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Bankruptcy Prediction Models in Galician companies. Application of Parametric Methodologies and Artificial Intelligence*

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Abstract:
This paper provides empirical evidence on the prediction of non-financial companies' failure. We develop several models to evaluate failure risk in companies from Galicia. We check the predictive ability of parametric models (multivariate discriminant, logit) compared with auditor's report. Models are based on relevant financial variables and ratios, in financial logic and a in financial distress situations. We examine a random sample of companies in cross-sectional perspective, checking the predictive capacity at any given time, also verifying is models give reliable signals to anticipate future events of financial distress. Findings suggest that our models are extremely effective when applied in medium and long term, and that they offer higher predictive capabilities than external audit.

Key Words:
Business Failure, Financial Distress, Prediction of Insolvency, Audit Reports

***JEL Classification**: G33, C45, C59*

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1. Introduction

Business failure has been, and will undoubtedly be in the future, a topic of special interest for a wide range of operators. Company extinction usually has severe consequences for a broad set of agents: owners, creditors, employees, administration and other members of value system and the society. It is difficult to anticipate these situations in an efficient and effective way, hence the description of the failure process and the development of predictive modelling are major issues for academics and practitioners.

External audit should provide reliable evidences to predict business failure. In fact, auditors are engaged to audit financial statements assuming that the company will continue as a going concern, therefore they are expected to issue a going-concern opinion prior to the bankruptcy filing.

Some authors have reported that companies with qualified opinion experience more, and more intense, episodes of financial distress (Wilkins, 1997). But also, an abnormally high number of failed companies received qualified opinions, and even clean reports (Venuti, 2004; Arnedo *et al.*, 2008). Qualifications can also be very different in nature - minor uncertainties, difficulties to gather some documents or information and severe events that can threaten company's survival -, and this degrades auditor's reporting quality. McKee (2003) estimates the auditor signalling rate for bankrupt companies in 50%.

These anomalies may reflect distortions in the independence (Simunic, 1984; Carcello and Palmrose, 1994; Schwartz and Soo, 1995; Ruiz and Gomez, 2001; Lam and Mensah, 2006; Robinson, 2008; Thalassinos, Liapis and Thalassinos, 2013) or biases in evidence evaluation – it has been suggested that auditors might have an unconscious bias towards business continuity (O'Clock and Devine, 1995). Auditors are reluctant to include going concern disclosures because such a new can cause financial distress by itself – this is the self-fulfilling prophesy hypothesis.

Based on seminal evidence provided by Beaver (1966) and Altman (1968), research has focused on the analysis of the external profile of financial failure: temporary insolvency, delays, bankruptcy. The goal is to itemize the main financial processes involved in financial distress, to build a predictive model. Several techniques have been applied: multiple discriminant analysis (Altman, 1968; Altman, Haldeman and Narayanan, 1977), conditional probability and probit - logit (Martin 1977; Ohlson, 1980; Zmijewski, 1984), recursive partitioning (Frydman, Altman and Kao, 1985) and artificial intelligence applications, both expert systems and artificial neural networks (Messier and Hansen, 1988; Bell, Ribar and Verchio, 1990; Hansen and Messier, 1991; Serrano and Martin del Brio, 1993; Koh and Tan, 1999; Brockett *et al.*, 2006). Some models are built upon fuzzy set theory and fuzzy logic (Dubois and Prade, 1992; Slowinski and Zopounidis, 1995; McKee and Lensberg, 2002) more recently, heuristic techniques have been applied to build multicriteria analysis models combining group decision support systems (GDSS) applications and recognized qualitative methods, such as the Analytic Hierarchy Process (AHP) (Sun and Li, 2009).

A recurrent obstacle is the identification of a reduced set of variables that can reliably describe and predict financial distress. There seems to be consensus on the relevance of financial information, including financial ratios; but it is also evident that more, and more diverse, information is needed. Some experiments have tested the use of criteria other than accrual (Elam, 1975; Norton and Smith, 1979; Platt, Platt and Pedersen, 1994) the effect of macroeconomic magnitudes (Rose, Andrews, and Giroux, 1982), and proxies intended to reveal internal events associated with failure, e.g. late submission of the Annual Accounts, qualifications in audit reports, and management skills (Peel, Peel and Pope, 1986; Keasey and Watson, 1987).

Predicting business failure has also been a growing concern in Spain in recent years. Some models have been developed for banking (Laffargue, Martin Vasquez, 1985; Pina, 1989; Rodríguez 1989; Martin del Brio and Serrano, 1993), insurance industry (Rodríguez Acebes, 1990; Lopez, Moreno and Rodriguez 1994; and Mora, 1994a), textile industry (Somoza, 2001) and also generalized models for non-financial entities and SMEs (Gabás, 1990; Garcia, Arqués y Calvo-Flores, 1995; Ramirez, 1996; Lizarraga, 1997). Some other models have been developed to meet the particularities of industries in limited geographical areas (e.g. Valencia, see Gandia, Garcia and Molina, 1995; Gallego Gómez and Yanez, 1996; Ferrando and White, 1998). This specialization, far from leading to inconsistency, is convenient because the predictive ability is conditioned by the profile of sampled companies and socioeconomic context. Therefore further implementation of the models requires a reassessment of coefficients (Moyer, 1977; Altman, 2000). We have few specific models for Galician companies; an effort to harmonize the specification and weights of factors is also needed.

Time frame is also relevant. It should be noted that, even though we can build and test models for different frames, the decision maker doesn't know whether the company is going to fail or not, neither when this event will happen. Pina (1989) and Mora (1994b) suggested the use of inter-temporal models; we intend to put them together in order to evaluate the internal coherence of predictions, and make a more informed opinion of financial failure risk.

This paper has three objectives:

1. Design models able to accurately identify businesses at risk of insolvency or failure, in the Galician socio-economic context, and contrast the stability of its predictions in the short, medium and long term.
2. Provide empirical evidence about the relevance of accounting information and financial ratios to evaluate the company's financial stability.

3. Verify the capacity of external auditors to anticipate financial distress and provide empirical evidence to determine if changes in auditor opinion can be interpreted as signs of financial stress.

First, we offer an outline of the estimation process and a comparison of forecasting models; then, we discuss model prediction capacity. Finally, we evaluate the relative effectiveness of warning signs supplied by auditors' reports.

2. Estimation and validation of the models

2.1. Sampling

The population under study is active companies based in Galicia, identified according to data supplied by the SABI database, in financial distress situation. We excluded companies with less than four years old, in order to debug the effect of initial mortality, and also those for which there were information gaps affecting the estimation of the models, in particular all those whose reports were not available. We also excluded companies in real estate industry, whose current situation would undoubtedly induce biases in model estimation. This matching strategy is justified because failed companies usually are a small proportion of the population: therefore population proportions are much more favourable for healthy, so a conventional random sampling would provide poor information of failure events and would lead to inefficient estimators.

We use a broad interpretation of financial failure, based on the modern view that includes several financial stress situations that are not necessarily a bankruptcy. The conventional definition of failure is appealing because it provides an objective and exhaustive classification, but it does not reflect events of tension such as liquidity shortages or funding problems in the short term (Pindado, Rodrigues and Torre, 2008) that do not necessarily lead to an immediate extinction of the company. Thus, out definition of financial distressed company include all those companies in population that verify one or more of the following conditions:

- Is filing for bankruptcy;
- Is involved in claims, in large amounts;
- Has refused several trade effects and is included in public logs such as BADEXCUG and RAI.

Models have been estimated upon a sample of 120 firms, relying in financial data from 1990 to 1997.

2.2. Variables

Table 1: Financial ratios

Activity	ACT01	Financial Expenses / Added Value
	ACT02	Personal Expenses / Fixed Asset
	ACT03	(Cost Employees + Depreciation)/ Added Value
	ACT04	Operating Income/ Operating Consumption
	ACT05	Added Value / Sales
Leverage	APL01	P.B.I.T. / Financial Expenses
	APL02	Financial Expenses / Total Liabilities
	APL03	Operating Result. / Financial Expenses
	APL04	Period Result / Total Liabilities
Indebtedness.	END01	Total Liabilities / Equity
	END02	(Equity –Period Result) / Current Liabilities
	END03	Equity / Liabilities
	END04	Long-Term Liabilities And Equity / Liabilities
Structure	EST01	Current Assets / Assets
	EST02	Equipment Depreciation / Non-Current Assets
	EST03	Working Capital / Assets
	EST04	Working Capital / Liabilities
	EST05	Working Capital / Sales
	EST06	Cash & Equivalent / Assets
	EST07	Net Result / Working Capital
	EST08	Measurement Decomposition Assets
Liquidity	LIQ01	Operative Cash Flow / Assets
	LIQ02	Operative Cash Flow / Liabilities
	LIQ03	Operative Cash Flow / Current Liabilities
	LIQ04	Operative Cash Flow / Sales
	LIQ05	Cash Flow / Assets
	LIQ06	Cash Flow / Liabilities
	LIQ07	Cash Flow / Current Liabilities
	LIQ08	Resources Generated CF / Sales
	LIQ09	Available / Current Liabilities
	LIQ10	Stocks / Current Liabilities
	LIQ11	Stocks + Liquid Asset / Current Liabilities
	LIQ12	Interval Without Credit
	LIQ13	Available / Current Liabilities
Yield	REN01	EBIT / Assets
	REN02	EBIT / Sales
	REN03	Net Result / Sales
	REN04	(Net Res. - Available – Stocks) / Assets)
	REN05	Net Result / Assets
	REN06	Net Result / Equity
Turnover	ROT01	(Current Assets – Stocks) / Sales
	ROT02	Stocks / Sales
	ROT03	Sales / Realizable Assets
	ROT04	Sales / Current Assets
	ROT05	Sales / Fixed Assets
	ROT06	Sales / Assets
	ROT07	Sales / Working Capital
	ROT08	Sales / Available Assets
Solvency	SOL01	(Current Assets – Stocks) / Current Liabilities
	SOL02	Current Assets / Liabilities
	SOL03	Current Assets / Curren Liabilities
	SOL04	Fixed Assets / Equity
	SOL05	Current Liabilities / Assets
	SOL06	Equity / Assets
	SOL07	Equity/ Fixed Assets
	SOL08	Current Liabilities / Assets
	SOL09	Pre-tax Profit/ Current Liabilities
Cash	TES01	Cash / Current Liabilities
	TES02	Cash / Sales

The choice of predictor variables is problematic due to the absence of a consolidated theory about business failure, the subsequent use of multiple subsets makes experimental results are not comparable, cross or temporarily. In our case the selection was based on two principles: popular in accounting and financial literature, and the frequency and level of significance in those studies more relevant to the prediction of business failure. In all cases, the ratios were calculated from the magnitudes listed in the Annual Accounts, without adjustments previously seen in literature as the valuation at market prices or using alternative accounting methods.

2.3. Factor analysis

Prior to model estimation, a factor analysis was performed to reduce the initial set of variables to a small number of synthetic, uncorrelated regressors. This is an important issue given that, as Lev (1978) states, financial ratios usually move in the same direction because they are built upon common components and because financial processes are interrelated.

All models require at least four factors to count with more than 50% of variance; the first factors are related to profitability, liquidity (cash flow and generated resources), the level of debt and creditworthiness. These results confirm, once again, the relationship between profitability ratios and cash flow, as stated by Gombola and Ketzer (1983) and Pina (1992). In the first three years prior to the failure the nature and sequence of these factors is similar, but not in the fourth one.

2.4. Multivariate Models

The estimation was performed using parametric multivariate techniques: multiple linear regression analysis, linear discriminant analysis and logit analysis, using step selection. This selection method does not guarantee an optimal final set of regressors, given that the selection is based on conditional contrasts, but is and efficient and logical strategy to find a good combination of variables and is consistent with the philosophy of making manageable and understandable models.

This methodology has been applied to develop absorbent models for each of the four years of planning horizon – these are the "Omega Models". The following tables (Table 2 to
Table 5) summarize the composition of these models, the significance levels of variables, the estimates, and the percentages of success.

Finally, we estimate a single model comprising all the available observations for the four years (
Table 6). This model is intended to integrate the four partial models, and to give a generic, time-independent prediction; it is also intended to support a sensitivity analysis to test the significance and stability of the estimates.

Table 2: Models "Omega-1" - 1 year before the failure

	Variables	MDA		Logit		LR	
		Coef.(f)	Sig.	Coef.(t)	Sig.	Coef.(wald)	Sig.
Apl04	Profit / loans	4,284		-110,66		-1,068	
		-106,2	0	-7,55	0,01	(-6,89)	0
End03	Equity / loans	-	-	5,584		-	-
				-2,78	0,1		
Rot06	Sales / total assets	0,201		-2,603		-0,005	
		-52,35	0	-4,38	0,04	(-1,98)	0,05
Sol06	Equity / total assets	1,311		30,815		-0,327	
		-74,69	0	-7,21	0,01	(-4,71)	0
Liq12	No credit period	-	-	2,929		-	-
				-4,67	0,03		
	Intercept	-0,339	-	8,444		0,584	
		-		-7,34	0,01	-11,41	0
	Global sig.	99,736	0	149,958	0	52,353	0
		(2)		(2)		(f)	
	Hit rate, failed companies	81,70%		98.3%		81,70%	
	Hit rate, healthy companies	100,00%		96,70%		100,00%	
	Hit rate, all companies	90,80%		97,50%		90,80%	

Table 3: Models "Omega-2" - 2 years before the failure

	Variables	MDA		Logit		LR	
		Coef.(f)	Sig.	Coef.(t)	Sig.	Coef.(wald)	Sig.
Apl04	Profit / loans	7,871		-111,23		-1,979	
		-91,85	0	-13,35	0	(-8,04)	0
Liq12	No credit period	0,61		-		-0,153	
		-50,6	0			(-2,38)	0,02
	Intercept	0,127		0,974		0,468	
		-	-	-4,28	0,04	-12,35	0
	Global sig.	72,928	0	123,008	0	50,608	0
		(2)		(2)		(f)	
	Hit rate, failed companies	85,00%		95,00%		85,00%	
	Hit rate, healthy companies	100,00%		93,30%		100,00%	
	Hit rate, all companies	92,50%		94,20%		92,50%	

Table 4: Models "Omega-3" - 3 years before the failure

	Variables	MDA		Logit		LR	
		Coef.(f)	Sig.	Coef.(t)	Sig.	Coef.(wald)	Sig.
Ren05	Profit / total assets	13,706		-33,765		-3,308	
		-17,7	0	-14,67	0	(-4,19)	0

Sol06	Equity / total assets	2,108		-6,216		-0,509	
		-40,38	0	-11,35	0	(-3,46)	0
Liq05	Cash flow Resources Generated / total assets	-7,734		-	-	1,867	
		-16,88	0			-3,75	0
	Intercept	-0,98		1,678		0,524	
		-	-	-10,42	0	-8,92	0
	Global sig.	51,182	0	85,743	0	21,331	0
		(2)		(2)		(f)	
	Hit rate, failed companies	73,30%		93,30%		73,30%	
	Hit rate, healthy companies	93,30%		91,70%		93,30%	
	Hit rate, all companies	83,30%		92,50%		83,30%	

Table 5: Models "Omega-4" - 4 years before the failure

	Variables	MDA		Logit		LR	
		Coef.(f)	Sig.	Coef.(t)	Sig.	Coef.(wald)	Sig.
Apl04	Profit / loans	6,53		-49,448		-1,586	
		-26,01	0	-18,79	0	(-4,73)	0
End03	Equity / loans	-0,883		4,284		0,215	
		-10,86	0	-6,78	0,01	-2,11	0,04
Est03	Working capital / total assets	-2,913		-	-	-0,707	
		-11,78	0			-3,01	0
Ren05	Profit / total assets	-	-	34,773		-	-
				-14,09	0		
Sol06	Equity / total assets	4,823		-17,348		-1,171	
		-12,63	0	-12,77	0	(-4,19)	0
Liq05	Cash flow Resources Generated / total assets	-3,891		-	-	-0,945	
		-13,71	0			-3,5	0
Liq12	No credit period	1,466		-	-	-0,356	
		-16,51	0			(-2,91)	0
	Intercept	-0,312		3,102		0,576	
		-	-	-17,18	0	-9,06	0
	Global sig.	52,371	0	90,257	0	10,863	0
		(2)		(2)		(f)	
	Hit rate, failed companies	70,00%		88,30%		70,00%	
	Hit rate, healthy companies	90,00%		90,00%		90,00%	
	Hit rate, all companies	80,00%		89,20%		80,00%	

Table 6: Models "Omega-global" - joint estimation four years prior to failure

	Variables	MDA		Logit		LR	
		Coef.(f)	Sig.	Coef.(t)	Sig.	Coef.(wald)	Sig.
Apl04	Profit / loans	0,399		-	-	-0,087	
		-32,41	0			(-2,00)	0,05
End03	Equity / loans	0,376		-	-	-0,082	
		-50,19	0			(-3,29)	0
Est03	Working capital / total assets	1,159		-3,711		-0,253	
		-67,68	0	-44,24	0	(-4,29)	0

Rot06	Sales / total assets	0,011		-	-	-0,002	
		-39,25	0			(-2,25)	0,03
Liq05	Cash flow rec. Gdos. / activo total	1,975		-11,254		-0,431	
		-95,74	0	-61,76	0	(-4,55)	0
	Intercept	-0,275		0,6743		0,56	
		-	-	-21,69	0	-23,49	0
	Global sig.	139,846	0	217,915	0	32,414	0
		(2)		(2)		(f)	
	Hit rate, failed companies	75,00%		78,30%		75,00%	
	Hit rate, healthy companies	82,50%		82,50%		82,50%	
	Hit rate, all companies	78,80%		80,40%		78,80%	

While we were working in this paper, in February 2010, a relevant local company filed for bankruptcy. Recent audit reports available (2004 and 2006) were clean, but our prediction models supplied clear warning signs: both the MDA and the MRL models point to bankruptcy in 100% of the simulations, while LOGIT warns in 37.5% of them (Table 7).

Table 7: A real, particular, case of application of forecasting models

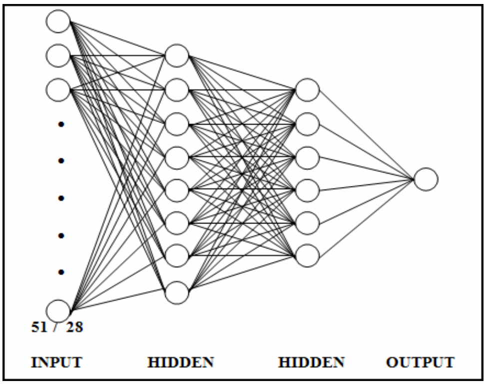
Date	**15/11/2007**	**15/11/2006**	**15/11/2005**	**15/11/2004**
MDA 1 AA	FAILURE	FAILURE	FAILURE	FAILURE
MDA 2 AA	FAILURE	FAILURE	FAILURE	FAILURE
MDA 3 AA	FAILURE	FAILURE	FAILURE	FAILURE
MDA 4 AA	FAILURE	FAILURE	FAILURE	FAILURE
MDA GLOBAL	FAILURE	FAILURE	FAILURE	FAILURE
LOGIT 1 AA	FAILURE	FAILURE	FAILURE	FAILURE
LOGIT 2 AA	FAILURE	FAILURE	SOLVENT	SOLVENT
LOGIT 3 AA	SOLVENT	SOLVENT	SOLVENT	SOLVENT
LOGIT 4 AA	SOLVENT	SOLVENT	SOLVENT	SOLVENT
LOGIT GLOBAL	SOLVENT	SOLVENT	SOLVENT	SOLVENT
MRL 1 AA	FAILURE	FAILURE	FAILURE	FAILURE
MRL 2 AA	FAILURE	FAILURE	FAILURE	FAILURE
MRL 3 AA	FAILURE	FAILURE	FAILURE	FAILURE
MRL 4 AA	FAILURE	FAILURE	FAILURE	FAILURE
MRL GLOBAL	FAILURE	FAILURE	FAILURE	FAILURE

2.5 IA Applications: neural networks

We use a neural network application to identify those companies that have a high probability of failure. When modelling the concepts of failure and financial distress, we used a Perceptron architecture with Multilayer Back-Propagation Learning with two hidden layers of nodes 8 and 6 respectively. Depending on the input variables, in all cases financial ratios, we have been used two types of configurations. On the one hand, we considered as input variables all financial ratios selected for this study with some minor changes to reduce the total number of variables: we have considered only the 28 most significant financial ratios of factor analysis, that is, those with greater weight in the factor and/or an eigenvalue greater than 0.8 on factor analysis. Extreme values have not been debugged – this is not a relevant issue for neural models. The final settings are 28 x 8 x 6 x 1 and 51 x 8 x 6 x 1.

Figure 1 shows the network architecture we have employed.

Figure 1: Multilevel Perceptron network structure



Processing nodes have as a sigmoid transfer function centred at zero on X and Y axes, hyperbolic-type function. Y-axis has an output range between -1 and 1. The environment normalizes the entries into that range, and de-normalizes the outputs.

The network was built with the development environment of Neuro-Solutions [97 Neuro-Solutions Version 3.02, Neuro Dimension Inc. 1997], running on PC platform under Windows 98, with the back propagation algorithm designed by Rumelhat, Hinton and Williams (1986), with default training coefficients: a value less than 1 in all connection weights between layers, and higher in the input layer, but always within the range between 0 and 1. The time factor has remained constant in all layers (0.7). During the training process we carried between 2,000 and 3,000 iterations or "times" of training, and we get optimal classification levels; we tried to avoid over fitting biases. The network gets very high rate levels, even though the number of iterations is only moderate. On the other side, the predictive ability of models decreases in the validation phase: parametric models outperform neural network except in years 3 and 4.

Table 8: Perceptron multilevel networks: hit rate in training stage

	NETWORK 51 x 50 x 8 x 6 x 1			NETWORK 28 x 8 x 6 x 1		
SAMPLE (60 HEALTHY – 60 FAILED)	**HEALTHY**	**Failed**	**TOTAL**	**HEALTHY**	**Failed**	**TOTAL**
YEAR 1 BEFORE FAILURE	100,0	98,3	99,2	98,3	100,0	99,2
YEAR 2 BEFORE FAILURE	100,0	98,3	99,2	100,0	98,3	99,2

YEAR 3 BEFORE FAILURE	98,3	100,0	99,2	98,3	100,0	99,2
YEAR 4 BEFORE FAILURE	98,3	100,0	99,2	100,0	96,7	98,3
GLOBAL MODEL	93,8	93,8	93,8	95,0	91,7	93,3

Table 9: Perceptron multilevel networks: hit rate in validation stage

	NETWORK 51 ó 50 x 8 x 6 x 1			**NETWORK 28 x 8 x 6 x 1**		
VALIDATION SAMPLE	**HEALTHY**	**FAILURE**	**TOTAL**	**HEALTHY**	**FAILURE**	**TOTAL**
YEAR 1 BEFORE FAILURE (29 Failed – 284 Healthy)	91,5	96,6	92,0	93,7	96,6	93,9
YEAR 1 BEFORE FAILURE (29 Failed – 284 Healthy)	79,2	82,7	79,6	82,7	82,7	82,7
YEAR 1 BEFORE FAILURE (29 Failed – 284 Healthy)	78,5	72,4	78,0	83,8	79,3	83,4
YEAR 1 BEFORE FAILURE (15 Failed – 284 Healthy)	63,4	93,3	64,9	73,6	73,3	73,6
MODELO GLOBAL (102Failed – 1.136 Healthy)	80,4	82,3	80,5	83,2	86,3	83,4

3. Discussion

The four models offer a very important effectiveness in predicting business failure in, at least, the four years prior to the event. Logit analysis offers a very acceptable hit level of 90% in the four years prior to failure, and also MDA models are able to anticipate most of distress situations – this is remarkable, given that the fulfilment of normality hypothesis is doubtful.

All final models operate on a core set of eight financial ratios; however its configuration is slightly different depending on prediction horizon. Two and three years prior to the event, optimal prediction levels are achieved with simple models (univariate and bivariate, except in third year, where the MDA model requires more variables). As we approach the failure event the number of distressed variables increases, and a specific profile emerges: difficulties to generate resources, mainly profit, and an increasing leverage. Failed firms show abnormal values for the following ratios: APL04, REN05 and SOL06, which therefore have high explanatory and predictive power. APL04 (Net Income / Total Liabilities) is also a relevant factor, as previous works stated.

A year before the failure event, and also four years before, we need to include up to five variables to get an acceptable predictive capacity. This suggests that the predictive power of the models weakens in long time horizons; maybe because companies do not yet have a defined profile of failure, hence the models require a greater volume of evidence to make a right classification. We believe that these companies try to stay on the market by adopting policies that, even though may help defer the event, cause widespread financial imbalances: obtain liquidity through the realization of assets, significant short-term debt, deterioration of the financial structure, reduce prices to maintain the level of sales, reduce customers credit, difficulties to maintain trade credits, earnings from discontinued operations, etc.

Both network models offer a satisfactory performance – analytic power is higher in 28-variable models. Given that we define discriminant variables as the most significant in each factor resulting from principal components analysis, the elimination of "noise" in the network causes a higher percentage of success in the validation stage.

As anticipated, the predictive ability of neural network models is usually higher than that of multivariate parametric models, although the performance of the latter is not far away. The exception to the above, albeit partially, is presented in years 3 and 4 before the failure, in which periods the network model composed of 28 variables, with a percentage of correct answers of 83.4% and 73.6% , respectively, exceeds the overall rate of successes obtained with discriminant analysis and linear regression, leading to better classify the failed companies. Regarding the overall model, neural networks results are as good as those from parametric multivariate models.

In summary, these findings come to agree with other investigations in the sense that while the neural networks are a tool to keep in mind in forecasting business failure, they do not clearly outperform the most common and recognized multivariate statistical techniques.

4. The role of audit in predicting financial failure

The high predictive power achieved with the estimated models is due to the existence of clear differences between healthy and failed companies. This is true, even though our notion of financial distress includes several situations that not necessarily lead to a immediate bankruptcy. However a large proportion of failed firms were able to get clean audit reports, or minor qualifications.

In a now classic work, Altman and McGough (1974) verified that the Z model outperformed the audit in detecting signs of stress or financial risk, at horizons of one and two years before the event and with reference to the significant qualifications affecting the going-concern. His explanation is that audit reports consider these financial tensions as temporary circumstances that the company can solve; thus, auditors do not put in question their survival. But the examples of companies that fail shortly after receiving reports clean (or without obvious signs of alert) are remarkable.

Later works came to agree with these hypothesis (e.g. Moiz, 1995; Citron and Taffler, 2001) and suggest that auditors may underestimate the financial risk factors, either due to a bias in favour of the continuity of the company - the general tendency to align with your current financial status - or to the fear that the revelation of these difficulties would further exacerbate the imbalances - the self-fulfilling prophecy hypothesis.

In order to verify the ability of the audit to provide warning signs, we selected a sample of audited companies that experienced financial difficulties over the past four years (validation sample.) Again, we use the extended concept of financial failure. First we check if the audit reports contain significant evidences about the risks faced by the companies, and provide accurate warning signals to anticipate failure. We then apply the models described in previous sections, providing additional evidence about the predictive ability of models and their comparative effectiveness in relation to the audit.

4.1. Selection of validation sample

The validation sample was selected using the same criteria used for the estimation sample used in the first phase of our study, with one obvious additional requirement: companies must be audited and reports must be available. SABI enrolls 72.581 Galician companies; 46.820 of them were audited but only 1.633 of the reports was available. On the other side, data about defaults and/or returned trade effects were obtained from RAI and BADEXCUG public registries. We found 434 records for those companies (some of them were listed in both registries); again, real estate industry was excluded. The final sample validation includes 38 companies; it is a seemingly small number, but it should be noted that it's a rather special category of companies: audited businesses whose financial difficulties were not revealed by going concern disclosures by auditors. Twenty-one of these companies experienced repeated incidents relevant to RAI and/or BADEXCUG, but did not go to bankrupt at the time of writing this work.

4.2. Content of audit reports

Qualifications were obtained from auditors' reports. All of the caveats were minor questions, and none of them expressed real warnings about going concern, financial distress or bankruptcy. Some of the qualifications were as follows:

- The company has valued its fixed assets at their purchase price, net of amortization, excluding impairment losses in value. However, accounting rules state that there will be an impairment loss of intangible assets when the book value exceeds their recoverable amount. At the date of this report, we do not have evidence on the recoverable value of fixed assets related to productive activity, for machinery, equipment, other facilities and other assets, net book value amounts to n.nnn thousand. Therefore, we cannot conclude on the reasonableness of the valuation of these assets and assumes a limitation on the scope of our work have not received the final business plan for the coming years, so we do not have the evidence necessary to analyze the recoverability Tax Credits on and ...

- We did not attend the physical count of inventory at the end on 31 December totalling n.nnn.nnn nnnn 'nn €, because we had not been engaged to audit the company yet; thus it has not been possible to verify the stock on that date by performing alternative audit procedures.
- The society is still implementing a new computer-based MIS for production control and cost management, so it was not possible to determine the costs attributable to each of their buildings during the year, which prevented us from reasonably evaluating the valuation of stock at year end; we could not apply other alternative audit procedures to a satisfactory degree.
- The corporation is, as in the previous year, immersed in several litigations, as disclosed in note nn of memory, with one of its partners who owns nn.n percent of the shares. If this situation persists for a long time, it could undermine the future viability of the company.
- Due to different interpretations of tax regulations in force, contingent liabilities may be difficult to assess objectively. However, in the opinion of society, these liabilities should not significantly affect the annual accounts as a whole. If the company had complied with the principle of prudence, a provision should have been recorded with the amount of n.nnn thousands of euros n.nnn listed in section d). Iii. "Debtor" of balance sheet. In this case, the loss for the year would increase to n.nnn 'nn thousands of euros, and Article 260 of TRLSA should be applicable.

4.3. Audit VS Parametric Models of Forecast

Table 8 shows the results of the simulation carried out on the validation sample; we shoe the hit rates achieved in the classification of the companies given the fact they have or not experienced financial stress or a definitive bankruptcy.

Table 8: Hit rates of "Omega Models" on the validation sample

Pronóstico global		
MDA 1 AA 91,5%	LOGIT 1 AA 74,2%	MRL 1 AA 97,0%
MDA 2 AA 89,4%	LOGIT 2 AA 55,9%	MRL 2 AA 94,5%
MDA 3 AA 99,6%	LOGIT 3 AA 54,7%	MRL 3 AA 94,9%
MDA 4 AA 89,4%	LOGIT 4 AA 55,9%	MRL 4 AA 86,0%
MDA GLOBAL 94,5%	LOGIT GLOBAL 53,4%	MRL GLOBAL 98,3%

Año 1.a.a		
MDA 1 AA 94,9%	LOGIT 1 AA 74,6%	MRL 1 AA 91,5%
MDA 2 AA 91,5%	LOGIT 2 AA 67,8%	MRL 2 AA 88,1%
MDA 3 AA 100,0%	LOGIT 3 AA 69,5%	MRL 3 AA 89,8%
MDA 4 AA 89,8%	LOGIT 4 AA 69,5%	MRL 4 AA 69,5%
MDA GLOBAL 98,3%	LOGIT GLOBAL 72,9%	MRL GLOBAL 93,2%

Año 2.a.a		
MDA 1 AA 89,80%	LOGIT 1 AA 72,90%	MRL 1 AA 98,30%
MDA 2 AA 86,40%	LOGIT 2 AA 57,60%	MRL 2 AA 96,60%
MDA 3 AA 100,00%	LOGIT 3 AA 54,20%	MRL 3 AA 94,90%
MDA 4 AA 89,80%	LOGIT 4 AA 54,20%	MRL 4 AA 93,20%
MDA GLOBAL 91,50%	LOGIT GLOBAL 52,50%	MRL GLOBAL 100,00%

Año 3.a.a		
MDA 1 AA 91,50%	LOGIT 1 AA 76,30%	MRL 1 AA 100,00%
MDA 2 AA 89,80%	LOGIT 2 AA 52,50%	MRL 2 AA 98,30%
MDA 3 AA 100,00%	LOGIT 3 AA 47,50%	MRL 3 AA 98,30%
MDA 4 AA 86,40%	LOGIT 4 AA 49,20%	MRL 4 AA 91,50%
MDA GLOBAL 93,20%	LOGIT GLOBAL 42,40%	MRL GLOBAL 100,00%

Año 4.a.a		
MDA 1 AA 89,80%	LOGIT 1 AA 72,90%	MRL 1 AA 98,30%
MDA 2 AA 89,80%	LOGIT 2 AA 45,80%	MRL 2 AA 94,90%
MDA 3 AA 98,30%	LOGIT 3 AA 47,50%	MRL 3 AA 96,60%
MDA 4 AA 91,50%	LOGIT 4 AA 50,80%	MRL 4 AA 89,80%
MDA GLOBAL 94,90%	LOGIT GLOBAL 45,80%	MRL GLOBAL 100,00%

5. Summary and conclusions

We have developed a set of models able to predict the financial failure of firms located in the Autonomous Community of Galicia, to cover the lack of studies of this type for this geographical area. These models are based on financial ratios, and have been estimated by well-known multivariable methods; the results support the value of financial ratios and financial statements as sources of useful evidences to evaluate financial distress and the risk of financial failure. Of the 59 financial ratios tested, the highest information content is concentrated in profitability, liquidity, leverage and solvency. Our results support the linkage between Profitability and Cash Flow. Distressed firms are less able to generate financial resources; this leads to an increased leverage, to an increasing pressure over income, to the erosion of the equity, and finally to bankruptcy; failed firms usually show an abnormal negative working capital, diminishing client credit periods, lowering prices, and an imbalanced liquidity.

Models show differences between failed and not failed companies become more evident about one year before the event. We believe this is because distressed companies try to avoid bankruptcy by adopting extreme financial decisions, as above mentioned. These arrangements can defer, but usually not avoid, bankruptcy: imbalances make more and more evident during the last year, and affect directly cash flow generation, asset turnover and leverage. Our short-term models are able to make accurate predictions by examining solvency, liquidity and profitability. The "OMEGA" model family offers consistent and very accurate predictions over failed companies; the percentage of errors is slightly higher for healthy companies in the long run. Ob the other side, the average rate of success of short-term models is very high in both groups. Given that the decision maker does not really know when the failure event will happen (if so), we believe that the joint application of the five models can provide very useful information, revealing which companies are prone to suffer financial distress in the future.

The prototype of neural network offers optimal levels of classification with a small number of iterations. In the validation phase, the ability of the network lowers, but is still appealing even though some ratios are eliminated. This confirms that the elimination of "noise" in the network improves its predictive ability. The forecasts are consistent and similar to those obtained with multivariate parametric models. From a global perspective, the neural network models is unable to outperform parametric models, even though provides quite acceptable results, especially in the real implementation with failed companies.

Both groups of models provide a useful decision support tool for a wide range of users who need to assess the financial risk of a company: managers, external auditors, analysts, creditors, financial institutions, investors, public agencies, etc. We believe they clearly outperform external audit in revealing warning signs about financial distress.

Our study also points out the main determinants of business failure among Galician companies, and the stages they pass through when approaching bankruptcy.

- Increase cash flow generation and profitability.
- Increase the ability to dynamically adapt financial policy to environment changes.
- Increase equity and self-financing, and fit financial structure to financial risk.

It is important to note that these models are not an alternative to the audit: they depend on the reliability of financial information, which is guaranteed by the external audit: auditor's responsibilities focus on regulatory compliance, rather than monitoring management quality. In fact going-concerns are quite abstract and in some extent subjective, and it might be extremely dangerous to issue a wrong or ill-timed warning. But a going concern disclosure should also reveal the actions that the company intends to implement to correct the situation, thus reducing uncertainty and increasing financial statements reliability.

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Annex: Sample of failed companies (validation sample)

Acerias As Pontes SL
Aceriusa SL
Astilleros M.Cíes S.L.
Aynar Pro XXI SL
Ayora Puertos y Obras SL
Boupamar
Calizas Marinas SA
Carpintería Naval José Pérez SL
Central Lechera Gallega SA
Congelados País SL
Congelados Troulo SA
Conservas Selectas Mar de Couso SA
Coprosider SL
Dehesa de Rubiales SL
Delio SL
Discovi SL
Disemba SL
Distribuidora Internacional de Alimentación SA
Edibar SL
Elaboradora de Cefalópodos SA
Eurogalia SL
Exportadora Shayne SL
Fergofrío SL
Ferlosa SL
Ferralla Lois SL
Ferrogres SL
Fomento de Áridos y Obras
Forum Filatélico SA
Galicia Frozen Fish SL
Generos de punto Ivan SL

Generos de Punto Montoto SL
Granimondi SA
Granitesa
Granitos Montefaro SA
Gruas y Transportes Vidal
Hidrospack SL
Hierros Touriño SA
Iberoitaliana de Pizarras
Industrias Pizarreras Garcia Aguado SL
Lalandi SL
Lamanor SL
Mariscos Coruña SL
Mebl y Trans SL
MGI Coutier España SL
Montajes Industriales del NO SA
Montajes Industriales del NO SA
Muebles Carballo SA
ONTE SA
Pescados Muiños SL
Plasticos Regueira SL
RC Celta de Vigo SAD
RC Deportivo de La Coruña
Roberto Mourino SA
Strategias de Medios Galicia SA
Transportes Ramos Piñeiro
UNICEN
Viajes Vincit SL
Vidriera del Atlántico SA
Volvoreta