Mixed logistic model with two independent random coefficients for financial crisis prediction: Argentinean companies

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Abstract: The paper develops a mixed logistic financial distress prediction model with two independent random coefficients and validates it for public Argentinean companies. This study complements existing literature on bankruptcy prediction in emerging economies advancing the application of contemporary econometric methods (Caro et al., 2013). Anticipating bankruptcy risks increases portfolios' profitability. Emerging economies and frontier markets differ from developed economies in political, cultural, social and institutional terms. Given those differences, investors and lenders need specific bankruptcy and financial distress prediction models. The model developed achieves an excellent performance using financial statements from firms listed in the Buenos Aires Stock Exchange during 1993–2000 with ratios accepted in the literature (Altman, 1993; Jones and Hensher, 2004). Results show that profitability, assets turnover and cash flow from operations reduce the likelihood of financial distress while leverage increases it for companies operating in a frontier market such as Argentina.

Keywords: mixed logistic model; financial statements; financial ratios; financial distress, bankruptcy prediction, Latin America; Argentina; accounting.

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1 Introduction

Bankruptcy has important economic and social consequences. The close relationship between economic and financial indicators derived from the company's financial reports and their future status, justifies the construction of financial distress predictive risk models. The predicting ability of earlier and simpler models has been maintained through the years (Agarwal and Taffler, 2007). These models provide valuable information for public and private policies.

Given the need for this type of models, studies began in the 1960s (Altman, 1968). The methodology first used paired non-random samples and applied linear and quadratic discrimination methods. In the 1980s, the first questions about non-randomised design appeared (Ohlson, 1980; Zmijewski, 1984), accompanied by the logistic regression modelling or binary probit model (Olhson, 1980; Jones, 1987; Maddala, 1991). An extension of these models includes the qualitative response variable as multinomial or ordinal (Leclere, 1999). The mixed logistic model, which takes into account unobserved heterogeneity between units, is one of the last discrete choice models developed for econometric applications (Train, 2003). Most recently, Jones and Hensher (2004) documented the mixed logistic model outperforms the standard logistic model.

The majority of advanced econometric models have been designed and applied in developed economies where these types of studies have been carried out since the late 1960s. Some research has been done in emerging economies where the potential contribution of these prediction models is even larger. Emerging economies and frontier markets operate in cycles, with a string of very good years followed by years of slow activity if not severe economic crisis. A paradigmatic case is Argentina because in boom periods it receives a significant dose of international investment (both direct and indirect) but the economy also sees major crises such as the hyperinflation of 1989 and socio-economic chaos of 2001. Following Altman et al. (2007), this study uses bankruptcy prediction models in an emerging economy in a period of economic growth and low bankruptcy rate because avoiding poor investment decisions is important for international investors when investments are made.

This study evaluates financial distress determinants of Argentinean companies focused on an eight years period of economic stability (1993–2000). Argentina is selected in part because of the existing literature where several econometric methods were applied to predict bankruptcy in economic stable periods. Díaz et al. (2001) and Caro et al. (2001) employed cross-sectional models to rank companies according to their condition in the 1990s while Sandin and Porporato (2007) applied cross-sectional models to classify companies in the same decade. These preliminary studies (Díaz et al., 2001; Sandin and Porporato, 2007) adapted international models (Altman, 1993) to enhance bankruptcy prediction. Nevertheless, the methodology used did not incorporate the data's longitudinal characteristic. Availability of financial statements allowed the development of so-called mixed models to predict bankruptcy with longitudinal data (Jones and Hensher, 2004) and Caro et al. (2013) estimated a risk model for Argentina using one random slope. Caro et al. (2013) offer the first attempt at using mixed logistic models with data from 1993 to 1998 of Argentinean companies while Giampaoli et al. (2016) extend the bankruptcy prediction to Peru and Chile. The objective of these studies was to determine if information contained in the financial statements of companies listed on the Buenos Aires Stock Exchange can predict which companies are more likely to fall into financial distress. The literature is here extended by incorporating two random slopes. The resulting excellent performance of the model, evaluated through the error rate, suggests that it is an appropriate econometric methodology to predict bankruptcy in periods of growth in emerging economies

Another significant contribution of this study is the method used that incorporates the time dimension. Using two to four financial statements for each company allows the method to incorporate the longitudinal information induced correlation, i.e., the same company observed during several years. Specifically, this paper develops a mixed logistic model to predict bankruptcy risk during 1993–2000, using financial statements of companies listed on the Buenos Aires Stock Exchange and ratios defined by Altman (1993) and Jones and Hensher (2004). Financial ratios of profitability, asset turnover, debt leverage, cash flow from operations, cash and equivalents and working capital, are used as variable predictors but not all of them proved to be significant.

The study contributes to the literature on information content in accounting, more specifically information content of annual reports. Information contained in financial statements of companies listed in the Buenos Aires Stock Exchange allows to accurately predict which companies are more likely to fall into financial distress. It has been argued that a mixed logistic method outperforms any other bankruptcy prediction method. When the dataset is nested, it usually works in random order; however, the coefficient's analysis for some variables might show variability, which leads to incorporate one or more random slopes. In Caro et al. (2013), the cash flow coefficient (CFO/TA) was included in the random part of the model arriving at a result that correctly classified 90.74% of companies in financial distress. In this work, the variability of the coefficients was tested, concluding that two ratios, profitability (EBIT/TA) and cash flows (CFO/TA), present a significant variability among companies. The most notable result of the new estimation methodology is its excellent performance, all companies were correctly classified (type I and type II error are 0%). The method here described can and should be tested in other emerging economies as its results with Argentinean data look promising.

The rest of the paper is organised into six sections including this introduction. The second section provides a brief literature review on bankruptcy prediction; the third section covers the fundamentals of the macroeconomic environment in Argentina and its effect on the quality of financial statements information. The fourth section focuses on the method which not only explains the model used but also details the sample selection. The fifth section presents the results while the last section offers conclusions.

2 Literature review: bankruptcy prediction models

There are studies related to the application of models to predict firms' financial distress in countries qualified both as developed and emerging economies. These studies emphasised the definition of variables that influence the state of unfavourable financial situations, the different meanings of financial distress, methodologies and results, among others.

Following the historical evolution of this line of research, the application of statistical methods have differentiated two key stages in its development, the descriptive stage, between the 1930s and 1960s and the predictive stage that started in the 1960s. In both phases, ratios are calculated with accounting information to investigate to what extent they represent valid tools for financial analysis. In the descriptive stage, Ibarra (2001) presents the research of Fitzpatrick (1932), Winakor and Smith (1935) and Merwin (1942); those studies were focused on describing the companies classified into two groups (healthy and failed), depending on financial ratios.

In the predictive phase, Beaver (1966, 1968) and Altman (1968) began to predict financial distress through univariate and multivariate linear discriminant methods, finding that accounting ratios are an appropriate source of information. Favoured by technological improvements and advanced statistical techniques, Altman continued to refine his original model applying both the linear and quadratic discriminant models in developed countries such as Germany, Australia, France, Italy, Japan and the United Kingdom. Based on these studies, models were applied in emerging economies despite some limitations, such as not having financial statements in real time or local accounting regulations that would impede comparability of financial information. In Latin America these models were applied in Brazil (Altman et al., 1979), Argentina (Swanson and Tybout, 1988), Uruguay (Pascale, 1988) and Mexico (Altman et al., 1995).

The main criticisms of these studies relate to non-random sample selection methods and the use of cross-sectional methodology which is not suitable when dealing with data related over time. Despite the critics, it has been argued that the predictive ability of a simple model based on multiple discriminant analysis is valid after decades it was proposed (Agarwal and Taffler, 2007). Other models based on factor analysis, logistic regression and neural networks were also applied. All these models continue to ignore data interdependency, because the same company presents their financial statements at consecutive fiscal year ends and all these financials are considered in the analysis of each company, therefore the same individual is measured over time (longitudinal data).

It was Train (2003) who introduced new methods of discrete choice. He explains the categorical response variable behaviour based on the co-variables using utility theory, which can be expressed as a function of different alternatives that can be chosen (Train, 2003). His work extends to any type of categorical response variable (dichotomous or not) and these methods objectives are behavioural model specification and parameter estimation, where simulation as a methodology plays an important role (Train, 2003). The mixed logistic model, which considers unobserved heterogeneity between units (companies, in our case), is one of the most recent discrete choice econometric models developed. Jones and Hensher (2004) show, among other things, that mixed logistic models outperform the standard logistic model for bankruptcy prediction.

Table 1 reflects different financial distress prediction models used in developed economies. It is considered more effective and useful for novice researchers in the field, to summarise the literature review in a table of quick reference. The statistical methodology applied range from linear and quadratic discriminant analysis, to logit, probit with different variations to arrive at longitudinal mixed logistic models.

Table 1 Financial distress prediction models in developed economies

Study	*Companies in the sample*	*Period analysed*	*Methodology*	*Significant ratios*	*Most important results*	*Criticism*
Beaver (1966, 1968)	158 (79 failed and 79 healthy) USA	1954–1964	Univariate: placement test, difference of means and likelihood ratio test.	Ratios of illiquid assets; liquid asset ratios: 1 those which consider current assets, quick, working capital and cash flow 2 related to debts 3 related to net sales.	The ratios of illiquid assets predict the financial distress better than the ratios of liquid assets in the first pre-distress periods.	No random selection of the sample. Univariate statistical methodology, which works with each ratio and does not relate them linked together.
Altman (1968)	66 (33 failed and 33 healthy) USA	1946–1965	Linear discriminant analysis	Working capital/total assets; retained earnings/total assets; earnings before interest and taxes/total assets; sales/total assets; market value of equity/book value of long-term debt	95% correct classification and 6% and 3% of the type I and type II errors.	No random sample selection. Statistical methodology used under assumptions that are not met. The model was applied for each period.
Altman et al. (1977)	106 (53 failed and 53 healthy) USA	1969–1975	Discriminant analysis	Rate of return; stability of earnings; interest coverage ratio; ratio of retained earnings; ratio of cash and equivalents; indicator of capitalisation; size of company	The correct classification rate was 89% and 96% for healthy companies and companies in financial distress, one year prior to bankruptcy.	Non-random selection of the sample. Subjective determination of cut-off points. No disclosure of final coefficients due to commercial reasons.
Ohlson (1980)	2,163 (105 failed and 2,058 healthy) USA	1970–1976	Logistic regression	Size of company; measurement of the financial structure; measurement of performance; index of current liquidity	Five years earlier the rate was 82% and 70% for healthy and failed firms.	Error rate obtained using random sampling is similar to previous studies that used non-random sampling.

Table 1 Financial distress prediction models in developed economies (continued)

Study	*Companies in the sample*	*Period analysed*	*Methodology*	*Significant ratios*	*Most important results*	*Criticism*
Altman (1984)	Altman (1968) and Altman et al. (1977) models applied to Japan, Great Britain, Germany, Switzerland, Ireland, Canada	Different time periods, mainly from the ‘70s	Discriminant analysis, factor analysis and logistic regression	Working capital/total assets; retained earnings/total assets; earnings before interest and taxes/total assets; market value of equity/book value of long-term debt; sales/total assets	Depending on which country is conducting the study, some ratios are significant. Different methodologies ranging from grading methods to standard linear models. It covers exploratory and predictive methods.	Non-random selection of the sample. Statistical methodology used under assumptions that are not met
Zmijewski (1984)	1,681 (81 failed and 1,600 healthy) USA	1972–1978	Discriminant analysis, probit and different methods of parameter estimation	Rate of return; liquidity ratio; debt ratio	Presence of bias in the estimates. No significant changes in the overall classification and prediction rates on random sampling or non-random, if prediction rates and individual classification.	Cross-sectional methodology in the analysis.
Taffler (1984)	Not published due to commercial reasons. UK	Not published due to commercial reasons	Principal components analysis and lineal discriminant	Most significant ratios: profitability and debt (leverage)	The goal of the study was correct classification and not financial distress prediction. If a company ended up in a risk zone it was due to the fact that it presented more similarities with failed companies than with healthy ones.	Cross-sectional methodology in the analysis.
Shirata (1998)	686 healthy and 300 failed. Japan	1986–1996	Methods of variable selection and discriminant analysis	Most significant ratios: Debt levels (annual change of debt and interest paid) and profitability	It correctly predicts 86% of the cases independently from the company’s industry and size.	Cross-sectional methodology in the analysis
Mossman et al. (1998)	190 failed and healthy. USA	1980–1991	Linear discriminant analysis. logistic regression	According to the model applied different ratios and market variables were used.	The model predicts better ratios one year before the financial distress, the cash flow two to three years before. Both are better than the returns and variance of returns	The model works separated with three variable groups that are not combined at any point.

Table 1 Financial distress prediction models in developed economies (continued)

Study	*Companies in the sample*	*Period analysed*	*Methodology*	*Significant ratios*	*Most important results*	*Criticism*
Grice and Dugan (2001)	2,067 (337 failed and 1,730 healthy); 819 (136 failed and 683 healthy) USA	1988–1991 1992–1999	Ohlson (1980) and Zmijewski (1984) methodology	Same as Ohlson and Zmijewski	Caution in the use of models already developed in other sectors, in other periods and with different concepts of financial distress.	No criticism because it offers a comparative analysis between models.
Charitou et al. (2004)	51 pairs of companies. UK	1988–1997	Two models: logit and neural networks	The following indicators were significant: cash flow, profitability and financial leverage.	It correctly predicts 83% of companies a year before the bankruptcy	No random selection of the sample. Cross-sectional methodology in the analysis. State as a limitation the lack of a theory that indicates which ratios can predict bankruptcy.
Jones and Hensher (2004)	3,032 (2,838 healthy, 78 with problems of insolvency and 116 failed). Australia	1996–2000	Mixed logit	Cash and equivalents; operational fund-flow; working capital; return; turnover; ability to pay debt service; industry	The methodology relaxes the assumptions of the error term and allows a meaningful interpretation of the role of the influence of the mean and variance of a particular variable. The mixed logit model performs significantly better than the standard logit.	Not mentioned, but in 2007 the authors will re-estimate the model and test its stability.
Jones and Hensher (2007a)	The same sample of Hensher and Jones (2004). Australia	1996–2000	Nested logit and standard logit	Debt to Assets; debt on operating cash flow; two periods of negative operating cash flow; debt to equity	The nested model is better than the standard because it relaxes the fulfilment of assumptions.	Does not consider information through time.
Jones and Hensher (2007b)	The same sample of Hensher and Jones (2004). Australia	1996–2000	Mixed logit method of optimisation with maximum likelihood estimation weighted exogenous sample (WESML)	The same ratios of Hensher and Jones (2004)	With new estimation methodology the model is re-estimated and tests its stability.	No criticisms.

Table 1 Financial distress prediction models in developed economies (continued)

Study	*Companies in the sample*	*Period analysed*	*Methodology*	*Significant ratios*	*Most important results*	*Criticism*
Nam et al. (2008)	367 companies. South Korea	1991–2000	Model of duration, hazard and logit	Different for each model	The correct classification rate was 58%, 61% and 69 % for 3, 2, and 1 year prior respectively. Models that incorporate time are better predictors than those that do not include it.	Does not identify companies in financial distress.
Beaver et al. (2009)	1,857 companies 135,455 observations USA	1962–2002	Standard logit and hazard model	Financial ratios Other market variables: discretion over financial reporting, research and development intensity, amplitude and recognition model	The model that considers time shows a decline in the predictive ability of financial ratios while increasing the predictive ability of new market related variables.	Difficult to collect new variables
Cultrera and Brédart (2016)	7,152 SMEs (3,576 bankrupt) Belgium	2002–2012	Logit model	Current ratio (liquidity); EBIT/TA; equity/TA; fiscal charges/value added; cash flow/total debt	Bankruptcy applied to a large sample of small and medium sized enterprises (SMEs). Predictive ratios: liquidity, profitability, debt structure and value added. Global prediction rates above 80%.	Does not consider information through time. Not all observations used in the model.

Table 2 Financial distress prediction models for companies operating in emerging economies (excluding Argentina)

Study	*Country*	*Sample and analysis period*	*Methodology*	*Significant ratios*	*Key findings*	*Criticism*
Altman et al. (1979)	Brazil	23 failed and 35 healthy companies. 1975–1977	Discriminant analysis model	Altman's model ratios	Correct classification rate: 88% one year before the financial distress and 78% for three years before the distress.	The difficulty in obtaining reliable data, in terms of quality and availability.
Pascale (1988)	Uruguay	44 pairs of companies. 1978–1982	Discriminant analysis	Activity level Asset turnover Debt ratio	The correct classification rate is 91.8%, type I error is 2.3%.	Non-random sample selection. Statistical methodology used under assumptions that are not met. Previous financial statement used differently depending on whether the companies were healthy (1 year) or in financial distress (3 years).
Abdullah et al. (2008)	Malaysia	52 companies (26 healthy and 26 in financial distress). 1990–2000	Multiple discriminant analysis and logistic regression model hazard	Leverage Profitability Cash to current liabilities	The correct classification rate of hazard model was 94% vs. 80% of the multiple discriminant analysis and 82% of logistic regression. Models that include time are better.	Non-random samples. Statistical methodology used under assumptions that are not met. To overcome this difficulty a hazard model that adds a time as a covariate is applied.
Li and Liu (2009)	China	817 companies (245 failed and 572 healthy). 1998–2005	Binary logit model	The return on assets, liquidity, leverage, age, size, sales to assets and the percentage of shares owned by the state were found to be significant variables	Companies that are totally or partially owned by the government show a lower probability of failure.	Cross sectional methodology in the analysis.

Table 2 Financial distress prediction models for companies operating in emerging economies (excluding Argentina) (continued)

Study	*Country*	*Sample and analysis period*	*Methodology*	*Significant ratios*	*Key findings*	*Criticism*
Pavlović et al. (2011)	Serbia	74 companies in total, 30 failed. 2008–2010,	Multiple discriminant analysis	Thirteen ratios classified as: Profitability Liquidity Solvency	Correct classification rate: 86% one year before the financial distress and 67% for two years before the financial distress.	Sandin and Porporato (2007) model not suitable for Serbian companies, no alternative model has been proposed.
Montalván et al. (2011)	Peru	1995–2007 for insolvent companies. 2000–2007 for healthy companies	Logistic regression	Leverage Profitability Macro variables: percentage change in sectoral GDP, percentage change in inflation, local currency lending rate and state of financial distress	The influence of macro variables that are usually not considered was highly significant.	Non-random sample selection. Statistical methodology used under assumptions that are not met. Different time periods for both types of companies.
Giampaoli et al. (2016)	Argentina, Peru and Chile	90 companies, of which 85 are financially healthy. 2009–2011	Mixed logistic regression	Working capital/total assets Cash/total assets Net operating cash flow/total assets Total sales revenue/total assets Returns/total assets	Compare classification by different prediction methods of mixed logistics models	Models and results are not fully explained as expected in an accounting journal.

Table 3 Financial distress prediction models for Argentinean companies

Study	*Sample and analysis period*	*Significant ratios*	*Methodology*	*Results*
Swanson and Tybout (1988)	No detail of number of companies. 1972–1984	Macro variables and ratios of liquidity and insolvency	Discriminant analysis and probit	Financial costs affect actual results and the risk of bankruptcy. A limitation is the availability and data.
Díaz et al. (2001)	50 companies (paired 25 healthy and 25 failed). 1995–2000	Liquidity index; solvency; ownership of assets; non-current liabilities to assets; self-financing; fixed assets	Regularised discriminant analysis including particular cases of linear and quadratic discriminant analysis is first used and then logistic regression.	Two alternative models are identified as the best to classify healthy or failed companies. The error rate using cross-classification was 22%.
Caro (2004)	50 companies (paired 25 healthy and 25 failed). 1995–2000	Ownership of assets; debt ratio; non-current liabilities; fixed assets; self-financing; liquidity; acid ratio; income to interest	Non-parametric methods were applied for classification: kernel, nearest neighbour and recursive (tree classification).	Non-parametric methods were applied, where the nearest neighbour method, with two neighbours gave a lower error rate (0.10) than the kernel method (0.16) and the recursive classification tree (0.22).
Sandin and Porporato (2007)	22 companies (11 healthy and 11 failed). 1991–1998	Thirteen ratios classified as: profitability; liquidity; solvency	Discriminant analysis using financial ratios.	Lower error rate one year before bankruptcy.
Díaz et al. (2010)	72 companies (48 healthy and 24 failed). 1993–2000	Rate of return; cash flow; sales to total assets; debt ratio; working capital; industry	Mixed models.	Significant error rate (first time this methodology was applied in Argentina).
Caro et al. (2013)	47 companies (30 healthy and 17 in financial distress)	Rate of return; sales to total assets; debt ratio.	Mixed logistic model with one independent random coefficient in the lineal predictor.	Mixed logistic model has a lower error I than the standard logistic model for this sample, 9.26% vs. 48.15%.

On the other hand, it is important to note if models obtained using financial data of companies from developed countries were applied to emerging economies without any adjustment regardless the different economic context, results might not be similar. To partly address this criticism, Altman (2005) developed the emerging market scoring model (EMS) as a tool to determine a rating for companies in emerging economies from a series of adjustments to the models used in the USA. In this way the investor can assess the relative value of debts in these economies. Through this study, Altman (2005) set a second goal in this area, to determine a rating for companies in countries where investors, banks and other stakeholders are not familiar with but need to make their investment or credit decisions. Table 2 summarises the main works that express different financial distress prediction models in emerging economies. Given the interest of this study, the table mainly captures innovations of Altman models used in different emerging economies. Given the focus of this study in Argentina, Table 2 covers the bankruptcy prediction model innovations used in Latin America: Brazil, Uruguay, Peru, and Chile.

Several studies used data from Argentina with various models and results. Focusing on the Argentinean context, Swanson and Tybout (1988) concluded that fluctuations in financial costs affect both the actual results (negatively) and the risk of bankruptcy. In turn, macroeconomic variables are very significant in the bankruptcy process and the illiquidity with insolvency could worsen the economic growth in general in these types of countries. Díaz et al. (2001) and Caro (2004) applied supervised classification methods to classify companies as healthy or in financial distress; Díaz et al. (2010) used mixed models to predict bankruptcy risk. Sandin and Porporato (2007) applied Altman's multiple discriminant analysis models to Argentinean companies and built a new cross-sectional model with better performance. Caro et al. (2013) offered the first attempt at using mixed logistics models to predict financial distress. Table 3 reflects a summary of the published works made with companies listed in the Buenos Aires Stock Exchange showing it is quite limited despite Argentina's reception of large amounts of investments in the 1990s [according to Fanelli (2002), Argentine bonds accounted for 25% of J.P. Morgan's benchmark index of emerging-market bonds in 2001].

This article contributes empirical evidence towards the ongoing discussion which method has better predicting ability in Argentina as a context where multiple methods have been used. In Argentina, the study of financial distress prediction of public companies in periods of economic growth shows some incipient investigations as listed in Table 3; to date, only one includes the temporary effect through a single random slope. When the dataset is nested, usually it works with random intercept; however, it is advisable to analyse if the coefficients of some variables also show variability, which leads to incorporate one or more random slopes. This work expands the literature through a methodological contribution in the estimation of a mixed model with two random coefficients. Each coefficient corresponds to predictors that impact companies with wide variability, and this is a variation in the econometric method not attempted yet in an emerging economy.

3 Context of Argentina between 1993 and 2000

During the 1990s Argentina embarked on a macroeconomic reform program focused on deregulation, financial stabilisation and trade liberalisation. The program resulted in a decade of privatisation of government-owned enterprises, rising unemployment and taxes, low inflation and sustained growth (see Table 4). It is common in emerging economies that after a period of growth its level of activity diminishes and even enters into recession, and Argentina was no exception. Argentina experienced a sharp slowdown in the economy between 1998 and 2000, coincidentally the peak of bankruptcies and preventive reorganisations were observed in June 2001 (Datarisk, 2006). Therefore, this study focuses on the period of stability with the goal to provide the best bankruptcy prediction model that can be applied in emerging economies that are growing because at that time is when most investment decisions, foreign and local, are made.

Table 4 Indicators of the Argentine economy[a]

Year	*Inflation*[b]	*GDP*[c] *In millions of pesos of 1993*	*Exchange rate*[d] *1 USD = 1 peso*
1993	10.6%	236	1
1994	4.2%	250	1
1995	3.4%	243	1
1996	0.2%	256	1
1997	0.5%	277	1
1998	0.9%	288	1
1999	–1.2%	278	1
2000	–0.9%	276	1

Notes: [a]Source of table: Sandin and Porporato (2007, p.297).
[b]Consumer price index, general level, year 1988, base index = 100 (source: INDEC).
[c]Gross domestic product at market prices in 1993 (source: INDEC).
[d]Effective exchange rate as of 30 December (source: BCRA).

Argentina's business environment in the 1990s radically changed with the opening of the economy and globalisation. New capital investments, both local and international, changed the face of the local economy. Capital markets began to change the role from speculative to a financial source market. This trend was partially reversed in the 2000s with the re-nationalisation of privatised firms and the contraction in foreign investment. The dynamics of the 1990s changed the face of financial statements. The large decline in inflation had a positive effect on financial statements. Throughout the 1970s, 1980s and the early 1990s, the accounting profession's major concern was how to report inflation. The focus on inflation resulted in hybrid valuation models, inadequate studies, and deformation of numerous accounting issues, but this was reversed from the 1990s, and culminated in the accounting profession adhering to IFRS in the 2000s.

Altman (1984) and Swanson and Tybout (1988) concluded in their studies that the financial data from Brazil and Argentina could provide useful information for decision-making. Globalisation, the decline in inflation and the preparation for adoption of international accounting standards (IFRS) made financial statements to become more complex and of higher quality in Argentina during the 90s. This improved the informational content of financial statements and therefore the usefulness of financial ratios as analytical tools. These factors make the financial statements between 1993 and 2000 a good database to use for the research of bankruptcy prediction models for companies listed in the Buenos Aires Stock Exchange. Although it is argued that bankruptcy prediction is also important in less stable conditions, that type of analysis would require other variables that are not always possible to measure. Consistent with existing literature, this study focuses on a period of economic stability. Worth to mention is the fact that 1993–2000 was not a period of constant year-to-year macroeconomic growth; although there are some years that do not show growth (1995, 1999 and 2000) the whole period is considered very stable attracting significant amounts of foreign investment.

4 Methodology

4.1 Sample selection and co-variables

A logistic model is used because the response variable is binary. It is argued that random effects models (RE) are best suited to estimate financial distress because "essentially just correct for the panel complication that observations are correlated over time for a given individual" [Cameron and Trivedi, (2009), p.607]. Additionally, the random effects model has the advantage of incorporating random slopes, which are important when the impact of predictors on the response changes per company. Companies were labelled as 1 if they were in financial distress or 0 if they were not in financial distress. In this study, companies in distress are those that list their shares in reduced round as defined in Chapter XIV of the Buenos Aires Stock Exchange Policy, i.e., companies that are in default and have called for the opening of its bankruptcy proceedings or have negative retained earnings or equity. The date on which firms enter this 'reduced round' is published in the Buenos Aires Stock Exchange's Bulletin.

For each failed company in the sample, two to four financial statements from previous years before entering the reduced round are considered. The sample of healthy companies included four years of financial statements, similar periods considered for failed companies. Thus, the database was composed of annual financial statements of 47 companies, 30 healthy and 17 in financial distress, totalling 150 observations for the period 1993–2000; excluded are financial and insurance companies. Although the number of observations is not large, it is significant in the context of Argentina where at the end of the 1990s there were a total of 137 companies quoted in the Buenos Aires Stock Exchange even counting financial and insurance firms. This study uses the same database of Caro et al. (2013) but applying a different and enhanced model to the same population of 17 companies in financial risk identified in the period under analysis. When the dataset is nested, as is this case, it usually works with a random intercept. However, the analysis of variable's coefficients shows significant variability, which leads to the incorporation of one or more random slopes. In Caro et al. (2013), the cash flow from operations coefficient (CFO/TA) was included in the random part of the model, arriving at a result that correctly classified 90.74% of companies in financial distress. In this study, the variability of the coefficients was tested, concluding that the impact of two ratios and not only one as before (EBIT/TA and CFO/TA) present a significant variability among companies.

The detail of companies and periods disclosed in Table 4 of Caro et al. (2013) has been replicated for this study. The ratios selected as co-variables (Table 5) are those defined by Jones and Hensher (2004) and Altman (1993), which are calculated based on the information contained in the annual reports published by the Buenos Aires Stock Exchange. All these decisions increase the validity and reliability of the study.

Table 5 Co-variables: financial ratios

Label	*Ratio*	*Definition*	*Source*
CFO/TA	Cash flow generated by operations to total assets	Measures the cash position over total resources.	Cash flow from operations is taken from the cash flow statement. Total assets is reported in the balance sheet
CE/TA	Cash and equivalents to total assets (liquidity)	Measures the proportion of liquid resources of the company.	Liquid assets are reported in the balance sheet
S/TA	Sales to total assets (assets turnover)	Is the coefficient that measures assets turnover	Sales are taken from the income statement and include revenues (and other income from operations).
D/E	Debt to equity (leverage)	Measure of indebtedness of the company.	Both debt and equity are reported in the balance sheet
WK/TA	Working capital to total assets (solvency)	It expresses the degree of liquidity of assets and indicates to what extent the immobilisation of total assets is offset by working capital.	Working capital is current assets less current liabilities, as reported in the balance sheet
EBIT/TA	Earnings before interest and taxes to total assets (profitability)	Profitability measured in terms of profits from operations.	Earnings before interest and taxes is taken from the income statement

4.2 Mixed logistic model: a case of binary response models

This study applies a model where the response variable is the binary variable indicating the group to which the company belongs (financial distress = 1; healthy = 0) and the predictor variables are financial ratios and companies' characteristics. A problem with dichotomous response is usually modelled by logistic regression, where the probability that the response variable (y_i) takes the value 1 (failing firm) assuming only one co-variable (x_i) in the lineal predictor is:

$$\Pr\left(y_i = 1/x_i\right) = h\left(\beta_1 + \beta_2 x_i\right) = h\left(z_i\right) \qquad i = (1, 2, \mathrm{K}\ , n)$$

Its logit transformation is:

$$\operatorname{logit}\left\{\Pr\left(y_i = 1/x_i\right)\right\} = \ln\left\{\frac{\Pr\left(y_i = 1/x_i\right)}{1 - \Pr\left(y_i = 1/x_i\right)}\right\} = z_i .$$

The logistic model assumes that responses are independent given the co-variables, which is appropriate when the data has no grouping. This requirement is not met in bankruptcy prediction studies because the structure of the data introduces dependence on multiple responses within each unit, even conditioning on the co-variables. Previous studies have compared the performance of the standard logistic model with a mixed model with one independent random coefficient (Caro et al., 2013). This study goes a step further and the particular model applied is a mixed logistic model with two independent random coefficients in the lineal predictor that is formulated as follows:

$$y_{ij} / \pi_{ij} \sim Bernoulli(\pi_{ij}) \tag{3}$$

$$\begin{aligned}\operatorname{logit}(\Pi_{ij}) = \beta_0 + (\beta_1 + b_{1j}) EBIT/TA_{ij} + (\beta_2 + b_{2j}) CFO/TA_{ij} + \beta_3\, CE/TA_{ij} \\ + \beta_4\, S/TA_{ij} + \beta_5\, D/E_{ij} + \beta_6\, WK/TA_{ij}\end{aligned} \tag{4}$$

$$\pi_{ij} = P(y_{ij} = 1/\mathbf{x}_{ij}, \mathbf{b}_j) \tag{5}$$

$$\mathbf{b}_j = \begin{bmatrix} b_{1j} \\ b_{2j} \end{bmatrix} \Big/ \mathbf{x}_{ij} \sim N_2(0, \Psi) \qquad \Psi = \begin{pmatrix} d_{11} & 0 \\ 0 & d_{22} \end{pmatrix} \tag{6}$$

where

β_k are the coefficients of each of the co-variables described in Table 6

$\mathbf{b}_j$ is the vector of random effects

Ψ is the matrix of random effects variances.

The model was adjusted using maximum likelihood estimation methods, integrating the random effects that are assumed to have a normal distribution. Due to the limitation that there are no analytical expressions available to solve this integral, numerical approximations are necessary, including the Gauss Hermite quadrature obtained with software routines. In this study the NLMIXED routine from SAS was used. The random effects are predicted through a post-estimation. Based on those predictions the model is evaluated with the purpose of determining if the companies have been correctly classified in the state where they belong.

5 Results

This section offers descriptive statistics, results and validation of the model. The first part contains the descriptive statistics of the sampled companies that quote their shares in the Buenos Aires Stock Exchange between 1993–2000. The companies are classified into two groups: in financial distress (value 1) and healthy (value 0). The model specified in the previous section is applied and the results detailed. Finally, the model validation is offered, where the type I and type II errors are calculated.

5.1 Descriptive statistics

By looking at the descriptive statistics of each ratio considered in this study, we can observe clear differences between the two groups of companies considered as seen in table 6. The average profitability (EBIT/TA) in healthy companies is 1.57% compared with negative 10.5% for companies in financial distress. The median for companies in financial distress is lower than the mean due to extreme values; two companies presenting large losses. This ratio shows higher variability in healthy companies. The average cash flow ratio (CFO/TA) in healthy companies doubles the ratio in companies in financial distress (16% vs. 8%). This reflects that some companies have negative cash flows from operations. The ratio shows higher variability among companies in financial distress. The average cash and equivalents ratio (CE/TA) for healthy companies is triple the average ratio for distressed companies (10% vs. 3%), confirming that companies in financial distress have a weak liquid position. The average asset turnover ratio (S/TA) is one third higher in healthy companies (0.97 vs. 0.61 times per year). A group of healthy companies have asset turnover ratios significantly above 1 and this is captured by the mean being higher than the median. The average debt to equity ratio or leverage (D/E) is almost triple in companies in financial distress (190% vs. 73%). A small group of companies in financial distress have larger leverage ratios and that is reflected by being the median lower than the mean. Finally, the average working capital ratio (WK/TA) shows clear differences between the two groups of companies, while it is negative for companies in financial distress (mean of 5%), it is positive in healthy companies at 16%.

Table 6 Descriptive statistics

		Percentile 25%	*Median*	*Percentile 75%*	*Mean*	*Standard deviation*	*Variation coefficient*
Profitability (EBIT/TA)	Healthy	0.30	4.52	8.72	1.57	16.30	10.41
	Distress	–16.06	–6.70	1.30	–10.41	17.84	1.71
Cash flow operations (CFO/TA)	Healthy	3.30	8.87	15.59	16.13	25.83	1.60
	Distress	0.56	2.96	8.20	8.11	17.53	2.16
Liquid assets (CE/TA)	Healthy	1.46	4.42	11.08	10.01	16.24	1.62
	Distress	0.71	1.98	3.81	3.27	3.76	1.15
Assets turnover (S/TA)	Healthy	51.58	81.93	121.43	97.73	62.78	0.64
	Distress	32.83	65.68	82.02	61.22	36.64	0.60
Leverage (D/E)	Healthy	31.04	60.41	94.92	73.43	68.79	0.94
	Distress	35.92	100.66	216.66	190.33	259.09	1.36
Working capital (WK/TA)	Healthy	–0.67	12.82	31.62	16.58	25.90	1.56
	Distress	–14.63	–2.06	4.24	–5.21	20.69	3.97

5.2 Model results

Random coefficients included in the model were selected based on the variability explained. The ratios used to measure profitability (EBIT/TA) and cash flow from operations (CFO/TA) present significant variability between groups of companies, justifying their inclusion in the random part of the model. These ratios are adequate to explain the proportion of heterogeneity induced by the data correlation. Table 7 details a set of likelihood rate tests (LRT); they are presented sequentially to be compared with a model without random effects and with one random effect like the one reported by Caro et al. (2013). Results show that model 3, which incorporates two random effects, has a better performance than model 2 with one random effect, which in turn are assumed to be independent. The complexity of the model allowed incorporating only two slopes as random effects. This selection was based on the variability of the estimates between companies.

Table 7 Likelihood rate tests to select the adequate model

Model		*–2log(likelihood)*	*Compared with*	*Dif*[a]	*p-value*
M1	Without random effects	138.50			
M2	With one random effect: EBIT/TA	110.70	M1	27.80	<0.0000
M3	Two random effect: EBIT/TA and CFO/TA	103.80	M2	6.90	0.0043

Note: [a]Dif: difference between –2log (likelihood) of the proposed model with the model of reference.

Incorporating random coefficients into the model allows identifying those ratios with the higher predictive ability to detect a company's failure. Most of the ratios are statistically significant ($\alpha = 0.10$) to explain the chance of failure, except for working capital to total assets (WK/TA) and cash and equivalents to total assets (CE/TA). As shown in Table 8, the positive sign of debt to equity (D/E) indicates that an increase in debt increases the chance of financial distress while for the remaining ratios, with negative sign, the increase will produce a decrease in the probability of financial distress.

Table 8 Parameters estimation in the mixed logistic model

Fixed effects	*Coefficient*	*Standard error*	*p-value*	*Odd ratios of significant variables*
Constant	0.5393	1.9314	0.7813	
EBIT/TA	–1.2379	0.5529	0.0302	0.29
CFO/TA	–0.2412	0.1246	0.0593	0.79
S/TA	–0.0939	0.0408	0.0262	0.91
D/E	0.0302	0.0131	0.0263	1.03
CE/TA	–0.1462	0.1276	0.2581	
WK/TA	0.1137	0.1114	0.3129	

Table 8 orders the ratios based on their discriminative ability. Profitability (EBIT/TA) comes at the top indicating that for each unit increase of the ratio, it decreases the chance of entering a financial distress situation by 71%. The second ratio is cash flow from operations (CFO/TA) with an odd ratio of 0.79 that indicates that for each unit increase of the ratio, it decreases the chance of entering a financial distress situation by 21%. The next ones in order of importance are assets turnover (S/TA) and leverage (D/E), with odd ratios of 0.91 and 1.03 respectively. The odd ratio of 1.03 indicates that for every unit the ratio increases the chance to fail increases by 3%. When adding a second random coefficient, it is observed that in the fixed part of the model the signs of all the indicators are maintained. In this estimation, four significant ratios are obtained, versus three of the reference models (M1 and M2 of Table 7). The profitability ratio (EBIT/TA) stands out, in such a way that increases its incidence in the classification. This change in the coefficients leads to a perfect allocation of cases to each group, both healthy and in financial distress.

5.3 Model validation

The predictive ability of the model can be derived by obtaining the estimated probability of failure for each of the firms by calculating the misclassification rate (error rate). An unbiased estimate of this rate is obtained by working with cross-validation method, which calculates the proportion of errors made, using a function that omits an observation from the dataset and classifying the omitted observation. In this work, given the complexity of the model, firms are classified with the function obtained for the total sample, arriving at the so-called apparent rate, which underestimates the true error rate. The estimated probability of failure is obtained by the value of the following expression for each company in each year:

$$\Pi_{ij} = \frac{\exp\begin{pmatrix} \hat{\beta}_0 + \left(\hat{\beta}_1 + \tilde{b}_{1j}\right) EBIT/TA_{ij} + \hat{\beta}_2\, CFO/TA_{ij} + \hat{\beta}_3\, CE/TA_{ij} \\ \hat{\beta}_4\, S/TA_{ij} + \beta_5\, D/E_{ij} + \beta_6\, WK/TA_{ij} \end{pmatrix}}{1 + \exp\begin{pmatrix} \hat{\beta}_0 + \left(\hat{\beta}_1 + \tilde{b}_{1j}\right) EBIT/TA_{ij} + \hat{\beta}_2\, CFO/TA_{ij} + \hat{\beta}_3\, CE/TA_{ij} \\ \hat{\beta}_4\, S/TA_{ij} + \hat{\beta}_5\, D/E_{ij} + \hat{\beta}_6\, WK/TA_{ij} \end{pmatrix}} \tag{7}$$

As shown above, in addition to estimating the fixed coefficient there must be a prediction of random effect for each observation. Once the probability is calculated, the next step is to assign each observation to one of the two groups under study. The excellent model performance is evident by the correct classification of 100% of the companies to the group where they belong for every period considered when the model validation is executed. As stated previously, the study obtained an apparent error rate, which underestimates the true error made by expanding the population model analysed.

6 Conclusions

This paper, using a mixed logistic model incorporating two random coefficients, analysed six accounting ratios' ability to predict companies' financial distress in Argentina during years of macroeconomic stability (1993–2000). Results indicate that the most important ratios in terms of discriminatory power are, in order of importance, those that measure profitability, cash flow from operations, asset turnover and leverage. None of the previous studies done with data from Argentina between 1993–2000 obtained such a low error type I, the closest has been Caro et al. (2013) who used a mixed logistic model incorporating one random coefficient, profitability. Since the 1960s, studies have predicted financial distress using various models based on the information contained in financial ratios. Not as much research has been done in emerging economies where the potential contribution of these prediction models is even larger. Argentina is a paradigmatic case of an emerging economy deserving this type of studies because when its economy flourished in the 1990s, it received a significant dose of direct and indirect international investment (Fanelli, 2002). In Argentina, there is significant research in this area using a variety of methods. Most of the work done to quantify the incidence of ratios in corporate financial distress applies cross-sectional models (Díaz et al., 2001; Caro et al., 2001, Sandin and Porporato, 2007); therefore, it is relevant the construction of more advanced models for panel data that incorporate the time dimension in the study.

The models usually used to predict financial distress are linear discriminant and logistic model. While the second allows relaxing the normality assumption, a key assumption that remains is the independence between observations. On the other hand, several measurements of the same units allow us to grasp unobservable heterogeneity by inducing correlation between the answers, making it necessary to work with models that incorporate this correlation. This can be done from a population average approach (marginal model) or random effects models, also known as mixed, in which the association can be modelled including the intercept and/or random coefficients (Rabe-Hesketh and Skrondal, 2008).

The logistic model assumes that responses are independent given the co-variables, which is appropriate when the data has no grouping. This requirement is not met in bankruptcy prediction studies because the structure of the data introduces dependence on multiple responses within each unit, even conditioning on the co-variables. Previous studies have compared the performance of the standard logistic model with a mixed model with one independent random coefficient (Caro et al., 2013). With the development of econometric models of discrete choice (Train, 2003), there have been numerous studies using the logistic model in binary and multinomial versions. Among the most significant works, it may be noted that of Jones and Hensher (2004) in proving that the mixed logistic model exceeds the performance of the standard logistic model. Jones and Hensher (2004) has been partially replicated here by including five ratios they have proposed that could be obtained from the information contained in the financial statements of Argentinean companies. Out of those five ratios, three proved to be significant in the context of Argentina between 1993–2000: cash flow from operations (CFO/TA, random), asset turnover and debt leverage (S/TA and D/E, both fixed). The other index that is significant is profitability (EBIT/TA, random), which is reported in several previous studies, particularly in Altman (1993) and Caro et al. (2013).

To achieve the improvement here reported in predictive ability, it was analysed if the coefficients of some financial ratios show variability that cannot be attributed to a random behaviour, this leads to the incorporation of one or more random slopes. In Caro et al. (2013) the key predictor was a ratio based on cash flow from operations (CFO/TA) that was included in the random part of the model, arriving at a result that correctly classifies 90.74% of companies in financial distress. In this study, the coefficients variabilities were tested, concluding that not only is cash flow from operations a key predictor, but also so is profitability (EBIT/TA) because both present significant variability among companies. When adding a second random coefficient, it is observed that in the fixed part of the model the signs of three indicators are maintained. In this estimation, four significant ratios are obtained, versus three reported in previous studies. In addition, the notable increase in the profitability ratio (EBIT/TA) increases its incidence in the classification of firms in financial distress. This change in the coefficients leads to a perfect allocation of cases to each group where they belong, either healthy or in financial distress.

Besides the econometric contribution of using two random slopes, this study contributes to the literature on information content of annual reports. It is argued that information contained in financial statements of companies listed in the Buenos Aires Stock Exchange allows to accurately predict which companies are more likely to fall into financial distress. The results here reported confirm that a mixed logistic method outperforms any other bankruptcy prediction methods even in emerging economies and this might be useful for investors and policy makers. The method here described can and should be tested in other emerging economies as its results with Argentinean data look promising.

This study confirms that the mixed logistic model is appropriate in this area of research because provides a correct allocation of 100% of the companies to the group where they belong for every period considered. This result was achieved by applying the apparent error rate, which underestimates the true error made by expanding the model obtained for the population under study. Previous studies of bankruptcy prediction in emerging economies have never applied a mixed logistic model with two random coefficients and obtained error rates of 0% as this study does. Future research needs to extend this model to other years and explore how it changes when the country goes through a period of economic and social turbulence. A limitation difficult to overcome in studies of this nature is the small population to study due to the reduced number of companies quoting their shares in local stock exchanges.

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