The Default risk of North American infrastructure companies: A sectoral approach from 2006 to 2018

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Abstract.

This paper investigated the probability of default of infrastructure companies from a sectoral perspective during the period from 2006 to 2018. For this it was used a logistic regression with binary dependent variable and explanatory variables of reduced risk models of default, besides dummy variables representing the sectors and a variable of the KMV-Merton model, Distance to Default, as predictor variables to evaluate a universe of 1,520 North American companies from 6 different sectors of infrastructure. The results show that oil and gas companies have a lower sensitivity to the variable Distance to Default than companies from other sectors, when this variable is used to explain the default probability of these companies.

Keywords: Sectoral Risk, Distance to Default, Infrastructure.

1. Introduction

One of the most sensible factors in the study of finance is the search for mechanisms to estimate the probability of default. This effort has triggered the emergence of several models aimed at solving this problem. Among them, models referenced in asset pricing techniques applied to the study of corporate liabilities were the pioneers in the task of modelling the company's default and linking it to an economic pricing model (LANDO & NIELSEN, 2010; CHEN & WU, 2014).

Merton (1974) contributed to clarify this application, creating an analogy between the capital structure of the companies and the idea of options on their assets. In face of that, a company's net worth could be compared to a European purchase option on its assets, where the exercise price of these options would be the value of their debt.

Currently, two theoretical approaches are considered for measuring the probability of companies defaulting. One of them is based on the so-called structural models, in which the contributions of Black & Scholes (1973) and Merton (1974) have improved the use of structural variables of companies, especially the value of their assets, to assess the likelihood of credit risk.

The second approach is based on the so-called reduced models, which allow the occurrence of default regardless of the evolution of the company's structural data. The reduced models are based on mechanisms focused on the search for stochastic risk rates, where the default probability dynamics do not depend on the credit recovery rate (SAUNDERS & ALLEN, 2002; ALTMAN ET AL., 2004).

The analysis of the correlation between common dynamic latent factors between companies may explain a considerable portion of the default risk, but sectoral and macroeconomic factors are generally ignored by conventional models (DUFFIE ET AL., 2009; CHEN & WU, 2014; JORION & ZHANG, 2009).

However, according to Giesecke (2004), there has not been enough research on approaches that incorporate the interdependence of default between companies. Therefore, developing consistent models to achieve this goal is still a challenge (CHEN & WU, 2014; ESCRIBANO & MAGGI, 2018).

With these factors in mind, the objective of this paper is to identify the sectoral differences on the measurement of default risk of corporate infrastructure companies, using as a tool a logistic regression model. To achieve this goal, this essay will answer the following research questions: i) What are the sectoral differences in the measurement of the risk of default of companies in the infrastructure sector? ii) Which variables affect the probability of default in companies of the infrastructure sector in the analyzed sample?

This paper is divided into five parts: Besides this introduction, we will analyze some mechanisms for credit risk measurement supported by the default probability measurement, Which are provided by the KMV-Merton model, as well as the Z-score models proposed by Altman (1968), the O-score proposed by Ohlson (1980), and the Zmijewski (1984) model. In the third part, we will show the methodology used in the study, as well as the data sources used for the sectoral impact measurement in the calculation of credit risk of infrastructure companies. In the fourth part, the results and the analyzes will be shown, and finally, in the final part, we will write the final remarks, presenting the limitations of this study, as well as suggestions for new research opportunities.

2. Default Risk

In finance, the term “risk” is associated with the impossibility of predicting future events. Thus, risk entails the probability of results different from those which had been expected, including negative and positive cases. Because both types of result depart from expectation, they are both susceptible of being classified as risk (DAMODARAN, 2012; CROSBIE & BOHN, 2003).

The theoretical approach of credit risk can be divided into at least two distinct schools of thought, (ZHOU, 2001; ALLEN; SAUNDERS, 2002). The first one, structural approach, the default probability analysis concentrates on the evolution of a company’s value. In this manner, default occurs when a company’s market value reaches a critical level that is delimited by its debt value (VASICEK, 1984, ZHOU, 2001, DUFFIE & LANDO, 2001).

The second generation of models is based on reduced form models focused on the search for stochastic risk rates, in which the dynamics of default probability is independent of the credit recovery rate, and both bear no relation to a company’s structural characteristics. In the reduced form models, the focus has become the assessment of contractual loss potential, given a time horizon and a trust level, where the event of default is seen as a random event.

2.1.KMV-Merton

The KMV-Merton model stems from the assumption that the capital structure of a company can be equaled to a series of options on its assets. In this way, the equity could be seen as a buying option on the company’s assets and the exercise price could be represented by its debt value. In this sense, the equity of a company is shown as a function of the company´s value.

Bharath and Shumway (2008) highlight that this model employs two non-linear equations to express the volatility value of the company’s equity within a certain default probability. The use of a risk-free rate, associated with the assumptions of the company´s equity value, allows the calculation of the Distance to Default, measure that expresses the distance that a company has until fall in default.

The KMV can be understood as an extension of Merton's model and employs the same modelling logic of the company's asset valuation and its ability to overcome the limit value of its debts. One of the variations of the KMV-Merton model is also employed by the American credit rating agency Moody's. The model used by this company can also be called KV model, and one of the basic differences in this version is that it is based on the measurement of several classes and debt maturity instead of considering it fixed in time (BHARATH & SHUMWAY, 2008; KLIESTIK ET AL., 2015).

Bharath and Shumway (2008) adapted the KMV-Merton model to create an alternative they called Naïve, where they bring the market value of the debt closer to its face value, and in doing so they reach the value and the market variation of the assets by means of a ponderation of the company's equity variation.

2.2.The Reduced Models of Altman (1968), Ohlson (1980) e Zmijewski (1984)

Reduced form models were an evolution in relation to structural models and latent variables also started to be used as default predictors (DUFFIE & LANDO, 2001). The first modern univariate model of default prediction determined that the cash flow over the total of debts can be considered the most important explicative variable for this prediction (BEAVER ET AL., 2005; HILLEGEIST ET AL., 2004).

In this vein, Altman (1968) proposed a multivariate model that could explain corporate default by means of a discriminant analysis method (LANDO & NIELSEN, 2010). Altman (1968) developed a model he coined Z-score, which is based on variables with the greatest significance in a model of multivariate discriminant analysis.

After that, Ohlson (1980) adopted the logistic analysis in place of the linear discriminant analysis in order to improve the model. The model was called O-score model (LANDO & NIELSEN, 2010; JAYASEKERA, 2018).

3. Development and infrastructure

Infrastructure can be understood as the set of structures and networks that connect cities and metropolitan areas to social and economic activities. Some examples of infrastructure are streets, roads, basic sanitation, telecommunications, etc. (GRIMSEY & LEWIS, 2002).

Any basic project of economic growth in a country needs to take into account alternatives for strategic investments in infrastructure. These can be designed with the intention of maintaining what has already been built or with new investments in mind. Thus, it is paramount that investments in infrastructure are designed in a way that contemplates strategic information, such as priorities, role of the private sector, sources of financing, quality requirements, among others (RUIZ-NUÑEZ & WEI, 2015).

3.1.Infrastructure funding

Until the nineties, governments were the leading investors in infrastructure in the world. However, the lack of public capital available for funding constructions, especially in developing countries, drove the usage of private sector investments in these projects, contributing to the reduction of risks associated with management inefficiency (KUMARI & SHARMA, 2017; GRIMSEY & LEWIS, 2002).

From the year 2000 onwards, limitations caused by stricter capital regulations, in addition to changes in the macroeconomic environment and the inefficiency of public management, have encouraged a greater participation of institutional investors in these projects (Della Croce & Gatti, 2014).

In this sense, Sharma and Vohra (2008) highlight the importance of private investment in infrastructure, because it not only provides the large amount of capital needed in these projects, but also provides more effective operational techniques, improves the capacity to meet deadlines, and offers more innovative technologies.

The sectorial influence on the calculation of default risk Investigations of default have always taken into account an individual analysis of the companies, measuring the impact of specific variables in the probability of bankruptcy, while ignoring the factors present in the interrelation between these companies (HERTZEL & OFFICER, 2012; PLATT & PLATT, 1991).

Koopman and Schwaab (2012) identify the influence of systematic risks on the variation of the default risk. For the authors, systematic factors correspond to about 35% of the variation in the rate of insolvency of American companies, being 25% derived from sectorial weaknesses. The accumulation of systematic risks is also evident in previous periods and during financial crises.

Chen and Wu (2014) emphasize that conventional default prediction models underestimate the influence of non-observable factors on the insolvency correlations of companies. Fragilities that are observable in macroeconomic and sectorial factors have a strong influence on the intensity of insolvency.

Finally, the inclusion of sectorial effects in the calculation of companies' default risk has increasingly highlighted the importance of this mechanism for improving models of bankruptcy prediction. On top of that, the clear existence of common default risk factors related to the industrial sector can be a way to prevent insolvency rates from being wrongly estimated. In addition to contributing to the emergence of more efficient default prediction tools (CHEN & WU, 2014; CHAVA & JARROW, 2004).

4. Methodology

According to Jayasekera (2018), some methodological paths contributed to the prediction exercise of a company, among them, mathematical models, models based on neural networks, market-based models, and statistical models such as logit/probit regressions , and models of discriminant determinations (JAYASEKERA, 2018; SAUNDERS & ALLEN, 2002).

Therefore, this work uses the logistic regression model (logit) used in situations where the dependent variable is binary categorical, and the other variables can be both numerical and categorical.

4.1.Logit Model

The linear default probability models use previous data to explain past loan payment data, and then, estimate default probabilities in future loans. However, when evaluating the occurrence or non-occurrence of a given event, the estimated probabilities of default may be outside the range 0 and 1, bringing information that is not relevant to the analysis (SAUNDERS & THOMAS, 1997; ALTMAN & SAUNDERS, 1997).

To overcome this problem, the logit and probit models allow the dependent variable to assume a qualitative binary choice format, which indicates the occurrence or non-occurrence of a particular event, such as the default of a company (WOOLDRIDGE, 2010).

In a logistic regression, the focus is based on the logistic transformation of π (x), given by:

$$(x) = ln\,[\frac{\pi(x)}{1 + (x)}] = \beta_0 + \beta_1 x$$

The method used to estimate parameters for logistic regression models is the Maximum Likelihood method, which has the objective of producing values for the parameters capable of maximizing the probability of obtaining the set of data that are observed.

4.2.Model and Variables

In the making of this essay, we used data from balance sheets, income statements of the financial year, and the price of American companies' stocks listed in the stock market and belonging to specific subgroups of infrastructure, based on the GICS (Global Industry Classification Standard).

Thus, the accounting variables belonging to the models of Altman (1968), Zmijewski (1984) and a variable pointed out by Lennox (1999) were considered the most relevant for these types of model. Hence, they were included in the model of our study.

Table 1: Variables

Name	Source	Variable
Size	Altman (1968)	SZ
Working Capital /Total Assets	Altman (1968)	WK
Retained Earnings/ Total Assets	Altman (1968)	RE
EBIT / Total Assets	Altman (1968)	EB
MKT Value of Equity / Total Liabilities	Altman (1968)	EQ
Sales / Total Assets	Altman (1968)	SL
Net Income / Total Assets	Zmijewski (1984)	NI
Total Liabilities / Total Assets	Zmijewski (1984)	LA
Current Assets / Current Liabilities	Zmijewski (1984)	LI
Cash Flow /Total Liabilities	Beaver (1967)	CF
Distance to Default	Duffie et al. (2007)	DD

Source: Prepared by the author

In addition to these accounting variables, the model included the size of the firm (SZ) (SHUMWAY, 2001; OHLSON, 1980, LENNOX, 1999), given by the natural logarithm of its assets.

The inclusion of the explanatory variable Distance to Default (DD) was justified by the works of Duffie et al. (2007) and Kealhofer (2003) who found significant dependence on the probabilities of future bankruptcy on this variable.

The variable Distance to Default was calculated based on the proposal of Bharath and Shumway (2008) that from a Naïve model reached a higher result without the need for iterative operations between the variables of the volatility of the prices of the assets and the market value of the company. In this work, the equity volatility component ▯ was obtained by the quarterly standard deviation of the profitability of daily stock prices. The risk-free asset rate used in the Distance to Default variable was the quarterly average of the previous quarter's (1-Year Treasury Constant Maturity Rate), as suggested by Bharath and Shumway (2008).

The variable Market Value of Equity also was based on the work of Bharath and Shumway (2008), where it is expressed by the value of the asset price multiplied by the number of shares traded. In the case of this study, we used the quarterly average of stock prices of companies multiplied by the number of shares traded.

$$\eta = \alpha + \beta_0 SZ + \sum_{j=1}^{5} \beta_j \, Dummy_i + \beta_6 WK + \beta_7 RE + \beta_8 EB + \beta_9 EQ + \beta_{10} SL + \beta_{11} NI + \beta_{12} LA + \beta_{13} LI + \beta_{14} CF + \beta_{15} DD + \varepsilon_{it}$$

To identify specific characteristics among the sectors, five Dummy variables were included, representing each of the six subgroups selected in the sample.

4.3. Database

The database used for the analysis was extracted from Bloomberg and was composed of accounting information of the Balance Sheet and Profit and Loss Account of 1520 companies and 24 variables, totaling a universe of 79,040 observations from the period of 2006 to 2018, quarterly.

Initial sample information refers to North American companies belonging to six specific segments of the infrastructure sector, based on the Global Industry Standardization Standard (GICS), namely: Water and Sanitation; Electricity; Renewable Electric Energy (ENR), Logistics and Transportation (LOG); Oil and Gas (PET); besides Telecommunications.

Gas utilities were excluded from the database, companies in which activities were diverse within these sectors. The justification for this exclusion was based on the low representativeness of these activities in sectors called infrastructure, as well as companies that had mixed information about their activity. The period analysed was from the first quarter of 2006 to the fourth quarter of 2018, with periodicity of 48 quarters.

The lack of temporal constancy in the data, with many information losses throughout the quarters, compromised the longitudinal analysis of the sample. Therefore, it was necessary to make some adjustments to the database, such as summarizing the information over time and applying the average of each of the variables of interest per company.

5. Results and Discussion

The data presented 404 companies with missing values in at least one of the variables. Similarly, the Water and Sanitation and Electric Energy sectors did not present any bankruptcy event throughout the period, being removed from the observations. In sum, the final analysis had a set of 1,066 companies.

Extreme values were identified in some variables, and to avoid discarding sampled data, as well as the incidence of outliers, the values of the variables were truncated at the ninety-ninth and first percentiles, as suggested by Shumway (2001).

Table 2: Sample Analysis

Variables		N	%
Sector	RNE	50	4.69%
	LOG	98	9.19%
	PET	842	78.99%
	TEL	76	7.13%
Default	Yes	100	9.38%
	No	966	90.62%

Source: Prepared by the author

It should be noted that the Water and Sanitation, besides the Energy sectors had 27 companies and 65 companies, respectively. In addition, the intention to separate Energy companies in two distinct sectors (Energy and Renewable Energy) was to improve the detail of the analysis.

However, within these sectors there was no classification capable of allowing greater detail regarding the generation, transmission or distribution of energy, nor with respect to its source.

Table 3: Descriptive Variables

Variables	N	Average	S.D.	Min.	1ºQ	2ºQ	3ºQ	Max.
SZ	1,066	1.86	1.55	-1.81	0.66	2,.2	3.13	4.68
WK	1,066	-19.03	111.2	-934.39	-0.33	-0.01	0.11	0.58
RE	1,066	-163.92	910.56	-7571.15	-5.19	-0.46	0	0.66
EB	1,066	-1.96	10.4	-83.31	-0.12	-0.01	0.01	0.09
SL	1,066	0.2	0.4	0	0.03	0.08	0.19	2.93
NI	1,066	-2.53	13.54	-109.04	-0.15	-0.02	0.01	0.39
LA	1,066	20.79	113.75	0.07	0.4	0.59	1.02	938.85
LI	1,066	3.83	8.16	0.04	0.85	1.51	3.01	57.29
CF	1,066	-1.69	8.53	-68.1	-0.28	0.05	0.21	2.26
DD	1,066	7,860.62	60,177.4	6.37	85.68	357.71	915.83	567,420.4
EQ	1,066	10,662.05	76,237.76	0.12	1.82	5.91	55.06	691,468.2

Source: Prepared by the author

The table 4 shows how default is distributed across sectors. It was verified that the Petroleum sector presented the highest percentage of bankruptcy 10.1%, while the Renewable Energy sector the lowest 4%, however, there was no significant difference (p-value = 0,460) between the percentages of bankruptcy by Fisher's exact test.

Table4: Descriptive Variables

Sectors	Default				p-value
	No		Yes		
	N	%	N	%	
PET	757	89,90%	85	10,10%	0,46
ENR	48	96,00%	2	4,00%	
LOG	90	91,80%	8	8,20%	
TEL	71	93,40%	5	6,60%	

Source: Prepared by the author

In the comparative analysis between the companies that failed and did not fail, the highlight is the variables: SZ, EB, LA, and EQ.

In the table 4 it is possible to verify how the quantitative variables are presented with respect to bankruptcy, as well as the p-value of the non-parametric Mann-Whitney test.

It is verified that at least 50% of the failed companies presented the variable SZ with values less than or equal to 2.63, while among the companies that did not fail, at least 50% presented this variable with numbers less than or equal to 1.93.

In addition, the variable EB, it was verified that at least 50% of the companies that failed presented values less than or equal to -0.02, while among companies that did not fail 50% presented this variable with numbers less than or equal to -0.01.

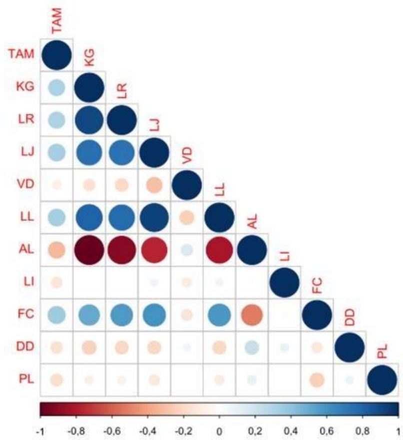
The variable LA also showed significance when the samples are compared. At least 50% of the companies that failed presented the variable LA with values less than or equal to 0.73, while in the companies that did not fail, at least 50% presented the variable LA with values less than or equal to 0.58.

Finally, at least 50% of the companies that failed have had variable EQ less than or equal to 2.87, while in the companies that did not fail, at least 50% showed this variable with numbers less than or equal to 6.43.

The other predictors did not present significant difference between the companies that failed and did not fail.

The correlation matrix presented in the figure 1 highlights the existence of multicollinearity among several variables. The variables with high positive correlation present dark blue color at their intersection, as for example, WK and RE, besides NI and EB. The variables with high negative correlation are dark red, for example, LA and WK.

Figure 1: Matrix Correlation



Source: Prepared by the author

The model initially proposed, expressed in the table 5 underscores the evidence that several predictor variables were not significant to explain bankruptcy (p-value $\geq$ 0.05).

In addition, the VIF (Variance Inflation Factor) result greater than 10 underscored the multicollinearity problem among the model variables.

Regarding the odds ratio (OR) results, it was verified that the variable SZ was significant, which means that the increase in one unit of this variable, while maintaining the other constant variables, increases the chance of failure in 41.3%.

The coefficient of the variable DD was multiplied by 100 to facilitate interpretation. The results indicate that the increase in 100 units, also kept constant, decreases the chance of bankruptcy by 6.6%.

Table5: Descriptive Variables

Variable	Inicial Model			
	β	IC	OR	Valor-p
(Intercept)	-2.405	[-2.92; -1.92]	-	0
SZ	0.346	[0.16; 0.54]	1.413	0
Setor = PET	-	-	-	-
Setor = ENR	-1.005	[-2.85; 0.23]	0.366	0.178
Setor = LOG	-0.429	[-1.28; 0.3]	0.651	0.281
Setor = TEL	-0.559	[-1.66; 0.32]	0.572	0.259
WK	0.006	[-0.01; 0.02]	1.006	0.4
RE	0	[0.00; 0.00]	1	0.547
EB	-0.066	[-0.19; 0.00]	0.936	0.109
SL	0.188	[-0.44; 0.72]	1.207	0.52
NI	0.043	[-0.01; 0.15]	1.043	0.244
LA	0.005	[-0.01; 0.02]	1.005	0.513
LI	-0.047	[-0.12; 0.00]	0.954	0.111
CF	0.01	[-0.04; 0.06]	1.01	0.686
DD/100	-0.069	[-0.12; -0.02]	0.934	0.007
EQ	0	[0.00; 0.00]	1	0.445
Hosmer-Lemeshow			0.364	
Maior VIF			48.358	
AUC			0.695	

Source: Prepared by the author

From the results obtained, the Backward method was applied to remove the variables with multicollinearity problem. Only the variables SZ, EB and DD remained as significant.

The p-value of the Hosmer-Lemeshow Test presented value greater than 0.05 in both cases, demonstrating that both models are adequate.

Remaining fixed all the other variables, it was verified that the increase in one unit of the variable SZ, the chance of default also increases in 46.8% in the adjusted model.

In addition, after adjusting the model, the EB variable became significant, indicating that its increase in one unit, while remaining the other variables fixed, the chance of bankruptcy increases by 2.3%.

The adjusted model also showed that the increase of 100 units of variable DD, with the other variables remaining fixed, the chance of bankruptcy decreases 6.5%.

Table 6: Descriptive Variables

Variable	Final Model			
	β	IC	OR	Valor-p
(Intercept)	-2.721	[-3.16; -2.32]	-	0
SZ	0.384	[0.20; 0.57]	1.468	0
Sector = PET				
Sector = ENR				
Sector = LOG				
Sector = TEL				
WK				
RE				
EB				
	-0.024	[-0.04; 0.00]	0.977	0.012
SL				
NI				
LA				
LI				
CF				
DD/100				
	-0.067	[-0.12; -0.02]	0.935	0.008
EQ				
Hosmer-Lemeshow	0.361			
Maior VIF	1.729			
AUC	0.67			

Source: Prepared by the author

Finally, after the identification of the second model, it was verified the differences between PET and non-PET sectors. For this, the final model was adjusted for each of the sectors, comparing the point and interval estimates of the regression coefficients.

Table 7: Oil x Non-Oil Companies

Variable	Oil companies				Non-Oil Companies			
	β	IC	OR	p-value	β	IC	OR	Valor-p
(Intercept)	-2.729	[-3.22; -2.29]	-	0	-2,713	[-3.87; -1.79]	-	0
SZ	0.403	[0.20; 0.62]	1.497	0	0,445	[0.02; 0.89]	1.561	0.043
EB	-0.022	[-0.04; 0.00]	0.978	0.048	-0,028	[-0.06; 0.01]	0.973	0.111
DD/100	-0.054	[-0.11; -0.01]	0.948	0.038	-0,203	[-0.42; -0.02]	0.816	0.036
Hosmer-Lemeshow			0.299				0.247	
Bigger VIF			1.688				1.806	
AUC			0.667				0.714	

Source: Prepared by the author

6. Conclusion

This study aimed to identify the existence of sectorial differences in the prediction of default risk of American infrastructure companies based on logistic regression with a binary dependent variable.

In this sense, we verified that the sectorial separation for the estimation of default probability might contribute to the identification of specific causes of this probability that are linked to sectorial idiosyncrasies. The variable Distance to Default showed good applicability for sectorial prediction.

The difference it shows among the analyzed sectors demonstrates that it is able to explain each sector analysed in a specific manner. Despite the limitations of this study, especially in terms of the small number of default events per sector, it can contribute to the creation of new research agendas that take into account sectorial specificities in calculating the default risk.

Another way to explore this topic is the usage of the DD variable as a dependent variable, which considers a given minimum threshold before its default point as the bankruptcy region, and the other positive values as non-bankruptcy region.

Future studies could include the existence of more significant variables, since such adjustment could make possible the increase of interest events. Finally, investigating the default probability of companies from different infrastructure sectors can contribute to the creation of specific mechanisms of corporate risk analysis in a more detailed manner, avoiding that poor performance in certain indicators penalizes companies in sectors that are not sensitive to these indicators.

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