TECHNOLOGICAL AND ECONOMIC DEVELOPMENT OF ECONOMY
ISSN 2029-4913 / eISSN 2029-4921

2018 Volume 24(2): 718–738
doi:10.3846/20294913.2017.1318312

INSOLVENCY OF BRAZILIAN ELECTRICITY DISTRIBUTORS: A DEA BOOTSTRAP APPROACH

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Received 23 August 2016; accepted 08 April 2017

Abstract. This study investigates the financial and operational indicators that explain the insolvency of Brazilian electricity distributors, using a data envelopment analysis (DEA) bootstrap approach. The Wagner and Shimshak (2007) stepwise procedure was used to select the variables that had the greatest impact on average efficiency estimated by DEA in the construction of an inefficient frontier. Through a second stage analysis, the Simar and Wilson (2007) bootstrapped truncated regression analyzed contextual variables associated with inefficiency, and consequently with firm insolvency. The sample was composed of electricity distributors, whose financial information for the 2000–2015 period was available on the Brazilian Securities Exchange (CVM) website. The results indicated that the Actual Equivalent Frequency of Power Interruptions/Regulatory Equivalent Frequency of Power Interruptions and Overall Indebtedness were the most important indicators in explaining insolvency. The second-stage analysis showed that the inefficiencies calculated using the selected indicators are positively related to insolvency criteria used by the literature, state control, dollar and geographical location, and negatively related to the domestic inflation index. The results provide valuable information for the Brazilian electricity sector's regulatory body, which recently began to hold public hearings prior to setting up procedures for monitoring financial sustainability using financial and operational indicators.

Keywords: electricity distributors, Brazil, insolvency, DEA, stepwise selection, inefficiency.

JEL Classification: C14, C67, G18.

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Introduction

The analysis of business insolvency has become the object of an extensive field of research, due to the direct and indirect costs that this situation can generate for company stakeholders (Warner 1977; Bhabra, Yao 2011; Boguslauskas *et al.* 2011; Gonçalves *et al.* 2016; Premachandra *et al.* 2011). Costs can be even greater if the company is an electricity distributor (ED) that is a natural monopoly, where a cessation of its activities thus generates impacts for society as a whole (Duane 2002; Viscusi *et al.* 2005).

Among the various methods found in the literature, DEA (data envelopment analysis) has appeared more recently as an alternative to the better known and traditional techniques used to analyze insolvency (Cielen *et al.* 2004; Kao, Liu 2004; Sueyoshi 2005; Premachandra *et al.* 2011; Paradi *et al.* 2004; Wanke *et al.* 2015; Premachandra *et al.* 2009; Simak 1997; Shetty *et al.* 2012; Sueyoshi, Goto 2009). DEA is a non-parametric frontier technique that does not presuppose the existence of a functional form and does not require the normal distribution of the variables used (Sueyoshi 2005). Since a pre-established functional form is not needed, the use of this technique does not incur the risk of bias when having to previously define a proxy for the group of insolvent firms, as is usually the case when discriminant analysis and logistic regression techniques are employed (Balcaen, Ooghe 2006; Balcaen *et al.* 2011). In addition, recent studies have presented evidence that DEA was superior to discriminant analysis and logistic regression as a technique for discriminating between solvent and insolvent firms (Premachandra *et al.* 2009; Sueyoshi 2006; Simak 1997).

The research on insolvency that analyzes using non-parametric models such as DEA guides the present study. In the Brazilian context, recent studies include Nova (2013), Kassai (2002), Nova (2010) and Onusic *et al.* (2007). However, none of these studies investigated the electricity distribution sector.

ANEEL (National Electricity Regulatory Agency), the Brazilian electricity sector's regulatory agency, is currently developing a project designed to monitor the economic and financial performance of EDs using financial and operational indicators. Technical Notes 353/2014 and 67/2016 proposed indicators to be discussed with society through a public consultation.

Thus, this study's aim is to propose financial and operational indicators that explain the insolvency of Brazilian EDs. This is performed using DEA to estimate an inefficiency frontier (Premachandra *et al.* 2011; Paradi *et al.* 2004; Sueyoshi 2005; Cielen *et al.* 2004) through the selection of indicators using the stepwise procedure of Wagner and Shimshak (2007). A second stage analysis is then undertaken, relating firms' in(efficiency) scores to different contextual variables. The underlying hypothesis is that these variables are associated with levels of efficiency and, thus, also related to ED state-of-insolvency (Simar, Wilson 2007).

The motivations for this study are firstly, to analyze insolvency in the electricity sector of an important emerging economy, Brazil. Although the models of insolvency are well documented in the scientific literature, there is little evidence as to whether these models fit the electricity sector (Oh 2014). Secondly, the Brazilian electricity sector regulator currently needs information regarding which financial and operational indicators should be used to monitor Brazilian EDs (ANEEL 2014a). Technical notes 353/2014 and 67/2016 presented ongoing discussions and showed that this theme is still being debated and requires a solution. Thirdly, the efficiency indices are regressed against contextual variables which incorporate specific characteristics of these firms. Fourthly, the analysis covered the 2000–2015 period, thus permitting the use of a broad Brazilian ED database.

This article is organized as follows: Section 1 presents a literature review. Section 2 is divided into three subsections, devoted respectively to presenting the methodological foundations for using DEA, the stepwise procedure of Wagner and Shimshak (2007) and the bootstrap truncated regression of Simar and Wilson (2007). Section 3 presents the results of the article and the respective robustness analysis in two subsections. The final section presents the article's conclusions.

1. Literature Review

1.1. Risk of insolvency in Brazilian EDs

Regulation of the Brazilian electricity distribution sector has undergone significant transformation over the past 30 years, due mainly to problems associated with the economic and financial sustainability of EDs (Burinskiene, Rudzkis 2010; Resende 2002). The following events are examples of drivers of important transformations: the privatization of many of the sector's firms in the 1990s; electricity rationing in 2001 and 2002; and more recently, the promulgation of Provisional Measure (PM) 579/2012 by Dilma Rousseff's government, which imposed restrictions on companies that wished to renew their concession contracts (Resende 2002; Costellini, Hollanda 2014).

ANEEL is currently seeking to enhance the economic and financial sustainability of the electricity distribution sector in Brazil. Public Consultation 15/2014 inaugurated discussions around the project to monitor EDs using financial and operational indicators. Technical Notes 353/2014 and 67/2016 subsequently added proposals for indicators that the regulatory body deemed important. Despite this, the theme is still being debated and analyzed by EDs, researchers and society as a whole. Seeking to contribute to the theme, Scalzer *et al.* (2015) used logistic regression to explain the state of insolvency of Brazilian EDs and found that Actual Equivalent Frequency of Power Interruptions/Regulatory Equivalent Frequency of Power Interruptions (Actual EFP/Regulatory EFP), Overall Liquidity, and Interest Coverage Ratio indicators were the most important in explaining insolvency in the same year, a year before and two years before the event respectively.

As provided for in Decree 8461/2015, the EDs that renewed their concession contracts in accordance with PM 579/2012 must observe the economic and financial efficiency criteria to be established by the regulator (ANEEL 2016). The distributors that fail to fulfill the parameters required for each indicator will incur progressive penalties, including the eventual loss of the concession contract.

1.2. DEA on insolvency analysis

The research on insolvency analysis has a vast literature, and uses different techniques with the goal of increasing predictive and explanatory capacity (Aziz, Dar 2006). Some surveys have reviewed these different methods in order to gauge the literature's advances (Jackson, Wood 2013; Aziz, Dar 2006; Balcaen, Ooghe 2006; Ravi Kumar, Ravi 2007; Dimitras *et al.* 1996; Altman 1984). These studies hold that the literature's development began with Beaver (1966) and moved historically towards the multivariate dimension with the development of discriminant analysis (Altman 1968) and subsequently advancing to logistic regression models (Ohlson 1980), which had fewer statistical assumptions and were therefore more appropriate for studies in finance and economics (Dimitras *et al.* 1996). In the wake of computational advances, many other quantitative techniques were developed and used, despite the still preponderant use of discriminant analysis and logistic regression in recent studies (Aziz, Dar 2006; Jackson, Wood 2013; Balcaen, Ooghe 2006).

DEA is a non-parametric technique introduced in the shape of a constant returns to scale model (CCR) by Charnes *et al.* (1978). Based on linear programing, the technique assesses the relative efficiency of Decision Making Units (DMUs) by assigning weights to the various inputs and outputs. Initially, the CCR model did not assume that DMUs could operate at different scales until Banker *et al.* (1984) introduced the variable returns to scale model (BCC), thus enabling DMUs to be compared with others of the same size. From then on, the use of DEA became widespread in various fields of research (Liu *et al.* 2013; Atici, Ulucan 2011).

Several studies have analyzed insolvency using DEA based on financial indicators. Cielen *et al.* (2004) and Sueyoshi (2006) compared the use of DEA with other mathematical discrimination techniques. Smith (1990) and Fernandez-Castro and Smith (1994) used DEA with financial indicators in order that the analysis would have a greater number of dimensions and thus not be limited to merely observing a numerator and denominator. Sueyoshi and Goto (2009), Premachandra *et al.* (2009) and Premachandra *et al.* (2011) used the Charnes *et al.* (1985) additive model, a translation-invariant for frontier estimation that avoids the problem found in Cielen *et al.* (2004) which used the CCR model despite having variables with negative data in their sample. Other studies using DEA to analyze insolvency are Paradi *et al.* (2004), Sueyoshi (2005), Kao and Liu (2004) and Shetty *et al.* (2012).

Following Pastor (1997), the output-oriented BCC model is translation invariant for the use of negative inputs, while negative outputs can be used in the input-oriented model. The output-oriented BCC model is represented as follows:

$$\max \varnothing - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right). \tag{1}$$

Subject to the following restrictions:

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{i0}; \tag{2}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = \varnothing y_{r0}; \tag{3}$$

$$\lambda_j \geq 0; \sum_{j=1}^{n} \lambda_j = 1, \tag{4}$$

where x_{ij} is the input matrix, y_{rj} is the output matrix, s_i^- are the input slacks, s_r^+ are the output slacks, λ_j is the intensity parameter which will be calculated by the model, ε is the non-Archimedean infinitesimal, and ∅ is the relative efficiency scores of DMUs. The restriction (4) defines the format of the technology with variable returns to scale. The output-oriented BCC model was adopted for this study, given that some of the database inputs have negative values, as can be observed better in Section 2.1.

1.3. Positioning of this study

The significant transformations recently undergone by the Brazilian electricity sector explain ANEEL's current need to obtain answers as to which indicators should be monitored in EDs (ANEEL 2014a, 2016). In addition, the analysis of insolvency using DEA brings methodological benefits that complement logistic regression and discriminant analysis techniques, mainly by using contextual variables to explain second-stage efficiencies (Banker 1993; Simar, Wilson 2007).

2. Method

2.1. Methodological foundations for using DEA

DEA has specific properties that are advantageous in the analysis of insolvency, especially in relation to discriminant analysis and logistic regression. As it is a non-parametric technique, it (a) does not need a pre-established functional form; (b) is free from assumptions regarding the distribution of variables; and (c) requires neither normality of variables nor uniformity of dispersion among groups in the variance-covariance matrix, assumptions that are difficult to fulfill in studies in the finance area (Ohlson 1980).

In addition, DEA does not need a previous criterion for defining insolvency and thus does not incur any risk of bias in the results (Balcaen *et al.* 2010; Balcaen, Ooghe 2006; Dimitras *et al.* 1996; Jackson, Wood 2013). Altman (1968) defined insolvent firms as being those that were under receivership. Beaver (1966) saw them as firms that were unable to honor their commitments when they became due. Wruck (1990) referred to them as firms with negative equity.

In order to evaluate the insolvency of EDs, the output-oriented BCC model was used to estimate an inefficiency frontier. The indicators whose highest values were associated with financial difficulties were used as outputs, while the indicators whose lowest values were associated with financial difficulties were used as inputs (Paradi *et al.* 2004; Premachandra *et al.* 2009; Simak 1997; Sueyoshi, Goto 2009; Premachandra *et al.* 2011). Thus, the closer the DMU gets to the inefficiency frontier, the greater its financial difficulties and the closer it is to a state of insolvency.

Despite the advantages of DEA, several studies have been performed that expose its limitations. Schmidt (1985) classified DEA as a non-statistical technique, due to its deterministic characteristic and lack of statistical rigor. Ali and Seiford (1990) and Pastor (1997) showed that some models are not translation-invariant when using inputs and outputs with negative values – an aspect that was ignored in the Cielen *et al.* (2004) analysis of insolvency. In addition, there is the classic difficulty of selecting input and outputs in DEA (Adler, Yazhemsky 2010; Jenkins, Anderson 2003; Kittelsen 1993; Titko *et al.* 2014; Wagner, Shimshak 2007).

In light of the above, several actions were taken in this study to minimize these limitations. Firstly, a bootstrap truncated regression was adopted in a second-stage analysis; this is in following with a development in the literature that uses statistical tools in DEA (Banker 1993; Simar, Wilson 2007). Secondly, the output-oriented BCC model with variable returns to scale was used so to avoid the problem of not being translation-invariant, given that some database inputs had negative values (Pastor 1997). In these cases, their respective minimum value +0.01, was summed in order to change the sign to a positive one. Finally, the Wagner and Shimshak (2007) stepwise procedure was used to select the variables, because its results showed parsimony, in contrast to other methods based on correlation analysis (Jenkins, Anderson 2003).

2.2. Database and selection of variables

The sample is based on data from financial statements publicly available on the website of the Brazil's capital markets regulator, Comissão de Valores Mobiliários (CVM), covering the 2000–2015 period. Annual data for a group of 25 companies was gathered from the Comdinheiro database. The set comprised 371 observations, given that information on some of them was available only for certain years. Thus, to maximize the amount of information used, each observation of each company is analyzed independently through pooled cross sections. The information on operational indicators was obtained from Brazilian Electricity Distributor Association (ABRADEE) website. The firms were classified as EDs if (a) their corporate objects include the distribution of electricity *and* (b) they obtain at least 94% of their annual operating revenue from electricity distribution. Table 1 shows the characteristics of each of the 25 EDs that include some of the contextual variables used in the second stage analysis explained in Section 2.3.

Business group in Table 1 is the company that had the largest direct interest in the capital stock of the EDs. The information shows that despite the many changes in the control structure of companies over the years, the four state-owned companies have lately remained with the same controllers. 17 EDs are located in the South, Southeast or Midwest regions, which are richer because they have per capita GDP of more than 18, and encompass the companies that purchase electricity from Itaipu. The analysis of how the *state* and *regional* location attributes affect ED efficiency is presented together with other contextual variables in Section 2.3.

Table 2 presents the 15 financial and operational indicators that are treated as inputs or outputs. Given the set of 371 DMUs, the proposed variables meet the usual criteria of proportionality between the amount of DMUs, inputs and outputs in DEA (Bogetoft, Otto 2011). The proposed variables are based on indicators used by the most important international rating agencies to evaluate the electricity distribution sector, and on the indicators

Table 1. Description of the 25 EDs composing the sample

ED	State	Regional location	Business group
AES Sul	No	1	AES Guaíba II (2000–2015)
Ampla	No	1	CBLC (2000), Endesa Int (2001–2002), Enersis (2003–2004), Endesa Brasil (2005–2015)
CEEE	Yes	1	State of Rio Grande do Sul (2000–2015)
Celesc	Yes	1	State of Santa Catarina (2000–2015)
Celg	Yes	1	State of Goias (2000–2015)
Celpa	No	0	QMRA Participações (2000–2014), Equatorial Energia (2015)
Celpe	No	0	ADL Energy (2000), Guaraniana (2001–2005), Neoenergia (2006–2015)
Cemar	No	0	Maranhão Invest. (2000–2001), Brisk Part. (2002–2006), and Equatorial Energia (2007–2015)
Cemig Distribuição	Yes	1	State of Minas Gerais (2000–2015)
Coelba	No	0	Guaraniana (2000–2003) and Neoenergia (2004–2015)
Coelce	No	0	Investluz (2000–2012) and Endesa (2013–2015)
Cosern	No	0	Coelba (2000–2006) and Neoenergia (2007–2015)
CPFL	No	1	Serra da Mesa (2000–2001), VBC (2002), and CPFL Energia (2003–2015)
CPFL Piratininga	No	1	Serra da Mesa (2000–2001), VBC (2002), and CPFL Energia (2003–2015)
EBE	No	1	Enerpaulo (2000–2002) and EDP (2003–2015)
Elektro	No	1	EPC (2000–2011) and Iberdrola (2012–2015)
Eletropaulo	No	1	LightGás (2000–2002), AES Elpa (2003–2015)
Energipe	No	0	Energisa (2000–2015)
Energisa MG	No	1	Gipar (2000–2006), Energisa (2007–2015)
Energisa MT	No	1	Caiuá (2000–2007), Rede Energia (2008–2015)
Energisa PB	No	0	Caiuá (2000–2007), Rede Energia (2008–2015)
Enersul	No	1	Magistra Part. (2000–2005), EDP (2006–2008), Rede Energia (2009–2015)
Escelsa	No	1	Iven (2000–2004), EDP (2005–2015)
Light	No	1	Lidil Comercial (2000–2001), EDF Int. (2002–2005), Light SA (2006–2015)
RGE	No	1	Serra da Mesa (2000–2001), CPFL Energia (2002–2015)

Note: In the Regional Location, 1 means located in the South, Southeast or Midwest regions. 0 means located in the Northeast or North regions.

used by electricity sector regulatory agencies in other countries. This study also used the indicators proposed by ANEEL (2014a, 2016) and those Scalzer *et al.* (2015) found to be important in explaining the insolvency of Brazilian EDs. Following the ANEEL (2014b) and ANEEL (2016) proposals, the study used the financial (X_1 *a* X_9, Y_1) and operational (X_{10}, X_{11}, Y_2, Y_3, Y_4) classes of indicators.

Table 2. List of indicators for the analysis of ED insolvency

Variable	Name of indicator	Formula	Category	References
X_1	Interest Coverage Ratio – *Adjusted*	(Ebitda + FR)/FE	Input	a, b, c, d, e, f, g, h
X_2	Operating Margin	Ebitda/NR	Input	a, c, h, i
X_3	Own Capital Ratio	Shareholders' Equity/TA	Input	c, g
X_4	Net Margin	Net Profits/NR	Input	e
X_5	Current Liquidity	CA/Current Liabilities	Input	b, e, j
X_6	Immediate Liquidity	CCE/Current Liabilities	Input	b
X_7	Return on Assets (ROA)	Operating Profit/TA	Input	a, e, f
X_8	Overall Liquidity	(CA + LTR)/TL	Input	b, g
X_9	Net Debt/EBITDA Ratio – *Adjusted*	(Ebitda + CCE)/Gross Debt	Input	a, c, h, i
X_{10}	Variation of GWh supplied	$(\text{GWh}_t - \text{GWh}_{t-1})/ \text{GWh}_{t-1}$	Input	i
X_{11}	Variation of number of consumers	$(\text{QCons}_t - \text{Qcons}_{t-1})/\text{Qcons}$	Input	i
Y_1	Overall Indebtedness	Total Debt/TA	Output	b, d, e, g, j
Y_2	Actual EDP /Regulatory EDP	EDP/Regulatory EDP	Output	g, h
Y_3	Actual EFP/ Regulatory EFP	EFP/Regulatory EFP	Output	g, h
Y_4	Continuity overall performance	Average of Y_3 and Y_2	Output	g, h, i

Note 1: The references are: a = S&P 2013, b = Moody's 2013, c = Fitch 2014, d = NYPSC 2014, e = ERCP 2001, f = SARI/EI, USAID 2004, g = Scalzer *et al.* 2015, h = ANEEL 2014b, i = ANEEL 2016, j = OEB 2014.

Note 2: FR = Financial Revenue, FE = Financial Expenditure, CCE = Cash and Cash Equivalents, NR = Net Revenue, TA = Total Assets, TL = Total Liabilities, CA = Current Assets, LTR = Long-Term Receivables, Ncons = Number of Consumers, EDP = Equivalent Duration of Power Interruption, EFP = Equivalent Frequency of Power Interruption.

The indicators that needed the firms' operating cash flow (Fitch 2014; Moody's 2013; S&P 2013) were not used because Cash Flow Statements only became mandatory in Brazil as of 2008, with the implementation of IFRS (International Financial Reporting Standards). Nevertheless, a robustness analysis was performed to ascertain any differences in results due to the adoption of IFRS in Brazil, as had occurred in other countries (Malíková, Brabec 2012; Moody's 2013). Other traditional indicators, such as Return on Shareholders' Equity (NYPSC 2014; OEB 2014; S&P 2013) and the Financial Result/EBITDA Ratio (ANEEL 2014a) were not included because they exhibited inconsistency problems when calculated using negative denominators. Problems of this kind and other types of data inconsistency are ignored by some studies of insolvency, as can be observed in Nenide *et al.* (2003) and Mendes *et al.* (2014).

Indicators X_1 (Interest Coverage Ratio – *Adjusted*) and X_9 (Net Debt/ EBITDA Ratio – *Adjusted*) were adapted relative to their original form. In X_1, Financial Expenditure was used as a proxy for Interest on Loans due to the lack of that information. In addition, Financial Revenue was added to the numerator to reduce distortions caused by Swap operations that had Financial Expenditure and Revenue as their counterpart. The formula of X_9 was transformed with the new indicator exhibiting a correlation of 0.83 with the original indicator, using only those cases in which inconsistency problems did not occur.

Another important issue concerns the selection of the variables to be included in the model. There is no consensus in the literature regarding the best way to select inputs and outputs (Jenkins, Anderson 2003; Premachandra *et al.* 2009; Wagner, Shimshak 2007). Furthermore, the selection of variables in DEA produces more unstable results than other techniques such as regression analysis (Thanassoulis 1993). Although the approach based on correlation is a common one, the literature rarely presents a criterion for determining which variable should be kept and which should be excluded from the analysis. For this reason, Jenkins and Anderson (2003) proposed a method for selecting variables based on multivariate variance retention, albeit with erratic results.

The present study uses the backward stepwise selection procedure proposed by Wagner and Shimshak (2007), which obtained consistent results using the same data as those in Jenkins and Anderson (2003), through a proposal based on the variation in the average DMU efficiency. The elimination of each input or output is simulated in steps, and the variable excluded is the one with the smallest variation in the average DMU efficiency with the restriction that at least one input and one output must remain. The analysis of each step enables comparison of the relative importance of indicators according to the elimination ordering (Wagner, Shimshak 2007). The Kolmogorov-Smirnov (KS) test was calculated for each step in order to evaluate the difference between the efficiency distribution densities, thence assess the relevance of the inclusion/exclusion of each variable (Bogetoft, Otto 2011).

In this article the stepwise selection algorithm proposed by Wagner and Shimshak (2007) was developed by the authors using R software and for the sake of brevity was omitted from this text. More details can be found in Wagner and Shimshak (2007).

2.3. Bootstrap truncated regression

This study uses the bootstrap truncated regression proposed by Simar and Wilson 2007, which proved to be more effective than Tobit. Through comparisons with a Monte Carlo experiment, the method obtained higher results due to reduced statistical noise. Despite this, conventional two-step approaches lack a well-defined data generating mechanism (Simar, Wilson 2007). The model tested has the following form:

$$\varnothing_i = a + Z_j\delta + \varepsilon_j,\ j = 1, \ldots, n, \quad (5)$$

where $\varnothing_i$ are the DEA's efficiency scores, a is a constant defined by the model, Z_j is the vector of contextual variables used for each DMU j, δ is the parameter estimated for each contextual variable, and ε_j is statistical noise. The distribution of ε_j is conditioned by the restriction $\varepsilon_j \geq 1 - a - Z_j\delta$ and, following Simar and Wilson (2007), it is assumed that the distribution is normal with zero mean and unknown variance. Replacing the unobservable true dependent variable by the one estimated by DEA:

$$\tilde{\varnothing}_i \approx a + Z_j\delta + \varepsilon_j,\ j = 1, \ldots, n, \quad (6)$$

where

$$\varepsilon_j \sim N(0, \sigma_\varepsilon^2)\text{, such that } \varepsilon_j \geq a - Z_j\delta,\ j = 1,....n. \quad (7)$$

The efficiency estimators were calculated through the maximum likelihood method given δ and σ_ε^2. Bootstrap consistent estimators were used to calculate confidence intervals for the estimates of δ and σ_ε^2 to a given significance level. The calculations of the Simar and Wilson (2007) algorithm were carried out with R codes and the use of the rDEA package (Simm, Besstremyannaya 2016). The algorithms used in the estimation of the parameters were deliberately omitted for the sake of brevity and can be found in Simar and Wilson (2007).

Table 3. Contextual variables proposed

Z_j	Name of the variable	Criterion adopted
Z_1	Criteria for Insolvency in the Literature	Dummy = 1 for some of the following conditions: negative Equity, Receivership or Intervention by ANEEL
Z_2	State	Dummy = 1 for companies in which the Federal Union, States or Municipalities control more than 50% of the voting capital
Z_3	Dollar	Annual average of the daily closing price measured in reais (BRL)
Z_4	IGPM	Percentage variation of the previous year's inflation index
Z_5	Regional Location	Dummy = 1 for location in the South, Southeast or Midwest regions of Brazil
Z_6	Price of Electricity in the Spot Market	Annual average of the Settlement Price of the Differences (PLD) traded in Brazil's Electricity Commercialization Chamber

Table 3 presents the contextual variables that are tested to evaluate the impact on efficiencies. No multicolineartity problems were found in numerical variables Z_3, Z_4 and Z_6, given that the highest correlation found among them was –0.23. Variable Z_1 represents the insolvency criteria adopted by the literature (Altman 1968; Ohlson 1980; Wruck 1990; Balcaen, Ooghe 2006). Variable Z_2 seeks to capture whether state companies are less efficient than the others (Bagdadioglu *et al.* 1996; Kumbhakar, Hjalmarsson 1998). Z_3 is evaluated because approximately 20% of the cost of distributors in the South, Southeast and Midwest regions is accounted for by purchases of electricity from the Itaipu power plant, which are measured in dollars (ANEEL 2015). In addition, the dollar may have a significant impact on Y_1 (Overall Indebtedness), which averaged 71% in the case of this study's sample, in line with the 72% level calculated by ANEEL (2015). Z_4 is the indicator used by ANEEL as a basis for annual tariff increases and is directly associated with ED revenues. Z_5 verifies whether geographical location in the richest regions with a per capita GDP of more than 18 generates a difference in relation to the poorest with less than 12, in addition to the fact that the richest regions are those purchase electricity from Itaipu. Finally, as Brazil's energy matrix is based on hydropower, low reservoir levels can lead to high levels of Z_6, thus increasing the short-term cost of electricity, given that this cost is passed on to consumers only in the following year. In 2015 this led ANEEL to create tariff flag mechanisms that increase or reduce electricity costs, in accordance with momentary generation conditions, to reduce this mismatch between ED expenditures and revenues.

3. Analysis of results

This section is divided into two stages. 3.1 presents an analysis of the variables associated with ED insolvency through the estimation of the inefficiency frontier in the output-oriented BCC model, and by performing a bootstrap truncated regression using efficiencies as the dependent variable. In 3.2, robustness analyses are undertaken to verify the sensitivity of the stepwise selection of variables and whether the adoption of IFRS (International Financial Reporting Standards) in Brazil has had an impact on efficiencies.

3.1. Variables that explain insolvency

N DEA models were estimated for each step, where *N* was equal to the sum of inputs and outputs that could be eliminated. Following Wagner and Shimshak (2007), Table 4 presents the ordered result of the variable's impact on ED efficiencies. The results of the KS test for each step showed that only two indicators could alter the initial density of step 0 efficiencies to the usual significance levels. Y_1 (Overall Indebtedness) stood out the most, with an average impact on efficiencies that was 4 times greater than Y_3 (Actual EFP/Regulatory EFP).

The number of DMUs on the frontier showed that the first variables eliminated were not able to alter the efficiency frontier and, furthermore, in the case of the last eliminations the reduction in the number of DMUs occurred gradually without big leaps between the steps.

Table 4. Variable elimination using the Wagner and Shimshak (2007) backward stepwise procedure

Step num.	Variable excluded	Average of $\Delta\varnothing$	DMUs on the frontier	KS test p-value
0	None	–	18	–
1	X_3	0.00000	18	1.000
2	X_4	0.00009	18	1.000
3	Y_4	0.00018	18	1.000
4	X_7	0.00060	18	1.000
5	X_9	0.00136	17	1.000
6	X_2	0.00428	17	1.000
7	X_5	0.00470	13	0.996
8	X_{11}	0.00618	12	0.990
9	X_8	0.00297	9	0.976
10	X_1	0.00292	7	0.880
11	Y_2	0.01360	5	0.830
12	X_6	0.01423	4	0.592
13	X_{10}	0.01491	4	0.241
14	Y_3	0.28223	2	0.000*
15	Y_1	1.12627	2	0.000*

Notes: In the case of the last input (step 13) and the last output (step 15), the presented calculations showed the changes in efficiencies if they were eliminated instead of the previous input (step 12) or the previous output (step 14) respectively;
*statistically significant to the 1% level.

Between steps 11 and 13, indicators Y_2 (Actual EDP/Regulatory EDP), X_6 (Immediate Liquidity) and X_{10} (Variation in GWh supplied), altered efficiency five times more than in step 10, despite not having altered density to the usual significance levels. The most important indicators in terms of average impact on efficiencies and densities were consistent with results of Scalzer *et al.* (2015), who identified Y_3 (Actual EFP /Regulatory EFP) as the most important insolvency indicator in the year of the event. In addition, the ex-ante definition of insolvency based on negative Shareholders' Equity/Assets (Wruck 1990) uses an indicator that has a correlation of –0.98 with Y_1 (Overall Indebtedness), i.e., the same indicator with opposite sign.

After estimating efficiencies using X_{10} (Variation in GWh supplied), Y_1 (Overall Indebtedness) and Y_3 (Actual EFP/Regulatory EFP), the Simar and Wilson (2007) bootstrap truncated regression was performed on the contextual variables; results are shown in Table 5. Despite assuming the normality of residuals, the regression generated non-parametric results, with the variables' significance therefore being analyzed through confidence intervals based on quantiles of the distributions.

The significance of Z_1 showed that the criteria used by the literature to define insolvency in studies employing logistic regression and discriminant analysis (Altman 1968; Altman, Saunders 1997; Balcaen, Ooghe 2006; Jackson, Wood 2013; Ohlson 1980; Wruck 1990) were able to capture the EDs with the lowest efficiencies in Brazil. In addition, and in line with the literature that analyses the performance of state firms in the electricity sector, Brazilian EDs that were state companies were less efficient than those in the private sector (Bagdadioglu *et al.* 1996; Kumbhakar, Hjalmarsson 1998).

Z_3 (Dollar) provided evidence of the probable importance of power purchases from the Itaipu plant (ANEEL 2015), a hypothesis that was corroborated by the significance of Z_5 (Regional Location), which simultaneously showed that those regions that purchase electricity from Itaipu *and* have the largest regional per capita GDPs, tend to underperform relative to the others. As predicted, the significance of Z_3 may also be associated with the size of Y_1 (Overall Indebtedness). Domestic inflation Z_4 demonstrated that the annual increase in tariffs granted by ANEEL was beneficial for EDs, and Z_6 's lack of significance showed that the mismatch between expenditures and revenues due to the high price of electricity in the spot market did not have an important impact on the firms' financial situation.

Table 5. Results of the bootstrap truncated regression using pooled data

Variable	δ	Confidence interval (α = 1%)		Confidence interval (α = 5%)		Confidence interval (α = 10%)	
		Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Z_1	–0.72*	–1.11	–0.47	–0.97	–0.51	–0.94	–0.54
Z_2	–0.12*	–0.25	0.00	–0.21	–0.04	–0.20	–0.05
Z_3	–0.13*	–0.22	–0.06	–0.20	–0.08	–0.19	–0.09
Z_4	0.69*	0.10	1.29	0.21	1.18	0.29	1.09
Z_5	–0.29*	–0.37	–0.21	–0.35	–0.23	–0.34	–0.24
Z_6	–0.02	–0.09	0.05	–0.08	0.03	–0.07	0.02
Intercept	2.39*	2.21	2.58	2.25	2.53	2.26	2.50

Note: *statistically significant to the 1% level.

3.2. Robustness analysis

New simulations were performed in order to verify the sensitivity of the stepwise selection procedure presented in Section 3.1. In Table 6, sensitivity analysis I does not use variables Y_{10}, Y_1 and Y_3, which calculated the efficiencies used in the regression in Table 5. Meanwhile, sensitivity analysis II ignores Y_4, Y_8 and Y_6, which were found to be significant in sensitivity analysis I. The results confirmed the importance of Y_6 (Immediate Liquidity) which had already been shown in Table 4 on being eliminated in step 12, despite not having altered densities to the usual significance levels. It was also observed that, in the absence of Y_3 (Actual EFP/Regulatory EFP), indicator Y_4 (Continuity Overall Performance) was more important than Y_2 (Actual EDP/Regulatory EDP) which had been eliminated in step 11 of Table 4. As seen previously, Y_4 is the average of Y_2 and Y_3, and thus Y_3's information remains in Y_4. The results of sensitivity analysis I are also in line with Scalzer *et al.* (2015), who also found that Y_8 (Overall Liquidity) was important when analyzing insolvent EDs. The sensitivity analysis II showed that no other variable was significant in changing ED efficiencies.

Table 7 shows the results of regressions with efficiencies calculated using the 3 significant variables of sensitivity analysis I and the variables of sensitivity analysis II.

The contextual variables of sensitivity analysis I were similarly significant and with the same sign for δ as in the regression in Table 5, despite Z_2 (State) and Z_4 (IGPM) being significant at the 5% level. Sensitivity analysis II showed that the absence of indicators capable of influencing the densities of efficiencies meant that the contextual variables did not have the explanatory power seen in previous analyses.

Table 6. Variable elimination sensitivity analysis

Nº of step	Sensitivity analysis I			Sensitivity analysis II		
	Excluded variable	Average of ΔØ	KS test p-value	Excluded variable	Average of ΔØ	KS test p-value
1	X_4	0.00073	1.000	X_7	0.0010	1.000
2	X_7	0.00085	1.000	X_4	0.0048	1.000
3	X_3	0.00338	1.000	X_2	0.0091	1.000
4	X_2	0.00314	1.000	X_9	0.0212	1.000
5	Y_2	0.00816	1.000	X_5	0.0243	0.996
6	Y_4	0.62528	0.000*	X_1	0.0310	0.954
7	X_9	0.00847	0.999	X_3	0.0601	0.715
8	X_5	0.02442	0.996	X_{11}	0.0691	0.419
9	X_1	0.02173	0.775			
10	X_{11}	0.03333	0.241			
11	X_8	0.06333	0.088***			
12	X_6	0.36294	0.000*			

Notes: Only 8 variables were analyzed in sensitivity analysis II as indicator Y_2 could not be eliminated (Wagner, Shimshak 2007). In sensitivity analysis I indicator Y_4 is presented in step 6 with the values that would occur if it was eliminated in instead of the penultimate output presented in step 5;
*statistically significant to the 1% level; ***statistically significant to the 10% level.

Table 7. Bootstrap truncated regression in the sensitivity analysis

Variable	δ	Confidence interval (α = 1%)		Confidence interval (α = 5%)		Confidence interval (α = 10%)	
		Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Sensitivity analysis I – Efficiencies calculated for X_8, X_6 and Y_4							
Z_1	−1.91*	−3.63	−0.46	−3.29	−0.81	−3.00	−0.99
Z_2	−0.61**	−1.36	0.03	−1.17	−0.11	−1.07	−0.18
Z_3	−0.52*	−0.98	−0.12	−0.85	−0.19	−0.80	−0.23
Z_4	2.53**	−0.92	6.04	0.00	5.13	0.46	4.63
Z_5	−0.81*	−1.26	−0.39	−1.14	−0.49	−1.11	−0.53
Z_6	−0.24	−0.61	0.12	−0.55	0.05	−0.50	0.00
Intercept	5.20*	4.23	6.27	4.47	5.97	4.52	5.86
Sensitivity analysis II – Efficiencies calculated for all non-significant variables							
Z_1	−45.23**	−128.09	7.10	−93.37	−5.92	−84.60	−12.46
Z_2	−13.38	−107.84	30.12	−52.53	14.42	−52.20	15.31
Z_3	−0.01	−21.34	19.41	−11.39	17.49	−10.23	14.86
Z_4	61.86*	4.67	140.40	15.82	108.55	21.03	99.58
Z_5	1.34	−19.60	28.29	−16.83	16.46	−20.39	9.61
Z_6	0.67	−21.21	16.70	−10.11	15.18	−9.86	14.54
Intercept	−18.49	−96.10	45.77	−94.12	23.19	−75.41	9.12

Notes: *statistically significant at the 1% level; **statistically significant at the 5% level.

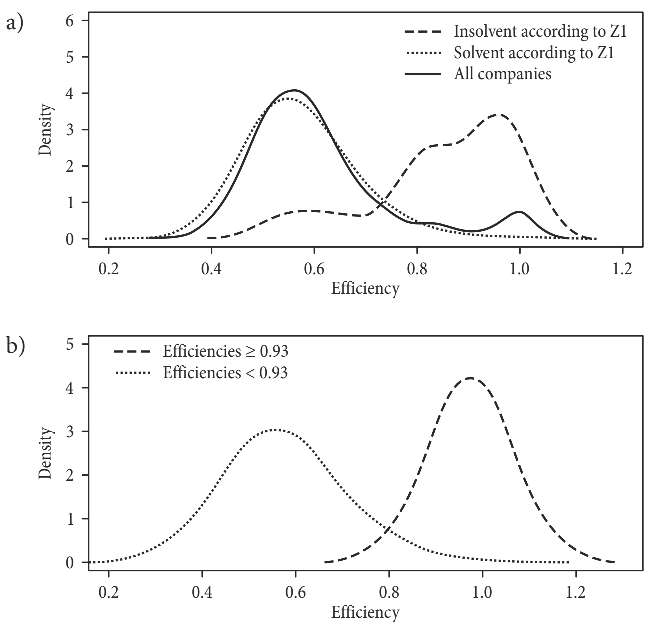

Fig. 1. Density comparisons between solvent and insolvent companies. Figure 1(a) shows the densities of the efficiencies according to Z_1 criteria, while Figure 1(b) show the densities according to the cutoff point of 0.93.

In addition, the analysis of the ROC (Receiver Operating Characteristic) curve was performed dividing the DMUs into two groups of solvent and insolvent firms, according to Z_1's insolvency criteria. The efficiencies that were treated as a dependent variable in the Table 5 regression were used as probabilities for classification in each group. The area below the ROC curve was equal to 92.72% and significantly different from 50% with a p-value 0, thus demonstrating a high discrimination capacity. The maximum overall efficiency of 97.3% was obtained with a cutoff of 0.93, showing a high concentration of insolvent firms among the DMUs closest to the inefficiency frontier. This was also confirmed when comparing the densities presented in Figures 1a and 1b.

Finally, in order to analyze the impact of IFRS on the results in Table 4, new simulations were performed dividing the DMUs into two groups – "up to 2009" and "as from 2010", according to Table 8. Although international accounting rules began to be adopted in Brazil in 2008, the great majority of rules were only applied from 2010 onwards, including concession accounting rules IFRIC 12 (ANEEL 2014a). Both before and after the adoption of IFRS, indicators Y_3 and Y_1 were the most important and significant in terms of altering densities, in agreement with the Table 4 results.

Table 8. Comparison of the stepwise selection before and after the adoption of full IFRS in Brazil

Nº of step	Stepwise selection using data up to 2009			Stepwise selection using data as from 2010		
	Excluded variable	Average of $\Delta\varnothing$	KS test p-value	Excluded variable	Average of $\Delta\varnothing$	KS test p-value
1	X_3	0.0000	1.000	X_9	0.0000	1.000
2	Y_4	0.0001	1.000	X_3	0.0000	1.000
3	X_4	0.0001	1.000	X_4	0.0000	1.000
4	X_9	0.0005	1.000	X_7	0.0000	1.000
5	X_2	0.0018	1.000	Y_4	0.0000	1.000
6	X_5	0.0062	0.998	X_2	0.0000	1.000
7	X_{11}	0.0085	0.994	X_8	0.0005	1.000
8	X_8	0.0032	0.994	X_6	0.0021	1.000
9	X_1	0.0033	0.980	X_{10}	0.0068	1.000
10	X_{10}	0.0142	0.704	X_1	0.0073	0.999
11	X_7	0.0146	0.547	X_5	0.0144	0.941
12	X_6	0.0228	0.341	X_{11}	0.0169	0.794
13	Y_2	0.0213	0.158	Y_2	0.0161	0.600
14	Y_3	0.3402	0.000*	Y_3	0.0872	0.000*
15	Y_1	0.6820	0.000*	Y_1	0.8006	0.000*

Note: *means that it is statistically significant to the 1% level.

Conclusions

This study brought contributions to the analysis of Brazilian ED insolvency, with the construction of an inefficiency frontier using the Wagner and Shimshak (2007) variable selection criteria accompanied by the Simar and Wilson (2007) bootstrap truncated regression.

Y_1 (Overall Indebtedness) and Y_3 (Actual EFP/Regulatory EFP) were the most important indicators, in line with Scalzer *et al.* (2015). The identification of Y_3 confirms that insolvent EDs may develop operational problems and reaffirms the need to analyze issues other than financial ones (Moody's 2013; ERCP 2001).

Because of the demands presented by ANEEL in the implementation of a new regulation that monitors financial and operational indicators of EDs (ANEEL 2014a, 2016), the results of this study yielded information that can ensure better average levels of efficiencies across all EDs. Monitoring of General Indebtedness levels can anticipate problems of high levels of leverage that undermine corporate cash management and generate short-term financial distress. In addition, the monitoring of Actual EFP/Regulatory EFP is a good indicator of identification of problems in the delivery of the final service of the companies, with the increase in the interruptions in the power supply that can be associated with low levels of investment in CAPEX, high levels of indebtedness, or other types of financial distress.

The results showed that despite the risk of bias incurred by studies that used logistic regression and discriminant analysis (Balcaen, Ooghe 2006; Dimitras *et al.* 1996), these criteria were able to capture the EDs with the lowest efficiencies in Brazil. Moreover, state firms were more likely to be insolvent. In Brazil, public policies are usually inefficient (Burinskiene, Rudzkis 2010; Costellini, Hollanda 2014); for example, Eletrobras sold electricity in 2014 at 28 BRL/MWH while the free market price was around 822 BRL/MWH. The significance of Z_3 (Dollar) and Z_5 (Regional Location) shows that the cost involved in purchasing electricity from the Itaipu plant in US dollars may affect EDs located in the South, Southeast and Midwest regions (ANEEL 2015). Tariff increases based on inflation have been beneficial, perhaps due to Brazil's high level of inflation, coupled with the high leverage levels of EDs and the low interest rates used by the National Economic and Social Development Bank (BNDES). Meanwhile, the fact that Z_6 (Spot Market Electricity Price) was not significant assumes that a shortfall in contracted electric power in the short term is not a relevant problem and may be due to the high working capital in this sector.

The robustness analysis showed that indicators that were significant in the change of efficiency densities held their coherence in the results of the Simar and Wilson (2007) regressions. In addition, the impacts of IFRS on financial statements (Malíková, Brabec 2012; Moody's 2013) did not alter the selection of the most important indicators.

The conclusions provide actionable information vis-à-vis Brazil's energy regulator (ANEEL 2014a, 2016), and make a valuable contribution to the scant literature on insolvency in the electricity sector (Scalzer *et al.* 2015). Future studies could test other non-parametric models that are translation-invariant, which is fundamental in insolvency studies (Sueyoshi, Goto 2009). Thus, the RAM (Cooper *et al.* 1999) or even the additive model (Charnes *et al.* 1985), which, though not having a measure for technical efficiency, is translation-invariant to the frontier (Premachandra *et al.* 2009, 2011). In addition, other variables such as CAPEX and Operational Cash Flow could be tested, as well as others that do not involve the financial or operational dimensions, such as the business group to which the ED belongs.

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