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Corporate reputation and market value: Evidence with generalized regression neural networks

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ABSTRACT

Corporate Reputation (CR) is a critical intangible asset for a firm. As a representation of its past actions and results, CR encompasses a number of features which conform the status of a firm regarding its competitors. This helps corporations not only to gain competitive advantages, but also to survive in times of economic turbulences. Despite its apparent relevance, it remains inconclusive and controversial whether CR affects firms' financial performance, a key point for current and potential investors. Our aim is to provide new evidence that could shed some light in determining the role of CR in stock market valuation. Since most of the previous research focus on this relationship using Multiple Regression (MR), it has been suggested that more conclusive results could be achieved using neural networks, but it has not been proven yet to the best of our knowledge. Using a sample of Spanish listed companies in the period 2008–2011, MR and a neural network technique, Generalized Regression Neural Network (GRNN), have been used. At an empirical level, results show that the mere presence of a firm in a reputation ranking has a positive impact on its market value, and that also a higher CR have a favorable influence on financial performance. At a methodological level, results of GRNN have proven to be more robust than those obtained using traditional MR.

1. Introduction

Corporate Reputation (CR) is undoubtedly an intangible asset which provides a competitive advantage for firms (Rose & Thomsen, 2004; Hall, 1992). However, controversy arises when the discussion
Q2 turns into how financial markets value that reputation. Some studies conclude that favorable reputations contribute to increase the market value of firms (Black, Carnes, & Richardson, 2000; Stuebs & Sun, 2011; Wang & Smith, 2008), while others reject this assertion (Brammer, Brooks, & Pavelin, 2004, 2009). This contradictory set of results motivates the search for new methodological perspectives, different from those traditionally used (as multiple regressions, MR), with the purpose of shedding some light on the controversy. Our study uses Generalized Regression Neural Networks (GRNN) to measure the relationship between CR and the firms' market value.

MR has an important role in identifying signs and meanings of variables, but the impact analysis of variables using GRNN takes into account non-linearity, adding significant results to our research by comparing both techniques. Since the two approaches are mutually informative, our research is intended to shed light on the importance of CR to explain the market value of firms, providing both conceptual and practical contributions. To the best of our knowledge, GRNN have not been used to investigate the effects of CR in the value of companies, modeling procedures using neural networks are expected to be more robust than the traditional MR, adjusted for potential nonlinearities between the variables under study (Pao, 2008).

The structure of the paper is organized as follows. After the introduction, relevant literature on the topic and research hypotheses are developed in Section 2. Section 3 presents research models and methods. Section 4 is dedicated to the data used and the selected sample, and Section 5 the results obtained in the investigation. Finally, main conclusions and future research suggestions are shown.

2. Literature review and hypotheses

CR is a collective representation of past actions and results of a company, and describes its ability to distribute the value created between different stakeholders. CR also measures the relative status of a company, both internally with employees and externally with stakeholders within a competitive and institutional environment (Fombrun & Van Riel, 1996).

According to the Resource-Based View, CR is an asset for the company, and as such, it has the ability to create value. This point has been empirically and theoretically demonstrated, proving that a good CR increases the expected reward in future interactions with others

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(Fombrun, Gardberg, & Barnett, 2000; Pfeiffer, Tran, Krumme, & Rand, 2012). The rationale behind this assertion is that CR acts as a mechanism to reduce asymmetric information, allowing the company to attract better resources under more favorable terms (De Quevedo Puente, De la Fuente Sabaté, & Delgado García, 2005). When it occurs, a company with a good CR is capable of getting better productive (first order) resources, linking past and future resources within the firm. Thus, CR becomes a second order resource whose task is to ease the attraction of new resources for the achievement of better conditions for business activity, and therefore constituting both CR and the other resources a differential strategic advantage over competitors (Hall, 1992). Kotha, Rajgopal, and Rindova (2001) state that CR is an inimitable, irreplaceable asset, unevenly distributed, and source of barriers within and between sectors through differentiation. In the words of Capraro and Srivastava (1997) and Fombrun and Shanley (1990), CR confers on the company a valuable, scarce and sustainable competitive advantage.

Previous literature has no doubts on the economic benefits provided by a good CR, but controversy still surrounds the valuation made by financial markets on CR (Agnihotri, 2014; Raithel & Schwaiger, 2015). As stated by Tischer and Hildebrandt (2014), several works have analyzed this relationship, but none of them have been able to confirm undoubtedly the influence of CR on financial performance. In some papers the claimed effects cannot be proven, and in some others the direction of causality is unclear.

There are several works concluding that CR is a valuable business resource, capable of generating sustainable competitive advantage over time, which causes a higher market value of their securities (Agnihotri, 2014; Black et al., 2000; Cole, Brown, & Sturgess, 2014; Hall Jr. & Lee, 2014; Raithel & Schwaiger, 2015; Tischer & Hildebrandt, 2014; Wang & Smith, 2008). Similarly, Stuebs and Sun (2011) and Wang and Smith (2008) consider that a good CR stands for the company's financial health, a highly valued aspect in the eyes of investors, since they use the presence of a firm in the reputation rankings as a signal to invest in. Cole et al. (2014) and Raithel and Schwaiger (2015) point out that given the level of competition among investment fund managers seeking better returns, they are required to look beyond the conventional parameters (accounting data) and find increasingly innovative ways to beat the market. One such way is estimating the value of CR.

Other studies, however, do not consider that the mere presence in the rankings of CR can be identified with obtaining higher yields, so CR does not cause any noticeable effect on the stock markets (Brammer et al., 2004, 2009).

The disparity of previous findings encourages us to test empirically, for the Spanish case, whether a listed company labeled as "reputable" (with a good or high CR in a reputation ranking) has a differentiating factor in terms of market value, compared with other listed companies not included in the ranking. Therefore we formulate the following Hypothesis 1:

Hypothesis 1. *(H1): In the Spanish stock market, the presence of firms in the CR rankings affects positively the market value of shares.*

Other group of studies have also found that the rankings of CR generate an implicit classification between the ranked companies, assigning to each of them a score that allows comparison with other firms. This implies that there will be "best" and "worst" companies, i.e., companies with better CR and companies with worse status among stakeholders. The key issue here is whether the market takes into account this stratification in the form of increased stock value. The literature shows again mixed and inconclusive results. Authors such as Rose and Thomsen (2004); Srivastava, McInish, Wood, and Capraro (1997); and Vergin and Qoronfleh (1998) show that firms with higher CR obtain a higher return for a given level of risk, increasing the market value of their stocks. In similar terms, Black et al. (2000); Chung, Schneeweis, and Eneroth (1999); Filbeck et al. (1997); Filbeck, Gorman, and Preece (1997); and Filbeck and Preece (2003) show that if the performance of companies with higher and lower CR is compared within the rankings, the former provide greater profitability.

However, some other works obtain the opposite effect in many aspects. Chung et al. (1999); Filbeck (2001); and McGuire, Schneeweis, and Branch (1990), state that it is not possible to beat the market by investing in companies with good CR. Some other authors conclude that a high CR even produces the opposite effect: the actions of the most reputable companies have lower returns, on average, that the actions of the less reputable companies (Anginer & Statman, 2010), or even negative income (Brammer et al., 2004). This reaction may be motivated by two investor behaviors: first, the tendency to invest in well-known companies or in those which have a good CR, both synonymous for quality (just as consumers buy branded products to their family); and second, investors are driven by the buying euphoria of certain companies, which leads them to overreact and to pay more than its value. Companies usually are not able to meet those high expectations, motivating the subsequent fall in the share price (Brammer et al., 2004; Brammer & Pavelin, 2004).

These results leave open the debate on whether a higher level of CR has a positive effect on the market value of a company. Therefore, we state our second hypothesis in the following way:

Hypothesis 2. *(H2): In the Spanish stock market, companies with the highest score in CR have a higher market value.*

Most of the previous research focused on the relationship between CR and market value has been using multiple regression analysis models (MR) as the preferred statistical method. Studies in other fields of financial research suggest that MR 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 (Abdou, Kuzmic, Pointon, & Lister, 2012; Pao, 2008). Chavarnakul and Enke (2008); Chen and Yu (2009); and Enke and Thawornwong (2005), state that GRNN is a NN architecture that can solve any problem of function approximation. Mostafa (2011) and Chavarnakul and Enke (2008) found that the GRNN prediction performance was superior to other statistical and stochastic methods applied to financial data. In addition, GRNN has several methodological advantages over other NN, such as its ability to train once the training set (Er, Yumusak, & Temurtas, 2010; Wu, 2011), and that previous decisions regarding the number of hidden layers and the adjustment of the initial weights are not required (Chavarnakul & Enke, 2008; Yaghobi, Rajabi, & Ansari, 2011). 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 by MR.

To our knowledge, no NN techniques have been used in research about CR and market value, and this is where we find another research gap that leads us to state the hypothesis 3 of our paper:

Hypothesis 3. *(H3): Generalized Regression Neural Network (GRNN) achieve more robust results than conventional multiple regression (MR) in analyzing the relationship between CR and market value of firms.*

3. Methods

One of the most widely used approaches to test the relationship between CR and market value is the "Ohlson model" (Ohlson, 1995). Originally this model has been applied by many authors to try to close the gap between market and book values, from the basis of the Gordon–Shapiro dividend–discount pricing model (Agarwal, Taffler, & Brown, 2011; Black et al., 2000; Kotha et al., 2001; Smith, Smith, & Wang, 2010; Wang & Smith, 2008). The method consists

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of calculating the present value of all the future cash flows that the investor estimates will obtain throughout the life of the investment, that is, the set of expected future dividends according to (1).

$$MV_i = \sum_{i=t}^{\infty} \frac{DIV}{(1+k)^i} \tag{1}$$

being MV_i the estimated market value for the shares of the company in the period i, DIV_i the total amount of expected future dividends in period i, and k the applicable discount rate. Although obtaining future dividends is subject to expectations (which are unobservable), the dividend can be calculated from current accounting data of the company, considering the condition of clean surplus,[1] as shown in (2).

$$BV_t = BV_{t-1} + RES_t - DIV_t \tag{2}$$

where BV_t refers to book value in periods t and t–1, RES_t is the result of period t, and again DIV_t is the amount of dividends paid in period t.

Ohlson's contribution implies that the difference between market and book values reflects the sum of all expected future abnormal results, i.e., those results obtained by the company in excess of those that would have been predicted given the current use of their assets and liabilities. Ohlson (1995) defines abnormal results (or benefits) as shown in (3).

$$RES_t^a = RES_t - r_t \quad BV_{t-1} \tag{3}$$

being RES_t^a the abnormal result obtained in period t, and r_t the opportunity cost of capital in period t.

Replacing (2) and (3) in (1) and operating conveniently, the Ohlson model equation is obtained as expressed in (4), which relates the market value of the firm to the book value plus the present value of the abnormal expected results:

$$MV_t = BV_t + \sum_{i=t}^{\infty} \frac{E_t[RES_{t+1}^a]}{(1+k)^i} \tag{4}$$

To make operative this equality, a linear equations system is established in (5) and (6), which takes into account the temporal relationship between autoregressive abnormal results of different periods and existing accounting variables (Iniguez & Reverte, 2012), as well as other informational variables that could influence the expectation of abnormal results.

$$RES_{t+1}^a = \omega \quad RES_t^a + v_t + \varepsilon_{1t+1} \tag{5}$$

$$V_{t+1} = \gamma \quad V_t + \varepsilon_{2t+1} \tag{6}$$

In these equations, v_t contains "other information" at time t, ω is a factor of persistence of abnormal results (known, with a value between zero and one), γ is a factor of persistence of the variable "other information" (as above, known and whose value ranges between zero and one). And finally, ε represents the error terms with mean zero.

Combining Eqs. (4–6), the operational version of the Ohlson model is obtained, as shown in Eq. (7):

$$MV_t = BV_t + \alpha_1 \; RES_t^a + \alpha_2 \; v_t \tag{7}$$

being

$$\alpha_1 = \frac{\omega}{1+k-\omega} \tag{8}$$

$$\alpha_2 = \frac{1+k}{(1+k-\omega)-(1+k-\gamma)} \tag{9}$$

This valuation model reconciles market and accounting values for a company through the abnormal results obtained, and allows the inclusion of other variables which add richness to the explanation of market values, clearly dependent of investors' expectations. It is thus the variable "other information" (v_t) which gives rise to the inclusion of additional variables that may be relevant by the abnormal profit, as in our case, corporate reputation.

Following previous literature, a reputable firm has the key competitive advantage of reducing the uncertainty inherent to social and commercial relations with its environment, an advantage that could result in a higher market value. For the Spanish case, we test whether a listed company considered as reputable has a differential factor with respect to other not-listed reputable companies (H1), referring to its market value. The model chosen to test this assertion appears in (10), and it is an adaptation from the Ohlson model (Ohlson, 1995) shown in (7).

$$\begin{aligned} MV_{it} = {} & \beta_0 + \beta_1 \cdot BV_{it} + \beta_2 \cdot RES_{it}^a + \beta_3 \cdot DREP_{it} \\ & + \beta_4 \cdot MQ_{it} + \beta_5 \cdot YEAR_{it} + \beta_6 \cdot IND_{it} + \varepsilon_{it} \end{aligned} \tag{10}$$

including $DREP_t$ as a variable which indicates the presence or absence of CR in the reputation ranking for the year t (Brammer et al., 2009; Delgado, De Quevedo & Díez, 2011; Stuebs & Sun, 2011; Wang & Smith, 2008). The inclusion of control variables becomes necessary in this model, as broadly endorsed in the literature (Sur & Sirsly, 2012). Thus we have considered a categorical variable (YEAR) indicating the year of observation, a reference to the industry to which the company belongs (IND), and a continuous variable reflecting the market share (MQ). The inclusion of the industry variable is consistent with other works that highlight its relevance in the study of the effects the CR (Flanagan, O'Shaughnessy, & Palmer, 2011; Pfarrer, Pollock, & Rindova, 2010). Market share hold by the firm within its sector and local market is included not only to control for dominant positions, but also to observe whether the intangibles of the company, including its CR, represent a sustained competitive advantage over time in relation to domestic rivals.

As stated above, the mere presence in a CR ranking could be enough to ensure the visibility of the company in the market, but we also suspect that the scores are as relevant as the presence in these rankings. To test H2, we use the modified Ohlson model previously exposed in (10), but changing the dummy variable $DREP_{it}$ by a continuous quantitative variable, REP_{it}, as the value of the overall score of CR. We finally obtain the model expressed in (11).

$$\begin{aligned} MV_{it} = {} & \lambda_0 + \lambda_1 \cdot BV_{it} + \lambda_2 \cdot RES_{it}^a + \lambda_3 \cdot REP_{it} + \lambda_4 \cdot MQ_{it} \\ & + \lambda_5 \cdot YEAR_{it} + \lambda_6 \cdot IND + \varepsilon_{it} \end{aligned} \tag{11}$$

A summary of the variables used in the models and their description is shown in Table 1.

MR is first applied in order to test the hypotheses regarding the dependent variable market value (MV) as a linear combination of independent variables and the error term ε_{it} to each firm i at time t. Then, GRNN are used, a technique designed for the continuous dependent variables regression. The neural network has four layers: an input layer, a hidden layer with the same number of neurons as the preceding layer (whose distances between centers are based on the core -kernel-, and typically using a Gaussian function), a summation layer (containing two neurons) and a decision layer, as shown in Fig. 1.

Because it is quite insensitive to outliers, GRNN are useful for the analysis of financial data, as demonstrated in a large part of the literature (Abdou et al., 2012; Enke & Thawornwong, 2005; Leung, Chen, & Daouk, 2000; Pao, 2008). This type of network was designed by Specht (1991) for the regression analysis in order to deal with problems involving nonlinearities. Furthermore, it has been shown that their algorithms are robust to changes in the values of the parameters (Tomandl & Schober, 2001).

GRNN can also measure the impact of the variables in the regression model, providing the sensitivity of the NN results for the change in the independent variables. Thereby each independent variable is

[1] This assumption states that the assets of the company can only grow through reinvestment of undistributed results to shareholders as dividends.

Table 1
Variables description.

Code	Measurement
Dependent variable	
MV_{it}	Shares market value of firm *i* for year *t*
Independent variables	
RES^{a}_{it}	Abnormal result of firm *i* for year *t*, calculated with the following expression: $RES^{a}_{t} = RES_t - r_t \cdot BV_{t-1}$ where: RES_t = Profit for year t; r_t = cost charge associated with equity (opportunity cost of the capital), taken in other studies as 10% (Wang & Murphy Smith, 2012[a]); BV_{t-1} = Book value of the company shares for year *t*–1
$DREP_{it}$	Presence or absence in CR ranking of company *i* for year *t*
REP_{it}	CR score of firm *i* for year t
$YEAR_{it}$	Reference year of observed data of the company *i*
IND_{it}	Spain's National Code of Economic Activities, 2009 version
MQ_{it}	Market share of firm *i* for year *t*

[a] Tests on the sample of model 2 indicate that the 5% trimmed mean of ROE (Return on Equity), usually used as a measure of the minimum cost required to own funds, gives a figure of 9.69%, very close to 10% that we considered as valid (while conservative).

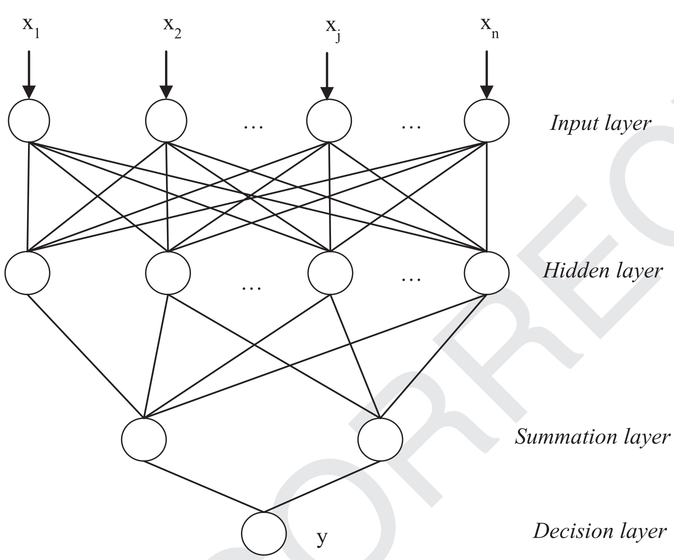

Fig. 1. GRNN Structure.

assigned an impact value of the dependent variable, expressed in percentage and being equal to 100%. In this paper, we have observed and calculated the changes occurred in the output GRNN model to obtain the sensitivity. First, we establish the value of all the variables and choose the one to calculate its sensitivity. Second, we fix the value of those variables that will not be analyzed and we only oscillate the value of that variable whose sensitivity we want to know. Third, the sensitivity of the variable analyzed (X) will be the sum of the absolute values obtained by subtracting the output value of the GRNN model from each value of X minus the network output value from the minimum value of X. This process will be repeated for each variable (Lisboa, Mehridehnavi, & Martin, 1994).

The sensitivity has been obtained by the following expression:

$$S_{ik} = {}^{N}_{n}|X_{kn} - X_{k\min}| \tag{12}$$

where S_{ik} is the measurement of the sensitivity of the input variable i on the output k, X_{kn} is the value of the output k obtained from the increase of n in the variable, and X_{kMin} is the value of the output k obtained with the minimum possible input value i.

Table 2
Industry distribution of the sample.

Activity	Description	Companies
B	Mining and quarrying	1
C	Manufacturing	24
D	Electricity, gas, steam and air conditioning supply	5
E	Water supply, sewage, waste management and remediation activities	3
F	Construction	20
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	7
H	Transportation and warehousing	4
I	Accommodation and food services	2
J	Information and communication	4
K	Financial and insurance	25
L	Real estate	8
M	Professional, scientific, and technical services	6
N	Administrative and support services	1
Q	Health care and social assistance	2
S	Other services	1
	TOTAL	113

4. Data and sample

Firms' data from the Monitor of Corporate Reputation (MERCO) annual survey for fiscal years 2008–2011 was used to test our hypotheses. This report includes the views of different stakeholders in order to calculate an overall score of CR for a number of companies operating in Spain. The choice of this ranking has been motivated by several reasons. First, there is a high availability of data in MERCO about the Spanish market (since 2001), which could result in a high level of awareness by the stakeholders. Thus, if in addition to other economic variables, CR influences investors' behavior and therefore the market value of firms, we should choose a measure whose results are easily available to the public. MERCO publishes data on its website (www.merco.info), and provides full disclosure through press and other national media.

Second, there are reasons referring to the process of generating the reputational assessment. MERCO construction process consists of four sequential assessments (Merco, 2013), including managers surveys for the development of a provisional ranking, assessments by different groups of experts, consumers and workers, and in situ valuations within the companies themselves. This assessment process differs from the used, for example, by Fortune magazine, which bases its ratings on evaluations of managers and financial analysts over several attributes of firms. We believe that, due to the scores' generation structure, MERCO may be less influenced by financial variables than Fortune ranking, so that the results obtained in this paper may add value as compared to other CR reports.

In order to select the sample of companies, and bearing in mind that variables related to market prices are included into the formulation of the hypotheses, we first decide to leave out of the analysis those companies not listed on the Spanish stock market. MERCO also analyzes the CR of firms that, without being Spanish, substantially perform important activities in this country. These companies are not listed on the Spanish market, although they are in their home markets or even in other ones. Since we wish to study the relationship between CR and market value for the Spanish case, we decided to exclude those companies from the sample. Financial companies are also excluded from the sample, both banks and insurance companies, because of the specific nature of their economic activity and the information provided in their financial statements. Additionally, some other companies have been removed, because no complete information was available in some of the years under study. After all these adjustments, the sample finally consists of 113 companies that provide a total of 422 observations (firm-years). Details of the companies in the sample appear in Table 2.

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Table 3
Descriptive statistics.

	Mean		Std. Dev.		Max.		Min.		*t*
	R	NR	R	NR	R	NR	R	NR	
BV	5050567,607	197447,950	7440738,865	405995,811	29400848,000	2043952,000	52439,000	−3166476,000	6,583***
RES[a]	215896,230	−31185,069	888352,228	253424,374	6292500,000	807979,000	−1944878,000	−39600007,200	3,632***
MQ	0,17462	0,0314	0,55650	0,0878	3,1453	0,9931	0,0001	0,001	2,675***

R: Reputable; NR: Non-Reputable;
*** : Sig. at 0.01

Table 4
Results model 1 (dependent variable, MV).

Model analysis	MR_1 Training Coefficient	MR_1 Testing	$GRNN_1$ Training Variable Impact %	$GRNN_1$ Testing
BV	0,642***	–	70,90	–
RES[a]	0,113***	–	16,90	–
DREP	0,059***	–	10,95	–
MQ	0,268***	–	0,60	–
YEAR	−0,035	–	0,35	–
IND	0,005	–	0,30	–
Diagnostic criteria				
F-ratio	394,460***	–	–	–
R^2	0,816	–	0,878	0,779
R^2 Adjusted	0,814	–	–	–
Durbin-Watson	1,147	–	–	–
Std. desv. abs. errors	–	–	2967018,706	3996498,467
RMSE	84559806,070	87937401,552	2967000,000	3996500,000
MAE	3666132,543	38127235,847	1031700,000	1392200,000

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

Financial data was obtained from the COMPUSTAT data base, and specific data relating to sectorial sales figures have been extracted from the Spanish National Statistical Institute.

With the objective of validating the models to estimate, a testing sample was used additionally, independent to those used in the estimation of the models. From a random selection, we reserved 70% of the data to construct a training sample, and 30% of the remaining details to obtain a testing sample.

5. Results

5.1. Exploratory analysis

In our study, the exploratory analysis aims to examine the data prior to use the selected regression techniques, so that the possible relationships between the data can be observed or previously guessed (Tukey, 1977). This exploratory analysis consists of a descriptive analysis of the variables in order to get the classical statistical parameters, and a test to determine whether CR is a differential factor in any of the aspects analyzed. The results appear in Table 3. Large differences between reputable and non-reputable firms are detected in the mean values for each of the variables. The difference in the average book value (BV) indicates that reputable companies have a much larger size (50,50,567.61 thousands euros against 1,97,447.95). Also, according to market share (MQ) it is observed that reputable companies have, on average, a larger proportion of the total sales in their respective sectors, probably due to its larger size. The same conclusions can be obtained attending to the standard deviations and the minimum and maximum values. It is particularly interesting to note the difference in the variable of abnormal results (RES^a) between reputable and non-reputable companies. As can be appreciated, the differences are not only in absolute value, but its sign is opposite. Non-reputable companies show an average abnormal result of 31,185.07 thousand euros, while reputable have shown an average of 215,896.23 during the period.

The two-sample *t* test is used to test whether two samples come from populations with the same distribution. The null hypothesis is that there are no significant differences between the distributions of both samples. According to the results shown in Table 3, the null hypothesis is rejected in all cases. These findings imply that there are considerable sampling differences between reputable and non-reputable companies both in size (measured by market share, MQ) and abnormal results (RES^a).

5.2. Confirmatory analysis

By contrasting H1 it is intended to determine, given a sample of companies listed on the Spanish continuous market for the period 2008–2011, whether the firms in a CR ranking have a comparative advantage in the form of higher market value, with respect to those listed and no reputable companies (Model 1). Table 4 shows the results of applying the two proposed methodologies, MR and GRNN. According to MR, all explanatory variables are highly significant (book value, BV; abnormal results, RES^a; presence in the CR ranking, DREP; and market share, MQ) with a confidence level of 99.0%. The relationship between them and the dependent variable is positive in all cases. However, control variables are not significant in the model, relegating their role to control the effect of the main explanatory variables. Overall, the explanatory power of the model is 81.6%.

Results of implementing GRNN are shown in Table 4. The most relevant data of the GRNN is the impact that each variable has on the model. As can be seen, the variable book value (BV) is by far the most important variable, representing 70.9% of the total impact of all the variables in the factor explained. This result seems logical, since the key for setting the market value of a company is the value of its assets and liabilities under the accounting perspective. Abnormal results

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Table 5
Results model 2 (dependent variable, MV).

Model analysis	MR_2 Training Coefficient	MR_2 Testing	$GRNN_2$ Training Variable impact %	$GRNN_2$ Testing
BV	0,541***	–	38,50	–
RES[a]	0,109***	–	34,90	–
REP	0,179***	–	22,00	–
MQ	0,279***	–	1,20	–
YEAR	−0,042	–	1,60	–
IND	0,003	–	1,80	–
Diagnostic criteria				
F-ratio	431,827***	–	–	–
R^2	0,830	–	0,820	0,800
R^2 Adjusted	0,828	–	–	–
Durbin-Watson	1,268	–	–	–
Std. desv. abs. errors	–	–	3605551,275	3793151,724
RMSE	81467910,840	86779364,121	3605500,000	3793200,000
MAE	3532081,883	3761361,682	1443300,000	1499600,000

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

Table 6
Comparative diagnostic.

Criteria	Model 1				Model 2			
	Training		Testing		Training		Testing	
	MR_1	$GRNN_1$	MR_1	$GRNN_1$	MR_2	$GRNN_2$	MR_2	$GRNN_2$
RMSE	84559806,070	2967000,000	87937401,552	3996500,000	81467910,840	3605500,000	86779364,121	3793200,000
MAE	3666132,543	1031700,000	38127235,847	1392200,000	3532081,883	1443300,000	3761361,682	1499600,000

(RES[a]) determine the 16.9%, the second variable in importance, a result consistent with the hypothesis of Ohlson (1995). The variable DREP, object of our analysis, represents 10.9% of the total impact, being third in terms of sensitivity. The level obtained allows us to confirm hypothesis 1, i.e., that the presence in the rankings of CR affects the firms' securities market value. Furthermore, the explanatory power of the model with GRNN improves with an 87.8% adjustment.

It is also necessary to note the sharp decline in both root-mean-square error and mean absolute error obtained by applying GRNN versus traditional MR. These results could be a first sign of confirmation of hypothesis 3, i.e., that GRNNs obtain more robust results in the analysis of the effect of CR on the market value of firms (MV).

Table 5 shows the results of applying MR and GRNN to model 2, which is the hypothesis of whether the companies with the highest score in CR have a higher market value of its shares (H2). By applying MR similar results to model 1 are obtained regarding the meaning of the variables and the sign of the coefficients. However, the value of the associated coefficients is different. Abnormal results (RES[a]) and market share (MQ) remain at a similar level, but resulting in more variation in the book value (BV), which decreases, and gaining strength the coefficient associated with the value of reputation (REP). It follows that belonging to a ranking of CR is not only beneficial to a company, but also obtaining higher scores contributes to a higher market value (MV). Again, control variables are not significant, but the model fit improves compared to Model 1 (0.830 vs. 0.816), confirming prior deduction.

Results from applying GRNN to model 2 also appear in Table 5. The impact of the considered variables confirms that they are the three most sensitive: in impact order, BV, RES[a] and REP. Thus, the reputation score (REP) becomes the third most influential model variable. This indicates that REP is an attribute taken into account in the financial markets, since it helps investors perceive the quality of traded securities and the expectations placed on them, generating an increase in price. The results obtained allow accepting H2. The limited sensitivity variable assigned MQ by the model (only 1.2%) also draws attention. This could indicate that the dominant position in terms of market share is not enough to explain the differences in value, contrary to the results of MR. Root-mean-square error and mean absolute error, as in the previous model, decrease significantly, which again indicates a greater robustness of the results with GRNN compared with those obtained by MR.

Table 6 finally compares the two diagnostic methods. Root-mean-square error and mean absolute error of the training and testing samples obtained with MR are similar, suggesting stability between both samples. However, it can be seen that root-mean-square error and mean absolute error with GRNN are much smaller than those obtained with MR. This confirms the hypothesis H3, i.e., that GRNN provides a better fit than conventional regressions to analyze the relationship between CR and the shares market value.

6. Conclusions

Our aims in this work have led us to investigate the relationship between CR and market value in Spain. For this purpose, GRNN has been applied as a method of analysis to add prospects that are not available to conventional multiple regression (MR). MR has an important role in the identification of signs and meanings of the respective variables, but the impact analysis of GRNN variables takes into account nonlinearities.

The results confirm the hypotheses of this research, namely that the presence of firms in the rankings of CR has a positive influence on the market value of its shares (H1), and that firms with higher CR also have more market value (H2). We have also been able to verify that GRNN gets more robust results than conventional MR (H3).

Referring to hypothesis H1, and through the impact analysis of variables provided by GRNN, it was found that BV is most sensitive variable in the model, representing 70.9% of the total impact of all variables in the explained factor. This result seems logical, as the

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value of assets and liabilities is a fundamental reference for determining the market value of a company. Abnormal results (RES[a]) determine 16.9% of total impact, being the second variable in importance, which is consistent with the hypothesis by Ohlson (1995). Also, the variable indicating presence in the rankings of CR (DREP) represents 10.9%, confirming that it is important for explaining the market value of the companies' securities.

Regarding hypothesis H2, BV, RES[a] and REP have also proved to be the most sensitive model variables. These results confirm that the score in CR (REP) is an attribute that is taken into account in the financial markets, since it helps investors to perceive the quality of traded securities and the expectations placed on them, generating increased market prices.

Other key findings are that market values are not conditioned by the industries which companies belong to. Second, the limited sensitivity having the variable market share (MQ) in both GRNN built models, contrary to what is suggested by MR models. Third, the positive relationship between CR and market value also remains throughout the study period (2008–2011), which has been of deep financial crisis in Spain. Fourth, GRNN provides more efficient models than traditional linear techniques in modeling complex functions, allowing the decision maker to focus attention where it is most needed and far less relevant and potentially misleading aspects.

The excellent results obtained in this research using GRNN may be due to its ability to solve any problem of function approximation. Based on its nonlinear regression foundations, GRNN uses a method that avoid the need to assume a certain functional form. Rather, the appropriated functional form is expressed as a probability density function (Chavarnakul & Enke, 2008; Enke & Thawornwong, 2005). GRNN can estimate the map inherent through any sample data, and the estimation can converge to optimal regression surface even if a few samples are used (Wu & Tsai, 2011).

In spite of the contributions of this study, there are some other features that should be taken into account for further research. It is widely known that CR is a concept not yet clearly defined, with different and heterogeneous measurements, so additional research is needed by using GRNN methods with alternative CR measurement sources. Furthermore, financial companies have not been considered in this research due to the special nature of their financial and economic characteristics. The relevance of the financial industry in the developed economies and its role in the present recessive period have attracted much attention from the media, damaging the CR of all banks and credit institutions. Therefore, these effects should be considered in future research. Finally, the study is limited in the number of NN methods, since GRNN fits better from a theoretical point of view. Other NN, such as Multilayer Perceptron or Hybrid Methods could be integrated in some future research questions.

Uncited references:

Delgado García, De Quevedo Puente, & De la Fuente Sabaté, 2010

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