The Value of Corporate Reputation in the Bankruptcy Risk

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ABSTRACT

In recent years CR has been considered by experts as one of the most important intangibles assets for sustainability of the companies. Existing literature designates several positive aspects of a good CR, highlighting that companies with better CR have superior financial performance. In this sense, some recent researches, conclude that a good CR decreases the risk for companies, focusing on the relation between CR and the variability of returns over a period of time. Nevertheless, as far as we know, there are no studies analyzing the relation between CR and bankruptcy risk, what it is an important component of the unsystematic risk, and an aim element in Strategic Management. This is why the aim of this paper is to show, based on empirical evidence, that a good CR helps companies to minimize bankruptcy risk. To answer this research question, a sample of Spanish companies in the Share Market between 2008 and 2012 has been used, and an algorithm based on Generalized Regression Neural Networks (GRNN). Results shown that a good CR is positively related to a lower bankruptcy risk, and those models built with GRNN are more robust than those others based on traditional statistical techniques, like Multi-Linear Regression models.

Keywords: Corporate Reputation, Bankruptcy Risk, Generalized Regression Neural Networks, Unsystematic Risk, Financial Performance.

I. INTRODUCTION

Many finding of the previous literature defines Corporate Reputation (CR) as an intangible asset that adds on value to the company [9] [10] [15]. In this context, several investigations detect a positive relation between CR and superior financial performance [8] [4] [6]. Among the advantages that a good RC has on the financial performance, some investigations conclude that a good CR reduces the risk in a company. Nevertheless, these researches have they all got general conclusions about the risk, specifically, about the variability of the returns over a period of time.

Nevertheless, previous literature has not studied the link between CR and bankruptcy risk, even though this is fundamental in Strategic Management. So, it has not been analyzed if good CR helps companies to reduce bankruptcy risk, and thus, the consideration of the implications of CR may be incomplete without examining its effects.

This paper fills the gap in previous literature, while examines the relationship between companies bankruptcy risk and their own CR. To aim this goal, empirical evidence is provided, showing that those companies that historically have a good CR also have lower bankruptcy risk. To aim this goal, a sample of Spanish companies in the Stock Market has been selected for the period 2009-2012. This sample includes those companies with highest levels of CR, according to the ranking MERCO, published by Villafañe & Asociados Consulting [12]. Algorithms based on neural networks have been applied to the sample, to classify them according to their own bankruptcy risk. Finally, applying regression models, we have checked and quantify how the value assigned to a bankruptcy risk is explained by the level of CR. For so, Multiple lineal regression (MLR) has been used to identify the signs of the studied variables, Generalized Regression Neural Networks (GRNN), to determine the impact of those variables in the values of bankruptcy risk. To achieve these goals, we also study different results obtained applying GRNN, comparing with traditional regression techniques (MLR). Both techniques are reciprocally informative and promise to light about the importance of CR to explain bankruptcy risk in companies.

Consequently, this paper aims to provide both theoretical and practical knowledge, and will be enhanced by the chosen methodology. As far as we know, GRNN has not been used to research the effects of CR in risk firms, and the use of neural network are expected to be better than traditional multiple regressions, because they adjust nonlinearities among the studied variables [14]. The structure of this paper is as follow: Section two provides the methology; results are shown in section 3. And finally, main conclusions are given.

II. METHODOLOGY

A. Conceptual framework

To analyze the CR effect on bankruptcy risk, a conceptual framework is necessary. Such a framework encompasses the main concepts relate to the research. In this case, CR is an important issue of Strategic Management that reduces bankruptcy risk and the unsystematic risk (Figure 1).

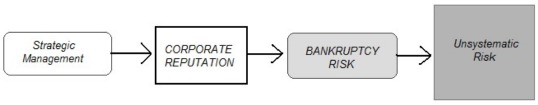

Figure 1.Corporate Reputation and Bankruptcy Risk Framework

B. Hypothesis

In this paper, we are considering some empirical studies which demonstrate that bankruptcy risk is an unsystematic risk [13] [1] [6], what provides theoretical arguments enough to develop an empirical analysis about the effects that CR can provoke to reduce bankruptcy risk in companies. To aim this goal, we have also considered that CR can affect the stakeholder´s behavior, provoking a decrease in the unsystematic risk for some reasons. Firstly, the unsystematic risk depends on the specific characteristic or behavior of every single company. Secondly, because CR is an asset that allows companies to establish higher prices of their goods or services [11] [10]. And thirdly, because a good CR attracts employees [10], permits a better access to financial sources [7] and stimulates the retention of customers [8].

This link between the advantages of a good CR and the companies´ unsystematic risk is the base of the firs hypothesis presented in this work.

Hypothesis 1 (H1): *Companies with good CR have lower bankruptcy risk.*

Most of the previous research focused on the relationship between CR and firm risk has been using statistical method. Studies in other fields of financial research suggest that statistical method cannot capture nonlinear relationships between the analyzed variables, and more robust results can be achieved with the use of neural networks (NN) as a method of analysis, specifically Generalized Regression Neural Networks [14]. Another advantage of GRNN is that, being a type of NN, is able to find out the sensitivity of the variables considered in the analysis, allowing comparison with the statistical significance provided, i.e. by MLR. To our knowledge, no NN techniques have been used in research about CR and risk firm, and this is where we find another research gap that leads us to state the hypothesis 2 of our paper:

Hypothesis 2 (H2): Generalized Regression Neural Network (GRNN) achieves more robust results than conventional MLR in analyzing the relationship between CR and risk firms.

C. Methods

This paper shows a model of analysis base on two phases to study the relation between CR and bankruptcy risk. In the first one, Multi-Linear Regression (MLR) is applied to test our hypothesis related to the dependent variable, bankruptcy risk, as a lineal combination of CR and other independent control variables. During the second phase, Generalized Regression Neural Networks (GRNN) is used to measure, minimizing the error, the impact of the variables in the model and the sensitivity of the results when changing the independent variables. Thereby, an impact value of the dependent variable, expressed in percentages and whose sum is 100% is assigned to ever independent variable. Figure 2 shows a graphic scheme of the model, expressed in two stages.

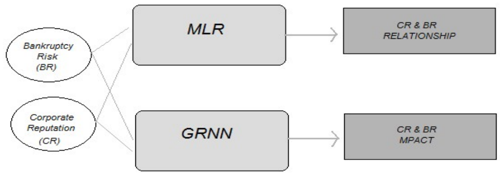

Figure 2. Two stages analysis model.

D. Regression performance indicators

The root mean square error (RMSE), mean absolute error (MAE), and R2 between the modeled output and measures of the training and testing data set are the most common indicators to provide a numerical description of the goodness of the model estimates. They are calculated and defined according to following equations:

$$RMSE = \left(\frac{1}{N}\sum_{i=1}^{N}[A_i - T_i]^2\right)^{1/2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|T_i - A_i\right|$$

$$R^2 = \frac{\sum_{i01}^{N}[A_i - \bar{T}]^2}{\sum_{i=1}^{N}[T_i - \bar{T})^2}$$

Where N is the *number of observations*; T_i is obser*ved* value; A_i is the predicted value, *and* $\bar{T}$ the average value of the explained variable on N observations.

RMSE and MAE indicate the residual errors, which give a global idea of the difference between the observed and predicted values. R^2 is the proportion of variability (sum of squares) in a data set that is accounted for by a model. When the RMSE and MAE are at the minimum and R^2 is high ($R^2 > 0.80$), a model can be judged as very good.

E. Data and Variables

1. Data

Sample data for this study has been taken from companies in the Spanish Stock Market for a period of time between 2009 and 2012. Financial companies have not been included in this study, being insurance companies or banks due to the specific characteristics of their own sector, their economic activity and their own impact in the financial information annually publicized. In addition, some other companies were excluded from this study due to the lack of total information, mainly because they stopped trading in the Stock market for some of the years in the analyzed period of time. So, for the period 2009 to 2012, the sample size is 553; 132 out of them have been selected for 2012; 136 for 2011; 131 for 2010, and finally, 133 companies for 2009.

Besides, and trying to valid the models and test their predictive capability, training data and validation data are used. From a random selection, 70% of the data has been reserved for training and 30% for testing.

Meanwhile, financial information about the data simple, have been taken from the data base S&P COMPUSTAT Global and Bureau Van Dick SABI. These databases provide information on key financial statements of companies (balance sheet, income statement and notes) for each year of study, required under international accounting standards. Specific data about sectorial sales have been analyzed from Spanish National Statistic Institute. Details of the firms in the sample appear in table 1.

Table 1. Industry distribution of the sample.

Activity	%
Mining and quarrying	1.884
Manufacturing	27.238
Electricity, gas, steam and air conditioning supply	4.424
Water supply, sewage, waste management and remediation activities	2.654
Construction	22.699
Wholesale and retail trade; repair of motor vehicles and motorcycles	8.194
Transportation and warehousing	3.539
Accommodation and food services	1.769
Information and communication	8.194
Real estate	8.079
Professional, scientific, and technical services	6.309
Administrative and support services	1.184
Health care and social assistance	2.342
Other services	1.491
TOTAL	100.000

2. Dependent variable

To classify the companies in the sample, according to bankruptcy risk, a set of six variables proposed by Callejón et al. [5] for European companies (table 2) has been used. This variable set has been obtained by a Multilayer Perceptron of NN model, and classifies 92.11%, sensitivity of 94.69% and specificity of 89.66%. Figure 3 shows results applying this variable set.

Table 2. Financial variables set for sample bankruptcy risk classification.

Variable	Equation	Pred. Sign (+/-)
V_1	EBIT / Current liabilities	-
V_2	Equity / Non-current liabilities	-
V_3	(Net income + Depreciation amortization and write-offs) / Current financial liabilities	-
V_4	EBIT / Total assets	-
V_5	Net profit / Total assets	-
V_6	log Total Assets	-

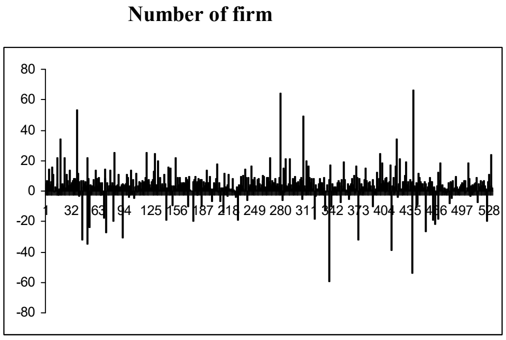

Figure 3. Bankruptcy risk value of the sample.

3. CR and Control Variables

To obtain CR values for the companies in the sample, the *Monitor Empresarial de Reputación Corporativa* (MERCO) has been used. This report reflects the views of different stakeholders, seeking to get a global punctuation of CR for a set of companies trading in the Spanish Stock Market. Several reasons justify the election of this ranking of CR. On the one hand, because there is plenty of availability and trajectory of data in MERCO (since 2001), and this originates a high knowledge and criteria for the stakeholders.

In this sense, if beside the economic variables, there is another type of influence of CR on the investors, we should choose a measure whose results are available for public in general with an easy access. MERCO publishes all the information in its website (www.merco.info), and diffusions through press and media in Spain. On the other hand, we can find some kind of reasons about the process of evaluating reputation. The process of building MERCO consists of four sequential reviews [12] that include questionnaires to managers to elaborate a provisional ranking, reviews from expert groups, consumers and workers, reviews in situ in the assessed companies. This process of review is different from the one used, for instance, in Fortune Review, which bases its scores in reviews of managers and financial analysts about some attributes of the company. In our own opinion, due to the way of generating the scores in MERCO, it could be not so influenced by financial variables as its American counterpart, so results obtained with this study can offer an added value, comparing with the data of other CR reports. Values obtained in this paper about CR for the companies in the sample, are shown in figure 4.

In addition, as we mentioned above, our analysis is focused on the influence of CR on risk, so it needs to be acknowledged that there is also a reverse influence. Economic agents tend to be risk-averse, and therefore if two firms record similar levels of financial performance, the one that appears to offer less risk should gain a better CR [9]. This suggests that the relationship between CR and risk can be endogenous, so the study needs an appropriate method to control for endogeneity.

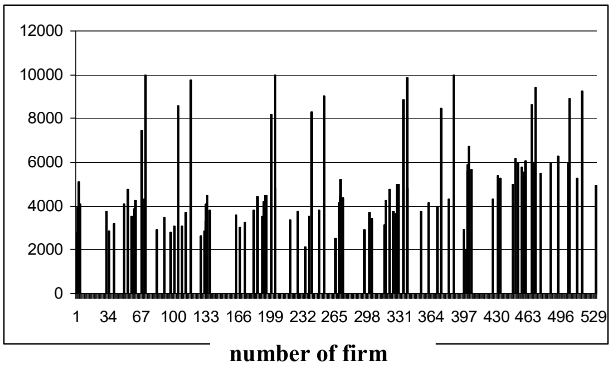

Figure 4. CR value of the sample.

This is why, trying to temper the influence of CR in the company risk, this study proposes five control variables that have been very used in previous studies. The first control variable is the size of the company, which is measured by the natural algorithm of total asset-. Secondly, we have focused on the industry diversification.

As a measure of diversification, we have used the market share, measured as the ratio of the total sales in a company to the total sales in their own sector for every single year of the studied period of time. Moreover, profitability has been included as the third control variable, defined as the ratio EBIT to total assets (ROA). The leverage of the companies has also been considered, using the ratio Total liabilities to total assets, as Beaver [2], had already suggested, because a high leverage in a company, can provoke a high risk.

Finally, and trying to control the effect of macroeconomic variables have on the companies risk, a dummy variable has been included, referred to the year of the data used.

III. RESULTS

A. Exploratory analysis

In this study, explanatory analysis seeks to examine data to use before applying regression techniques, so that possible links between the data can be detected previously [16]. This explanatory analysis consists of a descriptive analysis of the variables to know the classical statistical parameters and a test to determine if CR is a differential factor in some of the analyzed aspects. Results of this analysis are shown in table 3.

Noticing the mean values obtained for every single variable, and differentiating companies with higher CR (CR value>0) from those others with lower CR (CR value=0), differences are noticed. Companies with higher CR have a mean bankruptcy risk (BKR) much lower (3.377 versus 7.337). So it, profitability (ROA) for companies with higher CR is, meanly, higher than in companies with lower CR levels (9.039% versus 5.317%). Significant differences can also be found in measures of concentration (MQT) and in the size of the company (LTA), where higher mean values correspond to those companies with higher CR. Probably due to their size, companies with higher CR also have higher market share. Same conclusions are obtained according to standard deviation and their maximum and minimum values. The sample does not present significant differences from the mean values of level of debts (LEV), what is located at about 55% for all the companies.

Test t for two samples is useful to check if two samples come from the same distribution. The null hypothesis in this case is that there are no significant differences between the distributions of both samples. According to results shown in table 3, null hypothesis of identity of distributions is rejected in all cases, except for the variable LEV. These results confirm that there are significant differences among companies with higher CR and companies with lower CR, both in bankruptcy risk (BKR) and in profitability (ROA), share market (MQT) and size (LTA).

Tabla 3. Descriptive statistic.

Variables	Mean		St. Desv.		Max.		Min.		t stat.	Sign.
	SCR	ICR	SCR	ICR	SCR	ICR	SCR	ICR		
BKR	3.377	7.337	1.085	4.555	66.028	22.081	-59.763	-3.160	3.476	0.000***
ROA (%)	9.039	5.317	6.850	1.344	30.877	99.268	-3.780	-81.286	-2.502	0.010***
MQT	0.167	0.032	0.546	0.089	3.145	0.993	0.000	0.000	-4.901	0.000***
LEV(%)	55.636	55.724	2.443	3.474	97.474	338.503	0.419	0.051	0.024	0.981
LTA	6.753	5.457	0.572	0.651	7.969	6.840	5.649	3.541	-18.467	0.000***

SCR: Superior CR firms; ICR: Inferior CR firms; ***: Sig. at 0.01 nivel

B. Confirmatory analysis

Testing the hypothesis proposed in this study seeks to check if companies with higher CR have some kind of advantage in terms of lower bankruptcy risk, from those others trading in the stock market with lower CR. Table 3 shows results after applying both proposed methodologies, MR and GRNN. According to MR, the following variables turn to be significant: CR (REP), profitability (ROA), level of debts (LEV) and size (LTA) with a confidence level of 99%. Conversely, the other control variables related to share market (MQT) and the period of time (YEAR) were not significant. In global terms, the explanatory capability of the model is 82.7%.

Results applying GRNN are also shown in table 4. The most relevant information obtained from GRNN is the impact of every single variable on the model. As can be seen, the profitability variable (ROA) is highly the most relevant variable in the model because it represents 60.2% of the total impact of all the variables in the explained factor. This seems to be reasonable because one of the main factors to determine solvency is profitability [3].

Table 4. Results of regressions (dependent variable: Bankruptcy risk)

	MLR		**GRNN**	
	Training	Testing	Training	Testing
M. Analysis	Coefficient		Variable %	Impact
REP	-0.001**	-	10.137	-
ROA	-0.671***	-	60.234	-
MQT	-0.061	-	0.218	-
LEV	0.067***	-	10.320	-
LTA	-2.096***	-	18.910	-
YEAR	-0.244	-	0.181	-
Diagnostic criteria				
F-ratio	411.524***	-		
R^2	0.827	-	0,881	0,858
R^2 Adjusted	0.825	-		
Durbin-Watson	1.132	-	-	-
Std. desv. abs. Errors	-	-	2.818	3.182
RMSE	97.150	114.456	6.537	7.580
MAE	4.212	4.961	2.617	2.997

RMSE: Root Mean Square Error; MAE Mean Absolute Error; ***: Sig. at 0.01; **Sig. at 0.05

The variable CR (REP), aim of our study, represents 10.1% of the total impact, being located on third place. This level allows us to confirm the hypothesis of this study, that is, the value of CR affects negatively in bankruptcy risk for companies trading in the Spanish Stock Market, because those with higher levels of CR are the ones with lower bankruptcy risk. Also, the explanatory capability of the model improves using GRNN, 88.1% adjustment.

There is a need to highlight the Root Mean Squared Error RMSE and the Mean Absolute Error (MAE) of the training and testing samples with MLR are similar, what suggests stability between the training and the training data. But it can be seen that with GRNN, RMSE and MAE they are much lower than the ones obtained with MLR. These results could establish a first sign to confirm that GRNNs get better results in the analysis of the effects that CR produces in the financial performance of the companies.

IV. CONCLUSIONS

The goal of this work led us to investigate the relation between CR and bankruptcy risk. With that aim, a model was proposed in two stages. In the first one, MLR was applied to test our hypothesis related to the bankruptcy risk variable as a combination of CR and other independent control variables. In the second one, GRNN was used to measure the impact of the variables in the model and the sensitivity of the results, getting for every independent variable an impact value over the dependent variable.

Results confirm that hypothesis H1 of this paper: in the Spanish Stock Market, companies with higher levels of CR show lower bankruptcy risk. Likewise, the second hypothesis H2 has also been proved, GRNN achieves better results that MLR.

Analyzing the impact of the variables offered by GRNN, it could be proved that profitability variable (ROA) is the most sensitive in the model, because it represents 60.2% of the total impact of all the variables. Sensitivity to the size of the company (LTA) is the second one, representing 18.9%, level of debts (LEV) 10.3% and CR (REP) 10.0%. These results confirm that CR is an asset that reduces the bankruptcy risk, and so, the unsystematic risk of the companies. As we said above, CR is an asset that allows the company to establish higher prices of their goods or services [7] [10], attracts better employees [10], better access to financing [7] and stimulates customers retention [8]. All these advantages provoke better financial performance that can be translated to lower bankruptcy risk. This is why CR becomes and intangible advantage for companies in the trading stock market, helping them to get a real performance/profit. The company should understand that nowadays attention is focused on risk firm in general, and on bankruptcy risk in particular, and showing a good CR can help to get and develop a better financial performance.

Other important conclusions are that solvency is not conditioned by the market share (MQT). Secondly, the insensitivity of the year of study variable (YEAR) shows that the relation between CR and risk of insolvency maintain the same level during the hole period of time. Thirdly, GRNN provides more efficient models than traditional lineal techniques in the modeling of complex functions, allowing the decision maker to focus the attention on those variables where more needed.

Results can complement those others from previous literature about the effect of CR on risk firm, providing empirical evidence on an additional dimension of unsystematic risk, and also for using a measure of risk based on accounting data, because all previous studies have used measures based on market data.

Conclusions allow us to point interesting implications and futures lines of research. The managers should focus on improving CR seeking to reduce the bankruptcy risk. This way, a lower bankruptcy risk can lead a better financial performance that implies lower costs of finance for the company. Moreover, they can help those stakeholders that cannot eliminate the unsystematic risk through diversification, when knowing the effects of CR on bankruptcy risk.

Future research could also verify if the effect of CR on bankruptcy risk is verified for companies of the financial sector. And also, it could check if the use of GRNN allows to better measurements for the impact of CR in other dimension of the companies risk, and in other countries.

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