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Focused vs unfocused models for bankruptcy prediction: Empirical evidence for Spain

Modelos centrados vs descentrados para la predicción de quiebra: evidencia empírica para España

Gonzalo Laguillo, Agustín del Castillo, Manuel Ángel Fernández*, Rafael Becerra

Universidad de Málaga, España

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Abstract

Using financial information from Spanish companies belonging to different economic sectors, this study has developed focused and unfocused models for bankruptcy prediction. The comparison of both types of models has allowed us to determine the superiority of unfocused models, which in most cases show a great predictive capacity and reduce the elaboration cost of numerous focused models. This study also provides insight into the variables that explain bankruptcy in different economic sectors and helps decision making on the use of a specific model of bankruptcy prediction.

JEL Codes: C53; G33
Keywords: bankruptcy prediction; financial ratios; logistic regression; economic sectors

Resumen

Usando información financiera de empresas españolas pertenecientes a distintos sectores económicos, este estudio ha desarrollado modelos centrados y descentrados para la predicción de quiebra. La comparación de ambos tipos de modelos nos ha permitido determinar la superioridad de los modelos

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* Corresponding author.
E-mail address: mangel@uma.es (M. Á. Fernández)
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descentrados, que en la mayor parte de los casos muestran una gran capacidad de predicción y un fuerte ahorro de costes de elaboración frente al desarrollo de numerosos modelos centrados. Este estudio también aporta conocimiento acerca de las variables que explican la quiebra en los diferentes sectores económicos y ayuda a la toma de decisiones sobre la utilización de un determinado modelo de predicción de quiebra.

Códigos JEL: C53; G33
Palabras clave: Predicción de quiebra; ratios financieros; regresión logística; sectores económicos.

Introduction

The prediction of corporate bankruptcy has received special attention in financial research over the last five decades, with numerous studies focusing on determining the factors behind it. This monumental research task has generated a wide variety of models, supported in turn by very diverse methodologies. One of the paths initially taken by the literature was the development of models that had been built from a sample of companies belonging to several sectors and which, therefore, could be considered as off-center models (Casey and Bartczak, 1985; Odom and Sharda, 1990; Altman *et al*., 1994; Wilson and Sharda, 1994). The development of these off-center models has been important throughout time, predominantly those built using samples of medium and large companies from different sectors (Charalambous, Chatitou and Kaourou, 2000; Chen, Härdle and Moros, 2011; Sangjae and Wu, 2013). The literature on bankruptcy prediction also highlights the development of models based on samples of companies belonging to specific sectors of activity, which have been called centered models. The most popular of the centered models is the one used for credit institutions (Santomero and Vinso, 1977; Martin-del-Brio and Serrano-Cinca, 1995; Alam *et al*., 2000). Another of the most popular centered models has been used for industrial companies (Altman, 1968; Diamond, 1976; Appetiti, 1984; Zavgren, 1985; Grover, 2003). Recently, models have also been developed focusing on companies from other sectors, such as Internet companies (Wang, 2004), hospitality companies (Park and Hancer, 2012; Fernández, Cisneros and Callejón, 2016), agricultural companies (Mateos-Ronco *et al*., 2011), construction companies (Gill de Albornoz and Giner, 2013), and commercial and service companies (Keener, 2013).

A detailed analysis of the literature on bankruptcy prediction allows us to observe the existence of a definite pattern regarding the building of off-center models as opposed to centered models, with the former being much more numerous than the latter. However, it is not possible to draw a definite conclusion on the superiority of one type of model over another (Bellovary, Giacomino and Akers, 2007). The absence of a practical conclusion on the superiority of a centered model over an off-center model may be due to the fact that one type of model and another could not be compared homogeneously due to the disparity of methodologies, approaches, available databases, time periods and countries, among other issues. Therefore, the existence of this gap in the literature, which does not make it possible to elucidate the superiority of off-center models over centered models, is an important research issue that this work seeks to solve. To this end, this work has selected different samples of Spanish companies that were and were not in bankruptcy in the 2010-2015 period. Among these samples, some are integrated by companies that belong to different economic sectors and have been used to build off-center models. Other samples contain only companies from a certain sector of activity and have been reserved for the building of centered models. All the models have been built with the same methodology, specifically, Logistic Regression. Having both off-center and centered models developed from homogeneous samples, referring to the same time period and country, and built with the same methodology, has allowed obtaining robust conclusions on the design of bankruptcy prediction models in different economic sectors, and on the efficiency of off-center models, which in most cases imply a great saving of costs compared to the elaboration and development of numerous centered models.

Our work consists of the following parts. Following this introduction, section 2 offers a taxonomy of bankruptcy prediction studies. Section 3 presents the methods of analysis used in this research. Section 4 establishes the process of obtaining and treating the samples, the variables used, and the criteria considered for their selection. Section 5 presents the results of the empirical research. Finally, the main conclusions obtained are detailed.

Review of the literature and research hypotheses

The analysis of corporate bankruptcy has received considerate attention in financial research during the last five decades. Numerous research studies have been carried out focused on determining the factors that cause corporate bankruptcy, with a special focus on how to predict it before it happens. The pioneering authors of empirical studies on bankruptcy prediction were Beaver (1966) and Altman (1968), applying methods of Discrimination Analysis and Multi-discrimination analysis, respectively. From these initial studies, the main concern in the literature on bankruptcy prediction was not only to determine which factors to include in the models, but to assess which method was the most effective in making predictions. According to this criterion, much of the work has been carried out around the so-called pure individual classifiers. These include statistical classifiers, such as the Multi-discriminant analysis and Logistic Regression models, which are based on statistical theory (Ohlson, 1980; Zavgren, 1985; Tseng and Hu, 2010; Piñeiro, de Llano and Rodríguez, 2013). Since the 1990s, other methods such as artificial intelligence, based on Neural Networks (Tam, 1991; Tam and Kiang, 1992; Wu *et al*., 2008; Callejón *et al*., 2013), Vector Support Machines (Shin *et al*., 2005; Min and Lee, 2005), Genetic Algorithms (Rafiei et al., 2011; Etemandi et al., 2009), Decision Trees (Chen, 2011; Gepp *et al*., 2010; Li *et al*., 2010), and the Combination of Classifiers (Ravisankar and Ravi, 2010; Li *et al*., 2013; Sun *et al*., 2016) have also been used.

On the other hand, and with reference to the variables considered in the previous literature as bankruptcy predictors, it can be deduced that the most common was the “Profit after Taxes/Total Assets” ratio, and that the second most frequently used factor was the “Current assets/Current liabilities” ratio. In addition, the number of variables considered in the construction of the models has fluctuated between 1 and 57 (Bellovary, Giacomino and Akers, 2007).

Another term utilized in the literature is global bankruptcy prediction models, which refers to those that have been developed for companies across a country or region. Korol (2013) incorporates this approach and makes a comparison between two regions, Platt and Platt (2008) for three regions of the world, and Alaminos, del Castillo and Altman *et al*. (2016) at the global level using a Logistic Regression model. Similarly, Altman et al. (2017) apply the Z-score for a wide worldwide base of bankrupt companies and Jabeur (2017) uses Logistic Regression of partial least squares from a diverse base of French companies.

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In addition to the abovementioned works, which have largely developed off-center models, the literature also highlights those that have been constructed from samples of companies in specific economic sectors, and which are therefore called centered models. In the Agriculture sector, the work of D'Antoni, Mishra and Chintawar (2009) and of Mateos-Ronco et al. (2011) stands out. D'Antoni, Mishra and Chintawar (2009) used a sample of agricultural companies and concluded that characteristics such as size, type of ownership and age of the entrepreneur were decisive for the probability of bankruptcy. In the Industrial sector, Callejón et al. (2013) developed a model that achieves an accuracy of 92%, revealing that bankruptcy is negatively related to the ability to repay debt through the funds generated and the profitability of the company. Bartoloni and Baussola (2014) provided a centered model using methods of Multi-Discrimination Analysis and Enveloping Data Analysis and concluded on the superiority of the latter with regard to predictability. For the Construction and Real Estate sectors, Gill de Albornoz and Giner (2013) compared the accuracy of the centered models to that of the off-center models, proving the superiority of the former to the latter. Similarly, with companies in the Construction sector, Spicka (2013) built a centered model that showed that the inadequate relation between debt/profitability and the generation of insufficient reserves are potential causes of bankruptcy. With companies from the Commerce and Services sectors, Keener (2013) developed a centered model that demonstrated that bankrupt companies had fewer employees, a lower cash to current liabilities ratio and higher debt to equity ratios, and Fallahpour, Lakvan and Zadeh (2017) tested several Genetic Algorithms, finding that the profitability variables as the most significant. Finally, and with companies in the Hospitality sector, Park and Hancer (2012) built a centered model with which they detected that the variables Maneuvering Fund/Total Assets, Total Liabilities/Net Equity, and Total Liability/Total Assets were the best predictors of bankruptcy. For their part, Fernández, Cisneros and Callejón (2016) showed that by using information close to the time of bankruptcy (one or two years earlier), the most relevant variable to predict bankruptcy in hotels is that which relates EBITDA to current liabilities, but when using information farther away from the time of bankruptcy (three years earlier), the return on assets is the most significant variable.

Although the development of bankruptcy prediction models has been important, it is not possible to find conclusions on the superiority of off-center or centered models in the existing literature. As indicated earlier, this lack of conclusions comparing both types of models may be due to the fact that it has not been possible to homogeneously compare one type of model and another, given the disparity of methodologies, approaches, available databases, time periods and countries with which the existing models have been built. Consequently, this gap in the literature, which does not allow us to elucidate the superiority of off-center models over centered models, has motivated us to formulate the following research hypotheses:

Hypothesis 1 (H1): The introduction of sectoral qualitative variables in an off-center model improves its capacity to predict bankruptcy.

Hypothesis 2 (H2): An off-center model with sectoral qualitative variables predicts bankruptcy correctly in any economic sector.

The case of acceptance of hypothesis H1 would modify the off-center model, indicating that there are sectoral differences to explain the bankruptcy process of companies, but trying to maintain the maximum degree of similarity between the sectors. For its part, not rejecting hypothesis H2 would allow a single explanation of how companies go bankrupt in different sectors.

Methodology

This work uses Logistic Regression techniques and Model Selection Criteria to contrast the research hypotheses proposed. Logistic Regression is a classification technique in which the dependent variable exclusively considers two categories. Moreover, it departs from less restrictive assumptions than other statistical classification techniques and allows the model to incorporate qualitative variables (Visauta, 2003). The logistic function is limited between 0 and 1, providing the probability that an element is in one of the two established groups. This means that, from a dichotomous event, it predicts the probability that the event will or will not take place. If the probability estimate is greater than 0.5, then the prediction is that it does belong to that group, otherwise, the assumption would be that it belongs to the other group considered.

The model is based on the quotient between the probability of an event occurring and the probability that it will not occur. Thus, the probability of an event occurring, *P(Yi =1/xi)*, will be determined by expression (1).

$$P(Yi=1/xi) = \frac{e^{(\beta_0+\beta_1X_1+\ldots+\beta_kX_k)}}{1+e^{(\beta_0+\beta_1X_1+\ldots+\beta_kX_k)}} = \frac{1}{1+e^{-(\beta_0+\beta_1X_1+\ldots+\beta_kX_k)}} \quad (1)$$

where β_0 is the constant term and $\beta_1,\ldots,\beta_k$ are the coefficients of the variables.

The Odds ratio indicates the number of times the phenomenon is more likely to occur than not and is formulated according to (2).

$$\text{Odds} = \frac{P(Y_i=1)}{1-P(Y_i=1)} = \frac{1/(1+e^{-(\beta_0+\beta_1X_1+\ldots+\beta_kx_k)})}{1/(1+e^{(\beta_0+\beta_1X_1+\ldots+\beta_kX_k)})} =$$

$$= \frac{1+e^{(\beta_0+\beta_1X_1+\ldots+\beta_kX_k)}}{1+e^{-(\beta_0+\beta_1X_1+\ldots+\beta_kX_k)}} = e^{(\beta_0+\beta_1X_1+\ldots+\beta_kX_k)} \quad (2)$$

The estimated coefficients ($\beta_1,\ldots,\beta_k$) represent measures of changes in the Odds ratio. In this sense, a positive coefficient increases the probability of occurrence, whereas a negative value decreases the probability of occurrence of the same (Hair *et al*., 1999). Applying logarithms in (2) gives a linear expression of the model, as it appears in (3), in which the coefficients would be estimated by applying the maximum likelihood method.

$$Y_i^* = \ln\frac{P(Y_i=1)}{1-P(Y_i=1)} = \ln e^{(\beta_0+\beta_1X_1+\ldots+\beta_kX_k)} = \beta_0+\beta_1X_1+\ldots+\beta_kX_k \quad (3)$$

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On the other hand, and in reference to the Model Selection Criteria, this work uses both Akaike (AIC), as well as Schwarz (BIC) and Hannan-Quinn (HQC) in order to make the conclusions obtained very robust. These criteria have been successfully employed in previous research on bankruptcy prediction (for example, Alaminos, del Castillo and Fernández, 2016). AIC is the basic criterion among those based on statistical information (Akaike, 1974). In the general case, it is expressed as it appears in (4).

$$AIC= 2k - 2Ln (L) \quad (4)$$

where k is the number of parameters and L the maximum value of the likelihood function of the estimated model. The basic idea underlying the use of the AIC criterion for model selection is to maximize the logarithm of the expected likelihood function of a given model. Schwarz (1978) suggested that the AIC criterion might not be asymptotically justifiable and presented an alternative information criterion based on a Bayesian (BIC) approach. This criterion penalizes the number of parameters with *Ln (n)* instead of with 2. Thus, the expression of the BIC criterion would be as it appears in (5).

$$BIC = -2Ln (L)+Ln(n)\times k \quad (5)$$

with *k* being the number of parameters, L the maximum value of the likelihood function of the estimated model, and n the number of observations.

On the other hand, HQC can be considered a variant of the BIC criterion, with a penalty for the magnitude of the sample size. Hannan and Quinn (1979) initially suggested this criterion for selecting the order of self-regression, as it appears in expression (6). As for the AIC and BIC criteria, this criterion selects the model that minimizes the value of HQC.

$$HQC = -2Ln (L)+2Ln [Ln(n)] \times k \quad (6)$$

Data and variables

In order to contrast the research hypotheses established in this work, 12 samples of Spanish companies were used, 6 of them using information corresponding to 1 year before the bankruptcy of the companies (t-1) and another 6 with information from 2 years before bankruptcy (t-2). Samples for both t-1 and t-2 have been considered, including companies belonging to five economic sectors (agriculture, industry, construction, commerce and services, and hospitality), and which are used for the construction of off-center models. Samples from companies in a single sector have also been used for the development of centered models. In all samples, the same number of bankrupt and non-bankrupt companies has been considered, following the criteria applied in most bankruptcy prediction studies (Du Jardin, 2015). Within the scope of this work, a company is considered bankrupt if it has the legal status of bankruptcy, according to the considerations made by the Spanish bankruptcy law 22/2003 of July 9th, as well as the following modifications made to it (Royal Decree Law 3/2009 of March 27th on urgent measures in view of the evolution of the economic situation and Law 38/2011 of October 10th). For its part, the identification of companies belonging to each sector of activity has been done in function of the classification carried out by the CNAE-2009 codes, and the financial information of said companies was obtained from the SABI database (Iberian Balance Sheets Analysis System) belonging to Bureau van Dijk (for the financial years 2010-2015). A breakdown of the number of companies in each sample is shown in Table 1. For the construction of the models estimated in this work, 70% of the data for each sample (validation data) has been reserved for the construction of the models, while the remaining 30% of the data has been used to verify the predictive capability of said models (testing data).

Table 1.
Number of companies in the samples

	Estado	*t-1*	t-2
Off-center models	Not bankrupt	1.500	1.500
	Bankrupt	1.500	1.500
Centered models. Agriculture	Not bankrupt	300	300
	Bankrupt	300	300
Centered models. Industry	Not bankrupt	300	300
	Bankrupt	300	300
Centered models. Construction	Not bankrupt	300	300
	Bankrupt	300	300
Centered models. Commerce and Services	Not bankrupt	300	300
	Bankrupt	300	300
Centered models. Hospitality	Not bankrupt	300	300
	Bankrupt	300	300

Of all companies in the samples, financial information has been taken to comprise a set of variables as bankruptcy predictors. All the variables have been selected from the previous literature on centered and off-center models. For the off-center models, those that have been considered in 20 or more bankruptcy prediction works have been selected (Bellovary, Giacomino and Akers, 2007). For the Agriculture centered models, the variables proposed by D'Antoni et al. (2009), Mateos-Ronco *et al*. (2011), Dietrich *et al*. (2005) and Wasilewski and Madra (2008) were used. For the Industry sector models, those previously used by Callejón *et al*. (2013), Bartoloni and Baussola (2014), Zhang *et al*. (2013), Grüenberg and Lukason (2014) and De Andréz *et al*. (2012) were selected. For the Construction sector models, the variables proposed by Spicka (2013), Gill de Albornoz and Giner (2013), Mínguez-Conde (2006), Stroe and Barbuta-Misu (2010) and Treewichayapong *et al*. (2011) were used. For the Commerce and Services sector models, those used in the work of Keener (2003) and He and Kamath (2006) were used. Finally, for the Hospitality sector models, the specific variables were those used in the models by Park and Hancer (2012), Fernández, Cisneros and Callejón (2016), Cho (1994), Gu (2002), Youn and Zheng (2010) and Kim (2011). Additionally, and to be used in the off-center models, other qualitative variables have been incorporated (Agriculture Dummy, Industry Dummy, Construction Dummy, Commerce and Services Dummy, Hospitality Dummy) that take a value of 1 if the company belongs to one of the five economic sectors considered, and a value of 0 otherwise. Along with the previous variables, another dichotomous variable was used as a dependent variable, which takes the value of 1 if the company is identified as bankrupt and a value of 0 otherwise. Table 2 shows the definitions of all the variables used as bankruptcy predictors.

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Table 2.
Definition of the quantitative variables

Code	Definition
	Off-center model variables
VD1	Profit after Taxes/Total Assets
VD2	Current Assets/Current Liabilities
VD3	Operating Funds/Total Assets
VD4	EBIT/Total Assets
VD5	Total Revenue/Total Assets
VD6	Quick Ratio
VD7	Total Debt/Total Assets
VD8	Current Assets/Total Assets
VD9	Profit after Taxes/Net Equity
	Centered model variables, Agriculture
VCA1	Equity/Total Debt
VCA2	EBIT/Financial Expenses
VCA3	EBIT/Total Revenue
	Centered model variables, Industry
VCI1	Operating Income/Total Revenue
VCI2	Sales/Customers
VCI3	(Current Assets-Current Liabilities)/Capital
VCI4	Equity/Non-current Liabilities
VCI5	Financial expenses/Total Revenue
VCI6	Ln (Total Assets)
VCI7	Operating Income/Net Equity
VCI8	Total Revenue/Non-current Assets
	Centered model variables, Construction
VCC1	Financial Expenses/EBIT
VCC2	Operating Income/Total Revenue
VCC3	Equity/Total Debt
	Centered model variables, Commerce and Services
VCCS1	EBITDA/Total Liabilities
VCCS2	EBIT/Financial Expenses
VCCS3	EBIT/Current Liabilities
VCCS4	Sales/Stocks
VCCS5	Sales/Total Assets
	Centered model variables, Hospitality
VCH1	EBITDA/Current Liabilities
VCH2	EBITDA/Total Liabilities
VCH3	Total Financial Debt/EBITDA
VCH4	Total Financial Debt /Capital
VCH5	Credit Sales/Customers
VCH6	Free Cash Flows/Total Debt

Results

Tables 3-8 present the main descriptive statistics of the variables selected for the construction of off-center and centered models for each of the samples. In general, the variables present different average values for companies that are bankrupt compared to those that are not, which makes it possible to confirm that they can be used for the construction of the proposed models.

Table 3.
Descriptive statistics. Off-center models

		VD1	VD2	VD3	VD4	VD5	VD6	VD7	VD8	VD9
	Not bankrupt	0.05	3.37	0.24	0.05	2.14	2.34	0.23	0.60	0.04
t-1		(0.21)	(11.68)	(0.30)	(0.41)	(11.34)	(10.25)	(0.28)	(0.29)	(1.95)
	Bankrupt	-0.25	1.81	0.32	-0.20	1.33	0.74	0.42	0.59	0.30
		(1.00)	(4.67)	(0.44)	(0.72)	(1.89)	(1.22)	(0.47)	(0.31)	(2.39)
	Not bankrupt	0.05	3.39	0.24	0.05	2.14	2.36	0.23	0.60	0.03
t-2		(0.21)	(11.80)	(0.30)	(0.41)	(11.43)	(10.37)	(0.28)	(0.29)	(1.95)
	Bankrupt	-0.10	2.74	0.37	-0.07	1.46	1.63	0.38	0.61	0.07
		(0.50)	(20.69)	(0.38)	(0.44)	(2.76)	(20.27)	(0.86)	(0.31)	(2.58)

Standard deviation in parenthese

Table 4.
Descriptive statistics. Centered models. Agriculture

		VD1	VD2	VD3	VD4	VD5	VD6	VD7	VD8	VD9	VCA1	VCA2	VCA3
	Not bankrupt	0.02	1.55	0.20	0.04	0.93	1.03	0.33	0.45	0.08	2.87	4.99	0.08
t-1		0.03	0.97	0.28	0.04	0.67	0.95	0.21	0.28	0.07	4.56	13.18	0.17
	Bankrupt	-0.03	0.99	0.27	-0.01	0.66	0.46	0.47	0.46	0.16	0.75	-1.14	-0.02
		0.07	0.87	0.28	0.08	0.84	0.42	0.30	0.29	0.57	2.20	17.64	0.29
	Not bankrupt	0.05	3.39	0.24	0.05	2.14	2.36	0.23	0.60	0.03	2.52	2.85	0.08
t-2		(0.21)	(11.80)	(0.30)	(0.41)	(11.43)	(10.37)	(0.28)	(0.29)	(1.95)	(4.31)	(2.24)	(0.17)
	Bankrupt	-0.10	2.74	0.37	-0.07	1.46	1.63	0.38	0.61	0.07	0.96	1.88	0.09
		(0.50)	(20.69)	(0.38)	(0.44)	(2.76)	(20.27)	(0.86)	(0.31)	(2.58)	(1.19)	(2.93)	(0.10)

Standard deviation in parentheses.

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Table 5
Descriptive statistics. Centered models. Industry

		VD1	VD2	VD3	VD4	VD5	VD6	VD7	VD8	VD9	VCI1	VCI2	VCI3	VCI4	VCI5	VCI6	VCI7	VCI8
t-1	Not bankrupt	0.03	1.75	0.26	0.05	1.37	1.14	0.27	0.53	0.10	0.04	14.28	-0.09	27.49	0.01	7.36	0.20	4.75
		(0.05)	(1.40)	(0.21)	(0.06)	(0.75)	(1.20)	(0.19)	(0.22)	(0.15)	0.05)	(29.18)	(2.09)	(82.89)	(0.02)	(1.81)	(0.31)	(5.15)
	Bankrupt	-0.1	1.26	0.47	-0.06	1.32	0.82	0.3	0.57	0.08	-0.12	8.33	0.07	7.49	0.02	6.71	0.35	4.75
		(0.21)	(1.10)	(0.27)	(0.19)	(0.93)	(0.80)	(0.31)	(0.23)	(1.09)	(0.37)	(14.47)	(3.06)	(39.01)	(0.02)	(0.98)	(0.96)	4.80)
t-2	Not bankrupt	0.03	1.72	0.27	0.05	1.30	1.11	0.28	0.54	0.09	0.04	11.8	-0.27	57.63	0.01	7.40	0.14	4.82
		(0.03)	(1.29)	(0.21)	(0.04)	(0.71)	(1.10)	(0.19)	(0.22)	(0.18)	(0.04)	(19.41)	(3.70)	(239.00)	(0.02)	(1.73)	(0.61)	(5.74)
	Bankrupt	-0.03	1.24	0.51	0.02	1.32	0.76	0.23	0.6	-0.92	-0.03	7.41	0.03	5.64	0.03	6.75	-0.49	5.85
		(0.08)	(1.02)	(0.23)	(0.09)	(0.80)	(0.70)	(0.21)	(0.21)	(5.39)	(0.15)	(7.37)	(2.61)	(22.00)	(0.02)	(0.95)	(5.53)	(6.23)

Standard deviation in parentheses.

Table 6
Descriptive statistics. Centered models. Construction

		VD1	VD2	VD3	VD4	VD5	VD6	VD7	VD8	VD9	VCC1	VCC2	VCC3
t-1	Not bankrupt	0.05	4.04	0.33	0.00	0.72	2.27	0.34	0.60	0.24	0.03	0.34	5.11
		(0.10)	(7.74)	(0.30)	(0.43)	(0.89)	(4.44)	(0.29)	(0.31)	(1.12)	(0.71)	(0.80)	(10.31)
	Bankrupt	-0.07	4.20	0.61	-0.04	0.65	0.83	0.55	0.81	0.35	0.14	-0.19	0.36
		(0.22)	(7.69)	(0.32)	(0.21)	(0.77)	(1.60)	(0.30)	(0.22)	(2.05)	(1.19)	(1.26)	(2.77)
t-2	Not bankrupt	0.04	4.28	0.34	-0.01	0.63	2.49	0.34	0.6	0.19	0.09	0.38	4.99
		(0.07)	(8.12)	(0.30)	(0.43)	(0.74)	(5.12)	(0.29)	(0.31)	(0.90)	(1.13)	(0.99)	(10.53)
	Bankrupt	-0.01	3.52	0.62	0.01	0.79	0.77	0.48	0.82	0.08	0.60	-0.15	1.11
		(0.07)	(5.86)	(0.29)	(0.08)	(0.80)	(0.71)	(0.29)	(0.20)	(0.96)	(1.40)	(2.50)	(6.02)

Standard deviation in parentheses.

Table 7
Descriptive statistics. Centered models. Commerce and Services

		VD1	VD2	VD3	VD4	VD5	VD6	VD7	VD8	VD9	VCCS1	VCCS2	VCCS3	VCCS4	VCCS5
t-1	Not bankrupt	0.02	1.52	0.28	0.04	1.66	0.94	0.21	0.70	0.10	0.07	11.33	0.12	21.22	1.69
		(0.05)	(1.01)	(0.29)	(0.06)	(1.26)	(0.93)	(0.21)	(0.24)	(0.61)	(0.08)	(37.25)	(0.21)	(61.04)	(1.26)
	Bankrupt	-0.14	1.07	0.35	-0.12	1.19	0.59	0.43	0.61	0.18	-0.09	-6.65	-0.13	32.78	1.19
		(0.22)	(0.69)	(0.31)	(0.23)	(0.90)	(0.49)	(0.30)	(0.23)	(1.19)	(0.23)	(16.79)	(0.34)	(135.17)	(0.90)
t-2	Not bankrupt	0.01	1.52	0.30	0.04	1.70	0.88	0.21	0.69	0.08	0.06	4.78	0.09	13.03	1.70
		(0.04)	(1.27)	(0.28)	(0.06)	(1.30)	(0.94)	(0.21)	(0.24)	(0.32)	(0.06)	(30.88)	(0.16)	(19.48)	(1.30)
	Bankrupt	-0.03	1.18	0.40	0.00	1.46	0.70	0.32	0.66	0.28	0.01	0.91	-0.01	28.61	1.46
		(0.09)	(0.59)	(0.28)	(0.08)	(1.24)	(0.48)	(0.25)	(0.26)	(1.39)	(0.09)	(20.60)	(0.21)	(93.34)	(1.24)

Standard deviation in parentheses.

Table 8
Descriptive statistics. Centered models. Hospitality

		VD1	VD2	VD3	VD4	VD5	VD6	VD7	VD8	VD9	VCH1	VCH2	VCH3	VCH4	VCH5	VCH6
t-1	Not bankrupt	0.03	1.61	0.13	0.06	1.95	1.14	0.42	0.40	0.21	0.49	0.11	6.13	3.71	250.16	1.16
		(0.06)	(1.73)	(0.22)	(0.07)	(1.52)	(1.49)	(0.35)	(0.27)	(0.50)	(0.51)	(0.08)	(9.90)	(8.59)	(806.83)	(3.50)
	Bankrupt	-0.16	0.68	0.06	-0.15	1.25	0.54	0.56	0.32	0.00	-0.13	-0.10	-5.37	1.45	152.45	-0.12
		(0.22)	(0.73)	(0.20)	(0.22)	(1.21)	(0.66)	(0.35)	(0.26)	(1.54)	(0.43)	(0.21)	(23.29)	(9.80)	(608.31)	(2.32)
t-2	Not bankrupt	0.03	1.61	0.13	0.06	1.95	1.14	0.42	0.40	0.21	0.49	0.11	6.13	3.71	250.16	1.16
		(0.06)	(1.73)	(0.22)	(0.07)	(1.52)	(1.49)	(0.35)	(0.27)	(0.50)	(0.51)	(0.08)	(9.90)	(8.59)	(806.83)	(3.50)
	Bankrupt	-0.16	0.68	0.06	-0.15	1.25	0.54	0.56	0.32	0.00	-0.13	-0.10	-5.37	1.45	152.45	-0.12
		(0.22)	(0.73)	(0.20)	(0.22)	(1.21)	(0.66)	(0.35)	(0.26)	(1.54)	(0.43)	(0.21)	(23.29)	(9.80)	(608.31)	(2.32)

Standard deviation in parentheses.

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In order to contrast the research hypotheses proposed, the off-center and centered models shown in Table 9 have been constructed. For the construction of the off-center models, only the predictive variables that were significant in the previous literature have been used in such models. For the construction of the centered models, both the predicting variables of the off-center models and the specific variables of each sector have been used. From the comparison of the estimated models it is possible to detect significant differences between them since the centered models select variables specific to each sector as well as some of the off-center models. The off-center models are mainly comprised of six variables: Profit after Taxes/Total Assets (VD1), Current Assets/Current Liabilities (VD2), Operating Funds/Total Assets (VD3), EBIT/Total Assets (VD4), Total Revenue/Total Assets (VD5), Quick ratio (VD6) and Profit after Taxes/Net Equity (VD9). Therefore, they select variables that refer to profitability, liquidity and efficiency as the best bankruptcy predictors. In the case of Agriculture centered models, the main variables selected are four: Profit after Taxes/Total Assets (VD1), Quick ratio (VD6), Equity/Total Debt (VCA1) and EBIT/Financial Expenses (VCA2). In this case, these variables are related to profitability, liquidity and indebtedness. On the other hand, in the construction of Industry centered models, the following variables stand out: Profit after Taxes/Total Assets (VD1), Current Assets/Current Liabilities (VD2), Operating Funds/Total Assets (VD3), EBIT/Total Assets (VD4), Quick ratio (VD6), Current Assets/Total Assets (VD8), Equity/Non-Current Liabilities (VCI4) and Operating Income/Net Equity (VCI7), which together refer to profitability, liquidity and indebtedness. Regarding the Construction centered models, the most representative variables selected were Profit after Taxes/Total Assets (VD1), Quick ratio (VD6), Total Debt/Total Assets (VD7), Current Assets/Total Assets (VD8) and Financial Expenses/EBIT (VCC1), which also include aspects of profitability, liquidity and indebtedness. For the Commerce and Services sectors, the constructed models mainly select five variables: Profit after Taxes/Total Assets (VD1), Current Assets/Current Liabilities (VD2), Operating Funds/Total Assets (VD3), Total Debt/Total Assets (VD7), and Sales/Stocks (VCCS4). These variables refer to aspects of profitability, liquidity, indebtedness and efficiency. Finally, there are four significant variables in the Hospitality centered models: Profit after Taxes/Total Assets (VD1), Current Assets/Current Liabilities (VD2), EBITDA/Current Liabilities (VCH1), and Total Financial Debt/EBITDA (VCH3). In this case, they refer to aspects of profitability, liquidity and indebtedness.

As has been proven, the variables of profitability and liquidity are explicative in all of the estimated models. Furthermore, said models reach a high percentage of accuracy in the classification (generally above 80%).

If we compare the results obtained in the previous literature regarding the so-called off-center models, or those developed from heterogeneous samples of sectors, with those estimated in this work, it can be observed that the results obtained are in an intermediate range, with previous works that show better and worse results. Thus, we found works that present excellent results in the test sample, such as that by Shuk-Wern, Voon Choong and Khong (2011), with a 90% success rate, and others that are below our results such as that by Charambous, Chatitou and Kaourou (2000) with a 77.9% in the test. There is even the result of Chen, Härdle and Moros (2011) with a success rate in the test sample of 64.5%. With respect to the variables used, there is much heterogeneity, without finding a common pattern between the previous works and the global models developed in this work.

On the other hand, and in relation to the model estimated for the Agriculture sector, only

Vavrina, Hampel and Janová (2013) used Logistic Regression in their study, with a classification percentage in the training sample of 71.9% for one year before bankruptcy. In this sense, our model offers a better result, reaching 78.5% in our training sample and 75.6% in the test sample. Our estimated model of the Industry sector for t-1 obtained a result of 89.2% in the test sample, a very similar result to that obtained by Lin (2009) with 89.4%. Only the model of Zhang et al. (2013) exceeds our result, with a classification power of 95.2% in the test. Below these results are the works of Zhang et al. (1999), Darayseh, Waples and Tsoukalas (2003) and of Hu and Tseng (2005). With the work of Lin (2009) the only variable we found in common was VD5. With the work of Zhang et al. (2013) only the variables VD1 and VC17 were shared. In the Construction sector, our model had a classification success of 81.5% with the test sample for t-1, surpassing the result obtained by Mínguez-Conde (2006), as it reached only 76.9%. Among the variables used, we share variable VD1 with Mínguez-Conde (2006) and variables VD1, VD7 and VD8 with Treewichayapong, Chunhachinda and Padungsaksawasdi (2011) . As regards the Commerce and Services sector, our model obtained a classification percentage of 83.5% in the test sample. Below these results is the model by Kim (2011), which obtained a result of 80% with the training sample. The best model estimated for t-1 was for the Hospitality sector, with a classification success percentage of 91.2%. While this is a notable result, it is below the one obtained by Kim and Gu (2006b) who achieved a 93%. Two years before the bankruptcy (t-192), our model for the Hospitality sector registered a success rate of 81% in the test sample. The works of Kim and Gu (2006a) and Youn and Gu (2010) registered a success rate of 84% and 85%, respectively, with the training sample. However, they did not validate their models with test samples.

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Table 9
Centered and off-center models.

		Model specifications	Model adjustments				Classification success (%)	
			Omnibus Test	Hosmer Lemeshow Test	-2 log probability	R^2 Nagelkerke	Validation	Test
Off-center (without qualitative variables)	t-1	Y = - 0.460 - 21.653 VD1*** + 1.358 VD3*** + 7.758 VD4** - 0.286 VD5***	0.000***	0.139***	453.922	0.359	80.12	80.89
	t-2	Y = - 0.159 - 14.156 VD1*** - 0.080 VD2** + 1.451VD3*** - 0.400VD9**	0.000***	0.085***	398.738	0.441	73.04	71.13
Off-center (with qualitative variables)	t-1	Y = - 0.755 - 28.574 VD1*** - 1.189 VD2*** + 1.345 VD3*** + 13.108 VD4*** + 1.243 VD6*** - - 61.492 Construction Dummy** - 0.665 Commerce and Services Dummy**	0.000***	0.400***	318.395	0.611	82.53	81.77
	t-2	Y = - 0.048 - 14.530 VD1*** - 0.086 VD2** + 1.497 VD3*** - 0.425 VD9*** - 0.470 Industry Dummy	0.000***	0.100***	450.885	0.365	73.35	72.74
Centered (Agriculture)	t-1	Y = 0.753 - 32.529 VD1*** - 0.973 VD6** + 0.004 VCA2***	0.000***	0.487***	78.310	0.560	78.77	75.60
	t-2	Y = 0.804 - 13.429 VD1** - 0.147 VCA1***	0.000***	0.210***	98.333	0.327	65.64	69.65
Centered (Industry)	t-1	Y = 1.202 - 39.344 VD1*** - 1.422 VD2** + 8.394 VD3*** + 16.676 VD4** - 1.371 VD5*** + + 1.803 VD6*** - 3.367 VD8*** + 1.059 VCI7***	0.000***	0.353***	159.940	0.657	86.67	89.22
	t-2	Y = -1.413 - 105.627 VD1*** - 2.581 VD2** + 21.487 VD3*** + 610678 VD4*** + 3.603 VD6** - - 9.142 VD7*** - 12.284 VD8*** - 3.351 VD9** - 0.039 VCI4**	0.000***	0.189***	66.261	0.832	94.51	78.13
Centered (Construction)	t-1	Y = -2.092 - 14.624VD1*** -0.138VD6** +1.377VD7** +2.134VD8** +0.390VCC**	0.000***	0.117***	361.278	0.496	77.02	74.52
	t-2	Y = -2.006 - 16.729VD1*** + 1.775 VD3*** - 0.139 VD6** + 1.247 VD7** + 1.584 VD8** + + 0.289 VCC1**	0.000***	0.177***	260.006	0.559	80.86	81.54
Centered (Commerce and Services)	t-1	Y = - 0.066 – 28.061 VD1*** - 0.785 VD2** + 2.992 VD3*** + 2.165 VD7*** - 2.112 VD8** + + 0.006 VCC4**	0.000***	0.149***	217.607	0.584	79.96	83.54
	t-2	Y = - 0.788 + 9.135 VD1*** - 0.307 VD2** + 1.637 VD*** + 2.118 VD7***	0.000***	0.374***	364.380	0.277	70.98	79.53
Centered (Hospitality)	t-1	Y = 1.186 - 13.196 VD1*** - 1.096 VD2** - 0.440 VD5*** - 1.447 VCH1*** - 0.027 VCH3**	0.000***	0.131***	249.873	0.690	84.22	91.26
	t-2	Y = 0.231 - 0.476 VD2** - 14.835 VD4*** + 0.733 VD6***	0.000***	0.082***	234.212	0.379	72.64	81.01

**Significant at 0.05; ***Significant at 0.01

For the contrast of hypothesis H1, that is, whether the introduction of sectoral qualitative variables in an off-center model improves its predictive capability, the off-center models constructed with qualitative variables were compared to the off-center models without qualitative variables, using the AIC, BIC and HQC criteria. The results of this comparison are shown in Table 10. Bearing in mind that the decision rule for the three criteria is to select the model that offers the least value in the comparison, it is possible to conclude that off-center models (with qualitative variables) are superior to off-center models (without qualitative variables). In this manner, the results obtained allow accepting hypothesis H1, implying that the inclusion of qualitative variables representative of economic sectors enriches and increases the explanatory capability of the off-center models.

Table 10.
Comparison of the off-center models. Hypothesis H_1

Model Selection Criteria	Off-center models (without qualitative variables)		Off-center models (with qualitative variables)	
	t-1	t-2	t-1	t-2
AIC	398.74	461.92	330.40	458.89
BIC	405.34	468.52	341.35	466.19
HQC	395.24	458.42	325.39	455.55

Once it has been established that the off-center models (with qualitative variables) are superior to the off-center models (without qualitative variables), hypothesis H2 can be addressed, which tries to contrast whether an off-center model correctly predicts bankruptcy in any economic sector. For this purpose, the prediction capability of the off-center model (with qualitative variables) has been proven using the test samples of each of the five economic sectors selected in this work (Table 11). The results obtained show that off-center models (with qualitative variables) are capable of successfully predicting sectoral samples. Nevertheless, and in order to obtain greater robustness in the conclusions, these results have been submitted to the Selection Criteria for AIC, BIC and HQC models (Table 12). For t-1, hypothesis H2 is accepted since the off-center models (with qualitative variables) are superior to any centered model. However, this hypothesis is rejected for t-2, since the Industry centered model is superior to the off-center model. Therefore, the results obtained assume the existence of a global model to predict bankruptcy when information close to the moment of bankruptcy (t-1) is used. These results can be explained by the evidence in previous research which state that the risk of bankruptcy depends on global effects and not so much on the effect of the sectors (Jabeur, 2017; Altman *et al*., 2017; Alaminos, del Castillo and Fernández, 2016; Korol, 2013; Platt and Platt, 2008).

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Table 11
Results of the off-center models (with qualitative variables) in sectoral samples. Hypothesis H_2

	t-1					t-2				
	Agriculture	Industry	Construction	Com. and Serv.	Hospitality	Agriculture	Industry	Construcción	Com. and Serv.	Hospitality
Model Adjustment										
Omnibus test	0.012	0.000	0.000	0.000	0.000	0.004	0.000	0.000	0.000	0.000
Hosmer-Lemeshow Test	0.562	0.589	0.757	0.884	0.975	0.578	0.402	0.654	0.600	0.100
R2 Nagelkerke	0.414	0.728	0.624	0.703	0.757	0.369	0.415	0.374	0.461	0.605
Classification Matrix (%)										
Not bankrupt	75.00	93.00	84.60	91.50	88.90	69.20	79.30	72.00	75.90	76.60
Bankrupt	70.00	78.30	80.30	83.10	87.00	63.60	72.20	69.40	74.70	84.00
Total	72.70	85.80	82.50	87.30	88.00	66.70	75.90	70.80	75.30	80.40
Model Selection Criteria										
AIC	56.34	112.69	128.25	117.10	98.44	58.72	175.93	170.28	167.73	131.49
BIC	63.64	123.96	138.68	127.90	109.38	63.55	183.45	177.23	174.93	138.77
HQC	50.43	107.75	123.12	112.05	93.43	54.77	172.64	166.86	164.37	128.14

AIC: Akaike, BIC: Bayesian, HQC: Hannan-Quinn

Table 12
Comparison between off-center models (with qualitative variables) and centered models. Hypothesis H_2

	t-1			t-2		
	AIC	BIC	HQC	AIC	BIC	HQC
Agriculture						
Off-center models (with qualitative variables)	84.31	87.96	81.36	102.33	104.75	100.36
Centered models	56.34	63.64	50.43	58.72	63.55	54.77
Industry						
Off-center models (with qualitative variables)	175.94	190.97	169.36	84.26	101.17	76.86
Centered models	112.69	123.96	107.75	175.93	183.45	172.64
Construction						
Off-center models (with qualitative variables)	270.01	278.69	265.73	373.28	383.70	368.15
Centered models	128.25	138.68	123.12	170.28	177.23	166.86
Commerce and Services						
Off-center models (with qualitative variables)	229.61	240.41	224.56	373.38	379.58	369.02
Centered models	117.10	127.90	112.05	167.73	174.93	164.37
Hospitality						
Off-center models (with qualitative variables)	259.87	268.98	255.70	240.21	245.68	237.71
Centered models	98.44	109.38	93.43	131.49	138.77	128.14

AIC: Akaike, BIC: Bayesian, HQC: Hannan-Quinn

Conclusions

The objective of this work is to cover the existing gap in the literature regarding the superiority of off-center or centered models for bankruptcy prediction. We have tried to elucidate this issue with an *ad-hoc* design, overcoming the absence of definitive conclusions in previous literature due to the disparity of methods, approaches, available databases, periods of time, and countries previously considered. To this end, off-center models and models centered on five economic sectors have been constructed in this work, all of which used information from the 2010-2015 period corresponding to Spanish companies, one year (t-1) and two years (t-2) before bankruptcy.

The empirical results obtained have allowed confirming, firstly, that the inclusion of sectoral qualitative variables improves the predictive capability of off-center models. And secondly, that off-center models are superior to centered models in more accurately predicting when using information close to the moment of bankruptcy (one year earlier). However, when using information furthest from the moment of bankruptcy, off-center models are superior to centered models only in particular economic sectors, as the Industry centered model is shown to be superior to the off-center model tested with the sample of companies of said sector.

As consequence of the previous conclusions and the documentary and empirical research carried out, we believe that the present work contributes to corporate financial knowledge in different aspects. First of all, it manages to elucidate a question that, although already pointed out by other authors, had not been the object of study with a specific design, method and sample. Secondly, it allows conclusions to be drawn when dealing with a bankruptcy predicting strategy in different economic sectors. For the most part, an off-center model is able to successfully predict bankruptcy in samples of companies belonging to specific economic sectors, which would entail considerable cost savings in the elaboration and development of numerous centered models. Thirdly, this work has highlighted the use of sectoral explanatory variables of a specific nature, which provide much more specific knowledge of the factors that explain bankruptcy. The knowledge of these variables as specifically sectoral in the explanation of business failure can help economic agents and users of this information act preventively. Finally, given that the first step in risk management is to measure risk, an appropriate bankruptcy risk score can help in this regard. Therefore, before deciding to use a given model, it is necessary to have a foundation that indicates the limitations of the models and helps determine which of these (off-center or centered) are best suited to your circumstances.

The conclusions obtained in this work suggest future lines of research that may prove extremely useful in perfecting bankruptcy prediction models. Thus, it would be interesting, first of all, to check whether the results obtained with the sample of Spanish companies are the same as when the models are built with companies from other geographical areas, which would give these conclusions a high capacity for generalization. Similarly, it could also be relevant to modify the definition of the considered sectors, broadening the sample size, and thus to verify whether the conclusions obtained here would be the same in more or less broadly defined economic sectors. Finally, since the effectiveness of the models is likely to vary according to the macroeconomic conditions, it would be interesting to know the classification results of the models at different stages of the economic cycle.

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