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Financial distress in electricity distributors from the perspective of Brazilian regulation

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ABSTRACT

This study investigates which financial indicators can predict financial distress in Brazilian electricity distributors in relation to the targets established by the regulatory body. Specifically, identification of financial distress is possible based on the calculation of firm performance in relation to the regulatory targets, while its ability to predict is enabled by a multimodel inference for the selection of the best financial indicators based on the financial information data provided by the Brazilian regulator (ANEEL) of all existing 60 companies in the period from 2009 to 2015. Return on Assets (ROA) and liquidity measured by IL (Immediate Liquidity) and CL (Current Liquidity) stand out in their power to predict the companies with the worst regulatory performance. These results present valuable contributions to the development of new regulatory legislation in Brazil which resulted from the recent ANEEL public consultation aiming to implement monitoring of the economic and financial sustainability of Brazilian electricity distributors through financial indicators.

1. Introduction

Although the regulation of electricity distributors takes different forms of action in different countries, the objective is always to resolve the conflicts of interest inherent in the activities of natural monopolies (Agrell and Bogetoft, 2007; Bogetoft and Otto, 2011; Ochoa, 2007). According to modern economic theory, the regulator in the position of the principal seeks to control the activities of agents so that services are provided in an efficient and financially sustainable way (Bernstein and Sappington, 1999; Laffont and Tirole, 1993; Viscusi et al., 2005). Despite this, in the Brazilian case, many electricity distribution companies (EDCs) have faced financial problems in recent years, including some cases of requests for judicial recovery. Thus, the need for improved regulation of companies to predict future financial problems (ANEEL, 2014a, 2016).

In Brazil, regulation follows the Price-Cap Revenue (PCR) model that has existed since the creation of the regulatory agency ANEEL (National Electric Energy Agency) in 1997. At that time, the main laws that support the current regulatory characteristics were also created, such as the Concessions and Privatizations Law (Baer and McDonald, 1998; Kaplan, 1998; Lins et al., 2007; Prado, 2012; Resende, 2002; Sartori et al., 2017). Despite the institutional advances that occurred at that time, in 2014 ANEEL held Public Consultation No. 15/2014 to discuss which financial and operational indicators should be used monitor the economic and financial sustainability of EDCs (ANEEL, 2014a). In 2016, the reopening of that public consultation sought the improvement of the first proposal of indicators debated in 2014 and considerably reduced the number of indicators of the initial proposal (ANEEL, 2016).

This work investigates which financial indicators can be used to predict the financial distress of the Brazilian EDCs according to the regulatory goals established by ANEEL. Under incentive regulation — just as regulated agents are allowed to extract the efficiency gains obtained under the regulatory goals (Pierk and Weil, 2016; Nunez, 2007; Resende, 2002; Liston, 1993) — firms that are inefficient in relation to regulation absorb the losses of this inefficiency. Such firms are said to be in financial distress. In order to analyze these cases, we used a set of regulatory explanatory variables to measure firm performance under each regulatory goal and to estimate EBIT Realized on Regulatory EBIT as a dependent variable, that can discern the set of companies under financial regulatory distress through values lower than 1. In a second stage, following several studies in the insolvency literature (Charitou et al., 2004; Chava and Jarrow, 2004; Ohlson, 1980; Shumway, 2001), a logistic regression model with multimodel inference (Anderson, 2008; Burnham and Anderson, 2002) selects financial indicators from a set of indicators that rating agencies (Fitch, 2014; Moodys, 2013; Standard

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and Poors, 2013), international regulatory agencies (ERCP, 2001; OEB, 2014; USAID and SARI/EI, 2004) and ANEEL in its Public Consultation no 15/2014 (ANEEL, 2016, 2014a, 2014b) use or propose to analyze the financial situation of EDCs.

The results demonstrated that ROA (return on assets) stood out in its ability to discern companies under regulatory financial distress in all periods from 1 to 3 years of lag. In addition, the Immediate Liquidity and Current Liquidity indicators were also jointly relevant and significant in the different lag periods; together with the ROA flag, they demonstrated that the profitability and liquidity analysis should be monitored by ANEEL in its regulatory innovation project in Brazil.

The motivations of this study are first its focus on Brazil, an important emerging country that has an important electrical sector with an installed capacity of approximately 1,4 GW in a country of continental geographical dimensions (MarketLine, 2015; Torrini et al., 2016). Second, ANEEL has an open public consultation and seeks clarifications regarding the proposed objective of this work. In addition to the regulatory body's request for the implementation of new standards, Decree 8461/2015 issued by the Brazilian government reinforced the need for companies to comply with economic and financial efficiency criteria subject to progressive penalties for non-compliant companies, potentially leading to loss of the concession contract. Third, this study includes all Brazilian EDCs for the period from 2009 to 2015 via an ANEEL-compiled information database of financial statements and technical notes.

The remainder of the paper is organized as follows: Section 2 compares the characteristics of the Brazilian regulatory framework in terms of the different regulatory methodologies in the electricity distribution sector around the world. Section 3 describes the methods adopted to define regulatory financial distress and the mechanism to select the variables that best identify this situation. In Section 4, the results of the research are presented, including a robustness analysis that culminates with the recommendation of different algorithms for selection of variables in the diagnosis of financial distress. Section 5 presents the conclusions of the study.

2. Institutional framework and regulation in Brazil

2.1. Incentive regulation in Brazil

Natural monopolies have limited incentives to be efficient in reducing costs and maximizing production because they are not under pressure from market discipline (Bogetoft and Otto, 2011; Viscusi et al., 2005). In the case of the electricity distribution industry, this characteristic is all the more salient because of the lack of close substitutes for the services offered and the relatively inelastic demand.

Regulatory agencies in a number of countries are working to restrict the performance of EDCs through various types of regulatory models, including Rate of Return (ROR), Price-Cap Revenue (PCR) and the Yardstick Competition (Agrell et al., 2005; Arango, 2007; Chang et al., 2004; Førsund and Kittelsen, 1998; Johnson et al., 1998; Korhonen and Syrjänen, 2003; Kumbhakar and Hjalmarsson, 1998; Lins et al., 2007; Liston, 1993; Nunez, 2007; Pacudan and de Guzman, 2002; Reitenga, 2000; Resende, 2002; Souza et al., 2010). Although heavily used in the past, ROR has been abandoned by several regulatory authorities around the world due to its high cost of administration since it is based on the remuneration of costs declared by the regulated agent plus a rate of return on investment (Bogetoft and Otto, 2011; Nunez, 2007).

In Brazil, PCR was adopted by the National Electric Energy Agency (ANEEL), the electricity sector regulatory body. ANEEL was created in the wake of the 1997 restructuring of the sector through the enactment of Concession Laws and the privatization process of enterprises that were predominantly state-owned (Prado, 2012; Lins et al., 2007; Resende, 2002; Kaplan, 1998; Baer and McDonald, 1998). The new regulations replaced the previously used ROR. In the first years, the productivity factor X assumed a value of zero and only started to have positive values for almost all companies in 2003 (Resende, 2002). In Brazil, regulation by PCR specifies three types of adjustments to tariffs: annual, periodic and extraordinary. The annual adjustment follows the tariff adjustment index (TAI):

$$\mathrm{TAI} = \frac{\mathrm{VPA}_1 + \mathrm{VPB}_0(\mathrm{IGPM} - \mathrm{X})}{\mathrm{AR}_0} \tag{1}$$

where VPA_1 is the value of the unmanageable costs of the current period; VPB_0 is the value of manageable costs; IGPM is the rate of change of domestic inflation; X is the factor that represents productivity gains; and AR_0 represents the annual revenue. Periodic tariff adjustments occur every 4 or 5 years, depending on the company, and seek to reposition the company in a financial situation that at the same time ensures financial equilibrium with an attractive rate of return at the lowest possible cost to the final consumer (Bernstein and Sappington, 1999).

Since unmanageable costs (VPA) are fully reimbursed to EDCs in the subsequent year, the performance under the regulatory goals of VPB generates a profit for EDCs within the regulatory framework (Liston, 1993; Nunez, 2007). The VPB amounts, readjusted annually through the TAI, are previously defined through the periodically revised tariff repositioning. An efficient reference company (as defined by ANEEL) sets the regulatory goals that comprise VPB in an asymmetric information environment in which the EDCs manage and supply information to the regulator, which in turn performs the cost audit (Viscusi et al., 2005).

The VPB values calculated on the basis of the reference enterprise comprise the following four headings (ANEEL, 2015a): (i) depreciation expenses calculated on the Gross Remuneration Basis representing the prudent capital disbursements audited by the regulatory body; (ii) operating costs involving PMSO expenses (Personnel, Material, Services and Other); (iii) maximum default parameter provided to reflect unrecoverable revenue from the non-receipt of energy sold; and (iv) gross remuneration of capital, calculated by the regulatory WACC rate on the Net Remuneration Basis of Accumulated Depreciation (NCB).

The NCB presented in item iv involves the calculation of the fixed assets used in the electricity distribution service that must be remunerated, including CAPEX (Capital Expenditures) disbursed for the expansion or maintenance of these activities. There is, however, evidence of negative differences in the impacts of abnormal profits if the CAPEX is carried out for regulatory rather than voluntary purposes (Johnston, 2005).

ANEEL also establishes regulatory targets for the level of energy losses associated with theft and bad measurements, which, despite not being covered by VPB, may impact the financial results of companies through VPA. The amount that exceeds the level of regulatory losses previously defined by ANEEL cannot be passed on in the tariff charged by the final consumer and results in an energy purchase not otherwise covered by the EDC.

The achievement of the regulatory goals defined by ANEEL directly impacts firm profitability; thus, performance below that of the reference company negatively affects the result and constitutes a situation of financial distress. The pressure of regulation under the result of the electricity distributors to be efficient can have direct consequences on shareholder returns (Johnson et al., 1998; Johnston, 2005; Nunez, 2007).

2.2. Regulatory proposals to prevent financial distress in Brazil

The financial problems faced by several companies in the Brazilian electricity distribution sector over the last decade demonstrate the need to incorporate in the regulatory framework the means to ensure that services are provided with the lowest energy cost possible for the final consumer and at the same time an attractive profit margin that encourages companies to be efficient (Altoé et al., 2017; ANEEL, 2016, 2014b, 2014a; Costa et al., 2015; El Hage and Rufín, 2016; Perobelli and Oliveira, 2013). In this context, the regulator is responsible for ensuring that companies operating under a natural monopoly have efficiency and sustainability incentives and can avert financial distress.

Recently, ANEEL held Public Consultation 15/2014, later revised in April 2016, with the objective of implementing a method for monitoring economic and financial indicators to be able to foresee financial problems in EDCs. Initially, 35 proposed indicators contained information widely known from traditional financial analysis, such as Net Debt/EBITDA and Net Income/Net Revenue (Altman, 1968; Beaver, 1966) as well as some others with an operational emphasis that measure, for example, duration and frequency of power cuts and levels of losses in the power supply (Kumbhakar and Hjalmarsson, 1998; Lins et al., 2007). With dialog being fostered between companies and society, the reopening of the Public Consultation in 2016 resulted in the initial proposal being reduced from 35 to 16 indicators (ANEEL, 2016).

In order to predict financial problems, since the 1970s the insolvency literature has presented several methods and techniques seeking to formulate more accurate models (Altman, 1968; Beaver, 1966; Balcaen and Ooghe, 2006; Jackson and Wood, 2013). The logistic regression and discriminant analysis techniques were most frequently used (Aziz and Dar, 2006; Altman, 1984; Jackson and Wood, 2013), in spite of the fact that logistic regression relies on fewer assumptions due to the absence of the need for multivariate normality and homogeneity in the variance-covariance matrices of the explanatory variables (Ohlson, 1980). Because of this, the literature broadened the use of logistic regression in the 1980s in contrast to the popularity of research with discriminant analysis in the 1970s (Aziz and Dar, 2006; Dimitras et al., 1996; Jackson and Wood, 2013). Following this literature, this paper seeks to estimate which indicators best predict financial distress through the use of logistic regression.

Some papers have raised criticism about the design of research in the insolvency literature due to (i) the frequent bias in the selection of the sample of solvent and insolvent companies; (ii) the dichotomous classification for different insolvency criteria, and (iii) the instability of data over the period of interest (Balcaen and Ooghe, 2006; Dimitras et al., 1996; Eisenbeis, 1977). In order to avoid these problems, this paper uses the financial distress concept of the EDCs as a function of their performance in relation to the regulatory targets where performance below target means under financial distress, as can be best observed in Section 3.

2.3. Positioning of this research

ANEEL has demonstrated through public consultations the need for contributions to help develop regulatory standards for monitoring the financial and operational indicators of Brazilian electricity distributors (ANEEL, 2016, 2014b, 2014a). In the context of the Brazilian regulatory framework, this research identifies companies that are struggling to meet the regulatory targets in effect. In order to predict this financial distress in up to three lag periods, different algorithms of variable selection were used to estimate different logistic regression models (Aziz and Dar, 2006; Jackson and Wood, 2013; Ohlson, 1980) to ascertain which financial indicators should be adopted by ANEEL for monitoring purposes.

3. Method

3.1. Sample selection

The database comprises all 60 energy distributors in Brazil from 2009 to 2015, including financial information compiled from the annual regulatory accounting statements provided by ANEEL. Due to the new Accounting Manual for the Electricity Sector, which changed several structures of the publication format from 2015 (ANEEL, 2015b), we adapted all the headings of the financial statements between 2009 and 2014 to the new publication template following the adaptation guidelines of ANEEL itself (ANEEL, 2014c).

Table 1
List of indicators used to predict financial distress events.

Indicator name	Formula	Refs.
Interest Coverage Ratio (ICR) – *Adjusted*	*EBITDA/FE*	a–h
Operating Margin (OPM)	*EBITDA/NR*	a, c, h, i
Net Margin (NM)	*Net Earnings/NR*	e
Current Liquidity (CL)	*CA/Current Liabilities*	b, e, j
Immediate Liquidity (IL)	*CCE/Current Liabilities*	b
Return On Assets (ROA)	*Operating Profit/TA*	a, e, f
Overall Liquidity (OL)	*(CA + LTR)/TL*	b, g
Net Debt /EBITDA Ratio – *Adjusted* (ND.EBITDA)	*(EBITDA + CCE)/Gross Debt*	a, c, h, i
Overall Indebtedness (OI)	*Total Debt/TA*	b, d, e, g, j

Note 1: Refs.: a = (Standard and Poors, 2013), b = (Moodys, 2013), c = (Fitch, 2014), d = (NYPSC, 2014), e = (ERCP, 2001), f = (USAID and SARI/EI, 2004), g = (Scalzer et al., 2017), h = (ANEEL, 2014a), 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.

Additionally, the regulatory information used in the Technical Notes for the review and/or new tariff published annually by the regulatory body was collected through individual look-up of each document posted publicly on the Internet. Of the companies, three were excluded from the analysis because they do not participate in the national interconnected system of electricity, and therefore have different remuneration rules. In addition, three observations did not have the complete regulatory data needed for this research and were therefore also excluded.

The final database for all statistical tests of this work was restricted to observations containing data in both financial and regulatory dimensions of data in a set of 396 observations. Table 1 presents the financial indicators used in this research to predict the regulatory financial distress described in Section 3.2:

Indicators that used cash flow information, although used by rating agencies (Fitch, 2014; Moodys, 2013; Standard and Poors, 2013), were not selected in this paper due to companies' disclosing Cash Flow Statement information only from 2010. For the calculation of the Interest Coverage Ratio, the financial expenses considered only interest expense over debt to ensure uniformity of comparison because the financial expenses associated with derivative contracts did not have standardized accounting across companies. As can be seen in Table 1, The Net Debt/EBITDA indicator was algebraically adjusted so as to not incur negative denominator problems. The new adjusted indicator presented a correlation of 0.83 with the original indicator, using only those cases in which inconsistency problems did not occur. Problems of inconsistency caused by negative denominators in calculations of financial indicators are ignored in many surveys that use financial data; for this reason, we do not use ROE (return on equity) in this study. A broad discussion on this subject can be found in Nenide et al. (2003) and Mendes et al. (2014).

3.2. Distributors' performance under regulatory variables

Financial distress in electricity distributors results from inefficiencies related to the inability to meet the regulatory targets that cause the absorption of losses in the financial results (Pierk and Weil, 2016; Nunez, 2007; Resende, 2002; Liston, 1993). The performance of companies in relation to regulatory targets was measured using a multiple linear regression model with pooled data that seeks to explain the operational result measured by EBIT/Regulatory EBIT defined by ANEEL, as shown in Eq. (2):

$$\frac{Ebit_i}{Regulatory\ Ebit_i} = \beta_0 + \beta_1 Market_i + \beta_2 Losses_i + \beta_3 PMS_i + \beta_4 OCPI_i + \varepsilon_i \tag{2}$$

where the explanation of each of the explanatory variables is presented in Eqs. (3)–(6), and ε_i is the estimation of the regression error term. The requirements imposed by the Brazilian regulatory agency defined the explanatory variables in Eq. (2), while the dependent variable measures the performance of the company's operating results against the regulatory operating result for the i-th observation. In other words, the dependent variable measures the financial impacts incurred by the companies in relation to the regulation of the sector (Johnson et al., 1998; Lins et al., 2007; Reitenga, 2000) and excludes the performance of financial income and expenses from the analysis. According to this logic, companies that obtain values greater than 1 exceed the minimum regulatory performance and retain the efficiency gains accrued, while values less than 1 represent the retention of the inefficiency losses in meeting regulatory requirements (Pierk and Weil, 2016; Nunez, 2007; Resende, 2002; Liston, 1993). In this research, all dependent variable estimates smaller than 1 are treated as regulatory financial distress. The model was estimated with pooled data due to the large reduction of observations that would result were a balanced panel used.

The Market variable is the market variation of the EDC (i.e., the variation of the electricity consumed in relation to the provided electricity), according to the calculation presented in Eq. (3):

$$Market_i = \frac{(Market\ Held_i - VPB_i)}{Regulatory\ EBIT} \tag{3}$$

where the Market Held is the Net Operating Revenue of the company deducted from the components of Parcel A, VPB is the portion referring to the manageable costs as explained in Section 2.1, and Regulatory EBIT is the remuneration established by the regulatory agency by multiplying the regulatory WACC by the Net Remuneration Basis. Although not a variable under company control, unexpected variations in the Market Held can generate significant positive or negative impacts on the company's performance (ANEEL, 2010). The variable Losses is the value of losses incurred by the EDC in relation to the regulatory goal, as explained in Eq. (4):

$$Losses_i = \frac{(Realized\ Losses_i - Regulatory\ Losses_i)}{Regulatory\ EBIT} \tag{4}$$

where realized losses equals the sum of technical and non-technical losses and regulatory losses equals the value of the target set by the regulator. The price of energy purchased multiplied by the value of the losses in MW h transformed the final amount to monetary terms in reais (BRL). The variable PMS represents the expenses due to Personnel, Material and Services in relation to ANEEL's target Operational Costs, as explained in Eq. (5):

$$PMS_i = \frac{(\text{Realized } PMS_i - Operational\ Costs_i)}{Regulatory\ EBIT} \tag{5}$$

where the PMS realized is the amount related to Personnel, Materials and Services expenses in the financial statements, and Operating Costs are the regulatory goals stipulated by ANEEL based on an efficient reference company as benchmark. OCPI (Overall Continuity Performance Index) is the indicator that measures the performance of company service quality in terms of duration and frequency of power cuts, according to Eq. (6):

$$OCPI_i = \frac{(\text{Real.}DEC/Reg.\ DEC_i + Real.\ FEC/Reg.\ FEC_i)}{2} \tag{6}$$

where DEC is the duration of the power cut in terms of equivalent energy per consumer unit and FEC is the frequency of the power cut in terms of equivalent energy per consumer unit. The OCPI is the arithmetic average of the respective comparisons of DEC and FEC with their regulatory goals. With the exception of OCPI, which is an inherently non-monetary variable, all the explanatory variables of Eq. (2) were in terms of reais (BRL) and divided by Regulatory EBIT to consider the scale effect of each company.

Table 2
Correlation matrix and descriptive statistics of the explanatory variables of Eq. (2).

	Market	Losses	PMS	OCPI
Correlation Matrix				
Market	1.00	− 0.45 (***)	0.26 (***)	0.08 (*)
Losses	− 0.45 (***)	1.00	0.00	0.18(***)
PMS	0.26 (***)	0.00	1.00	0.10 (**)
OCPI	− 0.08 (*)	0.18 (***)	0.10 (**)	1.00
Descriptive Statistics				
Minimum	− 3.36	− 0.51	− 2.20	0.12
Median	0.16	0.01	− 0.11	0.84
Average	0.14	0.04	0.00	0.89
Maximum	4.72	1.35	3.81	3.46
Standard Deviation	0.78	0.17	0.80	0.39

*, **, *** means that they are statistically significant at the 10%, 5% and 1% levels respectively.

Table 2 shows that the explanatory variables of Eq. (2) do not have high levels of univariate correlation. In addition, the Variance Inflation Factor statistics for each variable estimated results from 1.19 to 1.25, which demonstrate that we need not worry about multicollinearity problems within the usual limits of the literature. Descriptive statistics are presented after the elimination of outliers at the multivariate level, which were identified according to their level of influence through the Cook's Distance calculation, which considers both leverage and discrepancy by measuring the impact of eliminating each observation in the estimated betas (Cook, 1977). The cutoff point for outliers is equal to 4/(n-k-1) where n is the sample size and k is the number of variables used (Kuhn and Johnson, 2013).

3.3. Model specification

To ascertain the variables with the best ability to predict financial distress in the light of regulatory goals, a logistic regression model for predicting financial problems (Charitou et al., 2004; Chava and Jarrow, 2004; Ohlson, 1980; Shumway, 2001) estimated the categories generated through the dependent variable on Eq. (2) after excluding the effects of the variable Market presented in Eq. (3). This adjustment in the estimated dependent variable, i.e. $\hat{Y}_i - \hat{\beta}_1 Market_i$, stems from the interest in analyzing only the regulatory aspects that are clearly manageable by the company. The observations with values greater than or equal to 1 make up the category of regulatorily sustainable companies, while those with values less than 1 make up the group under financial distress. Through the explanatory variables contained in Table 1, Eq. (7) estimates the dependent variable estimated in Eq. (2), as follows:

$$\ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 x_{1,t} + \ldots + \beta_k x_{k,t} \tag{7}$$

where the logit of probability is estimated by maximum likelihood and assumes the probability of a given event occurring, p_i is the probability of occurrence of the event studied for the i-th observation, and $1-p_i$ is the probability of occurrence of the event, where companies under financial distress assume a value equal to 1, and 0 otherwise. β_k are the parameters associated with the explanatory variables $x_{k,t}$ that represent each variable used, for the k indicators used, and for the different periods of a gap from − 1 (one year before), − 2 (two years before) and − 3 (three years before).

As with Eq. (2), the explanatory variables of Eq. (7) also underwent the same outliers elimination analysis, whereby the observations considered to be influential at the multivariate level were eliminated through the calculation of Cook's Distance (Cook, 1977). Despite this,

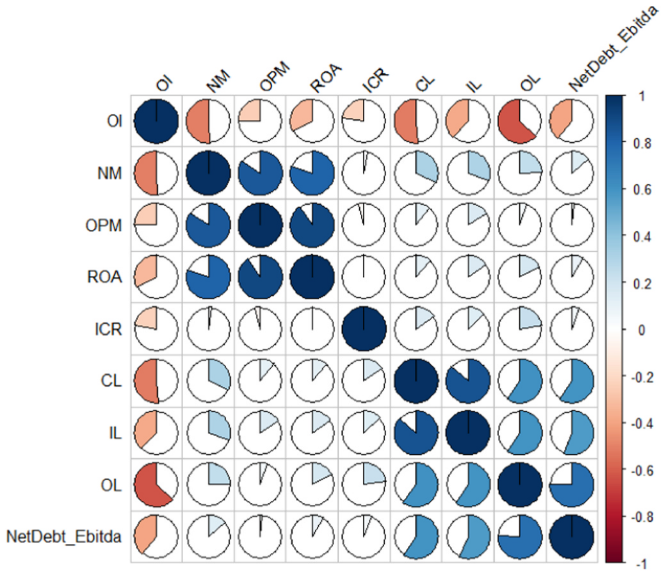

Fig. 1. Analysis of multicollinearity between the explanatory variables of Eq. (7).

we also estimated Eq. (2) without due treatment of outliers, and we observed that the estimates would become very erratic, which would not make sense in the relationship between the explanatory regulatory variables and the financial performance of the distributors. In addition, in the analysis of multicollinearity, Fig. 1 presents some clusters of indicators with high levels of correlation traditionally inherent in the behavior of financial indicators (Adler and Yazhemsky, 2010; Balcaen and Ooghe, 2006; Jenkins and Anderson, 2003). In spite of this, with the aid of the glmulti package (Calcagno, 2013) in R software, an algorithm estimated the 2^k combinations of models from Eq. (7), where k = 9 is the number of possible explanatory variables.

A theoretical-informational analysis with multimodel inference (Anderson, 2008; Burnham and Anderson, 2002) ordered all possible regressions according to Akaike Information Criteria (AIC) and Bayesian Information Criterion (BIC), and made it possible to identify the most relevant variables across the set of possible 2^k regressions. The use of AIC and BIC helps avoid problems of overfitting and does not suffer from the problem of performing multiple invalid hypothesis tests on the same sample as occurs in classic stepwise selection algorithms for variables (Kuhn and Johnson, 2013). The greater capacity of BIC to restrict the number of variables remaining in the regressions pointed to it as criterion for choosing the models, despite the similarities between the BIC and AIC calculations.

3.4. Robustness analysis under different variable selection techniques

A robustness analysis verified how other variables selection techniques identified the most relevant variables in predicting the financial distress in Eq. (7): (i) Recursive Feature Elimination (RFE), and (ii) the penalized model of Friedman et al. (2010). RFE has the advantage of being a stepwise backward that does not re-evaluate several models in each selection interaction, and where an independent metric chosen by the researcher orders the relevance of each explanatory variable and eliminates the less relevant when the ordering of relevancy is recalculated again (Guyon and Elisseeff, 2003). Meanwhile, the penalized model of Friedman et al. (2010) uses both regularization and variable selection parameters with mixed ratios between LASSO and ridge regression that allow reduction of the sum of the quadratic residuals of the model in exchange for allowing greater bias in the parameter estimation. Despite this limitation, it is possible that providing some level of bias can identify models with significant reductions in residue levels and with more relevant and less correlated variables (Friedman et al., 2010).

Fig. 2 shows that despite the clear identification of a large number of companies that are distant from the cutoff = 1, that defines the groups of the dependent variable to be used by variable selection algorithms, there is also a large group of relatively close companies to the cutoff. In addition, to avoid the possibility of classification bias in the dependent variable (Balcaen and Ooghe, 2006; Dimitras et al., 1996; Eisenbeis, 1977) due to the dichotomous definition of the companies under financial distress (greater than 1 and less than 1), a robust regression with bootstrap on the residuals estimated the efficiency of the explanatory variables selected by the algorithms selection of variables adopted throughout the paper.

4. Results and discussion

4.1. Analysis of the regulatory financial distress of the EDCs

The economic and financial sustainability of the Brazilian EDCs that ANEEL seeks to monitor through financial indicators (ANEEL, 2016, 2014a, 2014b) are evaluated in this work based on the achievement of

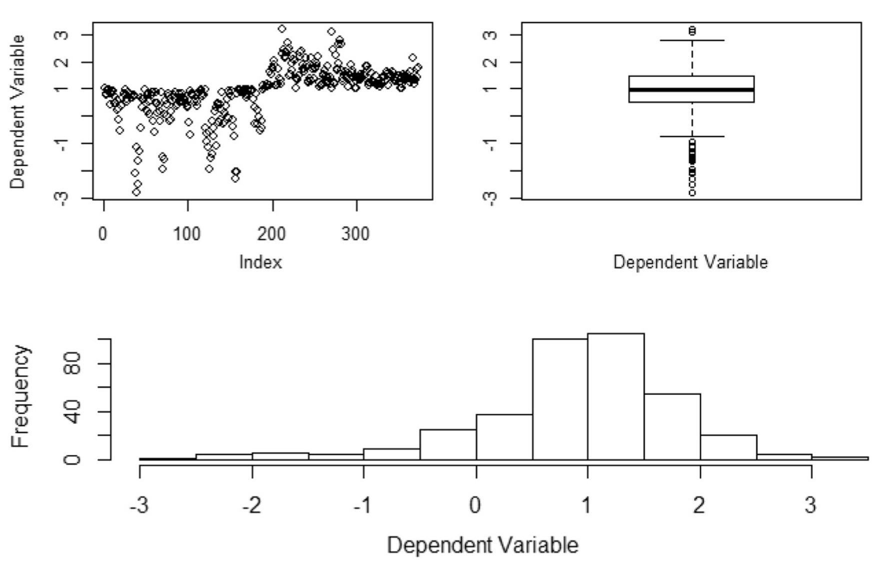

Fig. 2. Distribution of dependent variable of Eq. (2).

Table 3
Estimation of Eq. (2) with pooled data.

	Intercept	Market	Losses	PMS	OCPI
Coefficients	1.092	0.663	− 1.531	− 0.986	− 0.145
Standard Deviation	(0.087)***	(0.058)***	(0.308)***	(0.044)***	(0.092)

Sum of total squares: 481.02.
Residual sum of squares: 101.74.
R-square: 0.788; Adjusted R-square: 0.786.
F-statistics: 344.817 in 4 and 370 degrees of freedom, p-value: 0.000.
Note: *** statistically significant at the 0.1% level.

regulatory targets via the estimation of Eq. (2). Regulatory financial distress is defined as the estimation of the dependent variable when it assumes a value less than 1, after excluding the effects of the Market variable, since this variable is not under the control of the company. The analysis of the inefficiency of the companies in relation to the specific aspects of the regulation seeks to verify whether Brazilian regulation is able to influence the financial performance of the companies and demonstrate using which variables this relation is best obtained (Posner, 1974; Viscusi et al., 2005).

Table 3 shows that the estimation of Eq. (2) has a high degree of fit, which testifies to the effectiveness of regulatory standards in the performance of regulated companies (Agrell et al., 2005; Chang et al., 2004; Johnson et al., 1998; Kumbhakar and Hjalmarsson, 1998; Lins et al., 2007; Nunez, 2007; Reitenga, 2000). All variables were significant at the 0.1% level and with the expected sign in relation to the dependent variable after correction for homoscedasticity through the Breusch-Pagan LM test, except for the OCPI parameter, which presented the expected sign but obtained p-value of 11.79. Despite this, the OCPI was kept in the estimated model due to the theoretical basis of its negative effect on the result of the electricity distributors (ANEEL, 2014a). The inclusion and maintenance of OCPI is based on the regulation by ANEEL and the fact that, although not significant, it has an impact and we want to recognize this impact based on this regulatory aspect.

The results confirmed that EDCs that are inefficient in relation to energy loss targets, operating expenses measured by PMS, and the quality of distribution services measured by OCPI perform worse than companies that are regulatory efficient (Pierk and Weil, 2016; Nunez, 2007; Resende, 2002; Liston, 1993). ANEEL's current regulation is effective in creating incentives for companies to be efficient and to penalize inefficiencies, but this may not be sufficient for companies to make decisions that ensure economic-financial sustainability over time.

Fig. 3 shows the weights of each model of Eq. (7) estimated with the 9 variables of Table 1 standardized by the respective means and standard deviations of each variable. The estimation calculated the weights for the 512 different possible models as the probability of each model being the best model using the Kullback-Leibler test, which seeks to minimize the loss of information in the approximation of the estimated model to the real model. For this, the BIC value was used as a parameter because it was more restrictive to include new variables than the AIC, considering the high number of variables with high correlation shown in Fig. 1.

For all the periods adopted there are always one or two models that stand out in relation to the others, a difference that would not be so great if AIC were adopted as a criterion. Fig. 4 shows by multi-model inference the importance of each variable used, calculated by the sum of the weights of the models in which each variable appeared during the selection process. Although the use of the BIC criterion always identifies the same AIC variables for the level of importance greater than 0.8, the importance levels under the BIC criterion are always less than or equal to the importance levels calculated under the AIC criterion, which demonstrates greater restriction to the presence of more variables in the models. The results of Fig. 4, based only on the multimodel importance of the variables, identified a pattern of relevance for the indicators that involve liquidity (CL, IL) and profitability (ROA) for t-2 and t-3, and liquidity (CL, IL), profitability (ROA, NM) and indebtedness (ICR) for t-1.

Table 4 shows which were the best models selected by the BIC method that appeared in Fig. 3 with the highest evidence weight. Additionally, since the best models for each level of time lag in (i) considered variables with a high level of correlation, such as those between IL and CL and between ROA and NM, the second half of Table 4 estimated in (ii) presents the best Possible models after inclusion of the maximum correlation restriction among the variables in the value of 0.7, considered a high cut-off point in the literature (Kuhn and Johnson, 2013). The best selected models (ii) remained consistent with (i) through the selection and significance of ROA parameters in all three periods of lag and IL for one lag period.

Despite the multicollinearity between some variables, the models estimated in (i) presented a significant reduction of BIC and AIC in relation to the models estimated in (ii). This shows that CL and IL jointly add relevant explanatory power to the models and therefore could be maintained in the estimation of the dependent variable despite the multicollinearity among the variables (Wooldridge, 2011). The lack of significance of CL in (ii) for t-2 and t-3 shows that the indicator alone was not efficient in contributing to the ability to predict of the dependent variable, whereas the presence of IL in (ii) for t-1 demonstrated significant and negative sign. The lack of explanatory power of CL may be associated with greater working capital needs in the short term, while the IL would be more focused on measuring an instant liquidity that guarantees greater financial solvency (Palepu et al., 2013). In addition, ROA parameters showed negative signs in all estimates of (i) and (ii), so that an increase in the value of the independent variable reduces the probability of the occurrence of regulatory financial distress.

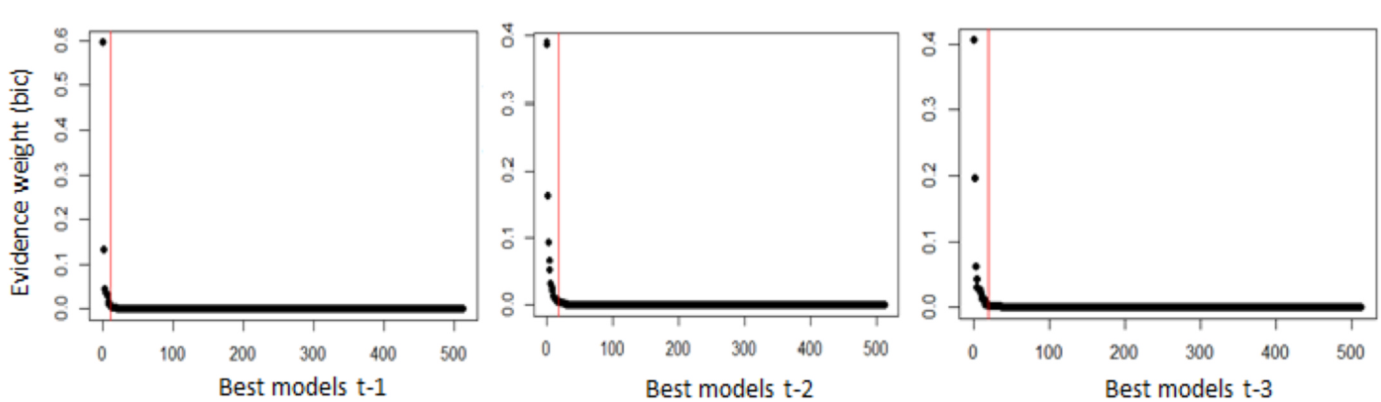

Fig. 3. Profile of the weights of the models.

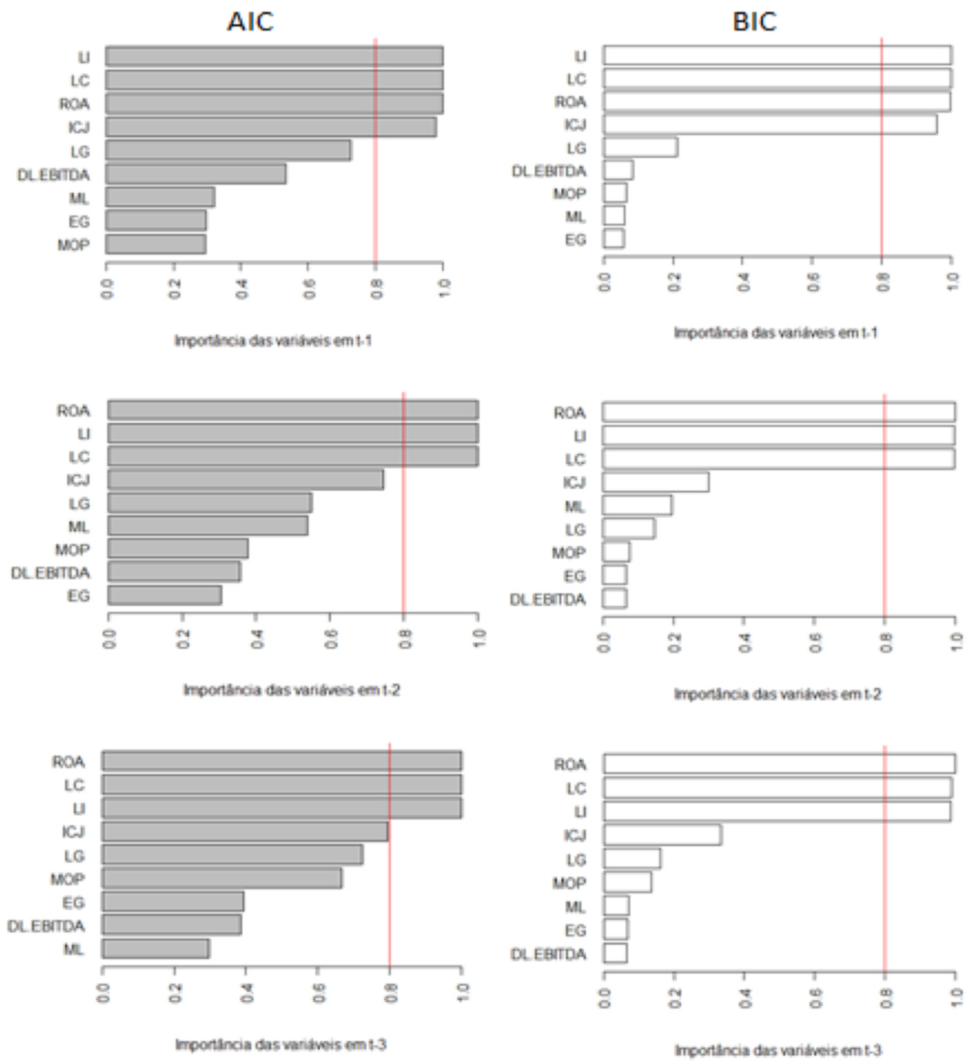

Fig. 4. Multimodel analysis of the importance of variables under the AIC and BIC criteria.

Table 4
Best models estimated using multimodel inference.

(i) Best model under criterion of lower BIC						Statistics
t − 1	Intercept	ICR	CL	IL	ROA	AIC = 359.65
Coefficient	0.215	10.118	1.423	− 1.552	− 1.476	BIC = 378.85
Standard Deviation	(0.433)	(16.603)	(0.289)***	(0.307)***	(0.198)***	
t − 2	Intercept	CL	IL	ROA		AIC = 323.14
Coefficient	− 0.319	1.367	− 1.296	− 1.443		BIC = 337.92
Standard Deviation	(0.464)	(0.304)***	(0.300)***	(0.202)***		
t − 3	Intercept	CL	IL	ROA		AIC = 263.69
Coefficient	− 0.327	1.628	− 1.459	− 1.414		BIC = 277.71
Standard Deviation	(0.537)	(5.197)***	(0.364)***	(0.217)***		
(ii) Best model with inclusion of correlation restriction < 0.7						Statistics
t − 1	Intercept	ICR	IL	ROA		AIC = 385.34
Coefficient	1.642	10.592	− 0.294	− 1.308		BIC = 400.70
Standard Deviation	(0.250)***	(13.171)	(0.134)***	(0.176)***		
t − 2	Intercept	CL	ROA			AIC = 342.27
Coefficient	0.974	0.225	− 1.321			BIC = 353.36
Standard Deviation	(0.364)***	(0.145)	(0.185)***			
t − 3	Intercept	CL	ROA	ICR		AIC = 277.57
Coefficient	1.081	0.248	− 1.371	0.919		BIC = 291.59
Standard Deviation	(0.397)***	(0.174)	(0.207)***	(2.452)		

*** Statistically significant at the 0.1% level.

4.2. Robustness analysis

The robustness analysis with different variable selection techniques showed results consistent with selection based on multimodel inference (Anderson, 2008; Burnham and Anderson, 2002) of Section 4.1. Fig. 5 shows that both the LASSO parameters (α) and the regularization parameters (λ) of the model of Friedman et al. (2010) were not very sensitive in significantly changing the values of the area below the ROC

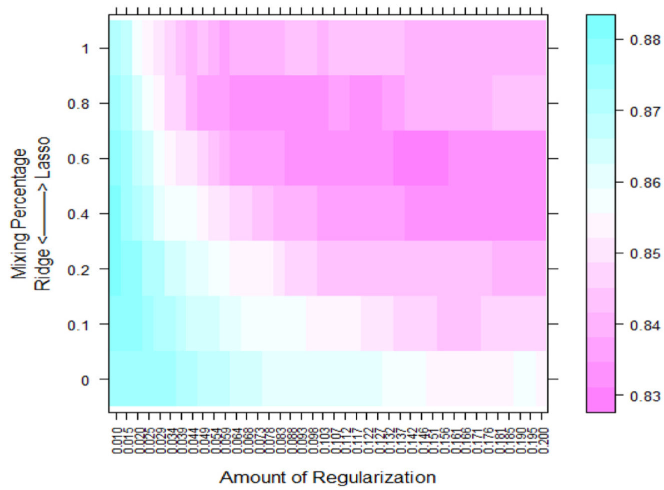

Fig. 5. AUC sensitivity for different lambda and alpha values.

curve (AUC). Thus, the maximum values of alpha = 1 and lambda = 0.2 were adopted in this model because they are the most restrictive in the selection of variables.

Table 5 presents the results of the models selected by the RFE method and the penalized model of Friedman et al. (2010) without considering the estimation of the intercept. In both models, 10-fold cross-validation produced resampling with 5 replicates to avoid overfitting problems and improve the credibility of estimated models (Kuhn and Johnson, 2013). Both methods obtained consistency in the selection of indicators in accordance with the results of Section 4.1, including statistical significance at the 0.1% level for all parameters.

Among the selected indicators, the ROA was highlighted due to its inclusion with negative sign in all the models for the different levels of lag, which demonstrated that the level of annual profitability is relevant and is negatively associated with the financial regulatory distress (Johnson et al., 1998). In the models selected by RFE, the inclusion of CL and IL, even though two highly correlated variables, showed that liquidity indicators were also relevant in predicting the regulatory financial distress. In line with the results in Table 4, when the inclusion of both liquidity indicators occurs simultaneously in the same model, the interpretation of the parameters of both variables may be compromised due to the high correlation between these two variables.

The results of Table 6 demonstrate that the risk of classification bias, when transforming a dependent variable into categorical in Eq. (7), did not interfere in the effectiveness of the variable selection techniques applied throughout the paper. An OLS with bootstrap through the randomization of the residuals test the original and continuous dependent variable fitted values. The variables ROA, IL and CL selected by the various selection algorithms throughout the paper demonstrated strong explanatory capacity of the continuous dependent variable, and with high levels of statistical significance.

5. Conclusions and policy implications

This research brought four main contributions to the analysis of the economic-financial sustainability of the Brazilian EDCs. First, it focuses on meeting the interests demanded by the Brazilian Electricity Regulatory Agency (ANEEL), which held Public Consultation 15/2014 to plan the implementation of economic-financial monitoring of Brazilian distributors through financial indicators (ANEEL, 2016, 2014a, 2014b). Second, the analysis of the companies' financial situation is studied through the concept of financial distress, which incorporates EDCs performance in relation to regulatory goals. Since the regulation itself already has tools that influence the financial situation of companies (Agrell et al., 2005; Chang et al., 2004; Johnson et al., 1998; Korhonen and Syrjänen, 2003; Kumbhakar and Hjalmarsson,

Table 5
Variables selected by the RFE method and penalized model of Friedman et al. (2010).

Recursive Feature Elimination					Statistics
t − 1	Intercept	IL	CL	ROA	AIC = 370.66
Coefficient	− 0.016	− 1.442	1.443	− 1.419	BIC = 386.02
Standard Deviation	(0.128)	(0.285)***	(0.284)***	(0.190)***	
t − 2	Intercept	ROA	IL	CL	AIC = 323.14
Coefficient	− 0.071	− 1.443	− 1.296	1.367	BIC = 337.92
Standard Deviation	(0.137)	(0.202)***	(0.300)***	(0.304)***	
t − 3	Intercept	ROA	IL	CL	AIC = 263.69
Coefficient	0.088	− 1.414	− 1.459	1.628	BIC = 277.71
Standard Deviation	(0.153)	(0.217)***	(0.364)***	(0.402)***	
Penalized Model of Friedman et al. (2010)					Statistics
t − 1	Intercept	ROA			AIC = 15.39
Coefficient	NA	− 0.906			BIC = 19.23
Standard Deviation		(0.108)***			
t − 2	Intercept	ROA			AIC = 16.27
Coefficient	NA	− 0.931			BIC = 19.97
Standard Deviation		(0.117)***			
t − 3	Intercept	ROA			AIC = 16.39
Coefficient	NA	− 0.962			BIC = 19.90
Standard Deviation		(0.129)***			

*** Statistically significant at the 0.1% level.

Table 6
Robust regression with bootstrap.

	Intercept	ROA	IL	CL	R-squared
Coefficients	− 0.575***	− 10.393***	− 0.842***	0.506***	46.83%
Confidence Interval 95%	(− 0.481, − 0.670)	(− 9.792, − 10.994)	(− 0.681, − 1.002)	(0.612, 0.401)	

*** Statistically significant at the 0.1% level.

1998; Lins et al., 2007; Nunez, 2007; Pacudan and de Guzman, 2002; Reitenga, 2000; Resende, 2002), the inefficiency of complying with regulatory goals generates negative financial consequences that can impact company solvency over time. Third, different variable selection algorithms and a penalized logistic regression model selected similar financial indicators to predict the regulatory financial distress for three lag periods from a group of financial indicators that are already adopted by other international utility regulators and rating agencies in the evaluation of companies in the sector (ERCP, 2001; Fitch, 2014; Moodys, 2013; OEB, 2014; Standard and Poors, 2013; USAID and SARI/EI, 2004). Fourth, to define the regulatory financial distress, a multiple regression model identified that four variables measured as a function of regulatory metrics were able to explain the variation of the companies' result in relation to the expected regulatory result: (i) the variation of the size of the Market, (ii) disbursements with Personnel, Materials and Services (PMS), (iii) levels of Losses, and (iv) the power cut frequency and duration indices (OCPI).

The capability of predicting financial problems through forecasting models provides regulators with indicators that can be adopted in the new regulatory proposal for Brazilian companies. ROA was the indicator that got the most attention because it was selected in all the exercises and for all the different lag periods. Studies such as Johnston (2005), Reitenga (2000), and Kumbhakar and Hjalmarsson (1998) emphasized the importance of analyzing the profitability of EDCs as an indicator that portrayed the impacts of different types of regulatory aspects. Liquidity indicators such as IL and CL also showed relevance for the different lag periods and demonstrated that liquidity also needs to be monitored by the Brazilian regulator. Although the interest coverage ratio (ICR) was selected in two simulations in Table 4, the strong absence of an indicator that represents the level of indebtedness reinforces that the existing regulatory environment would be able to avoid strong levels of financial leverage, and consequently, the insolvency of companies. This can be confirmed through ANEEL 2010 and MarketLine (2015), which report that Brazilian electricity distributors have a low level of indebtedness.

The results presented may be useful for ANEEL in the new bill to implement the economic and financial monitoring of Brazilian EDCs through the creation of a system of incentives and penalties for values that must be reached annually. The goals could be defined based on yardstick competition (Førsund and Kittelsen, 1998; Johnson et al., 1998; Korhonen and Syrjänen, 2003; Nunez, 2007; Pacudan and de Guzman, 2002; Resende, 2002; Souza et al., 2010) focusing on the comparison between company pairs or through incentive regulation based on a reference company (Liston, 1993; Nunez, 2007; Pierk and Weil, 2016; Resende, 2002).

We leave it to future research to verify whether other factors may be relevant in the analysis of financial economic sustainability, such as whether (i) the participation of large corporate groups can ensure that inefficient firms can remain solvent over time; (ii) larger or private companies have greater ability to remain financially sustainable than smaller or state-owned enterprises.

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