ANALYSIS OF ECONOMIC AND FINANCIAL SUSTAINABILITY OF BRAZILIAN DISTRIBUTORS OF THE ELECTRICITY SECTOR

ABSTRACT

This study presents a model that allows the anticipation of moments of economic and financial difficulties of the electricity sector distributors in Brazil. It uses a logistic regression model considering several financial indicators as independent variables. In addition, it was used as the dependent variable a binary indicator that points to the times when the distributor was seized by the National Electricity Agency of Brazil (ANEEL) or had, as a result in the period, negative equity or tiny equity ratio. Then, it is possible to conclude that this model increases significantly the forecasting power of bankruptcy in the electricity sector.

Keywords: Distributors of the Electricity Sector in Brazil; Forecast Insolvency; Economic and financial sustainability

1. Overview

The discussion about the Brazillian Electric Sector's infrastructure has been a permanent agenda of discussion all over the News. Beyond that, it has also been one major concern for the government, politicians and regulators, especially on recent years. The economic and financial sustainability of the distributors of the electric sector has been a growing regulatory interest, both by public and private agents, counterbalancing the historical control toward the low or affordable tariffs. Much is due to recent environmental and political happenings that influenced the industry results. In this case, the approach is necessary to ensure stability of the electricity supply, a pillar of the new electric sector model, according to ONS (National Operator of the Electric Sector).

Since it is an essential service to society, the power distribution sector may be considered too big or systematic to fail. This means that there is a high risk for the government, through the National Electricity Agency of Brazil (ANEEL) and other competent bodies, to provide extra financial resources or take over the management of the distribution companies (in the latter case). This would happen when they are not able to maintain economic and financial sustainability of their own operations, or the minimum quality required by the regulator (Law N°. 12.767/2012 and N°. 577/2012 Provisional Act). In this scenario, consumers would pay higher tariffs or get lower quality services, with more outages/blackouts and longer duration of them. Thus, depending on the market circumstances, this regulatory model (with focus only on lower tariffs) proved unfavorable to the consumer in the end. In this institutional setting, the main objective is present a predictive model for evaluating and monitoring the economic and financial sustainability of the power sector distribution companies. Aiming to anticipate critical situations in the distributors, this study compare financial indicators suggested by national and international academic papers and evaluate them for their ability to predict in advance when the distributors are likely to need financial rescue by the government or other private financial institutions or intervention in the management by ANEEL.

2. Literature Review

The regulation in the electricity sector initially aimed to unbundle the generation operations, transmission, distribution and commercialization of energy. According to Giannakis et al, 2005, while the sectors of generation and commercialization can be more competitive, energy transmission and distribution should suffer economic regulation in order to become more efficient.

The distribution sector in particular has natural monopoly characteristics, has huge economies of scale, provides an essential service that requires a minimum quality standard and generates externalities that need to be controlled by the government, such as pollution. These factors, according to Giannakis et al (2005) are sufficient to show that the regulation is more effective than choosing the free market.

2.1 Features and Recent Regulatory Evolution of the Electric Sector in Brazil

After the restructuring of the Brazilian Electric Sector (SEB) during the 1990s, from the General Law of Concessions and the Law N°. 9074 passed in 1995, there were some important privatizations in the sector. From the 1995 economic liberalization, the rates charged by the distributors are now calculated by the regulator through the regulatory system Price-cap, which sets an upper limit but also creates incentives for utilities.

In 1996, by Law N°. 9427/1996, was created the sector regulator, ANEEL This law also sought to promote a tariff that would guarantee adequate service to consumers, but also an adequate remuneration for the concessionaires, ensuring compliance with the agreements (Carção, 2014).

When a distributor was not able to continue to provide the service or are close to reaching that point, Law N°. 12.767/2012 now allows that there is intervention in the management of the concessionaire company for a period of up to one year, renewable for up to two, at ANEEL's discretion. Although creating an institutional environment of greater power to the regulator, it also generates greater responsibility for having to justify their actions and go to work under the management of these companies, even for a short period.

These recent institutional changes exposes the growing need of the government through its regulatory body in better understanding the financial sustainability of the concessionary companies, its ability to maintain operations with the desired level of quality and revisit the concept of low tariffs. These milestones can be considered as a breakthrough in the form of Price-cap regulation or adaptation of improvements proposed by benchmarking for regulatory models in the industry and are closely related to the purpose of this work to provide greater theoretical and practical tools for the analysis of this issue.

2.2 Current Discussion About Monitoring Economic and Financial Sustainability - Technical Note N°. 353/2014 and N°. 175/2015 of ANEEL

The first technical note was presented in December 2014 by the Superintendence of Economic and Financial Inspection (SFF) to formalize and open for discussion in society a number of indicators that aims to monitor the economic and financial sustainability of the power sector distribution. Another objective of the SFF was to ensure the monitoring of appropriate service requirements defined in the Public Service Concessions Law.

As stated in the Technical Note 353, in paragraphs 13 to 26, there is a direct relationship between economic and financial indicators with the operation of these companies. A company without financial resources to pay their commitments can in a short space of time, no longer be able to maintain the proper maintenance of their equipment, reduce the level of investment in innovation and new technologies, and reduce the quality of service to consumers.

In addition, it may have to resort to new financial resources to keep the operation running. In this case, the two options for these resources would be equity from its shareholders, or third-party capital, which would increase leverage.

To create the most indicators, the SFF used the Regulatory Statements as the basis for provision of financial information that should be used. This is the first and perhaps the main feature of the Brazilian electric sector that differentiates it from other countries, which normally use Corporate Statements. More specifically, they should use the information generated by Balance Monthly Standardized (BMP), the Quarterly Information Report (RIT) and the Annual Rendering of Accounts (PAC).

From this information, the SFF considered some principles that guided the formation of sets of indicators: comparability, reliability, specificity, regulatory purpose and simplicity. Thus, based on these five principles, the SFF has created five sets of indicators covering the debt size, efficiency, investments, profitability, shareholder return and operational performance. For each set was defined a leading indicator and some other complementary to detail the analysis.

This set of indicators, however, were not widely used and /or released by the regulator. It is possible that the difficulty of integrating all dimensions in order to achieve a more objective analysis and simultaneously compare the different distributors to each other, or to any benchmark, has created a barrier to its use. Thus, in July 2015 it was proposed a new indicator to verify the economic and financial sustainability of utilities.

The seventh clause of this technical note is the commitment of the concessionaires to work for the economic and financial sustainability of its operations throughout the concession period. A number of sanctions were imposed on them in case of noncompliance with the minimum guidelines set in the technical note. They must be constantly assessed for their costs and expenses, indebtedness and liquidity levels, investments in replacement, improvement and expansion and the payment of tax and tax liabilities and income distributions.

For this to be done, the first clause of Annex III proposes a single indicator for the first five years of the concession able to check all these factors. The calculation is made from the operational cash generation discounted replacement investments and debt interests. The condition that guarantees minimum standards of economic and financial sustainability is given by the result equal to or greater than zero for this ratio.

It can be seen from both the technical notes that there is a growing concern by ANEEL as the economic and financial sustainability of the power sector utilities, especially in the power distribution sector. However, it has not yet established a definitive standard to evaluate companies in the sector. In addition, the recommended indicators and its static analysis does not help to anticipate or predict critical events that represent the inability to continue the operational activities without any financial rescue or intervention by ANEEL.

Thus, this study aimed to propose a complementary alternative methodology that helps this constant and dynamic monitoring of the financial health of the power sector distribution.

2.3 Studies into Insolvency Forecast

Ohlson (1980) was one of the first to introduce the use of a logit model to study the prediction of insolvency companies. Three experiments were explored using the logit model. At first it was considered the interval of one year for forecast bankruptcy, in the second it was considered two years and in the third study, bankruptcy was forecast in a range of one or two years.

After some time without much news or methodological advances in the use of logit model for companies of failure prediction, then, two important works were developed by Shumway (2001) and Chava and Jarrow (2004) studying bankruptcy of US companies between 1962 and 1999. Both papers contributed greatly to the use of dynamic models in failure prediction analysis of companies from different sectors. While the first study questioned the so-called static models and presented a proposal more effective and with less methodological errors, the second study reinforced the findings of Shumway (2001) and added another variable related to the industry that was significant in predicting insolvency.

The variables used in both studies are the same suggested by Altman (1968) and Zmijewski (1984), being widely considered the failure prediction literature. In the case of Shumway (2001), the goal was to consider the same variables and propose a model with better explanatory power. Chava and Jarrow (2004), in addition to these variables, also used the variables suggested by Shumway (2001), more specifically, from the model that achieved the best performance among those tested.

With regard to the conclusions found in the two studies, it was clear then the contribution to the academic research of the importance of using dynamic models Logit for failure prediction papers. From both studies, it was supported empirically that the model used by Shumway (2001) has a failure prediction power better than the static models previously used in other studies.

In a more specific study, Foreman (2002) presented an analysis of the insolvency of the US telecommunications industry companies. He showed that when analyzing traditional financial indicators of profitability, capital structure and the ability to finance growth, you can identify almost completely, which companies will break two years from the analysis. The methodology used by the author consisted of a Binomial logit model and the estimation was done using maximum likelihood techniques.

Despite the use of many others in the tests found indicators that showed better efficacy to predict insolvency two years after the analysis were Earnings per Share, Return on Assets, Retained Earnings for Assets, Total Debt Ratio and Working Capital to Sales. As expected, low income values per Share and Return on Assets indicate high probability of insolvency. Moreover, it was observed, on the results of the cases studied, the role of working capital has the opposite effect usually presented in the literature. Ie, large amounts of working capital anticipated over-investments, which further increased the need for capital, increasing the likelihood of the firm becomes insolvent.

In another study in the UK, Charitou et al. (2004) used the logit model to study industrial bankruptcy in listed companies. A difference of this study for the above is the use of a larger number of indicators tested in the initial model. Five categories of indicators were considered, namely: financial leverage, operating cash flow, liquidity, profitability, activity and market. Taken together are tested in total 26 indicators.

One of the goals of Charitou et al. (2004) was also to analyze how operating cash flow indicator influenced the predictive ability of the models. It was found that the indicators have high predictive power in the case of UK businesses. This result corroborates the study of Gilbert et al. (1990), when it also concludes that the variables related to the companies' cash flow add explanatory power to the bankruptcy prediction models.

Campbell et al. (2008) also used the logit regression with accounting and market variables to examine the determinants of business failures and pricing companies shares with high probability. Were used as inputs all bankruptcy filings in the Wall Street Journal Index, SDC Database, SEC filings and CCH Capital Changes Report, computed monthly, from January 1963 until December 1998 for the indicator failure. It was also considered by the authors, a broader indicator of insolvency, which considers companies defund lists for financial reasons or who received evaluation Rating D, between January 1963 and December 2003.

A major contribution of the study of Campbell et al. (2008) was being able to extend the spectrum of predictive models developed by Shumway (2001) and Chava and Jarrow (2004), incorporating new variables with "sensible economic motivations." Furthermore, this new model has a power of greater explanation than the previous ones, as shown by the Likelihood Value, the Pseudo-R^2.

In Brazil, Brito and Neto (2008) also used a logit regression model to study the credit risk of large companies operating in Brazil. In fact, credit is generally understood as a value that must be received at some point of time, therefore, the risk of credit can be understood as the chance of this event does not occur. The econometric tools was then also used in the study to anticipate possible insolvency events.

According to the authors, the default event usually does not happen suddenly. There is a gradual deterioration that occurs in companies and, theoretically, could be seen from the accompaniment of the indicators. The indicators reflected information on liquidity, profitability, activity, structure and dynamic analysis (BRITO and NETO, 2008). It was used to analyze the significance of the explanatory variables, the chi-square statistic and for joint hypothesis, the Wald test. The fit level of the model was analyzed in the same way as in the paper by Campbell et al. (2008), from the pseudo-R^2, which measures the overall quality of the model. It was also used the Cox-Snell R^2 and R^2 Nagelkerke measures that have similar objectives and its classification shows that the higher the value obtained, the higher the fit.

In a more recent study, Hilscher and Wilson (2013) compared the forecast model using the logit technique with the credit rating given by international rating agencies. The basic Logit model used in the tests is similar to those presented by Shumway (2001), Chava and Jarrow (2004) and Campbell et al. (2008) and uses financial and market information. In addition, they analyzed the default prediction ability of the S & P credit rating (Standard & Poor's) and Moody's, and later sought to relate the classification with systemic risk.

The results show that the Pseudo-R^2 is more accurate in predicting when, in addition to credit rating, is also used the model to forecast default logit, especially in the short and medium term. The primary conclusion is that ratings alone are not optimal predictors of default. The authors conclude, finally, that any restriction requiring that the credit risk is explained by only a predictive measure would result in loss of relevant information. It is, instead, interesting separate insolvency prediction of systemic risk assessment.

3. Methodology

This study uses the logit regression model, explained above, and used widely to assess probability of default and credit risk. Despite receiving criticism for not having strong theoretical assumptions subsidizing this model, as Brito and Neto (2008) argued, robust empirical results found through several studies suggest that it is possible to predict with reasonable accuracy the insolvency of companies.

3.1 Universe and sample

To better understand the economic and financial situation of the power sector distribution from the point of view of the national regulator, the main recommended accounting indicators in national and international literature to forecast insolvency are used. Thus, the analysis of the universe consists of all distributors of the electricity sector operating in Brazil. In addition, was chosen to use the regulatory balance sheets of the distributors that have particular adjustments determined by the regulator.

The size of the universe was determined by all companies registered at ANEEL and comprises sixty-two distributors.

3.2 Source and data collection

There were used in this stage of the work data provided by ANEEL in 2015 and grouped and standardized by the Electricity Sector Studies Group of the Federal University of Rio de Janeiro (GESEL / UFRJ). The frequency of regulatory accounting reports available is annual and covering the years between 2007 and 2014. The 13 variables presented below were collected from regulatory accounting reports and, after structuring the base with the above accounting variables, the first step was to calculate the economic and financial ratios that are the independent variables of the model. The table below lists the variables and financial indicators.

Accounting Information		Financial Indicators	Ratios	References
AC	Current Assets	General Liquidity Ratio	(AC + RLP) / (PC + ELP)	1, 2, 5, 6, 7
LAJIR	Earnings before interests and taxes (EBIT)	Current Liquidity Ratio	AC / PC	1, 2, 3, 5, 7
LL	Net Profit	Return on Equity	LL / PL	5, 7
PC	Current Liabilities	Return on Assets	LAJIR / AT	2, 3, 4, 5, 7
ANC	Non-current assets	Return on Sales	LL / VL	7
AT	Total Assets	Working Assets	VL / AT	1, 2, 4, 5, 6, 7
DF	Financial Expenses	Operating Margin	LAJIR / VL	7
PL	Equity	EBIT over Financial Expenses	LAJIR / DF	7

ELP	Long-term liabilities	Retained earnings over Total Assets	(LA + RL) / AT	1, 2, 3, 5, 7
RL	Profit Reserve	Equity over Total Liabilities	PL / (PC + ELP)	7
RLP	Long-term receivables	Short-term Debt	PC / AT	7
VL	Net Sales	Immobilization of Equity	(ANC-RLP) / PL	7
LA	Accumulated earnings	Net Working Capital	(AC - PC) / AT	1, 2, 4, 5, 7
Reference Index				
1	Ohlson, 1980			
2	Shumway, 2001			
3	Foreman, 2003			
4	Chava and Jarrow, 2004			
5	Charitou et al., 2004			
6	Campbell et al (2008)			
7	Brito and Neto, 2008			

Table 1 – Accounting informations and Independent variables

After structuring database with the independent variables, the periods in which the distributors did not have all the information was not considered in the calculation of the indicators. This happened for the following companies:

2014, 2013 e 2012

- Companhia Energética de Roraima – Regulatories Balance Sheet and Income Statements (BPREG e DREREG)

2013

- Companhia Sul Sergipana de Eletricidade – Regulatory Income Statement (DREREG)

The dependent variable (INT_RSG) that is considered in all tests is a binary indicator that shows the moments when the distribution was seized by ANEEL or had to be rescued with new financial resources (equity or debt), without which could not have keep continuity of operation. For each distributor in each period of analysis, the indicator is equal to one if the distributor has undergone intervention in management by ANEEL, has had negative equity or tiny equity ratio (value less than ten percent of the ratio shareholders' equity and total assets), which would suggest the need for financial rescue. Otherwise, the dependent variable is considered equal to zero. After this analysis, we had the following result:

Total Observations		Problem cases
Number of time periods (years)	8	8
Number of companies	63	63
Observations 2007	63	9
Observations 2008	63	6
Observations 2009	63	5
Observations 2010	63	4
Observations 2011	63	6
Observations 2012	62	15

Observations 2013	61	12
Observations 2014	62	14
Total	500	71

Table 2 – Universe and Sample Analysis

As our interest in this model is to check the predictive ability of the chosen indicators, we chose to consider one and two periods of time lag in the study.

In both cases, after organizing the information in the database, the samples were separated into two groups. The first contained only the observations which the dependent variable was zero and the second group gathered all the observations which the dependent variable has value equal to one. As there was a big difference on the number of occasions between the two groups in both cases, it was decided to use the group of observations "problem" as basis and create a random sample in the other group with the same number of observations. After this procedure, they were regrouped to the base and the logit model was applied on the reduced sample.

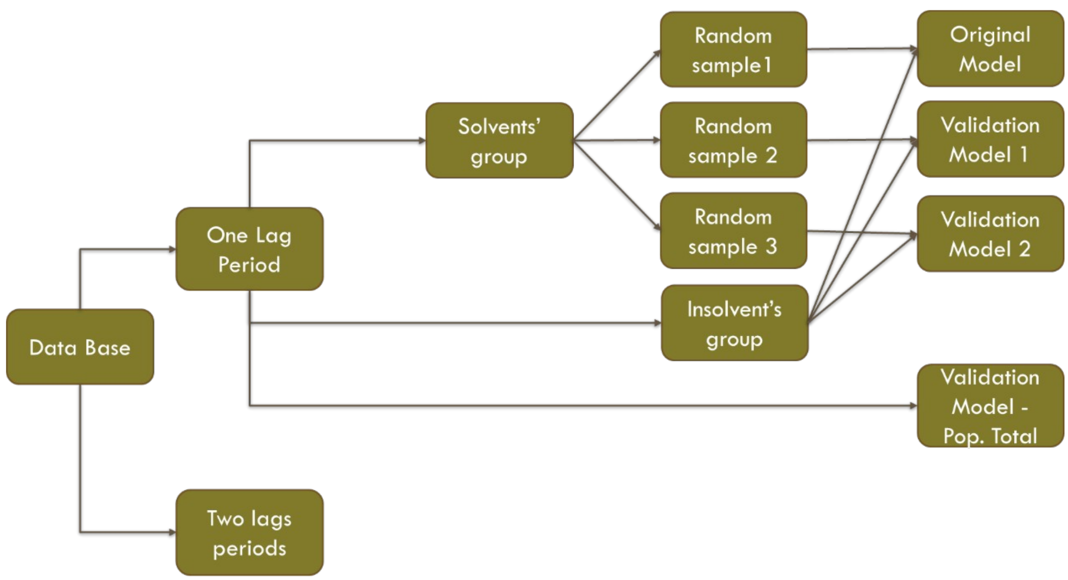

Figure 1 – Data and Model Adjustments, created by the author.

3.3 Applying the Logit Regression Model

For implementing the binary logit model it was used IBM SPSS software, version 22. Before starting the operation of the logit model to forecast the dependent variable of intervention/rescue of the power sector distributors, it was made a Pearson correlation test between the independente variables to eliminate any possible collinearity problems.

In addition, we used the Non-Parametric Mann-Whitney U Test to determine, for every variable, if there is a statistical significance difference of means between the groups of interest. Also, from the results of the Non-Parametric

Mann-Whitney Test correlated variables which had a higher p value were eliminated from the model. That was the decision criterion adopted to eliminate possible collinearity effects model. It is important that the variables are not highly correlated because, in this case, they would give similar information about how behave the dependent variable.

Initially, the regression is structured as a binary logistic model:

$$\ln\left(\frac{p}{1-p}\right)=b_0+b_1X_1+b_2X_2+\ldots+b_kX_k$$

However, the logistic regression also allows this assessment to be submitted in terms of probability from a simple transformation:

$$p=\frac{1}{1+e^{b_0+b_1X_1+b_2X_2+\ldots+b_kX_k}}$$

This is the probability associated with the event occurrence to be analyzed. In the logit regression, according to the authors Brito and Neto (2008), each coefficient measures the effect of changes in explanatory variables on the logarithm of chance, which is equal to the ratio p over (1-p). From this discrimination, as most studies using this method, the unknown parameters are estimated by Maximum Likelihood.

To verify the validity of the model as a whole is done by the Combined Hypothesis Wald Test. Then, it is checked whether each factor alone has some significance in the model sample by Chi-square statistic and its corresponding p-value as suggested by Chava and Jarrow (2004).

With the chosen model, its quality is checked to predict the event proposed, given the selected indicators in the previous phase. It should again be made a chi-square test to assess the significance of the coefficients individually and the Wald Test to evaluate the null hypothesis of the parameter estimated to be equal to zero. Moreover, it is used the Hosmer and Lemeshow test to analyze the model fit. It checks the differences between the adjusted and observed probabilities. Also, they are calculated the pseudo-R^2 Nagelkerke and Cox & Snell to check the quality degree of the model fit.

In order to analyze the model validation is conducted a ruggedness test which seeks to confirm results from other samples randomly generated from the procedure explained above. Therefore, the whole process is performed twice more to verify that the indicators remain significant, if the signals of the coefficients remain the same and values close to the original model.

4. Results

Initially, from the analysis of the results of Pearson and Mann-Whitney U Tests, it was decided to eliminate some variables that could present collinearity. After the decision on which indicators to maintain in the initial model, is held the first test of the logit model. The significance level is 10%. The process was performed as shown below:

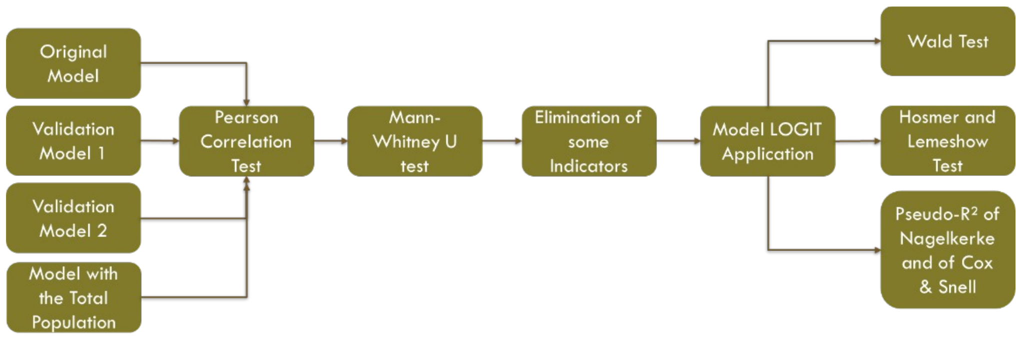

Figure 2 – Application of the Logit Model

This process was repeated until all independent variables used in the test were significant. As expected, with the removal of some variables there is a natural drop in overall predictive power of the model, but this is still very high also in the final result. The results were then analyzed in other validation models. Finally, the model was applied again on the entire population to see if the results are consistent with those obtained in each sample. Below are the main results for the models with one and two periods of lag.

Betas				
	Original Model	Validation Model 1	Validation Model 2	Validation Model - Total Pop.
Equity over Total Liabilities	-7,9	-6,902	-8,329	-9,619
Working Assets	-2,979	-4,557	-2,609	-2,796
Constant	3,459	4,265	3,604	2,236
Dependent Variable	correct percentage	correct percentage	correct percentage	correct percentage
0	77,4	82,3	83,9	98,4
1	83,9	82,3	85,5	62,9
Global	80,6	82,3	84,7	93,4
Pseudo R²				
R² Cox & Snell	0,473	0,501	0,513	0,341
R² Nagelkerke	0,631	0,667	0,685	0,612
Hosmer & Lemeshow Test				
Sig.	0,356	0,577	0,538	0,002

Figure 3 – Summary of the Final Results – 1 lag period, elaborated by the author.

Betas				
	Original Model	Validation Model 1	Validation Model 2	Validation Model - Total Pop.
Equity over Total Liabilities	-3,855	-3,815	-3,864	-5,091
Working Assets	-3,863	-2,888	-2,787	-3,423
Constant	3,427	2,902	2,776	1,748
Dependent Variable	Porcentagem correta	Porcentagem correta	Porcentagem correta	Porcentagem correta
0	80,4	80,4	80,4	98,4
1	80,4	80,4	80,4	41,8
Global	80,4	80,4	80,4	90
Pseudo R²				
R² Cox & Snell	0,39	0,378	0,356	0,252
R² Nagelkerke	0,52	0,505	0,474	0,445
Hosmer & Lemeshow Test				
Sig.	0,198	0,054	0,021	0,001

Figure 4 - Summary of the Final Results – 2 lag periods, elaborated by the author.

As can be observed in both cases, the indicators that best explain the dependent variable in all samples and the general population are on Equity over Total Liabilities and Working Assets. These independent variables of the final functions can significantly improve, robustly, the predictive capacity over the dependent variable worked on.

5. Conclusion

This study corroborates the results found in other articles on insolvency forecast. The use of accounting and financial indicators suggested in the methodology increase the predictive power of intervention situations or bailout, without which the distributor could maintain its operations. This result appears even stronger when the forecast is made within a shorter period (one lag period).

Therefore, this methodology is consistent with the new trend of regulatory policy practiced by ANEEL and can complement other indicators for economic and financial monitoring of utilities, such as those proposed in the technical notes that are being discussed by the various players in the industry.

Considering the significant indicators found in this study for the distribution of the electricity sector in Brazil, the results corroborate part of the Ohlson (1980), Shumway (2001), Chava and Jarrow (2004), Charitou et al. (2004), Campbell et al (2008) and Brito and Neto (2008). On the other hand, it shows other indicators that increased predictive power to other sectors not repeated here in the tests applied. This shows that there are financial and economic differences for analysis of different sectors at different times.

Despite the variables found being related to the ability to maintain operations at sustainable levels, other indicators such as Short-term Debt, General Liquidity Ratio, Return on Assets and net working capital, which usually indicate financially difficult situations were not significant when examining the distributors considering one or two periods of lag. For these indicators, the results differ from those found by Shumway (2001), Ohlson (1980), Foreman (2003), Chava and Jarrow (2004), Charitou et al. (2004), Campbell et al (2008) and Brito and Neto (2008). Campbell et al (2008) found only two significant endogenous factors, Working Asset and General Liquidity Ratio. Only the first one, Working Asset was significant for brasilian distributors in this study for the period 2007-2014.

Regarding the economic and financial part, the present study may help all interested in the subject in classify the distributors in each period for which it is necessary to increase the level of attention. However, because it is a dynamic methodology it is important to update the analysis whenever ANEEL or the distributors publish and make available new regulatory accounting reports.

For future researches that use similar methodological approach in the electricity distribution sector, it is considered relevant to include operational variables to check if they impact the financial health of these companies in subsequent periods. Furthermore, this research can be extended also to the generation sector, transmission and sale of electricity.

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