A MODEL TO FORECAST FINANCIAL FAILURE, IN NON FINANCIAL GALICIAN SMES.

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ABSTRACT

We are concerned with providing more empirical evidence on forecast failure, developing forecast models, and examining the impact of events such as audit reports. A joint consideration of classic financial ratios and relevant external indicators leads us to build a basic prediction model focused in non-financial Galician SMEs. Explanatory variables are relevant financial indicators from the viewpoint of the financial logic and financial failure theory. The paper explores three mathematical models: discriminant analysis, Logit, and linear multivariate regression. We conclude that, even though they both offer high explanatory and predictive abilities, Logit and MDA models should be used and interpreted jointly.

KEY WORDS

Business failure, Prognosis, Logit, MDA, Reliability.

[1] FYSIG was created by Professor Félix R. Doldán Tíe (retired); he continues collaborating with our research group, like in this paper, and his work has continued by his disciples.

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1 INTRODUCTION[1]

Financial failure - bankruptcy, temporary insolvencies, creditor's meeting, coalitions and divisions - is a recurrent question in financial literature, because of its theoretical relevance, and also because of its serious consequences for economic activity. The first contributions by Beaver (1966), Altman (1968) and Ohlson (1980) examined different methodological options to develop explanatory and forecast models. The most classic approach (Altman, 1968; Altman et al., 1977; Altman, 2000; Altman et al., 2010) enriched with the development of alternative methods, more reliable, and less dependent of methodological hypothetical conditions, namely Logit and probit analysis (Martin, 1977; Ohlson, 1980; Zmijewski, 1984). Recursive partitioning techniques (Frydman et al., 1985) and different artificial intelligence-based techniques, such as expert systems, neural networks (Messier and Hansen, 1988; Bell et al., 1990; Hansen and Messier, 1991; Mountain and Martin of the Mettle, 1993; Koh and So, 1999; Brockett et al., 2006), and support vector machines (SVM) (Shin et al., 2005; Härdle et al., 2005). The complex and unstructured nature of the analysis has also led to the the application of heuristic methods such as computer-supported social decision techniques (level 3 GDSS, e.g. Sun and Li, 2009) and fuzzy logic – based models (Dubois and Prade, 1992; Slowinski and Zopounidis, 1995; McKee and Lensberg, 2002).

Financial failure was first studied from a formalized perspective by Beaver (1966); his works examines whether financial ratios supply relevant information to evaluate and forecast crash scenarios, temporary insolvencies, dividends unpaid, and overdrafts. Beaver verified the predictive ability of cash flow to total debt, net income to total assets and several other capital and/or assets - based ratios.

Beaver's formulation (1966) contributes an enlarged vision of coherent financial failure which is also coherent with modern Finance; nevertheless it suffers some methodological limitations. The view of financial failure forecast as a multivariate

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problem is due to Altman (1968). He suggests the development of discriminant analysis models that, regardless their fitness, could be used as standard rules and therefore contribute to reinforce the objectivity of solvency analysis. Nevertheless MDA application is conditioned by its theoretical requirements, namely homoscedasticity and the normal conjoint distribution of factors; moreover, given its mathematical configuration, MDA models do not provide detailed information to specify the causes and the internal structure of the event failure, even when different time frames are taken into consideration (de Llano et al., 2010).

Ohlson (1980) suggests the use of logistic regression to evaluate the likelihood of failure, following Martin (1977) seminal work on financial companies. Ohlson (1980) improves Martin's original position contributing a theoretical basis that allows for estimations of the probability of failure of non-financial companies, according to four basic attributes: dimension, financial structure, financial yield, and liquidity. Besides methodological improvements, logit approach is coherent with the view of bankruptcy as a complex process where “several greys” can be identified. In fact, managers may be interested not in an exhaustive, rigorous, classification but in a measure of the likelihood that the company goes bankruptcy or suffers financial distress within a given period of time. Ohlson (1980) also corroborates that the combination of financial information and market indicators substantially improves the ability to forecast financial distress. Several external data and signs can be used to increase model’s fit, e.g. market prices, volatility, minimized external information flows, delays in financial statements’ deposit, qualified audit opinions, and auditor’s changes (Piñeiro et al., 2011).

The development and validation of these models has provided valuable information about the very nature of the financial and/or organizational processes leading to failure, and the key variables that managers should keep an eye on, in order to anticipate financial difficulties and evaluate borrowers’ credit risk: a few critical ratios (e.g. liquidity, profitability and working capital) (Rodríguez et al., 2010), macroeconomic and risk-related factors (Rose et al., 1982), proxies of the management quality (Peel et al., 1986; Keasey and Watson, 1987), and qualitative signs inferred from audits (Piñeiro et al., 2011).

Given the severity of financial failure, empirical work emphasized the ability of the models to identify firms under financial stress and forecast bankruptcy itself. Thus, validation is aimed, specifically, to avoid type II error (classify as healthy a financially distressed, high risk, company). But type I error is also clearly relevant because "false positives" can damage companies' reputation and induce a self-fulfilling prophecy, thus leading healthy companies to severe financial difficulties. Ohlson (1980) emphasized that error rates reported by previous studies (namely in Altman's MDA models) were remarkably low, and later works confirm the existence of biases in type I and type II errors (de Llano et al., 2010). Maybe because sampling and/or by mathematical reasons, models accomplishing remarkable results among bankrupted companies reach only moderate results when applied on solvents companies, and this suggest that models tend to overestimate failure probability: the proportion of healthy companies qualified as potentially bankrupt it is very high, remarkably higher than type I error. According to our experience, this bias is more likely in companies who develop characteristic activities, emerging business and/or show idiosyncratic financial properties, e.g. peculiar temporal patterns in cash flow generation. This is closely related with the need to recalibrate models (Moyer, 1977; Altman, 2000). Aside from its statistical relevance, type I errors may have severe consequences for companies: as they undermine the trust of lenders and markets, they can reduce companies' financial resources and lead them to a self-fulfilled insolvency.

This work offers evidence on the prediction of financial distress in non-financial Galician SMEs. These companies are uncommon by several reasons, e.g. a very small size, family-owned capital, relatively high leverage, and low management specialization, therefore generalized models (such as Altman's Z-score and market-based models) seem not applicable. We aim to develop a focused model to describe and support the forecasting of financial distress on the basis of financial data; a second objective is to provide empirical evidence to reduce the likelihood of type I errors.

2 METHOD

2.1 SAMPLE

Our work is based on two random samples of SMEs Galician companies: the first one is made of healthy companies and the second one is made of financially distressed companies. Bankruptcy is defined in wide terms as a situation of financial instability that might lead the company to fill for bankruptcy in the short or medium term; companies are classified according to the information supplied by financial statements and public registers (RAI, BADEXCUG). Thus one company may be classified as financially distressed even though no fill for bankruptcy has been presented. This approach offers a more flexible and effective way to express situations that, even though do not imply an irreversible bankruptcy, are logically linked with financial instability – e.g. abnormal leverage, lack of liquidity or overdue credits -.

2.1.1 Failed companies

SABI[2] database contains 75.640 Galician companies; three hundred and eighty four (384) of them have filed for bankruptcy within the last ten years. Sixty two of these companies (approximately, 16% of 384) received at least one qualified opinion from 1999 to 2009. In the same period, thirty nine companies received an adverse opinion and in forty four companies auditors issued a disclaimer opinion. Auditors' report is not available for the rest of the companies either because they are not required to audit their financial statements or because companies didn't meet their obligation to publish those statements and auditor's report.

2.1.2 Healthy companies

These second group is made of active, healthy SMEs. They have not filed for bankruptcy, nor are listed in insolvency public registers (they have not suffered any financial incident within the last ten years), therefore they are financially healthy companies, not affected by severe financial difficulties. These companies have also received, in all and each one of the exercises between 1999 and 2009, an unqualified audit report. The resulting sample is made of one hundred and seven (107) companies.

[2] Sistema de Análisis de Balances Ibéricos.

2.2 VARIABLES

Models are based in a subset of financial variables and ratios, selected by expert judgment according to the the frequency and level of significance showed in previous research works. In all cases, ratios were calculated from the magnitudes listed in the Annual Accounts, without any adjustment (e.g. alternative accounting methods or market-based valuation). Some of our models include external auditing-related indicators.

Var.	Content	Var.	Content
ACT01	Interests/ value added	LIQ10	Stock & inventories / short term loans
ACT02	Salaries/ non current assets	LIQ11	(Stock & inventories + credits & fin. Investments) / short term loans
ACT03	(Salaries + amortization) / value added	LIQ12	Non-credit period
ACT04	Income / costs	LIQ13	Credits & fin. Investments / short term loans
ACT05	Value added / sales	REN01	Ebit / total assets
APL01	Ebit / interests	REN02	Ebit / sales
APL02	Interests/ loans	REN03	Net profit / sales
APL03	Operating profit / interests	REN04	(Net profit - credits & fin. Investments – stock & inventories) / total assets
APL04	Net profit / loans	REN05	Net profit / total assets
END01	Loans / equity capital	REN06	Net profit / equity capital
END02	(Equity capital – net profit) / short term loans	ROT01	Current assets – stock & inventories / sales
END03	Equity capital / loans	ROT02	Stock & inventories / sales
END04	Long term loans / loans	ROT03	Sales / credits & fin. Investments cierto
EST01	Current assets / total assets	ROT04	Sales / current assets
EST02	Amortization / non current assets	ROT05	Sales / non current assets
EST03	Working capital / total assets	ROT06	Sales / total assets
EST04	Working capital / loans	ROT07	Sales / working capital
EST05	Working capital / sales	ROT08	Sales / cash
EST06	Cash / total assets	SOL01	(Current assets – stock & inventories) / short term loans
EST07	Net profit / working capital	SOL02	Current assets / loans
EST08	Assets decomposition	SOL03	Current assets / short term loans
LIQ01	Operating cash flow / total assets	SOL04	Non current assets / equity capital
LIQ02	Operating cash flow / loans	SOL05	Loans / total assets
LIQ03	Operating cash flow / short term loans	SOL06	Equity capital / total assets
LIQ04	Operating cash flow / sales	SOL07	Equity capital / non current assets
LIQ05	Cash flow gen. Res. / total assets	SOL08	Short term loans / total assets
LIQ06	Cash flow gen. Res. / loans	SOL09	(Net profit + taxes) / short term loans
LIQ07	Cash flow gen. Res. / short term loans	TES01	Cash / short term loans
LIQ08	Cash flow gen. Res. / sales	TES02	Cash / sales
LIQ09	Cash / short term loans		
NUM	Number of auditor changes	RATMOD	Rate of modified opinion reports
AVDUR	Average duration of auditors' contract	DISCLO	The failure to comply with the obligation to file and disclose

Var.	Content	Var.	Content
			its financial statements
CONCU	Concurrency of auditor changes and the revealing of uncertainties		

Figure 1. Independent variables

2.3 MULTIVARIATE METHODS

We have carried out several MDA, logit and LR estimations to test whether financial ratios and audit-related external signs can be used as predictors of financial distress in Galician SMEs. We then verify the predictive capacity of the models, applying them to the sample and estimating the corresponding prediction error-rate. In each case, a model has been estimated for each of the following time horizons: one year before failure, two years before failure, three years before failure, and four years before failure. This methodology has been applied to develop *absorbent* models for each of the four years of planning horizon – these are the "Omega Models"-. A fifth time-independent model has also been estimated, to support a sensitivity analysis and test the significance and stability of the estimates. Finally, we estimate a logit model in order to evaluate the informational content of auditor' reports and several related indicators.

All models were estimated applying using step selection. This selection method does not guarantee an optimal final set of factors (because of conditional contrasts), but it is and efficient and logical strategy to find a good combination of variables; it is also consistent with the parsimony principle - making simple and understandable models -.

3 RESULTS AND DISCUSSION

3.1 DISCRIMINANT ANALYSIS (MDA) MODELS

Final MDA models combine several measures of leverage, capital structure, profitability, activity and liquidity. Short term forecasts rely mostly in immediate liquidity and current loans, while financial stability in the long run seems to be more related with leverage and capital structure, profitability, and term structure of assets[3].

- $MDA.1 = -0'339 + 4'284APL_{04} + 0'201ROT_{06} + 1'311SOL_{06}$
- $MDA.2 = 0'127 + 7'871APL_{04} + 0'61LIQ_{12}$

[3] See appendix.

- $MDA.3 = -0'98 + 13'706REN_{05} + 2'108SOL_{06} + 7'734LIQ_{05}$
- $MDA.4 = -0'312 + 6'53APL_{04} - 0'883END_{03} - 2'913EST_{03} + 4'823SOL_{06} - 3'891LIQ_{05} + 1'1466LIQ_{12}$
- $MDA.Global = -0'275 + 0'399APL_{04} + 0'376END_{03} + 1'159EST_{03} + 0'011ROT_{06} + 1'975LIQ_{05}$

3.1.1 MDA in failed companies

When applied to failed companies, MDA models achieve a satisfactory hit rate (up to 98% in some cases, and 85% in average, four years before the failure). Average hit rate increases as the company approaches bankruptcy, thus model's reliability diminishes in the long run (**¡Error! No se encuentra el origen de la referencia.**).

Forecast Failure s/(H,F)	1yb	2yb	3yb	4yb	5yb	6yb	7yb	8yb	9yb	10yb	11yb
MDA 1 Forecast	96,3%	94,6%	93,9%	92,3%	91,0%	91,7%	90,7%	89,4%	85,9%	82,0%	80,2%
Healthy	6	9	16	20	23	20	20	21	26	29	18
Failure	154	158	245	240	233	220	194	177	159	132	73
MDA 2 Forecast	93,7%	94,0%	92,0%	90,4%	89,8%	91,3%	91,6%	89,7%	85,8%	87,0%	87,9%
Healthy	10	10	21	25	26	21	18	20	26	21	11
Failure	149	158	240	235	230	219	196	175	157	140	80
MDA 3 Forecast	98,1%	98,8%	98,4%	98,1%	97,6%	100,0%	96,3%	98,0%	96,2%	97,5%	96,7%
Healthy	3	2	4	5	6	0	8	4	7	4	3
Failure	156	165	254	252	248	237	209	195	179	155	89
MDA 4 Forecast	90,7%	90,6%	85,4%	85,8%	84,0%	83,3%	86,7%	84,7%	81,0%	85,4%	85,7%
Healthy	15	16	38	37	41	40	28	30	35	23	12
Failure	147	154	223	223	216	200	183	166	149	134	72
MDA GLOBAL Forecast	90,3%	84,8%	84,0%	82,8%	82,4%	81,7%	77,2%	79,8%	77,6%	78,0%	82,4%
Healthy	15	25	42	45	45	44	49	40	41	35	15
Failure	139	139	220	216	210	196	166	158	142	124	70

Figure 2. Hit rate (MDA, failed companies, full information available)

Models' reliability is also affected by information lags. It is remarkably that models' performance seems to be correlated with the amount of information available, and this flow of information gets more and more scarce as financial distress deepens. We were able to obtain financial information for 155, 146, 262 and 261 companies (of a total of 265) for one, two, three, and four years before the company failed. Companies cutting the external flow of financial information are more likely to fail in the short and medium term.

In our sample, the number of more than eight years-old companies is modest because several corporate operations – e.g. mergers, absorptions and evolution to *plc* – may have happened; these situations are quite common, given the special nature of the business in

out our sample and also induce information lags. When models are applied to the unabridged sample, regardless information lags, hit rate diminishes but is still satisfactory.

Forecast Failure s/(H,F)	1yb	2yb	3yb	4yb	5yb	6yb	7yb	8yb	9yb	10yb	11yb
MDA 1 Forecast No information	39,6%	37,0%	1,5%	1,9%	3,4%	9,4%	19,2%	25,3%	30,2%	39,2%	65,7%
Forecast Error	2,3%	3,4%	6,0%	7,5%	8,7%	7,5%	7,5%	7,9%	9,8%	10,9%	6,8%
Hit rate	58,1%	59,6%	92,5%	90,6%	87,9%	83,0%	73,2%	66,8%	60,0%	49,8%	27,5%
MDA 2 Forecast No information	40,0%	36,6%	1,5%	1,9%	3,4%	9,4%	19,2%	26,4%	30,9%	39,2%	65,7%
Forecast Error	3,8%	3,8%	7,9%	9,4%	9,8%	7,9%	6,8%	7,5%	9,8%	7,9%	4,2%
Hit rate	56,2%	59,6%	90,6%	88,7%	86,8%	82,6%	74,0%	66,0%	59,2%	52,8%	30,2%
MDA 3 Forecast No information	40,0%	37,0%	2,6%	3,0%	4,2%	10,6%	18,1%	24,9%	29,8%	40,0%	65,3%
Forecast Error	1,1%	0,8%	1,5%	1,9%	2,3%	0,0%	3,0%	1,5%	2,6%	1,5%	1,1%
Hit rate	58,9%	62,3%	95,8%	95,1%	93,6%	89,4%	78,9%	73,6%	67,5%	58,5%	33,6%
MDA 4 Forecast No information	38,9%	35,8%	1,5%	1,9%	3,0%	9,4%	20,4%	26,0%	30,6%	40,8%	68,3%
Forecast Error	5,7%	6,0%	14,3%	14,0%	15,5%	15,1%	10,6%	11,3%	13,2%	8,7%	4,5%
Hit rate	55,5%	58,1%	84,2%	84,2%	81,5%	75,5%	69,1%	62,6%	56,2%	50,6%	27,2%
MDA GLOBAL Forecast No information	41,9%	38,1%	1,1%	1,5%	3,8%	9,4%	18,9%	25,3%	30,9%	40,0%	67,9%
Forecast Error	5,7%	9,4%	15,8%	17,0%	17,0%	16,6%	18,5%	15,1%	15,5%	13,2%	5,7%
Hit rate	52,5%	52,5%	83,0%	81,5%	79,2%	74,0%	62,6%	59,6%	53,6%	46,8%	26,4%

Figure 3. Hit rate (MDA, failed companies, including those affected by information lags)

3.1.2 MDA in healthy companies

The application of MDA models to the sample of 107 healthy companies shows a comparatively poor performance (. Hit rate is lower than 40% in most of the scenarios, thus the model is absolutely not a relevant decision support, but it is noticeable that the same model fits extremely well the sample of failed companies. This is akin to similar biases reported by previous studies. One possible explanation is the fact that the sample of healthy companies is more complex and heterogeneous than the sample of failed companies – as we have seen, the latter can be defined by a few ratios –; this might lead to a higher rate of misclassifications in healthy companies. Anyway this bias should be taken into account by practitioners because empirical evidence suggest that MDA models might overstate bankruptcy risk.

Forecast Healthy s/(H,F)	1yb	2yb	3yb	4yb	5yb	6yb	7yb	8yb	9yb	10yb	11yb
MDA 1 Forecast	39,3%	37,4%	43,9%	43,9%	44,9%	47,7%	45,8%	43,9%	46,7%	53,3%	48,1%
Healthy	42	40	47	47	48	51	49	47	50	56	50
Non healthy	65	67	60	60	59	56	58	60	57	49	54
MDA 2 Forecast	43,9%	36,4%	40,2%	36,4%	41,1%	39,3%	42,1%	38,3%	38,3%	42,9%	43,3%
Healthy	47	39	43	39	44	42	45	41	41	45	45
Non healthy	60	68	64	68	63	65	62	66	66	60	59
MDA 3 Forecast	9,3%	11,2%	8,4%	5,6%	8,4%	9,3%	8,4%	10,3%	7,5%	8,6%	10,6%
Healthy	10	12	9	6	9	10	9	11	8	9	11
Non healthy	97	95	98	101	98	97	98	96	99	96	93
MDA 4 Forecast	42,1%	33,6%	35,5%	24,3%	29,9%	31,8%	35,5%	33,6%	33,6%	28,6%	34,6%
Healthy	45	36	38	26	32	34	38	36	36	30	36
Non healthy	62	71	69	81	75	73	69	71	71	75	68
MDA GLOBAL Forecast	32,7%	26,2%	28,0%	23,4%	28,0%	27,1%	25,2%	24,3%	24,3%	21,9%	21,2%
Healthy	35	28	30	25	30	29	27	26	26	23	22
Non healthy	72	79	77	82	77	78	80	81	81	82	82

Figure 4. Hit rate (MDA, healthy companies)

It is remarkable that, the more advanced is the forecast, the lower is the company's estimated creditworthiness, whatever it is really healthy or not. The forecast improves as the failure gets closer, but credit risk tends to be systematically overestimated in all business categories, both in long and short term. One interpretation is that MDA score offers early warnings about latent financial instabilities that may evolve to a real financial distress, or not, subject to management decisions and environmental conditions; companies should be analysed in more detail to clarify the real credit risk.

3.2 LOGIT MODELS

Several logit models have been estimated following Ohlson (1980) seminal work; in this case, the exhaustive 10K-based listing of failed companies has been replaced by a more fuzzy dependent variable expressing not only fillings for bankruptcy but also delays in payments (e.g. dishonoured bills and unpaid invoices) formally registered by public databases. Final models have been estimated by applying a step-by-step procedure to select relevant factors[4]:

[4] See appendix.

- $$LOGIT.1 = \frac{1}{1+e^{-(8'444-11'066\,APL_{04}+5'584\,END_{03}-2'603\,ROT_{06}+30'815\,SOL_{06}+2'929\,LIQ_{12})}}$$
- $$LOGIT.2 = \frac{1}{1+e^{-(0'974-111'23\,APL_{04})}}$$
- $$LOGIT.3 = \frac{1}{1+e^{-(1'678-33'765\,REN_{05}-6'216\,SOL_{06})}}$$
- $$LOGIT.4 = \frac{1}{1+e^{-(3'102-49'448\,APL_{04}+4'284\,END_{03}+34'773\,REN_{05}-17'348\,SOL_{06})}}$$
- $$LOGIT.Global = \frac{1}{1+e^{-(0'673-3'711\,EST_{03}-11'254\,LIQ_{05})}}$$

3.2.1 Logit models in failed companies

We have first simulated the application of logit models to the failed companies' sample. Hit rate is high in most cases (up to 88%) but, also, unstable in different terms and different model structures; results are especially poor in *logit.2* model, which is based in just one variable (APL04 – net profit over loans) but, overall, MDA models outperform logit models. Moreover, forecasting performance of logit models degrades rapidly in the long term, thus models reliability seems to be limited to a few years prior to the failure.

Forecast Failure s/(H,F)	1yb	2yb	3yb	4yb	5yb	6yb	7yb	8yb	9yb	10yb	11yb
LOGIT 1 Forecast	81,8%	87,3%	87,9%	87,5%	85,0%	82,4%	84,5%	86,6%	83,6%	78,1%	70,0%
Healthy	29	21	31	32	38	42	33	26	30	35	27
Failure	130	145	226	225	216	197	180	168	153	125	63
LOGIT 2 Forecast	65,8%	58,2%	54,5%	54,3%	45,6%	48,3%	39,3%	42,1%	41,5%	30,2%	31,9%
Healthy	54	69	117	117	137	122	128	113	107	111	62
Failure	104	96	140	139	115	114	83	82	76	48	29
LOGIT 3 Forecast	78,6%	70,8%	64,0%	62,3%	57,2%	59,6%	48,9%	52,0%	48,7%	44,7%	50,0%
Healthy	34	49	94	98	110	97	112	96	96	89	46
Failure	125	119	167	162	147	143	107	104	91	72	46
MD 4 Forecast	76,8%	81,8%	77,1%	76,6%	75,3%	72,5%	69,8%	70,9%	68,9%	62,0%	65,9%
Healthy	36	30	60	61	63	66	64	57	56	60	29
Failure	119	135	202	200	192	174	148	139	124	98	56
MDGLOBAL Forecast	73,6%	70,6%	66,7%	66,3%	64,3%	66,5%	66,1%	62,6%	62,6%	59,9%	60,4%
Healthy	43	50	87	88	92	81	75	76	71	67	38
Failure	120	120	174	173	166	161	146	127	119	100	58

Figure 5. Logit hit rate (failed companies, full information)

Forecast Failure s/(H,F)	1yb	2yb	3yb	4yb	5yb	6yb	7yb	8yb	9yb	10yb	11yb
LOGIT 1 Forecast No information	40,0%	37,4%	3,0%	3,0%	4,2%	9,8%	19,6%	26,8%	30,9%	39,6%	66,0%
Forecast Error	10,9%	7,9%	11,7%	12,1%	14,3%	15,8%	12,5%	9,8%	11,3%	13,2%	10,2%
Hit rate	49,1%	54,7%	85,3%	84,9%	81,5%	74,3%	67,9%	63,4%	57,7%	47,2%	23,8%
LOGIT 2 Forecast No information	40,4%	37,7%	3,0%	3,4%	4,9%	10,9%	20,4%	26,4%	30,9%	40,0%	65,7%
Forecast Error	20,4%	26,0%	44,2%	44,2%	51,7%	46,0%	48,3%	42,6%	40,4%	41,9%	23,4%
Hit rate	39,2%	36,2%	52,8%	52,5%	43,4%	43,0%	31,3%	30,9%	28,7%	18,1%	10,9%
LOGIT 3 Forecast No information	40,0%	36,6%	1,5%	1,9%	3,0%	9,4%	17,4%	24,5%	29,4%	39,2%	65,3%
Forecast Error	12,8%	18,5%	35,5%	37,0%	41,5%	36,6%	42,3%	36,2%	36,2%	33,6%	17,4%
Hit rate	47,2%	44,9%	63,0%	61,1%	55,5%	54,0%	40,4%	39,2%	34,3%	27,2%	17,4%
LOGIT 4 Forecast No information	41,5%	37,7%	1,1%	1,5%	3,8%	9,4%	20,0%	26,0%	32,1%	40,4%	67,9%
Forecast Error	13,6%	11,3%	22,6%	23,0%	23,8%	24,9%	24,2%	21,5%	21,1%	22,6%	10,9%
Hit rate	44,9%	50,9%	76,2%	75,5%	72,5%	65,7%	55,8%	52,5%	46,8%	37,0%	21,1%
LOGIT GLOBAL Forecast No information	38,5%	35,8%	1,5%	1,5%	2,6%	8,7%	16,6%	23,4%	28,3%	37,0%	63,8%
Forecast Error	16,2%	18,9%	32,8%	33,2%	34,7%	30,6%	28,3%	28,7%	26,8%	25,3%	14,3%
Hit rate	45,3%	45,3%	65,7%	65,3%	62,6%	60,8%	55,1%	47,9%	44,9%	37,7%	21,9%

Figure 6. Logit hit rate (all failed companies)

3.2.2 Logit models in healthy companies

Again, forecasting ability of logit models show a remarkable instability. Unexpectedly, error rate is higher in the short term (one and two years before failure) and in the very long term (ten and eleven years before failure), while hit rate tends to increase in the medium term (four to six years before failure). We believe this must be read in conjunction with economic recession: solvency, profitability and financial stability might be deteriorating progressively due to the adverse external conditions; models might be unable to cope with this changes because, even though several specific attributes (e.g. leverage and management quality) can modulate bankruptcy likelihood, financial crisis is driven by systemic factors that are not addressed by company-level models.

Despite these anomalies, logit models clearly outperform MDA models in classifying healthy companies. As some previous works have stated (de Llano et al., 2010 & 2011), MDA and logit models performance differs depending on whether company under

analysis is (really) failed or healthy: MDA tends to overstate the likelihood of a bankruptcy, while logit regression tends to overestimate the probability of failure. This highlights the need to jointly interpret MDA and logit analysis results.

Healthy Forecast s/(HS,F)	1yb	2yb	3yb	4yb	5yb	6yb	7yb	8yb	9yb	10yb	11yb
LOGIT 1 Forecast	16,8%	20,6%	18,7%	18,7%	21,5%	27,1%	22,4%	23,4%	27,1%	28,6%	28,8%
Healthy	18	22	20	20	23	29	24	25	29	30	30
Failure	89	85	87	87	84	78	83	82	78	75	74
LOGIT 2 Forecast	73,8%	81,3%	87,9%	91,6%	92,5%	88,8%	89,7%	90,7%	89,7%	90,5%	91,3%
Healthy	79	87	94	98	99	95	96	97	96	95	95
Failure	28	20	13	9	8	12	11	10	11	10	9
LOGIT 3 Forecast	83,2%	81,3%	83,2%	86,9%	89,7%	89,7%	86,0%	86,0%	82,2%	85,7%	86,5%
Healthy	89	87	89	93	96	96	92	92	88	90	90
Failure	18	20	18	14	11	11	15	15	19	15	14
LOGIT 4 Forecast	68,2%	71,0%	80,4%	80,4%	82,2%	83,2%	79,4%	76,6%	72,9%	77,1%	82,7%
Healthy	73	76	86	86	88	89	85	82	78	81	86
Failure	34	31	21	21	19	18	22	25	29	24	18
LOGIT GLOBAL Forecast	75,7%	77,6%	77,6%	77,6%	82,2%	81,3%	77,6%	80,4%	76,6%	74,3%	76,9%
Healthy	81	83	83	83	88	87	83	86	82	78	80
Failure	26	24	24	24	19	20	24	21	25	27	24

Figure 7. Logit hit rate (healthy companies)

3.3 LINEAL REGRESSION MODELS

Linear regression (LR) performance is in a clear abandonment stage in the literature because of its shortcomings, namely a very poor forecasting performance and the previously stated difficulty to verify the requirement of normally distributed predictors. Anyway we have estimated a set of LR models for 1 – 4 years before the bankruptcy, and then conducted a simulation to establish models reliability.

- $MRL.1 = 0'584 - 1'068APL_{04} - 0'005ROT_{06} - 0'327SOL_{06}$
- $MRL.2 = 0'468 - 1'979APL_{04} - 0'153LIQ_{12}$
- $MRL.3 = 0'524 - 3'308REN_{05} - 0'509SOL_{06} + 1'867LIQ_{05}$
- $MRL.4 = 0'576 - 1'586APL_{04} + 0'215END_{03} - 0'727EST_{03} - 1'171SOL_{06} - 0'945LIQ_{05} - 0'356LIQ_{12}$
- $MRL.Global = 0'56 - 0'087APL_{04} - 0'082END_{03} - 0'253EST_{03} - 0'002ROT_{06} - 0'431SLIQ_{05}$

Forecasting reliability is extremely high in failed companies (up to 99% four years before failure), nevertheless LR models fall flat in healthy companies: almost all companies are classified as failed, whatever their financial situation and credit risk are, and average hit rate is lower than 5% in healthy companies. This is because LR underlying estimation method does not effectively meet the rationale of financial healthiness, that is, the several equilibrium relations the company must address in order to assure survival; the discrete, dichotomous, nature of dependent variable (failed vs. non failed) is also a relevant question, given that standard LR is intended for continuous variables.

Forecast Failure s/(H,F)	1yb	2yb	3yb	4yb	5yb	6yb	7yb	8yb	9yb	10yb	11yb
MRL 1 Forecast	85,0%	95,8%	96,6%	98,8%	98,4%	96,7%	99,5%	99,5%	100,0%	98,8%	98,9%
MRL 2 Forecast	75,5%	89,3%	93,5%	93,5%	94,1%	91,3%	94,4%	94,4%	95,6%	94,4%	96,7%
MRL 3 Forecast	81,8%	93,4%	96,5%	97,7%	97,2%	97,0%	98,6%	98,5%	97,8%	97,5%	98,9%
MRL 4 Forecast	71,8%	86,4%	88,0%	88,0%	87,9%	87,1%	90,5%	89,9%	90,4%	89,9%	85,7%
MRL GLOBAL Forecast	92,6%	95,9%	97,3%	98,4%	97,7%	97,5%	98,1%	98,5%	98,4%	96,8%	100,0%

Figure 8. LR hit rate (failed companies)

Forecast Healthy s/(H,F)	1yb	2yb	3yb	4yb	5yb	6yb	7yb	8yb	9yb	10yb	11yb
MRL 1 Forecast	3,7%	2,8%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
MRL 2 Forecast	14,0%	12,1%	1,9%	3,7%	2,8%	1,9%	1,9%	0,9%	1,9%	1,9%	2,9%
MRL 3 Forecast	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
MRL 4 Forecast	20,6%	20,6%	2,8%	5,6%	3,7%	3,7%	3,7%	3,7%	5,6%	3,8%	3,8%
MRL GLOBAL Forecast	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%

Figure 9. LR hit rate (healthy companies)

3.3.1 Enhancing the basic models with audit-based qualitative signs

As far as failure prediction relies in financial data, the external control of the reliability of the accounting process becomes paramount. Auditors are expected not only to verify formal requirements but, also, to warn investors when the audited company faces uncertainties that may threaten its survival. Empirical evidence suggests that modified opinions (qualified opinion, disclaimer, and adverse opinion) may also convey some informational content to external users (Piñeiro et al., 2011): some previous works have found that the “disclaimer” report is frequently used to signal extreme client firm’s

distress, and a statistically significant relationship between auditor rotation, financial distress and the likelihood of an unqualified opinion (Robinson, 2008). Companies try to minimize the probability of a qualified opinion and/or a disclosure by changing repeatedly its external auditor (Schwartz and Menon, 1985; Schwartz and Soo, 1995; Ruiz and Gómez; Blay, 2005) and the resulting situation can be modelled as a game (Matsumura et al., 1997; Tucker and Matsumura, 1998).

We have formulated a logit model to verify the informational content of these external signs, namely to evaluate if they can improve our ability to infer unrevealed financial distress situations. Factors were subjectively selected according to their relevance in the literature: number of auditor changes, rate of modified opinion reports, average duration of auditors' contract, the failure to comply with the obligation to file and disclose its financial statements, and the concurrency of auditor changes and the revealing of uncertainties.

Coefficients of the model		B	E.T.	Wald	gl	Sig.	Exp(B)	C.I. 95,0% for EXP(B)	
								L	H
Step 1(a)	RATMOD	0,04	0,01	26,47	1	0,00	1,04	1,02	1,05
	Intercept	-1,54	0,37	17,09	1	0,00	0,21		
Step 2(b)	RATMOD	0,03	0,01	20,91	1	0,00	1,03	1,02	1,05
	DISCLO	21,10	8988,63	0,00	1	1,00	1,45E+09	0,00	.
	Intercept	-22,94	8988,63	0,00	1	1,00	0,00		
Step 3(c)	AVDUR	-0,32	0,14	4,96	1	0,03	0,73	0,55	0,96
	RATMOD	0,03	0,01	14,39	1	0,00	1,03	1,01	1,04
	DISCLO	21,74	8642,69	0,00	1	1,00	2,77E+09	0,00	.
	Intercept	-22,16	8642,69	0,00	1	1,00	0,00		

Model fits fairly well original data, both in estimation and simulation stages. Average hit rate reaches 80%, which is a very satisfactory outcome given the qualitative, indirect nature of the independent variables, and model's parsimony. Final model is based in just three factors:

- The rate of modified opinion reports (RATMOD)
- Average duration of auditors' contract (AVDUR)
- The failure to comply with the obligation to file and disclose its financial statements (DISCLO)

Our results corroborate that it is feasible to infer the existence of unrevealed financial distress on the basis of qualitative signs derived from audit reports, even if auditors have not issued a going-concern qualification. Companies suffering financial distress have a peculiar auditing profile: high rotation of auditors, short term contracts, cost interdependencies (complementary services), an abnormally high rate of disclaimer of opinion reports, difficulties to meet external information duties (file and disclosure of financial statements), and even audit omissions. Our model corroborates that these profile can be quantified and used to effectively discriminate financially instable companies.

However, the cross-sectional nature of the model implies that, unlike MDA and logit models, it fails in forecasting the inter-temporal failure probabilities: it is only capable of predicting the evolution of the company within one period of time. We are currently exploring different alternatives in order to improve the model.

4 CONCLUSIONS

Several methodologies have been applied to forecast financial distress and the likelihood that a company will go bankruptcy. Most of them are applicable just in concrete industries or geographical areas. Our work contributes several forecasting models intended to be applied in Galician SMEs, and empirical evidence about their reliability. Both MDA and logit models attain hit rates up to 80% (logit models do well in 90% of the healthy companies). However a systematic bias has been detected: MDA models reach good results in identifying distressed companies, and a relatively poor performance in healthy companies, while logit models seem to be more suitable to identify healthy companies; therefore, MDA models tend to overstate bankruptcy probability, while logit models seem to systematically undervalue the inherent credit risk of the company.

This bias seems to be more acute in MDA models, maybe because this methodology enforces a discrete view of bankruptcy: a company can only be classified in one of two clearly different categories (active vs. failed); but financial distress embraces several instability situations and most of them do not lead to a bankruptcy. This might explain why MDA models tend to classify as failed those companies in the “grey zone”, that is,

companies that are not clearly healthy and, therefore, overstate the likelihood of a bankruptcy.

A joint interpretation of MDA and logit models should lead to a more precise view of the financial healthiness of a company. Our work contributes evidence to enhance the reliability of both models by including additional variables regarding external auditing: average duration of auditors' contracts, rotation, rate of qualified opinion reports, and non-observance of duties regarding the publication of financial information.

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6 APPENDIX

	Variables	MDA		Logit		LR	
		Coef.(f)	Sig.	Coef.(t)	Sig.	Coef.(wald)	Sig.
Apl04	Net profit/ Loans	4,284 (106,2)	0,000	-110,66 (7,55)	0,006	-1,068 (-6,89)	0,000
End03	Equity capital/ Loans	-	-	5,584 (2,78)	0,095	-	-
Rot06	Sales/ total assets	0,201 (52,35)	0,000	-2,603 (4,38)	0,036	-0,005 (-1,98)	0,050
Sol06	Equity capital/ total assets	1,311 (74,69)	0,000	30,815 (7,21)	0,007	-0,327 (-4,71)	0,000
Liq12	Non-credit period	-	-	2,929 (4,67)	0,030	-	-
	Intercept	-0,339 -	-	8,444 (7,34)	0,006	0,584 (11,41)	0,000
	Global sig.	99,736 (χ2)	0,000	149,958 (χ2)	0,000	52,353 (f)	0,000

Figure 10. Models - one year before failure

	Variables	MDA		Logit		LR	
		Coef.(f)	Sig.	Coef.(t)	Sig.	Coef.(wald)	Sig.
Apl04	Net profit/ Loans	7,871		-111,23		-1,979	
		(91,85)	0,000	(13,35)	0,000	(-8,04)	0,000
Liq12	Non-credit period	0,610		-		-0,153	
		(50,60)	0,000			(-2,38)	0,019
	Intercept	0,127		0,974		0,468	
		-	-	(4,28)	0,038	(12,35)	0,000
	Global sig.	72,928	0,000	123,008	0,000	50,608	0,000
		(χ2)		(χ2)		(f)	

Figure 11. Models – two years before failure

	Variables	MDA		Logit		LR	
		Coef.(f)	Sig.	Coef.(t)	Sig.	Coef.(wald)	Sig.
Ren05	Net profit/ total assets	13,706		-33,765		-3,308	
		(17,70)	0,000	(14,67)	0,000	(-4,19)	0,000
Sol06	Equity capital/ total assets	2,108		-6,216		-0,509	
		(40,38)	0,000	(11,35)	0,000	(-3,46)	0,001
Liq05	Cash flow gen. res. / total assets	-7,734		-	-	1,867	
		(16,88)	0,000			(3,75)	0,000
	Intercept	-0,980		1,678		0,524	
		-	-	(10,42)	0,001	(8,92)	0,000
	Global sig.	51,182	0,000	85,743	0,000	21,331	0,000
		(χ2)		(χ2)		(f)	

Figure 12. Models – three years before failure

	Variables	MDA		Logit		LR	
		Coef.(f)	Sig.	Coef.(t)	Sig.	Coef.(wald)	Sig.
Apl04	Net profit/ Loans	6,530		-49,448		-1,586	
		(26,01)	0,000	(18,79)	0,000	(-4,73)	0,000
End03	Equity capital/ Loans	-0,883		4,284		0,215	
		(10,86)	0,000	(6,78)	0,009	(2,11)	0,037
Est03	Working capital / total assets	-2,913		-	-	-0,707	
		(11,78)	0,000			(3,01)	0,003
Ren05	Net profit/ total assets	-	-	34,773		-	-
				(14,09)	0,000		

	Variables	MDA		Logit		LR	
		Coef.(f)	Sig.	Coef.(t)	Sig.	Coef.(wald)	Sig.
Sol06	Equity capital/ total assets	4,823		-17,348		-1,171	
		(12,63)	0,000	(12,77)	0,000	(-4,19)	0,000
Liq05	Cash flow gen. res. / total assets	-3,891		-	-	-0,945	
		(13,71)	0,000			(3,50)	0,001
Liq12	Non-credit period	1,466		-	-	-0,356	
		(16,51)	0,000			(-2,91)	0,004
	Intercept	-0,312		3,102		0,576	
		-	-	(17,18)	0,000	(9,06)	0,000
	Global sig.	52,371	0,000	90,257	0,000	10,863	0,000
		(χ2)		(χ2)		(f)	

Figure 13. Models – four years before failure

	Variables	MDA		Logit		LR	
		Coef. (f)	Sig.	Coef. (t)	Sig.	Coef. (wald)	Sig.
Apl04	Net profit/ Loans	0,399		-	-	-0,087	
		(32,41)	0,000			(-2,00)	0,045
End03	Equity capital/ Loans	0,376		-	-	-0,082	
		(50,19)	0,000			(-3,29)	0,001
Est03	Working capital / total assets	1,159		-3,711		-0,253	
		(67,68)	0,000	(44,24)	0,000	(-4,29)	0,000
Rot06	Sales/ total assets	0,011		-	-	-0,002	
		(39,25)	0,000			(-2,25)	0,025
Liq05	Cash flow gen. res. / total assets	1,975		-11,254		-0,431	
		(95,74)	0,000	(61,76)	0,000	(-4,55)	0,000
	Intercept	-0,275		0,6743		0,560	
		-	-	(21,69)	0,000	(23,49)	0,000
	Global sig.	139,846	0,000	217,915	0,000	32,414	0,000
		(χ^2)		(χ^2)		(f)	

Figure 14. Global model – one to four years before failure