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Modelling and Testing the Assessment of Risk of Defaulting of Companies in the Context of the Basel Accord: A Brazilian Case Study

Modelando y probando el riesgo de insolvencia empresarial en el contexto del Acuerdo de Basilea – Un Estudio del Caso Brasileño

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ABSTRACT. This paper is concerned with the use of statistical methods to predict companies' defaulting behaviour in the context of the New Basel Accord, which requires that banks use objective criteria and techniques for modelling the assessment of risk. Our results indicate that traditional statistical techniques can perform well in this context. These results are achieved using non-traditional financial ratios alongside traditional ratios. We believe that this indicates a need for change in some principles and conventions of accounting in order to fit better with real company performance.

Key words: Basel Accord, default modelling, non-traditional financial ratios.

RESUMEN. Este artículo enfoca el uso de métodos estadísticos para la predicción de la insolvencia de empresas en conformidad con el concepto del nuevo Acuerdo de Basilea, el qual determina que los bancos utilicen técnicas y criterios objetivos para modelar el riesgo de crédito. Los resultados obtenidos indican que las técnicas estadísticas tradicionales son eficientes en la predicción de la insolvencia. Los modelos desarrollados utilizan índices económico-financieros tradicionales y no-tradicionales en la literatura del área contable. Los resultados también sugieren que algunos principios y convenciones contables podrían ser objetos de re-estudio en el sentido de espejar con más claridad la real situación financiera de las empresas.

Palabras clave: Acuerdo de Basilea, modelando insolvencia empresarial, índices económico-financieros no-tradicionales

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INTRODUCTION

Based on the available historical evidence as well as the inherent nature of financial institutions, it is reasonable to conclude that they have engaged in risk modelling since the time that they were first formed. For centuries most banks operated using only intuitive models based on personal judgement and experience. This procedure can be called a traditional or classic credit analysis and relies on two distinct but interrelated issues: the borrower's character and the borrower's economic/financial performance.

As argued by Caouette, Altman and Narayanan (1998) classic credit analysis has a number of flaws. In the first place, it is extremely expensive to maintain. By definition, it requires significant redundancies. At all times, a bank must have enough experts available to handle its business volume and it must also have a large number of people in training to become experts. Furthermore, classic credit analysis has often lulled banks into a false sense of security, failing to protect them against many of the systematic risks embedded in their business. According to Caouette et al (1998), in recent decades the traditional approach has led to disappointing results since banks have done a relatively poor job of pricing and managing credit risk.

Today, the environment of credit has changed and the circumstances of lending have changed. Consumer lending has undergone a significant transformation over the past two decades due to the introduction of credit scoring models. However, the process of granting commercial credit has also changed, but at a much slower pace (Ferguson, 2001).

Experience with recent crises forced banking authorities – the Bank for International Settlements (BIS) and the main Central Banks around the world – to draw a number of lessons. The result was the New Basel Capital Accord (BIS, 2003) which laid down guidelines that all banks should develop systematic/validated methods for assessing the risks associated with business loans. As a result, the new rules of the BIS may increase the operational security of the banks in the granting of credit as they establish objective criteria and techniques for modelling the assessment of risk, cutting down dependence on subjective personal judgment. McQuown (2003) argued that Basel II compliance will allow banks to reduce unexpected losses, improve profitability, increase risk-carrying capacity, and undertake more originations.

Following the Basel Accord, it is realistic to expect that additional analytic tools will be developed permitting banks to manage credit risk more effectively over the coming years. We can therefore hope that credit scoring models will provide the foundation for these changes. Even though statistical models were outlined 30 years ago, middle market lending is still primarily a subjective process and there are no benchmarks in commercial lending in wide usage. Paucity of default information continues to prove a principal obstacle to researchers.

This paper presents some early results from research which is concerned with the development of statistical models to assess the risk of default in the light of the New Basel Accord, using a data set from a large Brazilian bank. Section 2 of this paper briefly reviews the relevant literature. Section 3 describes the methods used, section 4 presents the main results, section 5 discusses the implications of the results and section 6 links the limitations of this study with future research.

BRIEF REVIEW OF LITERATURE AND THE ENVIRONMENT OF CREDIT

In the credit risk business literature, different approaches to assess probability of default have been suggested. Moody's (2001) approach divides the models into traditional credit analysis (human judgement), structural models and non-structural models. Although the first method is still in use today in many banks (Altman et al, 2001), the debate in the academic world is focused on structural and non-structural models. There is no academic definition of these models but the differences between them can be understood by looking at examples taken from the literature.

The leading example and the most popular structural model of default is the expected default frequency model (EDF) created by the KMV Corporation in 1995. The KMV Model is based conceptually on Merton's model (1973). In order to calculate the probability of default using the Merton model for a firm with traded equity, the market value of the equity and its volatility, as well as contractual liabilities, are estimated. The market value of the equity is calculated using the Black-Scholes approach to pricing, which employs similar concepts to those used in determining a call option. This kind of model appears to be well conceived, being usually presented in a consistent and complete way which allows interested parties to know exactly what is going on. However, its application is in fact very restricted since it is only applicable to stock corporations. For example, in Latin America stock corporations account for a very small group of firms and even in Europe they represent the smaller group compared alongside non stock enterprises.

With respect to non-structural models, “Z-score” defined by Altman (1968) is the reference most used by researchers in general. Using 66 companies, he constructed a model which resulted in a discriminant function composed of 5 financial ratios. However, his approach has been criticised lately because the characteristics of most firms change from year to year whereas the Z-score is considered as a static model. Schumway (2001) introduced a “hazard model” to predict bankruptcy. In his research he resolved the problems of static models by explicitly accounting for time. The dependent variable in a hazard model is the time spent by a firm before defaulting.

There is a commonly held view that a major drawback for researchers when developing models which can effectively assess the credit risk of individual obligors, is the limited availability of high-frequency objective information to use as model inputs. When historical data is available, it has been claimed that model validation can proceed in a more objective and rigorous context (Falkenstein, Boral and Carty (2000)). However, examining the major academic papers on commercial default models over the past 30 years, they found that the median number of defaulting companies used in these studies is only 40.

In relation to statistical techniques, discriminant analysis has been the most popular method of bankruptcy prediction. However, it has been criticised for methodological reasons, see for example Einsenbeis (1977), Ohlson (1980), Zmijewski (1984), Zavgren (1985) and Funning and Coger (1994). The main criticism is that discriminant analysis depends on normality of variables and assumes that the group dispersion (variance-covariance) is equal across time. Tucker (1996) argues that other methods such as logistic regression are preferable to conventional multivariate regression. The latter is inappropriate for modelling a dichotomous dependent variable as the distribution of errors is unlikely to be normal and predicted values may not be interpreted as probabilities, as they are not bounded by 0 and 1. Indeed, Hosmer and Lemeshow (1989) showed that logistic regression modelling requires far fewer assumptions than multiple discriminant analysis and multivariate regression analysis, whilst generally producing models which exhibit similar or better predictive powers. Lennox (1999) argued that well-specified logit and probit models can also identify failing companies more accurately than discriminant analysis.

More recently, Artificial Neural Networks (ANNs) have been employed in credit risk models. O’Leary (1998) analysed 15 articles that applied ANNs to predict corporate bankruptcy. But he concluded that since each study uses different data, different software, different variables, different training and testing and a variety of other factors, it was difficult to directly compare the fifteen studies. Altman et al. (1994) found little or no difference in classification performance between ANNs and conventional multivariate statistical techniques. However, Back et al (1997) showed that ANNs perform better than logit and discriminant analysis when the sample size is large.

It should also be noted that in the literature relating to the forecasting of company insolvency, there is a predominance of studies carried out in the USA with American enterprises. For use in other parts of the world these models must be tested and where appropriate adapted to the reality of each country or bank. Companies in developed countries, for example, tend to present higher leverage than those in developing countries, where interest rates are generally higher. Further, each country has a different taxation regime, which may aid or hinder the company performance. Therefore, it is essential to develop models based on specific data from each institution, region or country, according to the new rules laid down by the BIS. In this context banks have to apply some techniques which take into account, in their entirety, the risks to which they are exposed.

There is also an important issue concerning the use of the standard recognised group of financial ratios in bankruptcy studies which, to our knowledge, has not been dealt with in previous studies. Although there is no theoretical basis for which predictors should be used for different bankruptcy models, a huge number of possible candidate ratios are cited in the financial distress literature which aim to cover the dimensions of liquidity, activity, financial structure, profitability and growth. However, we do not belong to the stream which considers that accounting practices are inelastic, embedded in thought processes and as a consequence are unchangeable. For example, Heath (1980) argued that the practice of classifying assets and liabilities as current and non current began early in the last century in response to the perceived needs of commercial banks. He considers that this practice is a vestige of a bygone era and should be abandoned because it is misleading. Hence, whilst references like Walsh (1996) mention that the current ratio (current assets/current liabilities) is a favourite of institutions that lend money, according to the Accounting Standards Board's bulletins those classifications are solely for accounting purposes and are nor designed to meet the needs of banks and investors. Thus, new requirements in the credit market exhort us to investigate different approaches, despite the rigid format of the balance sheet.

The remainder of this paper reports and discusses the results of applying the established statistical techniques of logistic regression and discriminant analysis to aid the process of granting credit to firms which are customers of Brazilian banks in the context of the new Basel Accord. A particular aspect of our analysis is the employment and testing of financial ratios different to those commonly used.

METHODOLOGY

The methodology comprises four steps.

Definition of the Data Set

Initially 400 firms which were customers of the 8th largest Brazilian Bank by assets in 2000 were selected as follow: (a) 200 companies which were recorded as written-off credit in 2000 and (b) 200 companies randomly selected among the firms which were having regular transactions with the bank in the same period. Due to problems of insufficient information, 77 were taken out of the sample. Thus, the final data set is composed of 323 companies. The firms are diverse, drawn from industrial, commercial and service sectors.

The dependent variable indicates whether or not the company is in default/financial distress in 2000. The independent variables are financial ratios derived from the Balance Sheet and Profit and Loss Accounts (e.g. liquidity, leverage and profitability) for the previous year, 1999.

Definition of Default or Financial Distress

As opposed to most previous studies, which define defaults only by bankruptcy events, we are able to employ the definition of default described in the Basel Accord (BIS, 2003), as we are using internal data from a bank. Thus, a default is considered to have occurred with regard to a particular obligor when one or more of the following events have taken place:

- The obligor is past more than 90 days due on any credit obligation.
- The bank puts the credit obligation on non-accrued status.
- The bank makes a charge-off or account-specific provision resulting from a significant perceived decline in credit quality subsequent to the bank taking on the exposure.
- The bank consents to a distressed restructuring of the credit obligation.
- The obligor has sought or has been placed in bankruptcy or similar protection where this would avoid or delay repayment of the credit obligation.

Definition of Time Horizon

Following the Basel Accord recommendation we are wanting to predict the probability of default for a one year term,. Moreover, one year also reflects the best period if we bear in mind that it is a typical interval over which: (a) new obligor information can be revealed; (b) internal budgeting, capital planning and accounting statements are prepared; and (c) credit limits are normally reviewed for renewal.

The Variable Selection Process

The selection of variables is often a very important part of modelling default risk. While some distinctions are relatively insignificant, the inclusion or exclusion of certain variables can make a major difference to the predictive power of statistical models (Hekanaho, et.al, 1998).

Without entering into a debate on the fundamentals of accounting principles and conventions, we include in this paper some unconventional financial ratios in the light of what has already been proposed by Fleuriet (1980) and Heath (1980). Obviously, we are supplementing and adjusting the ideas to the Brazilian context and to that of our data set in particular. The essence of our proposition is to reorganise the groups – current assets and current liabilities. The rearrangement referred to means sorting out the accounts in a way that they fit more naturally according to the company's activities. Therefore, we suggest separating the current assets and liabilities into two groups. The first relates to its financial operations and the second relates to its trading operations. For example, in the first group all sorts of short term financial assets and liabilities are classified: cash, deposit accounts, securities, bank loans, trade finance and related parties. In the second group are the short term accounts connected with the main activity of the firm such as customers, inventories, prepayments, provision for doubtful debtors, suppliers, accrued expenses and accrued taxes based on payroll and trading matters. The difference between assets and liabilities will be called 'erratic working capital' in the case of the first group, and will be called 'needs of working capital' in the case of the second group. The measurement intended by this approach aims to assess the real capacity of the company to meet its obligations, in other words to address its de facto liquidity. The complete list of financial ratios used in this study is given in **table 1**.

Table 1. Financial Ratios

Traditional Ratios	Unconventional RatiosUnconventional Ratios
1) QUICK RATIO	29) NET RELATED PARTIES/NET SALES
2) CURRENT RATIO	30) DISCOUNTED TRADE BILLS/CUSTOMERS
3) TOTAL LIQUID RATIO	31) OTHER LIABILITIES/NET SALES
4) FIXED ASSET RATIO	32) INSTALMENTS OF ARREARS TAXES/NET SALES
5) SHORT TERM DEBT RATIO	33) WORKING CAPITAL/NET SALES
6) TOTAL DEBT RATIO	34) NEED OF WORKING CAPITAL/NET SALES
7) TOTAL BANK DEBT RATIO	35) ERRATIC WORKING CAPITAL/NET SALES
8) BANKING AS % OF LIABILITIES	36) NEED OF WORKING CAPITAL/WORKING CAPITAL
9) INVENTORIES PERIOD	37) ERRATIC WORKING CAPITAL/WORKING CAPITAL
10) CUSTOMER COLLECTION PERIOD	38) ERRATIC WORKING CAPITAL/NEED OF WORKING CAPITAL
11) SUPPLIERS PERIOD	
12) OPERATING CYCLE	39) WORKING CAPITAL/TOTAL ASSETS
13) FINANCIAL CYCLE	40) NEED OF WORKING CAPITAL/TOTAL ASSETS
14) ASSET TURNOVER	
15) PBIT/NET SALES	
16) PBT/NET SALES	
17) NET PROFIT MARGIN	
18) PBIT/SHAREHOLDER'S FUNDS	
19) PBT/SHAREHOLDER'S FUNDS	
20) RETURN ON EQUITY	
21) PBIT/TOTAL ASSETS	
22) RETURN ON ASSETS	
23) INTEREST/NET SALES	
24) INTEREST/BANK LOANS	
25) INTEREST COVERAGE RATIO	
26) FUNDS FROM OPERATIONS/TOTAL ASSETS	
27) FUNDS FROM OPERATIONS/NET SALES	
28) PBT/NET SALES	

THE MODELS

Two different statistical models were fitted using SPSS 13.0, Logistic Regression and Discriminant Analysis. In both cases variables were selected by the stepwise forward procedure. This procedure essentially ensures that only statistically significant variables are included, and goes some way to reducing the risk of overfitting the model to the data which would tend to over-inflate the predictive performance of the model. The results were as follows.

Model Summary for Logistic Regression

The variables selected in the logistic regression model are shown in **table 2**. As we are modelling the probability of default, we can see that the companies which have more need of working capital (B= .886), more instalments of arrear taxes (B= 1.221) and more short term debt (B= .292) will present more risk of default. On the other hand, firms with higher amounts of erratic working capital (B= -3.934), higher amounts of funds from operations (B= -3.643) and longer financial cycle (B= -.011) are less likely to default.

Table 2. Variables Selected in Logistic Regression Model

		B	S.E.	WALD	df	Sig.	Exp(B)
Step 1[a]	shortdebt	.292	.117	6.270	1	.012	1.339
	fincycle	-.011	.004	6.385	1	.012	.989
	NWK.NS	.886	.172	26.507	1	.000	2.425
	EWK.NS	-3.934	.689	32.626	1	.000	.020
	IAT.NS	1.221	.338	13.023	1	.000	3.392
	FFO.NS	-3.643	1.495	5.935	1	.015	.026
	Constant	-2.783	.531	27.449	1	.000	.062

a. Variable(s) entered on step1: shortdebt, fincycle, NWK.NS, EWK.NS, IAT.NS, FFO.NS.

shortdebt= short term debt; fincycle= financial cycle; NWK.NS= need of working capital/net sales; EWK.NS= erratic working capital/net sales; IAT.NS= instalments of arrears taxes/net sales; FFO.NS= funds from operations/net sales.

We also note that three of the unconventional financial ratios defined in **table 1** have been selected in the logistic regression model, namely NWK.NS (need of working capital/net sales), EWK.NS (erratic working capital/net sales), and IAT.NS instalments of arrears taxes/net sales). The implication of this is that the model has been improved by the inclusion of the unconventional ratios.

Having estimated the logistic regression model we are then interested to know how well it is able to predict defaulting companies. **Table 3** presents the predictive performance of the logistic regression model. It shows that 92.9% of the defaulting companies (group 1) and 97.6% of the non-defaulting companies are predicted correctly, with an overall accuracy of 95.4%.

Table 3. Predictive Performance of Logistic Regression Model

	Predicted		
Observed	Group 0	Group 1	% Correct
Group 0	164	4	97.6
Group 1	15	144	92.9
% Correct			95.4

Note that when classification tools are used, default risk models can err in one of two ways. First, according to Sobehart et al (2001) the model can indicate low risk when, in fact, the risk is high (Error type I). The cost to the bank can be loss of principal and interest. Second, the model can assign a low credit quality when, in fact, the quality is high (Error type II). Potential losses resulting from this Type II error (commercial mistake) include the loss of return and origination fees when loans are either turned down or lost through non-competitive bidding. Such mistakes can also incur other costs, e.g. angry customers tend to terminate their relationship. The loss amount remains implicit as a forgone gain. It would be desirable to minimise the weighted sum of costs caused by errors. Unfortunately, minimising one type of error usually comes at the expense of increasing the other.

Model Summary for Discriminant Analysis

The variables selected in the discriminant function are shown in **table 4**. In this case we can see that decreases in fixed assets (fixedasset) and needs working capital/net sales (NWK.NS) lead to a decrease in the discriminant function, i.e. in this case they indicate a tendency to default. On the other hand current ratio (curr.rat), internal return rate (IRR) and erratic working capital/net sales (EWK.NS) indicate a tendency not to default. From an accounting and finance point of view we also note that these variables represent a perfect balance because they represent liquidity, structure and profitability.

As with the logistic regression we note the selection of unconventional financial ratios, in this case NWK.NS and EWK.NS, from which we can again conclude that they have led to a better model than one based solely on conventional ratios.

Table 4. Variables Selected in Discriminant Analysis Model

Standardized Canonical Discriminant Function Coefficients

	Function
	1
curr.rat	.688
fixedasset	-.266
IRR	.257
NWK.NS	-.519
EWK.NS	.534

curr.rat= current ratio; fixedasset= fixed asset ratio; IRR= internal return rate; NWK.NS= need working capital/net sales; = erratic working capital/net sales.

Table 5 presents the predictive performance of the discriminant analysis. It shows that 90.3% of the defaulting companies (group 1) and 93.5% of the non-defaulting companies are predicted correctly, with an overall accuracy of 92.0%. In line with most findings in previous studies, logistic regression has outperformed discriminant analysis in relation to predicting the original group membership (4.6% error rate versus 8.0%). However, the overall accuracy of 92.0% classified correctly by discriminant analysis is by no means a poor result.

Table 5. Predictive Performance of Discriminant Analysis Model

	Predicted		
Observed	Group 0	Group 1	% Correct
Group 0	157	11	93.5
Group 1	15	140	90.3
Overall %			92.0

DISCUSSION AND CONCLUSIONS

Inadequate credit processes are recognised as one of the most important errors in bank lending in the 1990s. This stimulated increased intensity in the development of new analytic tools to measure, control, assess and manage credit risk, and means that the present time is an exciting period for practitioners and researchers in this field. However, this period has also been marked by uncertainties about the reliability and the true value of the new techniques and tools for managing credit risk. Whilst many banks are adopting new approaches and are moving away from the traditionally held view that judging credit is fundamentally an art, significant gaps in knowledge still remain in this area.

In this context we have proposed and tested a statistical modelling approach to predict the risk of default of Brazilian companies, using the Basel II concept of default.

Our primary conclusion is that our results indicate that the Basel Accord definition of default can be successfully applied in the study of businesses failure through the use of statistical models, even when relatively non-complex techniques like discriminant analysis and logistic regression are employed. In line with most previous research our study confirms the findings that logistic regression outperforms discriminant analysis

The benefits of statistical models in comparison to traditional credit analysis in this context are not only their ability to predict group membership. For instance, they are more transparent and objective which allows banking authorities and bank executives to better evaluate the risk involved, both for obligors individually and for whole portfolios. Their transparent and objective basis also means that they can become more consistent, are easily understood, managed and updated. Moreover the speed of application of these models to new credit requests means that they can provide more capacity for competition between lenders. Finally, they represent an economy for banks and lenders in general due to their low cost in comparison to traditional methods.

In addition this study has reinforced the potential benefits of using financial ratios other than those traditionally employed in most of previous studies, in order to obtain better insights into financial distress and to obtain more accurate models. Our results showed that important explanatory variables in both the models turned out to be 'unconventional financial ratios'. This finding may well indicate an important way forward for future models as financial institutions attempt to take on board the requirements of Basel II Accord. One broader implication of this result is that some accounting conventions may need to be revised in order to better meet the needs of banks and investors, which are perhaps the most important providers of funds in the economy.

As the implications of Basel Accord are that it should be applicable worldwide, our study in the Brazilian context represents an interesting application outside the countries on which previous research has tended to concentrate. Our results are consistent with and extend upon results obtained elsewhere. However the variables selected in the models also reinforce the idea that credit risk models will be better developed 'locally' taking into account the 'local' risks to which each bank is exposed and the economic conditions in which the companies operate. For instance, the variable IAT.NS reflects a specific period in which the Brazilian Government refinanced due taxes for companies which were highly in debt.

Finally, it seems very likely that the approach and issues addressed in this paper will remain very important in banking and finance, given the need to assess risks in a systematic fashion. There is no doubt that credit scoring combines advantageous characteristics: it is more robust, transparent, objective, clear, speedy, uniform, reliable, impartial, self oriented and cheaper than traditional methods. Moreover, credit scoring methods easily meet the rules laid down in the New Basel Accord.

LIMITATIONS AND FUTURE RESEARCH

Like most of previous researches this paper uses a small sample of companies. However, this research is ongoing. A much larger dataset of more than 6,000 companies is currently being analysed. It will be of interest to discover to what extent similar results are found. This much larger data set will also provide the opportunity to experiment with other, more data-hungry modelling methods, and to undertake out of sample and out of time validation.

Another research area is concerned with the school of thought surrounding Basel II that banks should develop separate models for the obligor and the facility. The obligor model should predict the probability of default (PD) based on default definition and the facility model should predict the loss given default (LGD).

This paper addresses only the first model (PD) based on cross-sectional data.

Another area for research is to investigate the potential benefit in developing models that incorporate economic factors or variables such as interest rates, exchange rates and performance of specific economic sectors.

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