ANALYSING CAPITAL STRUCTURE OF SPANISH CHEMICAL COMPANIES USING SELF-ORGANIZING MAPS

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Abstract

This paper analyses the capital structure of the Spanish chemical industry during the period between 1999 and 2013, with a twofold objective. First, to determine whether the assumptions of Pecking Order Theory are fulfilled throughout the study's timeframe. Second, this study shows how the financial crisis that started in 2007 has affected the capital structure of the companies included in our sample.
In order to tackle these questions we adopt an innovative methodology in this field, applying a particular kind of unsupervised neural network, Self-organizing Maps. This methodology allows to cluster firms avoiding the need to establish relationships between the different variables involved in the problem beforehand.
Companies are clustered into groups with different degrees of accomplishment of the Pecking Order Theory. The hypothesis about risk is the one that experiences a greater variation in the period before and after the crisis. Moreover, companies' capital structure has been lightly disrupted by the crisis.

Keywords: Pecking Order Theory, Capital structure, Self-organizing maps, Financial crisis.
JEL Code: G32, C45, G33

1. INTRODUCTION

1.1. The Capital Structure Problem

The capital structure problem became relevant with the development of the model by Modigliani & Miller (1958). This model concluded that in a situation in which the hypotheses of a perfect financial market are met, the company's market value is independent of its capital structure. Later, the same authors loosened the hypotheses by incorporating taxes and thus the tax advantage that debt versus equity entailed (Modigliani & Miller, 1963).

Subsequently, authors as Robichek & Myers (1965), Baxter (1967), Stiglitz (1969), Kraus & Litzenberger (1973), Fama (1978) and Kim (1978) analysed how the extensive use of debt can lead companies to a risk of default. Insolvency costs were introduced, giving rise to the Trade-off Theory. According to this theory, a company will increase its volume of debt to the level at which the tax benefits of another unit of debt are offset by the increased bankruptcy costs of that extra debt unit. On their side, Jensen & Meckling (1976) define agency costs as the costs arising from the conflict of interests between shareholders (not managers) and the company's managers and between shareholders and debt providers. Leland (1998) reformulates the Trade-off Theory by incorporating agency costs.

A third approach, based on asymmetric information between internal shareholders and managers (*insiders*) and external investors (*outsiders*) defines two new problems: the problem of adverse selection and the problem of moral hazard. According to Harris & Raviv (1991), these problems lead to the emergence of two new theories, Signalling Theory developed by Leland & Pyle (1977) and Ross (1977) whereby the company's capital structure is used as a mechanism for conveying signals to the market, and Pecking Order Theory, developed by Myers (1984) and Myers & Majluf (1984), whereby the capital structure is used to reduce inefficiencies in investment decisions (i.e. underinvestment and overinvestment).

Of all the theories on capital structure, Trade-off Theory and Pecking Order Theory are currently competing to explain the capital structure of businesses. This paper focuses on the hypotheses of Pecking Order Theory.

The hypotheses of Pecking Order Theory, postulated by Myers & Majluf (1984), conclude that the costs arising from asymmetrical information between managers and shareholders/investors mean that the former establish the following hierarchy of different funding sources in order to minimise adverse selection costs:

1- Internally generated resources
2- External debt
3- Capital enlargement by new issues of shares

Since then, many studies have attempted, without consensus, to determine whether Pecking Order Theory adequately describes how companies are financed.

1.2. The incidence of the Financial Crisis

On the other hand, the financial crisis which began in the summer of 2007 in the United States subprime market soon spread to other geographical areas, including the countries in the Eurozone. The increased perception of risk in credit operations had an impact on the liquidity of wholesale and interbank markets, and affected the entire financial system.

The Spanish economy was one of those that suffered most from the consequences of the financial crisis. Spain had just experienced the biggest investment cycle in the country's history. This investment was accompanied by an increase in borrowing, which increased external financial dependence in the economy as a whole.

This paper is the third in a series which began in 2010, and which seeks to determine how the crisis has influenced the way companies finance their investments. A sample of 157 companies belonging to the Spanish chemical sector was chosen with that objective in mind. There were two main factors in the choice of sector. First, the chemical sector is very important in the Spanish economy and second, the sector was less heavily influenced by the factors that have made the Spanish economy more sensitive to the crisis (i.e. a longer investment cycle coupled with lower productivity).

In the first study, it is analysed the same sample of Spanish companies during the period 1999-2006. The study concluded that the hypotheses of Pecking Order Theory were partially fulfilled. We found a negative relationship between Spanish chemical companies' profitability (the ability to generate internal resources) and their degree of leverage, but there was no relationship between the risk that these companies presented and their level of debt (Cámara-Turull, Borràs Balsells, Sorrosal Forradellas, & Fernández Izquierdo, 2010).

A second study analysed the 140 firms that survived from the same sample during the period between 2007 and 2010 (bankrupt companies and those that had undergone corporate merger or acquisition (M&A)

processes were excluded). As a result of the financial crisis, risk became a key variable in explaining the volume of corporate debt (Cámara-Turull, Borràs Balsells, Sorrosal Forradellas, & Fernández Izquierdo, 2012).

This study expands the analysis to cover the period until 2013, and has two objectives. First, to determine whether companies' capital structure has been disrupted by the financial crisis and whether the assumptions of Pecking Order Theory are fulfilled throughout the study's timeframe. It is important to note that the sector is in the throes of transformation related to stricter legal requirements (the application of the REACH[1] and CLP[2] regulations). During the period between 2008 and 2013, 13 companies from the original sample underwent business M&A processes, and 6 companies went bankrupt.

1.3. Self-Organizing Maps

In all three studies, it is used an unusual methodology in the analysis of capital structure: Self-Organizing Maps (SOM). SOM is an artificial neural network introduced by Kohonen (1982, 1988). In contrast to many other neural networks based on supervised learning, SOM is based on unsupervised learning[3], that makes it one of the best known algorithms in artificial neural networks. (Back *et al.*, 1998; Chen, 2012; Chen *et al.*, 2013; du Jardin and Séverin, 2011, 2012; du Jardin, 2015; Kiviluoto, 1998; López Iturriaga and Sanz, 2015; Serrano-Cinca, 1996).

SOM consists of two neural layers. The input layer has as many neurons as variables are considered in the problem. Its function is to capture the input data and transfer them to the output layer. Each neuron of the input layer is connected to each neuron of the output layer through synaptic weights (w_{ij} corresponds to the weight that connects the neuron i in the input layer with the neuron j in the output layer).

The output layer is a two dimensional map. The input data are located at the map according to the similarity between all the variables used to define input information.

[1] REACH (Regulation (EC) No. 1907/2006 of the European Parliament and the Council) is the European regulation on the Registration, Evaluation, Authorisation and Restriction of Chemicals. It was approved on 18 December 2006 and came into force on 1 June 2007.
[2] CLP - Regulation (EC) No. 1272/2008 of the European Parliament and of the Council of 16 December 2008 on the Classification, Labelling and Packaging of substances and mixtures.
[3] SOM uses competitive learning process (a particular kind of unsupervised learning). In contrast to supervised artificial neural networks, unsupervised networks do not need to define groups a priori; instead they are based on the similarities and differences between the values of all the variables that define the capital structure of each company.

By reducing the dimensions of the analysis an easiest and natural visualization of data is provided. Next, we briefly describe how SOM works.

The input vector k is presented to the network. In our study, k represents each company.

Afterwards, as similarity measure, the Euclidean distance between the input vector and the weights vector that joins the input neurons with each of the output neurons is calculated (Expression **¡Error! No se encuentra el origen de la referencia.**)). The neuron in the output layer that minimizes this distance will be the "winning neuron".

$$d_j^k(t) = \sqrt{\sum_{i=1}^{N} \left(x_i^k(t) - w_{ij}^k(t)\right)^2} \qquad (1)$$

Initially, $t = 0$, the synaptic weights take small random values.

In order to reduce the distance between the input vector and the weights vector associated to the winning neuron, the synaptic weights are updated according to the following rule:

$$w_{ij}^k(t+1) = w_{ij}^k(t) + \alpha(t)h_j^k(t)\left[x_i^k(t) - w_{ij}^k(t)\right] \qquad (2)$$

Where $\alpha(t)$ is the learning rate, a function that takes values from 0 to 1 and it decreases as the number of iterations increases. The neighborhood function ($h(t)$) allows to update the winning neuron's weights and its neighborhood (neurons close to the winning neuron at a radio that decreases with the number of iterations). This process facilitates the activation of the same winning neuron or other neuron close to it when similar input vectors are presented.

This process is repeated for the rest of input vectors and a maximum number of iterations T previously defined.

In this paper, the variables considered are the leverage ratio, profitability, growth, risk and the tax shield. They have all been used in previous studies, and are the same as those proposed by Fama & French, (2002) for validating the Pecking Order Theory. SOM are applied to cluster firms based on the variables proposed, and to determine whether the companies in each group have levels of debt that are similar and consistent with the Pecking Order Theory. We repeat the analysis for both periods, the years previous to the financial crisis (1999-2007) and the period after the financial crisis started (2008-2013). As shown by Hornik et al.

(1989), the advantage of using these artificial neural networks is that they enable non-linear relationships between data sets to be identified, complex functions to be approximated and items to be grouped based on the similarities between all their defining variables, with no need for any prior assumptions about the nature of the variables and their functional relationships.

The paper is organized in 5 sections. Section 2 presents the use of artificial neural networks in finance and defines the variables and hypotheses used in the study. Section 3 introduces the proxy variables. Finally, in sections 4 and 5, there are the results and main conclusions of the work.

2. METHODOLOGY AND DATA

2.1. Artificial Neural Networks in Finance

Modern finances have largely been based on assumptions such as the normality of variables and the linearity of the relationship between variables. The development of econometrics has led to the appearance of increasingly sophisticated methods and instruments, although they all presuppose the functional relationships of the model. The contribution of these instruments to the development of the field of finance is undeniable; however, their characteristics limit the range of phenomena that they can handle.

The search for methods to address complex phenomena and problems with non-linear relationships has increasingly led to the use of artificial neural networks in research into finance. They were initially used in financial markets (for forecasting prices, volatility, etc.) but in recent years have increasingly begun to be used in other areas of finance, and especially in corporate finance.

Unlike the traditional statistical methods, artificial neural networks make no prior assumptions about variables. This is what makes them capable of tackling unstructured problems where it is impossible to establish the function beforehand. The algorithms used by some artificial neural networks enable them to "learn" the relationships between variables directly from the data itself.

Neural networks are extensively used in many areas of finance, including:

- Credit rating, for example the studies by Bergerson & Wunsch (1991); Dutta & Shekhar (1988); Glorfeld & Hardgrave (1996); Desai et al. (1996); Huang et al. (2004); Jensen (1992); Kim et al. (1993).

- Business failure, such as the studies by Chen et al. (2013); du Jardin & Séverin (2012); du Jardin (2010); Fletcher & Goss (1993); Lee et al. (1996); Lee & Choi (2013); Odom & Sharda (1990); Rahimian et al. (1993); Sánchez-Lasheras et al. (2012); Séverin (2010); Tsukuda & Baba (1994); Yu et al. (2014) and Zhou et al. (2012).
- Bank failure prediction, where we found, among others, Bell (1997); López & Sanz (2015); Swicegood & Clark (2001); Tam & Kiang (1992) and Tam (1991).
- Predictions of financial asset prices, including the studies by Kryzanowski et al. (1993); White (1988); Enke & Thawornwong (2005); Hamid & Iqbal (2004); Hoptroff (1993); Rather et al. (2015); Jain & Nag (1995); Wang & Wang (2015); Wang et al. (2011); Wong & Selvi (1998); Grudnitski & Osburn (1993).
- Time series analysis, such as the studies by Adhikari & Agrawal (2014) and Azoff (1994).
- Financial Management, including the studies by Back, Sere, & Vanharanta (1998); Barr & Mani (1994); Eklund, Back, Vanharanta, & Visa (2003); Hawley, Johnson, & Raina (1990); Kamruzzaman (2006); Länsiluoto, Eklund, Back, Vanharanta, & Visa (2004); Magnusson, Arppe, Eklund, Back, Vanharanta & Visa (2005); Smith & Gupta (2000) and Swales & Yoon (1992).

But we found no applications of neural networks to any of the corporate finance problems that have most concerned researchers, that is, the capital structure of companies and its relationship to the company's market value.

As we have mentioned in the previous section, we introduce the use of SOM for its flexible design and its application to grouping problems.

2.2. Hypothesis of Study

As noted by Bevan & Danbolt (2002), Harris & Raviv (1991) and Titman & Wessels (1988), the choice of explanatory variables is crucial in interpreting the results. Below it is described the hypothesis on the relationship between the level of debt and some economic and financial variables (profitability, growth, risk and non-debt tax shield) and the factors explaining the financial structure of the company that are used in order to check the hypothesis considered.

Hypothesis 1. The relationship between the level of debt and profitability is negative. The greater the profitability, the greater the capacity to generate resources internally and therefore the lower the need for debt. The return on investment capital $\left(\text{ROIC}=\frac{\text{EBIT}}{\text{Equity+Debt}}\right)$ was selected as a proxy variable for profitability. Return on equity $\left(\text{ROE}=\frac{\text{Net Income}}{\text{Equity}}\right)$ has not been used in order to avoid the imbalances caused in companies that have negative equity.

Hypothesis 2. The relationship between the volume of debt and potential growth is positive. The greater the company's growth, the greater its financing needs and consequently, the greater the need for debt. There is a variant of this hypothesis that focuses on future growth, and in this case, the higher the expected future growth, the lower the volume of debt. This is because a low financial risk profile and a higher debt capacity are maintained, which enables future growth to be addressed with no need for other more expensive sources of financing (Myers & Majluf, 1984). The proxy variable for defining growth is the year-on-year change in total assets and operating income.

Hypothesis 3. The higher the company's risk (defined as the volatility of cash flows), the lower its level of debt. This is because an increased risk entails an increase in the costs of debt. To identify the company's cash flow volatility -risk- it is used the proxy variable, suggested by Fama & French, (2002), it is to say, the natural logarithm of real assets,. Those authors assume that larger companies are more diversified, and therefore have lower levels of volatility in their cash flows.

Hypothesis 4. A larger non-debt tax shield entails an increase in the internal resources generated by the company, meaning that its relationship with the company's level of debt will be negative (unless the EBITDA is insufficient to cover the depreciations, for example). The ratio of depreciation, measured as assets depreciation over total assets, is the proxy variable for the non-interest tax shield.

According to this four hypothesis, the financial variables used in the study and their characteristics, are shown in Table 1.

Table 1. Financial variables used in the study

Proxy variable	Definition	Hypothesis	Relationship with the debt level
Return on investment capital (ROIC)	$\text{ROIC}=\frac{\text{EBIT}}{\text{Equity+Debt}}$	Hypothesis 1	Negative
Operating income (OpInc) annual increase	$\frac{\text{OpInc}_t - \text{OpInc}_{t-1}}{\text{OpInc}_{t-1}}$	Hypothesis 2	Positive
Total asset (TA) annual increase	$\frac{\text{TA}_t - \text{TA}_{t-1}}{\text{TA}_{t-1}}$	Hypothesis 2	Positive
Natural logarithm of real assets	$\ln(A)$	Hypothesis 3	Negative
Ratio of depreciation	$\frac{\text{Assets depreciation}}{TA}$	Hypothesis 4	Negative

We used the leverage ratio (debt/equity) as the proxy variable to determine the company's level of debt. Although there is some controversy as to whether the leverage ratio should be used at book value or at market value (Rajan & Zingales, 1995; Titman & Wessels, 1988) only one of the companies in the sample is listed on a stock market. As obtaining the market value of unlisted companies is very difficult, it is used the book values for the leverage ratio like in studies such as Banerjee et al. (2004), Bradley et al. (1984) and Graham & Harvey (2001).

Some authors pointed out a significant difference on the capital structure of a company according to its size or age (Vendrell Vilanova, 2007). Therefore, for greater homogeneity in each group, the analysis includes age and size, using the years since the company's establishment and its number of employees, respectively, as proxy variables.

Taking into account the measurements of profitability, potential growth, risk, non-interest tax shield, size and age of each company from the sample, the objective of this paper is to identify groups of companies with homogeneous characteristics applying SOM. By analysing the characteristics of each group and the leverage ratio of the companies within it, it is possible to determine the extent to which the hypotheses are fulfilled in each group.

2.3. Description of the sample

The sample of Spanish chemical sector companies was obtained from the SABI database. A total of 160 companies in the Spanish chemical Industry were randomly selected, with the only condition that all the data is available. Although one of the advantages of SOM is that they can work with noisy data or even with non complete data, the aim of the paper is to analyse the accomplishment of the Pecking Orther Theory in the Spanish chemical industry. As we work with a sample of companies, we have selected the ones with complete information in order to do not add innecesary misinformation.

In order to analyse the situation before the start of the crisis and during its aftermath, the data is divided into two periods. The first period covers the years between 1999 and 2007, and the second period covers the years between 2008 and 2013.

After performing some consistency tests according to general accounting principles, nine companies are discarded for the period 1999-2007. A sample of 151 companies with complete data for the 9 years remained for the period 1999-2007.

Thus, according to the analysis carried out, there will be 151 input vectors, one for each company in the pre-crisis period. Each vector X_k is defined by 34 values (see Table 2). Thus x_{ik} is the value of ratio i in the company identified as k, being $i = 1, \cdots, 34$.

Table 2. Variables used in input vectors. Pre-crisis period (1999-2007)

Variable 1	Number of employees 1999	Variable 18	Total assets increase 2002
Variable 2	Number of employees change 1999-2007	Variable 19	ROIC 2003
Variable 3	ROIC 1999	Variable 20	Operating income growth 2003
Variable 4	Operating income growth 1999	Variable 21	Total assets increase 2003
Variable 5	Total assets increase1999	Variable 22	ROIC 2004
Variable 6	Ratio of depreciation 1999	Variable 23	Operating income growth 2004
Variable 7	Ratio of depreciation change 1999-2007	Variable 24	Total assets increase 2004
Variable 8	ln(A) 1999	Variable 25	ROIC 2005
Variable 9	ln(A) change 1999-2007	Variable 26	Operating income growth 2005
Variable 10	ROIC 2000	Variable 27	Total assets increase 2005
Variable 11	Operating income growth 2000	Variable 28	ROIC 2006
Variable 12	Total assets increase 2000	Variable 29	Operating income growth 2006
Variable 13	ROIC 2001	Variable 30	Total assets increase 2006
Variable 14	Operating income growth 2001	Variable 31	ROIC 2007
Variable 15	Total assets increase 2001	Variable 32	Operating income growth 2007

Variable 16	ROIC 2002	Variable 33	Total assets increase 2007
Variable 17	Operating income growth 2002	Variable 34	Age (2013)

The sample was reduced to 118 companies for the period 2008-2013. The reasons were: i) 14 companies were ruled out due to a lack of data for the entire series. ii) 6 companies were bankrupt during the years 2008-2013, iii) 13 companies underwent M&A processes.

In the post-crisis period, there will be 118 vectors, on for each company in this period. Each vector X_k is defined by 25 values (see Table 3). Thus x_{ik} is the value of ratio i in the company identified as k, being $i = 1, \cdots, 25$.

Table 3. Variables used in input vectors. Post-crisis period (2008-2013)

Variable 1	Number of employees 2008	Variable 14	Operating Income growth 2010
Variable 2	Number of employees change 2008-2013	Variable 15	Total assets increase 2010
Variable 3	ROIC 2008	Variable 16	ROIC 2011
Variable 4	Operating Income growth 2008	Variable 17	Operating Income growth 2011
Variable 5	Total assets increase 2008	Variable 18	Total assets increase 2011
Variable 6	Ratio of depreciation 2008	Variable 19	ROIC 2012
Variable 7	Ratio of depreciation change 2008-2013	Variable 20	Operating Income growth 2012
Variable 8	ln(A) 2008	Variable 21	Total assets increase 2012
Variable 9	ln(A) change 2008-2013	Variable 22	ROIC 2013
Variable 10	ROIC 2009	Variable 23	Operating Income growth 2013
Variable 11	Operating Income growth 2009	Variable 24	Total assets increase 2013
Variable 12	Total assets increase 2009	Variable 25	Age (2013)
Variable 13	ROIC 2010		

Once we dispose of the companies expressed as vectors, we introduce this information in the SOM. We have implemented the network with the SOM Toolbox for Matlab, developed by the Laboratory of Computer and Information Science at the Helsinki University of Technology.

Before the Toolbox creates de network, data are normalized using the logistic function (all variables scaled are in the range [0,1]). In this way, the results are not affected for the different initial scales of the variables. The rest of functions and parameters are the ones that Toolbox have stablished by default (see http://www.cis.hut.fi/somtoolbox/). The hexagonal grid obtained as a result has been converted to a bigger rectangular one in order to facilitate its visualization.

After the training process is completed, the debt level of each group in the output map is defined as follows:

1. The companies are ordered from higher to lower debt level.
2. According to the debt percentile assigned to the companies in a group, each group debt level is identified.
3. Crossing the position of each group in the output map with its debt level, the diferent hypothesis would be contrasted. To do that, we analyse the position of each group through the value of each variable using the characteristics maps.
4. The differences between the pre and post-crisis would show if all the Pecking Order Theory hypotheses are equally sensitive to the crisis.

3. RESULTS

In an initial descriptive analysis, when the data from before the crisis is compared with those after its onset, some significant differences can be observed:

- The average value of the leverage ratio after the onset of the crisis fell by approximately 31% compared to the average pre-crisis value.
- The average firm size was higher in the post-crisis period. This may be due to the sectoral restructuring process discussed above.
- The average profitability values fell from 12.06% in 1999-2007 to 7.35% in 2008-2013.
- The average values of the growth rates of sales and assets prior to the start of the crisis for the sample were 7.52% and 8.76%, respectively, and fell to significantly lower values in the post-crisis period. In specific terms, the average growth rate for sales was 4.77% and the average growth rate of assets was 4.19%.
- Finally, the average risk fell in the period 2008-2013 in comparison to the pre-crisis data. This is related to the measure of risk used (natural logarithm of assets) since it links risk to the company's size, with the larger companies presenting least risk because they are assumed to have greater diversification. Considering the M&A process that the sector has experienced, the average size of firms has increased and the average risk has therefore declined.

The downward trend in profitability, growth and the tax shield is more significant when it is considered that companies in the sample that went bankrupt or were absorbed during the period 2008-2013 were excluded.

Having performed this preliminary descriptive analysis, we present the results obtained from SOM for each period.

3.1. Pre-crisis period (1999-2007)

After completing the training process, Figure 1 presents the map obtained for the period 1999-2007. Based on a dual purpose optimization programme for i) the minimum number of groups, and ii) maximum homogeneity within each group, the following seven groups are identified:

- **Group A.** Contains the smallest companies in the sample, with the lowest profitability, growth and tax shield of all the groups. At the same time, and despite being the second group in terms of companies' age, it presents a high risk.
- **Group B.** Composed by the oldest companies and above average size. They present low profitability and very low growth. They have a moderate risk (below average) and, with group D, the largest tax shield of the sample.
- **Group C.** With group A, this group has the smallest companies and the smallest tax shield. Their profitability is above average and growth is moderate, at around average levels. It is also the group containing the companies with the greatest risk.
- **Group D.** The companies in this group are average in terms of size, profitability and risk. They have slightly above average growth and are slightly below average in age. These companies have the highest tax shield.
- **Group E.** This group contains the largest companies in the sample and those with a lower risk. They are companies with below average profitability, moderate growth and a medium-high tax shield. These companies are above the average age for the sample.
- **Group F.** Although they are young and small companies, they have higher rates of profitability and high growth rates, albeit with high risk. Their tax shield level is below average.
- **Group G.** This group consists of companies that are above average in terms of size and profitability. They have the highest growth rates in the sample. They are low risk, relatively young companies with a tax shield that is slightly below average.

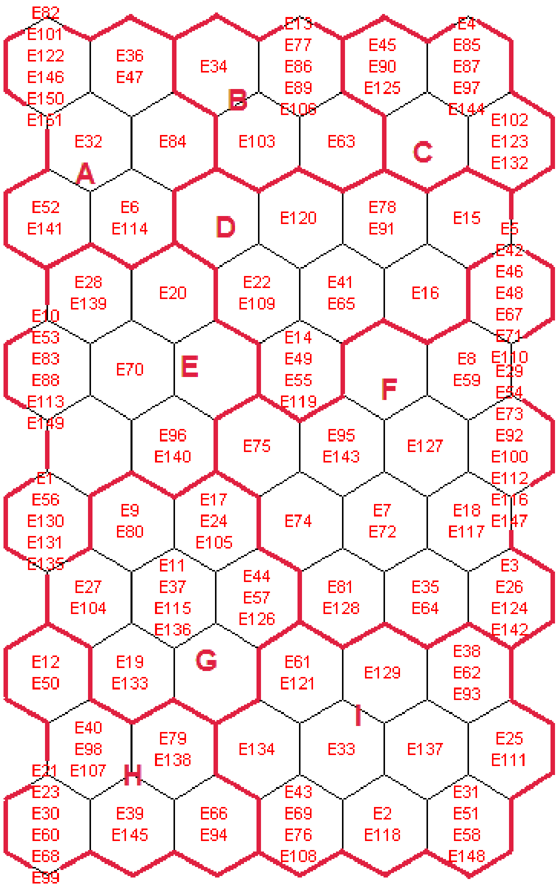

Figure 1

Table 4 shows the different groups ordered from low to high borrowing requirements as reflected in each hypothesis.

On analysing the level of debt of the companies in the various groups, can be observed that the groups with the highest leverage ratio were groups D and F, followed by groups G and A, in that order. These are followed by groups B and C, and finally group E, which had the lowest level of debt.

Table 4. Groups ordered from low to high debt requirement according to the hypothesis (1999-2007)

	From low to high debt volume according to hypothesis						
Hypothesis 1	Group F	Group G	Group C	Group D	Group E	Group B	Group A
Hypothesis 2	Groups A and B		Groups C and E		Group D	Group F	Group G
Hypothesis 3	Group C	Groups F and A		Group D	Group B	Groups E and G	
Hypothesis 4	Groups B and D		Group E	Group G	Group F	Groups A and C	

Based on the data obtained, Table 5 compares the level of debt required to fulfil each hypothesis with the level of corporate debt observed in the companies in each group. To that end, it is used pseudolinguistic labels where $(+++)$ is the situation with the highest level of debt and $(---)$ is the situation with the lowest level of debt. The interval between the maximum and minimum level of debt assumed following each hypothesis has been split in six ranges (from + + + to – – – in a linear decreasing order). The groups have been labelled according to the position taken in the interval. Finally, the pseudolinguistic labels for each hypothesis have been compared with the ones corresponding with the real debt level.

Table 5. Level of debt that emerges from each hypothesis and observed level of debt (1999-2007)

	Group A	**Group B**	**Group C**	**Group D**	**Group E**	**Group F**	**Group G**
Hypothesis 1	+ + +	+ +	−	+	+ +	− − −	− −
Hypothesis 2	− − −	− − −	−	+ +	−	+ +	+ + +
Hypothesis 3	− −	+ +	− − −	+	+ + +	− −	+ + +
Hypothesis 4	+ + +	− − −	+ + +	− − −	− −	+ +	+
Leverage ratio	+ +	− −	− −	+ + +	− − −	+ + +	+ +

After analysing the fulfilment of the various hypotheses in the different groups, the overall fulfilment of the hypotheses will be analysed. We consider that a hypothesis is fulfilled when the prediction matches the leverage ratio or is one degree above or below it, with the sign unchanged according to Table 5.

In this period, the only two hypotheses indicative of the level of debt are hypotheses 2 and 4, which refer to growth and the non-debt tax shield respectively. By contrast, hypotheses 1 and 3 are only met in two of the seven groups analysed, groups A and C in hypothesis 1 and groups C and G in hypothesis 3. Hypothesis 1, which refers to profitability, is fulfilled in the groups containing the smallest companies. Meanwhile, hypothesis 3, concerning risk, is not only not fulfilled in five of the groups but there is also a completely opposite relationship in 4 of them, i.e. the riskier companies present larger volume. This is consistent with the fact that most of the companies analysed obtain their debt from the banking sector and the monitoring of risk in their operations was relaxed in the pre-crisis period.

3.2. Post–crisis period (2008-2013)

Following the same procedure as in the pre-crisis period, Include Figure 2 shows the map obtained for the period 2008-2013. The interpretation of the eight groups based on the location of the companies on the map is as follows:

Group A. This group consists of the smallest companies (with groups B and C) in the sample. Companies in this group are those with the lowest levels of profitability and growth in the sample. With a tax shield that is below average and with the highest risk, they are also the oldest companies.

Group B. With groups A and C, the companies in this group are the smallest in the sample. They have below average tax shield and profitability, have low growth and high risk.

Group C. This group consists of the smallest and youngest companies. They have growth rates and a tax shield that are below average, around average profitability and risk that is above average.

Group D. The companies in this group are in the top half of the sample in terms of size and age. Their profitability and risk are below average, their growth rates are average and they have the highest depreciation ratio, which leads to increase internal financing from the tax shield.

Group E. These are medium-sized companies with around average profitability. These companies have the highest growth rate of all those in the sample. They have the second highest depreciation ratio, average age and average risk.

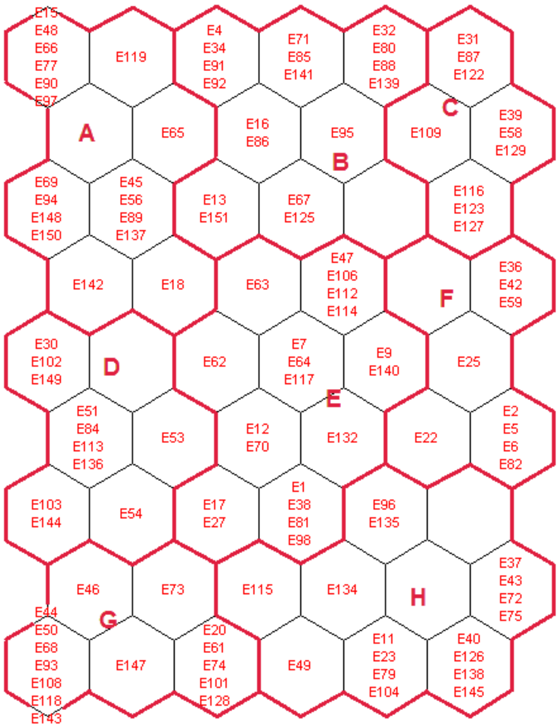

Figure 2

Group F. These are medium-sized companies, with the second highest profitability levels, average to high growth, the lowest tax shield, which are relatively young and have medium risk.

Group G. With group H, this group comprises the largest companies, with above average profitability and average to high growth. The depreciation ratio is also average to high, they are very young and have low risk.

Group H. These are the largest companies in the sample, with the highest profitability, above average growth and an average tax shield and age. Finally, this is the group with the lowest risk companies.

Table 6 shows the different groups ordered from low to high borrowing requirements as reflected in each hypothesis considered.

Table 6. Groups ordered from low to high debt requirement according to the hypothesis (2008-2013)

	From low to high debt volume according to hypothesis							
Hypothesis 1	Group H	Group F	Group G	Group E	Group C	Group B	Group D	Group A
Hypothesis 2	Group A	Groups B and C		Group D	Group F	Group G	Group H	Group E
Hypothesis 3	Group A	Group B	Group C	Group E	Group F	Group D	Group G	Group H

Hypothesis 4	Group D	Group E	Group G	Group H	Groups A and B	Group C	Group F

The groups are ordered from high to low level of debt as follows: G, A, E, F, C, D, H and finally B.

Based on the data obtained, Table 7 compares the level of debt that would be required to fulfil each hypothesis with the debt level observed in the companies in each group, and to that end once again it is used pseudolinguistic labels, with $(+++)$ being the situation with the highest level of debt and $(---)$ the situation with the lowest level of debt.

Table 7. Level of debt that emerges from each hypothesis and observed level of debt (2008-2013)

	Group A	Group B	Group C	Group D	Group E	Group F	Group G	Group H
Hypothesis 1	+ + +	+	+	+ +	−	− −	− −	− − −
Hypothesis 2	− − −	− −	−	+	+ + +	+ +	+ +	+ +
Hypothesis 3	− − −	− −	−	+	−	+	+ +	+ + +
Hypothesis 4	+	+	+ +	− − −	− −	+ + +	−	−
Leverage ratio	+ +	− − −	+	−	+ +	+	+ + +	− −

As with the analysis of the period before the crisis, after analysing the fulfilment of the various hypotheses in the different groups (Table 7), the fulfilment of all the hypotheses are analysed. The criteria for considering whether a hypothesis is fulfilled is the same as the one applied for the 1999-2007 period.

When analysing the post-crisis situation, it is apparent that none of the hypotheses are fulfilled in more than half of the groups. In any case, hypotheses 1 (profitability) and 3 (risk) are fulfilled in more groups than in the pre-crisis period. The hypothesis that is fulfilled to the greatest extent is the one referring to growth, but in this case it is not as determinant as in the pre-crisis period.

Although there is no previous studies on this matter applying artificial neural networks, our results are in line with those obtained by other authors who has applied "classical" methodologies. Myers (2003) states that with the suitable sample and context, any of the theories on capital structure could be validated. As Frank & Goyal (2007) expose, there are several papers that reject or accept both Pecking Order and Trade-off theories. Anyway, none of the actual theories satisfies all the stylized facts on capital structure.

4. CONCLUSIONS

The aim of this study was to ascertain whether Pecking Order Theory was a valid theory to explain the capital structure of Spanish chemical companies. To that end, it is applied a different methodology to the most frequently used methods, i.e., Kohonen self-organizing maps. This type of artificial neural network enabled us to address the problem without establishing prior relationships between the variables used.

An initial descriptive analysis of companies showed that in the post-crisis period, most of the companies' performance indicators worsened: the size of the companies, their profitability and growth rates all declined. The only variable that improved was risk, which had lower levels than in the period before the crisis. This is because of the measure of risk used (natural logarithm of assets) since it links risk with company's size. As in the post-crisis period the average company's size has increased due to the M&A process, the risk has therefore declined.

After grouping companies by SOM it is possible to compare the performance of the various hypotheses.

For the pre-crisis period, it is found that no group fulfilled all the hypotheses individually. Nevertheless, analysing the overall hypothesis, we take into account the relationship among these hypothesis. For example, a company with a high profitability could faced a high debt (rejecting hypothesis 1) due to a very high growth rate but it validates the essence of the theory. We have studied each group on the output map keeping in mind these relationships. Groups A, B, C, D and G can explain their volume of debt by Pecking Order Theory, while it would be difficult to justify for the rest of groups. The hypothesis that is fulfilled the least is the one referring to risk. This could be explained considering that most of the companies sampled are SMEs, the banking sector is the main provider of their debt, and the banks relaxed their requirements in terms of risk during the period before the crisis.

It is also found no group that fulfilled all the hypotheses in the post-crisis period. In general, the level of fulfilment for the hypotheses remained constant or declined, except for hypothesis 3. Risk has assumed a greater weight in the post-crisis period, without being determinant. According to the results of this study, the level of debt of the companies in groups C, D, F and H could be explained by Pecking Order Theory, while it is unclear for the other groups.

In order to answer the objectives of this paper, it can be asserted that Spanish Chemical companies' capital structure has been lightly disrupted by the crisis. Basically, in the post-crisis period, risk has become a more relevant variable on the capital structure of these companies. Moreover, the assumptions of Pecking Order Theory are only partially fulfilled throughout the study's timeframe and the typology of firms that fulfilled have changed from the pre-crisis to the post-crisis period.

REFERENCES

Adhikari, R., & Agrawal, R. K. (2014). A combination of artificial neural network and random walk models for financial time series forecasting. *Neural Computing and Applications*, *24*, 1441–1449. https://doi.org/10.1007/s00521-013-1386-y

Azoff, E. M. (1994). Neural Network Time Series Forecasting of Financial Markets.

Back, B., Sere, K., & Vanharanta, H. (1998). Analyzing financial performance with self-organizing maps. In *Neural Networks Proceedings* (Vol. 1, pp. 266–270).

Banerjee, S., Heshmati, A., & Wihlborg, C. (2004). The dynamics of capital structure. In Michele Bagella, L. Becchetti, I. Hasan, & W. C. Hunter (Eds.), *Research in Banking and Finance* (Vol. 4, pp. 275–297). JAI Press Inc.

Barr, D. S., & Mani, G. (1994). Using neural nets to manage investments. *Ai Expert*, *9*(2), 16–21.

Baxter, N. D. (1967). Leverage, Risk of Ruin and the Cost of Capital. *The Journal of Finance*, *22*(3), 395–403. https://doi.org/10.1111/j.1540-6261.1967.tb02975.x

Bell, T. B. (1997). Neural Nets or the Logit Model? A Comparison of Each Model's Ability to Predict Commercial Bank Failures. *Intelligent Systems in Accounting, Finance and Management*, *6*(January), 249–264.

Bergerson, K., & Wunsch, D. C. (1991). A commodity trading model based on a neural network-expert system hybrid. In *IJCNN-91-Seattle International Joint Conference on Neural Networks* (Vol. i, pp. 289–293). IEEE. https://doi.org/10.1109/IJCNN.1991.155192

Bevan, A. A., & Danbolt, J. (2002). Capital structure and its determinants in the UK – a decompositional analysis. *Applied Financial Economics*, *12*(3), 159–170. https://doi.org/10.1080/09603100110090073

Bradley, M., Jarrell, G. A., & Kim, E. H. (1984). On the Existence of an Optimal Capital Structure: Theory and Evidence. *The Journal of Finance*, *39*(3), 857–878. https://doi.org/10.1111/j.1540-6261.1984.tb03680.x

Cámara-Turull, X., Borràs Balsells, F. X., Sorrosal Forradellas, M. T., & Fernández Izquierdo, M. Á. (2010). Validating the pecking order theory in the Spanish Chemical Industry. In A. M. Gil-Lafuente & J. M. Merigó (Eds.), *Computational Intelligence in Business and Economics* (Vol. 3, pp. 221–228). World Scientific.

Cámara-Turull, X., Borràs Balsells, F. X., Sorrosal Forradellas, M. T., & Fernández Izquierdo, M. Á. (2012). Capital structure in the Spanish Chemical Industry. How does the financial crisis affect? In *Methods for Decision Making in an Uncertain Environment* (Vol. 6, pp. 356–363). World Scientific.

Chen, M.-Y. (2012). Visualization and dynamic evaluation model of corporate financial structure with self-organizing map and support vector regression. *Applied Soft Computing*, *12*(8), 2274–2288. https://doi.org/10.1016/j.asoc.2012.03.046

Chen, N., Ribeiro, B., Vieira, A., & Chen, A. (2013). Clustering and visualization of bankruptcy trajectory using self-organizing map. *Expert Systems with Applications*, *40*(1), 385–393. https://doi.org/10.1016/j.eswa.2012.07.047

Desai, V. S., Crook, J. N., & Overstreet, G. A. (1996). A comparison of neural networks and linear scoring models in the credit union environment. *European Journal of Operational Research*, *95*(1), 24–37. https://doi.org/10.1016/0377-2217(95)00246-4

du Jardin, P. (2010). Predicting bankruptcy using neural networks and other classification methods: The influence of variable selection techniques on model accuracy. *Neurocomputing*, *73*(10–12), 2047–2060. https://doi.org/10.1016/j.neucom.2009.11.034

du Jardin, P. (2015). Bankruptcy prediction using terminal failure processes. *European Journal of Operational Research*, *242*(1), 286–303. https://doi.org/10.1016/j.ejor.2014.09.059

du Jardin, P., & Séverin, É. (2011). Predicting corporate bankruptcy using a self-organizing map: An empirical study to improve the forecasting horizon of a financial failure model. *Decision Support Systems*, *51*(3), 701–711. https://doi.org/10.1016/j.dss.2011.04.001

du Jardin, P., & Séverin, É. (2012). Forecasting financial failure using a Kohonen map: A comparative study to improve model stability over time. *European Journal of Operational Research*, *221*(2), 378–396. https://doi.org/10.1016/j.ejor.2012.04.006

Dutta, S., & Shekhar, S. (1988). Bond Rating: A Non-Conservative Application of Neural Networks. In *Proceedings of the IEEE International Conference on Neural Networks* (p. II443-II450).

Eklund, T., Back, B., Vanharanta, H., & Visa, A. (2003). Using the self-organizing map as a visualization tool in financial benchmarking. *Information Visualization*, *2*(3), 171–181. https://doi.org/10.1057/palgrave.ivs.9500048

Enke, D., & Thawornwong, S. (2005). The use of data mining and neural networks for forecasting stock market returns. *Expert Systems with Applications*, *29*(4), 927–940. https://doi.org/10.1016/j.eswa.2005.06.024

Fama, E. F. (1978). The Effects of a Firm's Investment and Financing on the Welfare of its Security Holders. *American Economic Review*, *68*(3), 272–284. https://doi.org/10.2307/1805260

Fama, E. F., & French, K. R. (2002). Testing Trade-Off and Pecking Order Predictions about Dividends and Debt. *The Review of Financial Studies*, *15*(1), 1–33. https://doi.org/10.1093/rfs/15.1.1

Fletcher, D., & Goss, E. (1993). Forecasting with neural networks. *Information & Management*, *24*(3), 159–167. https://doi.org/10.1016/0378-7206(93)90064-Z

Frank, M. Z., & Goyal, V. K. (2007). Trade-Off and Pecking Order Theories of Debt. *Handbook of Empirical Corporate Finance*, *1*, 135–202. https://doi.org/10.1016/B978-0-444-53265-7.50004-4

Glorfeld, L. W., & Hardgrave, B. C. (1996). An improved method for developing neural networks: The case of evaluating commercial loan creditworthiness. *Computers & Operations Research*, *23*(10), 933–944. https://doi.org/10.1016/0305-0548(96)00009-3

Graham, J. R., & Harvey, C. R. (2001). The theory and practice of corporate finance: evidence from the field. *Journal of Financial Economics*, *60*(2–3), 187–243. https://doi.org/10.1016/S0304-405X(01)00044-7

Grudnitski, G., & Osburn, L. (1993). Forecasting S&P and gold futures prices: An application of neural networks. *Journal of Futures Markets*, *13*(6), 631–643. https://doi.org/10.1002/fut.3990130605

Hamid, S. A., & Iqbal, Z. (2004). Using neural networks for forecasting volatility of S&P 500 Index futures prices. *Journal of Business Research*, *57*(10), 1116–1125. https://doi.org/10.1016/S0148-2963(03)00043-2

Harris, M., & Raviv, A. (1991). The Theory of Capital Structure. *Journal of Finance*, *46*(1), 297–355. https://doi.org/10.2307/2328697

Hawley, D. D., Johnson, J. D., & Raina, D. (1990). Artificial Neural Systems: A New Tool for Financial Decision-Making. *Financial Analysts Journal*, *46*(6), 63–72. https://doi.org/10.2469/faj.v46.n6.63

Hoptroff, R. G. (1993). The principles and practice of time series forecasting and business modelling using neural nets. *Neural Computing & Applications*, *1*(1), 59–66. https://doi.org/10.1007/BF01411375

Hornik, K., Stinchcombe, M., & White, H. (1989). Multilayer feedforward networks are universal approximators. *Neural Networks*, *2*(5), 359–366. https://doi.org/10.1016/0893-6080(89)90020-8

Huang, Z., Chen, H., Hsu, C.-J., Chen, W.-H., & Wu, S. (2004). Credit rating analysis with support vector machines and neural networks: a market comparative study. *Decision Support Systems*, *37*(4), 543–558. https://doi.org/10.1016/S0167-9236(03)00086-1

Jain, B. A., & Nag, B. N. (1995). Artificial Neural Network Models for Pricing Initial Public Offerings. *Decision Sciences*, *26*(3), 283–302. https://doi.org/10.1111/j.1540-5915.1995.tb01430.x

Jensen, H. L. (1992). Using Neural Networks for Credit Scoring. *Managerial Finance*, *18*(6), 15–26. https://doi.org/10.1108/eb013696

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, *3*(4), 305–360. https://doi.org/10.1016/0304-405X(76)90026-X

Kamijo, K., & Tanigawa, T. (1990). Stock price pattern recognition-a recurrent neural network approach. In *1990 IJCNN International Joint Conference on Neural Networks* (pp. 215–221 vol.1). IEEE. https://doi.org/10.1109/IJCNN.1990.137572

Kamruzzaman, J. (2006). *Artificial Neural Networks in Finance and Manufacturing*. IGI Global.

Kim, E. H. (1978). A Mean-Variance Theory of Optimal Capital Structure and Corporate Debt Capacity. *The Journal of Finance*, *33*(1), 45–63. https://doi.org/10.1111/j.1540-6261.1978.tb03388.x

Kim, J. W., Weistroffer, H. R., & Redmond, R. T. (1993). Expert systems for bond rating: a comparative analysis of statistical, rule-based and neural network systems. *Expert Systems*, *10*(3), 167–172. https://doi.org/10.1111/j.1468-0394.1993.tb00093.x

Kimoto, T., Asakawa, K., Yoda, M., & Takeoka, M. (1990). Stock market prediction system with modular neural networks. In *1990 IJCNN International Joint Conference on Neural Networks* (pp. 1–6 vol.1). IEEE. https://doi.org/10.1109/IJCNN.1990.137535

Kiviluoto, K. (1998). Predicting bankruptcies with the self-organizing map. *Neurocomputing*, *21*(1–3), 191–201. https://doi.org/10.1016/S0925-2312(98)00038-1

Kohonen, T. K. (1982). Self-organized formation of topologically correct feature maps. *Biological Cybernetics*, *43*(1), 59–69. https://doi.org/10.1007/BF00337288

Kohonen, T. K. (1988). An introduction to neural computing. *Neural Networks*, *1*(1), 3–16. https://doi.org/10.1016/0893-6080(88)90020-2

Kraus, A., & Litzenberger, R. H. (1973). A state-preference model of optimal financial leverage. *The Journal of Finance*, *28*(4), 911–922. https://doi.org/10.1111/j.1540-6261.1973.tb01415.x

Kryzanowski, L., Galler, M., & Wright, D. W. (1993). Using artificial neural networks to pick stocks. *Financial Analysts Journal*, *49*(4), 21–27.

Länsiluoto, A., Eklund, T., Back, B., Vanharanta, H., & Visa, A. (2004). Industry-specific cycles and companies' financial performance comparison using self-organizing maps. *Benchmarking: An International Journal*, *11*(3), 267–286. https://doi.org/10.1108/14635770410538754

Lee, K. C., Han, I., & Kwon, Y. (1996). Hybrid neural network models for bankruptcy predictions. *Decision Support Systems*, *18*(1), 63–72. https://doi.org/10.1016/0167-9236(96)00018-8

Lee, S., & Choi, W. S. (2013). A multi-industry bankruptcy prediction model using back-propagation neural network and multivariate discriminant analysis. *Expert Systems with Applications*, *40*(8), 2941–2946. https://doi.org/10.1016/j.eswa.2012.12.009

Leland, H. E. (1998). Agency costs, risk management, and capital structure. *The Journal of Finance*, *53*(4), 1213–1243.

Leland, H. E., & Pyle, D. H. (1977). Informational Asymmetries, Financial Structure, and Financial Intermediation. *The Journal of Finance*, *33*(2), 371–387.

López Iturriaga, F. J., & Sanz, I. P. (2015). Bankruptcy visualization and prediction using neural networks: A study of U.S. commercial banks. *Expert Systems with Applications*, *42*(6), 2857–2869. https://doi.org/10.1016/j.eswa.2014.11.025

Magnusson, C., Arppe, A., Eklund, T., Back, B., Vanharanta, H., & Visa, A. (2005). The language of quarterly reports as an indicator of change in the company's financial status. *Information and Management*, *42*(4), 561–574. https://doi.org/10.1016/j.im.2004.02.008

Modigliani, F., & Miller, M. H. (1958). The Cost of Capital, Corporation Finance and the Theory of Investment. *The American Economic Review*, *48*(3), 261–297.

Modigliani, F., & Miller, M. H. (1963). Corporate Income Taxes and the Cost of Capital : A Correction. *The American Economic Review*, *53*(3), 433–443.

Myers, S. C. (1984). The Capital Structure Puzzle. *The Journal of Finance*, *39*, 575–592.

Myers, S. C. (2003). *Financing of corporations*. *Handbook of the Economics of Finance* (Vol. 1). Elsevier. https://doi.org/10.1016/S1574-0102(03)01008-2

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, *13*, 187–221. https://doi.org/10.1016/0304-405X(84)90023-0

Odom, M. D., & Sharda, R. (1990). A neural network model for bankruptcy prediction. In *1990 IJCNN International Joint Conference on Neural Networks* (pp. 163–168 vol.2). IEEE. https://doi.org/10.1109/IJCNN.1990.137710

Rahimian, E., Singh, S., Thammachote, T., & Virmani, R. (1993). Bankruptcy prediction by neural network. In R. R. Trippi & E. Turban (Eds.), *Neural networks in finance and investing* (pp. 159–176). Chicago: Probus Publ.

Rajan, R. G., & Zingales, L. (1995). What Do We Know About Capital Structure - Some Evidence From International Data. *Journal of Finance*, *50*(5), 1421–1460. https://doi.org/10.2307/2329322

Rather, A. M., Agarwal, A., & Sastry, V. N. (2015). Recurrent neural network and a hybrid model for prediction of stock returns. *Expert Systems with Applications*, *42*(6), 3234–3241. https://doi.org/10.1016/j.eswa.2014.12.003

Robichek, A. A., & Myers, S. C. (1965). *Optimal financing decisions*. Prentice Hall.

Ross, S. A. (1977). The Determination of Financial Structure: The Incentive Signalling Approach. *Bell Journal of Economics*, *8*(1), 23–40.

Sánchez-Lasheras, F., de Andrés, J., Lorca, P., & de Cos Juez, F. J. (2012). A hybrid device for the solution of sampling bias problems in the forecasting of firms' bankruptcy. *Expert Systems with Applications*, *39*(8), 7512–7523. https://doi.org/10.1016/j.eswa.2012.01.135

Serrano-Cinca, C. (1996). Self organizing neural networks for financial diagnosis. *Decision Support Systems*, *17*(3), 227–238. https://doi.org/10.1016/0167-9236(95)00033-X

Séverin, É. (2010). Self organizing maps in corporate finance: Quantitative and qualitative analysis of debt and leasing. *Neurocomputing*, *73*(10–12), 2061–2067. https://doi.org/10.1016/j.neucom.2009.12.024

Sharda, R., & Patil, R. B. (1992). Connectionist approach to time series prediction: an empirical test. *Journal of Intelligent Manufacturing*, *3*, 317–323. Retrieved from http://link.springer.com/article/10.1007/BF01577272

Smith, K. A., & Gupta, J. N. D. (2000). Neural networks in business: techniques and applications for the operations researcher. *Computers & Operations Research*, *27*(11–12), 1023–1044. https://doi.org/10.1016/S0305-0548(99)00141-0

Stiglitz, J. E. (1969). A Re-Examination of the Modigliani-Miller Theorem. *The American Economic Review*, *59*(5), 784–793.

Swales, G. S., & Yoon, Y. (1992). Applying Artificial Neural Networks to Investment Analysis. *Financial Analysts Journal*, *48*(5), 78–80. https://doi.org/10.2469/faj.v48.n5.78

Swicegood, P., & Clark, J. A. (2001). Off-site monitoring systems for predicting bank underperformance: a comparison of neural networks, discriminant analysis, and professional human judgment. *International Journal of Intelligent Systems in Accounting, Finance & Management*, *10*(3), 169–186. https://doi.org/10.1002/isaf.201

Tam, K. Y. (1991). Neural network models and the prediction of bank bankruptcy. *Omega*, *19*(5), 429–445. https://doi.org/10.1016/0305-0483(91)90060-7

Tam, K. Y., & Kiang, M. Y. (1992). Managerial Applications of Neural Networks: The Case of Bank Failure Predictions. *Management Science*, *38*(7), 926–947. https://doi.org/10.1287/mnsc.38.7.926

Titman, S., & Wessels, R. (1988). The Determinants of Capital Structure Choice. *Journal of Finance*, *43*(1), 1–19.

Tsukuda, J., & Baba, S. (1994). Predicting japanese corporate bankruptcy in terms of financial data using neural network. *Computers & Industrial Engineering*, *27*(1–4), 445–448. https://doi.org/10.1016/0360-8352(94)90330-1

Vendrell Vilanova, A. (2007). *La dinámica de la estructura de capital. Evidencia para la empresa industrial Española*. *Tesis doctoral*.

Wang, J.-Z., Wang, J.-J., Zhang, Z.-G., & Guo, S.-P. (2011). Forecasting stock indices with back propagation neural network. *Expert Systems with Applications*, *38*(11), 14346–14355. https://doi.org/10.1016/j.eswa.2011.04.222

Wang, J., & Wang, J. (2015). Forecasting stock market indexes using principle component analysis and stochastic time effective neural networks. *Neurocomputing*, *156*, 68–78. https://doi.org/10.1016/j.neucom.2014.12.084

White, H. (1988). Economic prediction using neural networks: the case of IBM daily stock returns. In *IEEE International Conference on Neural Networks* (pp. 451–458 vol.2). IEEE. https://doi.org/10.1109/ICNN.1988.23959

Wong, B. K., & Selvi, Y. (1998). Neural network applications in finance: A review and analysis of literature (1990–1996). *Information & Management*, *34*(3), 129–139. https://doi.org/10.1016/S0378-7206(98)00050-0

Yu, Q., Miche, Y., Séverin, É., & Lendasse, A. (2014). Bankruptcy prediction using Extreme Learning Machine and financial expertise. *Neurocomputing*, *128*, 296–302. https://doi.org/10.1016/j.neucom.2013.01.063

Zhou, L., Lai, K. K., & Yen, J. (2012). Bankruptcy prediction using SVM models with a new approach to combine features selection and parameter optimisation. *International Journal of Systems Science*, *45*(3), 241–253. https://doi.org/10.1080/00207721.2012.720293