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Keywords technical efficiency, stocastic frontier analysis, electricity distribution markets, weather, South America

JEL Classification C23, C52, D24, L94, Q50

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Does Weather Have an Impact on Electricity Distribution Efficiency? Evidence from South America

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Abstract

This paper analyses the influence of weather variables on the efficiency of electricity distribution utilities in Argentina, Brazil, Chile and Peru. The data covers 82 firms that operate in the previously mentioned countries which represent more than 90 per cent of the distribution market of energy delivered for the period 1998-2008. The stochastic frontier analysis (SFA) is applied with a translog input distance function approach. A combination of cost and cost-quality models is proposed to create better discussions. Weather data are collected from 429 meteorological stations and lightning data (flash rate) are collected from 3,423 coordinates provided by NASA. A geographic information system (GIS) is used for locating the firms' service areas and for allocating their respective meteorological stations and coordinates. Results suggest that on average under cost models there is a significant increase in efficiency when weather is incorporated in the production function. Firms from Brazil and Peru are those which operate in less favourable weather conditions. Under the cost-quality models, on average the effect of weather is much lower. From this, it appears to be that firms have internalised the effects of weather and have adapted their networks with consideration to the environment in which they operate. A company-level analysis indicates that across models an important number of companies are affected by weather. Regulators are advised to make the case for the proper adjustments of efficiency scores when specific firms face important efficiency changes due to weather.

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1. Introduction

It is important that regulators are aware of weather conditions that characterise the operating service area in order to evaluate the cost effect that the firm could face due to unfavourable weather conditions. It is of interest for firms to collect and analyse weather variables and adapt their network to the particular characteristics of the service area in order to reduce the risk of failures in the system. The timely response to failures is a key issue for improving distribution system reliability.

In this study, the influence that weather has on firms' efficiency is evaluated. The change of technical efficiency, by adding and removing weather across models, is analysed. This paper looks at a more integrated approach to regulation when doing international comparisons. This study answers the question about how firms respond (in terms of efficiency change) when weather and quality issues are taken into consideration in the models. In addition, this study identifies the countries and firms that are exposed to less favourable weather conditions and vice versa. Furthermore, this study responds to the question about whether or not the firms have been able to adapt their networks to the climatic conditions that affect their respective service area.

Models have been categorised into cost models and cost-quality models. This classification is useful in order to evaluate any kind of trade-off when quality is taken into account. The influence of weather has been analysed as follows: (1) globally, (2) country-level and (3) company-level. The results of this study will help to understand the importance of including exogenous factors such as weather due to its impact on firms' efficiency in terms of cost and quality. This is one of the first studies that analyses the impact of weather on firms' efficiency at the regional level.

Technical efficiency in 82 electricity distribution firms that operate in South America is analysed. The countries that are part of this study are Argentina, Brazil, Chile and Peru. The impact of weather is evaluated across different models. The stochastic frontier analysis is used as the method. A translog input distance function has been selected due to its flexibility and its convenience to manage multiple inputs and outputs. This study has incorporated weather into the non-stochastic component of the production function. The second section provides a brief explanation of the relationship between weather factors and firms' efficiency and some specific examples are given. The third section shows results from recent studies that also evaluate the influence of weather on firms' efficiency in terms of cost and quality. The following section then explains the methods. The fifth section provides a description of the data collection and the selection of models. The sixth section discusses the results and the final one states the conclusions.

2. The Influence of Weather on Electricity Networks

The overhead lines, underground cables, transformers and switching stations are the key components in the transmission and distribution network that are more susceptible to weather conditions. Among them, the overhead lines are the ones that face the strongest external factors such as weather. Results from the national electric reliability study conducted by the US Department of Energy, DOE (1981) suggest that most distribution interruptions are initiated by severe weather–related interruptions in which inadequate maintenance is one of the main contributors. The study finds that failures in the distribution system are responsible for 80 per cent of all interruptions.

Burke and Lawrence (1983) performed a four-year study for evaluating the faults (current) on distribution systems in 13 electricity utilities in USA. They find that around 40 per cent of all permanent faults happen during periods of adverse weather. In addition, the study finds that the faults occurring on underground distribution systems only account for 5 per cent of all conductor-related faults. A study from Yu *et al.* (2009b) suggests that weather is an important cause of electricity blackouts. This accounts for 20 per cent, 14 per cent and 15 per cent of the total cases analysed in the European, Latin American and Asian regions respectively.

The main weather variables that affect the normal functioning of the overhead lines are lightning (flashes), wind, extreme temperatures, snow, ice, storms, rain and humidity. The high energy resulting from lightning strikes can burn the protective line isolators which subsequently may damage the transformers and switching devices. Damages in the transmission network are generally produced when lightning directly strikes the line. In the distribution network, the damage can be produced by a direct incidence and may also be due to the overvoltage induced in the lines when lightning strikes close to these. Pabla (2005) states that lightning is responsible for about one-third of all faults on HV and distribution systems during storm days and that around 75-80 per cent of these faults are temporary. Lightning damage is one of the main concerns for many utilities because these cause the highest expense in breakdown of distribution equipment. Short (2006) summarises the fault rates (per 100 circuit mile per year) found in different studies regarding overhead circuits. He states that the fault rates increase significantly in higher lightning areas. For instance, utilities that operate in southern US, which has a high lightning area, have a rate of 352 faults while those that operate in England with low lighting face a rate of 35 faults. According to Pinto and Almeida Pinto (2008), the damage produced by lightning in Brazil is around 600 million reales per year, which represents 1 per cent of the electricity sector revenues and in the USA the damage is around 10 billion reales per year.

Winds can also damage the transmission lines. The wind speed combined with the line height and air density determines the dynamic pressure over the lines. Due to the low temperature, the equipment's functionality can be reduced through cold and frost. The ice and snow load on the lines can cause higher traction, rope swinging and greater wind contact surface which can result in lines twisting or breaking. In addition, dynamic pressure increases due to the greater contact surface and the rope swing over time can cause a mechanical malfunctioning of the grid (Rothstein and Halbig, 2010). According to Gönen (2007), snow and ice storms are considered one of the most damaging and extensive service interruptions on distribution systems, which often cause the breakage of overhanging trees and produces damage to the distribution circuits. Humidity is also a concern due to the corrosion that it can produce to metal components such as pylons (towers). Finally, according to Pabla (2005), the tropical environment accounts for the majority of outages. This environment is characterised by high temperatures, dust, high humidity, heavy rainfall, high wind velocities and severe thunderstorms.

Empirical evidence supports the fact that weather plays an important role on electricity blackouts. In July 1991, several states from the southern US were affected by windstorms in which nearly one million customers lost electrical power. This caused around US$ 125 million of damage[2]. In January 1998, four states (New York, Maine, Vermont and New Hampshire) and two Canadian provinces (eastern Ontario and Quebec) were affected by an ice storm that caused the cutting of electrical power for more than 3 million customers with around one-half billion dollars of conservative damage[3].

A major UK electricity supply interruption in 1998 was preceded by storms with winds of around 200 Km/h. Nearly 3.5 million electricity consumers were affected and the estimated damaged was around £1.7 billion (OFREG, 2000). In December 2005, Niigata prefecture from Japan faced a severe snowstorm which caused an electricity blackout to around 650,000 customers[4]. In late 2009, a major blackout affected most states of Brazil due to a failure of a key transmission line affecting around 60 million customers in which 18 states (out of 26) were left without power. The failure was caused by a major thunder storm with heavy rain and strong winds that short-circuited a key high-voltage transmission line shutting down the largest hydroelectric facility, the Itaipu Dam[5]. However, the worst of the Brazilian blackouts was in 1999 when lightning struck a power substation in Sao Paulo generating a chain reaction; as a result around 97 million Brazilians were plunged into darkness[6].

3. Previous Studies of the relationship between a Firm's Efficiency and Weather

There are a number of empirical studies that try to explain the effect of the environmental variables on the efficiency of electricity network utilities. Studies that include in their models cost, physical, quality and environmental variables are mainly discussed in this section.

Korhonen and Syrjänen (2003) evaluate the cost efficiency of 102 electricity distribution companies from Finland for the period 1998. Data Envelopment Analysis (DEA) was the method selected. The influence of environmental variables such as forest cover in the distribution area (km^2) and average snow depth in winter (cm) is analysed. Quality variable, represented by the three-year average of customers' total interruption time (h) is also added to the model. The final variables were selected based on correlations and lineal regressions. Environmental variables were excluded from the model due to the low

[2] Source: NOAA. http://www.spc.noaa.gov/misc/AbtDerechos/casepages/jul7-81991page.htm, retrieved 30/11/2013.
[3] Source: NOAA, http://www.nws.noaa.gov/os/assessments/pdfs/iceflood.pdf, retrieved 30/11/2013
[4] Source Chinadaily. http://www.chinadaily.com.cn/english/home/2005-12/22/content_505712.htm, retrieved 30/11/2013
[5] Source: CNN. http://edition.cnn.com/2009/WORLD/americas/11/11/brazil.blackout/index.html, retrieved 30/11/2013
[6] Source: http://www.foxnews.com/story/2009/11/12/brazil-blackout-sparks-concerns-about-infrastructure/, retrieved 30/11/2013

variation in efficiency that they produced in the majority of companies. However, it is important to remark that the change of efficiency for a few companies was relatively high when forest cover was included, between 10 per cent and 40 per cent. This would suggest that even though on average the influence is not significant, an individual analysis would be recommended for some of them.

Yu *et al.* (2009a) study the effect of weather on the cost and quality performance of 12 UK electricity distribution utilities for the period 1995/96 to 2002/03. Economic efficiency and technical efficiency are evaluated. Two-stage data envelopment analysis is used for estimators. Factor analysis is used for compressing the set of weather variables into two composite variables. They find that in general, the effect of weather on efficiency performance is small on average. The study finds that weather affects economic efficiency only under specific models, which in addition to cost and physical variables include distribution losses and customer minutes lost. Results suggest that weather does not affect technical efficiency, however, when network length is dropped from the models a significant influence of weather is observed. These results suggest that to some extent the introduction of network length internalises the effect of weather on efficiency scores. However, it must be noted that the UK weather variation is low by world standards.

Growitsch *et al.* (2010) analyse the effect of geographic and weather conditions on the cost and quality performance of 128 Norwegian electricity distribution utilities for the period 2001/2004. Factor analysis is used for reducing the number of geographic and weather variables, which amount to nearly 100 in the respective companies' service area. Stochastic frontier analysis under the time-varying inefficiency approach is used. Different models are compared based on Battese and Coelli's (1992, 1995) and Greene's (2004, 2005) models. The latter ones refer to true fixed effects models. On the one hand, when comparing Battese and Coelli's 1992 and 1995 models, the study finds that the incorporation of geographic and weather variables (factors) on the inefficiency term increases the average efficiency by more than ten percentage points. On the other hand, when comparing Greene's 2004 and 2005 models, the study suggests that the average efficiency does not vary when geographic and weather conditions (factors) appear on the inefficiency term.

Nillesen and Pollitt (2010) evaluate the effect of error measurement and environmental factors[7] on US electricity companies' performances. The sample covers 109 private utility companies and the data collected refers to 2003. DEA and Tobit regression (two-stage approach) are used for estimations. The first layer of best-practice companies is excluded in order to correct the measurement error. The robustness of the DEA results is demonstrated due to the low variation of efficiency scores in comparison with those computed with the full sample. Regarding the environmental factors, the study finds that climate conditions do not explain the differences in relative efficiency. However, after doing some corrections such as comparing firms under the sample average environmental conditions, results suggest that more extreme climate factors have a negative impact on efficiency.

[7] Represented by (1) heating degree days (HDD) and (2) the average three-day maximum snowfall.

Jamasb *et al.* (2010) analyse the effect of weather conditions on costs[8] and service quality of 12 UK electricity distribution networks for the period 1995/96 to 2002/03. A parametric approach is used for this purpose with linear and quadratic cost functional forms. Weather variables are included as cost determinants. The study evaluates the convenience of grouping ('composite variables') the whole sample of weather variables available. However, results suggest that weather composites are not statistically significant and that inappropriate weights could be one of the reasons. In addition, the study suggests that marginal cost of quality improvements cannot be estimated consistently when weather composites are used. Therefore, the use of the variables selection method is preferred. Using this approach, results show that minimum air temperature, number of days when minimum concrete temperature is below zero degrees, number of days with heavy hail, and number of days with audible thunder are among the weather factors that affect the cost function.

Llorca *et al.* (2013) analyse the efficiency of 59 US electricity transmission companies for the period 2001-2009. A parametric approach (cost function) was the methodology selected for modelling. Three weather variables have been included in the model: annual minimum temperature, average of daily precipitation and average of daily mean wind speed. They find that adverse weather conditions affect negatively the transmission utilities in terms of efficiency and costs. They also suggest that instead of investing in additional operating costs, investing in capital is a better strategy to handle adverse weather conditions.

From the literature review above, some conclusions can be arrived at. First, benchmarking methodologies vary among the previous studies. Parametric (deterministic and non-deterministic) and non-parametric (DEA) approaches are the most popular. Second, when an important number of weather variables are evaluated, factor analysis appears to constitute a useful tool for simplifying the number of weather variables. However, it is important to take into consideration the disadvantages that this approach has. These are associated with inappropriate weights and with the difficulty of computing marginal costs for quality improvements when weather composites are included. Third, all the benchmarking studies are single-country studies and are focused only on developed economies. Benchmarking studies that involve weather variables are relatively recent and limited in comparison with those in which weather is omitted. On the one hand, the discussion of climate issues and quality of supply performance could have influenced the interest in these kinds of studies in recent years. On the other hand, the low number of studies could be associated with the difficulty of collecting weather data, especially if developing economies are part of the studies. Fourth, there is empirical evidence that weather can affect companies' efficiency. The significance of efficiency change depends on the model specification. It is observed that the inclusion or exclusion of specific variables in the model can affect the global results. Even though some of the studies suggest that on average weather does not produce important changes for technical efficiency, individual analysis would be recommended to evaluate the companies that are more vulnerable to weather conditions.

[8] Total costs are represented by operating costs, capital costs and energy loss costs.

This study represents the first cross-country study (with a focus on developing economies) that evaluates the effect of weather on companies' efficiency. The data collection in terms of weather was very challenging and involved an important coordination effort with different institutions (such as meteorological offices and NASA) in order to collect the data on time and in the format required. This contributes to having more reliable results and makes this study a reference for future research in developing economies with diverse and challenging weather conditions.

4. Methods

A parametric framework is used for measuring technical efficiency. Stochastic Frontier Analysis (SFA) is the method selected which was developed simultaneously by Meeusen and van den Broeck (1977) and Aigner *et al.* (1977). SFA allows for the incorporation of the error term which is composed of the stochastic component and the non-negative inefficiency term.

SFA enables multiple inputs and outputs in the form of distance function which was initially proposed by Shephard (1970). In this study, it is useful to adopt the input distance function with the translog functional form[9]. The restrictions required for the homogeneity of degree one in inputs and the symmetry assumptions for the second order coefficients are applied. Panel specification with time varying inefficiency structure is selected because it is necessary to measure the trend of efficiency over time.

The input distance function is normalised based on one input. The introduction of the environmental component in the production function relates to the following equation:

$$
\begin{aligned}
-ln\,x_{Kit} = {} & \alpha_0 + \sum_{m=1}^{M} \gamma_m ln\,y_{mit} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \gamma_{mn}\, ln\,y_{mit}\, ln\,y_{nit} \\
& + \sum_{k=1}^{K-1} \beta_k ln\,x^*_{kit} + \frac{1}{2}\sum_{k=1}^{K-1}\sum_{l=1}^{K-1} \beta_{kl}\, ln\,x^*_{kit}\, ln\,x^*_{lit} \\
& + \sum_{k=1}^{K-1}\sum_{m=1}^{M} \alpha_{km}\, ln\,x^*_{kit}\, ln\,y_{mit} + \sum_{j=1}^{J} \delta_j z_{jit} + \frac{1}{2}\theta_{tt} t^2 + \theta_t t \\
& + \sum_{k=1}^{K-1} \varphi_k\, ln\,x^*_{kit}\, t + \sum_{m=1}^{M} \varphi_m\, ln\,y_{mit}\, t + v_{it} - u_{it}, \\
x^* = {} & \frac{x_{kit}}{x_{Kit}} \qquad \text{(Eq.1)}
\end{aligned}
$$

where x_{kit} is one of the k-th input of firm i; y_{mit} is one of the m-th output of firm i; α, γ, β, δ, θ and φ are the parameters to be estimated; t is the time trend. Z_{jit} is one of the j-th environmental variables of firm i. Environmental variables are represented by weather

[9] The translog functional form provides a second-order differential approximation. In comparison with the linear and Cobb-Douglas functional forms which provide a first-order differential approximation, the translog functional form does not impose restrictions on the first or second derivatives itself. Its coefficients represent elasticities thus the results are interpreted quickly. The flexibility of a translog functional has a cost due to the increase of parameters to be estimated. For further details see Christensen *et al.* (1973).

variables and they have not been expressed in logs due to the existence of negatives and zero values. See section 5.4 for details of weather variables.

Following Battese and Coelli (1992), the trend of inefficiency term over time can be represented as:

$$u_{it} = u_i \exp(-\eta(t - T)) \qquad \text{(Eq. 2)}$$

where η (eta) is the unknown parameter to be estimated, T is the last time period of i-th firm, u_i is associated with technical inefficiency, is *independent and identically distributed and has a truncated normal distribution,* $N^+(u, \sigma_u^2)$. The eta parameter allocates a common technical efficiency trend among producers. This is one of the main disadvantages of this approach. When eta is higher than 0, that means $\eta(T - t) > 0$ technical efficiency improves over time ($u_{it} > u_i$). Similarly, when eta is lower than 0 technical decreases over time and when eta is equal to 0, technical efficiency does not vary over time.

It has been assumed that environmental variables influence the shape of the input distance function directly. A different approach is that in which environmental factors are included in the inefficiency term (Kumbhakar *et al*., 1991). In this case, the maximum likelihood estimators would be computed under the assumption that inefficiency has a distribution that varies with Z and that is no longer identically distributed. Thus, u_i would be defined as follows:

$$u_i \sim N^+(\mu_i, \sigma_u^2) \qquad \text{(Eq. 3)}$$

where, $\mu_i = \delta_o + \sum_{j=1}^{J} \delta_j z_{ij}$ and δ_o, δ_j are the parameters to be estimated.

Battese and Coelli (1995) propose a similar model but applied to a panel data context. For a better discussion of the results, this last approach has been also applied in order to compare both methods (environment in production function versus environment in inefficiency term). The use of specific tests (such as log likelihood ratio test) is appropriated for determining the approach that provides the best fitness.

It is important to remark that the treatment of environmental variables has been discussed in different studies. In summary, it is clear that some of them assume that the environment can affect the shape of the production function (in this case input distance function). Other studies support the idea that environmental variables act as explanatory variables of inefficiency only[10]. Under the last approach we can distinguish mainly two scenarios. The first one is called second-stage in which the first step consists on estimating the conventional frontier model but omits the environmental variables. In the second step, the predicted technical efficiencies are regressed on a set of explanatory variables (environmental variables). Some authors find important econometric problems when applying the second stage approach, see Kumbhakar and Lovell (2000) and Coelli *et al.* (2005). Two different categories are also discussed in some studies: third and fourth stage.

[10] See Mota (2004). Coelli *et al.* (1999) and Growitsch *et al.* (2010) compare their results under the following approaches: environment in production and environment in inefficiency term.

See Yang and Pollitt (2009) for a complete description of the different stages and their application for measuring efficiency in the Chinese Coal-Fired Power Plants.

5. Data Collection and Models

The data consists of an unbalanced panel for 82 electricity distribution companies for the period 1998-2008, 60 of which are private-owned companies. The utilities operate in Argentina (18), Brazil (39), Chile (11) and Peru (14) and account for more than 90 per cent of the total distribution market in those four countries in terms of energy delivered. The list of companies is shown in Appendix 1. The service area associated with each company is shown in Appendix 2. Among the data that was collected we have (1) cost data (operating costs, capital costs), (2) physical data (number of customers, energy delivered, length of network, number of workers, service area), (3) quality variables (losses, interruptions per customer: duration and number) and (4) weather variables (maximum absolute temperature, minimum absolute temperature, total rain, flash rate, average humidity, maximum humidity, number of days in a year with: gales, storm, hails and frost days).

The following section provides a general description of the data collected (costs, physical, quality and weather variables) and the respective sources. Table 1 shows the 2008 descriptive statistics for the 82 companies across the countries.

5.1 Cost Data

Operating costs (opex) generally include labour costs, materials and third party services. This study is concentrated on the distribution and retail business, thus generation and transmission costs have been excluded.

Some adjustments were made due to the difference that exists in presenting operating costs across countries. The way of presenting financial figures was not homogenous across companies and consequently national and regulatory accounting was analysed for grouping cost figures based on the three categories (ANEEL, 2007; SEC, 2006; MINEM, 1994). A concordance table was built for this purpose. In general across the four countries, opex is composed of (1) distribution cost, (2) retail cost and (3) administrative and general expenses. Some companies also have generation and transmission costs which were excluded. The administrative and general expenses associated with generation and transmission business were also excluded.

Table 1: 2008 Descriptive Statistics – Distribution Electricity Utilities

Variables (2008)	Units	Argentina			Brazil			Chile			Peru			Total		
		Min.	Max.	Mean	Min.	Max.	Mean	Min.	Max.	Mean	Min.	Max.	Mean	Min.	Max.	Mean
Cost variables																
OPEX	US$ (million)	15.3	375.8	115.7	14.9	1010.0	191.0	12.86	269.3	73.8	3.1	127.7	34.4	3.1	1010.0	132.31
CAPEX	US$ (million)	9.45	228.34	55.68	4.7	583.8	168.8	3.32	175.5	41.1	2.5	122.1	35.4	2.5	583.8	106.40
Physical variables																
Customers (residential)	million	0.09	2.24	0.49	0.08	5.48	1.40				0.02	0.97	0.28	0.02	5.48	0.942
Customers (total)	million	0.10	2.53	0.66	0.10	6.69	1.64	0.06	1.53	0.44	0.03	1.03	0.33	0.03	6.69	1.1
Energy delivered (residential)	GWh	252	7738	1353	160	14427	2468				23	2066	445	23	14427	1777
Energy delivered (free market)[1/]	GWh	40	3700	691	0	19459	2185	12	2687	536	0	929.05	118	0	19459	1178
Energy delivered (cooperatives)	GWh	0	1728	236										0	1728	236
Energy delivered (total)	GWh	672	18616	4891	492	41898	9126	218	12535	2545	82	5334	1159	82	41898	5982
Length of network	Km (000')	6.0	51.8	17.7	2.9	453.4	75.3	1.0	26.9	11.2	0.9	21.5	10.6	0.9	453.4	43.8
N° of workers	number	85	3130	891	153	8031	1798	57	790	322	26	666	270	26	8031	1132
Service Area	Km^2 (000')	3.3	203.0	86.9	1.8	1570.8	248.0	2.1	87.4	44.7	2.4	140.9	45.0	1.8	1570.8	72.7
Quality variables																
Total losses	GWh	57	2247	718	44	6686	1437	20	786	229	9	510	124	9	6686	897
Total losses	percentage	7.8%	23.8%	12.3%	4.5%	37.2%	15.6%	5.9%	14.7%	9.6%	8.1%	14.1%	11.1%	4.5%	37.2%	13.3%
Technical losses	percentage				3.6%	23.7%	8.7%							3.6%	23.7%	8.7%
Non-technical losses	percentage				0.2%	25.7%	5.4%							0.2%	25.7%	5.4%
Average Frequency of interruptions/customer	times/year	5.5	12.5	8.8	5.2	51.6	14.7				5.8	36.5	18.4	5.2	51.6	14.8
Average Duration of interruptions /customer	hours/year	8.7	21.5	14.9	5.9	77.2	19.9				13.4	148.0	42.2	5.9	148.0	24.3
Other Variables			Total			Total			Total			Total			Total	
Private companies	number		16			29			11			4			60	
Public companies	number		2			10			0			10			22	
Total companies	number		18			39			11			14			82	

[1/] In the case of Chile it refers to 2007 figures.

Sources: Companies' annual reports, National and Regional Energy Regulators, Energy Ministries, Associations of Electricity Distribution Utilities

Capital costs (capex) are represented by total asset additions, including work in progress. All figures were adjusted to 2008 prices based on the consumer price index (CPI) and the purchasing power parity (PPP) conversion factor[11]. The main sources of information are companies' annual reports. An important number of reports were collected during the fieldwork from energy regulators, associations of electricity distribution companies, utilities and from the national security and insurance agencies[12]. CPI was provided by the national statistical offices[13]. The PPP conversion factor was obtained from the World Bank International Comparison Program Database.

5.2 Physical Data

The number of customers is composed of residential, industrial and rural businesses as well as government customers. The classification varies among countries. Energy delivered refers to the total sale of energy in the regulated and free market (free customers). In the case of Argentina, it also includes energy delivered to cooperatives. Depending on the size of their demand, free customers are able to select their supplier and pay a fee to the electricity distribution firm for the use of its network. For doing suitable comparisons regarding the energy delivered, an energy-balance approach was built for each firm. This allowed the identification in most cases of the input energy and the output energy per type of customer (regulated, free, cooperatives, utilities) and losses (total losses). Length of network is focused on with the distribution business; however this concept varies across countries. Based on an individual analysis among countries, this study concludes that distribution networks in general are those with voltage levels up to 34.5 kV and that are associated with low and medium voltages. In most of cases, high voltage refers to the transmission business and has been excluded.[14]. Number of workers refers to the number of employees. Service area represents the area in which the companies operate.

Physical data were collected mainly from companies' annual reports, energy regulators and associations of electricity distribution companies. For instance, some regulators such as ANEEL from Brazil and OSINERGMIN from Peru provided specific information such as length of network, which was very useful for completing the dataset. ANEEL also provided information that helped to build the energy-balance for each firm, such as a breakdown of energy delivered, which included the free market (free customers). ADEERA, the association of electricity distribution firms from Argentina, was also an important source of information regarding network length. Information obtained from system operators and from the World Bank database was very useful to complement the data for network length (World Bank, 2008). Regarding service area, some specific reports and databases were used in order to locate the

[11] GDP (Local currency unit – LCU, per international $).
[12] Energy regulators: from Argentina), ANEEL (Brazil National Security Commission (CNV) from Argentina, Securities and Exchange Commission (CVM) from Brazil, Securities and Insurance Supervisor (SVS) from Chile and National Supervisory *Commission* for Companies and Securities (CONASEV).
[13] National Institute of Statistics and Censuses for Argentina (INDEC), Brazilian Institute of Geography and Statistics (IBGE), National Statistics Institute for Chile (INE), National Institute of Statistics and Information (INEI) for Peru.
[14] For instance, transmission lines represent around 4.5 per cent and 2.5 per cent of the total length regarding electricity distribution firms from Argentina and Chile respectively. 2008 Figures.

service area geographically for each firm using a geographic information system (GIS). Further details are given in section 5.4.

5.3 Quality Data

Total power losses, average duration of interruptions per customer and average number of interruptions per customer were obtained mainly from companies' annual reports, regulators and associations of electricity distribution companies. Total losses are composed of technical and non-technical losses. Interruptions involve those that are equal to three minutes or longer, are planned and unplanned, internal and externals and exclude major interruption events. In the case of Argentina and Peru, quality variables regarding the duration and frequency of interruptions were provided directly from regulators. They provided the information in the format required. It is worth noting that only in the case of Peru, major interruptions were not possible to exclude. OSINERGMIN provided two kinds of indicators. The first ones, which were obtained from individual indicators N (number of customer interruptions) and D (customer interruption duration), refer in general to those interruptions produced in urban areas. Around 80 per cent of the total number of customers is concentrated in these areas (OSINERGMIN, 2003). These indicators involve the three voltage levels and include interruptions produced by fortuitous events.

5.4 Weather Data

The availability of weather data varies across countries. Argentina provided the most complete panel. Weather data were collected from national meteorological offices[15] and from the National Aeronautics and Space Administration of the USA (NASA). The meteorological offices provided information regarding weather data that was recorded in 458 stations, from which 429 are placed inside the service area of the companies that are part of this study, see Appendix 4. Meteorological offices provided coordinates (latitude, longitude) for each met station. ArcGis is the application that was used. Maximum absolute temperature, minimum absolute temperature, total rain, number of days in a year with: gales, storm, hails and frost days, humidity are among the data collected (monthly data)

NASA provided data that refers to flash density (number of flashes/km^2/year), e.g. lightning. The data set used was that from LIS (Lightning Imaging Sensor) HRFC (High Resolution Full Climatology), with tropical coverage for the period 1998-2008 with a resolution of 0.5 degrees[16]. Similar to the procedure followed previously, a geographic information system was used for plotting the flash rate coordinates. Around 3,423 coordinates (grid data) with information about flash rates were identified inside the service area regarding the whole sample of companies[17], see Appendix 4.

[15] National Meteorological Service (SMN) of Argentina, National Institute of Meteorology (INMET) of Brazil, Meteorological Direction (DMC) of Chile and the National Service of Meteorology and Hydrology (SENAMHI) of Peru.
[16] This means 0.5 * 0.5 (latitude, longitude).
[17] Based on the coverage (~35^{o}N/S) the total number of coordinates provided by NASA is 100,800 (720*360). Gauss was the software used for arranging the data in the format required for ArcGis. The authors are very grateful to Luis Orea who helped us to manage and arrange the satellite data into Gauss.

As we can see, the location of the companies' service area in a geo-referenced system is required for matching the meteorological stations and flash rate coordinates that correspond to each firm. The first step was to get the digital maps for the four countries. Depending on the country's administrative and political boundaries, maps could be obtained at department, municipal, district and commune among other levels. Usually these boundaries are related to the service or concession area that is allocated to a specific utility. In the case of Argentina, the digital map at departmental level was provided by the National Agricultural Research Centre from Argentina (INTA). Regarding Brazil, the map was downloaded from the geo-referenced information system of the electric sector (SIGEL) from ANEEL. This map contains information on the companies' service area at municipal level. The Chilean National System of Coordination of Territorial Information (SNIT) from the Ministry of National Property provided the digital map at the commune level. In Peru, the digital map was provided by the National Geographic Institute (IGN)[18]. The second step was to get the companies' service area data set. The information at departmental level was found in the annual reports from the Secretary of Energy from Argentina[19]. In the case of Brazil, the digital map includes this dataset. Regarding Chile and Peru, the data set was provided by the Superintendence of Electricity and Fuel (SEC) at communal level and OSINERGMIN at district level respectively. In the case of Peru, information regarding area (at district level) was complemented by the data set provided by the National Institute of Statistics and Information (INEI). With the digital maps and firms' service area data set, it was possible to geo-reference the firms' service areas and allocate the meteorological stations and flash rate coordinates for each one. In the majority of cases, the number of meteorological stations and flash rate coordinates associated with a firm's service area was higher than 1. Thus, averages were taken. The maximum ratio of station per firm's service area is 51 (CEMIG, a Brazilian company). On average we have the following ratios: 3.3 for Argentina, 7.5 Brazil, 1.5 Chile and 5.3 Peru respectively. Table 2 summarises the weather data per country and type of variable.

[18] There are around 535 departments in Argentina, 5,562 municipalities in Brazil, 342 communes in Chile and 1,833 districts in Peru.
[19] Secretaría de Energía (2008).

Table 2: 2008 Descriptive Statistics – Weather Variables

Variable (2008) [1/]		Units	Argentina			Brazil			Chile			Peru		
			Min.	Max.	Mean	Min.	Max.	Mean	Min.	Max.	Mean	Min.	Max.	Mean
Temperature [2/]														
Max. Absolute	tmax	degrees Celsius	37.0	42.8	40.2	34.0	42.1	38.5	27.5	37.3	33.5	22.0	39.2	33.6
Min. Absolute	tmin	degrees Celsius	-18.8	-1.8	-6.2	-5.4	21.2	7.2	-6.6	9.9	-0.7	-13.5	16.8	2.3
Rain [3/]														
Total rain	rain	mm	208.5	1060.6	657.4	822.1	2782.8	1560.0	0.0	1538.2	486.2	5.6	2139.4	542.1
Wind														
Gales [4/]	gal	N° days/year	0.0	36.0	14.5							0.0	1.5	0.2
Max. Speed	ms	Km/h year				5.6	17.0	9.9						
Humidity (relative)														
Average	hum	percentage				61.63	86.8	74.7	54.8	80.4	69.5	59.5	83.7	71.6
Maximum	humax	percentage				96.9	100.0	99.1	99.4	99.4	86.7			
Flashes [5/]														
N° flashes per km	fr	flashes/km^2/year	2.0	7.0	4.2	0.6	8.2	4.2	0.0	0.7	0.2	0.0	4.8	1.4
Others														
Storms	st	N° days/year	18.0	81.0	38.0									
Hails	hail	N° days/year	0.0	2.5	1.0									
Frost days [6/]	fd	N° days/year	4.0	64.3	21.0				0.0	64.0	17.2	0.0	145.0	20.1
Met Stations / NASA														
Coordinates				Total			Total			Total			Total	
Total Met Stations		number		46			293			16			74	
Total NASA Coordinates		number		408			2704			108			203	

[1/] All figures refer to the minimum, maximum of mean value inside a specific company' service area. For instance, in the case of Argentina, the minimum value of rain refers to ESJ and the maximum value refers to EDESA.

[2/] Based on average monthly data.

[3/] Rain is defined as total annual value.

[4/] Gales are defined as those winds with speed equal to 63km/h or higher. In the case of Peru, figures refer to 2007 period. Data were provided only for the period 1998-2007.

[5/] Flashes refer to the number of lightnings per km2.

[6/] Frost days are those days in which the minimum air temperature falls below 0 C°. This variable is also known as "helada".

Source: SMN, INMET, DMC, SENAMHI, NASA

5.5 Selection of Variables and Model Specifications

In this section the selection of the preferred variables and models (cost, physical, quality and weather variables) is discussed, which are based on previous studies and also on the availability of data. The selection of weather variables will first be considered.

A total of five weather variables have been analysed: total rain, maximum absolute temperature, minimum absolute temperature, humidity and flash rate (lightning). However, the last two were discarded. The inclusion of humidity to the production function was analysed, due to the concerns that some firms expressed in terms of its effect on the operation and maintenance of the electricity network. On the one hand, the introduction of humidity in the models does not produce any effect on the production function; its value is very weak and it is not statistically significant either. On the other hand, correlation analysis indicated a medium lineal relationship between total rain and flash rate. The correlation coefficient was 0.58 at the 1 per cent level. Due to this fact, three scenarios per model were analysed:

- Scenario 1: includes total rain (rain), maximum and minimum absolute temperatures (tmax, tmin), flash rate (fr)
- Scenario 2: includes total rain, maximum and minimum absolute temperatures
- Scenario 3: includes flash rate, maximum and minimum absolute temperatures

Table 3 presents the parameters of weather variables when these are included in the production function[20]. All the weather parameters have the correct sign; the worse the weather conditions, the higher the costs. It can be seen that the effect of weather variables depends on the scenario and models. In the first scenario, the most significant variable is the maximum absolute temperature but only for cost-quality models

Table 3: Weather estimators per model

Model	Scenario 1					Scenario 2				Scenario 3			
	rain	tmax	tmin	fr	γ	rain	tmax	tmin	γ	fr	tmax	tmin	γ
M1	-0.000*	-0.005	-0.003	-0.003	0.84	0	-0.004	-0.007***	0.84	-0.005	-0.005	-0	0.83
M2	0	-0.005	-0.002	-0.002	0.80	0	-0.005	-0.005**	0.80	-0.004	-0.005	-0	0.80
M3	-0.000**	-0.011***	-0.003	-0.003	0.96	-0.000*	-0.009***	-0.005**	0.95	-0.005*	-0.010***	-0	0.96
M4	0	-0.011**	-0.005*	-0.004	0.98	0	-0.010**	-0.004	0.98	-0.003	-0.009**	-0	0.98
M5	0	-0.012***	-0.002	-0.003	0.97	0	-0.010***	-0.004	0.96	-0.004	-0.011***	-0	0.98
M6	0	-0.010**	-0.004	-0.003	0.98	0	-0.010**	-0.004	0.97	-0.003	-0.008*	-0	0.98

Significance levels: * p<0.1; ** p<0.05; *** p<0.01

In cost models, total rain is statistically significant but weak due to their very low coefficient. The minimum absolute temperature is only statistically significant at 10 per cent in Model 4. Flash rate is not statistically significant across models. Under the second scenario, we have a similar picture to the previous one, however, in this case the minimum absolute temperature is statistically significant in relation to the cost models. An increase

[20] A total of 18 models were analysed. This is a simplified table that only shows the weather coefficients, their respective significance level and gamma values. A completed table is shown later regarding the preferred weather models.

in the coefficient is also observed on average in absolute values, it varies from 0.0025 to 0.0064. The coefficients of the maximum absolute temperature remain the same in general. Regarding the last scenario, a similar trend as seen in the first scenario is noticed. Maximum absolute temperature continues being the weather variable that influences efficiency the most when quality variables are taken into account. Flash rate is only significant in Model 3. In terms of cost models, none of the weather variables is statistically significant. In terms of the inefficiency term, the authors observe that the gamma values indicate that firms are not fully efficient when weather is introduced across the three scenarios. Gamma varies from 0.80 to 0.98. All gamma values are statistically significant at the 1 per cent level.

Based on the previous discussion, it can be seen that maximum and minimum absolute temperatures are the weather variables that most influence the shape of the technology under cost-quality and cost models respectively. Thus, it is convenient to select Scenario 2 as the preferred model. This combines total rain, and maximum and minimum absolute temperature. This is the model that captures the effect of weather variables most on the production function. Following Jamasb *et al.* (2010), given the complexity of weather variables it is better to focus on the overall effect rather than the individual effect of a specific weather variable, due to the possible correlations that can exist between weather variables. Under this approach, it is convenient to select Scenario 2 even though the three variables are not statistically significant across all the models.

Having defined the set of weather variables, this study proceeds to define the remaining variables (cost, physical and quality). These variables have been selected based on previous studies. In summary, six models have been selected, see Table 4.

Table 4: Models

Variable	Type of variable	Cost-quality		Cost-quality models			
		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
OPEX (x1)	Monetary	I	I	I	I	I	I
CAPEX (x2)			I			I	I
CUST (y1)	Physical	O	O	O	O	O	O
ENG (y2)		O	O	O	O	O	O
LEN (y3)		O	O	O	O	O	O
LOSS (x3)	Quality			I	I	I	I
CHL (x4)					I		I
W1 (rain)	Weather	E	E	E	E	E	E
W2 (tmax)		E	E	E	E	E	E
W3 (tmin)		E	E	E	E	E	E

I: input, O: output, E: environment, OPEX: operating costs, CAPEX: capital costs,

CUST: Number of customers, ENG: energy delivered, LEN: length of network,

CHL: customer hour lost, W1: total rain, W2: maximun absolute temperature

W3: minimum absolute temperature

The number of variables varies across models. The maximum number is ten, of which four are inputs, three are outputs and the remaining three are environmental variables. Two categories of models have been defined: (1) cost models and (2) cost-quality models. Model 1, Model 3 and Model 4 are those in which costs are only represented by opex. In the rest of the models, capex is added. Model 4 and Model 6 are those in which quality variables are fully included. Customer hours lost (CHL) is defined by the product of average duration of interruption per customer and total number of customers.

This study has assumed that weather has a direct influence on the production function and that each utility faces a different production frontier. The other option is to consider that weather variables influence the inefficiency term directly, which means that weather would impact only on the difference given by the deviations from the frontier. For a better discussion, the results have been compared with the second approach. Section 6.1 shows the results under both approaches. Among the studies that add environmental variables to the production function are Pollitt (1995), Estache *et al.* (2004), Rossi (2007) and Jamasb *et al.* (2010). Mota (2004), Nillesen and Pollitt (2010) and Growitsch *et al.* (2010) assume that the environment influences directly on efficiency. Coelli *et al.* (1999) compare and discuss both approaches but in relation to the airline market.

6. Results

6.1 Maximum Likelihood estimators

Having selected the weather variables, the results based on these will now be discussed. The results are presented based on three cases: translog without weather (Case A)[21], weather in the distance function (Case B) and weather in inefficiency (Case C). Case A refers to those models in which weather has not been included. Case B comprises the preferred models, which means weather variables are included in the production function. Case C composes models in which it is assumed that weather influences the inefficiency term. This section discusses the maximum likelihood estimators for each case and supports the selection of our preferred models (Case B).

Table 5 shows the maximum likelihood estimators for all the models. STATA was used for computing the first and the second ones (Case A and Case B models) and Frontier 4.1 for estimating the last one (Case C models). Geometric means are computed, thus first order coefficients represent elasticities at the sample mean. The time trend was also adjusted to the mean, where first order coefficients refer to the technical change at the sample mean. It is evident that the input distance function is well specified and most parameters are statistically significant. In general, first order output estimators have the correct sign, which means that coefficients of number of customers, energy delivered and length of network are negative. Only some exceptions are observed in M1 Case C, M4 Case A and Case C, and M6 Case C, but the coefficients are not statistically significant. An increase in output level suggests an increase in input levels.

[21] In this scenario, weather variables have been removed across the six models.

Table 5: Input distance function maximum likelihood estimators

Variables	Model 1			Model 2			Model 3		
	M1 Case A	M1 Case B	M1 Case C	M2 Case A	M2 Case B	M2 Case C	M3 Case A	M3 Case B	M3 Case C
	Coef. *t* Stat	Coef. *t* Stat	Coef. *t* Stat	Coef. *t* Stat	Coef. *t* Stat	Coef. *t* Stat	Coef. *t* Stat	Coef. *t* Stat	Coef. *t* Stat
α_o	0.600 (7.85)	0.541 (10.29)	0.407 (9.61)	0.594 (6.45)	0.550 (8.97)	0.439 (4.49)	0.490 (10.36)	0.477 (13.56)	0.333 (15.81)
ln(y1)	-0.525 (-7.29)	-0.538 (-7.27)	-0.721 (-17.52)	-0.506 (-7.23)	-0.518 (-7.20)	-0.671 (-15.39)	-0.596 (-10.37)	-0.604 (-10.81)	-0.629 (-20.95)
ln(y2)	-0.318 (-6.97)	-0.294 (-6.07)	-0.217 (-8.32)	-0.329 (-7.95)	-0.307 (-6.85)	-0.238 (-9.14)	-0.313 (-9.18)	-0.287 (-8.13)	-0.319 (-15.63)
ln(y3)	-0.098 (-2.49)	-0.099 (-2.73)	0.014 (0.64)	-0.126 (-3.13)	-0.128 (-3.50)	-0.036 (-1.71)	-0.081 (-2.79)	-0.089 (-2.96)	-0.022 (-1.36)
0.5*ln(y1)^2	0.005 (0.02)	0.032 (0.14)	-0.232 (-1.45)	0.226 (1.00)	0.248 (1.13)	-0.415 (-3.01)	-0.475 (-2.55)	-0.380 (-2.01)	-0.357 (-2.65)
0.5*ln(y2)^2	-0.127 (-2.81)	-0.129 (-2.88)	0.015 (0.26)	-0.136 (-3.18)	-0.138 (-3.25)	-0.003 (-0.06)	-0.110 (-3.28)	-0.119 (-3.50)	-0.069 (-1.45)
0.5*ln(y3)^2	0.105 (1.15)	0.089 (1.04)	-0.372 (-6.77)	0.098 (1.16)	0.085 (1.05)	-0.383 (-7.69)	0.012 (0.18)	-0.008 (-0.13)	-0.153 (-3.09)
ln(y1)*ln(y2)	0.076 (0.83)	0.054 (0.60)	0.031 (0.37)	0.011 (0.12)	-0.010 (-0.12)	0.097 (1.35)	0.179 (2.56)	0.119 (1.65)	0.148 (2.09)
ln(y1)*ln(y3)	-0.027 (-0.20)	-0.019 (-0.14)	0.327 (3.77)	-0.137 (-1.08)	-0.121 (-0.97)	0.405 (5.16)	0.172 (1.62)	0.140 (1.33)	0.224 (2.98)
ln(y2)*ln(y3)	-0.066 (-0.90)	-0.052 (-0.74)	-0.066 (-1.47)	0.015 (0.21)	0.020 (0.30)	-0.102 (-2.49)	-0.111 (-2.03)	-0.050 (-0.85)	-0.091 (-2.45)
ln(x2/x1)				0.139 (10.64)	0.132 (10.12)	0.218 (15.05)			
ln(x3/x1)							0.494 (24.02)	0.487 (23.87)	0.323 (19.57)
ln(x4/x1)									
0.5*ln(x2/x1)^2				0.056 (3.16)	0.056 (3.23)	0.014 (0.64)			
0.5*ln(x3/x1)^2							-0.231 (-5.15)	-0.218 (-4.95)	-0.344 (-6.90)
0.5*ln(x4/x1)^2									
ln(x2/x1)*ln(x3/x1)									
ln(x2/x1)*ln(x4/x1)									
ln(x3/x1)*ln(x4/x1)									
ln(y1)*ln(x2/x1)				0.099 (2.66)	0.121 (3.32)	0.011 (0.23)			
ln(y1)*ln(x3/x1)							-0.058 (-1.00)	-0.025 (-0.42)	-0.165 (-3.13)
ln(y1)*ln(x4/x1)									
ln(y2)*ln(x2/x1)				0.035 (1.75)	0.020 (1.02)	0.124 (4.88)			
ln(y2)*ln(x3/x1)							0.219 (5.93)	0.192 (5.29)	0.215 (7.01)
ln(y2)*ln(x4/x1)									
ln(y3)*ln(x2/x1)				-0.099 (-4.45)	-0.102 (-4.70)	-0.076 (-2.74)			
ln(y3)*ln(x3/x1)							-0.073 (-2.15)	-0.074 (-2.22)	0.006 (0.20)
ln(y3)*ln(x4/x1)									
t	0.023 (4.85)	0.023 (5.46)	0.003 (1.03)	0.017 (3.31)	0.018 (3.77)	-0.001 (-0.34)	0.009 (2.94)	0.011 (3.62)	0.002 (0.79)
0.5*t^2	-0.008 (-5.69)	-0.008 (-5.74)	-0.008 (-3.70)	-0.013 (-8.88)	-0.012 (-8.71)	-0.017 (-8.51)	-0.007 (-7.00)	-0.007 (-7.24)	-0.005 (-3.24)
t*ln(y1)	0.000 (0.00)	-0.006 (-0.85)	0.000 (-0.02)	-0.005 (-0.74)	-0.012 (-1.73)	0.001 (0.06)	0.020 (4.01)	0.017 (3.21)	0.013 (1.64)
t*ln(y2)	-0.002 (-0.45)	0.003 (0.68)	-0.016 (-2.46)	0.003 (0.56)	0.008 (1.76)	-0.009 (-1.50)	-0.026 (-7.39)	-0.023 (-5.98)	-0.028 (-5.46)
t*ln(y3)	0.009 (2.22)	0.008 (2.19)	0.025 (4.47)	0.003 (0.90)	0.004 (1.01)	0.010 (1.90)	0.006 (2.14)	0.006 (2.06)	0.017 (4.15)
t*ln(x2/x1)				0 (-0.08)	-0.002 (-0.57)	0.004 (1.00)			
t*ln(x3/x1)							0.024 (5.91)	0.024 (6.03)	0.020 (3.58)
t*ln(x4/x1)									
z1 (rain)		0.000 (-1.09)			0.000 (-0.54)			0.000 (-1.71)	
z2 (tmax)		-0.004 (-0.87)			-0.005 (-1.07)			-0.009 (-2.62)	
z3 (tmin)		-0.007 (-2.96)			-0.005 (-2.31)			-0.005 (-2.16)	
δ_o			0.135 (1.13)			0.248 (1.61)			-0.242 (-1.33)
w1 (rain)			0.000 (2.82)			0.000 (1.38)			0.000 (3.44)
w2 (tmax)			0.019 (2.24)			0.008 (1.34)			0.066 (3.53)
w3 (tmin)			0.002 (0.66)			0.007 (3.41)			0.015 (3.68)
γ	0.819 (19.52)	0.844 (21.16)	0.831 (16.58)	0.784 (17.59)	0.804 (18.61)	0.742 (7.24)	0.959 (44.73)	0.950 (42.45)	0.911 (38.37)
LLF	239.6	257.0703	-23.27	297.3	313.16	85.34	479.5	482.8	128.20
N^o of observations	809	790	790	797	788	788	807	788	788

Case A: without weather, Case B: weather in production function and Case C: weather in inefficiency

Table 5: Input distance function maximum likelihood estimators *(continued)*

Variables	Model 4						Model 5						Model 6					
	M4 Case A		M4 Case B		M4 Case C		M5 Case A		M5 Case B		M5 Case C		M6 Case A		M6 Case B		M6 Case C	
	Coef.	*t* Stat	Coef.	*t* Stat	Coef.	*t* Stat	Coef.	*t* Stat	Coef.	*t* Stat	Coef.	*t* Stat	Coef.	*t* Stat	Coef.	*t* Stat	Coef.	*t* Stat
α_o	0.449	(13.21)	0.500	(12.26)	0.364	(11.02)	0.455	(11.33)	0.466	(13.27)	0.287	(12.95)	0.466	(13.21)	0.515	(12.75)	0.308	(5.17)
ln(y1)	-0.651	(-10.12)	-0.654	(-10.03)	-0.774	(-19.26)	-0.573	(-11.16)	-0.585	(-10.98)	-0.608	(-22.00)	-0.631	(-9.45)	-0.640	(-9.47)	-0.747	(-18.67)
ln(y2)	-0.314	(-7.78)	-0.280	(-6.46)	-0.196	(-6.23)	-0.325	(-10.13)	-0.295	(-8.39)	-0.325	(-17.32)	-0.309	(-7.52)	-0.270	(-6.18)	-0.235	(-7.82)
ln(y3)	0.009	(0.26)	-0.023	(-0.67)	0.013	(0.48)	-0.089	(-3.40)	-0.103	(-3.80)	-0.055	(-3.55)	-0.014	(-0.40)	-0.042	(-1.23)	0.012	(0.44)
$0.5*\ln(y1)^2$	0.548	(1.86)	0.488	(1.65)	0.067	(0.31)	-0.339	(-1.74)	-0.272	(-1.48)	-0.453	(-4.03)	0.712	(2.35)	0.700	(2.29)	-0.137	(-0.51)
$0.5*\ln(y2)^2$	0.245	(2.29)	0.181	(1.70)	0.204	(1.91)	-0.119	(-3.70)	-0.128	(-3.90)	-0.084	(-2.29)	0.232	(2.10)	0.185	(1.72)	0.047	(0.41)
$0.5*\ln(y3)^2$	-0.144	(-1.67)	-0.184	(-2.23)	-0.448	(-6.40)	-0.045	(-0.72)	-0.060	(-0.98)	-0.168	(-3.57)	-0.126	(-1.52)	-0.160	(-1.99)	-0.402	(-4.31)
ln(y1)*ln(y2)	-0.457	(-2.92)	-0.414	(-2.59)	-0.312	(-2.12)	0.138	(2.08)	0.083	(1.21)	0.187	(3.36)	-0.484	(-2.93)	-0.474	(-2.84)	-0.116	(-0.72)
ln(y1)*ln(y3)	-0.073	(-0.53)	-0.059	(-0.44)	0.290	(3.28)	0.142	(1.38)	0.119	(1.20)	0.264	(3.87)	-0.129	(-0.96)	-0.130	(-0.98)	0.295	(2.53)
ln(y2)*ln(y3)	0.181	(2.81)	0.205	(3.11)	0.114	(1.91)	-0.062	(-1.21)	-0.008	(-0.15)	-0.099	(-2.95)	0.185	(2.83)	0.221	(3.26)	0.074	(1.21)
ln(x2/x1)							0.084	(8.01)	0.078	(7.57)	0.178	(14.03)	0.057	(4.77)	0.055	(4.68)	0.122	(4.98)
ln(x3/x1)	0.466	(16.73)	0.449	(15.60)	0.300	(10.33)	0.458	(22.25)	0.454	(22.55)	0.283	(16.00)	0.429	(15.19)	0.411	(14.07)	0.293	(10.76)
ln(x4/x1)	0.092	(5.22)	0.101	(5.63)	0.088	(4.07)							0.093	(5.31)	0.102	(5.71)	0.053	(2.47)
$0.5*\ln(x2/x1)^2$							0.048	(3.69)	0.049	(3.83)	-0.010	(-0.56)	0.031	(1.81)	0.037	(2.19)	-0.025	(-0.82)
$0.5*\ln(x3/x1)^2$	-0.158	(-2.55)	-0.139	(-2.24)	-0.437	(-5.14)	-0.211	(-4.81)	-0.206	(-4.74)	-0.225	(-4.57)	-0.103	(-1.60)	-0.101	(-1.57)	-0.367	(-4.58)
$0.5*\ln(x4/x1)^2$	-0.039	(-1.58)	0.002	(0.08)	-0.036	(-0.94)							-0.013	(-0.55)	0.023	(0.78)	-0.057	(-1.39)
ln(x2/x1)*ln(x3/x1)							-0.055	(-3.67)	-0.052	(-3.54)	-0.032	(-1.45)	-0.025	(-1.22)	-0.021	(-1.03)	-0.040	(-1.03)
ln(x2/x1)*ln(x4/x1)													-0.032	(-2.02)	-0.031	(-1.93)	0.012	(0.44)
ln(x3/x1)*ln(x4/x1)	-0.030	(-0.93)	-0.064	(-1.98)	0.003	(0.08)							-0.028	(-0.90)	-0.059	(-1.88)	0.061	(1.31)
ln(y1)*ln(x2/x1)							0.086	(3.04)	0.098	(3.49)	0.006	(0.15)	0.046	(1.21)	0.064	(1.69)	-0.066	(-1.09)
ln(y1)*ln(x3/x1)	0.229	(3.03)	0.241	(3.12)	0.079	(0.90)	-0.01	(-0.17)	0.010	(0.19)	-0.120	(-2.43)	0.214	(2.88)	0.221	(2.95)	0.007	(0.08)
ln(y1)*ln(x4/x1)	-0.068	(-1.28)	-0.106	(-1.88)	-0.087	(-1.33)							-0.106	(-2.03)	-0.144	(-2.55)	-0.031	(-0.47)
ln(y2)*ln(x2/x1)							0.025	(1.55)	0.015	(0.97)	0.107	(4.88)	0.013	(0.52)	0.000	(0.01)	0.101	(2.44)
ln(y2)*ln(x3/x1)	-0.027	(-0.44)	-0.056	(-0.92)	0.169	(2.44)	0.201	(4.93)	0.171	(4.67)	0.171	(5.85)	-0.03	(-0.51)	-0.052	(-0.89)	0.224	(3.45)
ln(y2)*ln(x4/x1)	0.043	(1.06)	0.102	(2.27)	0.047	(0.93)							0.067	(1.69)	0.121	(2.69)	-0.025	(-0.51)
ln(y3)*ln(x2/x1)							-0.081	(-4.87)	-0.082	(-5.01)	-0.048	(-2.14)	-0.026	(-1.28)	-0.031	(-1.59)	0.017	(0.56)
ln(y3)*ln(x3/x1)	-0.148	(-3.62)	-0.153	(-3.74)	-0.157	(-3.22)	-0.134	(-4.25)	-0.120	(-3.76)	-0.039	(-1.33)	-0.147	(-3.69)	-0.150	(-3.74)	-0.176	(-3.49)
ln(y3)*ln(x4/x1)	0.044	(1.57)	0.037	(1.29)	0.090	(2.29)							0.054	(1.94)	0.052	(1.81)	0.090	(2.29)
t	0.015	(4.84)	0.016	(4.59)	0.010	(2.74)	0.003	(0.74)	0.007	(2.02)	0.000	(-0.14)	0.013	(3.96)	0.014	(3.81)	0.008	(2.10)
$0.5*t^2$	-0.006	(-5.91)	-0.006	(-5.59)	-0.006	(-2.79)	-0.009	(-8.55)	-0.009	(-8.52)	-0.012	(-7.34)	-0.009	(-8.22)	-0.009	(-7.76)	-0.011	(-5.24)
t*ln(y1)	0.006	(0.90)	0.000	(0.05)	0.003	(0.28)	0.012	(2.56)	0.010	(1.91)	0.012	(1.66)	0.01	(1.45)	0.003	(0.50)	0.019	(1.76)
t*ln(y2)	-0.011	(-2.03)	-0.008	(-1.51)	-0.007	(-0.83)	-0.02	(-5.57)	-0.017	(-4.35)	-0.023	(-4.45)	-0.014	(-2.47)	-0.010	(-1.74)	-0.016	(-1.85)
t*ln(y3)	0.005	(1.72)	0.009	(2.72)	0.004	(0.81)	0.005	(1.77)	0.005	(1.74)	0.008	(2.04)	0.002	(0.60)	0.005	(1.60)	-0.007	(-1.26)
t*ln(x2/x1)							0.002	(0.63)	-0.001	(-0.52)	0.004	(1.10)	0.003	(0.99)	0.001	(0.33)	0.001	(0.26)
t*ln(x3/x1)	0.010	(1.74)	0.014	(2.55)	-0.001	(-0.15)	0.021	(4.21)	0.025	(5.70)	0.017	(3.25)	0.009	(1.46)	0.013	(2.17)	-0.003	(-0.39)
t*ln(x4/x1)	0.010	(2.92)	0.008	(2.43)	0.012	(1.89)							0.008	(2.28)	0.006	(1.86)	0.010	(1.60)
z1 (rain)			0.000	(-0.15)					0.000	(-0.79)					0.000	(-0.41)		
z2 (tmax)			-0.010	(-2.26)					-0.010	(-3.05)					-0.010	(-2.20)		
z3 (tmin)			-0.004	(-1.56)					-0.004	(-1.62)					-0.004	(-1.53)		
δ_o					-0.069	(-0.52)					-0.464	(-1.90)					-0.323	(-1.31)
w1 (rain)					0.000	(2.89)					0.000	(2.54)					0.000	(1.95)
w2 (tmax)					0.040	(2.81)					0.079	(3.01)					0.070	(1.84)
w3 (tmin)					0.019	(3.61)					0.030	(3.58)					0.028	(4.22)
γ	0.988	(80.35)	0.978	(63.35)	0.893	(21.88)	0.968	(44.66)	0.957	(40.39)	0.863	(20.18)	0.984	(82.07)	0.974	(63.04)	0.837	(6.95)
LLF	422.6		422.1		128.2		530.8		533.8		226.2		450.6		448.4		203.6	
N° of observations	535		520		520		795		776		776		535		520		520	

Case A: without weather, Case B: weather in production function and Case C: weather in inefficiency

Output elasticities sum on average -0.9648, -0.9593 and -0.9590 regarding Case A, Case B and Case C models respectively. Elasticities from cost models are the lowest. This suggests that in general, a very slight decrease in the return to scale at the sample mean can be seen. From these results, small economies of scale are also noticed. The introduction of weather does not produce an important increase in economies of scale. This upward movement is on average 0.57 per cent and 0.61 per cent regarding models from Case B and Case C respectively. In general, cost models are those with the highest value of economies of scale.

In terms of technical change and concerning Case A and Case B models, all the time coefficients are positive and statistically significant, which indicates a mean technical progress of 1.33 per cent and 1.48 per cent per year for Case A and Case B models respectively. This means that the introduction of weather produces a minor upward increase of 0.15 percentage points of technical progress. The cost models are those that contribute the most, with a mean technical progress of 2.0 per cent and 2.1 per cent per year respectively. Regarding Case C, technical change is not statistically significant except for M4 Case C. In terms of the non-neutral technical change, which is denoted by the time interacted with each output (in log), those that correspond to customers and length of network in general have a positive impact on opex reduction and energy delivered has the inverse effect. However, coefficients of cost quality models are in general those that are statistically significant.

Regarding models that include weather variables, Case B and Case C, the coefficients have the correct sign. As previously mentioned, in Case B models, maximum and minimum temperatures are the variables that influence most the production function. The influence of total rain is weak and is only statistically significant in M3 Case B. For Case C models it can be seen that the level of significance increases in comparison with Case B models and that total rain still remains weak. Furthermore, the influence of maximum and minimum temperature on inefficiency is higher in cost-quality models than in cost models. Estimators vary from 0.008 to 0.079 regarding maximum temperature and from 0.002 to 0.030 regarding minimum temperature. The positive sign of these estimators indicate that inefficiency increases when these values also rise.

Gamma (ɣ) [22], which explains the contribution of the inefficiency component on the variation of the composite error term, is on average 0.917, 0.918 and 0.846 for Case A, Case B and Case C models respectively. These values are higher for cost-quality models than for cost models, which means that the fact that firms are not fully efficient is much more efficiently explained when quality variables are introduced to the models. On average for these models, gamma is equal to 0.974, 0.965 and 0.876 respectively; all of them are statistically significant at 1 per cent. In terms of the fitness of weather models, results from likelihood ratio tests indicate that Case A models are rejected in most cases in favour of Case B models[23] and fully rejected in favour of Case C models[24] at 1 per cent. This indicates that the effect of weather should not be ignored.

[22] $\gamma = \frac{\sigma^2_u}{\sigma^2}$, where $\sigma^2 = \sigma^2_u + \sigma^2_v$

[23] Model 1 and Model 2 from Case A are rejected at 1 per cent and Model 3 at 10 per cent. Model 4, Model 5 and Model 6 cannot be rejected. However a Wald test suggests that Model 4 and Model 6 are rejected at 5 per cent and Model 5 at 1 per cent.

[24] In this case, all models from Case A are rejected in favour of models from Case C at 1 per cent.

This result is also in line with that from Jamasb *et al.* (2010), who use the Wald test for testing the convenience of including weather in the cost function. Coelli *et al.* (1999) also find similar results using the likelihood ratio test. The non-inclusion of weather is rejected in favour of models that include weather in the production function (input distance function).

Regarding Case B (preferred models) and Case C models, it is also convenient to analyse and compare both approaches in order to identify the approach that provides the best fitness. The selection between Case B and Case C models appears to be a difficult task. In order to determine the best approach, weather in production versus weather in inefficiency, a set of nested models, was built for doing proper comparisons. It is noteworthy that Case B and Case C models are not nested in each other. Two models are nested when one model is an extension of the other one. Nested models are used as an artifice for comparing models using specific tests such as log likelihood ratio (LLR) test. Following Coelli *et al.* (1999), the artificial nested models are built including weather variables in production and also in inefficiency as explanatory variables of technical efficiency. Estimators for the nested models are shown in Appendix 5. The idea is to test a null hypothesis using a likelihood test between (1) the nested models and the Case B models and (2) the nested models and the Case C models. On the one hand, the tests indicate that all models from Case B cannot be rejected in favour of the nested models. On the other hand, the tests suggest that models from Case C are rejected in favour of the nested models at 1 per cent. This implies that models in which weather directly affects the production function are preferred due to the better fitness to the sample data. This result reinforces the selection of Case B as the preferred model. The following section discusses the results based on Case B models.

6.2 Technical Efficiency

6.2.1 Global Effect

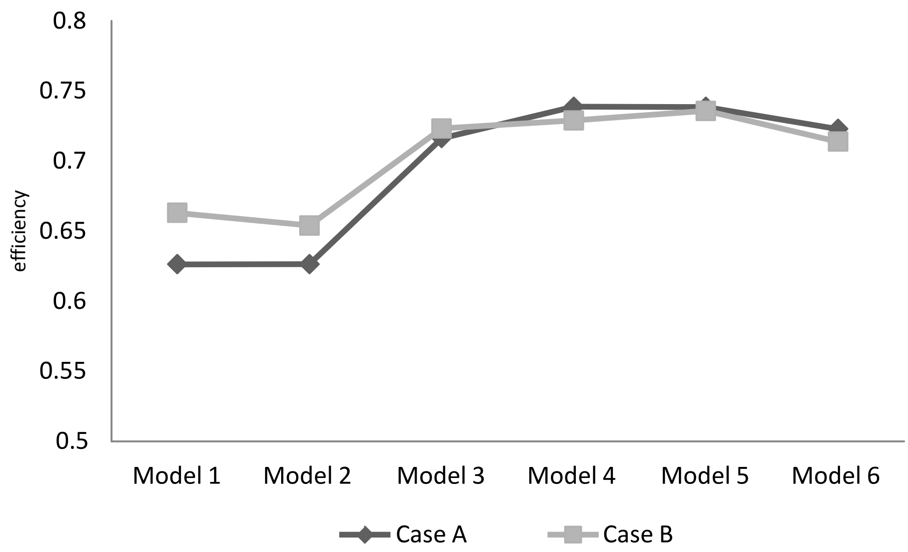
The global effect is measured by the variation of technical efficiency when comparing Case A models (without weather) with Case B models (with weather). Figure 1 depicts the efficiency score for Case A models and Case B models (weather in input distance function). Efficiency scores from Case B models vary from 0.663 to 0.714 and are on average higher than those from Case A models. In addition, it can be seen that the influence of weather is more significant for cost models than for cost-quality models[25]. Efficiency scores increase on average by 5.12 per cent regarding cost models. For cost-quality models, the variation is very low around -0.51 per cent. Even though the average variation is not high, a country-level analysis indicates that weather influences technical efficiency importantly to some of the countries that are part of this study.

These results suggest that to some extent the inclusion of quality adjusts for weather, however, this does not justify regulators ignoring weather and only looking at quality. It is important to note that these results refer to average results. A country-level analysis and a company-level

[25] The ANOVA test suggests that the variation on companies' efficiency (when weather variables are added) is statistically significant at 1 per cent only for Model 1 and Model 2.

analysis would suggest that the variation is important for some countries and for some firms. The next two sections provide further explanation regarding these results.

Figure 1: Efficiency comparison (with and without weather)



This study's results are also in line with those from Growitsch *et al.* (2010). Based on Battese and Coelli (1992, 1995), their results suggest an increase of average efficiency by more than ten percentage points when weather variables and geographic factors are taken into consideration. When comparing this study's results with those from Yu *et. al* (2009b), quality variables such as energy losses and customer minutes lost are those variables that have most internalised the effect of weather on efficiency, instead of the network length suggested by Yu *et al*. (2009b). From this study's results, the authors note that the inclusion or exclusion of network length does not affect the influence that weather has on efficiency. The increase in efficiency remains almost the same.

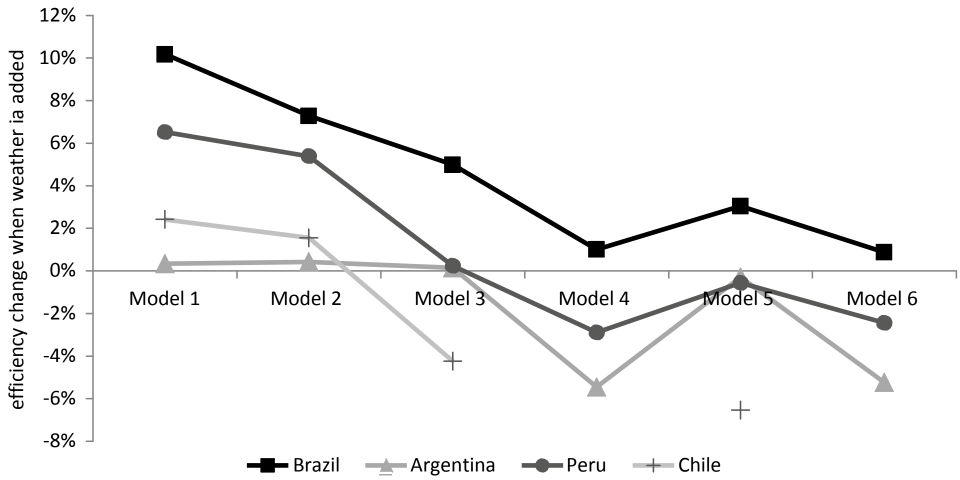
6.2.2 Country-Level Effect

Figure 2 shows the impact that weather has on a firm's efficiency at country-level[26]. A comparison between models without weather (Case A) and with weather in input distance function (Case B) for each country was made. The impact is measured as the change in efficiency (in percentage) when weather is added. For example, from Figure 2 the trend of efficiency change regarding firms from Brazil indicates an increase of efficiency as follows: 10.1 per cent (Model 1), 7.3 per cent (Model 2), 5 per cent (Model 3), 1 per cent (Model 4), 3.1 per cent (Model 5) and 0.9 per cent (Model 6). The results based on the category of models are discussed in this section.

[26] These results refer to the average change of efficiency at country level. Appendix 6 shows the variance of the efficiency change per model and per country.

First, regarding cost models, the country with the highest increase in efficiency is Brazil followed by Peru and the country with the lowest increase is Chile[27]. These results suggest that firms from Brazil and Peru would operate in less favourable weather conditions than those from Argentina and Chile. Regarding Model 1, Brazilian firms increase efficiency by 10.1 per cent and the Argentinian ones only increase by 0.34 per cent. When comparing Model 1 with Model 2, in general the impact is more significant when costs refer only to opex. In the case of Brazil and Peru, this suggests that to some extent capital cost could be internalising the effect of weather due to the decrease in the efficiency change. Regarding Argentina, the effect is not significant. In summary, the introduction of weather variables in technology in relation to cost models produces on average an increase in efficiency as follows: 8.7 per cent in Brazil, 0.4 per cent in Argentina, 6 per cent in Peru and 2 per cent in Chile.

Figure 2: Change on efficiency due to weather at country-level



Second, in terms of cost-quality models, on average the influence of weather on efficiency is much lower than the previous case. However, under this approach firms from Chile present the highest variation in efficiency when comparing Model 3 and Model 5. This variation has a negative sign, which means that efficiency decreases. When customer hours lost is included, see Model 4 and Model 6, firms from Argentina are the most affected and efficiency reduces on average by 5 per cent. In summary, the effect of weather on the input distance function under the cost-quality models generates the following changes in efficiency: 2.5 per cent in Brazil, -2.7 per cent in Argentina, -1.4 per cent in Peru and -5.4 per cent in Chile. These results suggest that on average firms are able to adjust their networks taking into account the environment in which they operate, such as weather in order to improve the reliability of the system. If this assumption is true, weather would not significantly affect losses and interruptions. It is likely that firms have installed specific equipment and devices that protect their networks from tropical environments. This makes more sense in the case of Brazil and Peru. On the other hand, a negative sign would mean that the firm has adapted their networks based on their

[27] The ANOVA test shows that the change in efficiency (due to the inclusion of weather) is not statistically significant across all models and countries. Regarding Brazil, the difference is significant in Model 1 and Model 2 at 1 per cent and Model 3 at 10 per cent. In terms of Argentina, the difference is significant in Model 4 and Model 6 at 1 per cent. In relation to Chile, the difference is significant only in Model 3 and Model 5 at 1 per cent. Finally, regarding Peru, the difference is significant in Model 1 and Model 2 at 1 per cent and Model 4 at 10 per cent.

environmental reality in which they operate and at the same time it benefits from weather. This assumption makes more sense in the case of Chile, in which the level of losses is very low in comparison with the other three countries and at the same time weather conditions seem to be more favourable.

These results are in line with other empirical studies in the sense that weather matters for efficiency. The size of impact depends on the model specifications and the combination of inputs, outputs and environmental variables selected (Yu *et al*., 2009a; Jamasb *et al*., 2010; Nillesen and Pollitt, 2010; Growitsch *et al.,* 2010).

The use of dummy variables for capturing any systematic differences across countries was also analysed. Brazil was selected as the base country. The idea is to analyse the individual effect (per country) based on firms from Brazil. Results show that the coefficients of the dummy variables are not statistically significant across all models. In addition, the inclusion of these dummies makes that the weather variables in general (with some exceptions) are not statistically significant. Thus, it appears to be the case that to some extent the systematic differences between Brazil and the remaining three countries are capturing the effect that weather could have on this.

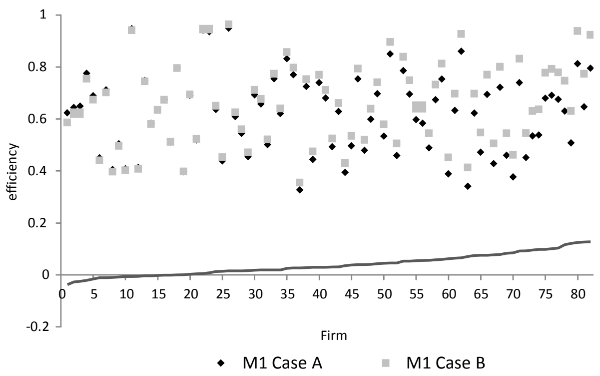
6.2.3 Company-level Effect

Finally, a company-level analysis is conducted in order to evaluate the impact that the inclusion of weather has on firm-level efficiency. For this purpose, the average efficiency score for each model and for each firm was plotted for the period 1998-2008, see Figure 3. The firms were sorted based on the gap between efficiency under Case A and Case B models. Dark dots indicate efficiency without weather (Case A) and light dots indicate efficiency with weather (Case B).

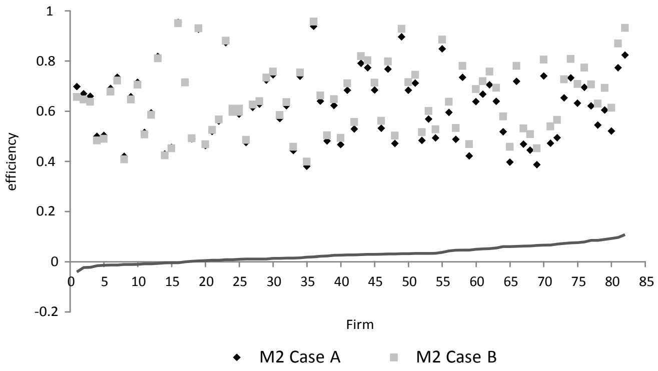
The gap increases proportionally to the number of firms. For instance, in Model 1 the majority of firms increase their efficiency when weather is taken into account. The area between the horizontal axis and the green line indicates the number of firms that increase (right side) or decrease (left side) their efficiency when weather is added. For instance, in Model 1 the maximum gap is 0.13 which means that a firm could increase its efficiency from 0.79 to 0.92 when weather is added. The number of firms that experience an increase in efficiency is as follows: 64 (Model 1), 65 (Model 2), 49 (Model 3), 29 (Model 3), 45 (Model 5) and 29 (Model 6)[28]. The frequency of upward increases is much higher in cost models than in cost-quality models. On average, the percentage of firms that increase efficiency is 79 per cent for cost models and 52 per cent for cost-quality models.

[28] For Model 1, 2, 3, 4, 5, and 7 the total number of firms is 82. For Model 6 and 8 the total number is 62 due to the lack of Customer Hours Lost (CHL) data for some of the firms.

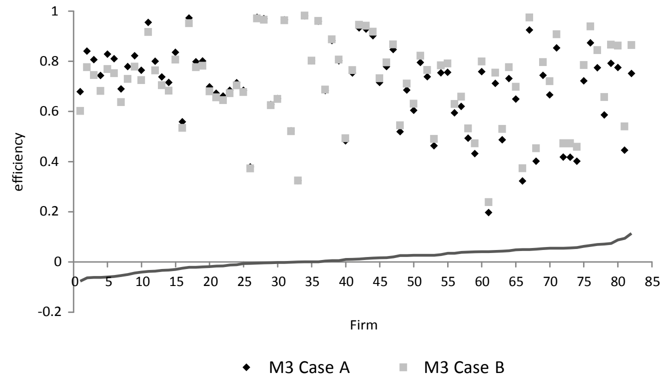
Figure 3: Average change of efficiency (1998-2008) per model



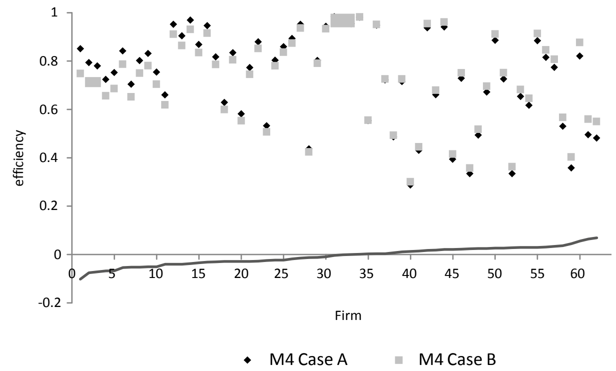
(3a) Model 1



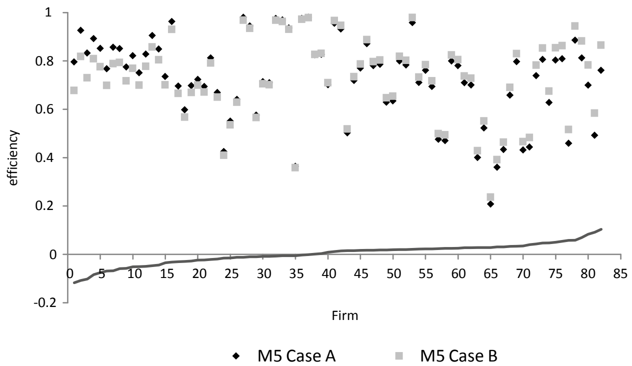
(3b) Model 2



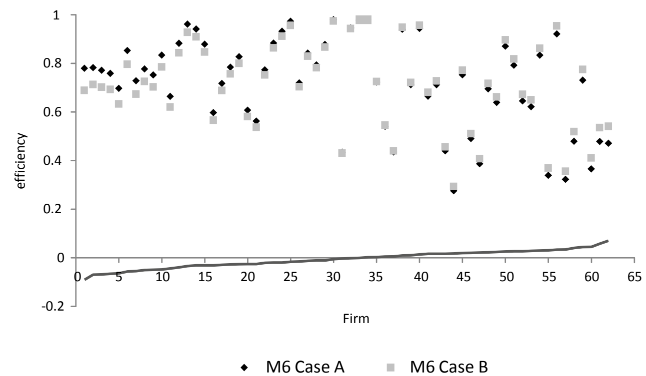
(3c) Model 2



(3d) Model 4



(3e) Model 5

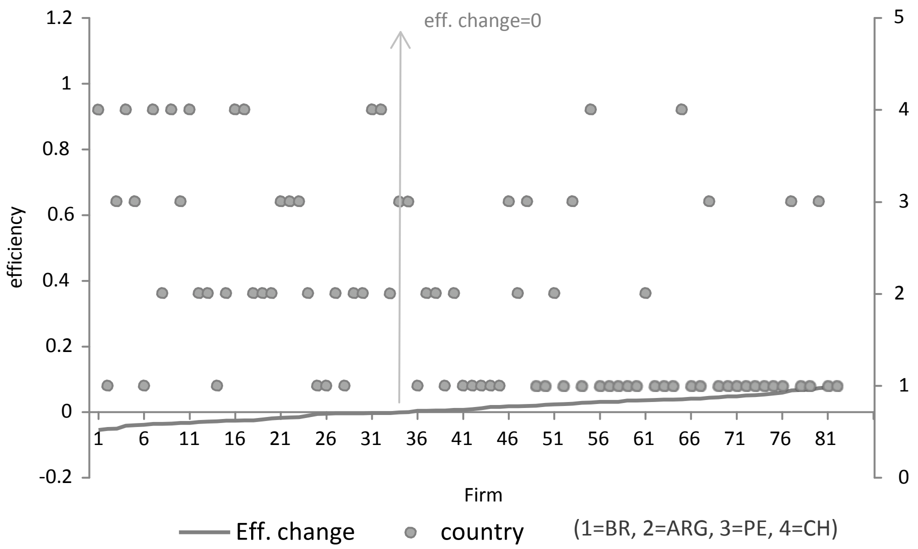


(3f) Model 6

In addition, the average increase in efficiency (in percentage points) regarding these firms is as follows: 5.23 (Model 1), 3.96 (Model 2), 3.83 (Model 3), 2.5 (Model 4), 3.21 (Model 5) and 2.42 (Model 6). These results are in line with those from the country-level analysis. From these figures and regarding cost models, it is noticed that a decrease of 1.27 percentage points occurs when capex is added. As mentioned before, this suggests that the effect of weather could be being internalised by capital costs. In terms of cost-quality models, the trend is very similar in the sense that when total costs are included (Model 4 and Model 6) the increase in efficiency is lower.

Figure 4 summarises the efficiency change across the six models when weather is added. As a result, taking into consideration cost models and cost-quality models, it is clear that on average a total of 48 firms increase their efficiency when weather is introduced with an average upward increase of 3.4 percentage points. The number of firms that decreases their efficiency is 34 with an average downward movement of 2.2 percentage points.

Figure 4: Average change of efficiency (1998-2008)



Brazil is the country with the highest percentage number of firms that increase their efficiency, representing 84.6 per cent, followed by Peru with 50 per cent, Argentina with 33.3 per cent and Chile with 18.2 per cent. In addition, these firms increase their efficiency by 3.7 percentage points, 1.6 percentage points, 3.5 percentage points and 3.4 percentage points respectively. These results confirm the previous findings and indicate that in general, firms from Brazil and Peru operate in less favourable weather conditions than companies based in Argentina or Chile. In Figure 4, the density of firms (which increase or decrease their efficiency) is indicated by the 'circle' marker. This takes the value of 1 for Brazilian firms, 2 for Argentine firms, 3 for Peruvian firms and 4 for Chilean firms.

In addition to the efficiency change, a ranking analysis at firm-level for each model indicates that firms from Brazil and Peru are those that tend to increase their ranking in comparison with firms from Argentina and Chile. This result is also in agreement with that related to efficiency change, in which firms from Brazil and Peru are those with the highest percentage of firms that raise their efficiency when weather is introduced. Table 6 illustrates the number of firms that increase (↑), decrease (↓) or remain in the same position (≈) for each country and across models. It can also be observed that depending on the models, the change of rankings for some specific firms is very impressive with the maximum upward change of 28 positions and the maximum downward change of 24 positions, both related to Model 5. Thus in general on average across models (cost and cost-quality models) the introduction of weather produces important ranking changes for some firms. In summary, 37 firms improve, 38 firms worsen and 7 firms remain in the same position. The ranking variation differs across countries, where firms from Brazil are those with the highest number of firms that increase their rankings (61.5 per cent), followed by Peru (50 per cent), Argentina (22.2 per cent) and Chile (18.2 per cent). On average, the number of firms that change their ranking by more than 10 positions is 14 with the maximum upward change of 16 positions and the maximum downward change of 16 positions as well.

Table 6: Ranking variation per type of model

Country	Ranking variation - Number of firms per model																	
	Model 1			Model 2			Model 3			Model 4			Model 5			Model 6		
	↑	↓	≈	↑	↓	≈	↑	↓	≈	↑	↓	≈	↑	↓	≈	↑	↓	≈
Brazil	26	9	4	27	10	2	22	9	8	18	14	7	24	10	5	18	12	9
Argentina	1	17	0	1	16	1	6	10	2	0	8	1	9	8	1	3	6	0
Peru	6	7	1	7	5	2	4	8	2	5	8	1	5	9	0	4	8	2
Chile	2	9	0	1	9	1	1	9	1				1	10	0			
Total	35	42	5	36	40	6	33	36	13	23	30	9	39	37	6	25	26	11

↑: upper position, ↓: lower position, ≈ : no variation

From the previous discussion the authors state that the addition of weather could significantly affect the efficiency and rankings of some firms. Regarding efficiency, important variations are observed where the maximum increase and decrease is 12.8 per cent (Model 1) and 14.8 per cent (Model 5) respectively. In terms of ranking, important changes across models are also noticed for some specific firms with ranking variation up to 28 positions (Model 5), with firms from Brazil those with the highest impact. Following Coelli *et al.* (2003), when specific firms face important variations in efficiency due to the introduction of environmental variables, regulators are recommended to invite these specific firms and to make a case for deciding the appropriate adjustment of their respective efficiency scores. The same criteria should be applied when important ranking variations are faced.

The effect of ownership on efficiency was also tested. These results suggest that on average public firms operate in worse weather conditions than private firms. This result is understandable for two reasons. Firstly, less developed areas used to be affected by worse weather conditions in comparison with the most developed areas. Secondly, firms that operate in less developed areas tend to be more likely to be publicly-owned.[29]

[29] The level of the human development index (HDI) was used to measure the level of development for this purpose. However, due to the lack of information regarding HDI across countries (data was available for only some specific years), it was not possible to statistically determine the significance of these results.

Conclusions

In this study, technical efficiency was estimated for 82 electricity distribution firms that operate in South America for the period 1998-2008. A stochastic frontier approach was selected and weather variables were included in the analysis. For determining the preferred weather models, different approaches were analysed such as the inclusion of weather in production and its inclusion in the inefficiency term. Based on statistical hypothesis testing, the authors conclude that the inclusion of weather in the production function is the preferred approach.

The results suggest that rain and high and low absolute temperatures combined are the weather variables that affect the shape of the input distance function under cost models and cost-quality models. A country-level analysis indicates that under cost models, firms from Brazil and Peru increase their efficiency significantly when weather is included, while in the case of Argentina and Chile, the increase is much smaller. From this we conclude that firms from Brazil and Peru operate in less favourable weather conditions than those from Argentina and Chile. In terms of cost-quality models, the impact of weather on efficiency is on average much lower. Results suggest that Chile is the country where weather has the biggest effect but this influence produced a downward effect on efficiency. From this, it can be concluded that on average firms are able to adapt their networks taking into account their own environment. There is a strong possibility that firms had installed special equipment and devices in order to protect their networks from non-favourable weather conditions (such as tropical environments), which helps to reduce customer minutes lost and also energy losses. Thus, it makes sense to state that quality variables (such as customer minutes lost) and energy losses are those variables that have most internalised the effect of weather on efficiency.

A company-level analysis shows that across models an important number of firms exist where weather affects the efficiency. This reflects to some extent the appropriate selection of weather variables due to the large effect they can have. In addition, the number of weather variables is also convenient because it allows regulators to control degrees of freedom. The authors have observed that some specific firms face a large variation in efficiency and in rankings when weather is added. Thus, regulators should make a case study to invite these specific firms to make a case for deciding the appropriate adjustment of their respective efficiency scores.

Finally, this study's findings suggest that regulators are advised to practice international performance comparisons across countries that include the addition of physical and cost variables quality as well as weather factors. The empirical analysis confirms that weather impacts on efficiency, especially for cost models. This result is more evident when a country-level analysis is performed. Even though the effect of weather on technical efficiency is on average not significant for cost-quality models, a company-level analysis suggests that for some specific firms, weather affects their performance in an important way.

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Appendix 1: List of Firms

Country	Utility name	Country	Utility name
ARGENTINA	1 Edenor	**BRAZIL**	42 Enersul
	2 Edesur		43 Ceb
	3 Edelap		44 Cepisa
	4 Edea		45 Ceal
	5 Eden		46 Sergipe
	6 Edes		47 Celtins
	7 Epec		48 Manaos
	8 Edeersa		49 Ceron
	9 Ejesa		50 Catlec
	10 Edelar		51 Ceam
	11 Edemsa		52 Caiua
	12 Edersa		53 Electroacre
	13 Edesa		54 Borborema
	14 ESJ		55 Paranapanema
	15 Edesal		56 Bragantina
	16 EPSF		57 Nacional
	17 Edese	**CHILE**	58 Chilectra
	18 Edet		59 CGE
BRAZIL	19 Coelba		60 Chilquinta
	20 CPFL_Paulista		61 Saesa
	21 Eletropaulo		62 Conafe
	22 Cemig Distribution		63 Emeletric
	23 Ligth		64 Frontel
	24 Copel Distribution		65 Elecda
	25 Celpe		66 Emelat
	26 Coelce		67 Eliqsa
	27 Ampla		68 Emelari
	28 Celesc	**PERU**	69 Edelnor
	29 Celg		70 Luz del Sur
	30 Escelsa		71 Ede Cañete
	31 Celpa		72 Electro Sur Medio
	32 CPFL_Piratininga		73 Electrocentro
	33 Elektro		74 Electro Norte Medio
	34 Bandeirante		75 SEAL
	35 Cemar		76 Electro Norte
	36 Ceee		77 Electro Noroeste
	37 RGE		78 Electrosur
	38 AES_SUL		79 Electro Sur Este
	39 Cosern		80 Electro Oriente
	40 Saelpa		81 Electro Ucayali
	41 Cemat		82 Electro Puno

Appendix 2: Map of Firms' Service Area

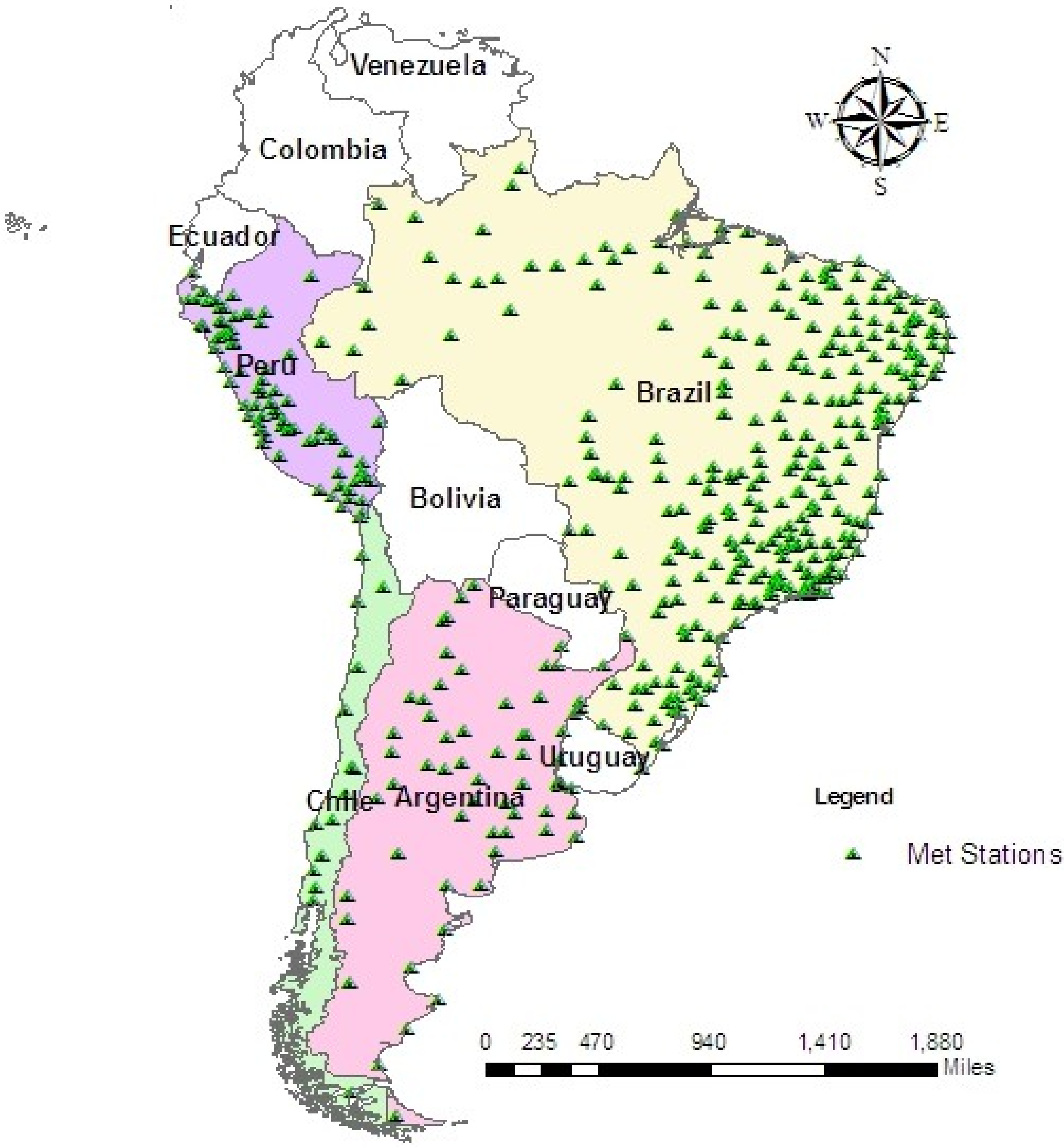
PERU
Firms:
Energy
Firms'
(000')

d: 97.6%
rea: 8111 Km2

CHILE
Firms:
Energy
Firms'
(000')

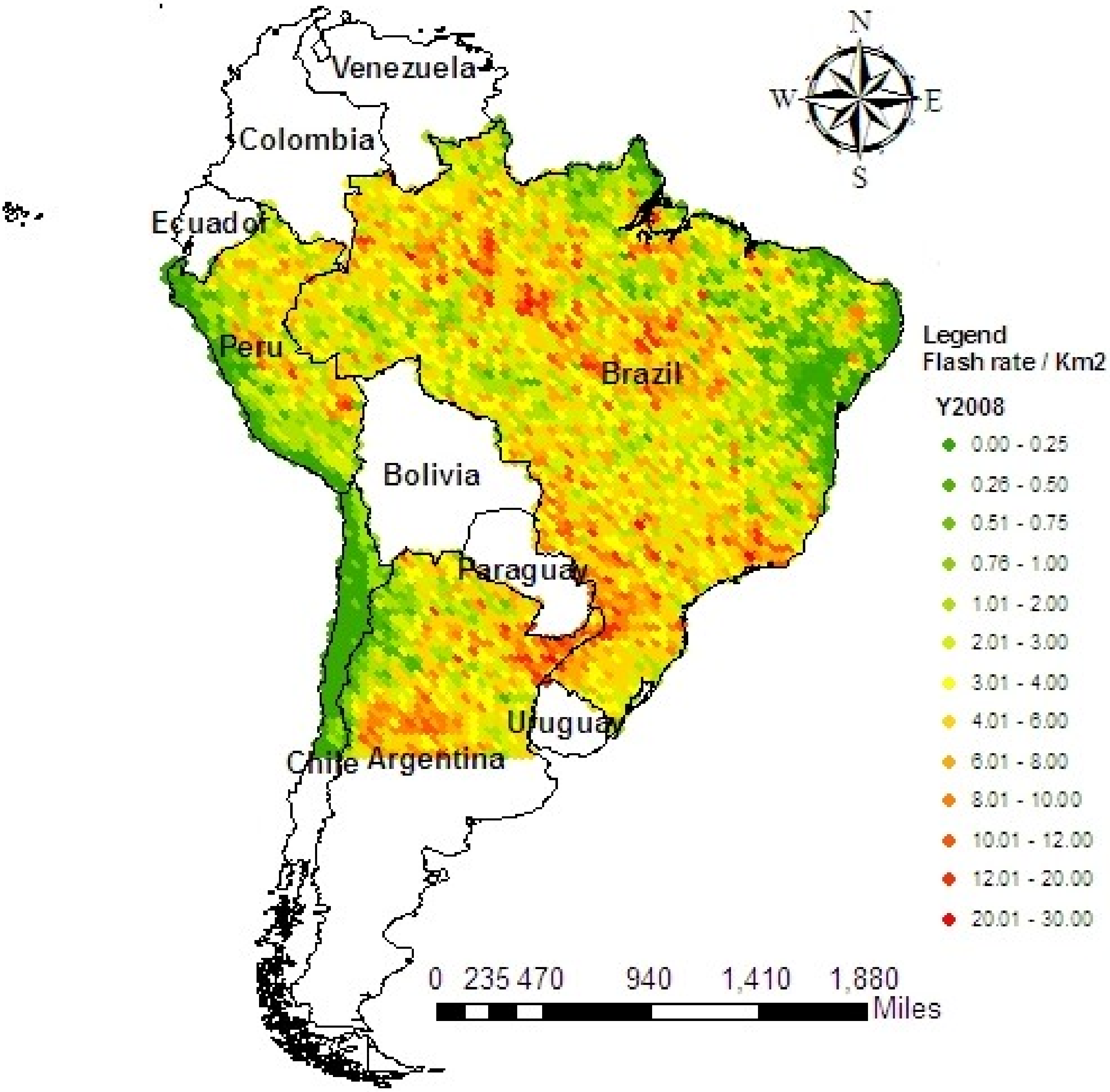
Note: The service areas shown on the map refer only to those firms that are part of this study.
Own elaboration.

Appendix 3: Meteorological Stations per Country



Note: Met stations refer to the total number of stations available per country.
Met stations' coordinates provided by Met Offices. Own elaboration.

Appendix 4: Flash Rate Coordinates per Country – Period 2008

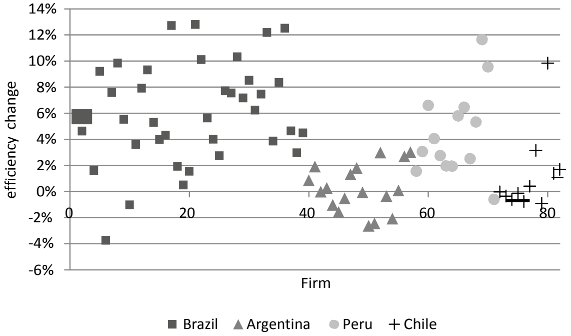


Note: Coordinates refer to the total number of coordinates available per country.
NASA provided the respective coordinates. Own elaboration.

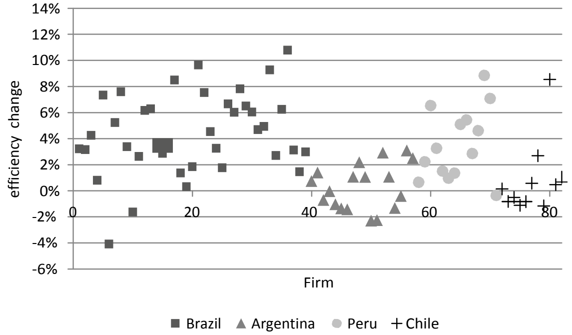
Appendix 5: Nested Models

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Coef. *t* Stat	Coef. *t* Stat	Coef. *t* Stat	Coef. *t* Stat	Coef. *t* Stat	Coef. *t* Stat
α_o	0.49 (13.93)	0.33 (4.71)	0.38 (13.25)	0.45 (19.59)	0.29 (12.58)	0.40 (13.85)
ln(y1)	-0.68 (-16.65)	-0.66 (-16.80)	-0.57 (-16.53)	-0.78 (-16.73)	-0.57 (-17.88)	-0.71 (-18.76)
ln(y2)	-0.25 (-9.50)	-0.26 (-10.15)	-0.35 (-15.50)	-0.24 (-7.03)	-0.35 (-16.70)	-0.28 (-9.23)
ln(y3)	-0.01 (-0.66)	-0.05 (-2.51)	-0.06 (-3.23)	0.05 (1.72)	-0.09 (-5.30)	0.02 (0.55)
0.5*ln(y1)^2	-0.23 (-1.47)	-0.33 (-2.40)	-0.29 (-2.10)	0.13 (0.45)	-0.40 (-3.51)	-0.44 (-2.06)
0.5*ln(y2)^2	-0.03 (-0.55)	-0.01 (-0.28)	-0.10 (-1.85)	0.20 (1.82)	-0.10 (-2.67)	0.01 (0.08)
0.5*ln(y3)^2	-0.36 (-6.60)	-0.31 (-5.59)	-0.10 (-1.96)	-0.33 (-4.18)	-0.14 (-2.99)	-0.49 (-6.98)
ln(y1)*ln(y2)	0.06 (0.81)	0.09 (1.31)	0.16 (2.18)	-0.27 (-1.70)	0.19 (3.37)	0.03 (0.19)
ln(y1)*ln(y3)	0.31 (3.57)	0.32 (3.86)	0.17 (2.14)	0.17 (1.42)	0.24 (3.46)	0.42 (4.62)
ln(y2)*ln(y3)	-0.06 (-1.34)	-0.09 (-1.98)	-0.08 (-2.20)	0.11 (1.59)	-0.10 (-3.00)	0.03 (0.45)
ln(x2/x1)		0.23 (14.44)			0.18 (14.17)	0.11 (5.53)
ln(x3/x1)			0.32 (18.07)	0.32 (9.17)	0.29 (16.25)	0.31 (10.22)
ln(x4/x1)				0.05 (2.45)		0.04 (2.01)
0.5*ln(x2/x1)^2		0.02 (1.07)			0.00 (-0.14)	-0.06 (-2.19)
0.5*ln(x3/x1)^2			-0.35 (-6.64)	-0.49 (-4.89)	-0.21 (-4.24)	-0.31 (-3.55)
0.5*ln(x4/x1)^2				-0.10 (-2.85)		-0.11 (-2.86)
ln(x2/x1)*ln(x3/x1)					-0.04 (-1.85)	-0.04 (-1.19)
ln(x2/x1)*ln(x4/x1)						0.03 (1.20)
ln(x3/x1)*ln(x4/x1)				0.04 (0.77)		0.00 (0.06)
ln(y1)*ln(x2/x1)		0.01 (0.19)			0.02 (0.49)	-0.12 (-2.18)
ln(y1)*ln(x3/x1)			-0.20 (-3.43)	0.07 (0.71)	-0.19 (-3.76)	0.05 (0.57)
ln(y1)*ln(x4/x1)				0.00 (0.00)		0.03 (0.45)
ln(y2)*ln(x2/x1)		0.13 (4.87)			0.11 (4.74)	0.14 (3.96)
ln(y2)*ln(x3/x1)			0.21 (6.34)	0.16 (2.19)	0.18 (5.99)	0.15 (2.13)
ln(y2)*ln(x4/x1)				-0.04 (-0.77)		-0.07 (-1.52)
ln(y3)*ln(x2/x1)		-0.08 (-2.98)			-0.06 (-2.42)	0.04 (1.21)
ln(y3)*ln(x3/x1)			0.01 (0.24)	-0.15 (-3.03)	-0.01 (-0.34)	-0.16 (-3.44)
ln(y3)*ln(x4/x1)				0.10 (2.61)		0.10 (2.45)
t	0.00 (1.18)	0.00 (0.69)	0.00 (1.29)	0.01 (3.03)	0.00 (0.72)	0.01 (2.95)
0.5*t^2	-0.01 (-3.30)	-0.02 (-8.16)	-0.01 (-2.88)	-0.01 (-3.71)	-0.01 (-6.93)	-0.01 (-5.61)
t*ln(y1)	-0.01 (-0.71)	0.00 (0.37)	0.01 (1.54)	-0.01 (-0.81)	0.01 (1.73)	0.01 (0.72)
t*ln(y2)	-0.01 (-2.25)	-0.01 (-1.79)	-0.03 (-5.12)	0.00 (0.40)	-0.02 (-4.16)	-0.01 (-1.44)
t*ln(y3)	0.03 (5.11)	0.01 (1.33)	0.02 (3.89)	0.00 (0.13)	0.01 (1.54)	0.00 (-0.34)
t*ln(x2/x1)		0.00 (0.72)			0.00 (0.75)	0.00 (0.39)
t*ln(x3/x1)			0.02 (3.71)	0.00 (-0.54)	0.02 (3.36)	-0.01 (-0.73)
t*ln(x4/x1)				0.02 (3.08)		0.01 (2.42)
z1 (rain)	0.000 (5.26)	0.000 (3.27)	0.000 (4.09)	0.000 (1.22)	0.000 (5.41)	0.000 (2.50)
z2 (tmax)	0.001 (0.37)	0.004 (1.14)	-0.001 (-0.29)	0.007 (2.20)	-0.003 (-1.12)	0.007 (2.23)
z3 (tmin)	-0.001 (-0.40)	-0.001 (-0.55)	0.001 (0.66)	0.007 (3.25)	0.001 (0.45)	0.007 (3.16)
δ_o	0.283 (4.50)	0.096 (1.13)	0.025 (0.25)	0.223 (3.85)	-0.335 (-2.21)	-0.001 (-0.02)
w1 (rain)	0.000 (6.60)	0.000 (5.32)	0.000 (6.44)	0.000 (2.85)	0.000 (5.87)	0.000 (3.44)
w2 (tmax)	0.020 (2.72)	0.029 (3.38)	0.045 (3.92)	0.032 (4.15)	0.070 (3.69)	0.045 (3.95)
w3 (tmin)	0.001 (0.25)	0.004 (1.42)	0.011 (2.76)	0.018 (3.46)	0.023 (4.16)	0.030 (5.98)
gamma	0.855 (23.92)	0.294 (1.29)	0.891 (34.86)	1.000 (263.87)	0.809 (15.66)	0.972 (43.00)
Log likelihood	-11.0	93.4	138.1	182.6	244.7	217.4
N of observations	790	788	788	520	776	520

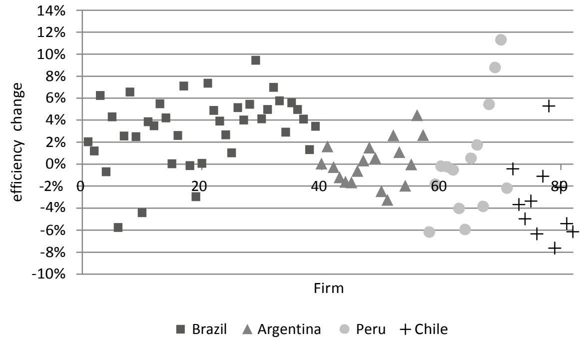
Appendix 6: Efficiency Change at Country Level and per Model



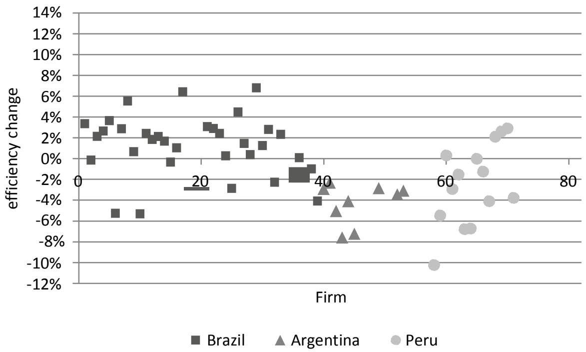
Model 1



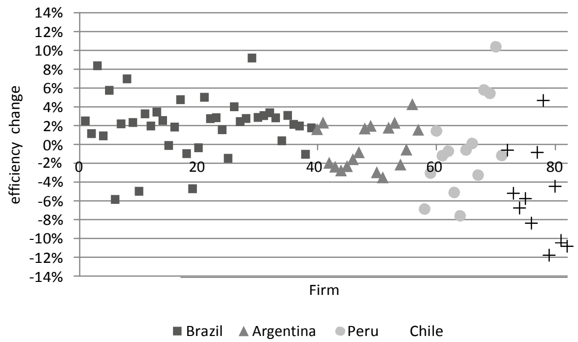
Model 2



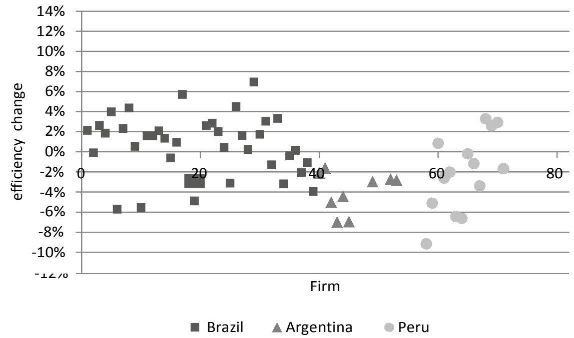
Model 3



Model 4



Model 5



Model 6