out that overhead transmission lines are exposed to a wide range of weather conditions and, that both failures rates and the probability of overlapping failures tend to increase sharply during periods of extremely adverse weather conditions. Rothstein and Halbig (2010) find that many atmospheric and hydrological parameters not only affect electricity generation and consumption, but also electricity transportation. Indeed, overhead lines are affected by atmospheric influences in several ways, such as failures by lightning, wind, additional weight (e.g. ice or snow), low temperatures, humidity and moisture.

[1] Typically distribution and transmission charges combined compose around 25% of the pre-tax and environmental charges residential bill.

Despite the potential role of weather conditions in electricity transportation, only a few recently published papers have analyzed firms' performance in the electricity distribution sector controlling for environmental factors. These include Nillesen and Pollitt (2010), Yu *et al.* (2009), Jamasb *et al.* (2010, 2012) and Growitsch *et al.* (2012). On the other hand, as far as we are aware there are only four published papers that separately study the performance of transmission firms, and none of them have controlled for weather characteristics and inefficiency determinants. Using a sample of US firms, Pollitt (1995) analyzed differences in efficiency between state-owned and private electricity transmission companies. He did not find significant differences between both types of firms using parametric and non-parametric specifications of the frontier model. Using US data, Huettner and Landon (1978) and Dismukes *et al.* (1998) have examined the existence of returns to scale in the provision of electric transmission services. Huettner and Landon (1978) do not find increasing returns to scale, except for one category of sales expenses. In contrast, Dismukes et al. (1998) find significant economies of scale for all the NERC (North American Electric Reliability Corporation) reliability regions using data for the period 1986-1991. Recently, von Geymueller (2009) carried out a comparison of static and dynamic DEA models in electricity transmission using data of 50 US utilities for the period 2000-2006. The author finds that static models tend to overestimate firms' inefficiency because they do not take into account the existence of quasi fixed inputs.

Our paper contributes to the literature analyzing firms' performance in the electricity transmission industry with an empirical analysis of the US electricity transmission system for the period 2001-2009. The analysis of economic characteristics of the technology (such as economies of scale or economies of density) and the inefficiency of each US utility relies on the estimation of several specifications of the heteroscedastic frontier model proposed by Caudill *et al.* (1995). In this model, the variance of the inefficiency term depends on a wide range of variables such as weather variables, a measure of companies' cost structure and growth rates of energy demand. Hence, unlike previous papers, our stochastic frontier models allow us to identify the determinants of firms' inefficiency in this industry.[2] An additional contribution of the present paper is that we control for weather characteristics by including a set of weather variables as determinants of firms' inefficiency that were gathered specifically for the present application. In addition, as our sample period is more recent than those analyzed in previous papers we can see whether there has been an improvement in average efficiency in the US electricity transmission industry.

The estimated coefficients provide useful information about the firms' performance with both policy and managerial implications. We find using more recent data and larger firms than in previous papers that, given network infrastructure, electricity transmission networks exhibit natural monopoly characteristics. Our results also indicate that more adverse conditions generate higher levels of inefficiency. However, we find that investing in capital is a better strategy than incurring additional operating costs to deal with adverse weather conditions. On the other hand, we find that, as expected, firms' performance gets better when demand tends to be steady as firms cannot adjust their inputs without cost over time. The average efficiency at the beginning of the period is larger than in previous studies. But, regardless of the estimated model, our results indicate that efficiency has declined (and diverged) over

[2] Our model also allows us to discuss whether the environmental factors should be treated as determinants of firms' performance or as technological cost drivers.

time, suggesting that there is room for improvement in the performance of the US electricity transmission system.

This paper is organized as follows. Section 2 provides a brief review of transmission and distribution literature and the most commonly used approaches to implement in incentive regulation schemes. Section 3 describes the theoretical cost function that we estimate as well as the empirical specification of the model. Section 4 presents the data and variables used in the empirical analysis. Section 5 reports the parameter estimates and the results obtained from those estimates. Section 6 presents the main conclusions.

2. Benchmarking in electricity transmission

The electricity sector is an industry with different and interrelated activities, which are affected by production and consumption decisions across the whole system. The US electricity system traditionally has been composed of large vertically integrated utilities. Nevertheless, in the last two decades several reforms have been implemented with the aim of disaggregating most utilities into differentiated segments. These reforms have led to different treatments of the separated activities: generation and supply (retail) are regarded as potentially competitive markets, while transmission and distribution networks are treated as natural monopolies that have to be regulated (see Joskow, 2011). As Jamasb and Pollitt (2007) point out, from an economic perspective, the aim of electricity unbundling is to provide utilities with incentives to improve their operating and investment efficiency and to ensure that consumers benefit from the gains. The main methods used to achieve these objectives are the incentive regulation mechanisms, which include financial rewards and penalties for the firms linked with their performance.

Joskow (2011) notes that much of the research in this sector has focused on the competitive markets although the regulated segments provide the infrastructure for the competitive segments and represent an important amount of the total price paid by final consumers and they have an important joint effect with competitive segments on social welfare. For these reasons, electricity transmission has played an important role in the success of liberalised power markets. Electricity reforms have led to the creation of some bodies to perform the coordination functions that formerly were internal to the firms. To deal with this issue and the stresses in transmission system after years of underinvestment, the Federal Energy Regulatory Commission (FERC) pursued the implementation of a Standard Market Design and encouraged the so-called Regional Transmission Organizations (RTO) to facilitate efficient trade over wide areas and transmission investment. According to Greenfield and Kwoka (2011), the RTOs – such as PJM - provide transmission services but do not own transmission facilities and they are not responsible for the maintenance and repair, or fixed investment costs, of the transmission facilities over which they direct the flow of power. Their essential role is as independent service provider that administers the terms and conditions of transmission services and maintains the short-term reliability of the network.

Despite the importance of RTOs in the overall performance of the electricity system, the transmission utilities and the structure of the network charges have a great effect on network use and its development. Following Brunekreeft *et al.* (2005, p.74-75), the setting of the charges at an appropriate level is a key issue because it affects "the locational choices of new generation (and of energy intensive users), as well as influencing the bidding behavior of generators, and the willingness of neighboring electricity markets to trade and cooperate". As a result, "ideally the structure of network charges should encourage: *i*) the efficient short-run use of the network (dispatch order and congestion management); *ii*) efficient investment in expanding the network; *iii*) efficient signals to guide investment decisions by generation and load (where and at what scale to locate and with what choice of technology-base-load, peaking, etc.); *iv*) fairness and political feasibility, and *v*) cost-recovery" (Brunekreeft *et al.*, 2005, p.75).

There are different regulatory practices across the world to set the total amount of network charges in the electricity market which are mostly based on benchmarking, i.e. on measuring firm's efficiency against the firms with best practice performance (see Brophy Haney and Pollitt, 2012). As regulators reward or punish firms according to their (in)efficiency level, the reliability of these scores is particularly crucial for regulatory credibility. Any efficiency estimate tries to measure the gap between actual cost (production) and the optimal point on the cost (production) frontier, which must be estimated from the available data. Published papers have basically employed two approaches to estimate cost (production) frontiers. The first approach includes parametric techniques that require specifying a particular functional form for the cost or production frontier, such as the Stochastic Frontier Approach (SFA) or Ordinary Least Squares (OLS). The second approach is the non-parametric Data Envelopment Analysis (DEA) which requires fewer assumptions about the shape of the efficiency frontier. Both parametric and nonparametric techniques have their pros and cons, and the selection of an appropriate estimation method is contentious and may influence the obtained results and the consequent regulatory policy implications (see, for instance, Coelli *et al.*, 2005).

Despite the relevance of transmission networks in the electric power industry is very difficult to implement a statistical benchmarking for most of the countries due to the lack of domestic comparators (Brophy Haney and Pollitt, 2012). International benchmarking can be an alternative to deal with this issue, but the regulators face several problems. Joskow (2011, p.54-55) notes that the layout of the transmission network depends on countless factors, such as "the distribution of generators and load, population density, geographic topography, the attributes and age of the legacy networks' components and various environmental constraints affecting sitting of new lines, transformers and substations". Moreover, there is no standardization or homogeneity among countries about the voltage boundaries between transmission and distribution networks. For instance, in the UK the transmission network is formed by elements that run at 275 kV and above, while in other countries like the U.S. or France transmission network is formed by elements that run above 60 kV, making an international comparison a challenging task. Regarding the inputs and outputs that should be taken into account in an empirical analysis on efficiency of transmission systems, Pollitt (1995) pointed out that it might be desirable to take every specific factor of the company into account due to the complexity of the network. Each transmission system is unique because of the different kinds of inputs that they use and the environment in which they operate.

By constrast, statistical benchmarking methods have been largely used in electricity distribution to determine the relative efficiency of individual firms' operating costs and service quality compared to their peers.[3] Some countries such Germany, Nordic countries and Switzerland have a large number of utilities. This provides a

[3] Jamasb and Pollitt (2001) show the most used approaches and provide a survey of benchmarking studies applied mainly in OECD countries.

suitable basis for the use of advanced benchmarking techniques and without necessarily having recourse to international benchmarking. It is generally desirable for regulators to have a large number of utilities for comparison and efficiency benchmarking.

As mentioned above, obtaining reliable (and fair) measures of firms' inefficiency requires controlling for the different environmental conditions under which each utility operates. This is especially acute in benchmarking because of the financial implications that this analysis can have over the firms and their effect over the whole network. For this reason, recent studies in electricity distribution have tried to control for the effect on firms' performance of several environmental factors, such as weather conditions, across the electricity distribution system. For instance, Korhonen and Syrjänen (2003) develop an approach to evaluate the cost-efficiency of Finnish electricity distribution companies based on DEA paying attention to environmental variables under which the companies operate. Yu *et al.* (2009) have also highlighted the importance of considering external factors when evaluating the effectiveness of regulatory policies in the UK electricity distribution industry. These authors show using nine weather variables that severe weather conditions tend to increase service interruptions, and this in turn increases costs associated with replacing the damage equipment and restoring power.

Jamasb *et al.* (2010 and 2012) also find that weather matters in the UK distribution network and conclude that weather variables should be included as cost drivers.[4] Using weather and geographic composites, Growitsch *et al.* (2012) do not find a large influence of environmental variables on the distribution companies' efficiency and the average efficiency rankings. However, the effect on the cost is remarkable. Their simulations predict up to 30% lower costs than average, for utilities that operate in areas with extremely good environmental conditions, and up to 39% higher costs than average, for utilities that operate in areas with extremely bad environmental conditions. On average, they predict higher costs of about 5% as a result of hostile weather conditions.

Finally, Nillesen and Pollitt (2010) have also applied a benchmarking analysis including environmental conditions to study the performance of electricity distribution companies in the U.S. and correcting those variables for estimating the potential efficiency gains. They do not find that companies with unfavorable conditions are worse performers.

3. Theoretical model and empirical specification

In this section we introduce the theoretical cost model that allows us to analyze the economic characteristics of the technology, such as economies of scale or economies of density, of US electricity transmission firms. In general terms, the cost function to be estimated can be written as:

$$\ln C = \ln C(y, n, p, t) \tag{1}$$

where C is a measure of total costs, y is a vector of outputs, n measures the network length, p is a vector of input prices, and t represents the time trend. As usual, if firms

[4] Their results also suggest that the lack of inclusion of variables related to weather conditions might downward bias the estimated coefficients of other relevant variables, and, in particular, those associated to marginal cost of quality improvements.

minimize cost, this function should be linearly homogeneous with respect input prices, and increasing in outputs.

Our cost variable is total expenditure (i.e. operating plus capital costs) due to the presence of possible trade-offs between operating and capital expenditures (Giannakis *et al.* 2005). The literature on electricity networks also suggests a positive relationship between cost and network length, thus the system size variable used in our application. Besides the network length, Ofgem (2011, p.44-46) recognizes the peak demand, the energy delivered and the age of assets as the fundamental cost drivers in electricity transmission. All of these variables are included in our cost function except age of assets as its effect on total cost is not clear as older assets imply higher operating costs but lower capital outlays.[5]

Economies of scale and density of electricity transmission firms can be computed once equation (1) is estimated. We associate economies of scale with *horizontal* system expansion, that is, increases in demand that require enlarging the current network to meet extra demand.[6] These economies can be then measured by the sum of cost elasticities with respect to the outputs, *y*, and the network length, *n*:

$$ES = \frac{\partial \ln C}{\partial \ln y} + \frac{\partial \ln C}{\partial \ln n} \tag{2}$$

While a value of ES less than one indicates the existence of economies of scale, a value higher than one indicates the existence of decreasing returns to scale. Looking at the results obtained for US electricity transmission by Huettner and Landon (1978), Pollitt (1995) and Dismukes *et al.* (1998) we expect to find economies of scale in our empirical application.

On the other hand, we associate economies of density with *vertical* system expansion, i.e. expansion in transmitted electricity that do not require additional network. These economies can be measured by the sum of elasticity of cost with respect to the outputs, *y*.

$$ED = \frac{\partial \ln C}{\partial \ln y} \tag{3}$$

In this case, the cost elasticity of network is not taken into account, as we are considering an increase in output levels, given the actual length of the transmission network.

Measuring gaps between actual costs and efficient (i.e. minimum) costs requires estimating a cost frontier from the available data. The stochastic frontier literature suggests that deviations with respect to the cost frontier cannot be entirely attributed to inefficiency and hence we must control for other sources of deviations (i.e. random noise) to achieve this objective. To capture other sources of deviations, Aigner *et al.* (1977) proposed using an econometric specification of the cost function (1) that includes two random terms, measuring respectively random noise and inefficiency. This model can be presented as follows:

$$\ln C_{it} = \alpha + X_{it}'\beta + v_{it} + u_{it} \tag{4}$$

where *i* stands for firms and *t* for time, X_{it} is a vector of explanatory variables, α and β are parameters to be estimated, $v_{it} \sim N(0, \sigma_v^2)$ is the classical symmetric random noise,

[5] We included age of assets in our first estimates but this variable was not statistically significant.

[6] Note that here density is held constant because both output levels and network size is expanded simultaneously.

and u_{it} is a one-side error term which captures inefficiency. Following Aigner *et al.* (1977), we assume that this term follows a half-normal distribution, i.e. $u_{it} \sim N^+(0,\sigma_u^2)$. We also assume that v_{it} and u_{it} are not correlated with each other or with the explanatory variables.

An important caveat of this basic model is that it does not allow the examination of the determinants of firms' performance, which is the main issue examined in this paper, as the inefficiency term in (4) has constant variance. It might also yield biased estimates of both frontier coefficients and firm-specific inefficiency scores (see Caudill and Ford, 1993).[7]

There are some models in the stochastic frontier literature that permit incorporating efficiency determinants.[8] Among the set of proposed heteroscedastic models in the literature, we propose estimating a model that satisfies the so-called *scaling property,*[9] which implies that our inefficiency term can be written as a deterministic function times a one-sided random variable that does not depend on any efficiency determinant. In this case, u_{it} can be written as:

$$u_{it} = h(m_{it}, \gamma) \cdot u_{it}^* \tag{5}$$

where $h(\cdot)$ is a scaling function that always takes positive values, m_{it} is a vector of efficiency determinants, γ is a vector of parameters to be estimated, and u_{it}^* is a random term that follows a half-normal distribution with constant variance, σ_u^2. As equation (5) implies that our inefficiency term u_{it} is distributed as $N^+(0,\sigma^2_{it})$, where $\sigma_{it} = h(m_{it},\gamma)$, the defining feature of models with the scaling property is that firms differ in their mean efficiencies, but not in the shape of the distribution of inefficiency. That is, the scaling property implies that changes in m_{it} affect the scale but not the shape of u_{it}.

In this model u_{it}^* can be viewed as a measure of "raw" inefficiency that does not depend on any observable determinant of firms' inefficiency. On the other hand, the scaling function $h(\cdot)$ can be interpreted as the portion of total estimated inefficiency that researchers are able to explain with the variables included in $h(\cdot)$. This function hence "adjust" the underlying, and unexplained, inefficiency level upwards or downwards due to the influence of some potential inefficiency determinants.

Although it is an empirical question whether or not the scaling property should hold, it has some features that we find attractive (see Wang and Schmidt, 2002). For instance, we prefer the above multiplicative decomposition of u_{it} instead the alternative additive decomposition of the form $u_{it}(m_{it},\gamma) = h(m_{it},\gamma) + \tau_{it}$ introduced by Huang and Liu (1994) and Battese and Coelli (1995) because the additive decomposition can never actually be a decomposition into independent parts as $u_{it}(m_{it},\gamma) \geq 0$ requires $\tau_{it} \leq h(m_{it},\gamma)$. In our model, we can decompose u_{it} into explained and unexplained inefficiency simply dividing the estimated inefficiency by the estimated value of $h(\cdot)$. Moreover, the interpretation of γ does not depend on the distribution of inefficiency, and simple scaling functions yield simple expressions for the effect of m_{it} on mean efficiency. In

[7] Although the stochastic specification in (4) is able to control for random noise, the presence of unobserved heterogeneity among observations might bias the efficiency measures. Different empirical strategies have been developed in the literature to deal with this problem (see Greene, 2005a, b, and more recently Wang and Ho, 2010). However, these strategies do not easily deal with rarely changing variables, i.e. variables with little within or temporal variation such as network length or energy delivered. For a discussion on this issue, see Greene *et al.* (2011).

[8] For a review of this literature see Kumbhakar and Lovell (2000).

[9] See Álvarez *et al.* (2006) for a review of the models that incorporate this property in the literature on frontier production functions.

this sense, if we follow Caudill *et al.* (1995) and use an exponential scaling function so that $h(m_{it},\gamma) = \exp(m_{it}'\gamma)$, then the γ are just the derivatives of $\ln(u_{it})$ with respect to m_{it}, and have standard interpretations as marginal effects. In addition, if $h(m_{it},\gamma)$ only includes a time trend as a determinant of inefficiency (i.e. m_{it}=t), our model is similar to Battese and Coelli (1992) but using a pooled specification for the inefficiency term.

Inserting (5) into (4) and assuming an exponential scaling function, the model to be finally estimated can be written as:

$$\ln C_{it} = \alpha + X_{it}'\beta + v_{it} + exp(m_{it}'\gamma) \cdot u_{it}^{*} \tag{6}$$

4. Data and sample

We use a panel data set of 59 U.S. electricity transmission companies for the period 2001-2009. Most of these data were collected by various members of the EPRG at the University of Cambridge. That information was requested by the British regulator, Ofgem, in order to carry out an international benchmarking of electricity and gas utilities. When the transmission operations are part of a larger utility - also involved in generation or distribution - shared costs are allocated on pro-rata basis. As can be seen in the data appendix, an allocation key based on the ratio between wages and salaries specific from transmission and the total labour expenses of the utility, were used for the assignment of shared costs to transmission. The main source of the electricity transmission data was the FERC form 1, an annual report of major electric utilities, and the variables collected included the: quantity of assets, voltage levels by asset, maximum demand, load density, demand growth, maturity of service area, age/condition of network, network density and flow patterns.[10]

Although the choice of input and output variables is an important issue, there is no clear consensus about the variables that should be included to describe the performance of transmission and distribution companies. Jamasb and Pollitt (2001) show the wide range of variables that have been used in benchmarking analysis of electric utilities. They find that the most common used inputs in studies of electric utilities are operating costs, number of employees, transformer capacity, and network length. Regarding the outputs, the most included variables are units of energy delivered, number of customers, and the size of service area.

As we have mentioned in Section 3, our cost variable is Totex. This variable is the sum of Opex, which includes operation and maintenance expenses incurred by the

[10] The original dataset was collected by the members of the EPRG and it includes information of electricity and gas utilities in the US from 1994 to 2009 and also contains information on non-US firms from other countries for a shorter period. Following Ofgem's (2011, p. 20) report, non-US transmission firms were not included in the analysis due to data limitations. Despite of the initial proposal on international benchmarking in that report, so far, these data have not been used. In our paper the sample was reduced to the last 9 years because labour costs in the electric power transmission industry are only available from 2001 to 2009. We have removed observations with missing and implausible values. We have also dropped a few number of isolated observations and maintained firms with (at least three) consecutive observations in order to minimize changes in our estimates when we change the specification of our model. It should be noted that this procedure does not give us a balanced panel, as we do not have the same number of observations per firm. Our final sample is an unbalanced panel data set of 405 observations without discontinuities across time.

company over one year, and Capex, which is the sum of annual depreciation on capital assets and the annual return on the balance of capital.[11]

Following the basic economic theory of production and the literature on electricity networks, we use as explanatory variables of total cost: two types of outputs, a variable that measures the system size, labour and capital price, an investment variable and a time trend. Our output variables are *Peak Load* (PL) and *Electricity Delivered* (DE). While the first one is the maximum peak load of the year during 60 minutes and it might reflect transmission investment requirements given a fixed transmission capacity, the second one is the total annual energy delivered by the system which may imply an incremental effect in operating cost due to a greater use of electricity transmission assets. In Figure 1 we show the evolution over time of the output variables divided by Totex, which can be interpreted as partial and observable productivity (efficiency) measures.[12] We can see in this figure a clear negative trend of the peak loads given the total expenditure of each firm. In the case of electricity delivered, the temporal pattern of this variable is not so clear. These graphs give us a first idea about the negative evolution of the efficiency in our sample as the output level per dollar of cost, decreases, or in other words, the total unit cost per output, increases over time.

[Insert Figure 1]

Network length (NL) is usually viewed as one of the most important cost drivers of an electricity network (Jamasb and Pollitt, 2001). To measure the network length we have used pole miles. This variable measures the total sum of all transmission lines in miles regardless of the number of power cables on each power line so it is essentially a measure of the geographic spread of each company. We thought about using circuit miles instead pole miles, but the problem of circuit miles is that this variable refers to the number of power cables on each line multiplied by the distance between two points, but it does not take into account the capacity of the cable so it is an unreliable measure of the physical infrastructure.

The electricity industry is highly intensive in capital with much of the assets becoming quasi-fixed (or sunk cost) upon investment (Jamasb and Pollitt, 2007). This implies that adapting quasi-fixed inputs to the needs of the network is not costless and, hence, they cannot be instantaneously adjusted as it has been implicitly assumed in equation (2). To avoid this assumption, and following Morrison (1985), we include a measure of investment in our cost function. In particular, the *Investment Proxy* (INV) measures the total transmission plant 'additions' of the companies at the end of the year once the value of the land and the land rights have been deducted. We expect a positive coefficient for this variable as it allows us to control for adjustment costs incurred by putting new capital into place.

Regarding input prices, we include in the cost function a *Labour Price* variable (LPR) defined as the average annual wage for the electric power transmission and distribution industry by state.[13] Regarding the *Capital Price* variable (KPR), we have finally used a producer price index for power transmission, available at state level, as a

[11] RTO costs are included in the total costs. For more information about the calculation of Totex and the rest of variables, see the appendix.

[12] As we have an unbalanced panel of 59 firms, to depict this figure we have selected those firms that are observed during the whole sample period, i.e. 29 firms. This avoids comparing different sets of firms in different periods.

[13] Unfortunately this information is not available at firm-level.

proxy for capital price.[14] The source of these two variables is the Quarterly Census of Employment and Wages from the Bureau of Labor Statistics.

We use 9 variables that are expected to affect firms' performance and, hence, they are included as determinants of the efficiency term. In particular, we include the following variables: another time trend, three weather variables (minimum temperature, wind and precipitation),[15] the ratio Capex/Opex and two variables which measure the growth of the demand. We gradually introduce these variables in the model in order to examine the robustness of our parameter estimates.[16]

Our weather variables have been obtained from the surface daily weather information collected by the National Climatic Data Center for the 2001–2009 period. The files available for the around 3,000 weather stations located in the U.S. contain information about: mean, maximum and minimum temperatures, precipitation amount, wind speed, number of days with snow, hail, tornadoes, etc. Given the high correlation among several weather variables, we decided to include one variable for each one of these categories: *Temperature* (TMIN), *Precipitation* (PRCP) and *Wind* (WIND). The temperature variable is the annual minimum temperature in Fahrenheit degrees, wind speed is the average of the daily mean wind speeds in knots, and precipitation is the average of the daily precipitation in inches. These weather variables are measured at state-level, not at firm-level. In order to obtain a unique value of each variable per state and year, we have taken the average among the weather stations within a particular state except for the case of the temperature variable which is the minimum daily value measured by any of the above stations along the year. Then, each utility was associated with the weather of the state where its principal office is located[17]. We hereafter assume that more adverse conditions appear when wind speed and precipitation are high and minimum temperature is small.

As utilities may adapt their operating and investment practices over time to prevent power interruptions and to reduce the effect of adverse weather conditions, we interact our weather variables with the mean of the ratio of Capex and Opex (COR) for each firm i over the T_i available observations for this firm. We expect a negative coefficient if investing in Capex is a better strategy rather than incurring additional operational and maintenance costs in dealing with adverse weather conditions.

Finally we have included two variables that measure the average *Growth in Demand* for each firm over time. We distinguish between positive growth (POSGR) and negative growth (NEGR). The coefficients of these two variables should not be statistically significant if there are not adjustment cost and all inputs can be adjusted (without cost) from one year to the next. However, as the electricity industry is highly intensive in capital with much of the assets becoming sunk cost upon investment, we

[14] We have estimated our models using several indices and variables calculated with financial information of the companies. Their coefficients were not statistically significant or they even had unreasonable magnitudes from an economic point of view.

[15] We firstly introduced the weather variables in our cost function as determinants of the technology, i.e. of the frontier cost function. These variables become not significant once our weather variables were introduced simultaneously as inefficiency determinants. For this reason we include weather only in the stochastic part of our model as a determinant of the efficiency term.

[16] We have also tried to include other variables related with the regulation of the sector, like regional dummies for the NERC regions, the level of vertical integration and the percentage of own generated energy that flows through the transmission utility, but we either found convergence problems when maximizing the likelihood function or that the estimated coefficients were not statistically significant.

[17] We recognise that this is a limitation especially when transmission companies may cover more than one state.

expect significant coefficients for POSGR and NEGR. In particular, we expect a positive effect of POSGR on inefficiency indicating that utilities tend to anticipate future increases in the demand by investing in capital that is expected to be efficiently used in the future, but not in the present.[18] We expect a negative coefficient NEGR if there is a negative trend in demand and reducing quasi-fixed input levels is expensive due to the existence of adjustment costs.

The descriptive statistics of all monetary, physical variables and environmental used in the stochastic cost frontiers are shown in Table 1.

[Insert Table 1]

5. Empirical results

We estimate a Translog cost function. This function can be interpreted as second-order approximation to the companies' underlying cost function. All the variables are included in the model in logarithms, except the time trend. Each explanatory variable is measured in deviations with respect to its mean, so the first-order coefficients can be interpreted as the cost elasticities evaluated at the sample mean. As usual, homogeneity of degree one in prices as imposed by normalizing cost and labour price with capital price. Thus, the estimated equation can be written as follows:

$$\begin{aligned}\ln\left(\frac{C_{it}}{KPR_{it}}\right) &= \alpha + \sum_{p=1}^{3}\beta_p \ln y_{pit} + \frac{1}{2}\sum_{p=1}^{3}\sum_{q=1}^{3}\beta_{pq}\ln y_{pit}\ln y_{qit} + \\ &\beta_L \ln\left[\left(\frac{LPR_{it}}{KPR_{it}}\right)\right] + \beta_{LL}\left[\ln\left(\frac{LPR_{it}}{KPR_{it}}\right)\right]^2 + \sum_{p=1}^{3}\beta_{pL}\ln y_{pit}\ln\left(\frac{LPR_{it}}{KPR_{it}}\right) + \\ &\beta_T t + \beta_{TT}t^2 + \sum_{p=1}^{3}\beta_{pT}t\ln y_{pit} + \beta_{INV}\ln INV_{it} + u_{it} + v_{it} \qquad (7)\end{aligned}$$

where for notational ease, the vector y stands for outputs and network length, i.e. y=(PL, DE and NL). We show in Table 2 the estimated parameters using two alternative specifications for the stochastic part of the model: the basic stochastic frontier model introduced by ALS which is labeled as model M1, and several heteroscedastic stochastic frontier models that include inefficiency determinants. We propose introducing gradually four sets of inefficiency determinants in order to see the robustness of our parameter estimates. These models are labeled from M2 to M5.

[Insert Table 2]

In general, all models perform quite well as most of the first-order coefficients have the expected sign and their magnitudes are quite reasonable from a theoretical point of view. Certainly, the coefficients of the two outputs are always positive and statistically different from zero when measuring the incremental costs associated to either higher maintenance and operational costs or the need of new capital. A similar statement can be made about the coefficients of input prices, which are also positive and statistically significant. The coefficient on the time trend is negative, which indicates that costs decrease over time, i.e. there is technical change. However, this technical change is non-neutral as the coefficient on the time trend is negative when interacts with electricity delivered and network length, but it is positive when accompanies the peak

[18] As Jamasb and Pollitt (2007) note, achieving long-term efficiency improvements can involve short-term increases in Capex or Opex that may not generate immediate efficiency improvements. In fact, increases in short-term expenditure can deteriorate the firms' short-term relative performance. This might in turn discourage firms from efficiency-improving investments that have long-term gains.

load. The coefficient of the investment variable is positive and statistically significant which suggests, as abovementioned, the existence of adjustment costs associated to changes in quasi-fixed inputs when new capital is added. The estimated coefficients for these variables maintain the signs and similar values as we introduce the blocks of variables in the variance of the inefficiency term.

In model M2 we also introduce a time trend but as a determinant of the inefficiency. The coefficient of the time trend in this case is positive, indicating that efficiency levels decrease over time. In M3 we introduce three weather variables. Our results indicate that weather is an important issue in this industry. Moreover, the negative sign for the minimum temperature shows us that lower minimum temperature increases cost due to higher levels of inefficiency. Average wind speed and average precipitation have a positive coefficient indicating again that more adverse conditions generate higher levels of inefficiency. In model M4 we include the average ratio of Capex and Opex (COR) interacting with the weather variables to catch an idea about the best strategy to deal with adverse weather conditions. The estimated coefficients have the opposite sign to those obtained for the isolated weather variables, indicating that, as expected, that more capital-intensive utilities (e.g. with higher capital-to-opex ratios) are able to mitigate better the effect of unfavourable weather conditions, and hence tend to be, *ceteris paribus*, more efficient than those utilities using a higher proportion of operating inputs. This result suggests therefore that investing in equipment is a better strategy than incurring additional operating costs in mitigating the effects of unfavourable weather conditions.

The next set of variables incorporated in model M5 are two firm-specific rates of growth of the demand. We get the expected sign of the coefficients for POSGR and NEGR, indicating as we supposed that utilities are more efficient in stable environmental conditions or, more specifically, when the demand is unchanging.

As the most comprehensive model M5 nests the previous ones, we employ a likelihood ratio test to analyze whether simpler models are as good as model M5. As it can be viewed in Table 2, the performed tests allow us to reject models M1 to M4 in favour of the Model M5. We then use this model to examine in detail both the estimated levels of cost efficiency and the characteristics of the estimated technology.

In Figure 2 we depict the histogram of estimated levels of cost efficiency. The average efficiency in our sample is 85.2% using our preferred model.[19] Pollitt (1995) using 1990 data found an average efficiency of 80% for the total of the companies in his sample and 88.3% for larger firms. The latter value exceeds the one that we have found with our preferred model. This seems to indicate that the performance of the electricity transmission utilities has not experienced a significant improvement from one period to the next. As we have mentioned in Section 3, the estimated inefficiency in our model can be decomposed into two independent components, one explained and the other unexplained. The latter component can be simply obtained dividing the estimated efficiency scores by the values of the scaling function and we obtain the "raw" scores of inefficiency. The average raw efficiency obtained after the correction is virtually equal to the one obtained from the estimates. This implies that the inefficiency determinants in

[19] Using the ALS model, the average efficiency is 77.3%. This is lower than the mean value of efficiency obtained with our preferred heteroscedastic model. Regarding the ranking of firms the correlation coefficient between the rakings obtained with M1 and M5 is also too low as it takes the value of 0.54. These differences might be taken as an anecdotal evidence of the biases that might appear in an empirical application when inefficiency determinants are not taken into account.

model M5 allow us to explain the raw inefficiency but not to reduce the inefficiency estimated.

[Insert Figure 2]

We show in Figure 3 the temporal evolution of our efficiency scores. The graph shows that the average level decreases over time, starting at 91.7% and finishing at 77.3%. It should be noted that this worsening of firms' performance is also obtained using more restricted model, such as Model 2 that only includes a time trend as an efficiency determinant and its coefficient is positive indicating that average inefficiency rises over time. All estimated models suggest increasing divergence in performance over time. Overall, the estimated evolution in performance and the lack of convergence in firms' inefficiency scores seem to suggest that there is scope for improvements in the performance of the US electricity transmission system.

[Insert Figure 3]

Next, we use our preferred Model 5 to examine some characteristics of the estimated technology. Like in previous papers, the estimated elasticities allow us to measure economies of scale and density, but in this case using more recent data.

Figure 4 depicts the elasticity of total cost with respect to peak load, delivered electricity and network length estimated for each observation, sorted in increased order at the observation-level. Peak load seems to be the most important cost driver with an average elasticity equal to 0.48. This figure also allows us to examine the reliability of our estimated elasticities when we move away from the sample mean. Although the first derivative of our cost function just provides a first-order approximation to the underlying elasticity at the sample mean, most observation-specific elasticities are in a reasonable order of magnitude, except for the negative values on the left in two of the curves. In these cases, our estimates should be viewed with caution as they correspond to some observations which are far away from the sample mean.[20]

[Insert Figure 4]

Adding the first-order coefficients of the two outputs we find that the elasticity of density evaluated at the sample mean is quite similar in all models, varying from 0.49 to 0.54. These values suggest the existence of important economies of density in the electricity transmission industry. That is, given network infrastructure, electricity transmission networks exhibit natural monopoly characteristics. Greenfield and Kwoka (2011) find increasing returns to scale with values between 0.39 and 0.53 for US RTOs that arises from two types of variation: geographic expansion and demand increase over a fixed network.

To analyze economies of scale, which involves expansions in both output and network, we need to add the cost elasticity of the network length to the elasticity of density. The elasticity of scale evaluated at the sample mean in Model 5 is 0.69. Figure 5 shows the estimated economies of scale and density for all the observations, each series sorted by increasing order. Most firms in our sample exhibit increasing returns to scale, except teen that indicate decreasing returns to scale with a value of the elasticity higher than one. These results suggest that electricity transmission networks still exhibit

[20] For most functional forms (e.g., the Translog function) there is a fundamental trade-off between flexibility and theoretical consistency. For instance, maintaining global monotonicity (e.g. positive elasticities and marginal costs) is impossible without losing second order flexibility. For example, Barnett *et al.* (1996) show that the monotonicity requirement is by no means automatically satisfied for most functional forms, and that violations are frequent.

natural monopoly characteristics when network is expanded to meet the extra demand. Using data for 1990, Pollitt (1995) finds, however, different degrees of economies of scale depending on firms' size for the US transmission utilities. In particular, he finds that decreasing returns to scale are more common in small utilities while increasing returns to scale are more common in medium and large companies. This seems to be consistent with the results obtained here, as in our sample we only have large firms. Dismukes *et al.* (1998) also show that all the NERC reliability regions in U.S. exhibit significant economies of scale for the transmission companies, while Huettner and Landon (1978) find that of six expenses categories, only sales expenses exhibits increasing returns to scale over the whole of the observed output range.

[Insert Figure 5]

6. Conclusions

The electricity industry in most developed countries has been restructured in recent decades with the aim of reducing costs, improving service quality and encouraging electricity utilities to perform efficiently. The remaining regulated segments (i.e. transmission and distribution) provide the infrastructure for the competitive segments and represent an important amount of the total price paid by final customers. Despite the fact that electricity transmission is the baseline for distribution and commercialization, there is a lack of empirical studies that analyze both economic characteristics of the technology and firms' inefficiency in electricity transmission.

To fill this gap in the literature we have analyzed firms' performance in the US electricity transmission industry for the period 2001-2009. The analysis of the economic characteristics of the technology and inefficiency of US utilities relies on the estimation of several stochastic cost frontiers. Our stochastic frontier models allow us to identify determinants of firms' inefficiency in this industry. In particular, we have included a wide range of variables as determinants of firms' inefficiency such as weather variables, a measure of companies' cost structure and growth rates of energy demand. Unlike previous papers, we control for weather conditions, one of the most decisive uncontrollable factors in electricity transportation, by including a set of weather variables that were gathered specifically for the present application.

We have found that there has not been an improvement in average efficiency in the US electricity transmission industry over the period 2001-2009. Moreover, regardless of the estimated model, our results indicate that efficiency has declined (and diverged) over time, suggesting that regulatory benchmarking techniques can identify room for improvement in performance of the US electricity transmission system.

The estimated coefficients provide useful information about firm's performance with both policy and managerial implications. We have found using more recent data than in previous papers that, given network infrastructure, electricity transmission networks exhibit natural monopoly characteristics. This result explains why electricity transmission is still regulated.

In efficiency analysis and incentive regulation of utilities it is important to control for the effect of differences in environmental factors on the performance of regulated firms. This is particularly important in the case of incentive regulation and benchmarking of electricity networks where the results of efficiency analysis have important financial implications for the firms. In this sense, our results clearly indicate that more adverse conditions generate both higher levels of inefficiency and higher costs for firms operating in areas with unfavourable weather conditions. Regulators should then take into account this cost disadvantage in setting efficiency targets within incentive regulation. We also find that investing in capital is a better strategy to deal with adverse weather conditions rather than incurring in additional operating costs. This might suggest a regulatory framework that favours capital investments to deal with unfavourable weather conditions.

Finally we have found that, as expected, firms' performance gets better when demand tends to be steady as firms cannot adjust their inputs without cost over time. This result, combined with the previous finding on the importance of capital expenditure to deal with weather conditions, suggests that regulators should also take into account that achieving long-term efficiency improvements can involve short-term increases in both capital and operational costs and, hence, a deterioration in firms' short-term relative performance.

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Table 1. Descriptive statistics

	Variable	Units	Mean	Max.	Min.	Std.Dev.
Totex	Cost	US$	144,602,000	667,127,000	20,713,600	120,324,000
Peak Load	Output	MW	6,173	23,111	380	5,533
Electricity Delivered	Output	MWh	6,280,310	74,584,700	56,730	8,839,980
Network Length	Network	Miles	4,064	16,292	1,087	3,253
Capital Additions	Investment	US$	57,051,200	911,518,000	508,295	87,748,400
Annual Salary	Input Price	US$	62,075	94,005	34,024	10,523
Producer Price Index	Input Price	Index	179.05	222.40	155.00	21.35
Minimum Temperature	Weather	°F	-10.35	19.90	-59.80	16.51
Wind Speed	Weather	Knots	6.84	9.60	4.63	1.01
Precipitation	Weather	Inches	0.07	0.16	0.01	0.03
Capex/Opex	Other	Ratio	1.18	5.90	0.13	0.70
Growth in Demand	Other	%	0.03	244.11	-74.96	17.72

Table 2. Parameter estimates of the Translog cost function.

	M1		M2		M3		M4		M5	
	(ALS)		(M1+Trend)		(M2+Weather)		(M3+W*COR)		(M4+Growth)	
Variable	**Coef.**	**t-ratio**	**Coef.**	**t-ratio**	**Coef.**	**t-ratio**	**Coef.**	**t-ratio**	**Coef.**	**t-ratio**
Constant	12.972	523.54	12.983	372.56	13.038	309.34	13.055	336.83	13.057	333.11
$\ln PL_{it}$	0.435	18.27	0.446	13.95	0.481	15.61	0.478	16.90	0.484	17.50
$\ln DE_{it}$	0.056	5.03	0.054	3.20	0.057	3.32	0.057	3.52	0.050	2.90
$\ln NL_{it}$	0.190	7.41	0.187	5.34	0.161	4.90	0.167	5.18	0.159	4.77
$\ln (LPR_{it}/KPR_{it})$	0.472	5.22	0.464	3.72	0.533	3.93	0.607	4.37	0.592	4.27
$\frac{1}{2} (\ln PL_{it})^2$	-0.084	-1.96	-0.071	-1.08	0.005	0.08	0.028	0.48	0.020	0.32
$\frac{1}{2} (\ln DE_{it})^2$	0.038	3.12	0.036	2.11	0.027	1.72	0.029	1.86	0.023	1.43
$\frac{1}{2} (\ln NL_{it})^2$	0.189	2.55	0.183	1.82	0.223	2.52	0.243	2.87	0.226	2.69
$\frac{1}{2} (\ln (LPR_{it}/KPR_{it}))^2$	0.562	1.27	0.445	0.66	0.017	0.02	-0.085	-0.12	-0.074	-0.11
$\ln PL_{it} \cdot \ln DE_{it}$	0.029	1.64	0.026	0.92	0.012	0.45	0.014	0.56	0.021	0.79
$\ln PL_{it} \cdot \ln NL_{it}$	0.171	3.94	0.162	2.70	0.126	2.48	0.115	2.33	0.132	2.43
$\ln PL_{it} \cdot \ln (LPR_{it}/KPR_{it})$	0.650	3.95	0.573	2.47	0.491	2.16	0.425	1.99	0.436	2.03
$\ln DE_{it} \cdot \ln NL_{it}$	-0.088	-4.23	-0.088	-2.90	-0.072	-2.53	-0.072	-2.68	-0.079	-2.90
$\ln DE_{it} \cdot \ln (LPR_{it}/KPR_{it})$	-0.131	-1.86	-0.137	-1.61	-0.091	-1.11	-0.070	-0.87	-0.086	-1.07
$\ln NL_{it} \cdot \ln (LPR_{it}/KPR_{it})$	-0.663	-3.63	-0.593	-2.36	-0.569	-2.25	-0.580	-2.42	-0.560	-2.31
t	-0.011	-1.77	-0.022	-2.43	-0.031	-3.10	-0.030	-3.05	-0.030	-3.15
t^2	-0.003	-1.40	-0.002	-0.96	-0.002	-0.76	-0.002	-0.79	-0.002	-0.67
$t \cdot \ln PL_{it}$	0.058	6.64	0.052	4.81	0.041	4.21	0.039	4.15	0.038	4.08
$t \cdot \ln DE_{it}$	-0.020	-4.07	-0.019	-3.41	-0.011	-1.97	-0.009	-1.78	-0.009	-1.67
$t \cdot \ln NL_{it}$	-0.059	-5.10	-0.054	-4.01	-0.042	-3.36	-0.041	-3.43	-0.040	-3.39
$\ln INV_{it}$	0.061	3.80	0.058	3.16	0.078	4.33	0.075	4.37	0.078	4.36
Variance of u										
Constant			-2.075	-14.90	-2.919	-8.42	-3.480	-9.48	-3.661	-9.08
t			0.112	2.47	0.274	3.35	0.350	4.06	0.359	4.11
$TMIN_{it}$					-0.039	-3.01	-0.034	-2.09	-0.039	-2.27
$WIND_{it}$					0.761	3.34	0.895	3.20	0.863	3.04
$PRCP_{it}$					21.323	3.08	21.181	2.57	22.873	2.73
$TMIN_{it} \cdot COR_i$							0.088	2.60	0.080	2.32
$WIND_{it} \cdot COR_i$							-0.817	-1.80	-0.939	-1.91
$PRCP_{it} \cdot COR_i$							-15.942	-1.06	-11.762	-0.78
$POSGR_i$									0.046	2.25
$NEGR_i$									-0.042	-1.06
Sigma	0.387		0.380		0.363		0.383		0.384	
Lambda (λ)	3.035		2.792		1.910		1.949		1.994	
Log LF	1.14		4.11		19.68		30.11		34.45	
Chi-squared LR test	66.636		60.681		29.558		8.689		-	
	(9)		(8)		(5)		(2)		-	

Note: The unrestricted model in all model selection LR tests is M5. Degrees of freedom in parenthesis

Figure 1.
Annual evolution of outputs divided by Totex

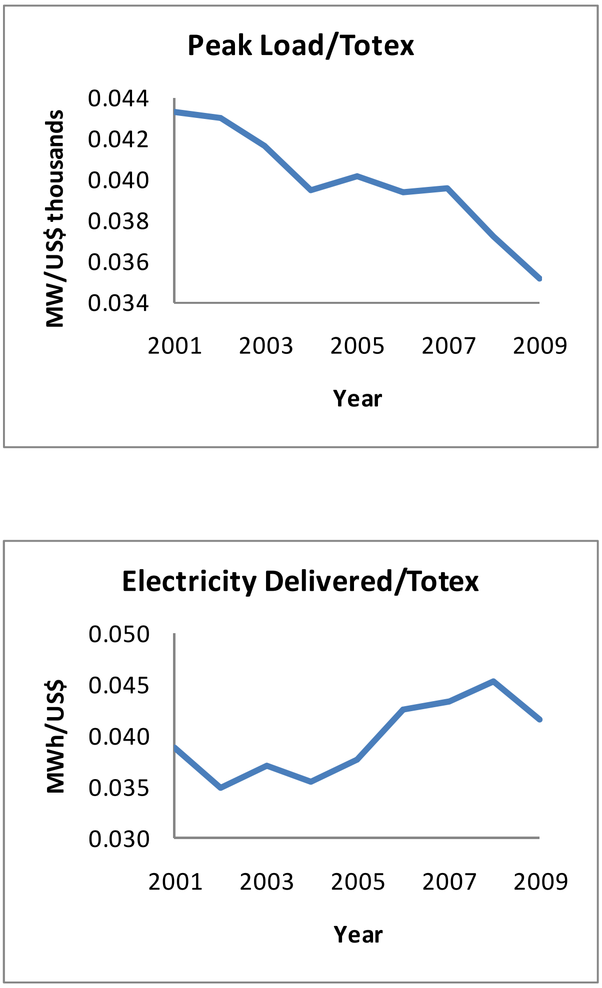


Figure 2.
Histogram of efficiency scores for the firms using the heteroscedastic model

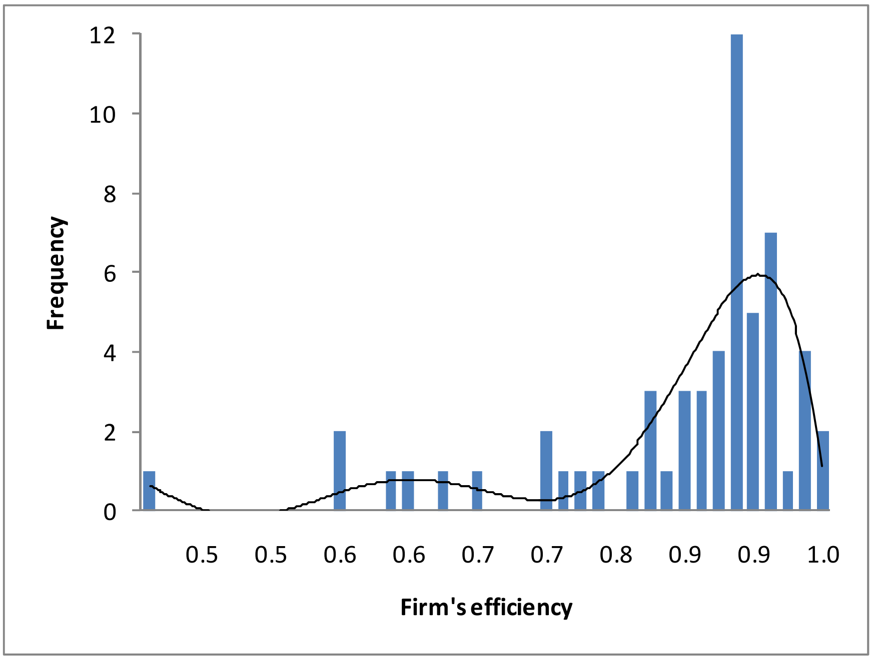


Figure 3.
Annual evolution of the efficiency for the electric transmission sector

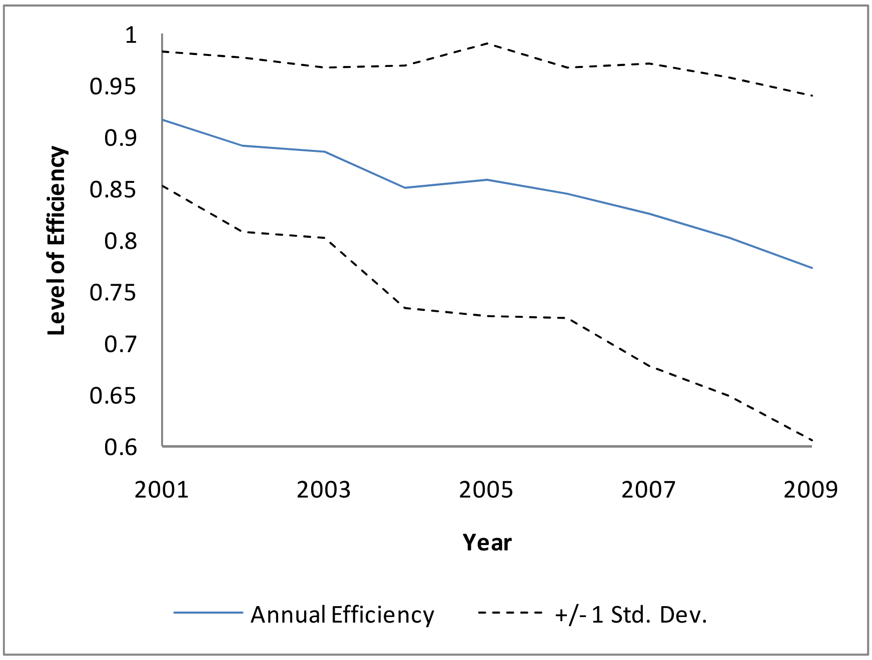


Figure 4.
Elasticities of cost for outputs and network

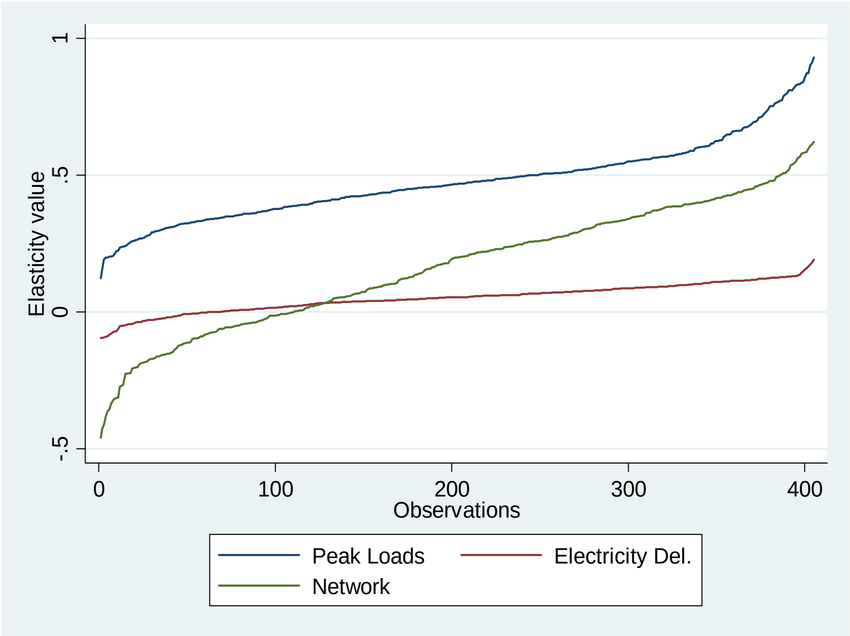
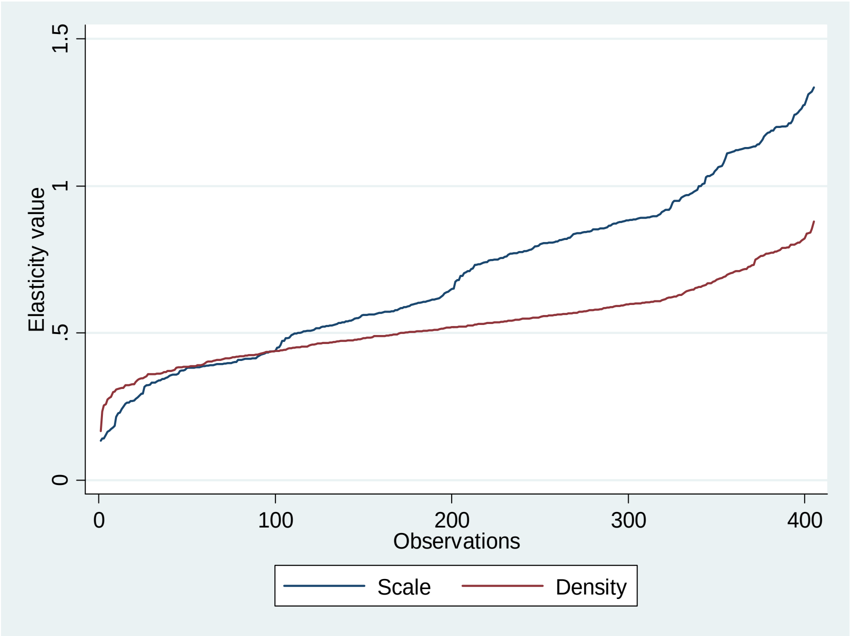


Figure 5.
Elasticities of scale and density



APPENDIX

Data appendix A: Variables and definitions from FERC FORM No. 1

Variable		Definition	FERC pages	FERC account names/notes
	AK	Allocation key (wages)	SWTR / (SWTT - SWAG)	
	SWTR		354-21b	Salaries and wages (transmission)
	SWTT		354-28b	Salaries and wages (total)
	SWAG		354-27b	Salaries and wages (admin. and general)
OPEX		Operational expenditure	100 * (TTE + AK * (TAGE - EPB - RCE - GAE)) / CPI	
	TTE		321-112b	Total transmission (op. and main.) expenses
	TAGE		323-197b	Total administrative and general expenses
	EPB		323-187b	Employee pensions and benefits
	RCE		323-189b	Regulatory commission expenses
	GAE		323-191b	General advertising expenses
CAPEX		Capital expenditure	100 * (DEP + IR * KBAL) / CPI	
	DEP	Depreciation	DETP + AK * (DEPGP + DEPCP)	
	DEPTP		336-7b	Depreciation (transmission plant)
	DEPGP		336-10b	Depreciation (general plant)
	DEPCP		336-11b	Depreciaton (common plant)
	KBAL	Capital balance	OCK - ADEP	
	OCK	Original cost of capital	BTP + AK * BGP	
	BTP		207-58g	Balance end of year (total transmission plant)
	BGP		207-99g	Balance end of year (total general plant)
	ADEP	Accumulated depreciation	ADTTP + ADTRP + AK * ADTGP	
	ADTTP		219-25c	Accumulated depreciation total (transmission plant)
	ADTRP		219-27c	Accumulated depreciation total (regional plant)
	ADTGP		219-28c	Accumulated depreciation total (general plant)

TOTEX	Totex	OPEX + CAPEX	
PL	Peak Load	401b	(d) Peak load (MW)
DE	Electricity Delivered	401a-17	(b) MWh (total)
NL	Network Length	422	(f) + (g) Length of transmission lines (miles)
COR	Capex / Opex	CAPEX / OPEX (average over time for each firm)	
GROWTH	Growth in Demand	[(TE current year - TE previous year) / TE previous year] * 100	

Data appendix B: Variables from other sources.

Variable	Definition	Source
LPR	Annual Salary	Data Quarterly Census of Employment and Wages (from the US Bureau of Labor Statistics)
KPR	Producer Price Index	US Bureau of Labor Statistics
TMIN	Minimum Temperature	National Climatic Data Center (NCDC)
WIND	Average Wind Speed	National Climatic Data Center (NCDC)
PRCP	Average Precipitation	National Climatic Data Center (NCDC)
CPI	Consumer Price Index	International Labour Organisation - LABORSTA
IR	Interest rate (6%)	Nillesen and Pollitt (2010), p.66