Financial Distress and Bankruptcy Prediction using Accounting, Market and Macroeconomic Variables

by

Mario Hernández Tinoco

Submitted in accordance with the requirements for the degree of
Doctor of Philosophy

The University of Leeds
Leeds University Business School
Accounting and Finance Division
Centre for Advanced Studies in Finance
Credit Management Research Centre

September 2013

The candidate confirms that the work submitted is his own, except where work which has formed part of jointly-authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

The following thesis section is based on work from a jointly-authored publication

Thesis Section	Jointly-authored Publication
Chapter 4: Financial Distress and Bankruptcy Prediction among Listed Companies using Accounting, Market and Macroeconomic Variables	Hernandez Tinoco, M. & Wilson, N. (2013). Financial Distress and Bankruptcy Prediction among Listed Companies using Accounting, Market and Macroeconomic Variables. *International Review of Financial Analysis*, forthcoming.

The candidate confirms that he is the principal author of the above publication. The work contained in the article arose directly out of the work for this PhD thesis. The candidate undertook the literature review, data collection and statistical analyses and made a significant contribution to the conceptual framework used.

Dedication of this Thesis

To Alejandra Tinoco and Ana María Sánchez

Acknowledgements

I would like to express my appreciation and thanks to Professor Nicholas Wilson and Professor Phil Holmes for their guidance, support and advice throughout the course of my doctoral studies. Their experience and encouragement has provided an invaluable source of motivation to me throughout my education. I would also like to express my thanks to Professor Kevin Keasey, Associate Professor Francesco Vallascas, Professor Michael Collins, Professor Mae Baker-Collins, Michelle Dickson, all of my colleagues in CASIF, and countless others all of whom have encouraged and supported me during my studies.

Financial support from the Consejo Nacional de Ciencia y Tecnología (CONACYT) is gratefully acknowledged.

Abstract

This thesis investigates the information content of different types of variables in the field of financial distress/default prediction. Specifically, the thesis tests empirically, for the first time, the utility of combining accounting data, market-based variables and macroeconomic indicators to explain corporate credit risk. Models for listed companies in the United Kingdom are developed for the prediction of financial distress and corporate failure. The models used a combination of accounting data, stock market information, proxies for changes in the macroeconomic environment, and industry controls. Furthermore, novel finance-based and technical definitions of firm distress and failure are introduced as outcome variables. The thesis produced binary and polytomous models with enhanced predictive accuracy, practical value, and macro dependent dynamics that have relevance for stress testing. The results unambiguously show the advantages, in terms of predictive accuracy and timeliness, of combining these types of variables. Unlike previous research works that employed discrete choice, non-linear regression methodologies, this thesis provided new evidence on the effects of the different types of variables on the probability of falling into each of the individual outcomes (e.g., financial distress, corporate failure). The analysis of graphic representations of changes in predicted probabilities, a primer in the field of risk modelling, offered new insights with regard to the behaviour of the vectors of predicted probabilities following a given change in the magnitude of a specific covariate. Additionally, and in line with the main area of study, the thesis provides historical evidence on the types of variables and the information sharing mechanisms employed by American and British investors and financial institutions to assess the riskiness of individuals, businesses and fixed-income instruments before the emergence of modern institutions such as the credit rating agencies and prior to the development of complex statistical models, filling thus a crucial gap in the credit risk literature.

Table of Contents

Acknowledgements .... **ii**

Abstract .... **iii**

Table of Contents .... **iv**

List of Tables .... **vii**

List of Figures .... **ix**

List of Abbreviations .... **x**

1. Introduction **1**

1.1. The historical evolution of risk assessment and credit information sharing in the United States and the United Kingdom. 2

1.2. The relevance of accounting, market, and macroeconomic variables in bankruptcy and financial distress prediction models. 3

1.3. A finance-based definition of firm's distress and a technical approach of corporate failure. 4

1.4. The estimation of marginal effects and changes in predicted probabilities for the interpretation of financial distress/corporate default prediction models. 5

1.5. Structure of the thesis. 7

2. A Historical Study on the Evolution of Risk Assessment and Credit Information Sharing in the United States and the United Kingdom in the Nineteenth Century **8**

2.1. Introduction. 8

2.2. The Role of Credit Information Sharing as a Solution to the Information Asymmetries between Borrowers and Lenders. 13

2.3. Origins and Evolution of the First Forms of Credit Information Sharing in the United Kingdom: Mutual Societies for the Protection of Trade and the Subjective Assessment of Risk. 17

2.4. Consumer and Business Credit Information Sharing in the First Half of the Nineteenth Century: Mercantile Houses in the United Kingdom and the Emergence of the First Rating Systems based on Personal and Business Characteristics. 24

2.5. The Emergence of the First General Profit-seeking Organisations for the Provision of Credit Information in the United States: Credit Reporting Agencies and the Systematic Assessment of Risk based on Personal and Business Characteristics. 30

2.6. Credit Information on Corporations and Securities in the Second Half of the Nineteenth Century in the United States and the United Kingdom: the Assessment of Risk based on Specialized Publications and Statistics. 36

2.7. Conclusion. 43

3. Sample Selection and Descriptive Statistics **46**

3.1. Sample Selection 46

3.2. Variable Definitions. 47

3.2.1. Accounting Ratios 48

3.2.2. Macroeconomic Variables. 49

3.2.3. Market Variables. 49

3.3. Descriptive statistics. 51

3.3.1. Annual Distribution of Outcomes. 51

3.3.2. Time series presentations of the macroeconomic measures and the number of corporate failure/financial distress observations. 52

4. The Role of Accounting, Market and Macroeconomic Variables for the Prediction of Corporate Default among Listed Companies 54

4.1. Introduction. 54

4.2. Review of the Literature. 56

4.3. Default Prediction Methodologies. 61

4.4. Outcome Definition and Independent Variable Selection. 65

4.4.1. Outcome Definition 65

4.4.2. Independent Variable Selection 68

4.4.2.1. Accounting Ratios 68

4.4.2.2. Macro-Economic Variables 70

4.4.2.3. Market Variables 72

4.5. Methods: Panel Logit Model Specification 79

4.6. Analysis of Results. 84

4.6.1. Marginal Effects and Changes in Predicted Probabilities. 104

4.6.2. Classification Accuracy Tables. 110

4.6.3. Model Validation. 114

4.7. Conclusions. 114

5. Financial Distress and Bankruptcy Prediction among Listed Companies using Accounting, Market and Macroeconomic Variables 118

5.1. Introduction. 118

5.2. Review of the Literature. 119

5.3. Outcome Definition and Independent Variable Selection. 124

5.3.1. Outcome Definition 124

5.3.2. Independent Variable Selection 128

5.4. Methods: Panel Logit Model Specification 132

5.5. Analysis of Results. 136

5.5.1. Marginal Effects and Changes in Predicted Probabilities. 153

5.5.2. Classification Accuracy Tables. 160

5.5.3. Model Validation. 163

5.5.4. Performance Comparison Benchmarks. 164

5.6. Conclusions. 169

5.7. Appendix. 172

5.7.1. Computation of Model 3 using the Neural Networks Methodology (Multilayer Perceptron). 172

5.7.2. Estimation of Model 3 with Industry controls. 174

6. Polytomous Response Financial Distress Models for Listed Companies using Accounting, Market and Macroeconomic Variables 177

6.1. Introduction. 177

6.2. Review of the Literature. 179

6.3. Outcome Definition. 183

6.3.1. Outcome Definition 184

6.4. Methods: Polytomous Response Logit Model Specifications. 191

6.5. Independent Variable Specifications and Ex-ante Hypotheses. 196

6.5.1. Accounting Ratios. 196

6.5.2. Market Variables. 198

6.5.3. Macroeconomic Indicators. 199

6.5.4. Implications for the Comparison of Response categories in the Models. ...200

6.6. Analysis of results. 205

6.6.1. Multinomial Function Coefficients. 208

6.6.2. Model Fit Statistics. 214

6.6.3. Marginal Effects and Changes in Predicted Probabilities. 216

6.6.4. Classification Accuracy Tables. 226

6.7. Conclusions. 231

6.8. Appendix. 233

7. Conclusions 236

7.1. Summary of main findings. 236

7.2. Historical evidence on the types of variables and credit information sharing mechanisms in the United States and the United Kingdom. 236

7.3. Default prediction using accounting, market and macroeconomic variables. 238

7.4. Bankruptcy and financial distress prediction using accounting, market and macroeconomic variables. 240

7.5. A polytomous response logit financial distress corporate failure model. 241

7.6. Directions for future research. 243

Bibliography 245

List of Tables

Table 3-1 Distribution of Outcomes Per Year 51

Table 3-2 Summary Statistics of Annual Observations. Financially Distressed, Not Financially Distressed and Failed Firms 52

Table 4-1 Summary Statistics of Corporate Failure of UK Firms. 66

Table 4-2 Correlation Matrix and Multicollinearity Diagnostics Statistics. 78

Table 4-3 Summary Statistics for Model 1 82

Table 4-4 Summary Statistics for Model 2. 82

Table 4-5 Summary Statistics for Model 3 83

Table 4-6 Logit Regression of Default Indicator on Predictor Variables (*t-1*) 89

Table 4-7 Logit Regression of Default Indicator on Predictor Variables (*t-2*) 90

Table 4-8 Model Performance Measures 95

Table 4-9 Marginal Effects 105

Table 4-10 Bias-Adjusted Classification Table 113

Table 4-11 Model Validation – Areas Under the ROC Curve 114

Table 5-1 Summary Statistics of the Annual Observations. Financially and Not Financially Distressed Firms 126

Table 5-2 Summary Statistics of Corporate Failure of UK Firms 127

Table 5-3 Correlation Matrix and Multicollinearity Diagnostics Statistics 131

Table 5-4 Summary Statistics for Model 1 133

Table 5-5 Summary Statistics for Model 2 134

Table 5-6 Summary Statistics for Model 3 135

Table 5-7 Logit Regression of Financial Distress Indicator on Predictor Variables 141

Table 5-8 Model Performance Measures 146

Table 5-9 Marginal Effects 155

Table 5-10 Bias-Adjusted Classification Table 162

Table 5-11 Model Validation – Areas Under the ROC Curve 164

Table 5-12 Logistic Regression and Neural Networks Performance Comparison Results 165

Table 5-13 Bias-Adjusted Classification Table. Logistic Regression and Artificial Neural Networks Comparison 168

Table 5-14 Classification Table using Altman's Z-Score 169

Table 5-15 Industry Code Construction 174

Table 5-16 Logit Regression of Financial Distress Indicator on Predictor Variables – Models with Industry Dummies 175

Table 5-17 Model Performance Measures – Models with Industry Dummies 176

Table 6-1 Summary Statistics of the Annual Observations. Financially and Not Financially Distressed Firms 186

Table 6-2 Correlation Matrix and Multicollinearity Diagnostics Statistics 190

Table 6-3 Summary Statistics for Model 1 202

Table 6-4 Summary Statistics for Model 2 203

Table 6-5 Summary statistics for Model 3 204

Table 6-6 Likelihood-ratio and linear hypothesis testing results 207

Table 6-7 Multinomial Logit Regression of 3-Level Response Variable on Predictor Variables - Model 1 - Accounting + Macroeconomic Variables Model 210

Table 6-8 Multinomial Logit Regression of 3-Level Response Variable on Predictor Variables - Model 2 - Market + Macroeconomic Variables Model 211

Table 6-9 Multinomial Logit Regression of 3-Level Response Variable on Predictor Variables - Model 3 - Comprehensive Model 213

Table 6-10 Comparative Model Fit Statistics 215

Table 6-11 Marginal Effects – Model 1 and Model 2 218

Table 6-12 Marginal Effects – Model 3 219

Table 6-13 Bias-Adjusted Classification Accuracy Table in *t-1* 229

Table 6-14 Bias-Adjusted Classification Accuracy Table in *t-2* 230

Table 6-15 Multinomial Logit Regression of 3-Level Response Variable on Predictor Variables - Model 4 - Comprehensive Model with Industry Effects 233

Table 6-16 Marginal Effects – Model 4 with Industry Effects 234

Table 6-17 Bias-Adjusted Classification Accuracy Table – Comprehensive Model with Industry Effects 235

List of Figures

Figure 3-1 Financial Distress/Failure & thre Retail Price Index ... 53
Figure 3-2 Financial Distress Failure & the 3-Month UK Bill Rate ... 53
Figure 4-1 Comparison of Areas under the Receiver Operating Characteristic Curve of Model 1, Model 2, and Model 3 estimated in period *t-1* ... 100
Figure 4-2 Comparison of Areas under the Receiver Operating Characteristic Curve of Model 3, Model 4, and Model 5 estimated in period *t-1* ... 101
Figure 4-3 Comparison of Areas under the Receiver Operating Characteristic Curve of Model 1, Model 2, and Model 3 estimated in period *t-2* ... 102
Figure 4-4 Comparison of Areas under the Receiver Operating Characteristic Curve of Model 3, Model 4, and Model 5 estimated in period *t-2* ... 103
Figure 4-5 Changes in Predicted Probabilities – Financial Statement Ratios ... 107
Figure 4-6 Changes in Predicted Probabilities – Market Variables ... 108
Figure 4-7 Changes in Predicted Probabilities – Macroeconomic Indicators ... 109
Figure 5-1 Comparison of Areas under the Receiver Operating Characteristic Curve of Model 1, Model 2, and Model 3 estimated in period t-1 ... 150
Figure 5-2 Comparison of Areas under the Receiver Operating Characteristic Curve of Model 2, and Model 3 estimated in period *t-1* ... 151
Figure 5-3 Comparison of Areas under the Receiver Operating Characteristic Curve of Model 1, Model 2, and Model 3 estimated in period *t-2* ... 152
Figure 5-4 Comparison of Areas under the Receiver Operating Characteristic Curve of Model 2, and Model 3 estimated in period *t-2* ... 153
Figure 5-5 Changes in Predicted Probabilities – Financial Statement Ratios ... 157
Figure 5-6 Changes in Predicted Probabilities – Market Variables ... 158
Figure 5-7 Changes in Predicted Probabilities – Macroeconomic Indicators ... 159
Figure 5-8 Model 3. Multilayer Perceptron – Areas under the ROC Curve ... 172
Figure 5-9 Model 3. Multilayer Perceptron Diagram ... 173
Figure 6-1 Marginal effects on the Probabilities of Non-Financial Distress, Financial Distress and Corporate Failure in *t-1* ... 221
Figure 6-2 Changes in Predicted Probabilities – Financial Statement Ratios ... 223
Figure 6-3 Changes in Predicted Probabilities – Market Variables ... 225
Figure 6-4 Changes in Predicted Probabilities – Macroeconomic indicators ... 226

List of Abbreviations

AME	Average Marginal Effect
AMEX	American Stock Exchange
AUC	Area Under the (ROC) Curve
CDS	Credit Default Swap
CRSP	Center for Research in Security Prices
DIS	Financial Distress State
FAI	Corporate Failure State
FD	Financially Distressed
FTSE	Financial Times Stock Exchange
IRB	Internal Ratings Systems
KMV	Kealhofer, McQuown and Vasicek
LSPD	London Share Price Database
MCS	Mutual Communication Society
MDA	Multiple Discriminant Analysis
MPT	Modern Portfolio Theory
NATPS	National Association of Trade Protection Societies
NFD	Not Financially Distressed
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
PD	Probability of Default
ROC	Receiver Operating Characteristics
RPI	Retail Price Index
SAS	Statistical Analysis System
SEDOL	Stock Exchange Daily Official List
SIC	Standard Industrial Classification
TANH	Hyperbolic Tangent
UK	United Kingdom
US	United States
VIF	Variance Inflation Factor
TOL	Tolerance Value
SME	Small and Medium-sized Enterprises

1. Introduction

The development of financial distress/bankruptcy prediction models has been of significant interest to a wide range of financial actors over the last four decades. Given the dynamic nature of the characteristics of financially distressed and bankrupt firms over time, it is essential for regulators, practitioners, and academics, to periodically test and enhance the performance of existing financial distress/corporate default prediction models. This is notably important as the areas of application of such models have been broadened to include: the monitoring of the financial situation of institutions by regulators, the evaluation of the financial viability of corporations by auditing firms, the measurement of the riskiness of portfolios, the pricing of credit derivatives and other fixed-income securities, among others. Very recently, the financial crisis of 2007-08 highlighted the shortcomings of risk management practices within the lending environment and risk assessment at the micro level (Probability of Default estimation). Lenders and other investors in the corporate sector along with regulators require timely information on the default risk probability of corporates within lending and derivative portfolios. For banks, developing effective 'Internal Rating Systems' (IRB) for corporate risk management requires building probability of default (PD) models geared to the specific characteristics of corporate sub-populations (e.g., SME's, private companies, listed companies, sector specific models), tuned to changes in the macro environment, and, of course, tailored to the availability and timeliness of data.

The present thesis develops new risk models for listed companies that predict financial distress and corporate failure, employing new and enhanced finance-based definitions of these outcomes. The novelty of this thesis is that, unlike previous research works, the estimated models use a combination of accounting data, stock market information and proxies for changes in the macroeconomic environment to investigate whether a model containing these three types of variables is able to enhance the predictive accuracy, goodness-of-fit as well as the timeliness of prediction models. Moreover, through the use of relevant transformations to the output generated by multivariate regression analysis as well as graphical representations of the behaviour of vectors of predicted probabilities, the models are intended to be of use to gain a better understanding of the individual effects of the different types of variables on the probability of financial distress and corporate default. The purpose is thus to produce models with practical value through flexible and sound methodologies resulting in improved predictive accuracy and macro dynamics that have relevance for stress testing. In accordance with this field of study, the present thesis begins by tackling a conspicuous gap in the credit risk literature that is directly relevant to the use of different types of variables to assess risk through time. It investigates, for the first time, the types of variables and the information sharing mechanisms employed by American and British investors and financial institutions to assess the creditworthiness of individuals, businesses and fixed-income instruments before the emergence of modern institutions such as the credit rating agencies (or credit reference agencies) and prior to the development of complex statistical models, filling thus a crucial gap in the literature.

1.1. The historical evolution of risk assessment and credit information sharing in the United States and the United Kingdom.

As suggested by Wilson (2008), it is clear that the granting of credit is made possible by the flows of information on projects, businesses and borrowers, and "in difficult times it gravitates towards the established information networks."[1] In effect, there is a very ample body of literature suggesting that asymmetric information is the main obstacle between borrowers and lenders exchanges and that it can therefore prevent the efficient allocation of credit in a given economy. Historically, lenders have tried to overcome information asymmetry problems by collecting information on their own borrowers and their businesses through long term business relationships on the one hand, and on the other, by establishing contractual mechanisms of information sharing based on the principle of reciprocity. Nevertheless, there is still a very important gap in the literature that could provide a better understanding of the role of the different types of variables and the information sharing mechanisms on the assessment of credit risk: to the best of my knowledge, there are no *historical* studies that directly relate to the evolution of information sharing organisations or the type of credit information that individual lenders and organisations used to assess the riskiness (creditworthiness) or the likelihood of default/timely payment of borrowers. The present study's aim is to fill this gap: employing a historical approach, it traces the types of credit information that lenders used to assess borrowers' risk through the evolution of credit information sharing organisations from the nineteenth century, where the main antecedents of modern institutions can be found.

[1] Wilson (2008), p. 13. Section 1. Background.

Moreover, the promised study utilises a comparative procedure and documents the evolution of credit sharing information in two of the most historically relevant financial centres: the United Kingdom and the United States. In modern days, there are various methods to judge on the creditworthiness of individuals, businesses, and fixed-income instruments. Credit scoring models are the prevailing tools used in order to assess the creditworthiness of the various financial actors. Scoring models utilise payment histories, accounting data, financial statements, and even non-financial information as their primary inputs to assess the ability of existing and potential recipients of credit to make timely payments of contracted financial obligations. Credit grantors obtain credit information through information sharing devices, such as credit rating agencies or credit reporting agencies, whose main role is to gather relevant knowledge and distribute it to subscribers of their services. The output frequently takes the form of ordinal scales of creditworthiness or written reports that allow credit grantors to make informed business decisions. However, this kind of credit information, whose collection is now facilitated by the willingness of obligors as well of obligees to voluntarily share it, was not easily obtainable in the nineteenth century in the United Kingdom and in the United States, where credit experimented a very fast expansion due to the exponential growth of trade stemming from the Industrial Revolution and later with the development of public corporations issuing debt in the form of securities. The present thesis contributes to the literature by providing evidence on the question of the types of variables and credit information sharing methods employed to assess credit risk in a period where the antecedents of modern organisations can be found.

1.2. The relevance of accounting, market, and macroeconomic variables in bankruptcy and financial distress prediction models.

The thesis tests, for the first time in financial distress prediction models for quoted companies in the United Kingdom, the relative contributions (individual and as groups) of three types of variables to the predictive accuracy of the model: financial, macroeconomic and market variables. Prior research has tested the ability of market variables to predict bankruptcy employing methodologies such as the Black and Scholes contingent claims or option-based approach (Bharath and Shumway, 2008; Hillegeist et al., 2004; Reisz and Perlich, 2007; and Vassalou and Xing, 2004). However, the results obtained from these models (that entail numerous restrictive assumptions) have been controversial. In a recent paper, Agarwal and Taffler (2008) perform a comparison of market-based and accounting-based bankruptcy prediction models, and find that traditional models based on financial ratios are not inferior to KMV-type, option-based models for credit risk assessment purposes. Hence, many efforts have been carried out to demonstrate the superiority of market-based models over accounting-based models and vice versa.

To this point, the default prediction literature is characterised by a competing approach, where there is a clear division line between market and accounting variables. The present thesis adopts a different approach where the use of these types of variables is not mutually exclusive. It tests whether the market variables (dependent, in some measure, upon the same financial information) add information that is not contained in financial statements and therefore act as complement in financial distress/default prediction models. Clearly, the inclusion of market-based variables in accounting-based models is appealing on several grounds: first, market prices reflect the information contained in accounting statements plus other information not in the accounting statements (Agarwal and Taffler, 2008), making them a comprehensive mix potentially useful for the prediction of corporate default. Second, the inclusion of market-based variables can considerably increase the timeliness of prediction models; while financial accounts are available in the United Kingdom on a quarterly basis, at best (prior research have used annual data conventionally), market prices are available on a daily basis. Third, market prices might be more appropriate to predict bankruptcy, as they reflect future expected cash flows (accounting statements, in contrast, reflect the past performance of the firm). And fourth, market-based variables can provide a direct assessment of volatility, a measure that could be a powerful predictor of bankruptcy risk and that is not contained in financial statements (Beaver et al., 2005). Additionally, the thesis tests the relevance of the incorporation of industry effects as well as time variant data into credit risk models that captures changes in the macro-economic environment.

1.3. A finance-based definition of firm's distress and a technical approach of corporate failure.

Most of prior default prediction models for quoted companies employ a definition of the criterion event that is contingent upon its ultimate legal consequence: bankruptcy. However, this legal definition of default is not without issues. For instance, insolvency can be a lengthy legal process and the 'legal' date of failure may not represent the 'economic' or the 'real' event of failure. Analysis of UK companies demonstrates a considerable time gap (up to three years or 1.17 years in average) between the period that a firm enters a state of financial distress (that caused the firm to default) and the date of legal default/bankruptcy.

This evidence is consistent with the finding by Theodossiou (1993) that firms in the United States stop providing accounts approximately two years before the bankruptcy filing. The implication is that a firm in this situation is already in serious financial distress at some point two years before the legal bankruptcy event. Moreover, it is possible that a firm in a state of financial distress does not change the legal status that a bankruptcy filing would entail (Balcaen and Ooghe, 2004). Moreover, changes in insolvency legislation, (e.g. the Enterprise Act 2004 in the UK or Chapter 11 in the US) which have attempted to create a 'rescue culture', have changed the nature and timing of the legal bankruptcy process. Wruck (1990) states that there are several stages that a firm can go through before it is defined as dead: financial distress, insolvency, filing of bankruptcy, administrative receivership (in order to avoid filing for bankruptcy), for instance. Moreover decline can be managed by the sale of assets (pre packs) and eventual dissolution rather than formal bankruptcy.

The present study tests for the first time, for quoted companies in the United Kingdom, the advantages of a finance-based definition of firm distress. This development has been highlighted as important in the academic literature (Pindado et al., 2008; Barnes, 1990; and Barnes, 1987) and is justified by the fact that the failure of a firm to meet its financial obligations does not inevitably lead to a filing of bankruptcy. The thesis follows Pindado et al., (2008) and classifies a firm as financially distressed whenever: i) its earnings before interest and taxes depreciation and amortization (EBITDA) are lower than its financial expenses for two consecutive years; ii) the firm suffers from a negative growth in market value for two consecutive years. Additionally, the thesis follows Christidis and Gregory (2010) and classifies a firm as bankrupt when its status in the 2012 London Share Price Database is defined as: suspended, in liquidation or voluntary liquidation, when its quotation has been suspended for more than three years, when the firm is being held by a receiver (in receivership), in administration or in administrative receivership, or when there has been a cancellation or suspension of the firm.

1.4. The estimation of marginal effects and changes in predicted probabilities for the interpretation of financial distress/corporate default prediction models.

The parameters estimated from binary and multinomial response logit models, unlike those produced by linear models, cannot be directly interpreted because they do not provide useful information that fully describes the relationship between the independent variables and the outcome (Long and Freese, 2003). Previous financial distress and corporate failure prediction models constructed using binary response methodologies invariably focus on the overall discriminating and/or predictive accuracy of the models and very rarely do they provide an interpretation of the relationship between the predictor variables and the binary/multinomial outcome. Such studies report solely the estimates obtained from binary response models and provide an interpretation of the direction of the relationship based on the sign of the estimate. Nevertheless, the basic output (the coefficient estimates) obtained by performing binary/multinomial response logit models cannot fully explain the effects of the individual variables on the model's outcomes because of their non-linear nature. It is posited that marginal effects and changes in predicted probabilities are appropriate tools to treat this issue. The thesis intends to fill an important gap in the default/financial distress prediction literature, where the measurement of expected instantaneous changes in the response variable as a function of a change in a specific predictor variables while keeping all the other covariates constant, has been overlooked.

Furthermore, the thesis argues that the applications to finance of the multinomial logit methodology have not been explored enough, and that the literature on financial distress and corporate failure could significantly benefit not only from the analysis of its output in the form of prediction accuracy results (of three possible outcomes), but also from the new insights that can be obtained through appropriate transformations of the multinomial function coefficients in order to provide a direct interpretation of the effects of individual covariates on the likelihood of a firm moving into one of the three possible states. Leclere (1999) argues that a potential reason for the underutilisation of these types of models "is that the interpretation of the model coefficients in a bivariate probit or logistic regression already differs substantially from OLS regression. When the models move from a dichotomous to an *n*-chotomous dependent variable, the interpretation becomes more complex. Compounding this difficulty, the typical coverage in an econometric text fails to provide readers with a systematic approach to the interpretation of model coefficients." To fill this gap in the financial distress literature, marginal effects, defined as the partial derivative of the event probability with respect to the predictor of interest, and derived from the output of the polytomous response model, are estimated and interpreted in detail in the present thesis. Moreover, graphic representations of the changes produced in the vectors of predicted probabilities by a change in the level of a specific covariate (while keeping all other variables constant at their means) are presented to further analyse the individual effects of all types of variables in the models, providing thus additional insights on their patterns of behaviour as well as additional support to the interpretation of the marginal effects.

1.5. Structure of the thesis.

The thesis is organised as follows. Chapter 2, through a comparative analysis, provides historical evidence on the types of variables and the information sharing mechanisms employed by American and British investors and financial institutions to assess the likelihood of default/timely repayment of individuals, businesses and fixed-income instruments before the emergence of modern institutions such as the credit rating agencies and prior to the development of complex statistical models, filling thus a crucial gap in the literature. Chapter 3 presents new binary logistic models for the prediction of corporate default for quoted companies in the United Kingdom using a novel definition of failure that was built using the widely available information provided by the London Share Price Database. Chapter 4 develops binary logistic prediction models that use a finance-based definition of firm distress and a technical approach of corporate failure, and tests, as in the previous chapter, the advantages of combining accounting, market and macroeconomic data for the prediction of financial distress. Chapter 5 offers polytomous response logit models that consider corporate default as a dynamic process by including three possible financial states in a single model that incorporates accounting, market, and macroeconomic data as well as industry effects. All of the empirical chapters present the models and exploit the output generated by binary and multivariate logit models by deriving marginal effects and changes in predicted probabilities to interpret individual effects of the variables, and by offering more appropriate and flexible methods to evaluate the overall predictive accuracy. Chapter 6 concludes with a summary of the thesis' main findings and contributions as well as suggestions for further research.

2. A Historical Study on the Evolution of Risk Assessment and Credit Information Sharing in the United States and the United Kingdom in the Nineteenth Century

2.1. Introduction.

The use of credit as a practice that allows borrowers and lenders to exchange goods and services on the promise of future payment has evolved through history and has existed as long as trade itself. As discussed by Kermode (1991) and Bennett (1989), credit was essential to the performance of trading activities in the United Kingdom during the Middle Ages. In one widely cited dissertation on debt and credit in the urban economy of London in the late fourteenth and fifteenth centuries, Bennett (1989) argues that sales on credit "accounted for more than half of all credit transactions." [2] Referring to the commercial activity in the fifteenth-century Yorkshire, Kermode (1991) states that: "The art of commercial survival was to keep ventures and credit in a state of constant motion…" [3] Moreover, Hoppit (1986) suggests that in the eighteenth-century England "Trade credit was crucial to the functioning of exchange… many firms had more of their assets tied up in credit than in capital."[4] Now, as suggested by Wilson (2008), it is clear that the granting of credit is made possible by the flows of information on projects, businesses and borrowers, and "in difficult times it gravitates towards the established information networks."[5] In effect, there is a very ample body of literature suggesting that asymmetric information is the main obstacle between borrowers and lenders exchanges and that it can therefore prevent the efficient allocation of credit in a given economy. If lenders have no access to information on borrowers' characteristics or on the riskiness of their projects, there is a high probability that they will be making loans to high-risk businesses or individuals, ultimately leading to losses due to bad loans (adverse selection). Furthermore, lack of information also prevents lenders from controlling the actions of borrowers once they grant a loan (moral hazard). Thus, it is expected that the less information a lender possesses on a business or borrower, the more reluctant she or he will be to grant a loan (a

[2] In Wilson (2008), p. 13. Section 1. Background.
[3] Kermode (1991), p. 480-481.
[4] Hoppit ((1986), p. 64-66.
[5] Wilson (2008), p. 13. Section 1. Background.

higher level of credit rationing). Credit information plays therefore a crucial role in the practice of credit.

Historically, lenders have overcome information asymmetry problems by collecting information on their own borrowers and their businesses through long term business relationships on the one hand, and on the other, by establishing contractual mechanisms of information sharing based on the principle of reciprocity. The choice of one or the other methods of producing information have depended upon the scale and scope of their business: as trade grows in size and geography, the method of information sharing becomes more appropriate, as borrowers can benefit from economies of scale. As discussed by Jappelli and Pagano (2002), there is a portion of the academic literature that considers the first option (screening and monitoring their own borrowers) as the only way lenders can overcome informational problems. On the other hand, there is also a very extensive theoretical literature on the effects of information sharing. One of the most influential theoretical works (Pagano and Jappelli, 1993) finds that information sharing decreases defaults, improves the pool of borrowers, and decreases the average interest rate. Furthermore, this already vast theoretical literature has been complemented with an empirical study that statistically tested the impact of information sharing on default rates and lending activity, and documented the public and private information-sharing arrangements around the world (Jappelli and Pagano, 2002).

The considerable importance accorded to the impact of information-sharing mechanisms was augmented by the debt built up prior to 2007 and the role of the credit rating agencies in the financial crisis in the United States, as well as the rise in household debt in Britain since 2005, when, for the first time, it rose to over £1 trillion (by the first quarter of 2007, the level of outstanding debt was around £1.4 trillion). In addition, the year 2005 was marked by a surge in payment arrears in the United Kingdom, specifically, but not exclusively, on unsecured lending products. This trend continued through 2008 and peaked in the first quarter of 2010. Now, even if it started to experience a marginal decrease from the third quarter of 2010, was still in 2012 at a historical height and, given the negative outlook for most economies after the global financial crisis, is, unfortunately, not likely to recede in the short-term. But the interest in information sharing mechanisms and organisations is not circumscribed to the cases of the United Kingdom and the United States, recent studies document the developments of the credit reporting industry at an international level: Djankov et al. (2007) analyse data for 129 countries and show that the number of countries with a public credit registry as well as those with at least one private credit bureau has more than doubled over the 1978-2003 period.

The above academic literature and the recent financial developments in a wide range of countries confirm the importance of credit information sharing to the efficient allocation of resources in a modern financial system. In summary, up to the present day, there is a vast theoretical literature that has served as a guide to better understand the effects of credit information sharing; on the other hand, several practical/empirical studies have used data to provide more insights on the public and private organisations (*public credit registers* and *private credit bureaus*, respectively) that act as intermediaries between lenders for the sharing of credit information: these studies document their differences across countries and their effects on lending and default rates. Thus, it is clear that many efforts have been made to understand the effects of credit information sharing and the organisations that act as intermediaries in order to create and/or improve organisations, strategies and policies that enhance the allocation of credit. This applies for both developed and developing countries: the latter can benefit from new insights to enhance the information sharing mechanisms and policies, and the former could use the knowledge from past or current experiences to build appropriate organisations for efficient sharing of credit information. Nevertheless, there is still a very important gap in the literature that could provide a better understanding of this issue: to the best of my knowledge, there are no *historical* studies that directly relate to the evolution of information sharing organisations or the type of credit information that individual lenders and organisations used to assess the riskiness (or creditworthiness) of borrowers. In order to address this gap in existing literature, this paper analyses historical credit and lender information using contemporary techniques.

Employing a historical approach, this study traces the types of credit information that lenders previously used to assess borrowers' risk through the evolution of credit information sharing organisations from the nineteenth century; where the main antecedents of modern institutions can be found. Moreover, the promised study utilises a comparative procedure and documents the evolution of credit sharing information in two of the most historically relevant financial centres: the United Kingdom and the United States.

There are very few historical comparative studies regarding the evolution of the methods employed to assess credit risk in the United Kingdom and the United States. Such studies can provide important insights in order to better understand the context that allowed the emergence of modern institutional forms of credit information providers in the present day, such as the credit rating agencies, regarded by both practitioners and scholars as being one of the most salient forms of information sharing devices in contemporary financial markets[6], as well as credit bureaux or credit reference agencies. The history and evolution of the main credit rating agencies (Moody's, Standard & Poor's and Fitch) has been very well documented in a number of studies[7]; nevertheless, the question of the historical background that allowed their emergence and explained their evolution as major credit information providers for a wide range of financial actors, has been somewhat overlooked in the literature. Moreover, even if extant studies present important insights relating to some specific historical practices whose main purpose has been to overcome the information asymmetries among borrowers and lenders, there is not a comprehensive analytical study that aims to provide a general framework explaining the current state of the credit information providers from a historical perspective. The first objective of the present study is to fill this major gap in the literature.

As Richard Sylla (2001) points out, by the time John Moody published the first bond credit ratings in 1909, bond markets had been functioning for about three centuries in the Netherlands, two centuries in the United Kingdom and one in the United States, without using formal bond ratings (provided by independent agencies) in order to assess the riskiness of the numerous enterprises in need of finance. It is evident that investors in these countries were willing to lend money because of level of confidence they granted to the borrowers' ability and willingness to make timely payments in the future. Now this level of confidence stemmed from their assessments of creditworthiness based on acquired information on the state of the business of the borrower or commercial partner. Nevertheless, reliable information with regard to the businesses investors chose to put money in, was not as easily obtainable or straightforward as it is in the present day, mostly because accounting information was very rarely available, and when available, it was neither reliable nor complete. The question about the methods through which they acquired information on different types on investment opportunities has been rarely undertaken and thus remains a crucial topic for research. This subject is treated through a historical approach in order to present a general portrait of the evolution of credit information in the nineteenth century that provides us with a better understanding of the current state of the industry. Hence, given the magnitude and historical importance of the United Kingdom and the United States as global financial centres, and as the countries where the most important developments in information sharing took place, the second objective of the present study is to present the evolution of the methods used to gain access to credit

[6] See White (2001) and Partnoy (1999) for a discussion of the influential role of credit rating agencies in financial markets.
[7] See Cantor and Packer (1994) and Langohr and Langohr (2008), for a description of the industry, and a summary of studies related to its functioning

information in both countries in the nineteenth century, when the antecedents of institutional forms of credit information can be found.

From a historical viewpoint, credit information can be roughly divided in three categories: information on consumer credit, information on business (trade) credit, and information on corporations and specific debt instruments (fixed-income securities for example). The methods used to gather information on these main categories are evidently different in nature and have evolved over time; however, as it will be showed, they tended to be highly interrelated and acted as complements in most cases. In effect, from the early nineteenth century, in both the United States and the United Kingdom, personal information on a businessman was collected by granters of credit in order to infer the future possibilities of profit in that particular business and make an informed decision on whether it was wise to invest their money or not. Similarly, the current status of a business on a particular industry was used, in part, to evaluate the creditworthiness of a given security. The evolution of the methods used to acquire information by merchants, investors and large banking houses will therefore be studied through a comprehensive historical approach with the aim to provide new insights to a very rarely studied subject though of crucial importance.

The study is organised as follows. Section 2 presents a summary of the main mechanisms through which credit information sharing can provide a solution to the problem of asymmetric information as well as its main benefits. With reference to theoretical work on credit information sharing, Section 2 provides the motivation for the historical analysis, of both, the evolution of credit sharing information and types of credit information employed to assess individual risk profiles. Section 3 explores the historical origins of the first forms of credit information sharing organisations in the United Kingdom, their main focus (protection against fraud) as well as the subjective nature of the types of information employed to assess customers' creditworthiness. Section 4 discusses how the first organised forms of information sharing, primarily focused on the protection against fraud, evolved into the first efforts to produce ratings systems by the mercantile houses employing personal and business characteristics in the United Kingdom in the first half of the nineteenth century. Section 5 examines the case of the emergence of the first forms of profit-seeking information sharing organisations in the United States, such as the credit reporting agencies, and advances the reasons that explain the institutional differences between the two countries. Section 6 investigates the evolution of the types of information (such as specialised publications and statistics) used to estimate the creditworthiness of corporations and securities in the United States and the United Kingdom in the second half of the nineteenth century and offers arguments that explain the reasons for the existing differences between the two countries. Section 7 provides final thoughts on the historical analysis and concludes.

2.2. The Role of Credit Information Sharing as a Solution to the Information Asymmetries between Borrowers and Lenders.

The origins and evolution of modern and institutionalised information providers, such as the main credit rating agencies, credit bureaux or credit reference agencies, can be traced to the historical functioning of financial markets and explained by the existence of information asymmetries embedded in the investor-borrower relationship. Lenders screen and evaluate the creditworthiness of potential borrowers in order to price loans accordingly. Theoretical studies suggest that, in a perfectly efficient market, the risk profile of a borrower always reflects the interest rate on a loan; in other words, the higher the risk profile of an individual borrower, the higher the interest rate of the loan. Therefore, in theory, financially sound borrowers should always be able to obtain low interest rates on loans, whereas high-risk borrowers should always either be charged a very high interest rate or be rejected from obtaining funding altogether. Information plays therefore a fundamental role to assess individual risk profiles.

According to Jappelli and Pagano (2000), this information can originate from three sources: First, a lender (or a bank, as in Jappelli and Pagano, 2000) might already be in possession of information relevant to the assessment of individual risk (risk profile), which was acquired through an investment in a long-term relationship with a specific customer over time. Small banks, for instance, employ longstanding relationships (relationship banking) to obtain *soft* information and evaluate the profile of individual borrowers through 'multiple interactions with the same customer over time and/or across products.'[8] Second, a lender can obtain the information directly from readily available public records, by interviewing the potential borrower and/or visiting her or his business. The acquired information can then be processed (qualitatively and/or quantitatively, through statistical risk management methodologies) in order to take decisions about loan granting and to price it according to the individual risk characteristics. Lastly, the third way to get information on a potential credit candidate identified by Jappelli and Pagano (2000) is to

[8] Boot (2000), p. 10.

acquire it from other lenders who have previously performed business with the specific credit seeker and therefore possess valuable information. In return, the provider of the credit-relevant information requires a reciprocal obligation from the receiver to share her or his own information about potential borrowers when needed. Thus, an information sharing arrangement is essential between lenders.

Nevertheless, studies suggest that the real economy is characterized by imperfect information; that is, borrowers have a superior knowledge regarding their own creditworthiness (or their ability and willingness to pay their financial obligations within a previously agreed specific schedule) than lenders[9]. Furthermore, asymmetric information may inhibit the efficient allocation of resources through lending (Jaffee and Rusell (1976), Stiglitz and Weiss (1981)), and increase credit rationing. Akerlof (1970) describes a market in which a seller possesses more information than a buyer on a particular product, and shows that the existence of a given level of information asymmetry might work to the disadvantage of good quality sellers, thus giving rise to an adverse selection problem: in a capital market characterized by creditworthiness uncertainty, investors would not be able to differentiate between bad and good investments, resulting in an interest rate that does not reflect the underlying risk of borrowers. Thus, the benefits of the reduction of the information asymmetries in financial markets can be derived: the common knowledge of positive past credit performances should turn to the advantage of financially sound borrowers in the form of lower interest rates and more access to credit at lower costs. On the other hand, the reduction of information asymmetries could also take the role of an incentive for risky borrowers to try to improve their credit performances in order to obtain more advantageous credit terms. Overall, the enhancement of public information regarding the creditworthiness of borrowers should lead to a more efficient allocation of capital in a given economy, in accordance to both public and private interests. Analogously, an efficient bond market requires the information asymmetries to be reduced.

Extensive research has been performed on the role of information sharing in the reduction of information asymmetries between borrowers and lenders, and it is important for a number of reasons: first, information sharing can prevent the previously discussed adverse selection problems. In the absence of information relevant to the assessment of the specific risk profiles of potential credit candidates, there is a high probability that lenders end up granting credit to risky individuals, the most likely to accept the elevated price of loans stemming from the prevailing uncertainty with regard to the underlying

[9] Stiglitz and Weiss (1981).

creditworthiness of market participants. Using a theoretical framework, Pagano and Jappelli (1993) show that information sharing, the exchange of information among lenders through information brokers (private credit bureaus), can reduce information asymmetry between lenders and borrowers leading to an increase in aggregate lending when adverse selection is so extreme that financially sound borrowers drop out of the market. Jappelli and Pagano (2002) employ a new purpose-built dataset on modern private and public forms of credit information sharing institutions (private credit bureaus and public credit registries) and show that bank lending is higher in countries where information sharing is an established practice among lenders. Similarly, other empirical works such as Brown et al. (2009), Love and Mylenko (2003), Galindo and Miller (2001) and Powell et al. (2004) present evidence suggesting that the level of aggregate lending is positively associated with the existence of credit information sharing institutions.

Second, information sharing counters moral hazard. As discussed by Jappelli and Pagano (2002), 'information sharing can reinforce borrowers' incentives to perform, either via a reduction of lenders' (or banks') informational rents or through a disciplinary effect.'[10] With regard to the first mechanism to enhance the borrowers' incentives to perform, via a reduction of lenders' rents, Padilla and Pagano (1997) show (using a theoretical framework) that when lenders (or in this specific case, banks) commit to share with other lenders their private information about the creditworthiness of their customers, banks can encourage borrowers to perform better. When lenders have an informational monopoly about their borrowers and are therefore able to charge excessive or 'predatory' rates in the future due to an increase in their market power, borrowers have less incentives to perform, leading in turn to higher probabilities of default and increased overall interest rates. In other words, in the absence of credit information sharing, if borrowers perceive that the bank is able to appropriate a high proportion of their future investment's returns through excessive interest rates stemming from an informational advantage (and the resulting monopolistic position that gives rise to a hold-up problem), they will very likely exert lower efforts to perform. Therefore, the sharing of information between lenders about the creditworthiness of their customers limits the ability of the former to engage in opportunistic behaviour and extract informational rents through excessive interest rates on loans. This increases borrowers' incentives to perform better and results in a decrease of the likelihood of default of individual customers and an increase in overall aggregate lending.

[10] P. 2019.

In relation to the second mechanism to reinforce borrowers' incentives to perform, the disciplinary effect, Padilla and Pagano (2000) show that credit information sharing not only reduces (*ex ante*) adverse selection problems but also diminishes (*ex post*) moral hazard via a disciplinary effect. If lenders share default information about their borrowers, the latter must consider that default on one lender will negatively affect their reputation with all other future potential lenders, making credit more expensive through higher loan interest rates or even cutting her or him off from credit altogether. Therefore, the disciplinary effect arising from the existence of credit information sharing organisations should, theoretically, provide a stronger incentive for borrowers to exert a higher level of effort to perform, decreasing the probability of default of individual customers and ultimately increasing lenders' returns by reducing losses from bad debt. Conversely, without credit information sharing, borrowers might be tempted to repay their financial obligations only when they plan to maintain a longstanding relationship with a lender (Brown and Zehnder (2007)).

Nevertheless, the effects of information sharing as a disciplinary device on the behaviour and performance of borrowers are also dependent upon the type of information shared[11]: sharing customers' information about past defaults yields different results than sharing information about their quality. More specifically, the disciplinary effect materialises only when the exchange of information is exclusively focused on defaults. As shown by Padilla and Pagano (2000), divulging information about the borrowers' quality (instead of information about borrowers' past defaults) can reduce the disciplinary effect of information sharing, leaving the level of default and interest rates unchanged: in the banking context, if *ex ante* competition discards potential informational rents, then the level of loan interest rates cannot be diminished further. Therefore, 'when information about their quality is shared, borrowers have no reason to change their effort level, and equilibrium default and interest rates stay unchanged.'[12] Furthermore, if lenders share information about both past defaults *and* borrower characteristics, the disciplinary effect of information sharing is diluted: a high-grade borrower will not have a stronger incentive to perform or avoid default if she or he is aware that lenders will disclose her or his high intrinsic quality in addition to a previous event of default. This might be explained by the fact that the borrower can be certain that other lenders will not interpret default as a sign of low quality (Padilla and Pagano (2000)). Consistent with these findings, Doblas-Madrid and

[11] This is the main reason why the present study, employing a historical approach, focuses not only on the evolution of credit information sharing but also on the type of information that lenders shared and used to assess potential borrowers' creditworthiness.
[12] Jappelli and Pagano (2002), p. 2020.

Minetti (2013) show that information exchange has a positive effect on the payment behaviour of firms, especially in the case of young and small firms that have a reputation to be less informationally transparent.

In practice, modern forms of sharing information organisations such as the main credit rating agencies, for instance, claim that they help reduce the asymmetries among lenders and borrowers through an established and defined ranking system (credit ratings) that reflects the ability and willingness of an issuer of fixed-income securities to make full and timely payment of amounts due on a given security over its life. The ranking system used by credit rating agencies to assign ratings is based on calculations that should reflect the underlying probability that the financial obligations (principal and interest) will be met according to a defined schedule, on the one hand, and the rate of recovery should the firm go into default, on the other.

2.3. Origins and Evolution of the First Forms of Credit Information Sharing in the United Kingdom: Mutual Societies for the Protection of Trade and the Subjective Assessment of Risk.

As initially discussed, the use of credit as a practice that allows borrowers and lenders to exchange goods and services on the promise of future payment has evolved through history and has existed as long as trade itself. There is, nevertheless, substantial debate among historians and economic theorists with regard to the importance of credit to the practice of trade in early historical stages such as the Middle Ages in the United Kingdom[13]. In his pioneering study on medieval mercantile credit, Postan (1928) argues that the extent to which medieval trade was based on credit has been understated and that the common depiction of credit as being in an incipient or embryonic stage of development in the Middle Ages can be explained as follows: 'If mercantile credit was one of the basic principles of our economic civilization, then every successive stage of economic evolution made some contribution towards it, and therefore the further back we went the less important the function of credit became, until we reached a time when there was very little credit or none at all. Hence the prevailing notions of the absence or the undeveloped state of credit in the Middle Ages.'[14] Essentially, the dominant perception before Postan's (1928) historical study was that the level of commercial trade in the thirteenth and fourteenth centuries was not important or sophisticated enough to require

[13] See Postan (1928)
[14] P. 234.

the use of complex forms of credit, that early exchanges were therefore carried on primarily in bullion (transactions were mainly based on ready payment), and that the miscellaneous and sporadic lending and borrowing that took place in the Middle Ages was employed mainly by wealthy men only for consumption, emergencies, or to finance a war. Thus, according to this view, the primitive forms of lending and borrowing cannot be used as evidence of the importance of credit. Bücher (1901) provides one example of this notion of the use of credit in the Middle Ages: 'The amount of loan and consumption capital is exceedingly small. It may even be doubted whether in mediaeval trade credit operations can be spoken of at all. Early exchange is based upon ready payment; nothing is given except where a tendered equivalent can be directly received. Almost the entire credit system is clothed in the forms of purchase.'[15] Thus, it can also be inferred that commercial trades, such as purchases and sales as well as other common transactions at the time, were employed to disguise medieval loans, which in addition, were used not for production but for consumption.

The novelty and importance of Postan's (1928) study lies in the evidence presented that shows that, contrary to the general notion, credit was not only present but was even common practice in medieval trade. The analysis and discussion are based on a number of historical documents that corroborate the use of several specific forms of credit that played an individual and distinct economic role of their own. The most substantial part of the evidence can be found in historical records of debt such as 'recognizances,' or debts acknowledged before judicial tribunals and entered upon their roles; entries and documents relating to pleas of debt such as the petitions on debts among the early chancery proceedings at the public record office (among other types); and the surviving merchants' (national and foreign) documents dealing with debts and credits but not relating to their registration, enforcement or adjudication. There are, of course, other sources where medieval forms of lending and borrowing (different than those directly related to mercantile credit) are mentioned or described[16], however, Postan's (1928) objective was to prove that there was a systematic use of credit and that it was essential to the performing of trade between merchants in a number of economic areas. This is, arguably, the main reason that his study focuses on the historical evidence that directly relates to mercantile credit, of which the most notable types are: 'sales credits,' or credit that consisted primarily of deferred payments for goods sold or advances for future delivery; short-term loans, whose

[15] P. 128-129.

[16] It is worth noting that many loans were not enrolled or officially registered, especially in the early Middle Ages. It is not until 1283, after the passing of the Statute Burnell, and especially in the second half of the thirteenth and fourteenth centuries, that mercantile credit was officially registered, through recognizances, on special rolls kept by the authorities.

main purpose was to satisfy the instantaneous liquidity requirements of merchants (early or unexpected recall of loans from creditors, late payments from borrowers using sales/trade credit, are just some examples of the recurrent circumstances that required the use of additional credit as a source of cash); and investments in the form of partnerships whose main function was to finance enterprises that required greater amounts of capital than one individual was able or willing to commit.

Furthermore, analysing the cases of two important commercial regions in the United Kingdom, Middle-Age Yorkshire and London, Kermode (1991) reveals how fundamental medieval credit was for mercantile activities at the time. Her study confirms that credit in general, and trade credit in particular, was essential to the functioning of medieval commercial exchanges in England. In addition to the widely used forms of borrowing and lending such as sales credit or deferred payment analysed in Postan (1928), she argues that bills of exchange were also a very important financial instrument at the time. Bills of exchange were considered a safe method to transfer cash or settle a debt in a distant location; a merchant could buy them from a 'drawer' who had her or his own in the location where the payment was to be made. Furthermore, in order to mitigate the underlying risk of a credit operation, a merchant could act as a pledge for another merchant's loan by means of a previous reciprocal agreement. In Kermode's (1991) words: 'When a loan was negotiated, the borrower had to find *mainpernors*, or pledges who would act as surety against payment. A wealthy and successful businessman, with the confidence of its creditor, might not always need pledges, but a relative newcomer or someone with neither property nor reputation, or someone needing an exceptionally large loan, would be dealt with according to the solvency of his pledges.'[17] Kermode's (1991) study, and this statement in specific, is very important because on the one hand, it confirms the systematic use of credit and its importance to commercial activities in England since the Middle Ages; and on the other, it provides us with historical evidence that can be used as a tool to better understand the first methods employed by creditors to make a credit decision based on the riskiness of a borrower. In effect, in this early historic period, most of the evidence on the performance of credit operation is static and, in some cases, incomplete: according to Kermode's (1991) study, 'virtually all of the evidence for medieval credit comes from records of defaulting debtors.'[18] Thus, there is no direct and/or systematic evidence on the methods employed by borrowers to assess creditworthiness. However, through the evidence presented, it is possible to infer and highlight the main lines.

[17] P. 492.
[18] P. 481.

There is therefore important evidence suggesting that medieval credit was widely used throughout English economy,[19] and that a large proportion of loans advanced to borrowers used some form of collateral, such as bullion, rents or mortgages, as surety against payment in the absence of information on the underlying risk of the enterprise of a borrower. Moreover, the use of collateral in order to secure credit was also essential when trade was performed among merchants in distant locations. However, from the previous Kermode's (1991) citation that depicts the use of *mainpernors* in credit transactions, the words 'confidence' (of creditors) and (borrower's) 'reputation' clearly stand out as the first qualitative criteria employed to discriminate between high-risk and sound borrowers. In this way the reputation of a merchant could influence the loan decision (and the size of the loan) along with the viability of the venture or the quality of the collateral. Financial networks, largely determined by the geographical scope of the trade and the importance of cities as commercial centres, were thus essential to the level of credit, and the use of qualitative criteria (such as borrowers' reputation) to assess the creditworthiness of potential borrowers. The evidence advanced by the previous historical works, extremely rich and useful to the study of credit through a historical approach, has nevertheless some limits with regard to the methods used by merchants to evaluate the risk profile of borrowers, and it is not until the 18th century that we can find documents that directly relate to the first systematic attempts to uncover the underlying risk of borrowers and businesses and share this information by means of institutions.

One of the first institutionalised and formal methods of acquiring credit information emerged in the United Kingdom in the form of mutual societies for the protection of trade. This institution can be thought of as one product of the Industrial Revolution in the eighteenth century, period in which not only average income and population grew in an unprecedented manner, but that also affected human society in almost every aspect and transformed the economic and business activities of a great majority of countries. In this period, production was greatly increased through more and more efficient methods, and the division of labour brought expanded opportunities for trade between individuals, firms and nations; the amount of credit grew therefore at an unprecedented pace and, with this, the need to assess the ability and willingness of those receiving it. This constituted a large transformation in the way business was performed before the Industrial Revolution, as commerce generally took place within very limited geographical areas and credit was thus granted on the basis of personal knowledge.

[19] See also Bennett (1989)

Nevertheless, with the increase in credit granting, the cases of people systematically and intentionally deceiving creditors also augmented. Fraud was not uncommon, and some people that received credit in one place moved to another in order to borrow again without honouring their previously contracted obligations[20]. In order to protect themselves from these practices, traders used to gather informally at local inns or coffee houses where information on the names of fraudsters as well as the different deceitful practices were orally transmitted. Additionally, these gatherings provided an opportunity for the traders to exchange experiences and knowledge on the mutual businesses, the status of the industry, and even gossip on different subjects of interest and potential customers with whom it was dangerous or safe to do business or to whom it was not advisable to grant credit. Cuthbert Greig suggests that the first mutual credit reference agencies of this kind in the United Kingdom date back to the early seventeenth century; however, as discussed by Cameron McNeil Greig, records that could help ascertain the precise date of inception are now lost[21]. However, extant documents with regard to the codes and rules of the British society *The Guardians or, Society for the Protection of Trade Against Swindlers and Sharpers* allows to trace this kind of institution as early as March 25, 1776, the date when it was established[22].

The first society for the protection of trade, for which records are available, was thus the Society of Mutual Communication for the Protection of Trade (later renamed Mutual Communication Society and referred to as “ the MCS”), founded in 1801 at the British Coffee House, Cockspur Street, Charing Cross, London WC. This society specialised, unlike subsequent ones, in a particular area: it was mainly concerned with the provision of credit information for the protection of those supplying the “carriage trade” in the West End of London. The way in which information was disseminated among the members did not vary from its inception to its peak, when the society counted 2,000 members approximately: the associates had weekly meetings in order to exchange and update the information on the names of the people identified as fraudsters as well as the techniques they used to deceive creditors. Furthermore, the MCS had strict rules that members were compelled to follow if they wanted to continue being members of the organisation: first, the names of people identified as swindlers, recorded in the Books of

[20] See Greig (1992).

[21] Greig, C. *Commercial Credit and Accounts Collection*, First Edition. In Greig (1992). Greig’s work is one of the most useful sources of historical information on mutual societies for the protection of trade in the United Kingdom and a very detailed account of the history of UATP-Infolink in particular.

[22] UNIVERSITY OF LEEDS. *The Guardians: or, Society for the protection of trade against swindlers and sharpers. Established March 25, 1776*. [n.p.], [1780?]. *The Making of the Modern World.* Gale 2010. Gale, Cengage Learning. University of Leeds. 23 August 2010 Available at: http://0-galenet.galegroup.com.wam.leeds.ac.uk/servlet/MOME?af=RN&ae=U3601844161&srchtp=a&ste=14

the Society, were not to be divulged to non-members; second, the members were completely free to use the information at their discretion when deciding to grant credit or refuse it; third, members must always provide accurate information and restrain from taking part in any "malicious or slanderous intent." These were the basic rules to follow in order to be a member of the MCS, and other associations that emerged throughout the United Kingdom later adopted them. Additionally, the MCS provided, in Rules I and IV of its Constitution, the foundations of all subsequent organisations of this type, which serve to illustrate the methods of exchange of credit information as well as the funding system:

> I. Every Member is bound to communicate to the Society without delay, the Name and Description of any Person who may be unfit to trust, for the security and satisfaction of the other Members; and shall, on all occasions, impart, without reserve, any information that may be solicited by any of the Members.
>
> IV. All expenses, whatever for the support, use, or advantage of the Society, shall be equally borne by its members and paid out of the fund.

Rule IV is important in the sense that it highlights the main organisational difference, as shall be discussed, with regard to the independent, profit-seeking credit reporting agencies in the United States.

After the MCS, other more general organisations for the protection of trade followed. In 1823, under the initiative of Mr John Smith, proprietor of the Liverpool Mercury, a new mutual society was built. As reported by Greig (1992), the main focus of the new organisation was the exchange of information, and its Rules stipulated, "As mutual protection is the first principle of the Society, it is imperative upon every member to give information of… Swindlers and Sharpers." The same principles were established for the "Manchester Guardian Society for the Protection of Trade" in 1826, also through the initiative of Mr John Smith. That same year, the "Bath Society for the Protection of Persons and Property from Felons, Receivers of Stolen Goods, Swindlers, etc." was formed. In 1827, the "Hull, East Yorkshire and Lincolnshire Bankers, Merchants and Traders Association for the Protection of Trade and the Prosecution of Felons, etc.", followed. The London Association for the protection of Trade was established in 1842, followed by another in Leeds in 1848, Leicester in 1849, and Glasgow in 1852.

As can be observed, mutual societies for the protection of trade were dedicated to the dissemination of information regarding existing swindlers and their activities so as to prevent creditors from being the object of fraud. This information was circumscribed to members of the organisations, who in turn had the obligation to provide accurate reports of other dangerous people or fraud practices. In the case of the Manchester and Salford Protection Society, this information was communicated through a Monthly Report, and the extant documents provide highly illustrative examples of the credit information at the time. An example of a 1849 description of a particular fraudster in the Monthly Report is reproduced below, followed by another describing a specific form of deception:

> GILMOUR T. P. This arch imposter recently visited Manchester under the assumed guise of a converted Jew; he was immediately recognized and being followed by a crowd who threatened him with personal violence retreated into a newsroom where he remained for three hours; on his exit he was assailed with floor bags, soot bags, etc. and took refuge in a warehouse in Tulse-alley. He represented his object in visiting Manchester to have been chiefly of a religious character and that he was in the frequent habit of going into the country to pray (Query, prey?) by himself not wishing to be seen at his devotion. It is believed he took advice of Mr Beswick and retreated from Manchester early the following morning[23].

Also in 1849, the Monthly Report of the London Association for the Protection of Trade reported that fraud had been carried out by way of advertisements:

> in *The Times* and other papers offering a payment of 5s. or upwards to inform servant of suitable situations; they likewise advertise… for clerks and messengers at salaries from 20s. to £3 per week and immediate engagement is offered on an amount of cash, varying from £10 to £50, being lodged in the hands of the employer as security, to be returned on either party wishing to discontinue the engagement. An agreement is drawn up, and… the defrauding advertiser gives a receipt for the money advanced thereby making the affair a debt transaction and escaping the punishment the law provides for obtaining money under false pretences[24].

[23] Greig (1992), p. 81.
[24] Greig (1992) p. 96.

The mutual trade protection movement flourished throughout the nineteenth century in Great Britain as one source of acquiring credit information on customers. In 1848 the National Association of Trade Protection Societies (NATPS) was created, which, by 1939 counted some seventy societies. However, from the last years of the nineteenth century, and later with the outbreak of World War II, the rapid changes in information technologies and the advent of profit-seeking, centralised credit reporting agencies, the movement lost in influence and gradually eroded. In the United States these kind of organisation did not evolve, most likely because of the differences in geography and the derived high mobility of its population[25].

2.4. Consumer and Business Credit Information Sharing in the First Half of the Nineteenth Century: Mercantile Houses in the United Kingdom and the Emergence of the First Rating Systems based on Personal and Business Characteristics.

In the early nineteenth century, businesses in the United States could rely on letters of recommendation for information on the creditworthiness of their commercial partners given the small-scale nature of the existing trade credit exchanges. Recommenders could be either local or distant business partners (suppliers) with whom a borrower had performed some transaction in the past, and who therefore possessed sufficient knowledge about the customer's past payment behaviour. This method based on personal ties, which early nineteenth century American merchants relied upon, was characterized by a long-term business relationship; in other words, the men with which trade was performed were personally very well known to either the creditor or the recommender[26]. Recommenders could also be, although less frequently, "respectable members of his or her community", such as lawyers or bankers[27] because of their personal knowledge of the customer in question. However, lawyers and bankers, by nature, could only have knowledge of people limited to the locality in which they performed their activities. This information is thus dependent upon the proximity of personal ties. Their influence as providers of credit information can be thus traced to the beginning of the nineteenth century, which started to deteriorate from the 1820s, when the United States commercial activity, and therefore the volume of trade credit, was rapidly increasing.

[25] See Olegario (2001) and Sylla (2001).
[26] It is worth noting that this kind method of obtaining credit information was also very familiar in the United Kingdom at the beginning of the nineteenth century.
[27] Olegario (2001).

As it could be inferred, the geographical scope of trade credit was also expanding, which created the necessity to obtain better credit information on a growing number of potential and existing customers, operating in very distant territories, which in turn made the prevailing system of letters of recommendation inadequate and in many cases, of unreliable content. One solution to this problem was the hiring of agents by the concerned businessmen seeking credit information[28]; these agents had the task to travel to a particular, or even various places, in order to acquire information on the standing of the businesses of potential and existing business partners. Nevertheless, as this was a very costly way of obtaining information, it was restricted to very large firms only. Some business houses in the United States explored the possibility of relying on travelling salesmen to acquire credit information on distant customers in an effort to develop more formal methods as a solution to their lack of knowledge. However, as reported by Madison (1974), the main problem related to this method of knowledge about distant customers was the fact that these travelling men, too eager to expand their trade through the extension of credit, provided biased reports thus impairing the quality of their reports.

In the United Kingdom, in order to obtain credit information, large mercantile houses also used the method consisting of hiring local agents since the beginning of the nineteenth century. However, their role was not confined to the national sphere; houses such as Baring Brothers and Company, given the prominently international scope of their activities, hired agents to conduct credit investigations on their American business partners, given the magnitude of trade and finance carried out with the United States. Furthermore, given the fact that the City of London had acquired the first position in the world as the most advanced and sophisticated money and financial centre by the end of the Napoleonic wars (Dickson, 1967), mercantile and banking houses saw their business greatly expanded especially with North American associates. Therefore, as in the United Sates, the methods of personal ties and letters of recommendation for acquiring credit information became insufficient to provide an accurate portrait of creditworthiness in a very rapidly changing economic and financial environment with a fast growing number of correspondents whom these houses made business with.

After 1826 the financing of trade and marketing American bonds became one of the most important activities of the merchant bankers, and even if this activity was clearly dominated by Baring Brothers and Company, competition was relatively important and increasing among eight main houses: Wiggin and Company, Wildes and Company, Wilson

[28] This practice was common not only in the United States, but also in the United Kingdom.

and Company, W. and J. Brown and Company, Morrison, Cryder and Company, N. M. Rothschild and Sons, and Baring Brothers and Company. Success in business depended therefore upon the acquisition of reliable credit information about their respective correspondents. It was thus crucial to gain knowledge on the credit quality of correspondents and enterprises, particularly during the boom years of the early 1830's. It was within this historical context, characterized by a competitive environment and a lack of institutionalized and reliable forms of credit reporting, that the idea of the appointment of an agent with the sole responsibility of providing accurate and unbiased credit information emerged. As one might expect, this system was very high in cost and only the large merchant houses could afford it. In 1829, Baring Brothers and Company in the United Kingdom innovated with the appointment of an agent whose only task was to provide them with accurate reports on their American correspondents.

As shall be discussed, in the beginning of the nineteenth century, the acquisition of information on credit worthiness was a very problematic issue, as one of the most valuable sources of information we know today – payment histories – were not available in the case of individuals. Also, in the first half of the nineteenth century credit information sharing devices were reduced to mutual protection societies, where only members had access to information on obligors that did not pay their debts on a regular basis. Financial statements were also very hard to obtain, and, when available, these were unreliable in content because they were rarely audited and there existed no formal accounting principles to respect. Moreover, given the highly competitive environment where the large merchant bankers evolved, making a direct request to individuals for information on their own current credit standing or financial information, was notably problematic because potential or existent obligors could well be offended and go to a direct competitor of the merchant house in question who could provide credit without the need of additional financial information.

Hidy (1939) provides one of the most useful sources with regard to the practical aspects of the acquisition of credit information by the large merchant houses in the first half of the nineteenth century. As he explains, unable to obtain information in the form of hard data, obligees were compelled to use qualitative information as their primary input to assess creditworthiness, and the most easily obtainable proxy was businessmen's *character*. In the specific case of Baring Brothers and Company, systematic knowledge of the status of correspondents was judged in accordance with the following principles: "… a correspondent to be reliable must be an accurate judge of the currents of business, must be intensely interested in and devoted to his business operations, must have a capital adequate to his transactions, must be prudent, and above all must be thoroughly honest. Although a large capital was an attractive attribute of a correspondent, the personal integrity of the leading partner or director of the firm was of greater importance. Prudence and integrity were, indeed, the main indices of reliability and trustworthiness.[29]" This description is of considerable importance at the time when Baring Brothers and Company signed a contract with Thomas Wren Ward, a retired merchant of Boston (in order to control their business through personal information with American correspondents), because it provides us with the specific aspects that were taken into consideration when evaluating business opportunities in the United Sates.

Ward's collaboration with Baring Brothers and Company lasted from 1829 to 1853, period in which he rated "several thousands" of businessmen of all ranks and types, and performed the assessments of existing and potential correspondents regardless of their interest in applying for credit with the London house. Being fully aware of the difficulties described above for acquiring information, Wren Ward gathered knowledge (through private conversations with former correspondents and former business partners) of potential clients, and then translated this knowledge into a personal judgement of the individual applicant. Most importantly, his work led to one of the first types of credit rating systems in the modern sense of this concept, as it can be considered the predecessor of the one used by the credit rating agencies today. According to Hidy, the evaluations provided by Wren Ward to Baring Brothers and Company included: "the location of the firm, its capital, its particular preoccupation (dry goods importing, iron importing, import and export commission business, cotton exporting, and so on), its character –whether trustworthy and honourable or unreliable, the amount of credit that it was safe to give to it, the conditions under which the credit should be given, and any special items that might have a bearing upon the business activities of the house.[30]" Ward then created a system consisting of a list of companies to which he assigned a number individually expressing the standing of their respective credit conditions, and in 1834, January 1836, and January 1837 he sent to the London house copies of a list of past, active, and potential clients. Thus creating a credit rating system based on a grouping of companies according to their level of risk, Ward's description recalls the ones used by today's credit rating agencies, and can be found in Hidy's (1939) cited work:

[29] Hidy (1939), p.82.
[30] Hidy (1939), p. 85

> "No. 1 Contains the Foreign Houses without regard to character or standing but alphabetically arranged; No.2 may be considered as Houses not only entirely safe for what they may do, but likely to continue so under any possible circumstances. They possess of course different degrees of wealth, but are placed together in this list on account of wealth, character and habits of business taken together; No. 3 Is composed also of those whom I consider as quite safe and many wealthy, and many also of your best correspondents and almost all of the right sort of people, but who from the extent or nature of their business or from circumstances not necessary to enter into, may not be considered as ranking with those whom I suppose are to continue always beyond question; No. 4 Consists of a class many of whom I should consider safe and some even comparatively rich, but who from the smallness of their transactions, or from their having no abiding place and being abroad as Supercargoes would not seem to belong to a class to be trusted much, or at all unless through me, and it also contain many whom from their extension or want of capital might render it unsafe to trust, but contains few or none whose *morals* so far as we know is exceptionable; No. 5 *No trust*. This column consists of those who either have no capital or are not of that character to render it desirable to trust them at all; No. 6 *Houses having various connections*. Some of whom are safe and even wealthy, but dong with others renders it less important to cultivate and more important to look after; No. 7 *Houses having other connections*. Are those contained in our numbers, but doing business wholly with others; No. 8 *Don't Know*. This class contains many whom I have never known and with whom you do not appear to have had any active account or been exposed in any way, and of many others of whom my imperfect knowledge might rather mislead than be useful. They are therefore left to take their chance supposing you will not trust except where you may have certain knowledge of your own; No. 9 *Failed*; No. 10 *Dissolved*, and some *failed*; No. 11 *Dead*." (Hidy, 1939, p. 87-88)

If we take the ex post, realised rate of default by category as the base parameter in order to assess the performance of a rating system, we can easily conclude that the system pioneered by Baring Brothers and Company was highly effective. The rate of default for each number assigned is as follows: Ward noted that for all firms grouped in 1835, only six per cent of the firms included in group No. 2 had defaulted in 1843, the percentage of defaulted firms until that same year for category No. 3 was nine; and for group No. 4, sixteen per cent of firms defaulted. Moreover, these categories show the importance accorded to wealth in general terms, but also to morals and character of the men in charge of the companies assessed.

In the United States, very similarly to Baring Brothers and Company, another international house, the House of Brown, developed their own credit reports using a system comparable to Barings' in form and efficacy. In effect, thanks in part to the accuracy of these reports, even as late as 1857, when the Panic seriously damaged the businesses and profitability of the merchant houses, the Browns were able to cope with it and suffered very few losses (Perkins, 1973). Similar to the merchant bankers operating in the United Kingdom, American firms faced the same kind of problems with regard to the acquisition of credit information; payment histories were not available and financial information was not reliable in content because of the lack of general accounting standards. Additionally, in the nineteenth-century United States, there was not a central authority requiring firms to present consolidated annual statements mostly because each state possessed their own legislature, and only in a few of them was such legislature successfully imposed.

Credit information was therefore obtained through agents or reporters (as in the case of the London houses), hired to travel through some parts of the country, where creditors might have potential business partners, in order to gather knowledge on rough financial information (such as the business principal assets and liabilities[31]), but giving primary importance to the character of businessmen. However, in the case of the United States, the ways through which credit information was acquired were somewhat less formal that in the United Kingdom in the first half of the nineteenth century (at least until the emergence of the American credit reporting agencies in 1841 with the opening of the Mercantile Agency in New York); the principal sources were direct interviews with potential or existing customers when possible, the business and financial press, county and state tax and property records, and, in many cases, even through local gossip.

An example of a report from the 1850's is reproduced here in order to provide a clear portrait of the information gathered on a particular business:

Jones, Smith, & Brown
Alfred Jones, John Smith, Wm. Brown, Gen'l Dealers.

[31] Financial information as understood in modern times, such as measures of cash-flows, profits, costs, etc., was not available.

> "J" is about 50 years old, and a merchant at this place for 20 years, during which time he has been doing a good business, and has made money, never failed, is of good character, and a shrewd business man, Is now estimated worth about $25,000, of which $5,000 is in unencumbered real estate. He does a legitimate business, and never ventures into rash speculations. "S" and "B" are each about 35 years old, and smart business men. "S" had been in business and failed, settled honorably, acted as clerk, for "J" for two or three years, and was admitted a partner some two years since, paying in $5,000 in cash, principally a gift from his father, who is well off. "B" has been a clerk in the house about four years, and a good and popular one, is just admitted a partner, but does not add any capital. They continue to do a good business, are in good credit, and worthy of it[32].

2.5. The Emergence of the First General Profit-seeking Organisations for the Provision of Credit Information in the United States: Credit Reporting Agencies and the Systematic Assessment of Risk based on Personal and Business Characteristics.

As previously discussed, mutual societies for the protection of trade were organisations originated in the United Kingdom that exchanged credit information only between their members and were characterised by their non-profit seeking nature. In the United States, this kind of information sharing device could not be established most likely because of the vast geographical differences existing between the two countries. Nevertheless, the size of the American territory, combined with the rapid increase in the mobility of resources that characterized the United Sates from the 1830s required an information sharing system other than the informal exchange of letters of recommendation that had prevailed in an economy in which trade took place in very limited geographic areas. As trade was performed between distant suppliers and customers, the system of acquiring credit information through personal knowledge no longer sufficed; therefore, the necessity for "information on suppliers and customers of whom a businessperson had no knowledge increased"[33]. In effect, a rapidly growing population along with the rapid increase in the construction of canals and railroads and the considerable expansion of the volume of trade, especially in the antebellum years, made the need for knowledge about distant and unknown customers, a primary concern for merchants.

[32] Elijah W. Morgan, correspondence with American Collecting Agency. Morgan Family Papers, ca. 1830-1900, Box 1, Michigan Historical Collections, Bentley Historical Library, Ann Arbor. In Olegario (2001), p. 17.
[33] Sylla (2001), p. 7.

International banking houses, such as the House of Brown, hired agents in order to obtain credit information on existing and potential customers, but as discussed earlier, the costs derived from this method were considerable, and only the largest investment and merchant houses could afford it. In order to satisfy this somewhat more sophisticated credit information need of small and medium firms (with insufficient means to pay a private agent) realising trade credit, a new form of organisation appeared for the first time in the United States in 1841: the credit reporting agency. Since its inception, American credit reporting agencies, unlike British mutual societies for the protection of trade, were profit-seeking organisations that provided credit information to every credit grantor that requested it in exchange of a constant amount of money. Credit reporting agencies adopted a centralised structure with branches in various parts of the country providing the central office with credit reports from businesses operating in their respective area and, at the same time, supplying local credit grantors with information requested on customers from the region. This structure reflected the specific needs of the United States stemming from its vast geographical area and the high mobility of its resources in the nineteenth century.

It is evident that, since the years preceding the American Civil War, the old informal system of acquiring credit information through personal ties was not only imperfect but also inadequate to the rapidly evolving business needs; as reported by James Madison in a 1974 article "The inadequacy of existing methods of gaining credit information was demonstrated during the economic crisis of the 1830s and the early 1840s, when many merchants discovered that their earlier trust in some of their customers had been ill-founded. At the same time, rapid changes in the financial condition of individual businessmen made clear the need for more up-to-date information.[34]" There is an extensive literature on the history of the first American credit reporting agency, the Mercantile Agency, started in 1841 by Lewis Tappan, a New York dry goods and silk merchant; however, the difference with the present study is that the latter inserts the development of the *methods* for gaining credit information, by this and other credit reporting agencies, within a historical context that aims primarily to explain the evolution of information sharing devices in the nineteenth century in the United States and the United Kingdom.

Although the Mercantile Agency was the first centralised, profit-seeking agency to innovate in the field of providing credit information to businesses in the United States, the Bradstreet Agency, founded in 1849, can also be considered as one of the initiators of the

---

[34] Madison (1974), p. 166.

credit reporting *movement* in the nineteenth-century America. Both evolved in the same developing business environment and both (competing agencies) tried to cover the deficiencies in the existing information reporting methods used at the time. But financial problems after 1865 prevented the Bradstreet Agency from developing as fast as the Mercantile Agency until the last quarter of the nineteenth century, when it became a serious challenger to Dun's leadership[35]. Moreover, it is worth noting that Tappan's solution to the problem of acquiring reliable credit information can be interpreted as a reaction to the Panic of 1837, a crisis generated by a cascade of defaulted debt, and to the emerging new business conditions in the United States in the antebellum years; indeed, the initiator of the Mercantile industry was one of the many businessman affected by the unreliability of extant traditional methods for gaining credit information: as a wholesaler and a partner in a dry goods house in New York, he experienced first-hand the difficulty to obtain reliable information on his customers.

Given that Lewis Tappan already possessed credit information on many of his own customers, and that he knew the value of this information for many a business at the time, the solution he proposed consisted on the creation of an agency operating on a national scale and able to collect information on all sorts of potential recipients of credit in order to sell it to wholesalers and all sorts of grantors of credit interested in this kind of information. The method used to obtain credit information recalls the one used in the early nineteenth century by the large London houses; merchants, bank cashiers, newspaper editors, postmasters and, especially lawyers were hired as correspondents (agents) on a local basis in order to take advantage of their constant access to credit-relevant information about businessmen living in their towns and villages across the country. They submitted reports to the central office, located in New York, in the case of the Mercantile Agency once a year. These reports contained basically the occupation of the subject, a parsimonious estimate of his assets, as well as a status of his business. Moreover, similarly to Wren Ward's reports for Baring Brothers and Company, the character of the subjects was a very relevant question in the analysis of creditworthiness in many of the reports addressed to the agencies. As a contemporary account explains:

> "Hence the main object with the agency is, to furnish the home standing of the merchant obtained from intelligent and reliable sources, there. . . . There, and only there, can [w]e learn whether he owns property, and is a man of good character—

[35] The Mercantile Agency adopted different names; as Madison (1974) reports, it was known as Lewis Tappan & Co. (1841-1849), Tappan & Douglas (1854-1859), and R. G. Dun & Co. (1859-1933). See also Dun and Bradstreet (1966).

whether he does a legitimate or a speculative business—and whether he is competent, steady, and attentive, or otherwise.[36]"

Adding to the information on the character of the businessman, his assets and the state of his business, additional information on marital status, family background, age, former residence, and business experience was usually included by the correspondents in their reports. In order to give an example of a typical report, we reproduce one written in 1846 on a Cincinnati dry goods merchant:

> "A self-made man, age ab[ou]t 50, marr[ie]d, mem[ber] of Ch[urch] & in bus[iness] n[ea]r 20 y[ea]rs, owns R[eal] E[state] w[orth] 20^m unincumb[ere]d, tho[ugh]t to be a g[oo]d bus[iness]man, maintain his standing, in g[oo]d cr[edit], & consid[ere]d g[oo]d.[37]"

What was the aim of these reports? As Josh Lauer accurately reports: "At a fundamental level, these reports served just two purposes, both of which were predictive: estimating the individual's chance of success in business, and gauging the likelihood of securing repayment, particularly in the event of failure. Toward this end, the key information was encapsulated in what would later be formalized as the "three C's" of credit reporting: character, capacity, and capital.[38]"

In fact, there was not uncommon for correspondents to send reports to the central offices that contained only the individual's general reputation within the town or village in which he lived. The problem with this kind of information was that, as the reporters were not directly paid for their services by the agencies, in the beginning, there was the perception that the reports could be inaccurate and somewhat biased by informal practices such as rumours and even gossip circulating among people of doubtful motivations[39]. As can be observed from the example, even very general past payment behaviour commentaries of the individual in question were absent in the reports and the information provided is more anecdotal in nature than systematically obtained. This problem in gaining accurate credit information by the early agencies was the result of their hiring part-time agents that were not directly paid; in effect, the agents were compensated within a scheme

36 "The Mercantile Agency," *Hunt's Merchant's Magazine*, 24 January 1851, 47–48. In Lauer (2008), p. 309.
37 Dun Credit Ledgers, Ohio, Vol.78, p. 59, Dun & Bradstreet Collection (Baker Library, Graduate School of Business Administration, Harvard University). In Madison (1974), p. 167.
38 Lauer (2008), p. 309.
39 See Atherton (1946). In fact firms such as Baring Brothers and Company in London and Brown Brothers continued to rely on their own credit ratings. Additionally, some firms in the east of the United States preferred to continue to rely on their members or employees for estimates of the financial status of customers.

consisting of the mutual provision of services with the credit reporting agencies. In the case of lawyers, the agencies used to direct their subscribers' debt collection business in exchange for information on the credit subjects. As to the newspaper editors, their compensation amounted to the agencies' contribution in obtaining subscriptions and advertisements for the local newspaper. Other types of compensation discussed by Rowena Olegario include "recommending their correspondents as agents for insurance and steamship companies" and forwarding "requests from firms looking for representatives to sell their stock to the public", in the case of lawyers and bankers respectively[40]. This compensation schemes were dependent upon the accuracy and timeliness of the reports provided by the agents, and undoubtedly contributed to the development of the early agencies, nonetheless, these could hardly verify ex ante the precision of the information contained in such documents.

There were in fact numerous critiques to the insufficient coverage across the country as well as the incompleteness of the credit information that added to the early mistrust from the general business population (Wyatt-Brown, 1966). Therefore, the elevated cost in reputational capital for the agencies in cases where the veracity of the reports was proven deficient, made them undertake gradual improvements in their methods for gaining credit information. First of all, they introduced full-time, paid reporters from the years preceding and during the Civil War, and, as discussed by Madison, by the 1870s, the majority of agents operating in major cities were already full-time employees. At the same time, this direct contact with the employees allowed the agencies (in particular R. G. Dun & Co.) to have an enhanced control over the methods used to collect information and the necessary training for the reporters. Full-time paid reporters in larger cities were divided according to their areas of specialty; each reporter was in charge of a particular field of trade in order to optimize the quality of the reports through their abilities to assess the creditworthiness of those subjects and firms involved. Moreover, hard financial data evenly supplanted pure personal opinions on the character of businessmen: from the 1970s reporters not only asked specific questions about the business, but also required company balance sheets or financial statements through pre-printed forms prepared by the agencies. Reporters were trained to rely less on anecdotal forms of acquiring credit information and more on hard financial data from a variety of sources including personal interviews with businessmen. Finally, where inconsistencies were identified in the reports of the remaining part-time agents, still present in small towns and

[40] Olegario (2001),p. 15. See also Olegario (2000).

villages, full-time reporters were in charge of corroborating the information, which enhanced the quality of the documents as well as the reputation of the agency.

With regard to the dissemination of credit information, credit reporting agencies also gradually adopted new approaches in order to enhance quality. Initially, a subscriber requesting information on a potential customer used to call at the agency's offices in order to have the credit report read aloud by a clerk, but later, the agencies opened branches in different cities in order to decentralise the dissemination of information and divide it by geographical areas. Additionally, in 1857, the Bradstreet agency innovated with the publication of a Reference Book containing all the credit information on individual businesses; the Mercantile Agency followed only two years later. In this way, subscribers could use this book whenever they needed it without having to recur constantly to direct communication with the agencies' offices. However, the problem with the reference books was that they were published on an annual basis, and therefore, in the course of the year, changes in the standing of the credit conditions of potential customers resulted in outdated information. Branches of the agencies were thus used in order to solve this problem: reporters submitted updated credit information to their respective local offices and these branches were in charge to copy and transmit the information to the central office. Subscribers were thus able to get updated credit reports for a particular subject just by calling to their local branch, which was responsible for a specific trade region and to which reporters in the area provided with the solicited information.

This system was not perfect as this network system worked very well only for subscribers seeking information about customers located in the same city or town; those subscribers established in a city other than the one in which the central office was located, and who were seeking information for distant customers, had to make the request and wait for the central office to coordinate the transmission of information between the concerned areas. The delays resulting from this network structure were indeed the object of criticisms from subscribers. It was not until the 1850s, when the telegraph was well established within the agencies' communications that the solution to this problem commenced to emerge. Later, the use of the typewriter in the 1870s greatly facilitated the task. Overall, the role in the dissemination of credit information by the American reporting agencies was crucial in the development of new methods both in the United Sates and the United Kingdom, the latter starting the process with mutual societies and the hiring of agents to collect information, and the former establishing centralised profit-seeking reporting agencies with new methods of dissemination and collection of information.

2.6. Credit Information on Corporations and Securities in the Second Half of the Nineteenth Century in the United States and the United Kingdom: the Assessment of Risk based on Specialized Publications and Statistics.

In modern times it is possible to assess the creditworthiness of individuals as well as businesses through scoring models based on an analysis of payment histories as well as financial and accounting data. These models are used on a proprietary basis by profit-seeking providers of credit information such as Callcredit and Experian in the United Kingdom; Dun & Bradstreet, or Fair, Isaac and Company in the United States; and Equifax, operating in both countries. The informational input, from which an assessment on the creditworthiness is derived, is acquired by these agencies through lenders willing to share their payment records with them. In this way, business debtors can access the credit assessments on any potential business or new customer that allows them to make a lending decision based on the likelihood of timely payment. The scoring models are most useful to businesses that receive large numbers of applications as they have the potential to identify different levels of risk through fine gradations and ultimately make prudent and adequate decisions based upon their desired degree of risk. However, scoring models are a relatively recent development in credit information analysis; in the first half of the nineteenth century, it was very difficult to obtain reliable credit information on individuals as well as businesses. Individual payment histories were not available and the accuracy of financial information was very doubtful given the lack of regulated practice. Furthermore, many times creditors would not ask for these sources of information directly because of the possibility that the new customer take offense and go to another house more willing to provide credit without requiring this kind of information. Not surprisingly, adverse selection was a constant problem, which was compounded by the high degree of competition in both the United States and the United Kingdom.

Similarly, investors willing to buy debt from an enterprise in the form of securities had to make assessments of its creditworthiness and were therefore confronted with the problem of the quality of the available information. In fact, one of the main obstacles to the development of public securities markets in both the United States and the United Kingdom in the nineteenth century was the information asymmetry between the corporations offering debt securities and the investors in possession of the resources to buy them. The history of the development of public securities markets is also the history of the methods used in order to acquire information on the creditworthiness of corporations and thus overcome the existing information asymmetries. In order to have a better understanding of the evolution of credit information in the nineteenth century it is very important to present a brief historical context that includes the nature of the trading of debt as well as the associated informational issues. The first organized (although informal) form of trade in securities markets took place in the trade of government issues, and after 1720 it became the primary activity of the coffee shops in the City of London[41]. It was during the eighteenth century that securities markets grew considerably in size and importance in Europe and the United States. Stock exchanges emerged as increasingly organized markets for the trade of securities, which continued to be mostly dominated by government issues in both sides of the Atlantic.

In Europe, governments used debt to finance military conflicts and in the United States, to finance their war of independence as well as the Civil War. According to Niall Ferguson, Britain was the first country in Europe capable of generating enough balance of payments surpluses "to allow sustained capital export[42]" and by 1815 the British Empire's foundations were based on an increasing amount of international lending. At the time, sovereigns were already conscious of the fact that they needed to gain and maintain the confidence of investors if they wanted their issues to be successful. Therefore, with some exceptions, they refrained from cancelling their obligations unilaterally or failing to make interest payments when they were due. The creditworthiness of sovereign borrowers was thus based more on the "belief" of investors on the trustworthy or safe nature of government debt than on the analysis of information collected on the state of the country's finances or other kind of credit assessments. For instance, since 1749, date when the British government consolidated its debt into one single issue, known as consols, these could be easily bought and sold in the securities market, as investors were more and more attracted to them because of the timely payments of principal and interest from the British government through time (past payment history). As suggested by Michie (2006) "with the British government consistently honouring its debts and interest payments, investors were attracted to transferable securities whose value was directly or indirectly dependent on government payments.[43]"

Besides this easily observable measure of the creditworthiness of sovereign borrowers, there was also the perception, from the investors' side, that governments with

---

[41] The informal trade in sovereign debt was formalized as early as 1802 with the establishment of the London Stock Exchange.
[42] Ferguson (1998) p. 680.
[43] P. 43.

representative forms of government were more likely to honour their obligations than absolutist ones. This observation was first brought by Ferguson (1998) and used by Sylla (2001) in order to explain how the bond market provided an incentive two centuries ago, for governments to become responsible and representative, and concludes that "As more countries in Europe and around the world, adopted constitutions and representative forms of government during the nineteenth century, the international bond market grew in scale and scope. But it was for the most part a market in sovereign debt". In Ferguson's words, "a constitutional monarchy was seen in London as a better credit-risk than a neo-absolutist regime"[44]. The securities market of the eighteenth century and the first decades of the nineteenth century was indeed dominated by government debt and there was little progress made in the use of the bond markets by joint-stock companies to obtain funds. First of all, the securities market was almost exclusively used in order to fund wars or projects that required an initially vast amount of capital, like railways, canals or public utilities. Second, it seems that the safety and liquidity that characterised government issues was enough to satisfy demand from investors through long-term transferable securities. Third, most of joint-stock firms did not require large initial amounts of capital; they could be financed through traditional bank loans or even pools of funds stemming from the firm's associates or family members. Fourth, investment in joint-stock companies was perceived as more risky due to the unproved nature of the enterprise in question and the lack of information regarding the prospects of profit and therefore the creditworthiness of the borrower.

In the United States, before the war of Independence, the majority of securities traded were short-term bonds issued by individual states whereas businesses did not yet use transferable shares or bonds issues in order to obtain the funds they needed. Those Americans with excess of capital looking for remunerative investments used to buy securities in London, where securities markets were better organized and therefore safer to invest in. Clearly, a domestic securities market started to develop more rapidly in the 1780s with the war for independence through increased state borrowing. But even if the volume of issued securities by governments and firms increased considerably in this period, the organization of the market remained very precarious and most brokers entered the business as a part-time activity rather than a full-time profession with the degree of specialization achieved in the United Kingdom. One example of this is the fact that even after the war of independence, the United States government issued debt in Amsterdam to acquire the funds needed to finance war-related costs instead of using domestic markets.

[44] Ferguson (1998) in Sylla (2001), p. 6.

In the nineteenth century, especially in the second half, both the development and use of the concept of limited liability and the very large amounts of capital needed to build railroads and canals considerably stimulated the trade of securities of business corporations in the United Kingdom and the United States. However, the financing needs of the latter were the largest because of the geographic scale. Prior to the middle of the century, railroad corporations were relatively small in size and were therefore capable of fulfilling their financial needs through banks credit and stock issues. From the 1850s, however, railroad corporations rapidly expanded in size covering unsettled and undeveloped territories, which required large amounts of capital that could not be provided anymore by traditional sources of finance such as bank loans. Additionally, the scale of capital required for railroads (for the Western railroads in particular) exceeded by far the wealth of private individuals. Only pubic debt issues were judged as capable of fulfilling the vast funding needs of the firms operating on a national scale, but as the railroads corporations covered now very distant cities and towns, investors very rarely knew, or possessed information on the firm allowing them to assess their creditworthiness.

In the case of these new forms of corporation, where the also largest London merchant bankers invested considerable amounts (especially in the finance of North American trade and the marketing of American bonds since the 1800's[45]) accounting and financial information was very hard to obtain. As Henry Varnum Poor points out in the preface to his History of the Canals and Railroads of North America, even as late as 1860[46], the state of the information on railroad and canal corporations can be generalized to most of the corporate sector regardless of the industry: "There is not in this country as in most others, a central point at which the more important companies are either domiciled, or at which all are required to present annual statements of their affairs, for the reason that they derive their existence and powers from the legislatures of the several States. In a few States only, is such duty imposed. Where it is, it is often neglected, no penalty being suffered thereby. It is not uncommon for leading companies to publish no reports whatever. Some make them unwillingly, with no design to convey information upon the subject to which they relate. Reports that are full and explicit are accessible only to a small number of parties interested. Fewer still have the means of comparing results for consecutive years, without which it is impossible to form a correct opinion as to the manner in which a work has been conducted, or of its present or prospective value…[47]" This description of corporate

[45] For a discussion on the amounts and sources of foreign capital in the nineteenth century in the United States, see Davies and Cull (1994), p. 10-49, and on British foreign investments, Edelstein (1982).
[46] Date when the first edition of the History of the Railroads and Canals of the United States of America appeared.
[47] Poor (1970), preface.

reporting says much about its general state until the end of nineteenth-century America and provides an explanation of the reasons for the poor quality of information on creditworthiness and the search for new and more effective methods of acquiring it in order to make informed investments.

In this context, it is worth noting that railroads were the first regulated enterprises, but it was not until 1887 that the Interstate Commerce Commission (ICC) promulgated formal and uniform accounting standards in the United States. Given that railroad corporations were the first to apply accounting standards, it is evident that manufacturing corporations took even longer to develop the practice of disclosure of accounting information, and that the content of their reports was neither reliable nor complete throughout the nineteenth century, which impacted considerably the ways in which creditors (investors) acquired credit information. As early as 1869, the New York Stock Exchange tried to regulate disclosure of financial information (in order to reduce information asymmetries and enhance its reputation for quality) for all the companies traded there through the adoption of an official policy requiring annual financial reports. Nevertheless, this rule was rarely respected "to the extent that in 1885 the Unlisted Department was created for firms providing no information.[48]" This department disappeared in 1910, but it was not until 1926 that almost every company listed in the New York Stock Exchange disclosed audited annual financial reports. In the United Kingdom the standards of public disclosure required to enterprises were more developed: the Companies Act of 1844 required directors of corporations to make up a complete balance sheet, which in turn had to be approved by auditors, one of whom (at least) was usually elected by the shareholders. And as discussed by Barron Baskin, "the Italians may have invented double entry bookkeeping, but it was the British who invented modern financial reporting." Moreover, financial collapses such as the one suffered by the Bank of Glasgow in 1878 propelled regulation through compulsory edicts[49].

With regard to this very issue, the existing asymmetries in the development of the disclosure of financial information in the second half of the nineteenth century between the United Sates and the United Kingdom, Davis and Gallman (2001) bring to our attention that "the Board of Governors of the New York Stock Exchange recognized that savers were concerned about the problem of asymmetric information, and that if the Exchange were to flourish, it must provide signals of quality and reputation. They adopted

[48] Barron Baskin (1988), p. 228. See also Michie (1987), p. 206-208.
[49] Barron Baskin (1988), p. 228.

appropriate signalling policies. In England, such concerns had been largely alleviated among a substantial class of saver by the 1870s, although they may still have affected the typical investors' choice of securities. Not only was the number of savers who were willing to invest in paper assets increasing and the scope of their portfolios broadening, but the British investor had also become more venturesome…[50]" This difference in the level of dissemination of financial information between the two countries provides a partial but powerful explanation to the faster development of American reporting methods of gaining credit information as well as the emergence of credit rating agencies such as Standard and Poor's, Moody's and Fitch, in the United Sates only.

It is within this context that one can find one of the first and most fundamental methods of gaining information on railroad and industrial corporations creditworthiness in the late nineteenth-century America: through the specialized business and financial press. The United States was characterised by a rapidly growing demand for business and trade information at the time; there were therefore many periodicals published in order to satisfy this demand. These publications providing business information can be roughly divided into four types: the industrial, the commercial, the agricultural, and the scientific journals. However, industrial railroad journals received particular attention from the investors' community given the rapid expansion of railroads corporations and their vast capital requirements. As discussed, investors needed a reliable source of information on the creditworthiness of corporations issuing debt in the form of bonds and its importance was compounded by the lack of knowledge of firms given the considerable geographical scale of their operations, so these publications proved to be very useful in carrying successfully that the task of dissemination. During the 1850s four periodicals provided a good deal of information on railroads: *Hunt's Merchants' Magazine*, *United States Economist, Bankers' Magazine* and *The American Railroad Journal.*

In the beginning these publications included technical engineering information and statistics, and only gradually information relevant to businessmen interested in the business and commercial aspects of the industry was included. Railroad journalism in Europe, and especially in the United Kingdom, had already more sophisticated means of exchanging information on the technical side as well as on the business and financial aspect of railroads. In the United Kingdom, the engineering societies, the Institution of Civil Engineers and the Society of Mechanical Engineers were highly effective channels of communication for technical matters regarding the railroad industry, and the Railway

[50] P. 154.

Magazine, founded in 1843, "concerned itself primarily with defending the railroads from the attacks of canal and turnpike operators, property owners and conservative-minded persons throughout the Kingdom.[51]" And the British periodical *Railway Times*, a successful publication founded as early as 1837, provided financial information only, and was widely consulted by investors buying railway bonds. Moreover, by the mid-1840s, when railroad construction reached its peak, a half dozen railroad journals were being published in the United Kingdom. In the United States, "the editor of the *American Railroad Journal*[52], watching the success of the British financial papers, decided that his paper should follow suit… He told his readers that the time had come for the publication of a weekly paper concerned with the management and financial affairs of American railroads.[53]" However, the idea revealed itself premature, as the business of investing on railroad debt was yet to expand in the subsequent decades.

It was not until 1849, when Henry Varnum Poor became the editor[54] of The American Railroad Journal, that the paper gradually started to appeal to the American investors' community and successfully became a widely consulted financial tool that included systematic information on the property of railroads, their assets and liabilities, and earnings. And as reported by Richard Sylla, "after the American Civil War, Poor and his son started a firm to publish Poor's Manual of the Railroads of the United States, an annual volume that first appeared in 1868, " which reported financial and operating statistics covering several years for most of the major American railroads[55]. By the turn of the century, another American businessman, John Moody, who is credit with being the founder of the bond rating business, focused also on railroads as well as industrial corporations in general and published in 1900 the *Manual of Industrial Statistics* which provided information on stocks and bonds of financial institutions, government bonds, manufacturing, mining, utilities, and food companies. This publication did not contain credit ratings yet but had a considerable success because of the information asymmetries characterising the market at the time. Given the already mature state of railroad companies, the continental scale of the industry and the lack of useful information on railroad firms by the end of the nineteenth century, John Moody reports in his autobiography, "A high percentage of corporation securities had to be bought on faith rather than knowledge… Somebody, sooner or later

[51] Chandler (1956), p. 40.
[52] Founded in 1832.
[53] Chandler (1956), p. 40.
[54] Henry Varnum Poor's editorship of *The American Railroad Journal* lasted from 1849 to 1962.
[55] Sylla (2001), p. 9.

will bring out an industrial statistical manual, and when it comes it will be a gold mine. Why not do it myself?[56]"

2.7. Conclusion.

Information plays a fundamental role, both with regard to the granting of credit and its pricing. In modern days, there are various methods to judge on the creditworthiness of individuals, businesses, and fixed-income instruments. Credit scoring models are the prevailing tools used in order to assess the creditworthiness of the various financial actors. Scoring models utilise payment histories, accounting data, financial statements, and even non-financial information as their primary inputs to assess the ability of existing and potential recipients of credit to make timely payments of contracted financial obligations. Credit grantors obtain credit information through information sharing devices, such as credit rating agencies or credit reporting agencies, whose main role is to gather relevant knowledge and distribute it to subscribers of their services. The output frequently takes the form of ordinal scales of creditworthiness or written reports that allow credit grantors to make informed business decisions.

However, this kind of credit information, whose collection is now facilitated by the willingness of obligors as well of obligees to voluntarily share it, was not easily obtainable in the nineteenth century in the United Kingdom and in the United States, where credit experimented a very fast expansion due to the exponential growth of trade stemming from the Industrial Revolution and later with the development of public corporations issuing debt in the form of securities. The methods of gaining information used to assess creditworthiness developed according to the historical business context in both countries. As payment histories were not available, and financial information was neither reliable nor complete, credit grantors innovated in the methods for gaining information susceptible to provide them with reliable credit assessments.

The present study divided credit information into three main categories that interacted in the nineteenth century and contributed to the evolution of credit information in both countries: consumer credit information, trade credit information and information on corporations and securities. The nature of this choice of categorisation is not fortuitous, as it traces the historical interrelations and therefore their contributions to the development

[56] Moody (1933), p. 90.

of credit information sharing. Moreover, the study presented a comprehensive analysis, through a historical approach, of the different aspects of the evolution of this subject, unlike most works focused on descriptive accounts of the history of a credit entity. The first form of institutionalised credit sharing was the (non-profit) mutual society for the protection of trade in the UK, which shared information only between the members concerning the names and the activities of fraudsters in a specific area through periodic reunions. Large international merchant banking houses in the United Kingdom innovated with a method consisting of the hiring of an agent in charge of collecting information on individuals as well as businesses throughout the United Kingdom but also overseas.

As the London banks invested large amounts in American trade, bonds of corporations and railroads, and given the lack of data on payment histories and the incompleteness and unreliability of financial statements (when available), their agents used to gather credit information on potential and existing clients through the collection of information mainly on the owner's assets, and personal aptitudes for the business or *character*. Baring Brothers and Company, under the aegis of its American agent, created one of the first credit rating assessments. American bankers later adopted these techniques of gaining relevant credit information. However, as can be inferred, hiring private agents was very costly and could be afforded only by the largest banking houses. Now the rapid expansion of credit in the United States and the United Kingdom, and the fast growth of corporate railroads operating on a national scale (especially in the case of the United States, were business was carried out with very distant and thus unknown customers), necessitated more timely and accurate credit information than the letters of recommendation that were used in the first decades of the nineteenth century.

The creation of credit reporting agencies was the solution to the problems of asymmetric information as well as to the cost issue; economies of scale stemmed from this system that allowed the dissemination of information among every business or person subscribed to the service. Moreover, the innovative network structure used to gather and provide credit information to subscribers gradually solved the problem of timeliness and organisation of large databases. The emergence of this highly effective credit information sharing system in the United States can be explained through the geographical differences between the two countries but most importantly, it originated in the differences in the development of the techniques and regulations regarding financial disclosure. In effect, in the United Kingdom both the regulation and the practice of financial disclosure were more developed than in the United States in the nineteenth century. Furthermore, the vast capital needs of the rapidly flourishing railroad corporations and the national scale of their operations, promoted both enhanced financial disclosure though regulations and new methods for gaining credit information in the United States. It is not surprising therefore that the editors of two of the most important business and financial newspapers in the United States are credited with the invention of one of the most influential forms of credit information sharing devices in modern times: the credit rating agencies.

3. Sample Selection and Descriptive Statistics

3.1. Sample Selection

The main database for the study is composed of 23,218 observations for a total of 3,020 non-financial publicly quoted companies, which makes an average of around 7.6 annual observations per company. The period covered by the observations in the database ranges from 1980 to 2011, which yields a total of 32 years taking 1980 into account.

The available accounting data was taken from Datastream and Thomson One Banker (Worldscope); the macroeconomic variables were collected from Datastream; and the market variables were constructed merging the information available from Datastream, the London Share Price Database and Worldscope. Market information was added to the companies that were found in the Thomson One Banker database. The latter database was chosen because of its wide access to both academics and practitioners in risk management, as the present study looks to present results that can be easily replicated by both groups, avoiding thus the availability issues of databases and variables provided by private data firms (such as credit rating agencies) to very specific academic studies (some of them provided on a one-time basis) that could prove difficult to replicate for a professional risk manager, for instance. The merging of the accounting and market variables in one database resulted in fewer firms having both complete market-based time-series than accounting information. Additionally, the present thesis provides evidence of the usefulness of the inclusion of industry effects in financial distress/bankruptcy prediction logit models: The nine-sector[57] industry classification employed for the analysis is based on four-digit United Kingdom Standard Industrial Classification (SIC) codes taken from the Thomson One Banker (Worldscope) database.

Due to the existence of extreme values of variables for some observations in most databases (that could significantly alter the results of the analysis), the present study uses, for the first time in a corporate default prediction model, the hyperbolic tangent transformation (tanh transformation) to provide a satisfactory solution to this recurrent issue in preference to the frequently used technique of windsorising[58] the outliers in a

[57] Firms belonging to the 'Finance, insurance and real estate sector' were excluded from the analysis.
[58] The setting of all outliers to a specific percentile of the data. For instance, they typical 90% Winsorisation would set all the data below the 5th percentile to the value located in the 5th percentile. Similarly, all of the data above the 95th percentile would be set equal to the value located in the 95th percentile.

dataset. The hyperbolic function *tanh(x)* has been used and tested in robust signalling processing as well as in statistical estimation, and it has been shown to be very useful to decrease the effect of extreme values of a specific variable. It has been demonstrated that outlying cases can lead to abnormally large residuals and have an atypical impact on the fitted maximum likelihood linear predictors resulting from binary logistic regression models. Thus, the failure to effectively treat outliers could lead to a critical misrepresentation of the validity of the inferences drawn from the models. The real line can be mapped for a range of [-1, 1], and where x possesses a small value, then $\tanh(x) \approx x$. Thus, 'with appropriate scaling, TANH can be used to provide a linear transformation for input values in the neighbourhood of 'expected' values while reducing values that are outside the expected range.' (Godfrey, 2009, p. 1).

3.2. Variable Definitions.

From the database, consisting of 130 variables in total, several accounting, macroeconomic, and market variables were tested. The final variable selection is reported below. The selection method relied on previously reported results, theoretical propositions and empirical assessments. The data was subject to a rigorous cleaning and testing process and a novel approach for dealing with outlying observations was adopted. Using both univariate and multivariate (logit) procedures considerable experimentation was undertaken to arrive at the final choice of regressors. The variable selection included four accounting ratios: Total Funds from Operations to Total Liabilities, Total Liabilities to Total Assets, the No Credit Interval, and Interest Coverage; two macroeconomic variables: the Short-Term Bill Rate (inflation-adjusted or deflated), and the Retail Price Index (base 100). Five market variables were found to considerably increase the prediction accuracy of the model: the firm's stock price, the company's yearly abnormal returns, the lagged standard deviation of individual security residual returns, the firm's size relative to the total size of the FTSE All-Share market value, and the ratio Market Capitalisation over Total Debt.

3.2.1. *Accounting Ratios*

Identifier	Ratio	Definition
TFOTL	Total Funds from Operations to Total Liabilities	Performance measure. This ratio is intended to show the extent to which a company is able to generate funds from its operations to meet its financial obligations. Total Funds from Operations represents the sum of net income and all non-cash charges or credits; it is the cash flow of the firm. Total Liabilities, is composed of all short and long-term liabilities acquired by the company.
TLTA	Total Liabilities to Total Assets	Leverage measure. The ratio is commonly used to measure a firm's financial leverage by calculating the proportion of the company's assets that have been financed using short and long-term debt. Total Liabilities is composed of all short and long term liabilities acquired by a company. Total Assets of industrial firms, is the addition of total current assets, long-term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets.
NOCREDINT	No Credit Interval	Liquidity measure. It is an estimate of the length of time that a company could finance the expenses of its business, at its current level of activity, by drawing on its own liquid resources and on the assumption that it made no further sales. Formula: (Quick assets minus Current liabilities) / (Daily operating expenses). Where Quick Assets represent the assets that can be quickly and easily converted into cash or are already in cash form. The formula employed to calculate Quick assets is Current Assets minus Inventories. Similarly, Daily operating expenses are equal to (Sales minus Earnings Before Interest and Taxes minus Depreciation) / 365.
COVERAGE	Interest Coverage	The ratio measures a firm's ability to pay interest on outstanding debt. The ratio was calculated by

		dividing Earnings before interest, taxes and depreciation (EBITDA)[59] by the variable Interest charges or Interest expense on debt that represents the service charge for the use of capital before the reduction for interest capitalized.

3.2.2. Macroeconomic Variables.

Identifier	Variable	Definition
RPI	Retail Price Index	Inflation measure. An average measure of change in the prices of goods and services bought for the purpose of consumption by the vast majority of the households in the UK.
SHTBRDEF	United Kingdom Short Term (3-month) Treasury Bill Rate Deflated	Proxy for interest rates. Treasury Bills are defined as 'bearer Government Securities representing a charge on the Consolidated Fund of the UK issued in minimum denominations of £5,000 at a discount to their face value for any period not exceeding one year[60].

3.2.3. Market Variables.

Identifier	Variable	Definition
PRICE	The firm's equity price	The price per share traded. Last recorded transaction price of value for the trading instrument. Real-time or delayed based on user's entitlements.
ABNRET	The lagged cumulative security residual return	Each firm's past residual return[61] in year *t* was calculated as the cumulative monthly return of the twelve months prior to the year where the default event was observed, minus the FTSE All

[59] EBITDA measures the earnings of a firm before interest expense, income taxes and depreciation. Worldscope calculates EBITDA by taking the pre-tax income and adding back interest expense on debt and depreciation, depletion and amortization and subtracting interest capitalized.

[60] Definition taken from Datastream, Thomson Financial.

[61] In order to calculate residual/abnormal returns, firms' individual returns are employed as the main input. The investment return can be defined as the total gain or loss on an investment over a given period of time. The return incorporates the change in the asset's values plus any cash distributions (dividends or interest payments). The specific Datastream datatype used in the present study is the Total Return Index (RI) which shows 'a theoretical growth in value of a shareholding over a specific period, assuming that dividends are reinvested to purchase additional units of an equity or unit trust at the closing price applicable on the ex-dividend date.'

		Share Index cumulative monthly return for the same period (*t-1*).
IDYRISK	The lagged standard deviation of individual security residual returns	Volatility measure. Each firm's idiosyncratic standard deviation of each firm's stock returns was estimated by regressing (employing a linear regression) each stock's monthly returns in year *t-1* on the FTSE All Share Index cumulative monthly return for the same period which corresponds to the year prior to the observation of the event of default. The idiosyncratic risk of the firm is the standard deviation of the residual of this regression.
SIZE	The size of the company	The size of the company measured by its market capitalisation relative to the total size of the FTSE All Share Index (in order to make size static). It was calculated as the logarithm of each firm's size relative to the total market value of the FTSE All Share Index.
MCTD	Market Capitalisation to Total Debt	Market capitalization (or market cap) is the total value of the issued shares of a publicly traded company; it is equal to the share price times the number of shares outstanding. Total Debt is equal to all interest bearing and capitalised lease obligations. It is the sum of long and short term debt.

3.3. Descriptive statistics.

3.3.1. Annual Distribution of Outcomes.

Table 3-1 displays summary statistics for the time series distribution of the three types of outcomes investigated throughout the thesis: Non-financial distress (NFD), Financial distress (DIS), and Corporate failure (FAI). The entire sample is composed of 23,218 observations from 1980 to 2011. The advantage of the sample is that it is composed of the maximum amount of companies for which data was available, approximating thus the real proportion of outcomes in the United Kingdom.

Table 3-1 Distribution of Outcomes Per Year

This table reports summary statistics for the distribution of observations per year for the entire sample from 1980 to 2011. NFD stands for Non-financially distressed firms, DIS for firms in a state of financial distress, and FAI indicates those firms classified as failed companies.

Year	NFD	DIS	FAI
1980	54	0	0
1981	64	0	0
1982	76	0	0
1983	84	0	0
1984	106	0	0
1985	123	0	0
1986	138	0	0
1987	210	0	0
1988	331	0	0
1989	410	1	1
1990	464	6	3
1991	491	10	12
1992	488	16	4
1993	505	8	7
1994	519	7	4
1995	524	8	6
1996	646	6	10
1997	695	5	12
1998	641	13	18
1999	610	11	16
2000	627	9	26
2001	980	23	32
2002	1296	75	18
2003	1389	71	12
2004	1539	29	18
2005	1599	56	25
2006	1587	76	26
2007	1491	94	53
2008	1343	149	34
2009	1254	117	31
2010	1199	60	11
2011	481	19	6
Total	21964	869	385

A firm is classified as DIS when it files for bankruptcy when it meets both of the following conditions: i) its earnings before interest and taxes depreciation and amortisation (EBITDA) are lower than its financial expenses for two consecutive years, and ii) there is a negative growth of its market value for two consecutive periods. A firm is classified as FAI when its status in the 2012 LSPD is defined as: suspended, in liquidation or voluntary liquidation, when its quotation has been suspended for more than three years, when the firm is being held by a receiver (in receivership), in administration or in administrative receivership, or when there has been a cancellation or suspension of the firm[62].

Table 3-2 Summary Statistics of Annual Observations. Financially Distressed, Not Financially Distressed and Failed Firms

Panel A reports summary statistics for the entire sample. NFD stands for Non-financially distressed firms, DIS for firms in a state of financial distress, and FAI indicates those firms classified as failed companies.

Panel A: Classification of annual observations into Non-financially distressed, Financially distressed, and Failed companies.				
Response	Freq.	Per cent	Cumulative Freq.	Cumulative Per cent
NFD	21964	94.60	21964	94.60
DIS	869	3.74	22833	98.34
FAI	385	1.66	23218	100.00

Among the total number of observations (23,218), there are 21,964 firm-years classified as non-financially distressed/failed companies, 869 firm-years identified as financially distressed, and 385 firms classified as failed. As Table 5-1 shows, the percentage of non-financially distressed/failed companies is 94.6, while that of financially distressed firm-years and failed companies is equal to 3.74 and 1.66, respectively.

3.3.2. Time series presentations of the macroeconomic measures and the number of corporate failure/financial distress observations.

Figures 3-1 and Figure 3-2 report the time series on an annual basis of the macroeconomic measures employed throughout the thesis relative to the number of corporate failure/financial distress observations. The first figure displays, on the primary vertical axis, the respective number of outcomes relative to the first macroeconomic

[62] The LSPD numbers and definitions in the database are: 6) Suspension / cancellation with shares acquired later. Meanwhile, may be treated under rule 163/2; 7) Liquidation (usually valueless but there may be liquidation payments; 10) Quotation suspended – if suspended for more than three years, this may lead to automatic cancellation; 11) Voluntary liquidation, where value remains, and was / is being distributed; 16) Receiver appointed / liquidation. Probably valueless but not yet certain; 20) In Administration / Administrative receivership; 21) Cancellation and assumed valueless or suspended but assumed valueless.

measure included in the models developed in the thesis, which is intended to be a proxy for inflation: the Retail Price Index (on the secondary vertical axis). The second figure, on the other hand, reflects the number of observations relative to the second macroeconomic variable included in the models: the UK 91-day Bill Rate.

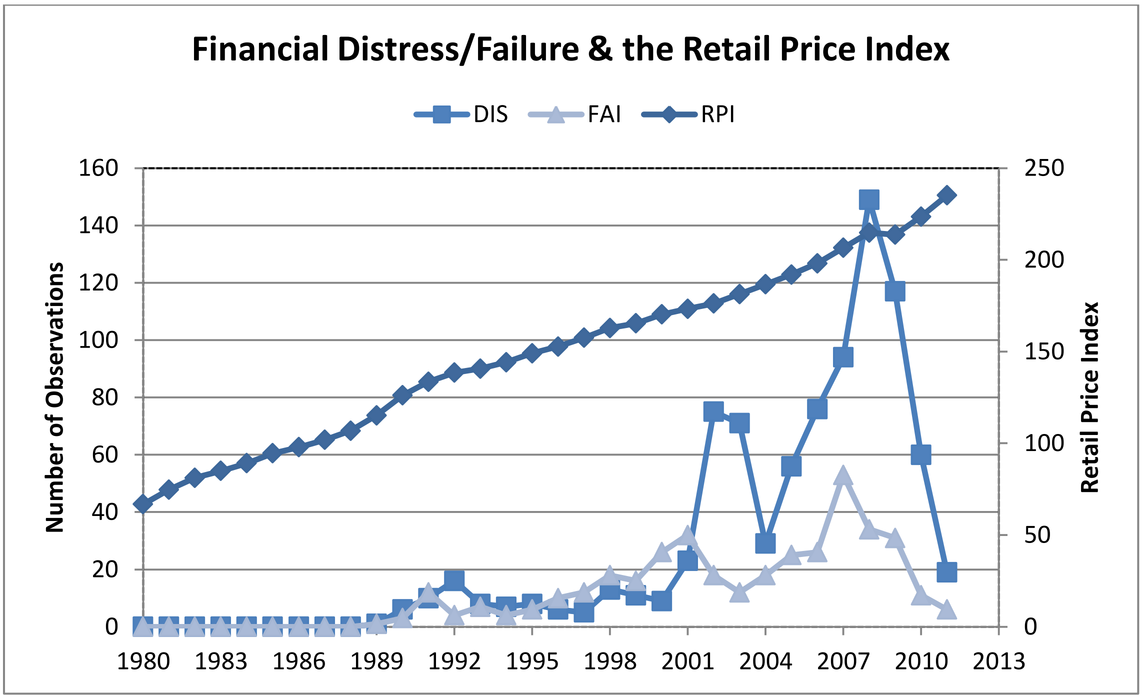

Figure 3-1 Financial Distress/Failure & thre Retail Price Index

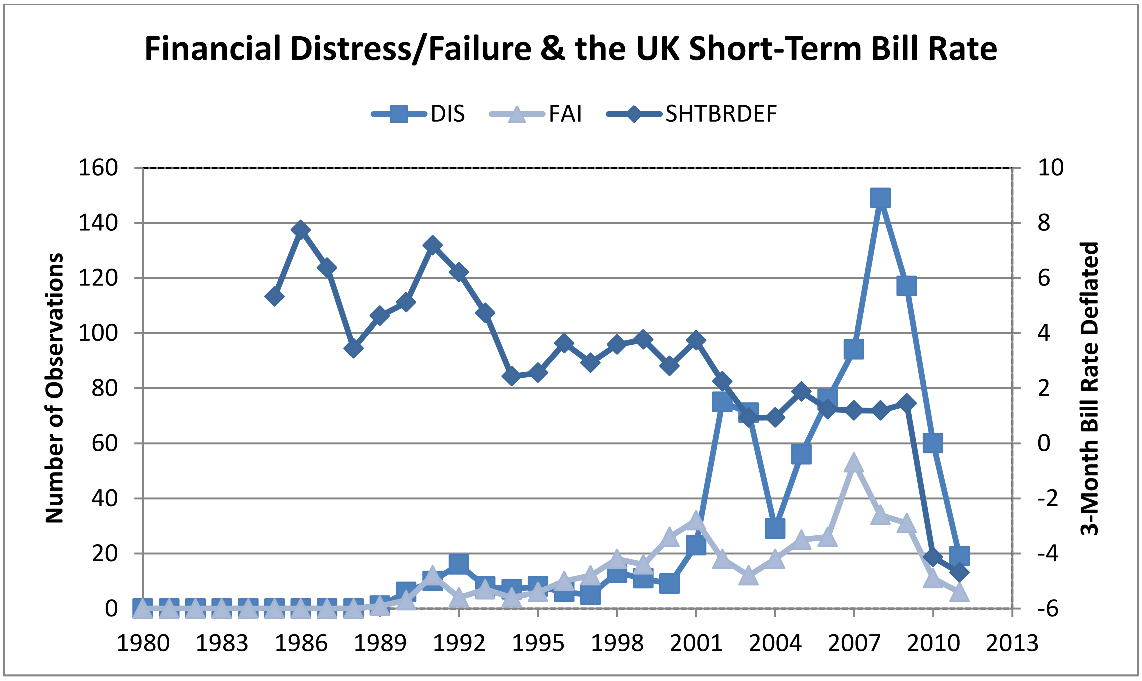

Figure 3-2 Financial Distress Failure & the 3-Month UK Bill Rate

4. The Role of Accounting, Market and Macroeconomic Variables for the Prediction of Corporate Default among Listed Companies

4.1. Introduction.

Credit risk measurement has evolved dramatically over the last 30 years; new statistical techniques have been developed and new variables have been tested in response to various developments worldwide. The literature concerned with the prediction of default of corporations is very extensive. However, the need to build more accurate and timely default prediction models has been systematically highlighted in the academic literature and emphasised by recent developments that directly affect the practice of credit risk management. *Inter alia*, the main general developments that justify the continuous need for research in the field of default prediction are: the marked increase in the riskiness of firms from 1997 onwards, as measured by 'z-score' analysis, both in the United Kingdom and abroad; the growing concerns about a credit crisis contagion effect caused by recent efforts to encourage investment by keeping very low levels of interest rates in the global economy (especially after the credit crisis of 2007); the application of Basel II, under which banks are allowed to use internal measures of credit risk based on ratings in order to set capital charges; the explosive growth in the credit derivatives market and off-balance sheet instruments with inherent default risk exposure; a decrease in the margins on loans caused by more intense competition between banks; and the declining value of real assets (collateral) in many markets, including those of developed and sophisticated financial economies.

In response to these developments, and their now global effects on very diverse financial systems, a large array of solutions have been proposed to alleviate their potentially negative effects. The majority and the most useful solutions advanced by academics as well as practitioners to this situation are to be found in the field of default/distress prediction models. New and more sophisticated credit-scoring models as well as early warning systems have been created, more powerful predictors (variables) have been included resulting in more accurate forecasts and prognosis, whose usefulness for practitioners has been considerably enhanced. It is worth noting that 30 to 40 years ago, many financial institutions and bankers still relied in what Altman and Saunders (1998) and Lauer (2008) refer to as the 4 "C's" of credit in order to make a (subjective) judgement on the granting of credit: Character (individuals' work habits, reputation and personal life); Capital (assets, liabilities, and leverage) Capacity (experience in business, history of successes and failures, volatility of earnings); and Collateral.

Nowadays, with the development of statistical techniques, more reliable than human judgement[63], new models concerned with the measuring of credit concentration risk have emerged (see Bennett (1984) and Altman and Kao (1992)), which estimate transition probabilities through Markovian stable and unstable models), as opposed to estimating the credit risk of individual loans to firms. More recently, the use of new methodologies focusing on the application of Modern Portfolio Theory (MPT) to loans and fixed income instruments has been translated into research works applying macro econometric models of national economies (the U.S., more specifically) in order to generate future possible states of the world, thus SIC sector loan payoffs, or loss rates (Chrinko and Guill (1991)). Moreover, the estimation of the risk of financial instruments is acquiring an increasingly important place in the academic literature; examples of this are: the measurement of portfolio risk of fixed income securities and of off-balance sheet instruments[64] as well as credit risk derivatives (Brewer and Koppenhaver (1992), Jagtiani et al. (1995)), and new models that aim to price credit risk. Furthermore, the Basel Capital Accord (Basel II)[65], initially published in June 2004 (whose main objective is the creation of an international standard that can be used by national regulators when establishing capital requirements for banks in order to guard against financial and operational risks), has emerged as another catalyst for the continuation and development of more accurate and more refined failure prediction models for the corporate as well as retail sectors of banks' lending portfolios.

This paper contributes to the academic literature in several ways. First, we motivate and introduce a new default prediction model for quoted companies in the United Kingdom. This model employs a definition of corporate failure based on Christidis and Gregory (2010) and uses all available information in the London Share Price Database (LSPD) 2012. In order to clearly separate all companies in the database into two populations, as required by models with a dichotomous dependent variable such dynamic logit models, the present study follows Christidis and Gregory (2010) and defines as failed

---

[63] There is an extensive literature suggesting that a statistical model usually outperform specialists (see Keasey and Watson (1987), Keasey and Watson (1991), Dawes and Corrigan (1974), Houghton and Sengupta (1984)).
[64] The development and use of off-balance sheet instruments in the last 30 years is perhaps one of the most dramatic developments. For a detailed survey of the evolution, see Saunders (1997).
[65] See Basel Committee on Banking Supervision (2004).

those firms that are liquidated, in receivership or suspended from quotation. In this way, we are providing an objective criterion (indicating why the security ceased to be quoted in the SEDOL) that can be objectively dated, and that is therefore valuable for practical purposes. A wider, *ex ante* approach is employed, in order to detect financial distress with a high degree of reliability that could be useful to practitioners to avert the high costs associated with a bankruptcy filing. Secondly, employing a multi-level empirical procedure this study details a corporate default prediction model that, with a carefully selected vector of variable chosen based on theory and intuition, exhibit high classification and predictive accuracy compares well to previous research works and limits type 1 and 2 errors. Third, and perhaps most importantly, the study tests, for the first time in default prediction models for public companies in the United Kingdom, the relative contributions (individual as well as collective) of three typed of variables: financial ratios, macroeconomic indicators, and market variables.

The chapter is structured as follows. In the next section we discuss the literature that is relevant to our modelling approach. The database and measures of the outcome variable and set of explanatory variables are described. The estimation methodology is discussed along with analysis, results and conclusions.

4.2. Review of the Literature.

The present study develops a new default prediction model for quoted companies in the UK that is based upon the types of death presented in the London Share Price Database. As in most of the previous default prediction models for quoted companies in the United States that employ a definition of the criterion event that is contingent upon its ultimate legal consequence (bankruptcy), the present study uses a technical or legal definition of corporate failure that reflects the 'most extreme forms of financial distress[66]': liquidation, receivership, suspension and cancellation. Our choice of the criterion event is justified by the fact that it constitutes a highly visible legal event that can be objectively dated (Keasey and Watson, 1991). There are, however, as noted by Agarwal and Taffler (2007), events other than the ones employed in the present study (liquidation, receivership, suspension and cancellation), such as capital reconstructions (involving loan write-downs and debt equity swaps or equivalent), acquisitions, major closures, and forced disposals of large parts of a firm (to repay its bankers) that result in loss to creditors and/or

[66] The term in quotes is borrowed from Christidis and Gregory (2010), 'Some New Models for Financial Distress Prediction in the UK.' Xfi – Centre for Finance and Investment and Discussion Paper no: 10/04, p. 6.

shareholders and can therefore be considered as proxies for failure. Evidently, there are some drawbacks of the definition of corporate failure used in this study, which will be discussed in detail in the following chapter, nevertheless, the present definition of the criterion event has a practical use for the estimation of the likelihood of default using binary choice models that require that the populations of failing and non-failing firms be 'well defined and clearly separated from each other.[67]' Moreover, similar to Agarwal and Taffler (2007), we have decided to work exclusively with firm insolvencies[68] 'on the basis that these are clean measures' of corporate failure. Finally, most of the previous default prediction studies in the United Kingdom take the change in the juridical situation as the moment of default (e.g. the Taffler (1983) UK-based *z*-score model).

Thus, a firm is classified as in default when its LSPD (2012) status is equal to any of the following definitions (that indicate the reason why the security ceased to be quoted in the SEDOL): 6) Suspension / cancellation with shares acquired later. Meanwhile, may be treated under rule 163/2; 7) Liquidation (usually valueless but there may be liquidation payments; 10) Quotation suspended – if suspended for more than three years, this may lead to automatic cancellation; 11) Voluntary liquidation, where value remains, and was / is being distributed; 16) Receiver appointed / liquidation. Probably valueless but not yet certain; 20) In Administration / Administrative receivership; 21) Cancellation and assumed valueless or suspended but assumed valueless. In addition, the present analysis also tracks the specific date when each one of these events occurs.

Previous research has also tested the ability of market variables to predict bankruptcy employing methodologies such as the Black and Scholes (1973) and Merton (1974) contingent claims or option based approach. Bharath and Shumway (2008), Hillegeist et al. (2004), Reisz and Perlich (2007), and Vassalou and Xing (2004) are some of the research works that have employed the contingent claims approach to estimate the likelihood of corporate failure. Many efforts have been carried out to demonstrate the superiority of market-based models over accounting-based models and vice versa. However, the results obtained from these models (that entail numerous restrictive assumptions[69]) and the subsequent performance comparisons with accounting-based models have been controversial. In a recent paper, Agarwal and Taffler (2008) perform a

[67] Balcaen and Ooghe (2004), p. 21.
[68] Administration, receivership, creditors' voluntary liquidation.
[69] The underlying assumptions of the theoretical Merton-Black-Scholes option-pricing model are, according to Saunders and Allen (2002) and Agarwal and Taffler (2008): normality of stock returns, and the existence of a single zero coupon loan (it does not distinguish between different types of loans), for instance.

comparison of market-based and accounting-based bankruptcy prediction models, and find that traditional models based on financial ratios are not inferior to KMV-type, option-based models for credit risk assessment purposes. They conclude that, 'in terms of predictive accuracy, there is little difference between the market-based and accounting models.[70]' Hillegeist et al. (2004) provide contrasting results indicating that the Black-Scholes-Merton option-pricing model provides significantly more information about the probability of bankruptcy that do either the Altman's Z-score or the Ohlson O-score.

To this point, the default prediction literature is characterised by a competing approach, where there is a clear division line between market and accounting variables. Hillegeist et al. (2004),[71] for instance, recommend that researchers use the Black-Scholes-Merton methodology instead of the traditional accounting-based measures as a proxy for the probability of bankruptcy. Nevertheless, despite the relative comparisons in performance of the competing approaches, the fact that both yield not too dissimilar results suggests that both contain useful information about firms' likelihood of default/financial distress. Furthermore, the individual characteristics of each type of variable (market and accounting) offer additional support for the development of a comprehensive model that test whether they are able to enhance its performance (therefore acting as complements) when they are included in the same equation.

Financial information has been used in the majority of classic models in order to predict failure. Balcaen and Ooghe (2004) cite the objectivity and availability as the main reasons for the use of financial ratios. More importantly, as failure is not a sudden event but rather the conclusion of several years of poor, negative performance, then financial accounts should be useful to detect and predict corporate failure (Agarwal and Taffler, 2008). However, concerns about the reliability of accounting information suggest that it might not give a fair and true view of companies undermining thus its usefulness as a predictor of failure: creative accounting practices and window dressing might be used especially when firms are in a state of financial distress or near failure. This is one of the reasons why, even if the double entry system of accounting has diminished the risk of manipulation of accounts, it is still recommended that default prediction models include other types of variables[72]: 'if researchers only include financial ratios into their failure prediction model, they implicitly assume that all relevant failure or success indicators –

[70] P. 1550.
[71] P. 28.
[72] Argenti (1976), Zavgren (1985), Keasey and Watson (1987), and more recently Maltz et al. (2003) offer support for the inclusion of non-financial variables to default prediction models.

both internal and external- are reflected in the annual accounts.[73]' It is clear that financial statements do not include all the information that is relevant to the prediction of financial distress, and market variables are very likely to complement this deficiency.

Rees (1995) suggests that market prices might be a useful predictor for the probability of bankruptcy as they include information on future expected cash flows. For Hillegesit et al. (2004) the stock market is an alternative source of information because it contains information from other sources in addition to the financial statements. Beaver et al. (2005) indicate that a probability of bankruptcy is embedded in market prices, even though this probability might not be directly extracted: 'as the probability of bankruptcy increases the non-linear nature of the payoff function for common stock becomes increasingly more important because of risky debt and limited liability.' Clearly the inclusion of market-based variables is appealing on several grounds: first, market prices reflect the information contained in accounting statements plus other information not in the accounting statements (Agarwal and Taffler, 2008), making them a comprehensive mix potentially useful for the prediction of corporate default. Second, the inclusion of market-based variables can considerably increase the timeliness of prediction models, as discussed by Keasey and Watson (1991); while financial accounts are available in the United Kingdom on a quarterly basis, at best (prior research have used annual data conventionally), market prices are available on a daily basis. Third, market prices might be more appropriate to predict bankruptcy, as they reflect future expected cash flows (accounting statements, in contrast, reflect the past performance of the firm). And fourth, market-based variables can provide a direct assessment of volatility, a measure that could be a powerful predictor of bankruptcy risk and that is not contained in financial statements. According to Beaver et al. (2005) the notion is that the greater the volatility, the higher the probability of bankruptcy.

Among the few studies that include a set of market variables to enhance the timeliness and power of default prediction models is Campbell et al. (2008), whose analysis examines the determinants of failure as well as the pricing of financially distressed stocks with a high probability of failure through a logit model that includes accounting and market variables. In addition to a set of two accounting variables, several market variables are tested: the monthly log excess return on each firm's equity relative to the S&P 500 index, the standard deviation of each firm's daily stock return over the past three months, the relative size of each firm measured as the log ratio of its market capitalisation to that of the

[73] Balcaen and Ooghe (2004), p. 35.

S&P 500 index, and the firm's log price per share truncated above at $15. The estimates of the study are computed with United States data for public companies.

Similarly, Chava and Jarrow (2004) test in their analysis, in addition to the Altman's (1968) accounting variables, the variables included in Shumway (2001): the accounting variables net income to total assets and total liabilities to total assets; and the market variables: relative size defined as the natural logarithm of the firm's equity value in relation to the total NYSE/AMEX market equity value, yearly excess returns calculated as the firm's cumulative monthly return minus the value-weighed CRSP NYSE/AMEX monthly index return, and the stock's volatility computed as the standard deviation using the last sixty observable daily market prices. In Shumway (2001) the same market variables are tested in a bankruptcy prediction model with some minor variations, namely the idiosyncratic standard deviation of each firm's stock returns, whose value is computed by regressing each stock's monthly returns on the value-weighted NYSE/AMEX index return for the same period (year). More recently, Christidis and Gregory (2010) follow Campbell et al. (2008) and test three market variables in a distress prediction model for UK quoted companies that includes also a set of accounting variables. As to the market variables, they replace book value of assets with market values and test whether log semi-annual excess returns over the FTSE All Share Index and firm stock returns' standard deviation (calculated over a six-month period) can enhance the predictive power of the model. Their findings suggest that market values have the ability to increase the accuracy of the distress prediction model.

The incorporation of time variant data into credit risk models that captures changes in the macroeconomic environment is important in two main respects. First it adds a dynamic element to the models that acts to adjust risk scores (likelihood of insolvency) in relation to changing macroeconomic conditions. Second such models would have a built-in facility to stress test PD estimates across the portfolio. There are few studies that have incorporated a macro-dependent hazard into the equations (Nam et al, 2008; Qu, 2008 and Mare, 2012). In this paper we control for macro conditions, inflation and interest rate changes, over the sample period.

In the next section we discuss the main methodologies used to predict corporate default in previous research works.

4.3. Default Prediction Methodologies.

In the extensive literature concerned with the prediction of failure, the role of the methodologies and statistical techniques cannot be overemphasized. During the last 40 years, many authors have applied a great variety of statistical techniques in order to reconcile the nature of the problem (e.g., probabilities of default; discriminant analysis, to compare a firm's current financial profile with that of previously failed/distressed or non-failed/non-distressed firms) with the available mathematical tools. The purpose of these efforts has been to find a combination capable of yielding the most accurate and reliable (stable) predictions regarding the conditions of a firm in a given period of time.

The first works in this area developed univariate and multivariate models and used a set of financial ratios. The Beaver (1966) and Altman (1968) papers are considered to be the seminal works respectively. The univariate methodology utilizes various key accounting ratios of corporations that are perceived as separating defaulted from non-defaulted firms. The ratios are computed and then compared to historically derived benchmarks in order to differentiate the profiles of the two groups of firms. As can be inferred, the assumption underlying the use of sets of accounting ratios is that, there is, if not proportionate[74], a clear relationship between the two variables whose ratio is calculated. In this regard, McDonald and Morris (1984), through an empirical analysis, provide evidence suggesting that traditional ratio analysis is able to capture the relationships between financial variables, outperforming Ordinary Least Squares (OLS) alternatives (with respect to residual variance and distributional tests) when applied to a homogeneous industry sample. Beaver (1966) constructed a symmetric matched sample consisting of 158 firms (79 failed and 79 non-failed), and analysed 14 financial ratios using a dichotomous classification test in order to determine the potential errors of a classification of firms in these two groups based on individual financial ratios. He provides evidence suggesting that a number of indicators can effectively discriminate between matched samples of the two groups for as long as five years prior to failure. The ratios recognized as having the best potential to predict failure were profitability, liquidity, and solvency.

However, as the nature of the study clearly suggests, and as Altman (1968) would show later, the empirical application of these results for assessing default potential of firms is questionable from a theoretical as well as an empirical point of view. In effect, one of the

[74] For a discussion on the "proportionality assumption" in the relationship between the 2 variables that conform a ratio, see Whittington (1980) and Keasey and Watson (1991).

main problems with the univariate methodology is that special importance is placed on individual signs as predictors of distress, when in reality, the negative implications of a particular ratio could be tempered or even offset by a particular strength measured by the analysis of another ratio studied individually.

A potential solution to the inconsistency problem of Beaver's univariate analysis was provided by Altman (1968), who used a multiple discriminant analysis (MDA) methodology as primary tool of analysis. The MDA technique is used to classify an observation (in this case a firm) into one of various pre-defined groupings, dependent upon the observation's individual characteristics. Altman utilised MDA to classify and make predictions of a qualitative dependent variable: failed or non-failed. He analysed a symmetric sample of 66 manufacturing firms (33 failed and 33 non-failed) for the period 1946-1965, and selected 5 ratios (from a list of 22 potentially useful ratios) as the most appropriate for predicting corporate bankruptcy: Liquidity, profitability, leverage, solvency and activity. The use of the MDA technique has the advantage of taking into account the entire range of ratios (as an entire profile of characteristics) common to the firms in question, as well as the interactions among them, unlike the univariate analysis, who evaluates the ratios one at a time. Another advantage of the MDA methodology in general is that it reduces the space dimensionality to G-1 dimensions, where G equals the number of pre-defined groups. In the case of the "failed/non-failed" distinction (G=2) it yields the simplest form of analysis: one dimension, which considerably simplifies the analysis in question. Furthermore, the resulting Z-score can assign weights to the variables such that the "between-groups" variance is maximized relative to the "within group" variance.

Following the seminal paper of Altman (1968) a very large number of studies have used MDA to address default/distress prediction problems. Among the most influential we can cite the following[75]: Deakin (1972), Edmister (1972), Blum (1974), Eisenbeis (1977), Taffler and Tisshaw (1977), Altman et al. (1977), Micha (1984), Gombola et al. (1987), Lussier (1995), Altman et al. (2005). Overall, these research works have yield high levels of discriminative accuracy with regard to the classification of firms in one of the two groups (failed or non-failed), but it is not certain if this automatically translates into the same levels of predictive accuracy, as discussed by Keasey and Watson (1991). In fact, in a strict sense, a model based on MDA cannot be considered as a prediction, although, in practice, as discussed by Blum (1974), when a firm is classified as pertaining to the failing group because it most resembles the failing firms in the next year (when the characteristics of the

[75] For a list of papers using MDA methodology, see Altman and Sabato (2007) and Altman et al. (2010).

failing sample are measured in year *t+1*), this result is interpreted as a prediction that the firm will fail in year *t+1*. In Agarwal and Taffler's (2007) words: "testing models only on the basis of how well they classify failed firms is not the same as true *ex ante* prediction tests." (p. 288).

The MDA methodology has been widely used in the credit risk measurement literature, which implies that there are some straightforward advantages in terms of availability and modelling, however, since the seminal paper of Ohlson (1980), logit models have acquired an important place in academic studies mostly because, theoretically, they can provide a solution to some technical issues related to the application of MDA techniques to the prediction of corporate failure/distress. First, with the MDA, individual estimation of the significance (relative weight) of the model's variables is not possible. MDA yields standardized coefficients that cannot be interpreted like the slopes of a regression equation. In other words, the coefficients do not indicate the relative importance of the variables. Second, as previously discussed, in essence, the MDA aims to find a linear function of accounting variables able to provide the best differentiation between the two classification groups (failed and non-failed), which requires an analysis of the entire set of characteristics (variables) in order to maximize the between group variance and minimize the within group variance among these variables. However, the underlying assumptions are that the independent variables included in the model are multivariate normally distributed[76] and that the group dispersion matrices (variance-covariance matrices) are equal across the groups[77].

A satisfactory solution to these issues was provided by the use of the logit methodology, which does not require the relatively restrictive assumptions of the MDA methodology. Moreover, as discussed by Altman et al. (2010), from a statistical point of view, "logit regression seems to fit well with the characteristics of the default prediction problem, where the dependant variable is binary (default/non-default) and where the groups are discrete, non-overlapping and identifiable. The logit model yields a score between 0 and 1, which conveniently gives the firm's probability of default. Lastly, the estimated coefficients can be interpreted separately as the importance or significance of each of the independent variables in the explanation of the estimated probability of default." Logit methodologies (and probit techniques) use cumulative probability distributions to yield a conditional probability of an observation belonging to a category,

[76] Although Mardia et al. (1979) suggest that multiple discriminant analysis is still appropriate even when multivariate normality is not present.
[77] See Barnes (1982), Karels and Prakash (1987), McLeay and Omar (2000).

depending upon the individual variables for the observation in question. The logit regression measures the importance of the independent variables through weights so as to obtain a score for a given observation, and, unlike MDA methodologies, these weights are utilized to maximize the joint probability of failure for the known failed firms and the probability of failure for the sound ones. Most importantly, this methodology can provide the individual significance of the variables included in the model. Not surprisingly, since the end of the 1970s (Martin (1977)), and most importantly from the publication of the seminal paper of Ohlson (1980), the logit methodology has been widely utilized in the default prediction models literature. The logit methodology has been used in studies both of small and large corporations. Among the most influential works in the first category (small firms) we can cite the following: Keasey and Watson (1987), Peel and Peel (1987), Storey et al. (1987). Among the studies concerned with large firms using the logit methodology we can cite: Martin (1977), Ohlson (1980), Mensah (1984), Gentry et al. (1985), Zavgren (1985), Platt and Platt (1991), Charitou and Trigeorgis (2000), Becchetti and Sierra (2003), Altman et al. (2010).

If there exist some important theoretical (statistical) differences between the MDA and the logit techniques, in practice, researchers or practitioners concerned solely with the "predictive power" of the model have found only minor variations between the two methodologies; Hamer (1983) develops and compares the performance of a linear discriminant model, a quadratic discriminant model, and a logit model, using four alternative variable sets (on firms which failed from 1966-1975) in each of the five years before failure. Her findings strongly suggest that the linear discriminant function and the logit model yield comparable results and that, overall, the linear and logit models "predict at least as well as the quadratic models." The misclassification rates range from 20% to 30% in each of the first three years before failure, the predictive accuracy starting to decrease after the fourth year. Lo (1986) compares discriminant analysis and logit analysis and shows that if the logit methodology is more robust than discriminant analysis for purposes of parameter estimation, both procedures yield consistent estimates under certain distributional assumptions, and the discriminant analysis estimator is asymptotically efficient.

4.4. Outcome Definition and Independent Variable Selection.

4.4.1. Outcome Definition

The promised analysis requires a definition of corporate failure, which can be viewed as the outcome of a process. A definition based on Christidis & Gregory (2010) is utilised. A firm is classified as failed when it is deemed to have formally defaulted on its obligations. The definition of the outcome variable was constructed using the information available in the 2012 London Share Price Database (LSPD). A firm is defined as in default whenever its status is defined as suspended, in liquidation or voluntary liquidation, when its quotation has been suspended for more than three years, when the firm is being held by a receiver (in receivership), in administration or in administrative receivership, or when there has been a cancellation or suspension of the firm.

Thus, a firm is classified as failed when its LSPD (2012) status is equal to any of the following definitions (that indicate the reason why the security ceased to be quoted in the SEDOL): 6) Suspension / cancellation with shares acquired later. Meanwhile, may be treated under rule 163/2; 7) Liquidation (usually valueless but there may be liquidation payments; 10) Quotation suspended – if suspended for more than three years, this may lead to automatic cancellation; 11) Voluntary liquidation, where value remains, and was / is being distributed; 16) Receiver appointed / liquidation. Probably valueless but not yet certain; 20) In Administration / Administrative receivership; 21) Cancellation and assumed valueless or suspended but assumed valueless. In addition, the present analysis also tracks the specific date when each one of these events occurs.

Table 4-1 presents summary statistics for the 381 failed firms that were classified according to the definition of corporate failure in this study using the 2012 LSPD database. Of a total of 3,022 individual firms, 381 were classified as failed and 2,641 were classified as financially healthy, yielding a proportion of 12.6% of corporate failures relative to the number of individual firms. On the other hand, it is also important to calculate the proportion of 'events' relative to the total number of observations in the sample, to ensure that there are 'enough' corporate failures to compute accurate estimated event probabilities. Using the logit regression in small samples (under about 200) can result in biased logit coefficients. Moreover, in rare events data, 'the biases in probabilities can be substantially meaningful with sample sizes in the thousands and are in a predictable direction: estimated event probabilities are too small.'[78] In the present study, the proportion of 'events' to the total number of observations is 1.64%, which is higher than most previous research works on the prediction of corporate default.

Table 4-1 Summary Statistics of Corporate Failure of UK Firms.

This table reports summary statistics for the firms in the last stage of financial distress, corporate failure. Obs is the total number of observations (firm-years) in the database, N is the number of normal (non-failed) firms, F is the number of failed firms according to the definition below, Total is the number of firms in the database, and %F is the proportion (in percentage) of failed firms relative to the Total number of firms in the database. The definition of corporate failure (that follows the approach of Christidis and Gregory (2010)) was constructed using the information available in the 2012 London Share Price Database (LSPD). A firm is classified as failed when its status in the 2012 LSPD is defined as: suspended, in liquidation or voluntary liquidation, when its quotation has been suspended for more than three years, when the firm is being held by a receiver (in receivership), in administration or in administrative receivership, or when there has been a cancellation or suspension of the firm[79].

Classification of Failed UK Quoted Companies.				
Obs	N	F[80]	Total	%F
23,218	2,641	381	3,022	12.6%

In specifying the models there are two main objectives. First, the intention is to build more accurate and timely corporate default prediction models, using data that is routinely available. The models are designed to obtain more accurate results compared to previous works in the academic field and are constructed with a parsimonious approach since they are intended to have practical value. Further, Zmijewski (1984) and more recently Pindado et al. (2008) have shown that in fact a large set of variables is not required for the models to reach their maximum level of accuracy. Pindado et al. (2008), for instance, employ a set of only three accounting variables to reach a high level of accuracy in their financial distress prediction model. The variables employed in their study are the ratios earnings before interest and taxes over total assets, financial expenses to total assets, and retained earnings to total assets, which represent profitability, financial expenses, and retained earnings, respectively. Zmijewski (1984) uses a set of accounting variables that includes proxies for return on assets, financial leverage, and liquidity. Moreover, in a study that intends to investigate the empirical relation between risk of bankruptcy and systematic

[78] King and Zeng (2000), p. 2

[79] The LSPD numbers and definitions in the database are: 6) Suspension / cancellation with shares acquired later. Meanwhile, may be treated under rule 163/2; 7) Liquidation (usually valueless but there may be liquidation payments; 10) Quotation suspended – if suspended for more than three years, this may lead to automatic cancellation; 11) Voluntary liquidation, where value remains, and was / is being distributed; 16) Receiver appointed / liquidation. Probably valueless but not yet certain; 20) In Administration / Administrative receivership; 21) Cancellation and assumed valueless or suspended but assumed valueless.

[80] For the purposes of the analysis, firms classified as failed in the database are assigned a value of 1, and zero otherwise according to the date of failure.

risk through the construction of a single composite score that reflects the ex-ante probability of bankruptcy for a company at a given point in time, Dichev (1998) employs a measure derived from exiting accounting models such as the 5-variable Altman (1968) Z-model, and the 7-variable Ohlson (1980) logit model.

The second objective of the analysis is to test the usefulness of other non-accounting variables, namely macroeconomic and market variables, with regard to their contribution to the accuracy and timeliness of corporate default prediction models for quoted companies. We investigate whether macroeconomic and market variables enhance the discriminating and predicting power of the models. There have been very few studies that analyse the performance of these three kinds of variables in a statistical default prediction model. It is deemed important to investigate macroeconomic and market variables since the former is potentially useful to act as a complement to the accounting variables and the latter adjusts estimated scores in relation to changes in the macroeconomic environment and provides the facility to impose stress testing scenarios.

Of course, accounting data can only be obtained on an annual basis, so even if the discriminating power of some previous and widely used models (such as the Altman (1968) model) is quite high, there is always the risk of the relying on out dated information. Furthermore, through a detailed analysis of the 'most extreme form of financial distress,' corporate failure, the present study shows that the firms that were classified as failed[81], stop providing accounting data one year on average (14 months) before the actual date of failure.

From the database, consisting of 130 variables in total, several accounting, macroeconomic, and market variables were tested. The final variable selection is discussed in detail below.

---

81 The definition of the response variable was constructed using the information available in the 2012 London Share Price Database (LSPD). A firm is defined as failed whenever its status is defined as suspended, in liquidation or voluntary liquidation, when its quotation has been suspended for more than three years, when the firm is being held by a receiver (in receivership), in administration or in administrative receivership, or when there has been a cancellation or suspension of the firm.

4.4.2. *Independent Variable Selection*

4.4.2.1. *Accounting Ratios*

A range of potential independent variables were selected and tested based on extant empirical studies. With regard to the accounting variables, four ratios were selected: Total Funds from Operations to Total Liabilities, Total Liabilities to Total Assets, the No Credit Interval, and Interest Coverage. The variable, Total Funds from Operations to Total Liabilities (TFOTL), funds flow ratio that represents a performance measure, was built using the data available in Worldscope. Total Funds from Operations represents the sum of net income and all non-cash charges or credits; it is the cash flow of the firm. The denominator of the ratio, Total Liabilities, is composed of all short and long-term liabilities acquired by the company. This variable has been successfully employed in other studies: e.g. Marais (1979) in a Bank of England Study and Ohlson (1980). This ratio is intended to show the extent to which a company is able to generate funds from its operations to meet its financial obligations. The real line of TFOTL can be mapped onto [-1,1], where a positive value indicates a good position of the firm with regard to its financial obligations and a negative value suggests that a firm might be in a position where it does not generate sufficient funds from its operations to comply with its acquired obligations and might default. The higher the value of this financial ratio, the less likely it is for a company to be in a distressed financial position. A negative sign for this ratio is expected, confirming the above hypothesis that a higher value of this ratio (approaching 1) decreases the probability of corporate failure (the estimate's sign should be negative).

The ratio Total Liabilities to Total Assets (TLTA) is a measure of financial leverage. The data used to produce this variable was also taken from Worldscope (as was the case of most of the accounting ratios in this study). Total Liabilities, as discussed, is composed of all short and long term liabilities acquired by a company. The denominator, Total Assets of industrial firms, is the addition of total current assets, long-term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets. The ratio is commonly used to measure a firm's financial leverage (and therefore financial risk) by calculating the proportion of the company's assets that have been financed using short and long-term debt. Zmijewski (1984) included TLTA (represented as FINL) in a three-variable accounting model, where it displayed the expected sign and was statistically significant. More recent studies, such as Shumway (2001) and Chava and Jarrow (2004) in the United States, and Christidis and Gregory (2010) in the United Kingdom, have tested it and confirmed its consistency and contribution to default/bankruptcy prediction models. The real line of TLTA can be mapped onto [-1,1], where an increasing large, positive value indicates an increasing leverage of the firm. Moreover, the higher the leverage, the higher the financial risk taken by the firm and therefore the higher its probability of default. This is because a highly leveraged company (a high TLTA ratio) could find itself in a very difficult and perilous position if creditors demand the repayment of the contracted debt. Likewise, a small or negative value of the accounting ratio TLTA should indicate that the assets of the firm are financed by equity instead of debt. A positive sign of the variable's estimate is therefore expected in the analysis, signifying that a high value of the ratio (a high leverage) should have a positive impact in the probability of corporate default. In the present analysis, it is investigated whether the ratio TLTA is able to enhance the accuracy of new corporate default prediction models for UK quoted companies.

The variable No Credit Interval (NOCREDINT) is intended to measure liquidity (Taffler, 1983; Agarwal and Taffler, 2007). Graham (2000) defines the No Credit Interval variable as 'an estimate of the length of time that a company could finance the expenses of its business, at its current level of activity, by drawing on its own liquid resources and on the assumption that it made no further sales.'[82] The input required to produce this accounting variable was taken from Worldscope: Quick assets, Total Current Liabilities, Sales, Earnings Before Interest and Taxes, and Depreciation. The NOCREDINT variable was calculated with the following formula: (Quick assets minus Current liabilities) / (Daily operating expenses). Where Quick Assets represent the assets that can be quickly and easily converted into cash or are already in cash form. The formula employed to calculate Quick assets is Current Assets minus Inventories. Similarly, Daily operating expenses are equal to (Sales minus Earnings Before Interest and Taxes minus Depreciation) / 365. The number resulting of this formula is, as expected, the number of days that a company can finance its expenses by drawing on its own current resources. However, as previously explained, the ratio was transformed using the TANH function in order to treat the problem of outlying values of the variable that could have an abnormal impact on the fitted maximum likelihood linear predictors as well as on the size of the residuals that resulted from the binary logistic regression. After the TANH transformation, the real line of the NOCREDINT variable can be mapped onto [-1,1], where an increasing large, positive value indicates an increasing capacity of the firm to finance its business expenses with its quasi-liquid and liquid resources given its current level of activity. Conversely, a small or negative value of this variable suggests a precarious liquidity position of the firm potentially

[82] P. 86.

leading to a stressed position with regard to its financial obligations. A negative sign of the No Credit Interval variable's estimate is expected, suggesting that a high value of the variable should have a negative impact on the firm's probability of default.

The final accounting ratio is Interest Coverage (COVERAGE) and measures a firm's ability to pay interest on outstanding debt (Altman and Sabato, 2007). The Interest Coverage ratio was therefore calculated dividing the variable Earnings before interest, taxes and depreciation (EBITDA)[83] by the variable Interest charges or Interest expense on debt that represents the service charge for the use of capital before the reduction for interest capitalized. Typically, a value smaller than 2-2.5 suggests that the firm might be having trouble to meet its financial obligations; a value below this threshold should be therefore considered as a serious warning sign: the firm is not creating enough cash from its operations, as measured by its Earnings before interest, taxes, and depreciation (EBITDA), in order to meet its interest expenses on debt. A value greater than 2.5 is interpreted as the firm being able to generate funds from its operations to meet interest payments. In the present study, the COVERAGE ratio was also transformed using the TANH function in order to treat the problem of outlying values of the variable that could have an abnormal impact on the fitted maximum likelihood linear predictors as well as on the size of the residuals that resulted from the binary logistic regression. After the TANH transformation, the real line of the COVERAGE variable can be mapped onto [-1,1], where an increasing large, positive value indicates an increasing ability of the firm to meet its debt obligations. A negative sign of the COVERAGE variable's estimate is therefore expected, suggesting that a high value of the variable should have a negative impact on the firm's probability of failure.

4.4.2.2. Macro-Economic Variables

In addition to the accounting ratios, two macroeconomic variables were selected (among a list of eleven macroeconomic indicators) and included in the final model: the Retail Price Index (RPI), and the United Kingdom Short Term (3-month) Treasury Bill Rate Deflated (or the real short term Treasury bill rate), both are represented on an annual scale in the present study. The first macroeconomic variable, the Retail Price Index indicator, a measure of inflation, was taken from Datastream (the Office for National

[83] EBITDA measures the earnings of a firm before interest expense, income taxes and depreciation. Worldscope calculates EBITDA by taking the pre-tax income and adding back interest expense on debt and depreciation, depletion and amortization and subtracting interest capitalized.

Statistics being the primary source), and it is defined by Thomson Financial as 'an average measure of change in the prices of goods and services bought for the purpose of consumption by the vast majority of the households in the UK.' The Retail Price Index is compiled and published monthly. There are just a few default/failure prediction studies where this variable has been tested, and its relationship with the probability of default has varied. As a measure of inflation, and thus as a 'hidden risk pressure' that acts as an incentive for those disposing of savings to invest them rather than see their purchasing power erode further in the future through inflation, it could be expected that the risk-taking capacity of investors increases in the same direction, lowering thus a firms' probability of default, as discussed by Qu (2008). However, as acknowledged by the same author, the direction of the relationship inflation-probability of default has not been unequivocally established due to the 'complexity of inflation's effect on the economy.'[84] Mare (2012), on the other hand, develops a failure prediction model for banks and finds that the measure of inflation employed is positively related to the probability of default. His rationale is that high inflation is rather the consequence of a generally weak macroeconomic environment, which in turn increases the number of banking crises. Now, as there is a direct relationship between the banking and the industrial sector, whose magnitude is dependent upon the choice of capital structure adopted by firms (the proportion of debt to equity), the present study's hypothesis is that a high RPI should increase a firm's probability of failure. A positive sign of the RPI variable's estimate is therefore expected, suggesting that a high value of this variable should have a positive impact on the firm's probability of failure.

The second macroeconomic variable included in the model is the Short Term Treasury Bill Rate Deflated (SHTBRDEF), which represents the 'real' short-term rate of 3-month United Kingdom Treasury Bills on an annual basis. Two main sources were used to construct this indicator: from the Bank of England website[85] the level of the discount rate from 1985 to 2011 was obtained; and from Datastream, the inflation rate employed in order to deflate the discount rate for the same period. Treasury Bills are defined as 'bearer Government Securities representing a charge on the Consolidated Fund of the UK issued in minimum denominations of £5,000 at a discount to their face value for any period not exceeding one year[86]. Treasury Bills are typically considered as the least risky investment available. They are much more liquid than gilts (with maturity ranging between 0 and 15 years) and therefore the yield rate on treasury bills is normally lower than on longer-term

[84] P. 194.
[85] http://www.bankofengland.co.uk
[86] Definition taken from Datastream, Thomson Financial.

securities. The present study included the annualised level of the 91 days (3-month) discount rate in order to test another measure intended to capture the state of the macroeconomic environment that could potentially have an effect on the probability of failure of industrial companies. This indicator is a proxy for interest rates, which, similar to the RPI variable, is very likely to affect industrial firms according to their capital structure. Lower interest rates facilitate businesses to borrow in order to invest in new equipment, inventories, building, research and development, etc. Furthermore, it is well known that the firm's expected return on investment is higher today when rates are low than when they are high, which acts as an incentive for businesses to invest more when they operate in a low interest rate environment. Business borrowing is perhaps the most affected by high interest rates; firms might be in need to recur to short term loans in order to offset temporary or cyclic short-falls in expenses, payroll, etc., thus a high level of interest rate make the cost of debt more expensive, as companies will have to pay more interest back to their lenders. It is therefore assumed that a high value of the level of SHTBRDEF will increase the probability of failure. A positive sign of the SHTBRDEF variable's estimate is therefore expected, suggesting that a high value of this variable should have a positive impact on the firm's probability of failure.

4.4.2.3. Market Variables

The study included five market variables in the models in order to test whether they increase the predictive power of an accounting and macroeconomic model. The first one is the firm's equity price (PRICE). Equity prices data was obtained from the Datastream database. The implicit underlying assumption used in the present study to justify the inclusion of market equity prices in the models is that they reflect a wide mix of public information concerning the future cash flows that can be expected from a company's share and, as suggested by Rees (1995), 'a subset of that information will be relevant to the likelihood of liquidation and the cash flow impact.'[87] Therefore, it is expected that equity prices contain relevant information about the probability of corporate failure even if they are not a direct measure of that probability (Beaver et al., 2005). It is also assumed that market prices will act as a complement to the financial statement and macroeconomic information by enhancing the predictive power of the general model, and not as competing or mutually exclusive alternatives that should be used in isolation. The reason is that equity prices incorporate financial statement data as well as other information publicly available as

[87] P. 310.

inputs, potentially making markets a more efficient processor of all available public information than accounting data alone (Rees, 2005) and therefore increasing the overall accuracy of failure prediction models. It is assumed that the financial position of the firm may lead to portfolio realignments that affect and adjust equity prices ahead of the corporate default event. Furthermore, Beaver et al. (2005), suggest that 'as the probability of bankruptcy increases, the non-linear nature of the payoff function for common stock becomes increasingly more important because of risky debt and limited liability.' [88] Nevertheless, it might be also the case that some equity prices incorporate random information that is not directly relevant to the financial distress or insolvency process, as discussed by Rees (2005), and that this might introduce noise into the analysis and impair the predictive accuracy of the model. However, there have been studies where equity prices have had a positive effect on the predictive power of the model (Beaver, 1966; Beaver et al., 2005; Christidis and Gregory, 2010). Moreover, the superior predictive accuracy of a default prediction model is not the only potential benefit drawn from the inclusion of equity prices; the timeliness of the models could also be greatly improved (Keasey and Watson, 1991). Accordingly, to the extent that market prices reflect investors' expectations of future cash flows or earnings, and that the company's earnings are affected by its financial position, it is expected that there is a close relationship between price levels/movements and the probability of corporate default. It is therefore assumed that a high value of the level of PRICE will decrease the probability of failure. In other words, a negative sign of the PRICE variable's estimate is therefore expected, suggesting that a high value of this variable should have a negative impact on the firm's probability of failure.

The second market variable included in this study is the lagged cumulative security residual return (ABNRET). In order to incorporate this variable in a corporate default prediction model, each firm's past residual return [89] in year t was calculated as the cumulative monthly return of the twelve months prior to the year where the default event was observed, minus the FTSE All Share Index cumulative monthly return for the same period (*t-1*). Moreover, as with the previous financial statement and macroeconomic variables and in order to confirm its predictive ability, the ABNRET variable was computed as the cumulative monthly returns two years prior to the observation of the corporate default event (*t-2*). Both of the variables required to construct ABNRET (Firm's

[88] P. 110.

[89] In order to calculate residual/abnormal returns, firms' individual returns are employed as the main input. The investment return can be defined as the total gain or loss on an investment over a given period of time. The return incorporates the change in the asset's values plus any cash distributions (dividends or interest payments). The specific Datastream datatype used in the present study is the Total Return Index (RI) which shows 'a theoretical growth in value of a shareholding over a specific period, assuming that dividends are reinvested to purchase additional units of an equity or unit trust at the closing price applicable on the ex-dividend date.'

monthly returns and FTSE All Share Index monthly returns) were taken from the Datastream database. The ABNRET variable was also transformed using the TANH function in order to treat the problem of outlying values of the variable that could have an abnormal impact on the fitted maximum likelihood linear predictors as well as on the size of the residuals that resulted from the binary logistic regression. After the TANH transformation, the real line of the ABNRET variable can be mapped onto [-1,1], where an increasing large, positive value suggests a lower probability of financial default. Following Shumway (2001), the theoretical underlying assumption used in the present study to justify the incorporation of lagged residual returns into the models is that they should be useful to predict failure as investors discount the equity of those firms that are in a stressed financial position or close to bankruptcy/default. Furthermore, ass discussed by Beaver et al. (2005), if the option-like feature of common equity is accurate, where equity can be interpreted as a call option on the assets of a company (the face value of the liabilities being the strike price), then the value of common equity acts as the 'equity cushion available to debt-holders before their principal and interest become jeopardized.' Therefore, a decline of the value of equity (and thus a diminished equity cushion) should entail a higher probability of failure. This hypothesis is consistent with the findings of Dichev (1998), who measures bankruptcy risk employing the Altman (1968) and Ohlson (1980) models, and shows that there is a negative association between equity returns and the likelihood of bankruptcy. Accordingly, it is posited that a high firms' returns relative to the FTSE All Share Index returns will decrease the probability of failure. In other words, a negative sign of the ABNRET variable's estimate is therefore expected, suggesting that a high value of this variable should have a negative impact on the firm's probability of failure.

The third market variable is a measure of the variability of the stock returns of a company: the lagged standard deviation of individual security residual returns (IDYRISK). The information required estimating individual stock returns, the firm's monthly returns and FTSE All Share Index monthly returns were taken from the Datastream database. Each firm's idiosyncratic standard deviation of each firm's stock returns was estimated by regressing (employing a linear regression) each stock's monthly returns in year *t-1* on the FTSE All Share Index cumulative monthly return for the same period which corresponds to the year prior to the observation of the event of default. The idiosyncratic risk of the firm is the standard deviation of the residual of this regression. The same procedure was employed to construct this measure for *t-2* or two years prior to the observation of the corporate default event. Again, this measure of volatility can provide information relevant to the prediction of default that is not contained in the traditional financial ratios (in fact a volatility measure could not be extracted from financial data due to the scarcity of accounts which are submitted quarterly at best in the United Kingdom). In fact, as discussed by Vassalou and Xing (2004), models based on financial statements take as input only information that is historical by nature and do not incorporate the volatility of firm's assets in order to estimate the likelihood of corporate failure. It is therefore important to test a measure of volatility because, as shown by models based on the contingency claims approach, corporations with similar levels of equity and debt might have different probabilities of default if their assets have different levels of volatility (Trujillo Ponce and Cardone-Riportella, 2012). As noted by Shumway (2001), it is expected that this variable is strongly related to bankruptcy in statistical and logical terms: higher volatility of the cash flows of a firm (resulting in more variable stock returns) should entail a higher probability of default. In line with Shumway's (2001) argument, the present study posits that, in logical terms, the likelihood of default is explained not only by the level of market variables such as abnormal returns (ABNRET), but *also* by the proportion of their variability that is attributed to firm-specific factors.

The volatility of the return on a typical stock can be decomposed into three components that sum to the total return volatility of a typical firm: the aggregate market return volatility, industry-specific and firm-specific residuals. Nevertheless, the present study focuses solely on the idiosyncratic volatility of the firm. The reason is that, as shown by Campbell et al. (2001), while market and industry variances have been fairly stable over the period of 1962-1997, firm-level variance 'displays a large and significant positive trend,' more than doubling in the same period, concluding that 'although the market as a whole has not become more volatile, uncertainty on the level of individual firms has increased substantially over a 35-year period.'[90] It is therefore worth investigating the usefulness of a variable reflecting the idiosyncratic volatility of returns as an explanatory variable for the prediction of corporate default. Moreover, as discussed by Beaver et al. (2005), other parsimonious bankruptcy models that predict 'stock-outs' of a liquid asset include a measure of the variability of the cash flows as well as their expected values. The fact that the variability of expected asset returns is a fundamental variable in contingent claims valuation models such as the Black-Scholes-Merton model is another theoretical rationale to test the usefulness of a volatility measure as explanatory variable for the prediction of default. After the TANH transformation, the real line of the IDYRISK variable can be mapped onto [0, 1], where an increasing large, positive value indicates high volatility of returns which in turn have a positive effect on the probability of bankruptcy. In other

[90] P. 3.

words, a positive sign of the IDYRISK variable is expected, suggesting that a value that is near 1 should have a positive impact on the firm's probability of failure.

The fourth market variable incorporated to the model represents the Size of the company measured by its market capitalisation relative to the total size of the FTSE All Share Index (in order to make size static). The information required to construct this specific variable was taken from the Datastream database where the index Market Value (MV) is calculated as the sum of the share price multiplied by the number of ordinary shares in issue for each index constituent[91]. In the present study, the variable SIZE, was calculated as the logarithm of each firm's size relative to the total market value of the FTSE All Share Index. The minimum value drawn from this method of calculation was -16.60 and the maximum value -2.37, with an average equal to -10.05. This range of values results from the fact that the logarithmic form of a small number (a firm market value relative to that of the FTSE All Share will result in a very small value) yields a negative sign. Firm size as measure by the market value can be a potentially powerful predictor of failure if the option-like feature of common equity is used again as a theoretical framework; the market value of equity of a firm in a stressed financial position is discounted by market participants (investors) which entails a reduction in the debt holders 'equity cushion.' This decline in the level of equity, induced by a negative investors' judgement of the firm's financial standing, can systematically move towards the 'strike price' (or the value of liabilities) until it reaches the point where it is insufficient to serve the firm's debt obligations (and the firm defaults). As suggested by Agarwal and Taffler (2008) 'the probability of bankruptcy is the probability that the call option will expire worthless or, in other words, that the value of the assets [as measured by the firm's market value, the size] is less than the face value of the liabilities at the end of the holding period.'[92] Therefore, it is predicted that a high value of the SIZE variable should entail a low probability of failure. Conversely, a relatively small-sized company should have a higher probability of default. In other words, a negative sign of the SIZE variable's estimate is therefore expected, suggesting that a high value of this variable should have a negative impact on the firm's probability of failure.

The final market variable that entered the final model is the ratio Market Capitalisation to Total Debt (MCTD). The variable Market Capitalisation was taken from Datastream whereas the variable Total Debt was taken from Thomson One Banker (Worldscope). Total Debt is equal to all interest bearing and capitalised lease obligations.

[91] In Thomson Reuters' 2008 'Datastream Global Equity Indices.' User Guide. Issue 5. P. 20. For companies with more than one type of common/ordinary share, market capitalization represents the total market value of the company.
[92] P. 1543.

As specified by Thomson Reuters, it is the sum of long and short term debt. This market variable was adjusted using the TANH function in order to solve the problem of outlying values. The real line of MCTD can be mapped onto (0,1), where a high value indicates that there is considerable scope for a decline in value of a firm's assets (as measured by the market value of equity) before its total debt exceeds its assets and it becomes financially distressed or insolvent. Conversely, a low value of the variable indicates that the firm's decline in value is very close to reaching the point of insolvency, or the point where its total debt exceeds its assets. The higher the value of this financial ratio, the less likely it is for a company to be in a distressed financial position. Thus, it is posited that a high value of the MCTD variable should entail a low probability of failure. Conversely, a low value company should involve a higher probability of failure. In other words, a negative sign of the MCTD variable's estimate is predicted, suggesting that a high value of this variable should have a negative impact on the firm's probability of default. Other than the market value dimension (that previous default prediction models in the United Kingdom have failed to incorporate), this variable is intended to solve an important problem highlighted in Beaver et al. (2005), namely that the variables ABNRET, and specially SIZE, used in this study, are not 'scaled in that [they are] not compared with the magnitude of debt outstanding.'[93] The case of the variable SIZE should be particularly stressed as it is measured by the company's market capitalisation relative to the total market capitalisation of the FTSE All Share Index (transformed employing the logarithmic function). It could be therefore argued that the variables MCTD and SIZE, having the same denominator, could be highly correlated giving rise to a multicollinearity problem that may affect the stability of the coefficients of the independent variables in response to marginal changes in the model and/or data. Correlation matrices were computed and presented in Table 4-2 along with other diagnostic tests[94].

[93] P. 111.

[94] Multcollinearity is present when there is linear dependency among two or more independent variables in a multivariate model. This problem arises because some of them may be measuring the same concept. Consequently, when a given independent variable is a linear or a quasi-linear combination of other independent variables, the affected estimates are unstable and the standard errors inflated. Tolerance value and is reciprocal, variance inflation tests are computed as $1 - R_k^2$ and $1/(1 - R_k^2)$ respectively, where R_k^2 is the determination coefficient for regression of the *i*th regressor on all the other regressors. Freud and Little (2000), show how the instability of the coefficient estimates is increased by the existence of multicollinearity. It must be mentioned that there is not a formal criterion to establish a VIF value threshold above which multicollinearity can be ascertained; it has been argued that a VIF value greater than 10 suggests significant collinearity. The VIF values of all the regressors incorporated in the present study's models, show they are all even below 5, which indicates that multicollinearity is not present in the models and that the levels of the coefficients obtained are therefore reliable.

Table 4-2 Correlation Matrix and Multicollinearity Diagnostics Statistics.

Panel A of this table reports the correlation matrix of all the variables in included in the model. It includes financial statement ratios, macroeconomic indicators and market variables. *P*-values represent the probability of observing this correlation coefficient or one more extreme under the null hypothesis (H0) that the correlation (Rho) is zero. Panel B reports the values resulting from tests intended to detect the presence of multicollinearity among all the variables incorporated in the model: Tolerance Value (TOL) and its reciprocal, Variance Inflation (VIF) are computed as $1 - R_k^2$ and $1/(1 - R_k^2)$ respectively, where R_k^2 is the determination coefficient for regression of the *i*th regressor on all the other regressors.

Panel A: Correlation Matrix

Variable	*TFOTL*	*TLTA*	*NOCREDINT*	*COVERAGE*	*RPI*	*SHTBRDEF*	*PRICE*	*ABNRET*	*IDYRISK*	*SIZE*	*MCTD*
TFOTL	1.00000										
TLTA	0.17057	1.00000									
	<.0001										
NOCREDINT	-0.09720	-0.44510	1.00000								
	<.0001	<.0001									
COVERAGE	0.72613	0.02865	-0.05983	1.00000							
	<.0001	<.0001	<.0001								
RPI	-0.19100	-0.12218	0.14404	-0.19691	1.00000						
	<.0001	<.0001	<.0001	<.0001							
SHTBRDEF	0.12491	0.09343	-0.10688	0.11610	-0.81383	1.00000					
	<.0001	<.0001	<.0001	<.0001	<.0001						
PRICE	0.37131	0.05951	-0.04823	0.37641	-0.19656	0.15184	1.00000				
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001					
ABNRET	0.24136	-0.04107	0.03765	0.27986	-0.00448	-0.02817	0.17361	1.00000			
	<.0001	<.0001	<.0001	<.0001	0.5379	0.0001	<.0001				
IDYRISK	-0.39001	-0.01277	0.03927	-0.44025	0.19503	-0.07843	-0.38666	-0.21194	1.00000		
	<.0001	0.0729	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001			
SIZE	0.36300	0.09781	-0.08105	0.40685	-0.23538	0.10799	0.58264	0.22538	-0.36444	1.00000	
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		
MCTD	0.08792	-0.34893	0.18940	0.13136	-0.04910	-0.00248	0.20164	0.19389	-0.25552	0.22630	1.00000
	<.0001	<.0001	<.0001	<.0001	<.0001	0.7461	<.0001	<.0001	<.0001	<.0001	

Panel B: Multicollinearity Diagnostic Statistics

Test	*TFOTL*	*TLTA*	*NOCREDINT*	*COVERAGE*	*RPI*	*SHTBRDEF*	*PRICE*	*ABNRET*	*IDYRISK*	*SIZE*	*MCTD*
TOL	0.48069	0.77587	0.86682	0.44685	0.31244	0.32346	0.61574	0.85806	0.67621	0.5822	0.76426
VIF	2.08035	1.28887	1.15364	2.23787	3.20065	3.09162	1.62407	1.16542	1.47882	1.71761	1.30846

4.5. Methods: Panel Logit Model Specification

The sample is divided into two groups, failed firms and healthy or non-failed firms. The outcome is a binary dependent variable. Our approach is to model the outcome within a panel logit framework, (Altman et al. 2010 and Altman and Sabato 2007), and follow Shumway (2001) and Nan et al. (2008) who show that a panel logit model, that corrects for period at risk and allows for time varying covariates[95], is equivalent to a hazard model. Other influential studies that have used the logit methodology for the development of default prediction models are Keasey and Watson (1987), Peel and Peel (1987), Storey et al. (1987). Among the studies concerned with large firms using the logit methodology we can cite: Martin (1977), Ohlson (1980), Mensah (1984), Gentry et al. (1985), Zavgren (1985, 1988), Platt and Platt (1991), Charitou and Trigeorgis (2000), Becchetti and Sierra (2003), Altman et al. (2010).

The logistic regression model used in this study is based on the following mathematical definition. Let $(Y_1, X_1), \dots (Y_n, X_n)$be a random sample from a conditional logit distribution. Next, let $x_{1j}, x_{2j} \dots x_{kj}$ be a collection of $\mathbf{k}$ independent variables denoted by the vector $\mathbf{x}'$. Assuming that each of these variables is at least interval scaled and that the conditional probability of the outcome is present is denoted by $\Pr(Y = 1|\mathbf{x}) = \boldsymbol{\pi}(\mathbf{x})$ then the logit of the logistic regression model is denoted by:

$$g(\mathbf{x}) = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1^0 X_{1j} + \boldsymbol{\beta}_2^0 X_{2j} + \cdots + \boldsymbol{\beta}_k^0 X_{kj}$$

and

$$\boldsymbol{\pi}(\mathbf{x}) = \frac{\exp \mathrm{g}(\mathbf{x})}{1 + \exp \mathrm{g}(\mathbf{x})}$$

then

$$\Pr[Y_1 = 1|\mathbf{x}'] = \boldsymbol{\pi}(\mathbf{x}) =$$

$$= \Pr\left[Y_j = 1\middle|X_{1j}, \dots X_{kj}\right] = \frac{1}{1 + \exp(-\boldsymbol{\beta}_1^0 X_{1j} - \cdots - \boldsymbol{\beta}_k^0 X_{kj})}$$

therefore

$$\Pr\left[Y_j = 1\middle|X_{1j}, \dots X_{kj}\right] = \frac{1}{1 + \exp(-\sum_{i=1}^{k} \boldsymbol{\beta}_i^0 X_{ij})}$$

[95] Shumway (2010), p. 123.

In addition to the estimates computed through this statistical methodology, marginal effects for each of the variables are also presented. This calculation, despite its usefulness in the interpretation of individual variables on the performance of the model, has been overlooked in previous default/distress prediction models. The present study fills this gap in the literature by computing marginal effects for all variables in the models. The calculations are intended to measure the expected instantaneous change in the response variable as a function of a change in a specific predictor variable while keeping all other covariates constant. The marginal effect of a predictor is defined by the SAS Institute as the partial derivative of the event probability with respect to the predictor of interest[96]. The marginal effects measurement is therefore very useful in order to interpret the effects of the regressors on the dependent variable for discrete dependent variable models, in this case, a logit binary choice model. Marginal effects are therefore mathematically expressed as follows:

For simplicity, consider now the same model but with only one regressor. It is called logit because:

$$\Pr\left[Y_j = 1 \middle| X_j\right] = F(\boldsymbol{\alpha}_0 + \boldsymbol{\beta}_0 X_j)$$

where X_j is the explanatory variable and α_0 and β_0 are unknown parametersto be estimated, and

$$\mathrm{F}(x) = \frac{1}{1 + \exp(-x)}$$

is the distribution function for the logistic (logit) distribution.

If $\boldsymbol{\beta}_0 > 0$ then $\Pr\left[Y_j = 1 \middle| X_j\right] = \mathrm{F}(\boldsymbol{\alpha}_0 + \boldsymbol{\beta}_0 X_j)$ is an increasing function of X_j:

$$\frac{\partial [Y_j = 1 | X_j]}{\partial X_j} = \boldsymbol{\beta}_0 F'(\boldsymbol{\alpha}_0 + \boldsymbol{\beta}_0 X_j)$$

where F' is the derivative of $F(x) = \frac{1}{1+\exp(-x)}$;

$$F'(x) = \frac{\exp(-x)}{(1 + \exp(-x))^2} = \frac{1 + \exp(-x)}{(1 + \exp(-x))^2} - \frac{1}{(1 + \exp(-x))^2}$$

[96] Usage Note 22604: Marginal effects estimation for predictors in logistic and probit models. http://support.sas.com/kb/22/604.html

$$= \frac{1}{1+\exp(-x)} - \frac{1}{(1+\exp(-x))^2} = F(x) - F(x)^2$$

$$= F(x)(1 - F(x))$$

Thus, the marginal effect of X_j on $\Pr[Y_j = 1|X_j]$ depends on X_j:

$$\frac{\partial[Y_j = 1|X_j]}{\partial X_j} = \boldsymbol{\beta}_0 F(\boldsymbol{\alpha}_0 + \boldsymbol{\beta}_0 X_j)(1 - F(\boldsymbol{\alpha}_0 + \boldsymbol{\beta}_0 X_j))$$

In practice, there are two frequently used approaches to estimate either average or overall marginal effects. According to the SAS Institute, one of them is to calculate the marginal effect at the sample means of the data and the other is to estimate marginal effect at each observation and then to compute the sample average of individual marginal effects to obtain the overall marginal effect[97]. For large samples, both approaches yield similar results, however, for the purposes of this analysis; the average of the individual marginal effects is preferred. The present study outputs the marginal effects estimated for each observation in the dataset and then computes the sample average of individual marginal effects in order to obtain the overall marginal effects. SAS software code was employed to get the estimated marginal effects.

[97] See SAS/ETS Web Examples. Computing Marginal Effects for Discrete Dependent Variable Models.

Table 4-3 Summary Statistics for Model 1

This table presents summary statistics for Model 1, which includes only financial statement variables. It covers the Mean, Standard Deviation, Minimum and Maximum Values and the number of observations that were used in the logistic regression for the ratios Total Funds from Operation to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), and Interest Coverage (COVERAGE). Panel A contains summary statistics for the entire dataset; Panel B for financially healthy firms, and Panel C for failed firms.

Variable	*TFOTL*	*TLTA*	*NOCREDINT*	*COVERAGE*
		Panel A: Entire Data Set		
Mean	0.069322	0.485737	-0.120307	0.532898
Std. Dev.	0.337566	0.188089	0.986233	0.818508
Min	-1	-0.432123	-1	-1
Max	1	1	1	1
Observations	18,158			
		Panel B: Financially Healthy Firms		
Mean	0.073826	0.48373	-0.112936	0.545882
Std. Dev.	0.335902	0.187087	0.987091	0.810734
Min	-1	-0.432123	-1	-1
Max	1	1	1	1
Observations	17,843			
		Panel C: Failed Firms		
Mean	-0.185767	0.599386	-0.537879	-0.202545
Std. Dev.	0.33396	0.208933	0.837612	0.916257
Min	-1	0.005761	-1	-1
Max	0.796339	1	1	1
Observations	315			

Table 4-4 Summary Statistics for Model 2.

This table presents summary statistics for Model 2, which includes financial statement ratios as well as macroeconomic variables. It covers the Mean, Standard Deviation, Minimum and Maximum Values and the number of observations that were used in the logistic regression for the ratios Total Funds from Operation to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), Interest Coverage (COVERAGE) the Retail Price Index (RPI), and the proxy for interest rates, the 3-month Short Term Bill Rate adjusted for inflation (SHTBRDEF). Panel A contains summary statistics for the entire dataset; Panel B for financially healthy firms, and Panel C for failed firms.

Variable	*TFOTL*	*TLTA*	*NOCREDINT*	*COVERAGE*	*RPI*	*SHTBRDEF*
			Panel A: Entire Data Set			
Mean	0.068245	0.485506	-0.116483	0.528139	178.27559	2.061429
Std. Dev.	0.339132	0.188782	0.986674	0.821606	32.152036	2.412037
Min	-1	-0.432123	-1	-1	94.59	-4.69551
Max	1	1	1	1	235.18	7.7407
Observations	17,952					
			Panel B: Financially Healthy Firms			
Mean	0.072782	0.483472	-0.108957	0.541189	178.15488	2.060159
Std. Dev.	0.337499	0.187782	0.987519	0.813904	32.242693	2.419031
Min	-1	-0.432123	-1	-1	94.59	-4.69551
Max	1	1	1	1	235.18	7.7407
Observations	17,637					
			Panel C: Failed Firms			
Mean	-0.185767	0.599386	-0.537879	-0.202545	185.03432	2.132532
Std. Dev.	0.33396	0.208933	0.837612	0.916257	25.739411	1.983302
Min	-1	0.005761	-1	-1	115.21	-4.69551
Max	0.796339	1	1	1	235.18	7.1745
Observations	315					

Table 4-5 Summary Statistics for Model 3

This table presents summary statistics for the full model, or Model 3, which includes financial statement ratios, macroeconomic indicators and market variables. It covers the Mean, Standard Deviation, Minimum and Maximum Values and the number of observations that were used in the logistic regression for the ratios Total Funds from Operation to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), Interest Coverage (COVERAGE) the Retail Price Index (RPI), and a proxy for interest rates, the 3-month Short Term Bill Rate adjusted for inflation (SHTBRDEF), the firm's Equity Price (PRICE), the firm's annual Abnormal Returns (ABNRET), the firm's Relative Size (SIZE), and the ratio Market Capital to Total Debt (MCTD). Panel A contains summary statistics for the entire dataset; Panel B for financially healthy firms, and Panel C for failed firms.

Variable	*TFOTL*	*TLTA*	*NOCREDINT*	*COVERAGE*	*RPI*	*SHTBRDEF*	*PRICE*	*ABNRET*	*IDYRISK*	*SIZE*	*MCTD*
Panel A: Entire Data Set											
Mean	0.089856	0.495185	-0.18222	0.582094	178.41205	2.057968	4.408757	-0.098878	0.122309	-10.083135	0.912645
Std. Dev.	0.28928	0.171132	0.976069	0.783736	32.300452	2.474547	1.719708	0.401444	0.080925	2.212375	0.18944
Min	-1	-0.162029	-1	-1	97.82	-4.69551	-4.60517	-0.999987	0.012299	-16.602146	0.002877
Max	1	1	1	1	235.18	7.7407	13.785052	0.997029	0.787179	-2.374161	1
Observations	14,203										
Panel B: Financially Healthy Firms											
Mean	0.094928	0.492868	-0.173282	0.597459	178.26942	2.057772	4.445545	-0.092124	0.120757	-10.044873	0.91643
Std. Dev.	0.286516	0.169794	0.977685	0.772992	32.396525	2.483145	1.691239	0.397685	0.079442	2.206104	0.183715
Min	-1	-0.162029	-1	-1	97.82	-4.69551	-3.912023	-0.999987	0.012299	-16.602146	0.002877
Max	1	1	1	1	235.18	7.7407	13.785052	0.996455	0.751478	-2.374161	1
Observations	13,929										
Panel C: Failed Firms											
Mean	-0.167974	0.612982	-0.636597	-0.198991	185.6627	2.067917	2.538613	-0.442228	0.201189	-12.028228	0.720245
Std. Dev.	0.311704	0.196133	0.764131	0.919496	26.004402	1.992703	2.084033	0.440864	0.111096	1.566622	0.327313
Min	-1	0.052458	-1	-1	115.21	-4.69551	-4.60517	-0.99966	0.015639	-15.922758	0.00588
Max	0.49607	1	1	1	235.18	7.1745	10.96388	0.997029	0.787179	-5.641377	1
Observations	274										

4.6. Analysis of Results.

Tables 4-6 and 4-7 present results from logistic regressions of the corporate default indicator on the predictor variables in *t-1* and *t-2*, respectively. As required by the binary logistic regression model, firms classified as failed were given a value of 1 and firms identified as financially healthy were given the value 0. This classification was carried out using the previously discussed definition of corporate default/insolvency developed specifically for this analysis. The present study develops three main *ex-ante* models to estimate corporate default likelihood and test the contribution of macroeconomic indicators and market variables to the predictive accuracy of models based on financial statement ratios.

Model 1 represents the 'Accounting only' model and incorporates the financial statement ratios Total Funds from Operations to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), and Interest Coverage (COVERAGE). Model 2 represents the 'Accounting plus Macroeconomic' model and includes, in addition to the accounting variables, the indicators Retail Price Index (RPI), and the Short Term Bill Rate adjusted for inflation (SHTBRDEF). Model 3 is the 'Full model' incorporating, in addition to the above financial statement ratios and macroeconomic indicators, five market variables: each firm's Equity Price (PRICE) transformed using the logarithmic function; the firm's cumulative monthly abnormal returns on an annual basis (ABNRET), generated as the firm's excess returns minus the FTSE All Share return index for the same period of time; the idiosyncratic standard deviation of individual security returns (IDYRISK), generated by regressing each stock's monthly returns in year *t-1* on the FTSE-All Share index return for the same year: the idiosyncratic risk is the standard deviation of the residual of this regression; the firm's relative size (SIZE) measured by the market capitalisation relative to the total size (market capitalisation) of the FTSE All Share index, in logarithmic form. Additionally, Model 4 and Model 5 are included in Table 4-6, representing a 'Market only' model and a 'Market plus macroeconomic variables' model, respectively, in order to compare their predictive accuracy with that of Model 1 and Model 2. The objective of this additional comparison is to test the predictive accuracy of accounting models against the performance of market models using logistic regression. Finally, Table 4-7 reports results from logit regressions of the default indicator on the predictor variables for the 5 models using the accounts, market and macroeconomic data from two years prior to the observation of the corporate default event (*t-2*) as further tests of the stability of the individual regressors' coefficients as well as the overall predictive ability of the models.

As mentioned above, the present study develops *ex-ante* models for the estimation of corporate default likelihood. In practice, the date of the event of corporate default is not known and risk managers are required to employ the data that is available at the time of the analysis in order to make an estimate of the likelihood of failure of a company. Accordingly, this study estimates the probability of default in the year prior to the observation of the event of failure (*t-1*) as well as two years prior to the event (*t-2*). In that way, the models provide evidence about the predictors that best discriminate between failed and healthy companies on the one hand, and on the other, test their predictive power. Thus, for the *t-1* models, all of the accounting ratios were computed using the financial statements of the year prior to the corporate default event. Accordingly, the macroeconomic indicators were calculated with information from the year preceding the default event: the Retail Price Index (RPI) in base 100 as well as the 3-month Bill rate (SHTBRDEF), which was annualised and deflated using the inflation rate in order to obtain a measure of the level of 'real' interest rates in the economy. As for the market variables, equity prices (PRICE) were incorporated to the model as the official closing price in *t-1*, the variable measuring abnormal returns (ABNRET) for year *t*, when the default event was observed, was calculated as the return of the firm in year *t-1* minus the FTSE All Share Index return in year *t-1*. Individual firms' annual returns were generated by cumulating monthly returns. The variable reflecting idiosyncratic risk (IDYRISK) or the idiosyncratic volatility of each firm's stock returns was computed as the volatility (standard deviation) of residual return from a linear regression of each firm's monthly returns (one year prior to the observation of the corporate default event) on the return on the FTSE All-Share Index for the same period (*t-1*). With regard to the variable that measures the relative size of the firm (SIZE), following Shumway (2001), individual firms' market capitalisation was measured at the end of the year before the corporate default event year. Finally, as for the ratio Market Capitalisation to Total Debt (MCTD), the latter was also measured with information taken from financial statements issued in *t-1*. The same procedure was followed to estimate the models in *t-2*.

Tables 4-7 and 4-8 report the resulting estimates from logistic regressions of the corporate default indicator on the independent variables for periods *t-1* and *t-2* respectively. All of the variables in the 'Accounting' model (Model 1) are statistically significant at 5-1% in *t-1*, suggesting that they are efficient predictors of the likelihood of corporate failure.

When the model is estimated in *t-2*, or two years before the corporate failure event was observed, the totality of the regressors retain the same level of statistical significance, which indicates that, when used in isolation in a default prediction model, the accounting variables are also consistent over time. Moreover, the coefficient's estimates possess the predicted sign: the negative sign of the proxy for the performance of a company, TFOTL, indicates that the higher the level of funds from operations a company produces (relative to its total liabilities) the higher its performance and, therefore, the lower its probability of corporate default or bankruptcy. Likewise, the sign of the variable NOCREDINT, a proxy for the liquidity of a company, suggests that the higher the level of liquidity of a company, the lower its default likelihood. The COVERAGE variable also displays the anticipated negative sign, where an increased or substantial ability to pay interest on outstanding debt, lowers the firm's corporate default likelihood. Contrary to the previous accounting ratios, the coefficient's estimate for the variable TLTA displays a positive sign, which indicates that a highly leveraged company (a high value of the TLTA variable) will display a higher likelihood of corporate failure. This latter result is also consistent with the present study's initial predictions. Interestingly, the TLTA coefficient displays the highest absolute value amongst the accounting statement variables, followed by TFOTL and COVERAGE, NOCREDINT possessing the smallest absolute value. The same analysis applies for the model estimated in *t-2*, which seems to indicate that the accounting ratios' coefficient estimates are stable over the two periods of time.

Tables 4-6 and 4-7 also present Cox and Snell's *R* squared as well as Nagelkerke's max rescaled R squared in order to have a comparison point of the relative increase or decrease in performance between the models. As expected, Nagelkerke's max rescaled R squared decreases for Model 1 when it is estimated from *t-1* to *t-2*. However, the decline in magnitude is only marginal, which indicates that the models' regressors are stable over time. However, these measures are included only to make comparisons easier, their interpretation needing to be treated with caution, as they do not have the same meaning for logit models as they have for ordinary least squares regressions. As previously discussed, a more appropriate and direct measure of the real performance of a logit model and therefore of the predictive accuracy of the model is the Area Under the Receiver Operating Characteristics Curve (AUC), and whose output will be discussed shortly.

Model 2, in addition to the accounting ratios, incorporates two macroeconomic indicators. Both of them, RPI and SHTBRDEF are statistically significant at 5-1% in the model estimated in *t-1*. In addition, the Nagelkerke's max rescaled R squared increases from 0.1178 to 0.1298 from Model 1 to the 'Accounting plus macroeconomic indicators' model (Model 2), implying that the macroeconomic variables contain additional information relevant to the prediction of corporate default. However, as discussed, the Nagelkerke's statistic is included for comparison purposes only and not as an appropriate measure of the overall predictive accuracy of the model[98]. Moreover, all of the variables included in Model 1 retain their statistical significance as well as the absolute magnitude of their coefficient estimates in Model 2 when it is estimated in *t-1*. However, even if all the accounting variables retain their statistical significance when Model 2 is estimated in *t-2*, there is a decline in the significance of the macroeconomic indicators: when Model 2 is estimated with information two years prior to the observation of the default event, RPI's significance declines from 5-1% to 10%. SHTBRDEF ceases to be statistically significant altogether. These results suggest that accounting ratios are superior in performance to macroeconomic indicators when the model is estimated with information two years prior to the observation of the default event. The signs of both indicators are also as posited in the present study: the positive sign of the RPI's variable's estimate indicates that a high level of inflation entails an increased likelihood of corporate failure. And the positive sign of the SHTBRDEF variable suggests that in a macroeconomic environment characterised by a high level of the real rate of interest, all other things being equal, the probability of failure for industrial firms increases. However, both macroeconomic regressors' estimates are lower in absolute magnitude than the accounting ratios, RPI displaying the smallest in absolute terms, which might suggest a smaller effect of the macroeconomic variables on the likelihood of corporate default.

Model 3 in Table 4-6 and 4-7 presents the results from logit regressions of the corporate failure indicator on the accounting and macroeconomic predictor variables included in Model 2 plus five market variables for the periods *t-1* and *t-2*, respectively: firm's stock prices, lagged abnormal returns, standard deviation of security returns, the relative size of the company and the ratio market capitalisation to total debt. All of the variables that entered Model 3, with the notable exceptions of COVERAGE and IDYRISK, are statistically significant at the 1-5% level when estimated in period *t-1*. COVERAGE and IDYRISK are not statistically significant, but were retained in Model 3 because they increase the predictive accuracy of the model as measured by the AUC. Nevertheless, when the model is estimated in *t-2*, only two accounting variables, (TFOTL

[98] It cannot be interpreted as in linear regression models. In the present case, as the logit methodology is being used to estimate the coefficients, it would be erroneous to say that the variables of Model 2 are able to explain a proportion of variability in a dataset equal to 12.98%. As discussed, an appropriate and reliable measure of the overall predictive accuracy of the model is the area under the receiver operating characteristics curve (AUC), which will be discussed in the following lines.

and NOCREDINT) and all of the market variables retain their statistical significance at the 1-5% levels. The only exception is IDYRISK, whose statistical significance marginally decreases from 1-5% to 10%. As for the macroeconomic indicators, both RPI and SHTBRDEF become insignificant. These results suggest that, when the 'Full' model is estimated in *t-2*, market variables are the most consistent set of regressors over time for the prediction of corporate default, as only two financial statement variables out of four maintain their statistical significance in this period. Interestingly, the variables that entered Model 3 with the highest coefficients in absolute terms in *t-1* are somewhat different when the model is estimated two years prior to default. The variable with the highest magnitude in absolute terms in *t-1*, MCTD, drops to the second place in *t-2*, to be replaced by IDYRISK in the latter period as the variable with the highest coefficient in absolute terms. TFOTL drops from the second to the fourth place, from *t-1* to *t-2*, respectively; TLTA drops from the third place to the fifth; IDYRISK goes up from the fourth place to the first; and ABNRET climbs from the fifth position to the third. In period *t-2*, the order in terms of the absolute magnitude of the coefficients is the following: IDYRISK, MCTD, ABNRET, TFOTL and TLTA. It is worth noting that in period *t-2* the order of the accounting variables relative to the market variables is now inversed, confirming the results obtained through the analysis of the statistical significance of the regressors: market variables possess superior information relevant to the prediction of default when the model is estimated with information two years prior to the event of default.

With regard to the signs of the coefficient estimates, they are all as predicted in the present study: a negative sign of the PRICE variable suggests that there is a negative relationship between equity price levels and the likelihood of failure for public companies, as market equity prices reflect investors' expectations of future cash flows or earnings, and the company's earnings are in turn affected by its financial position. The sign of the ABNRET's estimate, suggests that, as posited, there is a negative relationship between this regressor and the probability of default. Investors do seem to discount the equity of those firms that they consider are in a difficult financial position or close to default/bankruptcy, and the returns of the company seem to be negatively affected in consequence: individual returns of a company outperforming the returns of the FTSE All-Share Index are a sign of good financial health and therefore decrease the likelihood of corporate failure. Contrarily, company's returns that fall short to match the FTSE All-Share Index's returns (negative returns) are a consistent predictor of failure over time (this variable is statistically significant at the 5-1% level when the model is estimated in both *t-1* and *t-2*).

Table 4-6 Logit Regression of Default Indicator on Predictor Variables (*t-1*)

This table reports results from logit regressions of the default indicator on the predictor variables. The models were computed using the accounts, market and macroeconomic data from the year prior to the observation of the corporate default event (*t-1*). Additionally, results are also presented for a 'Market only' model and a Market model that incorporates macroeconomic variables (Model 4 and Model 5 respectively) in *t-1* for comparison purposes. The absolute value of *z*-statistics is reported in parenthesis. * denotes significant at 10%, ** denotes significant at 5%-1%.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
TFOTL	-0.9586**	-0.9158**	-1.0618**		
	(4.40)	(4.20)	(3.85)		
TLTA	1.7946**	1.8134**	0.9503**		
	(6.35)	(6.43)	(2.74)		
NOCREDINT	-0.4173**	-0.4254**	-0.4451**		
	(5.46)	(5.56)	(5.01)		
COVERAGE	-0.6032**	-0.5676**	-0.1630		
	(6.85)	(6.42)	(1.6223)		
RPI		0.0210**	0.0113**		0.00760**
		(5.61)	(2.83)		(2.05)
SHTBRDEF		0.2836**	0.1768**		0.1521**
		(5.45)	(3.46)		(3.20)
PRICE			-0.2545**	-0.2651**	-0.2754**
			(6.83)	(7.58)	(7.74)
ABNRET			-0.8528**	-1.1222**	-1.1090**
			(5.25)	(7.35)	(7.26)
IDYRISK			0.9671	1.7976**	1.7046**
			(1.46)	(3.11)	(2.89)
SIZE			-0.0883**	-0.1861**	-0.1842**
			(1.97)	(4.65)	(4.52)
MCTD			-1.1956**	-1.4131**	-1.3761**
			(4.99)	(7.17)	(6.91)
Constant	-5.0696**	-9.4834**	-6.4931**	-4.4254**	-6.0826**
	(29.84)	(11.79)	(6.31)	(7.54)	(6.67)
Pseudo R^2	0.0189	0.0210	0.0392	0.0332	0.0340
Max-rescaled R^2	0.1178	0.1298	0.2261	0.1876	0.1919

Table 4-7 Logit Regression of Default Indicator on Predictor Variables (*t-2*)

This table reports results from logit regressions of the default indicator on the predictor variables. The models were computed using the accounts, market and macroeconomic data from two years prior to the observation of the corporate default event (*t-2*) in order to confirm their predictive ability. Additionally, results are also presented for a 'Market only' model and a Market model that incorporates market variables in *t-2* for comparison purposes. The absolute value of *z*-statistics is reported in parenthesis. * denotes significant at 10%, ** denotes significant at 5%-1%.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
TFOTL	-0.8048**	-0.7908**	-0.8349**		
	(3.47)	(3.41)	(2.86)		
TLTA	1.3390**	1.3432**	0.6103		
	(4.45)	(4.48)	(1.61)		
NOCREDINT	-0.2858**	-0.2942**	-0.1961**		
	(3.90)	(4.00)	(2.40)		
COVERAGE	-0.4322**	-0.4075**	-0.0127		
	(4.63)	(4.35)	(0.12)		
RPI		0.00674*	-0.00337		-0.00422
		(1.86)	(0.85)		(1.14)
SHTBRDEF		0.0775	-0.0607		-0.0499
		(1.39)	(1.04)		(0.91)
PRICE			-0.2015**	-0.2120**	-0.2145**
			(4.84)	(5.38)	(5.40)
ABNRET			-0.9507**	-0.9401**	-0.9423**
			(5.44)	(6.04)	(6.03)
IDYRISK			1.2865*	1.9630**	2.0769**
			(1.76)	(3.09)	(3.24)
SIZE			-0.0917**	-0.1440**	-0.1488**
			(2.05)	(3.56)	(3.63)
MCTD			-1.1325**	-1.1838**	-1.1787**
			(4.17)	(5.21)	(5.15)
Constant	-4.6273**	-6.0052**	-3.1741**	-4.0867**	-3.2844**
	(26.47)	(7.68)	(3.00)	(6.72)	(3.51)
Pseudo R^2	0.0109	0.0112	0.0244	0.0221	0.0222
Max-rescaled R^2	0.0652	0.0660	0.1388	0.1225	0.1230

On the other hand, the sign of IDYRISK seems to confirm the initial prediction of this study that the standard deviation of security returns is positively related to the probability of default. In other words, the sign of the estimated coefficient confirms that, all things being equal, the greater the volatility of security returns, the higher the likelihood of default. The sign of MCTD indicates a negative relationship between this variable and the probability of corporate default. This study expected this ratio to enhance the predictive accuracy of the model and to be consistent over time as it was constructed to include, on the one hand, a market approach (through the measure of market capitalisation) and, on the other, to solve the problem highlighted in Beaver et al. (2005), namely that the variables ABNRET, SIZE and IDYRISK are not scaled in that they are not compared to the magnitude of debt outstanding. By including total debt as denominator, it solves the problem without giving rise to multicollinearity problems with the variable SIZE. As expected, MCTD is a powerful as well as consistent predictor of failure over time (it remains statistically significant at the 1-5% level in *t-2*, and it displays the highest coefficient in absolute terms in *t-1* and the second in *t-2*). The sign of the market variable SIZE is also as predicted: companies with a high level of SIZE (high market capitalisation relative to the FTSE All-Share market capitalisation) are more stable or (and/or well established), indicating a good level of the debt holders' 'equity cushion,' far from the 'strike price' (or the value of liabilities), and therefore judged by investors as capable of serving their debt obligations, which lowers the firm's probability of failure. From Model 3, it can be concluded that market variables possess information relevant to the prediction of default that complements the information provided by the financial statement indicators. Moreover, when Model 3 is estimated in *t-2*, market variables show a superior performance as measured by the temporal consistency suggested by the analysis of their statistical significance.

Table 4-8 presents model performance statistics for the five models estimated in both *t-1* and *t-2*. The area under the ROC curve (AUC) is a direct and appropriate measure of the predictive accuracy of models developed using the logit methodology. DeLong et al. (1998) state that argue that 'when a test is based on an observed variable that lies on a continuous grade scale, an assessment of the overall value of the test can be made through the use of a receiver operating characteristics (ROC) curve.' [99] Furthermore, Altman et al. (2010) state that 'The ROC curve plots the true positive against the false positive rate as the threshold to discriminate between failed and non-failed firms' changes. The area under the ROC curve is a measure of the predictive accuracy of the model, with a value of 1

[99] P. 837

representing a perfect model.' Gini rank correlation coefficients [100] and Kolmogorov-Smirnov statistics, also presented in Table 4-8, are widely used analysis tools by scoring analysts to assess the predictive accuracy of in-sample and hold-out tests (Altman et al., 2010). The advantage of these tests is that they are easy to interpret and to calculate, as both can be derived from the AUC. As Anderson (2007) argues, the Gini rank coefficient has been co-opted by credit scoring analysts who employ it as a measure of 'how well a scorecard is able to distinguish between goods and bads' where 'the end result is a value representing the area under the curve.' The Gini coefficient is very similar to the AUC, the difference being that the former calculates only the area between the curve and the diagonal of the Lorenz curve, whereas the latter calculates the full area below the curve[101]. As a reference point, in the context of professional credit scoring analysis, a Gini coefficient equal to or above 50% is a very satisfactory level in a retail environment, as discussed by Anderson (2007). In the context of the present study, the Gini rank coefficient is used in order to complement and check the consistency of the other measures presented.

The Kolmogorov-Smirnov test is performed to measure the maximum vertical deviation between two empirical cumulative distribution functions (good and bad) in credit score modelling. This measure is, according to Anderson (2007) and Mays (2004), 'the most widely used statistic within the United States for measuring the predictive power of rating systems.' [102] However, Anderson (2007) recommends not using this this statistic (or any other measure of the predictive accuracy of a model) in isolation, but rather as a complement to others such as the AUC or the Gini rank correlation coefficient, which is the approach adopted in the present study. Mays (2004) suggests that the acceptable values for this statistic range from 20% to 70%, above which the model is 'probably too good to be true.' Cox and Snell's R-squared is a measure based on the log-likelihood of the model, the log-likelihood of the original (baseline) model and the sample size, and Nagelkerke's Max-rescaled R-squared is a refinement of the former. In other words, both can be considered as measures of the same concept. In general, they can also be interpreted similarly (but not identically), to the R-squared in linear regression, as they are measures of the significance of the model[103]. The Hosmer-and-Lemeshow goodness-of-fit test for binary response logistic models is also provided. As discussed by Ragavan (2008), the subjects are divided into approximately ten groups of roughly the same size based on the

---

[100] The Gini rank correlation coefficient can be found as the Somer's D statistic in the SAS software and most statistical software packages.
[101] As such, it can be computed as ((2*AUC)-1) following Altman et al. (2010).
[102] Anderson (2007), p. 196
[103] See Cox and Snell (1989) and Nagelkerke (1991).

percentiles of the estimated probabilities. The discrepancies between the observed and expected number of observations in these groups are summarised by the Pearson chi-square statistic, which is then compared to a chi-squared distribution with *k* degrees of freedom, where *k* is the number of groups (11) minus *n* (2).[104] Thus, a small chi-square (<15) and a large *p*-value (>0.05) should suggest that the model is effective to predict the behaviour of the data, or that the fitted model is an appropriate one to be employed in order to predict the specified binary outcomes in the dataset.

Table 4-8 reports the performance of all the models in the study. From the results presented in Section A, which correspond to the models estimated in period *t-1*, it can be concluded that the addition of macroeconomic indicators and specially market variables can enhance substantially the performance of corporate default prediction models based on financial statement information. Moreover, it is demonstrated that a parsimonious default prediction model using information that is widely available to academics as well as practitioners, can display a high discriminating and predictive accuracy; in the present study, a comprehensive model (Model 3 or the 'full' model) that includes a set of three types of variables yields an AUC as high as 0.8685 when the model is estimated with information available one year prior to the default event. Unsurprisingly, in period *t-2*, when information available two years prior to default is employed, the predictive accuracy of the model decreases to 0.8004. These results suggest that the regressors retained in the model act as complementary and not as substitutes (or mutually exclusive). It is also important to highlight the fact that the high discriminating and predictive power of the full model in the present study might be explained by the specific combination of variables, which were selected taking into consideration the problems highlighted in previous research works with regard to the representation of the main, most likely, and potential indicators of corporate failure. A very large number of financial ratios, macroeconomic indicators and market variables were tested. Redundant or highly correlated variables (that could give rise to multicollinearity problems) were discarded, indicators that have proven their contribution to the performance of the models in previous research were included, and potentially useful new ones were tested. An example of a new indicator that had not yet been tested is the ratio market capitalisation to total debt (MCTD), which proved to contain information useful to the prediction of corporate failure. The result was a new prediction model with a new set or combination of variables for quoted companies in the

[104] P. 10.

United Kingdom that proved to be very well positioned relative to previous and well-known models for the prediction of corporate default[105].

The predictive accuracy of Model 1, the 'accounting only' model, is enhanced (although marginally) when two macroeconomic indicators (RPI and SHTBRDEF) are included. As measured by the area under the ROC curve, the performance in *t-1* is increased from 0.7911 to 0.8032. This suggests that macroeconomic variables contribute positively, though marginally, to the performance of a model based on financial statement information. As the Gini rank correlation coefficient and the Kolmogorov-Smirnov statistics are derived from computations based on the level of the AUC, it is not surprising that they follow the same pattern as the latter, and fall into the above mentioned highest ranges judged as acceptable by credit scoring professionals. Moreover, when market variables are incorporated into a comprehensive model that uses accounting ratios and macroeconomic indicators as inputs (Model 3), a considerable increase in the predictive accuracy of the model can be observed: in period *t-1*, the AUC is enhanced from 0.8032 to 0.8685 (from Model 2 to Model 3, respectively); this magnitude of the enhancement indicates that market variables contain a substantial amount of information that is not available in financial statements but that was taken into consideration by investors and market participants and act as a complement to the information provided by accounting ratios[106]. Furthermore, the present study also estimates Model 4 and Model 5 in order to directly compare the performance of the 'accounting only' model (Model 1) and the 'accounting plus macroeconomic variables' model (Model 2) against the 'market only' model (Model 4) and the 'market plus macroeconomic variables' model (Model 5) respectively.

From Panel A in Table 3-9 it can be observed that Model 4 displays an AUC of 0.8448, which indicates a considerably superior predictive accuracy than Model 1 (AUC = 0.7911). On the other hand, when macroeconomic indicators are added to both the market and accounting models, in Model 5 and Model 2, they display an AUC of 0.8496 and 0.8032, respectively. It is also important to note that the model with the highest predictive

[105] With the advantages of accuracy, simplicity and timeliness.

[106] An example of the information that is not included in financial statements (as by nature they contain only past information), might be the information regarding the future prospects of a firm such as an insufficient level of Research and Development expenditure, or the negative forecast for a specific industry due to industry-specific micro or macroeconomic developments taking place. Information of this kind is typically taken into account by investors and market participants in their analysis and is therefore reflected by market variables only such as equity prices or firms' returns.

accuracy is Model 3, the 'full' model, which yields an AUC of 0.8685; followed by Model 4 (the market plus macroeconomic indicators model), with an AUC equal to 0.8448; and Model 5 (the 'market only' model) with an AUC equal to 0.8496. The two accounting models follow with a considerable lag: Model 2 AUC is equal to 0.8032 and Model 3 AUC is equal to 0.7911. These results clearly indicate that market variables display a superior performance relative to accounting variables for the prediction of corporate failure in *t-1*, both in isolation and when macroeconomic indicators are included.

Table 4-8 Model Performance Measures

This table reports model performance statistics. Panel A shows measures for the five models estimated in period *t-1,* and Panel B displays the same measures for all of the models estimated in *t-2*. Model 1 is the 'accounting only' model, Model 2 is the 'accounting plus macroeconomic variables' model, Model 3 is the 'full' model, including market variables in addition to the variables in Model 2, Model 4 is the 'market only' model, and Model 5 is the 'market plus macroeconomic variables' model. The first measure is a direct measure of the predictive accuracy of models estimated using the logit methodology, the Area under the Receiver Operating Characteristics Curve (AUC); Gini coefficients, Kolmogorov-Smirnov statistics, Cox and Snell's R-squared, Nagelkerke's Max-rescaled R-squared and the models' Chi-squared are also presented. Additionally Hosmer and Lemeshow goodness-of-fit statistics are displayed.

Measure	Model 1	Model 2	Model 3	Model 4	Model 5
Panel A: Models' Performance in *t-1*					
AUC	0.7911	0.8032	0.8685	0.8448	0.8496
Gini Rank Coefficient	0.5822	0.6064	0.7370	0.6896	0.6992
Kolmogorov-Smirnov	0.4658	0.4851	0.5896	0.5517	0.5594
Cox & Snell's R^2	0.0189	0.0210	0.0392	0.0332	0.0340
Nagelkerke's R^2	0.1178	0.1298	0.2261	0.1876	0.1919
$\chi 2$* (4, 6, 11, 5, 7)	346.88	381.44	568.37	520.56	532.72
	(P<.0001)	(P<.0001)	(P<.0001)	(P<.0001)	(P<.0001)
Hosmer & Lemeshow Goodness-of-Fit Test					
χ^2 (8)	22.3816	13.9554	13.7600	18.1780	28.9434
Pr> χ^2	<.0043	<.0829	0.0882	0.0199	0.0003
Panel B: Models' Performance in *t-2*					
AUC	0.7140	0.7151	0.8004	0.7870	0.7868
Gini Rank Coefficient	0.4280	0.4302	0.6008	0.5740	0.5736
Kolmogorov-Smirnov	0.3424	0.3442	0.4806	0.4592	0.4589
Cox & Snell's R^2	0.0109	0.0112	0.0244	0.0221	0.0222
Nagelkerke's R^2	0.0652	0.0660	0.1388	0.1225	0.1230
$\chi 2$* (4, 6, 11, 5, 7)	173.8020	175.3484	300.7597	295.1036	296.3873
	(P<.0001)	(P<.0001)	(P<.0001)	(P<.0001)	(P<.0001)
Hosmer & Lemeshow Goodness-of-Fit Test					
χ^2 (8)	15.7295	8.3365	14.4307	4.7655	6.6192
Pr> χ^2	0.0464	0.4013	0.0712	0.7823	0.5782

* the parenthesis following the model's $\chi 2$ represent the degrees of freedom for each estimated model: 4 for Model 1, 6 for Model 2, 11 for model 3, 5 for Model 4, and 7 for Model 5.

Table 4-8 also presents the results of Hosmer and Lemeshow goodness-of-fit tests. According to the results shown in Panel A, Model 3 or the comprehensive model, is the most appropriate model to predict the data (to better discriminate and predict the specific binary outcomes in the dataset: healthy from failed companies). The test shows that Model 3 is the model with the smallest chi-squared and the largest *p*-value, suggesting that it is the most adequate. This conclusion finds additional support in the larger AUC of Model 3 relative to the rest of the models. These results should be, however, treated with caution: different results have been obtained in previous research works and its consistency and reliability are still subjects of controversy. In *t-1*, for instance, the Hosmer and Lemeshow goodness-of-fit tests show a large chi-square (>15) and a small *p*-value (<0.05) for Model 4 and Model 5, the 'market only' model and the 'market plus macroeconomic indicators' model, indicating that, despite a high predictive accuracy, the models might lack other independent variables that are capital in order to explain a higher proportion of the phenomenon that they are trying to elucidate[107]. On the other hand, it can be observed that the opposite is true for Model 2, which shows a small chi-square (13.9554) and a large p-value (0.0829), suggesting that this is an adequate model in spite of showing a lower predictive accuracy as measured by the AUC than both market models, Model 4 and Model 5.

Unsurprisingly, the predictive accuracy of the models estimated in *t-2* experience a decrease, which is consistent with previous default prediction models. However, the same patterns can be observed when financial statement ratios, macroeconomic indicators and market variables are combined in a single model. The only exception can be found between Model 4 and Model 5; when macroeconomic indicators are added to the 'market only' model, there is a very small decrease in predictive accuracy (from an AUC of 0.7870 to an AUC of 0.7868, respectively), indicating that market variables are (marginally) more reliable regressors than macroeconomic indicators when the probability of corporate failure is estimated with information available two years prior to the default event (*t-2*). However, because of the inconsequential decrease in performance, it could also be argued that the predictive accuracy remains unchanged when macroeconomic indicators are incorporated in a market model estimated in *t-2*. With reference to Model 3, it can be concluded that the addition of market variables to Model 2 (estimated in *t-2*) considerably increases the predictive accuracy by an even more impressive magnitude as when it was estimated in period *t-1*: from an AUC of 0.7151 to 0.8004. Furthermore, the Gini rank correlation

[107] The same analysis applies for Model 1, which is more consistent with its predictive accuracy: Model 1 shows the lowest predictive accuracy and the Hosmer and Lemeshow goodness-of-fit tests show a large chi-square and a small *p*-value, suggesting that the model lack other variables to explain a higher proportion of the phenomenon in question.

coefficients as well as the Kolmogorov-Smirnov tests display patterns consistent with the above discussion and confirm the previous results, both the results estimated in *t-1* and the ones estimated in *t-2*. Finally, the predictive accuracy of the models presented in this study can be located in the high end of the ranges specified by professional credit managers when measured through the Gini rank correlation coefficient and the Kolmogorov-Smirnov statistic.

As stated by Cleves (2002), 'occasionally, there is a need to compare the predictive accuracy of several fitted logit (logistic) or probit models by comparing the areas under the corresponding receiver operating characteristics (ROC) curves.' [108] In order to perform the comparisons, the present study applies for the first time, in failure prediction models, a methodology based on a non-parametric approach that employs the theory developed for generalised Man-Whitney *U*-statistics. The present study follows the methodology presented in DeLong et al. (1998) and takes thus into account the correlated nature of the data that arises when two or more empirical curves are constructed using tests performed on a same set of firms. This issue is paramount as most of the comparisons of ROC curves made in previous studies, not only in the field of finance but also in fields such as atmospheric science and medical diagnosis, for which predictions of specific outcomes are essential, employ the already available computations in most statistical analysis software packages. The problem with this approach is that the models to be compared (derived using the same dataset) are estimated on the same number or set of observations. For instance, as highlighted by Cleves (2002), when the commands 'roccontrast' in SAS or 'roccomp' in STATA are employed to compare the curves after running the logistic procedure, the programs use the same number of observations for all models, as they drop from the computation any observation[109] in which at least one of the covariate values is missing (which evidently varies between models). Therefore, difficulties can arise if there are missing values included in some models but not in others, as the exclusion of valid observations that would have otherwise been used in the normal estimation of the logit model, lead to erroneous and inconsistent computations of the area under the receiver operating characteristics curve.

---

[108] P. 301

[109] Stata's 'roccomp' command also drops from the computation any observation in which at least one of the predicted probabilities is missing. See Cleves (2002).

The comparison of curves in the present study takes into account the correlated nature of the data[110], on the one hand, and solves the problem of comparison of two or more models using a constant number of observations, on the other. Following DeLong et al. (1998) and combining the use of the SAS logistic statistical methodology (PROC LOGISTIC) with the ROC macros available from the SAS Institute[111], the present study reports a very useful visual comparison of the differences in predictive accuracy of the 'accounting only' model, the 'accounting plus macroeconomic indicators' model and the 'full' model using a non-parametric approach based on the theory on generalised Man-Whitney *U*-statistics. The graphic is constructed plotting the models' ability to identify true positives (sensitivity), on the Y axis, and its ability to detect true negatives (1-specificity). In other words, each individual ROC curve is generated (in the field of corporate failure prediction models) by plotting the proportion of true failed companies out of the companies classified by the model as failed ('True Positive Rate') against the proportion of false failed companies (healthy companies) out of the firms classified by the model as failed ('False Positive Rate') at various cutpoints. As to the use and interpretation of the plots' results, 'if a test could perfectly discriminate, it would have a value above which the entire abnormal population would fall and below which all normal values would fall (or vice versa). The curve would then pass through the point (0, 1) on the unit grid. The closer a ROC curve comes to this ideal point, the better its discriminating ability. A test with no discriminating ability will produce a curve that follows the diagonal of the grid.'[112] Additionally, the areas under the receiver operating characteristics curve of the three fitted models are tested for equality, where an overall p-value below 0.05 is indicative of differences between the areas. In other words, an overall p-value <0.05 signifies that the null hypothesis of equality of areas under the ROC curve can be rejected, thus confirming the reliability of the results.

The nonparametric comparison of the areas under correlated ROC based on the theory developed for generalised Man-Whitney *U*-statistics was performed, initially, on three models estimated in *t-1*: the 'accounting only' model, the 'accounting plus macroeconomic indicators' model, and the 'full' model that includes market variables. Then, another comparison based on the area under the ROC curve was performed between the 'full' model and the two market-based model (the 'market only' model and the

[110] The implicit correlation between the curves when two or more empirical curves are constructed using tests performed on a same set of firms.

[111] The use of the SAS PROC LOGISTIC and the macros available from the SAS Institute results in a method capable of comparing each model's receiver operating characteristics area computed using the entire available number of observations specific to each individual model and not a constant number of observations for all models, thus avoiding the problem highlighted by Cleves (2002).

[112] DeLong et al. (1988), p. 837

'market plus macroeconomic indicators' model) with the aim of presenting graphically the increase in predictive accuracy of a comprehensive model (including financial statement information, macroeconomic indicators and market variables) relative to models based on financial information and market variables respectively, on the one hand, and to test whether the AUC differs statistically between the models, on the other. Moreover, the above procedure for the three models estimated in *t-1* was repeated for the same three models estimated in *t-2*. The present study presents thus four figures allowing a comparison between models and between estimation periods that facilitates the analysis of the differences in predictive accuracy as well as the contribution of the different sets of variables (financial statement ratios, macroeconomic indicators, and market variables) over time. Figures 4-1 to 4-4 show a graphic representation of the discussion drawn from Table 3-9, with regard to the differences in the predictive accuracy of the models through the interpretation of their respective AUCs. First, with regard to the macroeconomic indicators, it can be confirmed that they contribute positively (though marginally) to the performance of the accounting model when it is estimated in both periods *t-1* and *t-2*. The same analysis applies when macroeconomic indicators are added to the market model in *t-1*; they contribute positively but marginally to its predictive accuracy. However, the results are less conclusive when macroeconomic indicators are added to the market model in *t-2*: their inclusion even results in a very small decrease in performance. It can be thus concluded that market variables contain more information relevant to the prediction of corporate default than macroeconomic indicators when the model is estimated with information two years prior to the event of default.

Second, the figures show that when the comprehensive (Model 3 or 'full' model) model is employed as a benchmark to assess the individual performance of the accounting (Figure 3-1 and 3-3) and market (Figure 3-2 and 3-4) models respectively, the 'full' model performs better than both of them individually. In other words, this clearly suggest that the likelihood of default is better captured by models that combine accounting and market variables than by individual models using one or the other set of variables in isolation. Third, the figures clearly show that the distance between the ROC curves of the market models and the comprehensive model are considerably smaller than the distance between the ROC curves of the accounting models and the comprehensive model in both *t-1* and *t-2*. This indicates that the benefit of including market variables to an accounting model is greater than the benefit of including accounting variables to a market model: moreover, when the models are estimated in *t-2* the distance is smallest between the market and comprehensive models, suggesting that they perform very similarly when they are estimated using information two years prior to the event of default. In other words, when employed in isolation, market variables seem to possess a higher explanatory power than accounting variables, as the performance of market variables closely follows the performance of the 'full' model, especially in *t-2*, where the difference is smallest. Finally, it is interesting to note that the four comparisons of the areas under the curve show an overall *p*-value =< 0.0001, which indicates that the null hypothesis (H0) of equality of areas under the ROC curve can be rejected. In other words, the small *p*-value resulting from the test strongly suggests that the three areas differ statistically and that therefore the analysis is reliable.

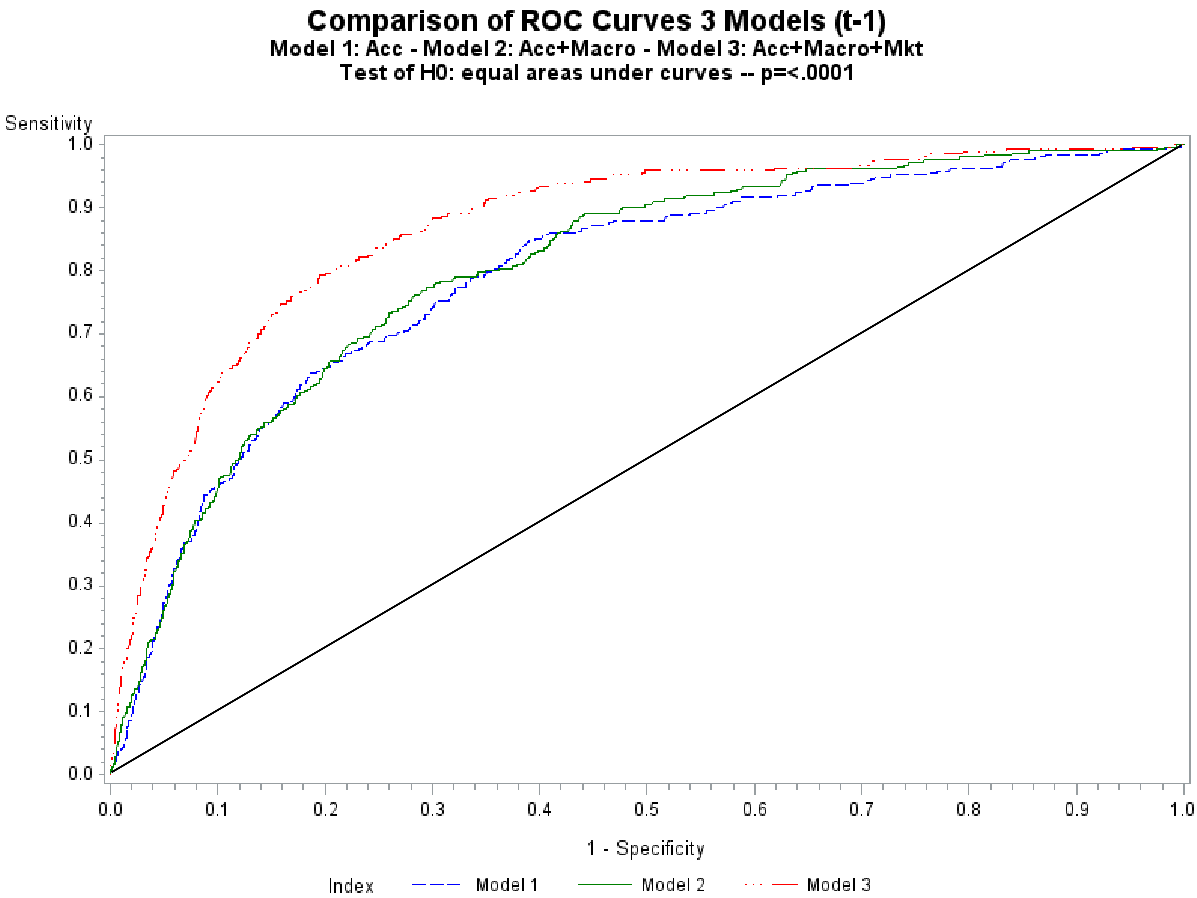

Figure 4-1 Comparison of Areas under the Receiver Operating Characteristic Curve of Model 1, Model 2, and Model 3 estimated in period *t-1*

The figure plots the AUC of the 'accounting only' model, the 'accounting plus macroeconomic indicators' model and the 'full' model, including market variables; Model 1, Model 2, and Model 3 respectively, estimated in period *t-1*. The comparison was performed using the non-parametric method to compare areas under correlated ROC curves presented in DeLong et al. (1988), where Model 1 AUC = 0.7911, Model 2 AUC = 0.8032, and Model 3 AUC = 0.8685. The discriminating accuracy of a model's AUC equal to the diagonal line in the graphic (0.50) would be no different than a random guess. Conversely, an AUC equal to 1 would signify that the model is able to perfectly discriminate the binary outcomes. Therefore, the closer the real value of an AUC to this theoretical value, the better its discriminating ability. The overall *p*-value =< 0.0001 indicates that the null hypothesis of equality of areas under the ROC curve can be rejected. In other words, the small *p*-value of this test strongly suggests that the three areas differ statistically.

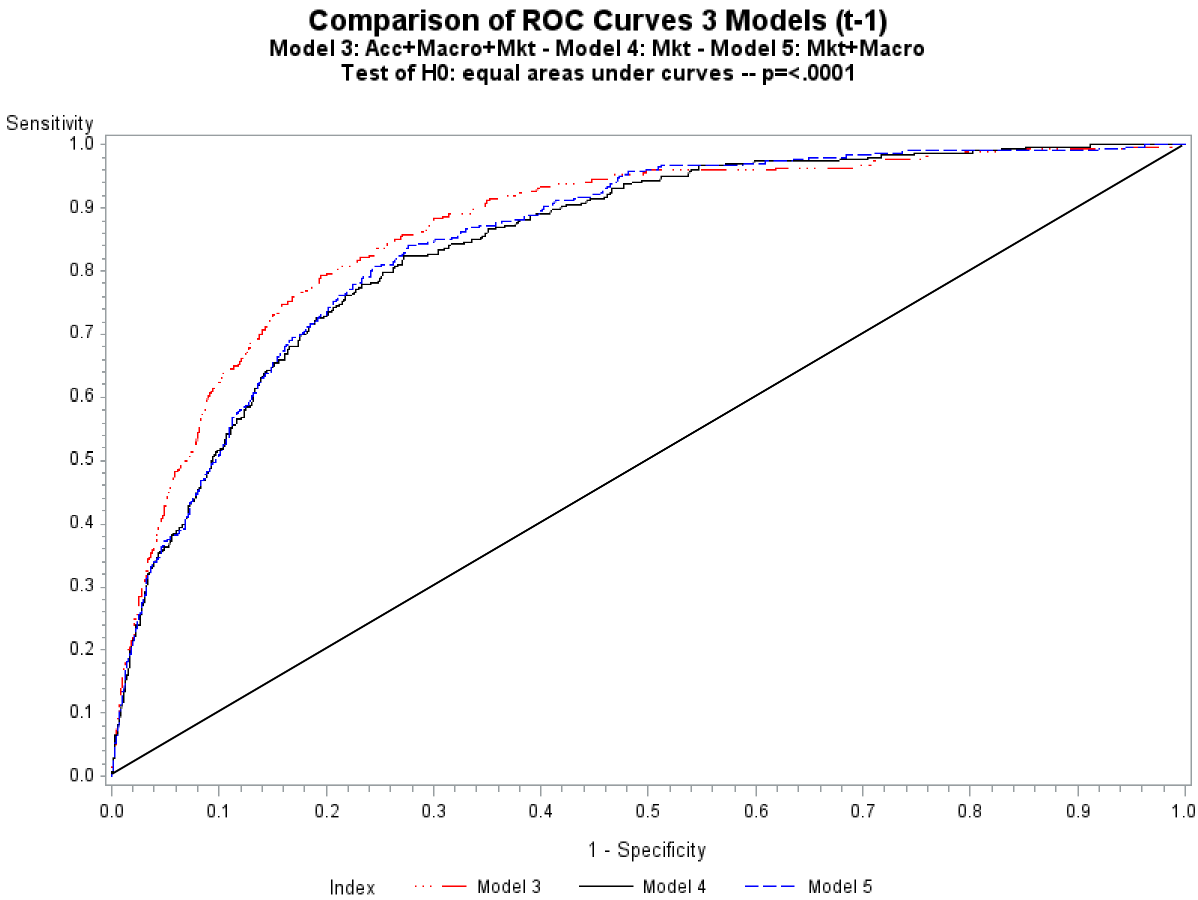

Figure 4-2 Comparison of Areas under the Receiver Operating Characteristic Curve of Model 3, Model 4, and Model 5 estimated in period *t-1*

The figure plots the AUC of the 'full' model, the 'market only' model and the 'market plus macroeconomic indicators' model; Model 3, Model 4, and Model 5 respectively, estimated in period *t-1*. The comparison was performed using the non-parametric method to compare areas under correlated ROC curves presented in DeLong et al. (1988), where Model 3 AUC = 0.8685, Model 4 AUC = 0.8448, and Model 5 AUC = 0.8496. The discriminating accuracy of a model's AUC equal to the diagonal line in the graphic (0.50) would be no different than a random guess. Conversely, an AUC equal to 1 would signify that the model is able to perfectly discriminate the binary outcomes. Therefore, the closer the real value of an AUC to this theoretical value, the better its discriminating ability. The overall *p*-value =< 0.0001 indicates that the null hypothesis of equality of areas under the ROC curve can be rejected. In other words, the small *p*-value of this test strongly suggests that the three areas differ statistically.

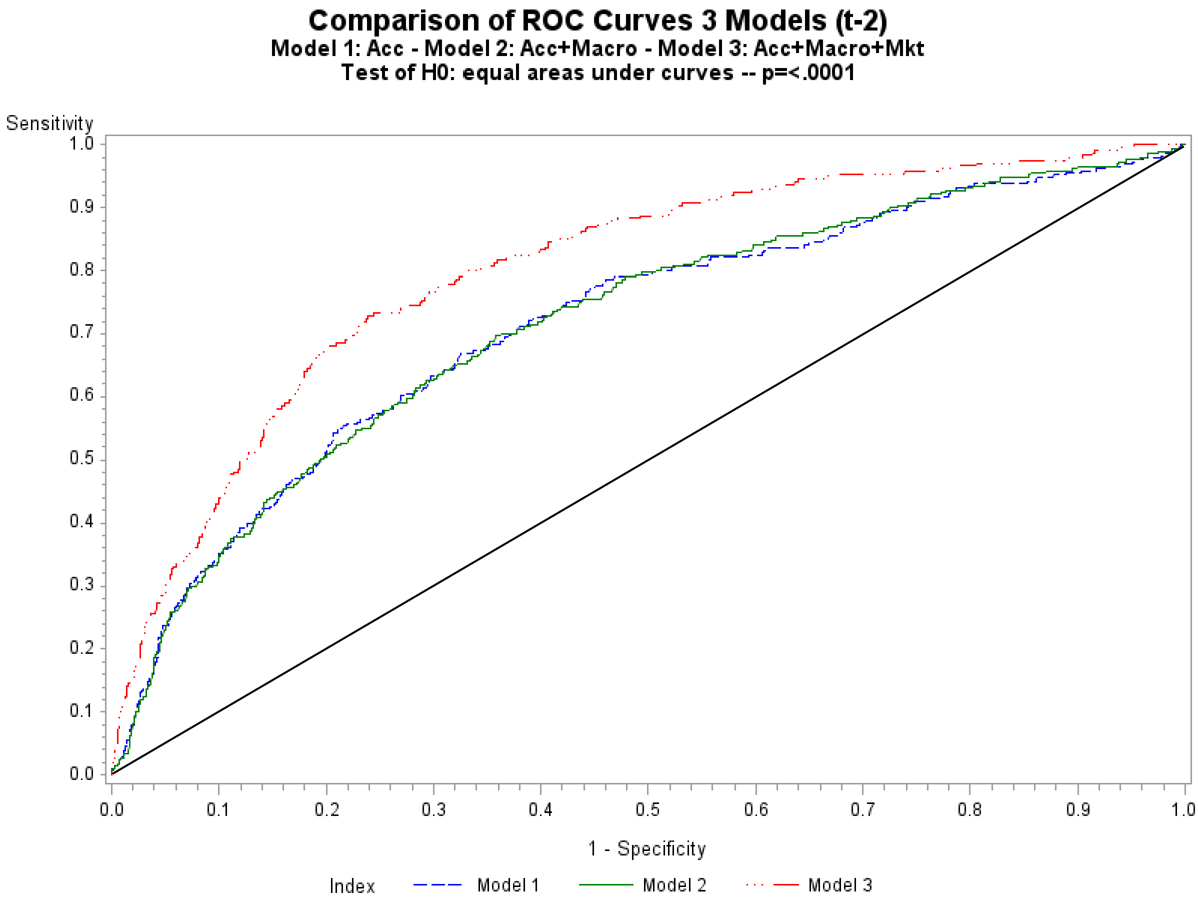

Figure 4-3 Comparison of Areas under the Receiver Operating Characteristic Curve of Model 1, Model 2, and Model 3 estimated in period *t-2*

The figure plots the AUC of the 'accounting only' model, the 'accounting plus macroeconomic indicators' model and the 'full' model, including market variables; Model 1, Model 2, and Model 3 respectively, estimated in period *t-2*. The comparison was performed using the non-parametric method to compare areas under correlated ROC curves presented in DeLong et al. (1988), where Model 1 AUC = 0.7140, Model 2 AUC = 0.7151, and Model 3 AUC = 0.8004. The discriminating accuracy of a model's AUC equal to the diagonal line in the graphic (0.50) would be no different than a random guess. Conversely, an AUC equal to 1 would signify that the model is able to perfectly discriminate the binary outcomes. Therefore, the closer the real value of an AUC to this theoretical value, the better its discriminating ability. The overall *p*-value =< 0.0001 indicates that the null hypothesis of equality of areas under the ROC curve can be rejected. In other words, the small *p*-value of this test strongly suggests that the three areas differ statistically.

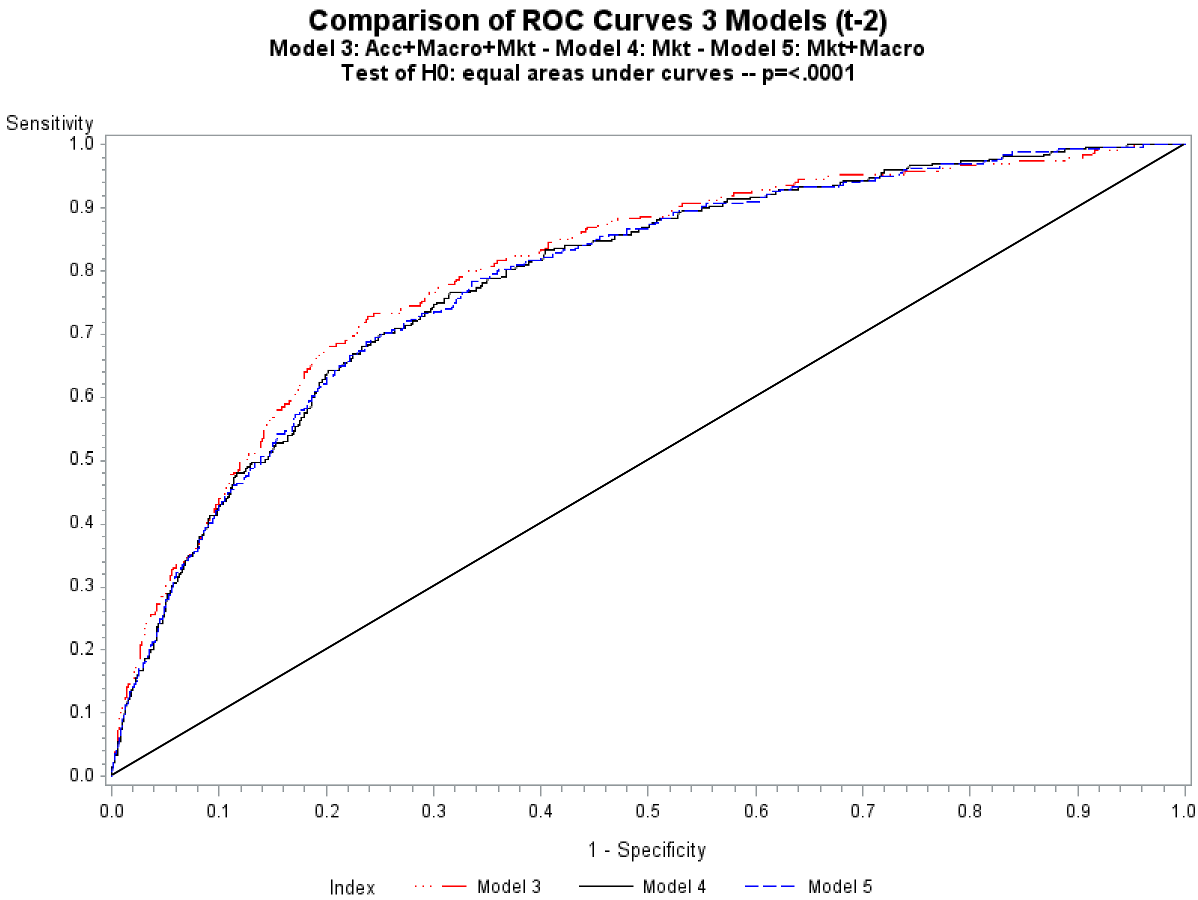

Figure 4-4 Comparison of Areas under the Receiver Operating Characteristic Curve of Model 3, Model 4, and Model 5 estimated in period *t-2*

The figure plots the AUC of the 'full' model, the 'market only' model and the 'market plus macroeconomic indicators' model; Model 3, Model 4, and Model 5 respectively, estimated in period *t-2*. The comparison was performed using the non-parametric method to compare areas under correlated ROC curves presented in DeLong et al. (1988), where Model 3 AUC = 0.8004, Model 4 AUC = 0.7870, and Model 5 AUC = 0.7868. The discriminating accuracy of a model's AUC equal to the diagonal line in the graphic (0.50) would be no different than a random guess. Conversely, an AUC equal to 1 would signify that the model is able to perfectly discriminate the binary outcomes. Therefore, the closer the real value of an AUC to this theoretical value, the better its discriminating ability. The overall *p*-value =< 0.0001 indicates that the null hypothesis of equality of areas under the ROC curve can be rejected. In other words, the small *p*-value of this test strongly suggests that the three areas differ statistically.

4.6.1. Marginal Effects and Changes in Predicted Probabilities.

The parameters estimated from binary response models, unlike those estimated by linear models, cannot be directly interpreted because they do not provide useful information that fully describes the relationship between the independent variables and the outcome (Long and Freese, 2003). Previous financial distress and corporate failure prediction models constructed using binary response methodologies invariably focus on the overall discriminating and/or predictive accuracy of the models and very rarely do they provide an interpretation of the relationship between the predictor variables and the binary outcome. Such studies report solely the estimates obtained from binary response models and provide an interpretation of the direction of the relationship based on the sign of the estimate. Nevertheless, the basic output (the coefficient estimates) obtained by performing binary response models cannot explain the effects of the individual variables on the model's outcomes because of their non-linear nature. Marginal effects and changes in predicted probabilities are appropriate tools to treat this issue.

This section presents results of the computation of marginal effects of individual regressors as well as graphic representations of predicted probabilities of failed companies. This section intends to fill an important gap in the default/financial distress prediction literature, where the measurement of expected instantaneous changes in the response variable (corporate default in the present study) as a function of a change in a specific predictor variables while keeping all the other covariates constant, has been overlooked. As previously discussed, marginal effects measurements (defines as the computation of the partial derivative of the event probability with respect to the predictor of interest) are very useful to the interpretation of the individual effects of the regressors on the dependent variable in discrete dependent variable models, or binary response models (logit regression in the present study). With regard to their calculation, the present's study's methodology consists of outputting the marginal effects estimated at each observation in the dataset and then computing the sample average of individual marginal effects in order to obtain the overall marginal effects. SAS statistical software code was employed to generate the estimated marginal effects. Figures of changes in predicted probabilities were generated by plotting the vector reflecting the variations in the predicted probability of default (the predicted probability that the failure indicator, Corporate_Default = 1) when the change in an individual regressor ranges from its approximate minimum to its maximum observed value, keeping all the other covariates constant at their means[113].

[113] The SAS statistical package was also employed for this calculation.

Table 4-9 Marginal Effects

This table reports the marginal effects (in percentages) for the 'accounting only' model, the 'accounting plus macroeconomic indicators' model, the 'full' model including also market variables, or Model 1, Model 2 and Model 3 respectively. Additionally, marginal effects are generated for a 'market only' model and a 'market plus macroeconomic variables,' Model 4 and Model 5, for comparison purposes. *n* represents the number of observations. Marginal effects are intended to measure the expected instantaneous changes in the response variable (the corporate default indicator) as a function of a change in a specific predictor variable while keeping all the other covariates constant. The methodology used in the present study to generate the marginal effects consists of outputting the individual marginal effects estimated at each observation in the dataset and then calculating their sample average in order to obtain the overall marginal effect.

Variable	Model 1		Model 2		Model 3		Model 4		Model 5	
	t-1	*t-2*	*t-1*	*t-2*	*t-1*	*t-2*	*t-1*	*t-2*	*t-1*	*t-2*
TFOTL	-1.592	-1.438	-1.529	-1.431	-1.842	-1.537				
TLTA	2.980	2.392	3.028	2.431	1.648	1.123				
NOCREDINT	-0.693	-0.511	-0.710	-0.532	-0.772	-0.361				
COVERAGE	-1.002	-0.772	-0.948	-0.737	-0.283	-0.023				
RPI			0.035	0.012	0.020	-0.006			0.014	-0.008
SHTBRDEF			0.474	0.140	0.307	-0.112			0.276	-0.096
PRICE					-0.441	-0.371	-0.483	-0.408	-0.500	-0.413
ABNRET					-1.479	-1.750	-2.046	-1.810	-2.012	-1.813
IDYRISK					1.678	2.368	3.278	3.779	3.093	3.996
SIZE					-0.153	-0.169	-0.339	-0.277	-0.334	-0.286
MCTD					-2.074	-2.085	-2.577	-2.279	-2.497	-2.268
n	18,276	15,909	18,070	15,703	14,255	12,249	15,468	13,263	15,468	13,263

The marginal effects presented in Table 4-9 reflect a measure of the impact of the regressors on the response variable. Marginal effects were computed for all five models with information one and two years prior to the event of default, for comparison purposes. The predictor variable with the largest absolute impact in Model 1 and Model 2 (the accounting-based models) is TLTA, followed by TFOTL, COVERAGE and CREDINT, in decreasing order of magnitude. The same analysis holds when the models are estimated in both *t-1* and *t-2*, invariably. The macroeconomic variables RPI and SHTBRDEF yield the smallest impact on the expected instantaneous changes in the response variable while keeping all other covariates constant. A clear pattern is also observed for the market based models (Model 4 and Model 5); the regressor with the largest impact in absolute terms is IDYRISK, followed by MCTD, ABNRET and PRICE, in decreasing order of magnitude in both *t-1* and *t-2*. Similar to the accounting-based models, the macroeconomic variables display the smallest individual impact on the expected instantaneous changes in the response variables corporate default while keeping all other covariates constant. Finally, from the overall marginal effects for the comprehensive model (Model 3), it can be observed that the regressor with the largest absolute impact is MCTD in *t-1* and IDYRISK in *t-2*, both market variables. The analysis of the relative effects of individual regressors included in the 'full' model reflects an important finding: when the model is estimated with information one year prior to the event of corporate default both market and accounting variable seem to have very similar individual effects on the response variable, however, when Model 3 is estimated with information two years prior to the event of default, market variables seem to have the largest absolute impact, suggesting that market variables perform better than accounting variables in *t-2*. In *t-1*, the decreasing order of magnitude (in absolute terms) of the regressors of Model 3 is as follows: MCTD, TFOTL, IDYRISK, TLTA, and ABNRET; whereas in *t-2* the order is IDYRISK, MCTD, ABNRET, TFOTL, and TLTA. It can be therefore concluded that market variables do contain additional information (performing even better that accounting variables in *t-2*) that is relevant to the prediction of corporate failure and that they perform best when they are used as complements to financial ratios.

Presenting and analysing marginal effects for all the models in the study filled a gap in the default prediction literature that lacked a measure of the individual instantaneous contribution of a change of a specific variable on the response variable (the specific definition of corporate failure used in the present analysis), while keeping all other regressors constant. Additionally, the present study goes further by presenting the vector of predicted probabilities for all the individual variables' specific minimum and maximum ranges where they have the most impact in the likelihood of corporate default, while keeping all the other covariates constant at their respective means. Thus, figures 3-4, 3-5, and 3-6 show the changes in predicted probabilities for accounting, macroeconomic and market variables, respectively, when the Corporate Default indicator is equal to 1. The importance of these figures is that they clearly show the magnitude as well as the directionality of each regressor reflected by the slope and inclination of the vectors, plotted at various levels of the independent variables.

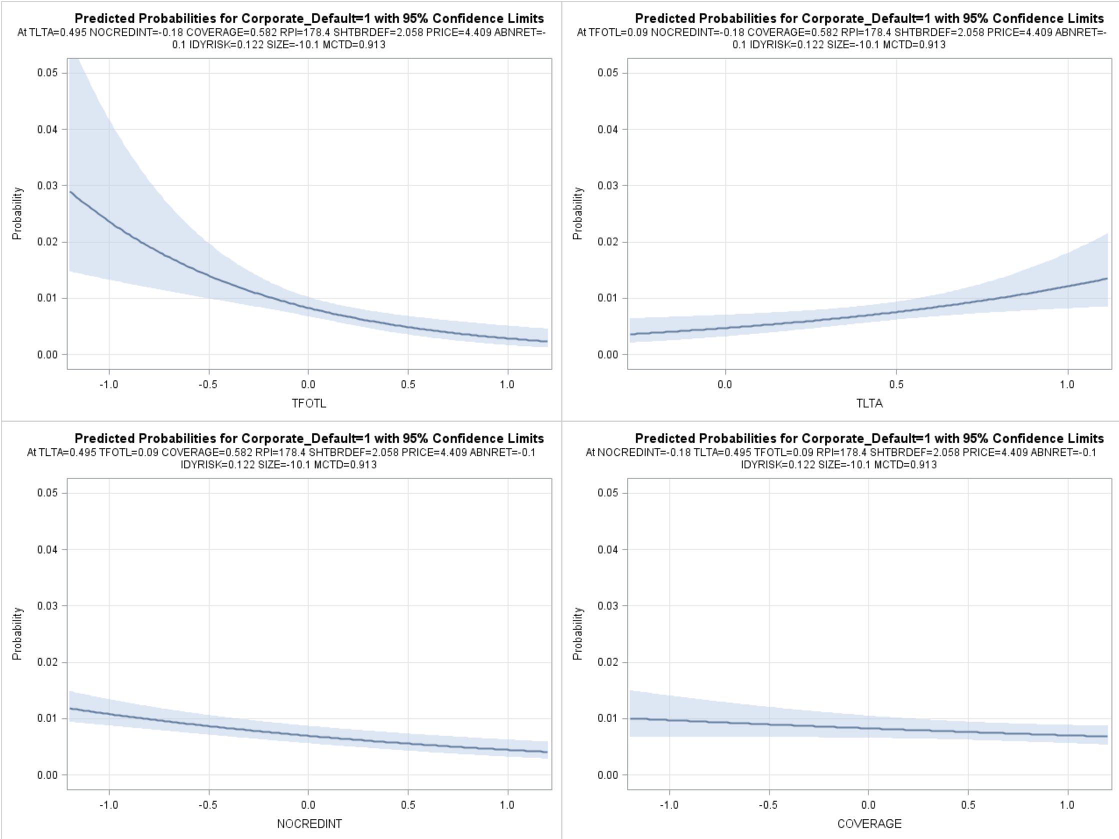

Figure 4-5 Changes in Predicted Probabilities – Financial Statement Ratios

The figure plots the vectors reflecting changes in predicted probabilities (for Corporate Default = 1) at different levels of the accounting independent variables Total Funds from Operations to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), and Interest Coverage (COVERAGE), keeping all the other covariates constant at their mean values (TFOTL = 0.09, TLTA = 0.495, NOCREDINT = -0.18, COVERAGE = 0.582, RPI = 178.4, SHTBRDEF = 2.058, PRICE = 4.409, ABNRET = -0.1, IDYRISK = 0.122, SIZE = -10.1, MCTD = 0.913). The computation was made taking into account all the variables included in the 'Full' model or Model 3 (financial statement ratios, macroeconomic indicators and market variables). Predicted probabilities are estimated employing an approximate value of the minimum and maximum ranges of the independent variables. In this way, the predicted probabilities for all levels of a variable can be observed. This figure reports the predicted probabilities for the 'Full' model estimated in period *t-1*, the vectors estimated using the full model in *t-2* have very similar shapes, so they were not reported in the present study.

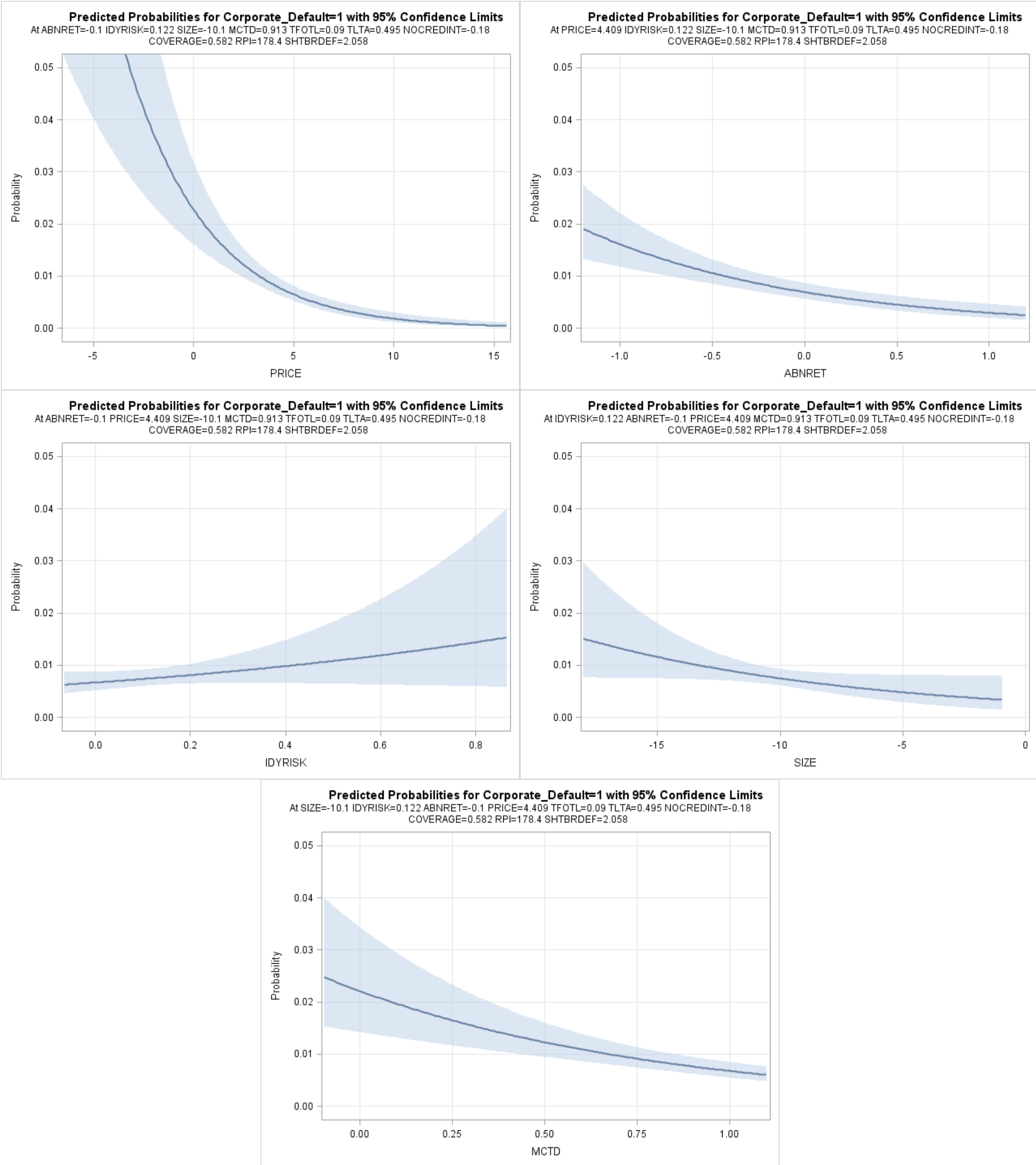

Figure 4-6 Changes in Predicted Probabilities – Market Variables

The figure plots the vectors reflecting changes in predicted probabilities (for Corporate Default = 1) at different levels of the market independent variables Share Price (PRICE), Abnormal Returns (ABNRET), the relative Size of the company (SIZE), and the ratio Market Capitalisation to Total Debt (MCTD), keeping all the other covariates constant at their mean values (TFOTL = 0.09, TLTA = 0.495, NOCREDINT = -0.18, COVERAGE = 0.582, RPI = 178.4, SHTBRDEF = 2.058, PRICE = 4.409, ABNRET = -0.1, IDYRISK = 0.122, SIZE = -10.1, MCTD = 0.913). The computation was made taking into account all the variables included in the 'Full' model or Model 3 (financial statement ratios, macroeconomic indicators and market variables). Predicted probabilities are estimated employing an approximate value of the minimum and maximum ranges of the independent variables. In this way, the predicted probabilities for all levels of a variable can be observed. This figure reports the predicted probabilities for the 'Full' model estimated in period *t-1*, the vectors estimated using the full model in *t-2* have very similar shapes, so they were not reported in the present study.

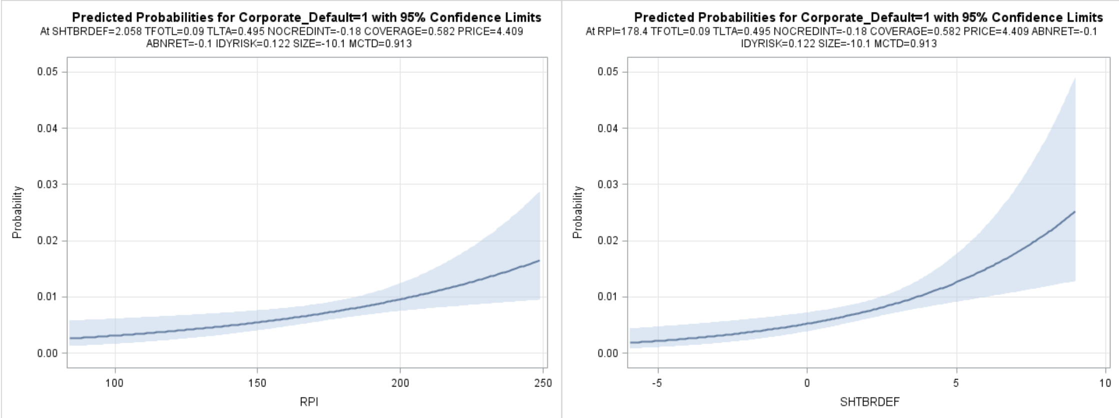

Figure 4-7 Changes in Predicted Probabilities – Macroeconomic Indicators
The figure plots the vectors reflecting changes in predicted probabilities (for Corporate Default = 1) at different levels of the macroeconomic independent variables Retail Price Index (RPI), and the proxy for interest rates, the Deflated Short Term Bill Rate (SHTBRDEF), keeping all the other covariates constant at their mean values (TFOTL = 0.09, TLTA = 0.495, NOCREDINT = -0.18, COVERAGE = 0.582, RPI = 178.4, SHTBRDEF = 2.058, PRICE = 4.409, ABNRET = -0.1, IDYRISK = 0.122, SIZE = -10.1, MCTD = 0.913). The computation was made taking into account all the variables included in the 'Full' model or Model 3 (financial statement ratios, macroeconomic indicators and market variables). Predicted probabilities are estimated employing an approximate value of the minimum and maximum ranges of the independent variables. In this way, the predicted probabilities for all levels of a variable can be observed. This figure reports the predicted probabilities for the 'Full' model estimated in period *t-1*, the vectors estimated using the full model in *t-2* have very similar shapes, so they were not reported in the present study.

Figure 4-5 shows the behaviour of the predicted probabilities of corporate default at different values of each of the financial statement ratios. From the figure we can observe that the TFOTL variable displays the steepest slope relative to the other ratios, indicating that a given change in the level of this variable[114] will have the largest impact on the predicted probability of corporate failure, when all other variables are kept constant at their means. The slope of the TFOTL vector also shows that there is a negative relationship between the predicted probability and the level of the variable: there is a considerable decrease of the predicted probabilities of corporate default as the TFOTL variable approaches its maximum value (1) after being transformed using the TANH function. The second variable in importance is TLTA: unlike TFOTL, there is a positive relationship between this ratio and the probability of corporate default. This analysis is consistent with the prediction of the present study, as TLTA is a measure of financial leverage: the higher the level of the variable, the greater the probability of failure. However, the impact is not as important as it is in the case of TFOTL as it can be observed that TLTA's slope is less steep than the firm's performance measure one. In other words, a change in its value produces a smaller effect than the one observed when there is a change in the magnitude of TFOTL, as shown by the slope of the vector. Changes in the magnitude of NOCREDINT, on the other hand, are negatively related to the probability of corporate default, an can be

[114] Reflecting a measure of the firm's performance.

considered as having the third most important impact among financial statement ratios, followed by COVERAGE, whose slope is almost flat, indicating a very small negative impact.

As posited, the market-based variables PRICE, ABNRET, SIZE, and MCTD display a negative relationship between variations in individual levels and predicted probabilities of corporate default. Also as expected, only the proxy for the firm's volatility of returns is positively related to the likelihood of default. The covariate with the largest impact is PRICE, as its vector displays the steepest slope, meaning that a change in the level of this variable (relative to the other covariates) will produce the highest change in the probability of failure. It is followed by MCTD, ABNRET, SIZE, and IDYRISK. Interestingly, the vectors' slopes of the macroeconomic indicators RPI and SHTBRDEF are steeper than the financial statement ratios TLTA, NOCREDINT, and COVERAGE, which could lead us to conclude that the have a larger impact on the predicted probability of corporate failure than the estimates of marginal effects would suggest. Nevertheless, this is hardly the case, as the ranges used to plot the slopes of the macroeconomic indicators are larger in absolute terms than those of the three financial statement ratios, which might explain the observed phenomenon.

4.6.2. Classification Accuracy Tables.

Classification tables have been used in previous works as additional tools to measure the predictive accuracy of the default/bankruptcy prediction models. Departing from this, the present study employs a more appropriate methodology that helps alleviate estimation bias. In order to classify a set of binary data, previous research works employ the same observations used to fit the model to estimate the classification error, resulting in biased error-count estimates. In other words, the widely-used 2x2 frequency tables' estimates, where correctly classified observations are displayed on the main diagonal of the table, are derived using all observations needed to fit the model. Intuitively therefore, any results are subjected to estimation bias since each observation has an effect on the model used to classify itself. One approach to reduce this bias, is 'to remove the binary observation to be classified from the data, reestimate the parameters of the model, and then classify the observation based on the new parameter estimates[115].' However, this method proves computational expensive for very large datasets. Therefore the present

[115] SAS Institute

study employs a logistic regression specification that provides a less computationally demanding one step approximation to the preceding parameter estimates[116]. The leave-one out jack knife approach is thus to employed to correct for over-sampling issues and to help alleviate potential biases common to analysis of classification tables that do not use a holdout sample.

In order to construct a bias-adjusted classification table, predicted corporate default event probabilities are estimated for each observation. If the predicted event probability equals or exceeds a given cutpoint value (whose real line is mapped onto [0,1]), then the observation is predicted to be in default, otherwise, it is predicted to be a non-event or a healthy firm. The probability levels chosen range from 0.010 to 0.060 in order to get high levels of Sensitivity and Specificity, combined as well as individually. The advantage of this methodology to construct classification tables is that it provides a useful tool to re-calibrate a default prediction model with different probability cutpoints depending on the costs assigned to the Type I and Type II errors.

The present study measures the accuracy of the classification through its Sensitivity (the ability of the model to predict a corporate default event correctly) and Specificity (the ability of the model to predict a non-default event correctly). In Table 4-10, the 'Correct' column shows the number of observations that were correctly predicted as failed and non-failed, respectively. The 'Incorrect 'column presents the number of non-failed observations that were incorrectly predicted as failed, and the number of failed observations that were incorrectly predicted as non-failed, respectively. The 'Percentages' column exhibits the rate of correct classifications, the proportion of corporate default responses that were predicted to be default events (Sensitivity, or the ability of the model to predict failure correctly), and the rate of non-default responses that were predicted to be non-default events (Specificity or the ability of the model to predict non-default events correctly), respectively.

Biased-adjusted classification tables were calculated for Model 2 (the 'Accounting plus macroeconomic indicators' model) and Model 3 (the 'Full' model) in order to assess the change in the classification accuracy when market variables are added to a model based on financial statement ratios (Panel A and Panel B in Table 4-10, respectively). Furthermore, Table 4-10 also exhibits a classification table for Model 3 estimated in period *t-2* (Panel C) in order to test whether the 'Full' model continues to be useful in predicting

[116] http://support.sas.com/documentation/cdl/en/statug/63033/HTML/default/viewer.htm#statug_logistic_sect037.htm

corporate default two years prior to the default event, thus confirming its predictive accuracy. In order to assess the classification accuracy, the probability level 0.020 was chosen as benchmark. The reason for this choice is that, first, this level is equal to the rate of failed to healthy companies for which complete data made the computation of predicted probabilities possible; and second, at this specific level, we obtain the smallest differences of Sensitivity and Specificity; at levels different than the 0.020 cutpoint, the trade-off (the gap between Sensitivity and Specificity) between the two measures is higher. It is concluded that, at a probability level of 0.020, there is a visible increase in classification performance from Model 2 to Model 3, which suggests that market variables provide information relevant to the prediction of corporate default that is not included in financial statement ratios or macroeconomic indicators. The increase in predictive accuracy when market variables are added to the 'Accounting plus macroeconomic indicators' model is equal to 2.4 percentage points as measured by the proportion of overall correct classifications in column 6 of table 3-10, at the 0.020 probability level (in bold) as cutpoint value: from 77.5 to 79.9 per cent of correct classifications in Model 2 and Model 3, respectively. This improvement in classification accuracy indicates that the three types of variables act as complementary, confirming the previous results obtained from the analysis of areas under the Receiver Operating Characteristics curve.

Unsurprisingly, when Model 3 is estimated in period *t-2*, the rate of correct classifications decreases from 79.9 to 75.6, or 4.3 percentage points relative to the same model estimated in period *t-1*, at the same 0.020 probability cutpoint. This suggests that the 'Full' model maintains a very decent level of accuracy to predict corporate failure two years prior to the event.

Perhaps more importantly, the present classification accuracy table possesses the advantage of allowing a risk manager to calculate higher percentages of Sensitivity and Specificity individually. This is particularly useful as Type I and Type II errors are not equally weighed by practitioners. A false positive error is not as expensive as a false negative: the cost of a firm predicted as failed when it is in fact healthy, is less than the cost of a firm predicted as healthy when it is in fact failed. Therefore, if this is the case, a risk manager would be more interested in increasing the rate of correctly classified failed firms (Sensitivity), choosing a lower probability level as cutpoint.[117]

---

[117] In this case the predicted probability used as cut point would have to be lower than the 0.020 level.

Table 4-10 Bias-Adjusted Classification Table

This table reports a biased-adjusted classification table for predicted default frequencies at different probability levels as cut-off values for Model 2 estimated in period *t-1*, and Model 3 estimated in period *t-1* and *t-2*, in panels A, B and C respectively. The 'Correct' column shows the number of observations that were correctly predicted as failed and non-failed, respectively. The 'Incorrect' column presents the number of non-failed observations that were incorrectly predicted as failed, and the number of failed observations that were incorrectly predicted as non-failed, respectively. The 'Percentages' column exhibits the rate of correct classifications, the proportion of default responses that were predicted to be corporate default events (Sensitivity, or the ability of the model to predict failure correctly), and the rate of non-failure responses that were predicted to be non-failure events (Specificity, or the ability of the model to predict non-failure correctly), respectively.

Probability Level	Correct		Incorrect		Percentages		
	Failed	Non-Failed	Failed	Non-Failed	Correct	Sensitivity	Specificity
			Panel A: Model 2 (*t-1*)				
0.010	281	9273	8364	34	53.2	89.2	52.6
0.020	**212**	**13701**	**3936**	**103**	**77.5**	**67.3**	**77.7**
0.030	164	15391	2246	151	86.6	52.1	87.3
0.040	133	16006	1631	182	89.9	42.2	90.8
0.050	112	16387	1250	203	91.9	35.6	92.9
0.060	83	16706	931	232	93.5	26.3	94.7
			Panel B: Model 3 (*t-1*)				
0.010	246	9061	4868	28	65.5	89.8	65.1
0.020	**217**	**11128**	**2801**	**57**	**79.9**	**79.2**	**79.9**
0.030	189	11994	1935	85	85.8	69	86.1
0.040	172	12452	1477	102	88.9	62.8	89.4
0.050	148	12770	1159	126	91	54	91.7
0.060	135	12976	953	139	92.3	49.3	93.2
			Panel C: Model 3 (*t-2*)				
0.010	210	6140	5816	29	52.1	87.9	51.4
0.020	**171**	**9052**	**2904**	**68**	**75.6**	**71.5**	**75.7**
0.030	132	10121	1835	107	84.1	55.2	84.7
0.040	106	10648	1308	133	88.2	44.4	89.1
0.050	86	10988	968	153	90.8	36	91.9
0.060	76	11232	724	163	92.7	31.8	93.9

This would be achieved, however, only at the cost of reducing the ability of the model to predict non-default events correctly (Specificity). The present study presented the rates of Specificity and Sensitivity at different probability levels as cutpoints to show the practical use of this approach to measure the accuracy of a corporate default prediction model and its advantages in relation to the widely employed 2x2 frequency tables that implicitly assign equal weights to type I and Type II errors.

4.6.3. Model Validation.

In order to validate the performance of the model, the main database was subdivided in two sub-periods: 2001-2006. The first one corresponds to the period after the collapse of the information technology bubble, which took place during 2000-2001, and the second one is the period following the global financial crisis of 2007-2011. Model 3 was applied to the two sub-periods in order to test whether the predictive accuracy holds when the model is estimated one year prior to the event of corporate default. As shown in Table 4-11, the predictive accuracy experiences only a very small decline when the model is tested using the two sub-period data: from an AUC of 0.8685 for the period 1980-2011 to 0.8636 for the period 2001-2006 and 0.8661 for the period 2007-2011. The decrease is less than one percentage point in both cases. Furthermore, the differences between sub-periods are also very small (also less than one percentage point) suggesting that the model is very consistent over time. As expected, there is a visible decline in the predictive accuracy when the model is estimated with information two years prior to the event of default. But despite the expected decrease in performance of the model in *t-2*, the model retains a high predictive accuracy overall.

Table 4-11 Model Validation – Areas Under the ROC Curve

This table reports the model validation results for Model 3 estimated in period *t-1* and *t-2*. The main dataset was divided in two sub-periods. The first one, 2001-2006, corresponds to the periods after the collapse of the information technology bubble, and the second one, 2007-2011, is the period that follows the global financial crisis that started in 2007. The predictive accuracy or the overall performance of the model is measured by the area under the Receiver Operating Characteristics curve.

	1980-2011	2001-2006	2007-2011
Model 3 in *t-1*	0.8685	0.8636	0.8661
Model 3 in *t-2*	0.8004	0.7795	0.8208

4.7. Conclusions.

In précis, the present study develops a new model tasked for the prediction of corporate default for quoted companies in the United Kingdom based on the Christidis and Gregory (2010) definition of corporate failure. Information used for the model comes courtesy of widely available data provided by the London Share Price Database (LSPD). Following the approach employed in Christidis and Gregory (2010), the focus of the present study is on firm insolvency and, as such, a firm was classified as failed when it was deemed to have formally defaulted on its obligations. This study's definition of corporate failure is based upon the types of death available in the LSPD and represents thus the last stage of financial distress: default, which can be viewed as the outcome of a process. Furthermore, in order to provide a 'clean' measure of the outcome (or the dependent variable), we classify a firm as failed if its status is one of the following: in liquidation, suspension, receivership, or cancellation. The advantage of this choice is that it was built with information specific to the United Kingdom's legal environment and that it constitutes a highly visible event that can be objectively dated, satisfying thus the requirements of binary choice models that the populations of failing and non-failing firms be well defined and clearly separated from each other.

The overarching contribution of the present study to the default prediction literature is the use of a more exact and appropriate definition of corporate failure. Second, a large dataset was built merging different types of information from data sources widely available to the academic as well as to the industry fields. Consequently this study relies not only on independent variables used in previous research works, but also uses a multi-level empirical procedure which tests and selects explanatory variables based on the individual contribution of coefficients to the model's explanatory power. In addition, this study employs for the first time in default prediction models, the hyperbolic tangent function to transform the variables included in the models in order to generate a linear transformation for input values located near expected values while reducing those that are outside the expected range. The advantage is that this method provides a formal solution to the recurrent problem of the presence of outliers that could have an abnormal impact on the fitted maximum likelihood linear predictors, as well as on the size of residuals from the resultant binary panel logistic regression.

Separately, this study presents a rationale for the use of each of the retained variables in the fitted models. The result is a corporate failure prediction model that yields high classification and predictive accuracy relative to previous research works. Third, using this definition of failure, the panel logit methodology is employed in order to provide a comparison of the classification accuracy and predictive power, through the analysis of individual as well as overall contributions, of three types of variables: financial statement ratios, macroeconomic indicators and market-based variables.

To our knowledge, this is the first time that such an analysis is carried out in the default prediction literature for listed companies in the United Kingdom. Prior research has tested the ability of market variables to predict bankruptcy employing methodologies such as the Black and Scholes Contingent claims or option-based approach. However, the results obtained from these models (that entail numerous restrictive assumptions) have been controversial. Many studies have focused on demonstrating the superiority of market-based models over accounting-based models and vice-versa, and the relevance of macroeconomic variables to the prediction of corporate default has rarely been tested. To this point, the default prediction literature is characterised by a competing approach where there is a clear division line between market and accounting variables. The present study adopts a different approach where the use of the three types of variables is not mutually exclusive. It is tested whether the market variables (dependent, in some measure, upon the same financial information) and macroeconomic indicators add information that is not contained in financial statements and therefore act as complement in default prediction models. The results presented in this study clearly indicate that this is the case: the comprehensive model (Model 3) yields the best performance in both *t-1* and *t-2*. With regard to the inclusion of market variables to an accounting-based model (that also included macroeconomic indicators), the considerable increase of the area under the Receiver Operating Characteristics (ROC) curve, from 0.8032 to 0.8685 in a model estimated in *t-1* and from 0.7151 to 0.8004 in a model estimated in *t-2*, indicates that market variables contain a substantial amount of information relevant to the estimation of the likelihood of corporate default that is not included in financial statement ratios.

A comparison of areas under correlated ROC curves (AUC) performed using a non-parametric method based on the theory on generalised Man-Whitney *U*-statistics, and the estimation of biased-adjusted classification tables confirmed these results. Furthermore, an analysis of these figures reveals that the distance between the ROC curves of the market models and the comprehensive model are considerably smaller than the distance between the ROC curves of the accounting models and the comprehensive model in both *t-1* and *t-2*. This indicates that the benefit of including market variables to an accounting model is greater than the benefit of including accounting variables to a market model: moreover, when the models are estimated in *t-2* the distance is smallest between the market and comprehensive models, suggesting that they perform very similarly when they are estimated using information two years prior to the event of default. In other words, when employed in isolation, market variables seem to possess a higher explanatory power than accounting variables, as the performance of market variables closely follows the performance of the 'full' model, especially in *t-2*, where the difference is smallest. An analysis of the estimates resulting from the logit regression of the Corporate Failure indicator on the predictor variables provides additional evidence that is consistent with this finding: when the comprehensive model is estimated in *t-2*, only two accounting variables, (TFOTL and NOCREDINT) and all of the market variables retain their statistical significance at the 1-

5% levels. The only exception, among market variables, is IDYRISK, whose statistical significance marginally decreases from 1-5% to 10%. These results suggest that, when the 'Full' model is estimated in *t-2*, market variables are the most consistent set of regressors over time for the prediction of corporate default, as only two financial statement variables out of four maintain their statistical significance in this period. Also in line with these findings, Hosmer and Lemeshow goodness-of-fit tests for binary response logistic models suggest that the 'full' model fitted with market and macroeconomic variables is an adequate model. On the other hand, results are less conclusive with regard to macroeconomic indicators, which contribute only marginally to the overall classification accuracy of the model. Fourth, the estimation of marginal effects fills an important gap in the default prediction literature by presenting expected instantaneous changes in the response variables as a function of a change in a specific predictor variable while keeping all the other covariates constant. Marginal effects, combined with figures reflecting changes in predicted probabilities, proved to be very useful tools to enhance our understanding of individual effects of the variables included in the models.

5. Financial Distress and Bankruptcy Prediction among Listed Companies using Accounting, Market and Macroeconomic Variables

5.1. Introduction.

The financial crisis of 2008 highlighted the shortcomings of risk management practices within the lending environment and risk assessment at the micro level (PD estimation). Lenders and other investors in the corporate sector along with regulators require timely information on the default risk probability of corporates within lending and derivative portfolios. For banks, developing effective 'Internal Rating Systems' (IRB) for corporate risk management requires building probability of default (PD) models geared to the specific characteristics of corporate sub-populations (e.g. SME's, private companies, listed companies, sector specific models), tuned to changes in the macro environment, and, of course, tailored to the availability and timeliness of data. The use of credit risk models has been well documented since Altman (1968). There is now an extensive literature on the modeling of corporate financial distress and bankruptcy but often, it reports work that is either based on using publically available historical accounting data (Altman, 1968) or relies on securities market information (Merton, 1974) to predict insolvencies.

Recent papers argue for a combined approach, Trujillo-Ponce and Cardone-Riportella (2012) test both accounting and market data (Credit Default Swaps, CDS) and suggest that *"accounting and market data complement one another and thus a comprehensive model that includes both types of variables appears to be the best option."* (p. 2). The outcome definition, bankruptcy, is taken from formal (legal) insolvency notices, debt servicing (Perraudin, 1997) and bond (Geske, 1977) or loan defaults, default swaps[118] (Ericcson et al, 2009) or stock market suspensions. These modeling approaches have been applied extensively to listed companies using statistical procedures such as MDA, logistic regression or hazard models. Recent work has extended the definition of bankruptcy to include wider measures of 'financial distress' based on financial statements. Further, attempts have been made to incorporate some dynamics by the inclusion of data reflecting changes in the macroeconomic environment, non- financial data and other time variant predictors. The

[118] The issuance of (rated) bonds and the related CDS market is relatively small amongst UK listed companies and therefore not considered in this study

present study contributes to the academic literature by, first, presenting distress prediction model for quoted companies in the United Kingdom that employ a 'finance-based' definition of distress, to detect early stages of financial distress, alongside the more formal approach using event data provided by the London Share Price Database. Timely prediction of financial distress could, in practice, help creditors mitigate some of the costs associated with bankruptcy fillings. Secondly, employing a multi-level empirical procedure, this paper outlines a financial distress prediction model that, with a rather small number of variables, boasts considerably higher classification and prediction accuracy relative to previous research. Third, and perhaps most importantly, this study contributes to the extant literature by providing the first prediction model for public companies in the United Kingdom, that tests the relative contributions (individual as well as collective) of three typed of variables: financial ratios, macroeconomic indicators, and market variables.

The chapter is structured as follows. In the next section we discuss the literature that is relevant to our modelling approach. We describe our database and measures of the outcome variable and set of explanatory variable. The estimation methodology is discussed along with analysis, results and conclusions.

5.2. Review of the Literature.

Most of prior default prediction models for quoted companies employ a definition of the criterion event that is contingent upon its ultimate legal consequence: either bankruptcy in the United States and creditors' compulsory and/or voluntary liquidation in the United Kingdom. These are highly visible legal events that can be objectively and accurately dated for use as an outcome variable. The likelihood of bankruptcy can be modelled using binary choice models that require that the populations of failing and non-failing firms be 'well defined and clearly separated from each other[119]. However, this legal definition of default is not without issues. For instance insolvency can be a lengthy legal process and the 'legal' date of failure may not represent the 'economic' or the 'real' event of failure. Analysis of UK companies demonstrates a considerable time gap (up to three years or 1.17 years in average) between the period that a firm enters a state of financial distress (that caused the firm to default) and the date of legal default/bankruptcy. This evidence is consistent with the finding by Theodossiou (1993) that firms in the United States stop providing accounts approximately two years before the bankruptcy filing. The implication

[119] Balcaen and Ooghe (2004), p. 21.

is that a firm in this situation is already in serious financial distress at some point two years before the legal bankruptcy event. Moreover, it is possible that a firm in a state of financial distress does not change the legal status that a bankruptcy filing would entail (Balcaen and Ooghe, 2004). Moreover, changes in insolvency legislation, (e.g. the Enterprise Act 2004 in the UK or Chapter 11 in the US) which have attempted to create a 'rescue culture', have changed the nature and timing of the legal bankruptcy process. Wruck (1990) states that there are several stages that a firm can go through before it is defined as dead: financial distress, insolvency, filing of bankruptcy, administrative receivership (in order to avoid filing for bankruptcy), for instance. Moreover decline can be managed by the sale of assets (pre packs) and eventual dissolution rather than formal bankruptcy.

The present study introduces for the first time, for quoted companies in the United Kingdom, a definition based on 'financial distress'. This development has been highlighted as important in the academic literature (Pindado et al., 2008; Barnes, 1990; and Barnes, 1987) and is justified by the fact that the failure of a firm to meet its financial obligations does not inevitably lead to a filing of bankruptcy. The study recognises that financial distress can be costly for creditors and that they would wish to take timely actions to minimise/avert these costs. It is therefore essential that a reliable financial distress prediction model be developed that uses not only the event of bankruptcy as the primary outcome, but includes the time when a company fails to meet its financial obligations. Wruck (1990) defines financial distress as the situation where the cash flow of a firm is not enough to cover its current financial obligations[120]. Asquith et al. (1994) analyse the options that junk bond issuers face in order to prevent bankruptcy and define financial distress in a similar way. Their definition of financial distress is based on interest coverage ratios. In practical terms, a firm is classified as financially distressed if its earnings before interest, taxes, depreciation and amortisation (EBITDA) are less than its reported financial expenses (interest expense on debt) for two consecutive year beginning in the year following its junk bond issue, or, if in any other year, EBITDA is less than 80 per cent of its interest expense. Similarly, Andrade and Kaplan (1998) define financial distress as the first year that a firm's EBITDA is less than financial expenses. However, the authors classify firms in this category (in addition to the first condition) whenever a firm attempts to restructure its debt, or defaults. The fulfilment of any of these conditions classifies a firm as financially distressed. Whitaker (1999), analyses the early stages of financial distress and points out that its effects are not limited to those firms that are unable to meet contractual debt obligations as they come due, but also to those firms whose likelihood of default increases.

[120] Such as debts to suppliers and employees, principal or interest payments in arrears, among others.

He states that, in fact, the effects of financial distress can be detected before the firm defaults, as a proportion of the loss in firm value occurs before default or bankruptcy. Whitaker (1999) defines financial distress as the first year in which a firm's cash flow[121] is less than current maturities of long-term debt. Moreover, market value is used in order to confirm financial distress i.e. whether the distressed firms in the sample had either a negative rate of growth in market value or a negative rate of growth in industry-adjusted market value.

Previous research has tested the utility of market variables in predicting bankruptcy by employing methodologies such as the Black and Scholes (1973) and Merton (1974) contingent claims or option based approach. Bharath and Shumway (2008), Hillegeist et al. (2004), Reisz and Perlich (2007), and Vassalou and Xing (2004) have employed the contingent claims approach to estimate the likelihood of corporate failure. More recently data on Credit Default Swaps (prices and spreads) have been used to proxy credit risk (Alexander and Kaeck, 2008). Many empirical papers have attempted to demonstrate the superiority of market-based models over accounting-based models and vice versa. However, the results obtained from these models (that entail numerous restrictive assumptions[122]) and the subsequent performance comparisons with accounting-based models have been controversial. In a recent paper, Agarwal and Taffler (2008) perform a comparison of market-based and accounting-based bankruptcy prediction models, and find that traditional models based on financial ratios are not inferior to KMV-type, option-based models for credit risk assessment purposes. They conclude that, 'in terms of predictive accuracy, there is little difference between the market-based and accounting models.[123]' Hillegeist et al. (2004) provide contrasting results indicating that the Black-Scholes-Merton option-pricing model provides significantly more information about the probability of bankruptcy that do either the Altman's Z-score or the Ohlson O-score. As surmised earlier the default prediction literature can be characterised by a competing approach, where there is a clear division between market and accounting variables. Hillegeist et al. (2004),[124] for instance, recommends that researchers use the Black-Scholes-Merton methodology instead of the traditional accounting-based measures as a proxy for the probability of bankruptcy.

---

121 Defined as net income plus non-cash charges.

122 The underlying assumptions of the theoretical Merton-Black-Scholes option-pricing model are, according to Saunders and Allen (2002) and Agarwal and Taffler (2008): normality of stock returns.

123 P. 1550.

124 P. 28.

More recent work suggests that both approaches yield similar results implying that both contain useful information about firms' likelihood of default/financial distress. Furthermore, the individual characteristics (e.g. timeliness) of each type of variable (market and accounting) give promise to the development of a model that is superior in performance than ones that rely on *either* accounting *or* market variables. Balcaen and Ooghe, (2004)[125] argue that '*if researchers only include financial ratios into their failure prediction model, they implicitly assume that all relevant failure or success indicators – both internal and external- are reflected in the annual accounts.*[126]' It is clear that financial statements do not include all the information that is relevant to the prediction of financial distress, and market variables are very likely to complement this deficiency.

Rees (1995) suggests that market prices might be a useful predictor for the probability of bankruptcy as they include information on future expected cash flows. For Hillegesit et al. (2004) the stock market is an alternative source of information because it contains information from other sources in addition to the financial statements. Beaver et al. (2005) indicate that a probability of bankruptcy is embedded in market prices, even though this probability might not be directly extracted: 'as the probability of bankruptcy increases the non-linear nature of the payoff function for common stock becomes increasingly more important because of risky debt and limited liability.' Clearly the inclusion of market-based variables is appealing on several grounds: first, market prices reflect the information contained in accounting statements plus other information not in the accounting statements (Agarwal and Taffler, 2008), making them a comprehensive mix potentially useful for the prediction of corporate default. Second, the inclusion of market-based variables can considerably increase the timeliness of prediction models; while financial accounts are available in the United Kingdom on a quarterly basis, at best (prior research have used annual data conventionally), market prices are available on a daily basis. Third, market prices might be more appropriate to predict bankruptcy, as they reflect future expected cash flows (accounting statements, in contrast, reflect the past performance of the firm). And fourth, market-based variables can provide a direct assessment of volatility, a measure that could be a powerful predictor of bankruptcy risk and that is not contained in financial statements. According to Beaver et al. (2005) the notion is that the greater the volatility, the higher the likelihood of bankruptcy.

[125] Argenti (1976), Zavgren (1985), Keasey and Watson (1987), and more recently Maltz et al. (2003) offer support for the inclusion of non-financial variables to default prediction models.
[126] Balcaen and Ooghe (2004), p. 35.

Among the few studies that include a set of market variables to enhance the timeliness and power of distress prediction models is Campbell et al. (2008), whose analysis examines the determinants of failure as well as the pricing of financially distressed stocks with a high probability of failure through a logit model that includes accounting and market variables. In addition to a set of two accounting variables, several market variables are tested: the monthly log excess return on each firm's equity relative to the S&P 500 index, the standard deviation of each firm's daily stock return over the past three months, the relative size of each firm measured as the log ratio of its market capitalisation to that of the S&P 500 index, and the firm's log price per share truncated above at $15. The estimates of the study are computed with United States data for public companies.

Similarly, Chava and Jarrow (2004) test in their analysis, in addition to the Altman's (1968) accounting variables, the variables included in Shumway (2001): the accounting variables net income to total assets and total liabilities to total assets; and the market variables: relative size defined as the natural logarithm of the firm's equity value in relation to the total NYSE/AMEX market equity value, yearly excess returns calculated as the firm's cumulative monthly return minus the value-weighed CRSP NYSE/AMEX monthly index return, and the stock's volatility computed as the standard deviation using the last sixty observable daily market prices. In Shumway (2001) the same market variables are tested in a bankruptcy prediction model with some minor variations, namely the idiosyncratic standard deviation of each firm's stock returns, whose value is computed by regressing each stock's monthly returns on the value-weighted NYSE/AMEX index return for the same period (year). More recently, Christidis and Gregory (2010) follow Campbell et al. (2008) and test three market variables in a distress prediction model for UK quoted companies that includes also a set of accounting variables. As to the market variables, they replace book value of assets with market values and test whether log semi-annual excess returns over the FTSE All Share Index and firm stock returns' standard deviation (calculated over a six-month period) can enhance the predictive power of the model. Their findings suggest that market values have the ability to increase the accuracy of the distress prediction model.

The incorporation of time variant data into credit risk models that captures changes in the macro-economic environment. The macroeconomic environment is important in two main respects. First it adds a dynamic element to the models that acts to adjust risk scores (likelihood of insolvency) in relation to changing macro-economic conditions. Second such models would have a built-in facility to stress test PD estimates across the portfolio. There are few studies that have incorporated a macro-dependent hazard into the equations (Nam et al, 2008; Qu, 2008 and Mare, 2012). In this paper we control for macro conditions, inflation and interest rate changes, over the sample period.

In the next section we describe the database used in the study, the construction of our outcome variable and the selection of independent variables.

5.3. Outcome Definition and Independent Variable Selection.

5.3.1. Outcome Definition

The promised analysis requires a definition of financial distress, which can be viewed as the outcome of a process. In line with earlier discussions and recent papers we focus on the ability of a firm to repay its financial obligations (Asquith et al., 1994). We develop an *ex-ante* model for estimating financial distress likelihood following Pindado et al. (2008) which employs two main conditions that need to be met in order to detect and predict financial distress in a given firm/year (observation): a firm is classified as financially distressed[127], *i) whenever its earnings before interest and taxes depreciation and amortization (EBITDA) are lower than its financial expenses for two consecutive years; ii) whenever the firm suffers from a negative growth in market value for two consecutive years.* With regard to the first condition, if EBITDA is lower than the interest expense on the company's debt then it can be concluded that the operational profitability of the firm is not sufficient to cover its financial obligations; on the other hand, with reference to the second condition, Pindado et al. (2008) state that the market as well as stakeholders are likely to judge negatively a firm that suffers from the operational deficit (described in the first condition) until an improvement in the financial condition is perceived again. Thus, the fall in market value for two consecutive years is interpreted as an indication that a firm is in effect in financial distress. As in Pindado et al. (2008), the study is thus introducing a dynamic approach, a novel development in existing financial distress definitions. The variables Earnings before interest and taxes depreciation and amortization (EBITDA) and Interest expense on debt were obtained from Thomson One Banker. In order to compute the changes in market value for the companies in the

[127] In a general logit model a firm is considered as financially distressed in the year that immediately follows the occurrence of both events by assigning a value of 1, and zero otherwise.

database, the present study used the information available in both Thomson One Banker and Datastream[128].

However, this study recognises the need to include an indicator of default in addition to the previous 'finance-based' definition of distress in order to complete the concept of financial distress and therefore enhance the scope and the discriminating/predictive power of the model for practical purposes. A definition based on Christidis & Gregory (2010) is utilised. Thus, a firm is classified as being in financial distress not only when it meets the previous two conditions, but when it is deemed to have formally defaulted on its obligations. The definition of the outcome variable was constructed using the information available in the 2012 London Share Price Database (LSPD). A firm is defined as in default / financial distress whenever its status is defined as suspended, in liquidation or voluntary liquidation, when its quotation has been suspended for more than three years, when the firm is being held by a receiver (in receivership), in administration or in administrative receivership, or when there has been a cancellation or suspension of the firm.

Thus, a firm is classified as financially distressed when its LSPD (2012) status is equal to any of the following definitions (that indicate the reason why the security ceased to be quoted in the SEDOL): 6) Suspension / cancellation with shares acquired later. Meanwhile, may be treated under rule 163/2; 7) Liquidation (usually valueless but there may be liquidation payments; 10) Quotation suspended – if suspended for more than three years, this may lead to automatic cancellation; 11) Voluntary liquidation, where value remains, and was / is being distributed; 16) Receiver appointed / liquidation. Probably valueless but not yet certain; 20) In Administration / Administrative receivership; 21) Cancellation and assumed valueless or suspended but assumed valueless. In addition, the present analysis also tracks the specific date when each one of these events occurs.

For simplicity, in the remainder of this study, the binary dependent variable including both of the above definitions of corporate failure and financial distress will be referred to as 'Financial Distress Indicator'. Accordingly, all firms classified as failed or financially distressed, will be referred to as 'financially distressed' or in 'financial distress.' Among the total number of observations, there are 1,254 firm-years classified as financially distressed; yielding a proportion of 5% of annual observations in financial distress (Table 5-

[128] Both databases were used as some missing information on specific companies in one database could be completed by the data of the other. A merging of the databases was therefore required in order to obtain larger time series and thus a more accurate model.

1). The available accounting data was taken from Datastream and Thomson One Banker (Worldscope); the macroeconomic variables were collected from Datastream; and the market variables were constructed merging the information available from Datastream, the London Share Price Database and Worldscope. Market information was added to the companies that were found in the Thomson One Banker database. The merging of the accounting and market variables in one database resulted in fewer firms having both complete market-based time-series than accounting information.

Table 5-1 Summary Statistics of the Annual Observations. Financially and Not Financially Distressed Firms

Panel A reports summary statistics for the entire sample used in the construction of the financial distress prediction model. NFD and FD are Financially and Not Financially Distressed Firms. %FD is the proportion (in percentage) of annual observations that meet the financial distress criteria of the study. The criteria used to classify firms into financially and not financially distressed firms are as follows. A firm is classified as FD when it files for bankruptcy (definition constructed using the London Share Price Database, see details below), or whenever it meets both of the following conditions: i) its earnings before interest and taxes depreciation and amortisation (EBITDA) are lower than its financial expenses for two consecutive years, and ii) there is a negative growth of its market value for two consecutive periods.

Panel A: Classification of annual observations into financially and not financially distressed firms.			
NFD	FD	Total	%FD
21,964	1,254	23,218	5.0%

Table 5-2 presents summary statistics for the 379 failed firms that were classified according to the definition of corporate failure in this study using the 2012 LSPD database. Among the 381 failed companies, 379 were used for the calculation of summary statistics[129]. Section B in Table 4-2 shows that, among the companies that form the sample of failed firms; there is a lag that ranges from 0 to 36 months before the date of failure. In other words, firms in financial difficulty, that eventually fail, cease providing accounts 1.17 years in average before the date of failure. The minimum lag of months is zero (meaning that the company that fails keeps providing accounts until the date of failure) and the maximum observed lag is 36; one firm in the sample ceased providing official accounts 3 years before failure[130].

129 Two companies were removed as they presented a lag in the number of months that was much higher than that observed for the Maximum in the present sample of failed firms. As such, both firms were considered as extreme observations (outliers) that can have an abnormally high influence on the results, and were therefore not employed in the calculation of the summary statistics presented in Table 2.

130 A likely explanation for this considerable lag is that the firm might already be facing serious financial stress at the time it ceases to provide accounting information and is therefore attempting to defer the accounts in order to prevent its financial state from deteriorating any further or from a suspension of the trading of its stock on the main exchange where it is quoted, which can be very costly.

Table 5-2 Summary Statistics of Corporate Failure of UK Firms

Panel A reports summary statistics for the firms in the last stage of financial distress, corporate failure. Obs is the total number of observations (firm-years) in the database, N is the number of normal (non-failed) firms, F is the number of failed firms according to the definition below, Total is the number of firms in the database, and %F is the proportion (in percentage) of failed firms relative to the Total number of firms in the database. The definition of corporate failure (that follows the approach of Christidis and Gregory (2010)) was constructed using the information available in the 2012 London Share Price Database (LSPD). A firm is classified as failed when its status in the 2012 LSPD is defined as: suspended, in liquidation or voluntary liquidation, when its quotation has been suspended for more than three years, when the firm is being held by a receiver (in receivership), in administration or in administrative receivership, or when there has been a cancellation or suspension of the firm[131]. Panel B reports the lag of months between the date of failure of the company and the last available account. N is the number of failed companies that were classified as failed according to the above 2012 LSPD definition, Min is the minimum number of months observed among the failed companies, and Max is the maximum observed number of months. The table also shows the Mean (14.21 Months or 1.17 years approximately) and the standard deviation (STD).

Panel A: Classification of Failed UK Quoted Companies.				
Obs	N	F[132]	Total	%F
23,218	2,641	379	3,020	12.6%
Panel B: Failed Companies: Lag of Months between the Date of Failure and the Last Available Account.				
N	Min	Max	Mean	STD
379	0	36	14.21	4.82

In specifying the models there are two main objectives. First, the intention is to build more accurate and timely financial distress prediction models, using data that is routinely available. The models are designed to obtain more accurate results compared to previous works in the academic field and are constructed with a parsimonious approach since they are intended to have practical value. Further, Zmijewski (1984) and more recently Pindado et al. (2008) have shown that in fact a large set of variables is not required for the models to reach their maximum level of accuracy. Pindado et al. (2008), for instance, employ a set of only three accounting variables to reach a high level of accuracy in their financial distress prediction model. The variables employed in their study are the ratios earnings before interest and taxes over total assets, financial expenses to total assets, and retained earnings to total assets, which represent profitability, financial expenses, and retained earnings, respectively. Zmijewski (1984) uses a set of accounting variables that includes proxies for return on assets, financial leverage, and liquidity. Moreover, in a study that intends to investigate the empirical relation between risk of bankruptcy and systematic risk through the construction of a single composite score that reflects the ex-ante

[131] The LSPD numbers and definitions in the database are: 6) Suspension / cancellation with shares acquired later. Meanwhile, may be treated under rule 163/2; 7) Liquidation (usually valueless but there may be liquidation payments; 10) Quotation suspended – if suspended for more than three years, this may lead to automatic cancellation; 11) Voluntary liquidation, where value remains, and was / is being distributed; 16) Receiver appointed / liquidation. Probably valueless but not yet certain; 20) In Administration / Administrative receivership; 21) Cancellation and assumed valueless or suspended but assumed valueless.

[132] For the purposes of the analysis, firms classified as failed in the database are assigned a value of 1, and zero otherwise according to the date of failure. Accordingly, the failed firms are included among the 1,254 financially distressed indicators in the database.

probability of bankruptcy for a company at a given point in time, Dichev (1998) employs a measure derived from exiting accounting models such as the 5-variable Altman (1968) Z-model, and the 7-variable Ohlson (1980) logit model.

The second objective of the analysis is to test the usefulness of other non-accounting variables, namely macroeconomic and market variables, with regard to their contribution to the accuracy and timeliness of financial distress prediction models for quoted companies. We investigate whether macroeconomic and market variables enhance the discriminating and predicting power of the models. There have been very few studies that analyse the performance of these three kinds of variables in a statistical financial distress prediction model. It is deemed important to investigate macroeconomic and market variables since the former is potentially useful to act as a complement to the accounting variables and the latter adjusts estimated scores in relation to changes in the macro-economic environment and provides the facility to impose stress testing scenarios.

Of course, accounting data can only be obtained on an annual basis, so even if the discriminating power of some previous and widely used models (such as the Altman (1968) model) is quite high, there is always the risk of the relying on out dated information. Furthermore, through a detailed analysis of the 'most extreme form of financial distress[133]', corporate failure, the present study shows that the firms that were classified as failed[134], stop providing accounting data one year on average (14 months) before the actual date of failure.

5.3.2. Independent Variable Selection

From the database, consisting of 130 variables in total, several accounting, macroeconomic, and market variables were tested. The selection method relied on previously reported results, theoretical propositions and empirical assessments. The data was subject to a rigorous cleaning and testing process and a novel approach for dealing with outlying observations was adopted. Using both univariate and multivariate (logit) procedures considerable experimentation was undertaken to arrive at the final choice of regressors. The variable selection included four accounting ratios: Total Funds from Operations to Total Liabilities, Total Liabilities to Total Assets, the No Credit Interval, and

133 The term in quotes is borrowed from Christidis and Gregory (2010), p. 6.

134 The definition of the response variable was constructed using the information available in the 2012 London Share Price Database (LSPD). A firm is defined as failed whenever its status is defined as suspended, in liquidation or voluntary liquidation, when its quotation has been suspended for more than three years, when the firm is being held by a receiver (in receivership), in administration or in administrative receivership, or when there has been a cancellation or suspension of the firm.

Interest Coverage; two macroeconomic variables: the Short-Term Bill Rate (inflation-adjusted or deflated), and the Retail Price Index (base 100). Four market variables were found to considerably increase the prediction accuracy of the model: the firm's stock price, the company's yearly abnormal returns, the firm's size relative to the total size of the FTSE All-Share market value, and the ratio Market Capitalisation over Total Debt. These were discussed in detail in the previous chapter.

In the previous chapter, where a corporate default prediction model was developed based on a UK-specific legal definition of failure, another market variable (in addition to the four market variables presented in the above lines) was tested and included in the final 'market' and 'full' models: IDYRISK or the lagged standard deviation of individual security residual returns. This variable was constructed to reflect the variability of the stock returns of a company[135]. The rationale for the inclusion of this variable in the models is that a measure of volatility might provide information relevant to the prediction of default that is not contained in the traditional financial ratios (in fact, a volatility measure could not be extracted from financial data due to the scarcity of accounts, which are submitted quarterly at best in the United Kingdom). As noted by Shumway (2001) it is expected that this variable is related to bankruptcy in statistical and logical terms: higher volatility of the cash flows of a firm (resulting in more variable stock returns) should entail a higher probability of default. In line with Shumway's (2001) argument, the present study posited that, in logical terms, the likelihood of default is explained not only by the level of market variables such as abnormal returns (ABNRET), but *also* by the proportion of their variability that is attributed to firm-specific factors[136]. This hypothesis was confirmed through the analysis of the performance of a comprehensive corporate default prediction model including accounting ratios, macroeconomic indicators and market variables: the inclusion of IDYRISK enhanced the accuracy of the model (as measured by the area under the Receiver Operating Characteristics (ROC) curve) and was found to be positively related to the likelihood of corporate failure, even if the results regarding its statistical significance were not as conclusive (they vary according to the estimation periods *t-1* and *t-2*). However, unlike the previous study that focused on corporate default, IDYRISK does not enhance the overall prediction accuracy of the comprehensive financial distress prediction model

[135] As indicated in the previous chapter, each firm's idiosyncratic standard deviation of each firm's stock returns was estimated by regressing (using a linear regression) individual stock's monthly returns in year *t-1* on the FTSE All Share Index cumulative monthly return for the same period which corresponds to the year prior to the observation of the event of corporate default. The idiosyncratic risk of the firm is the standard deviation of the residual of this regression. The same procedure was employed to construct this measure to estimate the models with information two years prior to the observation of the corporate default event.

[136] The previous chapter includes a detailed account that justifies the inclusion of this variable in a corporate default/financial distress prediction model.

(Model 3) nor is it statistically significant. Unreported results show that in the present study, when the model is estimated in *t-1*, the inclusion of the proxy for equity returns' variability IDYRISK, leaves the overall prediction accuracy of the model unchanged at the 0.9190 level, as measured by the area under the ROC curve. Furthermore, the variable is not statistically significant (its inclusion does not alter the statistical significance of the remaining variables either). On the other hand, when the model is estimated with information two years prior to the observation of the corporate failure event (in *t-2*), the inclusion of IDYRISK results in a (marginal) decrease of the overall prediction accuracy of the model, from a ROC curve level of 0.8918 (without IDYRISK) to 0.8913 (when IDYRISK is included). However, when the comprehensive model is estimated in period *t-2*, the inclusion of this variable (which does not reach the minimum levels of statistical significance either) alters the statistical significance of at least one accounting ratio: NOCREDINT. This financial statement variable passes from being statistically significant at the 5-10% level (without IDYRISK) to being non-statistically significant (when IDYRISK is included).

From these results it can be concluded that, at best, the inclusion of the proxy for a firm's equity returns variability in a comprehensive model keeps the overall accuracy of the model unchanged and, at worst, marginally hinders the model's predictive accuracy and makes the variables' logit estimates unstable. Therefore, in order to maintain the estimates' stability of the comprehensive model, it was decided to discard this variable from the logit estimation for the prediction of financial distress. Finally, the above analysis suggests that the market variables (other than the one measuring stock returns' variability) incorporated to the 'full' model already include most of the information that is relevant for the prediction of corporate default, making the information potentially contained in IDYRISK superfluous or redundant. More generally, the evidence indicates that the usefulness of independent variables is, to a certain degree, dependent upon the methodology employed to construct the definition of the binary outcome in prediction models.

Finally, in order to discard any multicollinearity problems among the variables included in all the models, correlation matrices and direct multicollinearity diagnostic tests were computed and presented in Table 5-3.

Table 5-3 Correlation Matrix and Multicollinearity Diagnostics Statistics

Panel A of this reports the correlation matrix of all the variables in included in the model. It includes financial statement ratios, macroeconomic indicators and market variables. *P*-values represent the probability of observing this correlation coefficient or one more extreme under the null hypothesis (H0) that the correlation (Rho) is zero. Panel B reports the values resulting from tests intended to detect the presence of multicollinearity among all the variables incorporated in the model: Tolerance Value (TOL) and its reciprocal, Variance Inflation (VIF) are computed as $1-R_k^2$ and $1/(1-R_k^2)$ respectively, where R_k^2 is the determination coefficient for regression of the *i*th regressor on all the other regressors.

Panel A: Correlation Matrix

Variable	*TFOTL*	*TLTA*	*NOCREDINT*	*COVERAGE*	*RPI*	*SHTBRDEF*	*PRICE*	*ABNRET*	*SIZE*	*MCTD*
TFOTL	1.00000									
TLTA	0.17057	1.00000								
	<.0001									
NOCREDINT	-0.09720	-0.44510	1.00000							
	<.0001	<.0001								
COVERAGE	0.72613	0.02865	-0.05983	1.00000						
	<.0001	<.0001	<.0001							
RPI	-0.19100	-0.12218	0.14404	-0.19691	1.00000					
	<.0001	<.0001	<.0001	<.0001						
SHTBRDEF	0.12491	0.09343	-0.10688	0.11610	-0.81383	1.00000				
	<.0001	<.0001	<.0001	<.0001	<.0001					
PRICE	0.37131	0.05951	-0.04823	0.37641	-0.19656	0.15184	1.00000			
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001				
ABNRET	0.25785	-0.06960	0.03254	0.29870	-0.04405	-0.05138	0.28852	1.00000		
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001			
SIZE	0.36300	0.09781	-0.08105	0.40685	-0.23538	0.10799	0.58264	0.29448	1.00000	
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		
MCTD	0.08792	-0.34893	0.18940	0.13136	-0.04910	-0.00248	0.20164	0.23896	0.22630	1.00000
	<.0001	<.0001	<.0001	<.0001	<.0001	0.7461	<.0001	<.0001	<.0001	

Panel B: Multicollinearity Diagnostic Statistics

Test	*TFOTL*	*TLTA*	*NOCREDINT*	*COVERAGE*	*RPI*	*SHTBRDEF*	*PRICE*	*ABNRET*	*SIZE*	*MCTD*
TOL	0.49947	0.77183	0.87329	0.47709	0.31558	0.32067	0.60705	0.81705	0.58202	0.77601
VIF	2.00214	1.29562	1.14509	2.09603	3.16874	3.11847	1.6473	1.22391	1.71817	1.28865

5.4. Methods: Panel Logit Model Specification

The sample is divided into two groups, financially distressed firms (either financially distressed or insolvent in law) and normal or non-financially distressed firms. The outcome is a binary dependent variable. Our approach is to model the outcome within a panel logit framework (Altman et al. 2010; Altman and Sabato 2007), and follow Shumway (2001) and Nam et al. (2008) who show that a panel logit model, that corrects for period at risk and allows for time varying covariates[137], is equivalent to a hazard model. The detailed mathematical development of the model employed in the present study can be found in the previous chapter.

In addition to the estimates computed through this statistical methodology, marginal effects for each of the variables are presented. The marginal effect of a predictor is defined as the partial derivative of the event probability with respect to the predictor of interest[138]. The marginal effects measurement is therefore very useful in order to interpret the effects of the regressors on the dependent variable for discrete dependent variable models, in this case, a logit binary choice model. The study reports the average marginal effects of each explanatory variable in the reported models.

The details regarding the formal mathematical development of the panel logit methodology and the formal derivation of marginal effects can be found in Section 5 of the previous chapter.

[137] Shumway (2010), p. 123.
[138] Usage Note 22604 : Marginal effects estimation for predictors in logistic and probit models. http://support.sas.com/kb/22/604.html

Table 5-4 Summary Statistics for Model 1

This table presents summary statistics for Model 1, which includes only financial statement variables. It covers the Mean, Standard Deviation, Minimum and Maximum Values and the number of observations that were used in the logistic regression for the ratios Total Funds from Operation to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), and Interest Coverage (COVERAGE). Panel A contains summary statistics for the entire dataset; Panel B for financially healthy firms, and Panel C for the firms in financial distress.

Variable	*TFOTL*	*TLTA*	*NOCREDINT*	*COVERAGE*
Panel A: Entire Data Set				
Mean	0.068572	0.486146	-0.121824	0.530676
Std. Dev.	0.338255	0.188591	0.986025	0.819871
Min	-1	-0.432123	-1	-1
Max	1	1	1	1
Observations	18,276			
Panel B: Non-Financially Distressed Firms				
Mean	0.089208	0.482734	-0.113742	0.593286
Std. Dev.	0.323753	0.183374	0.986886	0.77798
Min	-1	-0.432123	-1	-1
Max	1	1	1	1
Observations	17,349			
Panel C: Financially Distressed Firms				
Mean	-0.317646	0.550002	-0.273086	-0.641079
Std. Dev.	0.370257	0.260108	0.95777	0.69207
Min	-1	-0.302382	-1	-1
Max	0.99792	1	1	1
Observations	927			

Table 5-5 Summary Statistics for Model 2

This table presents summary statistics for Model 2, which includes financial statement ratios as well as macroeconomic variables. It covers the Mean, Standard Deviation, Minimum and Maximum Values and the number of observations that were used in the logistic regression for the ratios Total Funds from Operation to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), Interest Coverage (COVERAGE) the Retail Price Index (RPI), and the proxy for interest rates, the 3-month Short Term Bill Rate adjusted for inflation (SHTBRDEF). Panel A contains summary statistics for the entire dataset; Panel B for financially healthy firms, and Panel C for the firms in financial distress.

Variable	*TFOTL*	*TLTA*	*NOCREDINT*	*COVERAGE*	*RPI*	*SHTBRDEF*
Panel A: Entire Data Set						
Mean	0.067493	0.485921	-0.118042	0.525922	178.39851	2.048426
Std. Dev.	0.339813	0.189284	0.986466	0.822947	32.220261	2.427929
Min	-1	-0.432123	-1	-1	94.59	-4.69551
Max	1	1	1	1	235.18	7.7407
Observations	18,070					
Panel B: Non-Financially Distressed Firms						
Mean	0.088319	0.482455	-0.109658	0.589027	177.75165	2.068698
Std. Dev.	0.325357	0.184057	0.987328	0.781256	32.427066	2.442916
Min	-1	-0.432123	-1	-1	94.59	-4.69551
Max	1	1	1	1	235.18	7.7407
Observations	17,143					
Panel C: Financially Distressed Firms						
Mean	-0.317646	0.550002	-0.273086	-0.641079	190.36081	1.673542
Std. Dev.	0.370257	0.260108	0.95777	0.69207	25.31356	2.097986
Min	-1	-0.302382	-1	-1	115.21	-4.69551
Max	0.99792	1	1	1	235.18	7.1745
Observations	927					

Table 5-6 Summary Statistics for Model 3

This table presents summary statistics for the full model, or Model 3, which includes financial statement ratios, macroeconomic indicators and market variables. It covers the Mean, Standard Deviation, Minimum and Maximum Values and the number of observations that were used in the logistic regression for the ratios Total Funds from Operation to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), Interest Coverage (COVERAGE) the Retail Price Index (RPI), and a proxy for interest rates, the 3-month Short Term Bill Rate adjusted for inflation (SHTBRDEF), the firm's Equity Price (PRICE), the firm's annual Abnormal Returns (ABNRET), the firm's Relative Size (SIZE), and the ratio Market Capital to Total Debt (MCTD). Panel A contains summary statistics for the entire dataset; Panel B for financially healthy firms, and Panel C for the firms in financial distress.

Variable	*TFOTL*	*TLTA*	*NOCREDINT*	*COVERAGE*	*RPI*	*SHTBRDEF*	*PRICE*	*ABNRET*	*SIZE*	*MCTD*
					Panel A: Entire Data Set					
Mean	0.097363	0.497767	-0.19551	0.599672	178.08903	2.046149	4.427373	-0.108952	-10.046418	0.91036
Std. Dev.	0.27721	0.169538	0.973386	0.770045	32.874323	2.532696	1.702743	0.386299	2.22842	0.192053
Min	-1	-0.102771	-1	-1	94.59	-4.69551	-3.912023	-0.999988	-16.602146	0.002877
Max	1	1	1	1	235.18	7.7407	14.151983	0.999996	-2.374161	1
Observations	13,529									
					Panel B: Non-Financially Distressed Firms					
Mean	0.118203	0.492827	-0.184269	0.669078	177.4168	2.066005	4.526808	-0.086315	-9.913979	0.919151
Std. Dev.	0.258451	0.163083	0.975489	0.713444	33.102993	2.553595	1.630117	0.374557	2.189381	0.17828
Min	-1	-0.102771	-1	-1	94.59	-4.69551	-3.912023	-0.999829	-16.480853	0.006411
Max	1	1	1	1	235.18	7.7407	14.151983	0.999996	-2.374161	1
Observations	12,801									
					Panel C: Financially Distressed Firms					
Mean	-0.269089	0.584634	-0.393164	-0.620747	189.90931	1.696996	2.678938	-0.506989	-12.375197	0.755794
Std. Dev.	0.334293	0.242075	0.91392	0.70417	25.859392	2.10305	1.982343	0.372911	1.506558	0.318516
Min	-1	0.028495	-1	-1	115.21	-4.69551	-3.912023	-0.999988	-16.602146	0.002877
Max	0.724547	1	1	1	235.18	7.1745	10.96388	0.949759	-5.641377	1
Observations	728									

5.5. Analysis of Results.

Table 5-7 presents results from logistic regressions of the financial distress indicator on the predictor variables. As required by the binary logistic regression model, firms classified as financially distressed were given a value of 1 and firms identified as financially healthy were given the value 0. This classification was carried out using the previously discussed financially-based definition of distress developed specifically for this analysis. The present study develops three main *ex-ante* models for estimating financial distress likelihood and to test the contribution of macroeconomic indicators and market variables to the predictive accuracy of models based on financial statement ratios. Model 1 represents the 'Accounting only' model and incorporates the financial statement ratios Total Funds from Operations to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), and Interest Coverage (COVERAGE). Model 2 represents the 'Accounting plus Macroeconomic' model and includes, in addition to the accounting variables, the indicators Retail Price Index (RPI), and the Short Term Bill Rate adjusted for inflation (SHTBRDEF). Model 3 is the 'Full model' incorporating, in addition to the above financial statement ratios and macroeconomic indicators, four market variables: each firm's Equity Price (PRICE) transformed using the logarithmic function; the firm's cumulative monthly abnormal returns on an annual basis (ABNRET), generated as the firm's excess returns minus the FTSE All Share return index for the same period of time; the firm's relative size (SIZE) measured by the market capitalisation relative to the total size (market capitalisation) of the FTSE All Share index, in logarithmic form. Additionally, Model 4 and Model 5 are included in Table 5-7, representing a 'Market only' model and a 'Market plus macroeconomic variables' model, respectively, in order to compare their predictive accuracy with that of Model 1 and Model 2. The objective of this additional comparison is to test the predictive accuracy of accounting models against the performance of market models using logistic regression.

As mentioned above, the present study develops *ex-ante* models for the estimation of financial distress likelihood. In practice, the date of the event of financial distress is not known and risk managers are required to employ the data that is available at the time of the analysis in order to make an estimate of the likelihood of failure or financial distress of a company. Accordingly, this study estimates the probability of failure in the year prior to the observation of corporate financial distress (*t-1*) as well as two years prior to the financial distress event (*t-2*). In that way, the models provide evidence about the predictors that best discriminate between financially distressed and healthy companies on the one hand, and on the other, test their predictive power. Thus, for the *t-1* models, all of the accounting ratios were computed using the financial statements of the year prior to the financial distress event. Accordingly, the macroeconomic indicators were calculated with information from the year preceding the distress event: the Retail Price Index (RPI) in base 100 as well as the 3-month Bill rate (SHTBRDEF), which was annualised and deflated using the inflation rate in order to obtain a measure of the level of 'real' interest rates in the economy. As for the market variables, equity prices (PRICE) were incorporated to the model as the official closing price in *t-1*, the variable measuring abnormal returns (ABNRET) for year *t*, when the distress event was observed, was calculated as the return of the firm in year *t-1* minus the FTSE All Share Index return in year *t-1*. Individual firms' annual returns were generated by cumulating monthly returns. With regard to the variable that measures the relative size of the firm (SIZE), following Shumway (2001), individual firms' market capitalisation was measured at the end of the year before the financial distress event year. Finally, as for the ratio Market Capitalisation to Total Debt (MCTD), the latter was also measured with information taken from financial statements issued in *t-1*.

Table 5-7 reports the resulting estimates from logistic regressions of the financial distress indicator on the independent variables. All of the variables in the 'accounting' model (Model 1) are statistically significant at 5-1% in *t-1* year, which suggest that they are efficient predictors of the probability of financial distress. In *t-2*, or two years before the financial distress event was observed, all of the regressors retain their statistical significance except the accounting ratio Total Liabilities to Total Assets, which becomes statistically insignificant. This is the case not only for the 'accounting' model, but also for the 'accounting plus macroeconomic' model and the 'full' model[139]. The fact that all of the variables in Model 1 except one retain the same level of significance in both *t-1* and *t-2* before the distress event suggest that the financial statement ratios that were retained in the model possess a high discriminating and predicting power. Furthermore, the coefficient's estimates possess the predicted sign: a negative sing of the ratio TFOTL, which represents a measure of the performance of a company, suggests that the higher the level of funds from operations a company produces (relative to their liabilities) the higher its performance and therefore the lower its probability of entering financial distress. Similarly, the sign of

[139] In the remainder of the present study the term 'Model 1' will be used to make reference to the 'Accounting' only model, 'Model 2' to the model that includes macroeconomic indicators in addition to financial statement ratios, and the term 'Model 3' will be representing the 'full model,' or the model that includes financial statement ratios, macroeconomic indicators and market variables. In addition 'Model 4' and 'Model 5' will be used to make reference to a 'Market only' model and a 'Market plus macroeconomic indicators,' respectively.

the variable NOCREDIT suggests that the higher the liquidity of a company[140], the lower its financial distress likelihood. The COVERAGE variable also displays the anticipated negative sign, where an increased or substantial ability to pay interest on outstanding debt, lowers the firm's financial distress likelihood. The coefficient's estimate for the variable TLTA displays a positive sign which indicates, opposite to the previous accounting ratios, that a highly leveraged company (a high value of the TLTA variable) will display a higher likelihood of financial distress. This last result is also consistent with the present study's initial predictions. Interestingly, the COVERAGE coefficient estimate possesses the highest absolute value among the financial statement ratios, followed by TLTA and TFOTL, NOCREDITINT having the smallest value. The same applies for the model estimated in *t-2*, which suggests that the accounting ratios' coefficient estimates are stable over the two periods of time.

Table 5-7 also presents Cox and Snell's *R* squared as well as Nagelkerke's max rescaled *R* squared in order to have a comparison point of the *relative* increase or decrease in performance between the models. As expected, the Nagelkerke's max rescaled R squared decreases for Model 1 when it is estimated from *t-1* to *t-2*. However, the magnitude of the decline is only marginal, which suggests that the models' regressors are stable over time. Nevertheless, these measures are only included to make comparisons easier and their interpretation needs to be treated with caution, as they do not have the same meaning for logit regressions as they have for ordinary least squares regressions. As previously discussed, a more appropriate and direct measure of the real performance of a logit model is the area Under the Receiver Operating Characteristics curve[141] (AUC), whose output will be discussed in the following lines.

In addition to the accounting ratios, Model 2 incorporates two macroeconomic indicators. Both of them, RPI and SHTBRDEF are statistically significant at 5-1% in the model estimated in *t-1*, and retain the same statistical significance in *t-2*, which as in the case of three of four of the financial statement ratios, indicate that the stability of the variables over two periods. Furthermore, all of the variables initially included in Model 1 retain their statistical significance and the relative magnitude of their coefficient estimates in Model 2. The signs of both indicators are also as predicted in the present study: the positive sign of the RPI variable's estimate indicates that a higher level entails an increased

[140] Or, in the specific case of the No Credit Interval variable, the period that a company could finance its own business expenses, at its current level of activity, by drawing on its own liquid resources and on the assumption that it made no further sales

[141] In the remainder of the present study, the area under the Receiver Operating Characteristics curve will be referred to as 'AUC.'

likelihood of financial distress. And the positive sign of the SHTBRDEF indicator suggests that in a macroeconomic environment characterised by a high level of the real rate of interest, all other thing beings equal, the probability of financial distress for industrial firms increases. However, both macroeconomic regressors' estimates are lower in magnitude than the accounting ratios, RPI having the smallest estimate in absolute terms, which might suggest a smaller effect of the macroeconomic variables on the likelihood of firms' financial distress. With regard to the macroeconomic variables' contribution to the predictive accuracy of accounting the model, as directly measured by the AUC, it can be concluded that they contribute positively, although rather marginally, when the model is estimated in *t-1*: The AUC shows an increase from 0.87 to 0.88. However, when the model is estimated in *t-2*, the contribution of the macroeconomic indicators is less conclusive: a very small decrease is even observed from an AUC of 0.8523 to 0.8514, suggesting that in *t-2*, financial statement ratios alone are more powerful to predict financial distress than mixed with macroeconomic indicators.

Model 3 in Table 5-7 presents the results from logit regressions of the financial distress indicator on the accounting and macroeconomic predictor variables included in Model 2 plus 4 market variables: firms' stock prices, past abnormal returns, the relative size of the company and the ratio market capitalisation to total debt. All of the market variables that entered Model 3 are statistically significant at 5-1% when estimated in period *t-1*. With the notable exception of the SIZE, all of the variables retain the same levels of significance when estimated in *t-2*, suggesting that PRICE, ABNRET, and MCTD are powerful and consistent predictors over time of the likelihood of financial distress. SIZE was kept in the models as, in spite of its lack of statistical significance in *t-2*, it contributed positively to the predictive accuracy of the model as measured by the AUC. The only exception is NOCREDINT, which experienced a marginal decrease, from being statistically significant at 5-1% to 10% in the models estimated with data generated two years prior to the observation of the financial distress event. It should be also noted that the accounting ratio TLTA displays the same behaviour as in the previous analysis of Model 1 and Model 2; when Model 3 is estimated in period *t-1* the ratio is significant at 5-1%, however, when it is estimated in period *t-2*, it ceases to be statistically significant, which suggests that TLTA, despite having a positive contribution to the predictive accuracy of the model, is not consistent over time. As for the signs of the coefficient estimates, they all are as predicted in this study: a negative sign of the PRICE variable indicates that there is a negative relationship between stock price levels and the likelihood of financial distress of public companies, as market prices reflect investors' expectations of future cash flows or earnings, and the company's earnings are affected by its financial position.

The sign of the ABNRET's estimate, suggest that, as posited, there is a negative relationship between this regressor and the probability of financial distress. Investors do seem to discount the equity of those firms that are in a stressed financial position or close to default/bankruptcy, and the returns of the company seem to be affected in consequence: individual returns of a company outperforming the returns of the FTSE All Share Index are a sign of good financial health and thus decrease the likelihood of financial distress. Contrarily, company's returns that fall short to match the FTSE All Share Index's returns (negative returns) are a consistent predictor of financial distress over time (both in *t-1* and *t-2*). The sign of MCTD suggests a negative relationship between this variable and the probability of financial distress. The study expected this ratio to enhance the predictive accuracy of the model and to be consistent over time as it was constructed to include, on the one hand, a market approach (through the measure of market capitalisation) and, on the other, to solve the problem highlighted in Beaver (2005), namely that the variables ABNRET and SIZE are not scaled in that they are not compared to the magnitude of debt outstanding. By including total debt as denominator, it solves this problem without giving rise to multicollinearity problems with the variable SIZE. As expected, MCTD is a powerful as well as consistent predictor of financial distress over time. The sign of the market variable SIZE is also as predicted: companies with a high level of SIZE (high market capitalisation relative to the FTSE All Share market capitalisation) are more stable (and/or well established), indicating a good level of the debt holders' 'equity cushion,' far from the 'strike price' (or the value of liabilities), and therefore judged by investors as capable of serving their debt obligations lowering thus the likelihood of financial distress. As to the magnitude of the coefficients' estimates, ABNRET possess the highest absolute value in Model 3, estimated in *t-1* as well as *t-2*, followed by MCTD in *t-1* but not in *t-2*, where it displays a lower absolute magnitude, followed by SIZE and PRICE. It is therefore concluded that the market variables are also consistent predictors of the likelihood of financial distress over time.

Table 5-7 Logit Regression of Financial Distress Indicator on Predictor Variables

This table reports results from logit regressions of the financial distress indicator on the predictor variables. The models were computed for two periods: using the accounts, market and macroeconomic data from the year prior to the observation of the financial distress event (*t-1*), and the accounts, market and macroeconomic data from two years prior to the observation of the financial distress event (*t-2*) in order to confirm their predictive ability in addition to their discriminating power. Additionally, results are also presented for a 'Market' model that incorporates market variables in *t-1* for comparison purposes. The absolute value of *z*-statistics is reported in parenthesis. * denotes significant at 10%, ** denotes significant at 5%-1%.

Variable	Model 1		Model 2		Model 3		Model 4	Model 5
	t-1	*t-2*	*t-1*	*t-2*	*t-1*	*t-2*	*t-1*	*t-1*
TFOTL	-0.8105 **	-0.7327**	-0.7711**	-0.7357**	-1.0784**	-1.0001**		
	(6.74)	(6.18)	(6.30)	(6.19)	(6.51)	(6.26)		
TLTA	1.2825**	0.2048	1.3438**	0.2593	0.6102**	0.00600		
	(7.61)	(1.18)	(7.96)	(1.49)	(2.66)	(0.03)		
NOCREDINT	-0.2130**	-0.1670**	-0.2245**	-0.1685**	-0.1513**	-0.0938*		
	(4.80)	(3.79)	(5.07)	(3.81)	(2.83)	(1.82)		
COVERAGE	-1.3362**	-1.2792**	-1.2851**	-1.2481**	-0.9738**	-0.9678**		
	(22.99)	(22.36)	(22.00)	(21.56)	(14.24)	(14.21)		
RPI			0.0201**	0.0145**	0.0119**	0.00728**		0.0113**
			(8.45)	(5.85)	(4.27)	(2.60)		(4.57)
SHTBRDEF			0.1901**	0.2111**	0.1262**	0.1028**		0.1010**
			(6.51)	(5.63)	(3.84)	(2.45)		(3.48)
PRICE					-0.1043**	-0.0711**	-0.1716**	-0.1629**
					(4.00)	(2.79)	(6.92)	(6.49)
ABNRET					-1.1429**	-1.6046**	-1.7637**	-1.7378**
					(9.55)	(13.59)	(15.42)	(15.15)
SIZE					-0.2356**	-0.0440	-0.4398**	-0.4140**
					(7.23)	(1.47)	(15.49)	(14.43)
MCTD					-1.2944**	-0.6249**	-0.9757**	-1.0043**
					(7.53)	(3.16)	(6.97)	(7.13)
Constant	-7.8570**	-2.9831**	-7.8570**	-6.1015**	-7.2547**	-4.4563**	-6.9068**	-8.8751**
	(37.63)	(30.63)	(15.60)	(11.40)	(10.52)	(6.08)	(16.55)	(14.17)
Pseudo R^2	0.0926	0.0929	0.0965	0.0953	0.1420	0.1260	0.1017	0.1032
Max-rescaled R^2	0.2802	0.2626	0.2901	0.2674	0.4148	0.3527	0.2967	0.2984

Table 5-8 presents model performance statistics for the five models estimated in both *t-1* and *t-2*. The area under the ROC curve (AUC) is a direct and appropriate measure of the predictive accuracy of models developed using the logit methodology. DeLong et al. (1988) state that 'when a test is based on an observed variable that lies on a continuous or graded scale, an assessment of the overall value of the test can be made through the use of a receiver operating characteristic (ROC) curve.'[142] Furthermore, Altman et al. (2010) argue that 'The ROC curve plots the true positive against the false positive rate as the threshold to discriminate between failed and non-failed firms' changes. The area under the ROC curve is a measure of the predictive accuracy of the model, with a value of 1 representing a perfect model.' Gini rank correlation coefficients[143] and Kolmogorov-Smirnov statistics, also presented in Table 5-8, are widely used analysis tools by scoring analysts to assess the predictive accuracy of in-sample and hold-out tests (Altman et al., 2010). The advantage of these tests is that they are easy to interpret and to calculate, as both can be derived from the AUC. As Anderson (2007) argues, the Gini rank coefficient has been co-opted by credit scoring analysts, who employ it as a measure of 'how well a scorecard is able to distinguish between goods and bads' where 'the end result is a value representing the area under the curve.' The Gini coefficient is very similar to the AUC; the difference is that the former calculates only the area between the curve and the diagonal of the Lorenz curve, unlike the latter, which calculates the full area below the curve[144]. As a reference point, in the context of professional credit scoring analysis, a Gini coefficient equal to or above 50% is a very satisfactory level in a retail environment, as discussed by Anderson (2007). In the context of the present study, the Gini rank coefficient is used in order to complement and check the consistency of the other measures presented.

The Kolmogorov-Smirnov test is performed to measure the maximum vertical deviation between two empirical cumulative distribution functions (good and bad) in credit score modelling. This measure is, according to Anderson (2007) and Mays (2004), 'the most widely used statistic within the United States for measuring the predictive power of rating systems.'[145] However, Anderson (2007) recommends not using this statistic (or any other measure of the predictive accuracy of a model) in isolation, but rather as a complement to others such as the AUC or the Gini rank coefficient, which is the approach adopted in the present study. Mays (2004) suggests that the acceptable values for this statistic range from

---

[142] P. 837

[143] The Gini rank correlation coefficient can be found as the Somer's D statistic in the SAS software and most statistical software packages.

[144] As such, it can be computed as ((2*AUC)-1) following Altman et al. (2010).

[145] Anderson (2007), p. 196

20% to 70%, above which the model is 'probably too good to be true.' Cox and Snell's R-squared is a measure based on the log-likelihood of the model, the log-likelihood of the original (baseline) model and the sample size, and Nagelkerke's Max-rescaled R-squared is a refinement of the former. In other words, both can be considered as measures of the same concept. In general, they can also be interpreted very similarly (but not identically), to the R-squared in linear regression, as they are measures of the significance of the model[146]. The Hosmer and Lemeshow goodness-of-fit test for binary response logistic models is also provided. As discussed by Ragavan (2008), the subjects are divided into approximately ten groups of roughly the same size based on the percentiles of the estimated probabilities. The discrepancies between the observed and expected number of observations in these groups are summarised by the Pearson chi-square statistic, which is then compared to a chi-squared distribution with *k* degrees of freedom, were *k* is the number of groups (10) minus *n* (2).[147] Thus, a small chi-square (<15) and a large *p*-value (>0.05) should suggest that the model is effective to predict the behaviour of the data, or that the fitted model is an appropriate one to be employed in order to predict the specified binary outcomes in the dataset.

Table 5-8 shows the performance of all of the models in the study. From the results presented in Section A, which correspond to the models estimated in period *t-1*, it can be concluded that even if Model 1, the 'accounting only' model possesses an already high discriminating accuracy as measured by the AUC, the addition of macroeconomic indicators and market variables can contribute positively and substantially to the performance of the financial distress prediction models. Furthermore, it is demonstrated that a distress prediction model, does not require the inclusion of a large number of regressors (as in some previous academic studies) to display a high discriminating and predictive accuracy; in the present study, a set of only 10 regressors yielded an impressive AUC of 0.92 in period *t-1* (which decreased only marginally to 0.89 in period *t-2*), suggesting that the independent variables retained in the model act as complementary and not as substitutes (or mutually exclusive). It is also important to highlight the fact that the high discriminating and predictive accuracy of the full model in the present study might be explained by the specific combination of independent variables, which were selected taking into consideration the problems highlighted in previous research works with regard to the representation of the main, most likely, and potential indicators of financial distress. A very large number of financial ratios, macroeconomic indicators and market variables were

146 See Cox and Snell (1989) and Nagelkerke (1991).
147 P. 10.

tested. Redundant variables were discarded, indicators that have proven their contribution to the performance of the models in previous research were included, and potentially useful new ones were tested. An example of a new indicator that had not yet been tested is the ratio market capitalisation to total debt (MCTD), which proved to contain information useful to the prediction of financial distress. The result was a new distress prediction model with a new set or combination of variables for quoted companies in the United Kingdom that proved to be very well positioned relative to previous and well-known models for the prediction of company's default/distress[148].

From Model 1 to Model 2 in period *t-1*, an increase in the performance of the models measured by the AUC was observed (from 0.872 to 0.876), which indicates that macroeconomic variables contribute only marginally, though positively, to the predictive accuracy of a model based on financial statement ratios. As the Gini rank coefficient and the Kolmogorov-Smirnov statistic are both derived from computations based on the level of the AUC, they follow the same pattern as the latter, and fall into the (previously discussed) highest ranges that are considered by credit scoring professionals as acceptable. On the other hand, a considerable increase in the AUC is observed when market variables are added in Model 3 (from an AUC equal to 0.88 to an AUC equal to 0.92); the magnitude of the enhancement suggest that market variables contain a substantial amount of information that is not available in financial statements but that was taken into consideration by the markets and act as a complement to the information provided by accounting ratios[149]. Furthermore, the present study also estimates Model 4 and Model 5 in order to directly compare the performance of the 'accounting only' model (Model 1) and the 'accounting plus macroeconomic variables' model (Model 2) against the 'market only' model (Model 4) and the 'market plus macroeconomic variables' model (Model 5) respectively. It can be observed that accounting and market models in isolation yield almost the same predictive accuracy, with an AUC of 0.8718 and 0.8712 for the accounting and market only models respectively, and an AUC of 0.8763 and 0.8727 when macroeconomic variables are added to the models. In both cases, the inclusion of macroeconomic variables enhances, although marginally, the predictive accuracy. The accounting models have a

[148] With the advantages of accuracy, simplicity and timeliness.

[149] An example of the information that is not included in financial statements (as by nature they contain only past information), might be the information regarding the future prospects of a firm such as an insufficient level of Research and Development expenditure, or the negative forecast for a specific industry due to industry-specific micro or macroeconomic developments taking place. Information of this kind is typically taken into account by investors and market participants in their analysis and is therefore reflected by market variables only such as equity prices or firms' returns.

marginally better performance when estimated in period *t-1* using binary logistic regression as the main statistical methodology. It is therefore of paramount importance to highlight the prominent increase in predictive accuracy (from an AUC equal to 0.88 to 0.92) resulting from the combination of two models that yield an almost equal (both significantly minor to the 'full' model) predictive accuracy when they are estimated in isolation.

Table 5-8 also presents the results of Hosmer and Lemeshow goodness-of-fit tests. Despite the different results obtained in previous research works, and the controversy surrounding its consistency, the present study reports the results of the goodness-of-fit test as it points to an interesting observation worth taking into consideration: when Model 1 and Model 2 (the 'accounting only' model and the 'accounting plus macroeconomic variables' model respectively) are estimated, the Hosmer and Lemeshow goodness-of-fit test show a large chi-square and a p-value < .0001, both of which indicate that the model, although displaying a high predictive accuracy, might lack other independent variables that are crucial in order to explain a higher proportion of the phenomenon that a model is trying to elucidate. On the other hand, it can be observed that the opposite is true when market variables are incorporated to the 'accounting and macroeconomic variables model' in Model 3: the results for the Hosmer and Lemeshow goodness-of-fit test show a small chi-square (<15) and a large p-value (>0.05) that suggests that Model 3 is and adequate model. In other words, these values imply that the model fitted with macroeconomic variables is more appropriate to predict the data (to better discriminate and predict the specified binary outcomes in the dataset: healthy from financially distressed companies). This argument finds additional support in the significantly larger AUC (from 0.88 to 0.92) when market variables are present.

In order to test if the same results hold true for models based on market variables, the same test was applied to Model 4 and Model 5 (the 'market only' model and the 'market plus macroeconomic variables' respectively). Consistent with the previous analysis of results, Model 4 displays a chi-square with a value below 15 and a p-value well above the 0.05 threshold, suggesting that market variables are appropriate regressors to measure the likelihood of financial distress. Interestingly, when macroeconomic indicators are added to the 'market only' model, both Hosmer and Lemeshow goodness-of-fit statistics display better values than for the accounting models (Model 1 and Model 2). Furthermore, the same results apply for the models estimated in *t-2*, making the above interpretation more consistent.

Table 5-8 Model Performance Measures

This table reports model performance statistics. Panel A shows measures for the five models estimated in period *t-1,* and Panel B displays the same measures for all of the models estimated in *t-2*. Model 1 is the 'accounting only' model, Model 2 is the 'accounting plus macroeconomic variables' model, Model 3 is the 'full' model, including market variables in addition to the variables in Model 2, Model 4 is the 'market only' model, and Model 5 is the 'market plus macroeconomic variables' model. The first measure is a direct measure of the predictive accuracy of models estimated using the logit methodology, the Area under the Receiver Operating Characteristics Curve (AUC); Gini coefficients, Kolmogorov-Smirnov statistics, Cox and Snell R-squared, Nagelkerke's Max-rescaled R-squared and the models' Chi-squared are also presented. Additionally Hosmer and Lemeshow goodness-of-fit statistics are displayed.

Measure	Model 1	Model 2	Model 3	Model 4	Model 5
		Panel A: Models' Performance in *t-1*			
AUC	0.8718	0.8763	0.9190	0.8712	0.8727
Gini Rank Coefficient	0.7436	0.7526	0.8380	0.7424	0.7454
Kolmogorov-Smirnov	0.5949	0.6021	0.6704	0.5939	0.5963
Cox & Snell's R^2	0.0926	0.0965	0.1420	0.1017	0.1032
Nagelkerke's R^2	0.2802	0.2901	0.4148	0.2967	0.2984
$\chi2$* (4, 6, 10, 4, 6)	1776.13	1834.72	2072.44	1587.72	1588.23
	(P<.0001)	(P<.0001)	(P<.0001)	(P<.0001)	(P<.0001)
		Hosmer & Lemeshow Goodness-of-Fit Test			
χ^2 (8)	86.5081	55.8609	10.2224	12.5565	18.5788
Pr> χ^2	<.0001	<.0001	0.2498	0.1280	0.0173
		Panel B: Models' Performance in *t-2*			
AUC	0.8523	0.8514	0.8918	0.8355	0.8358
Gini Rank Coefficient	0.7046	0.7028	0.7836	0.6710	0.6716
Kolmogorov-Smirnov	0.5637	0.5622	0.6269	0.5368	0.5373
Cox & Snell's R^2	0.0929	0.0953	0.1260	0.0822	0.0831
Nagelkerke's R^2	0.2626	0.2674	0.3527	0.2302	0.2301
$\chi2$* (4, 6, 10, 4, 6)	1550.94	1573.33	1657.38	1167.70	1158.12
	(P<.0001)	(P<.0001)	(P<.0001)	(P<.0001)	(P<.0001)
		Hosmer & Lemeshow Goodness-of-Fit Test			
χ^2 (8)	97.7438	45.3124	13.7421	10.7357	18.1839
Pr> χ^2	<.0001	<.0001	0.0887	0.2171	0.0199

* the parenthesis following the model's $\chi2$ represent the degrees of freedom for each estimated model: 4 for Model 1, 6 for Model 2, 10 for model 3, 4 for Model 4, and 6 for Model 5.

Unsurprisingly, the predictive accuracy of the models estimated in *t-2* experience a decrease, which is consistent with previous default prediction models. However, the same patterns can be observed when financial statement ratios, macroeconomic indicators and market variables are combined in a single model. The only exception that can be observed is between Model 1 and Model 2; when macroeconomic variables are added to the 'accounting only' model, there is a marginal decrease in predictive accuracy (from and AUC of 0.852 to an AUC of 0.851), suggesting that financial statement ratios are (marginally) more reliable regressors than macroeconomic indicators when the likelihood of financial distress is estimated in *t-2*. Nevertheless, because of the inconsequential (very small) decrease in performance, it could also be argued that the predictive accuracy remains unchanged when macroeconomic indicators are included in an accounting model estimated in *t-2*. As to Model 3, it can be concluded that the addition of market variables to Model 2 (estimated in *t-2*) considerably increases the predictive accuracy by the same magnitude as when it was estimated in period *t-1*: from an AUC of 0.851 to 0.892. Model 5 also shows an increase in predictive accuracy relative to Model 4: from an AUC of 0.835 to 0.836, suggesting that, although marginally, macroeconomic variables contribute positively to the performance of the model. However, as in the case of Model 1 and Model 2, the contribution is so small that the performance could also be considered as unchanged. Again, this analysis confirms the consistency of the behaviour of macroeconomic indicators when added either to the *t-2* 'accounting only' model or to the 'market only' model. The additional Gini rank coefficients as well as the Kolmogorov-Smirnov tests display patterns consistent with the above discussion and confirm the previous results, both the models estimated in *t-1* and the ones estimated in *t-2*. Moreover, the predictive accuracy of the models presented in this study can be located in the high end of the ranges specified by professional credit managers when measured through the Gini coefficient and the Kolmogorov-Smirnov statistic.

As stated by Cleves (2002), 'occasionally, there is a need to compare the predictive accuracy of several fitted logit (logistic) or probit models by comparing the areas under the corresponding receiver operating characteristic (ROC) curves.'[150] In order to perform the comparisons, the present study applies for the first time, in financial distress prediction models, a methodology based on a non-parametric approach that employs the theory developed for generalised Man-Whitney *U*-statistics. The present study follows the methodology presented in DeLong et al. (1998) and takes thus into account the correlated nature of the data that arises when two or more empirical curves are constructed using tests performed on a same set of firms. This issue is paramount as most of the comparisons of ROC curves made in previous studies, not only in the field of finance but also in fields such as atmospheric science and medical diagnosis, for which predictions of specific outcomes are essential, employ the already available computations in most statistical analysis software packages. The problem with this approach is that the models to be compared (derived using the same dataset) are estimated on the same number or set of observations. For instance, as highlighted by Cleves (2002), when the commands 'roccontrast' in SAS or 'roccomp' in STATA are employed to compare the curves after running the logistic procedure, the programs use the same number of observations for all

[150] P. 301

models, as they drop from the computation any observation[151] in which at least one of the covariate values is missing (which varies between models). Therefore, difficulties can arise if there are missing values included in some models but not in others, as the exclusion of valid observations that would have otherwise been used in the normal estimation of the logit model, lead to inconsistent and erroneous computations of the area under the receiver operating characteristics curve.

The comparison of curves in the present study takes into account the correlated nature of the data[152], on the one hand, and solves the problem of comparison of two or more models using a constant number of observations, on the other. Following Delong et al. (1988) and combining the use of the SAS logistic statistical methodology (PROC LOGISTIC) with the ROC macros available from the SAS Institute[153], the present paper reports a useful visual comparison of the differences in predictive accuracy of the 'accounting only' model, the 'accounting plus macroeconomic indicators' model and the 'full' model using a non-parametric approach based on the theory on generalised Man-Whitney *U*-statistics. The graphic is constructed plotting the models' ability to identify true positives (sensitivity), on the Y axis, and its ability to detect true negatives (1 - specificity). In other words, each individual ROC curve is generated (in the field of financial distress prediction models) by plotting the proportion of true distressed companies out of the companies classified by the model as distressed ('True Positive Rate') against the proportion of false distressed companies (healthy companies) out of the companies classified by the model as distressed ('False Positive Rate') at various cutpoints. As to the use and interpretation of the plots' results, 'if a test could perfectly discriminate, it would have a value above which the entire abnormal population would fall and below which all normal values would fall (or vice versa). The curve would then pass through the point (0, 1) on the unit grid. The closer a ROC curve comes to this ideal point, the better its discriminating ability. A test with no discriminating ability will produce a curve that follows the diagonal of the grid.' [154] Additionally, the areas under the receiver operating characteristic curve of the three fitted models are tested for equality, where an overall *p*-value below 0.05 is indicative of differences between the areas. In other words, an overall *p*-

[151] Stata's 'roccomp' command also drops from the computation any observation in which at least one of the predicted probabilities is missing. See Cleves (2002).

[152] The implicit correlation between the curves when two or more empirical curves are constructed using tests performed on a same set of firms.

[153] The use of the SAS PROC LOGISTIC and the macros available from the SAS Institute results in a method capable of comparing each model's receiver operating characteristics area computed using the entire available number of observations specific to each individual model and not a constant number of observations for all models, thus avoiding the problem highlighted by Cleves (2002).

[154] DeLong et al. (1988), p. 837

value <0.05 signifies that the null hypothesis of equality of areas under the ROC curve can be rejected, thus confirming the reliability of the results.

The nonparametric comparison of the areas under correlated ROC based on the theory developed for generalised Man-Whitney *U*-statistics was performed, initially, on 3 models estimated in period *t-1*: the 'accounting' model, the 'accounting plus macroeconomic variables' model, and the 'full' model that includes market variables. Then, two out of the three models with the best predictive accuracy, based on the area under the ROC curve, were selected for another comparative test with the aim of presenting graphically the increase in predictive accuracy when market variables are added to Model 2, on the one hand, and to test whether the AUC differs statistically between the two models, on the other. Furthermore, the above procedure for the three models estimated in *t-1* was repeated for the same three models estimated in *t-2*. The present study presents thus four figures that allow a comparison between models and between estimation periods that facilitates the analysis of the differences in predictive accuracy as well as the contribution of the different sets of variables (financial statement ratios, macroeconomic indicators, and market variables) over time.

Figures 5-1 to 5-4 show a graphic representation of the discussion drawn from Table 5-7, regarding the differences in the predictive accuracy of the models through the interpretation of their respective AUCs: it can be thus confirmed that the contribution of macroeconomic indicators to the performance of the accounting model is positive, though marginal, when the model is estimated in *t-1*, however, results are less conclusive when the model is estimated in *t-2*: there is even a very small decrease in performance entailed by the inclusion of macroeconomic indicators. It can be therefore concluded that financial statement ratios are more powerful to predict financial distress in period *t-2*. On the other hand, the inclusion of market variables results in a substantial increase in the predictive accuracy of 'accounting plus macroeconomic indicators' models, showing consistency when they are estimated in both periods *t-1* and *t-2*. Finally, it is worth noting that the four comparisons of areas under the curve show an overall *p*-value =< 0.0001 which indicates that the null hypothesis (H0) of equality of areas under the ROC curve can be rejected. In other words, the small *p*-value resulting from the test strongly suggests that the three areas differ statistically and that the analysis is reliable.

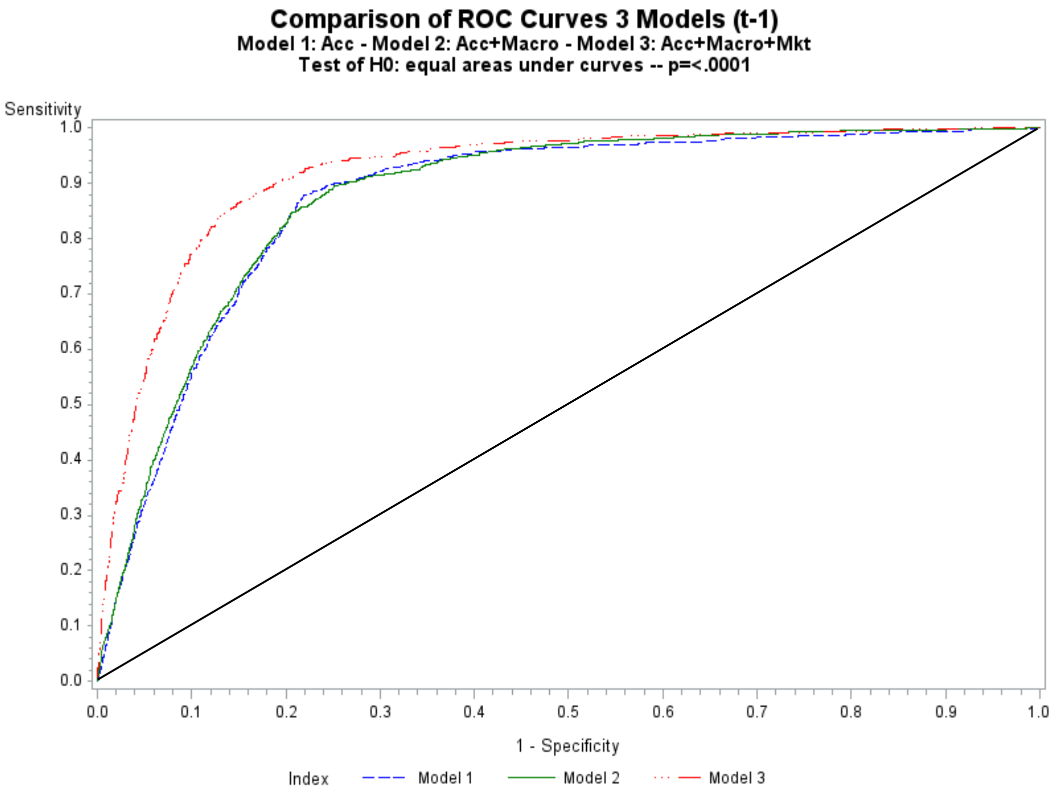

Figure 5-1 Comparison of Areas under the Receiver Operating Characteristic Curve of Model 1, Model 2, and Model 3 estimated in period t-1

The figure plots the AUC of the 'accounting only' model, the 'accounting plus macroeconomic indicators' model and the 'full' model, including market variables; Model 1, Model 2, and Model 3 respectively, estimated in period *t-1*. The comparison was performed using the non-parametric method to compare areas under correlated ROC curves presented in DeLong et al. (1988), where Model 1 AUC = 0.87, Model 2 AUC = 0.88, and Model 3 AUC = 0.92. The discriminating accuracy of a model's AUC equal to the diagonal line in the graphic (0.50) would be no different than a random guess. Conversely, an AUC equal to 1 would signify that the model is able to perfectly discriminate the binary outcomes. Therefore, the closer the real value of an AUC to this theoretical value, the better its discriminating ability. The overall p-value =< 0.0001 indicates that the null hypothesis of equality of areas under the ROC curve can be rejected. In other words, the small p-value of this test strongly suggests that the three areas differ statistically.

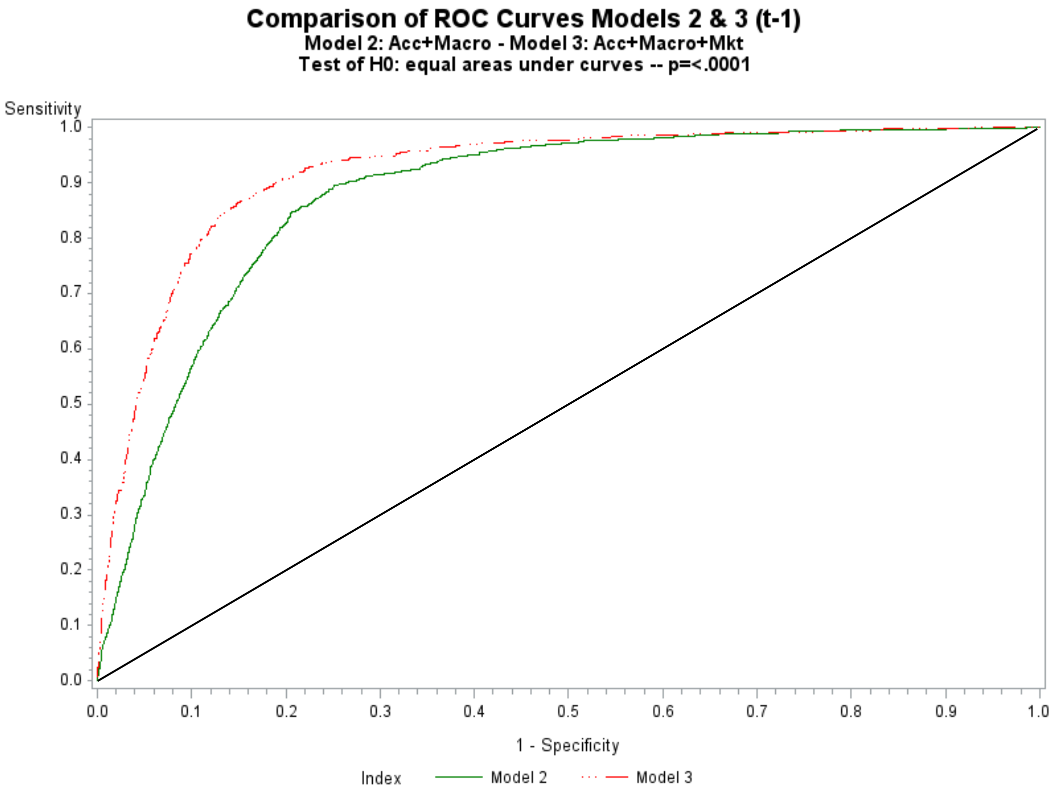

Figure 5-2 Comparison of Areas under the Receiver Operating Characteristic Curve of Model 2, and Model 3 estimated in period *t-1*

The figure plots the AUC of the two models with the best discriminating ability: Model 2 and Model 3 estimated in period *t-1*, the 'accounting plus macroeconomic indicators' model and the 'full model,' including market variables, respectively. The comparison was performed using the non-parametric method to compare areas under correlated ROC curves presented in DeLong et al. (1988), where Model 2 AUC = 0.88, and Model 3 AUC = 0.92. The discriminating accuracy of a model's AUC equal to the diagonal line in the graphic (0.50) would be no different than a random guess. Conversely, an AUC equal to 1 would signify that the model is able to perfectly discriminate the binary outcomes. Therefore, the closer the real value of an AUC to this theoretical value, the better its discriminating ability. Similar to the above comparison of the three models, the overall *p*-value =< 0.0001 indicates that the null hypothesis of equality of areas under the ROC curve for Model 2 and Model 3 can be rejected. In other words, the small *p*-value of this test strongly suggests that the three areas differ statistically.

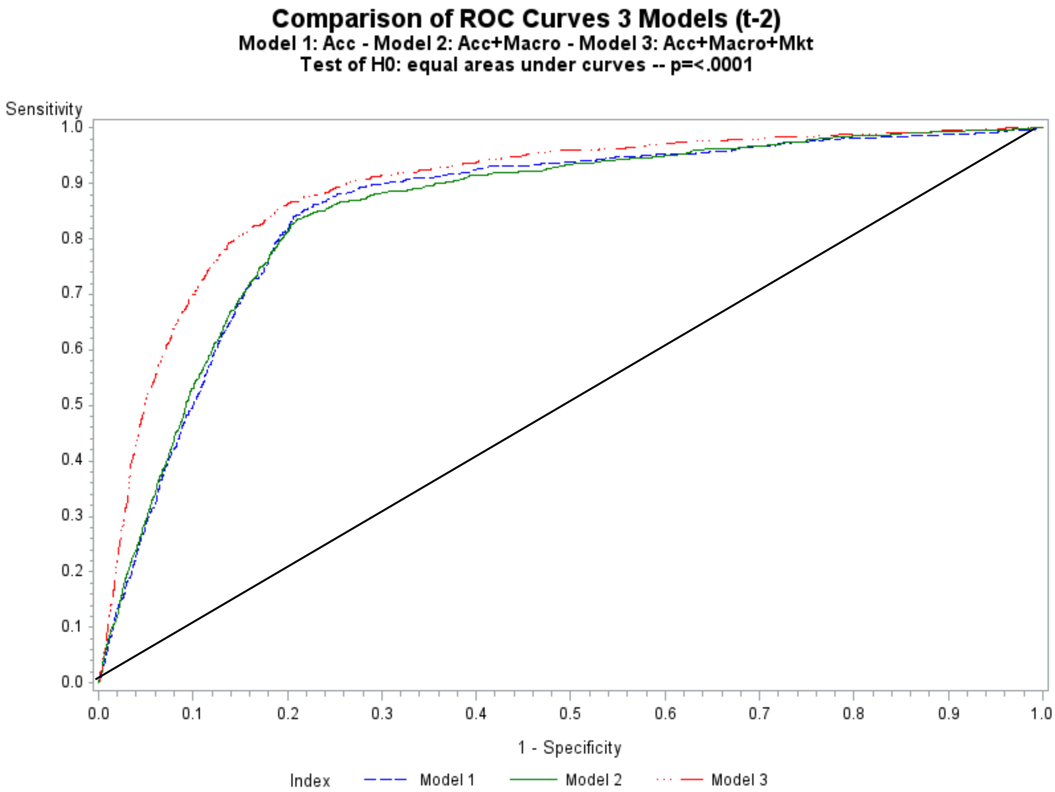

Figure 5-3 Comparison of Areas under the Receiver Operating Characteristic Curve of Model 1, Model 2, and Model 3 estimated in period *t-2*

The figure plots the AUC of the 'accounting only' model, the 'accounting plus macroeconomic indicators' model and the 'full model,' including market variables; Model 1, Model 2, and Model 3 respectively, estimated in period *t-2*. The comparison was performed using the non-parametric method to compare areas under correlated ROC curves presented in DeLong et al. (1988), where Model 1 AUC = 0.85, Model 2 AUC = 0.85, and Model 3 AUC = 0.89. The predictive accuracy of a model's AUC equal to the diagonal line in the graphic (0.50) would be no different than a random guess. Conversely, an AUC equal to 1 would signify that the model is able to perfectly predict the binary outcomes. Therefore, the closer the real value of an AUC to this theoretical value, the better its predicting ability. The overall *p*-value =<0.0001 indicates that the null hypothesis of equality of areas under the ROC curve can be rejected. In other words, the small *p*-value of this test strongly suggests that the three areas differ statistically.

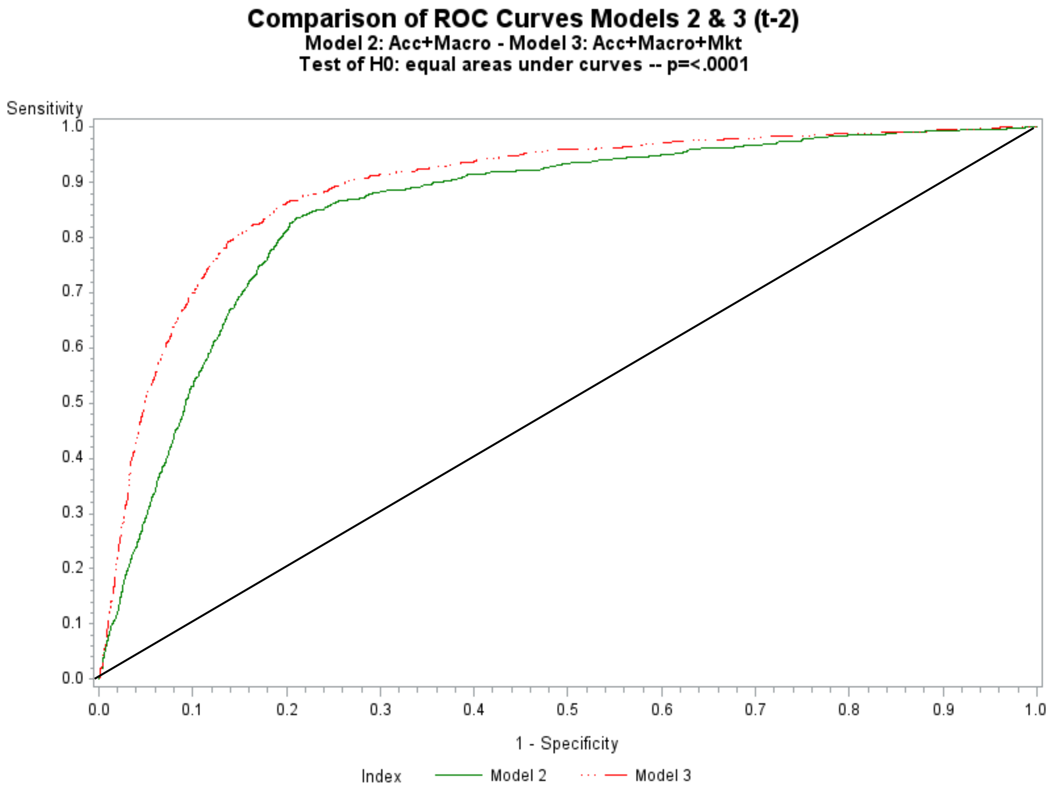

Figure 5-4 Comparison of Areas under the Receiver Operating Characteristic Curve of Model 2, and Model 3 estimated in period *t-2*

The figure plots the AUC of the two models with the best predictive ability: Model 2 and Model 3 estimated in period *t-2*, the 'accounting plus macroeconomic indicators' model and the 'full model,' including market variables, respectively. The comparison was performed using the non-parametric method to compare areas under correlated ROC curves presented in DeLong et al. (1988), where Model 2 AUC = 0.85, and Model 3 AUC = 0.89. The predictive accuracy of a model's AUC equal to the diagonal line in the graphic (0.50) would be no different than a random guess. Conversely, an AUC equal to 1 would signify that the model is able to perfectly predict the binary outcomes. Therefore, the closer the real value of an AUC to this theoretical value, the better its predictive ability. Similar to the above comparison of the three models, the overall *p*-value =< 0.0001 indicates that the null hypothesis of equality of areas under the ROC curve for Model 2 and Model 3 can be rejected. In other words, the small *p*-value of this test strongly suggests that the three areas differ statistically.

5.5.1. Marginal Effects and Changes in Predicted Probabilities.

The parameters estimated from binary response models, unlike those estimated by linear models, cannot be directly interpreted because they do not provide useful information that fully describes the relationship between the independent variable and the outcome (Long and Freese, 2003). Previous bankruptcy, default, and financial distress prediction models constructed using binary response methodologies- invariably focus only on the overall discriminating or predictive accuracy of the models presented and very rarely do they provide an interpretation of the relationship between the predictor variables and the binary outcome. Such studies report solely the estimates obtained from binary response models and provide an interpretation of the direction of the relationship based on the sign of the estimate. Nevertheless, the basic output (the coefficient estimates) obtained by performing binary response models cannot explain the effects of individual variables on the model's outcomes because of their nonlinear nature. Marginal effects and predicted probabilities are appropriate analytic tools to treat this issue

This section presents results of the computation of marginal effects of individual regressors as well as graphic representations of predicted probabilities of financial distressed companies. This section intends to fill an important gap in the default/financial distress prediction models literature, where the measurement of expected instantaneous changes in the response variable (financial distress indicator in the present study) as function of a change in a specific predictor variable while keeping all the other covariates constant, has been overlooked. As previously discussed, marginal effect measurements (defined as the computation of the partial derivative of the event probability with respect to the predictor if interest) are very useful to the interpretation of the individual effects of the regressors on the dependent variable in discrete dependent variable models, or binary response models (logit regression in the present study). With regard to their calculation, the present study's methodology consists of outputting the marginal effects estimated at each observation in the dataset and then computing the sample average of individual marginal effects in order to obtain the overall marginal effects. SAS statistical software code was employed to generate the estimated marginal effects. Predicted probabilities were generated by plotting the vector reflecting the variations in the predicted probability of financial distress (the predicted probability that the financial distress indicator, Financial_Distress = 1) when the change in an individual regressor ranges from its approximate minimum to its maximum observed value, keeping all the other covariates constant at their means[155].

The marginal effects presented in Table 5-9 reflect a measure of the impact of the regressors on the response variable. The predictor variables with the largest impact, in absolute terms, in Model 2 are invariably the financial ratios TLTA, COVERAGE, and TFOTL, in order of importance, with the NOCREDINT variable and macroeconomic indicators having the smallest impact on the expected instantaneous changes in the response variable while keeping all of the other covariates constant. This is also true when Model 2 was estimated in *t-2*.

155 The SAS statistical package was also employed for this calculation.

Table 5-9 Marginal Effects

This table reports the marginal effects (in percentages) for the 'accounting only' model, the 'accounting plus macroeconomic indicators' model, the 'full' model including also market variables, or Model 1, Model 2 and Model 3 respectively. Additionally, marginal effects are generated for a 'market only' model and a 'market plus macroeconomic variables,' Model 4 and Model 5, for comparison purposes. *n* represents the number of observations. Marginal effects are intended to measure the expected instantaneous changes in the response variable (the financial distress indicator) as a function of a change in a specific predictor variable while keeping all the other covariates constant. The methodology used in the present study to generate the marginal effects consists of outputting the individual marginal effects estimated at each observation in the dataset and then calculating their sample average in order to obtain the overall marginal effect.

Variable	Model 1		Model 2		Model 3		Model 4	Model 5
	t-1	*t-2*	*t-1*	*t-2*	*t-1*	*t-2*	*t-1*	*t-1*
TFOTL	-3.375	-3.427	-3.211	-3.464	-4.059	-4.267		
TLTA	5.340	0.958	5.595	1.221	2.297	0.026		
NOCREDINT	-0.887	-0.781	-0.935	-0.794	-0.569	-0.400		
COVERAGE	-5.564	-5.983	-5.351	-5.878	-3.665	-4.129		
RPI			0.084	0.068	0.045	0.031		0.048
SHTBRDEF			0.792	0.994	0.475	0.439		0.431
PRICE					-0.393	-0.303	-0.724	-0.696
ABNRET					-4.301	-6.846	-7.446	-7.424
SIZE					-0.887	-0.188	-1.857	-1.769
MCTD					-4.872	-2.666	-4.119	-4.291
n	18,276	15,909	18,070	15,703	13,529	12,305	14,807	14,578

Interestingly, when market variables are added to the models based on financial ratios, ABNRET and MCTD are among the 4 largest marginal effects in absolute terms in Model 3; MCTD and ABNRET having the largest marginal effects in Model 3 in period *t-1* and *t-2*, respectively.

The present study also estimates the marginal effects for the 'Market only' model and the 'Market plus macroeconomic indicators' model, Model 4 and Model 5, in order to assess the changes in the response variable following a change in the specific market variables while keeping all the other covariates constant. These estimations confirm the previous results: in both market models, the variables ABNRET, MCTD, SIZE and PRICE have the largest marginal effects, followed by the macroeconomic indicators SHTBRDEF and RPI, in order of importance and in absolute terms. It can be therefore concluded that market variables do contain additional information very important to the prediction of financial distress. Moreover, market variables act as complements to financial ratios.

Presenting and analysing marginal effects for all the models in the study has filled a gap in the financial distress prediction literature that lacked a measure of the individual instantaneous contribution of a change of a specific variable on the response variable (the Financial Distress indicator built for the present analysis), while keeping all the other regressors constant. Additionally, the present study goes further and presents the vector of predicted probabilities for all the individual variables' specific minimum and maximum ranges where they have the most impact in the probability of financial distress, while keeping all the other covariates constant at their respective means. Thus, Figures 5-4, 5-5, and 5-6 show the changes in predicted probabilities for accounting, macroeconomic and market variables, respectively, when the Financial Distress indicator is equal to 1. The importance of these figures is that they clearly show the magnitude as well as the directionality of each regressor reflected by the slope and inclination of the curves, plotted at various levels of the independent variables.

Figure 5-5, shows the behaviour of the predicted probabilities for financial distress at different values of each of the financial statement ratios. It can be observed that the COVERAGE variable displays the steepest slope relative to the other ratios, indicating that a given change in the level of this variable[156] will have the largest impact on the predicted probability of financial distress, when all the other variables are kept constant at their means. The slope of the COVERAGE vector also shows that there is a negative relationship between the predicted probability and the level of the variable: there is an important decrease of the predicted probabilities of financial distress as the COVERAGE variable approaches its maximum estimation value (1). A very similar pattern can be observed for the TFOTL ratio reflecting the liquidity of a company: the slope also negatively relates the predicted probability of financial distress to the magnitude of the variable, although a change in its value produces a slightly smaller impact than the one observed when there is a change in the magnitude of COVERAGE, as shown by the slope of the vector. Changes in the magnitude of TLTA, on the other hand, are positively related to the predicted probability of financial distress, and can be considered as having the third most important impact among financial statement ratios, followed by NOCREDINT, whose slope is almost flat, indicating a very small negative impact.

[156] Reflecting the firm's ability to pay interest on outstanding debt.

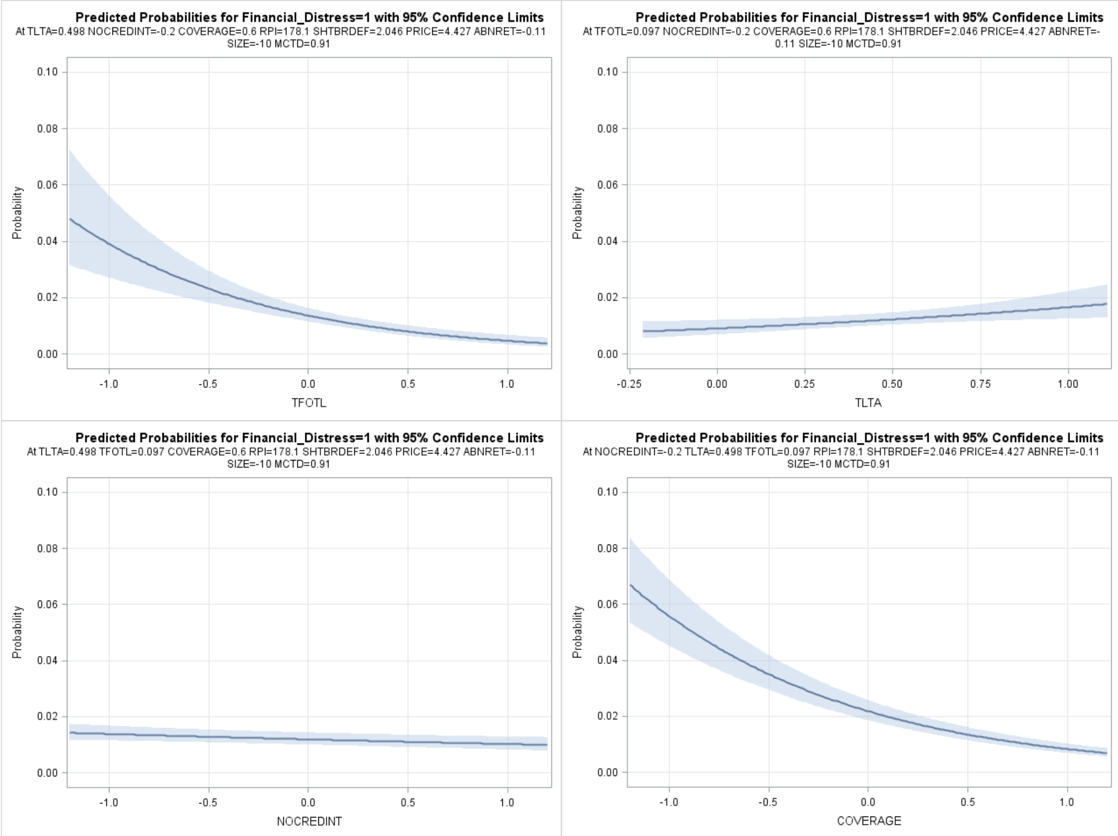

Figure 5-5 Changes in Predicted Probabilities – Financial Statement Ratios

The figure plots the vectors reflecting changes in predicted probabilities (for Financial Distress = 1) at different levels of the accounting independent variables Total Funds from Operations to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), and Interest Coverage (COVERAGE), keeping all the other covariates constant at their mean values (TFOTL = 0.097, TLTA = 0.498, NOCREDINT = -0.2, COVERAGE = 0.6, RPI = 178.1, SHTBRDEF = 2.046, PRICE = 4.427, ABNRET = -0.11, SIZE = -10, MCTD = 0.91). The computation was made taking into account all the variables included in the 'Full' model or Model 3 (financial statement ratios, macroeconomic indicators and market variables). Predicted probabilities are estimated employing an approximate value of the minimum and maximum ranges of the independent variables. In this way, the predicted probabilities for all levels of a variable can be observed. This figure reports the predicted probabilities for the 'Full' model estimated in period *t-1*, the vectors estimated using the full model in *t-2* have very similar shapes, so they were not reported in the present study.

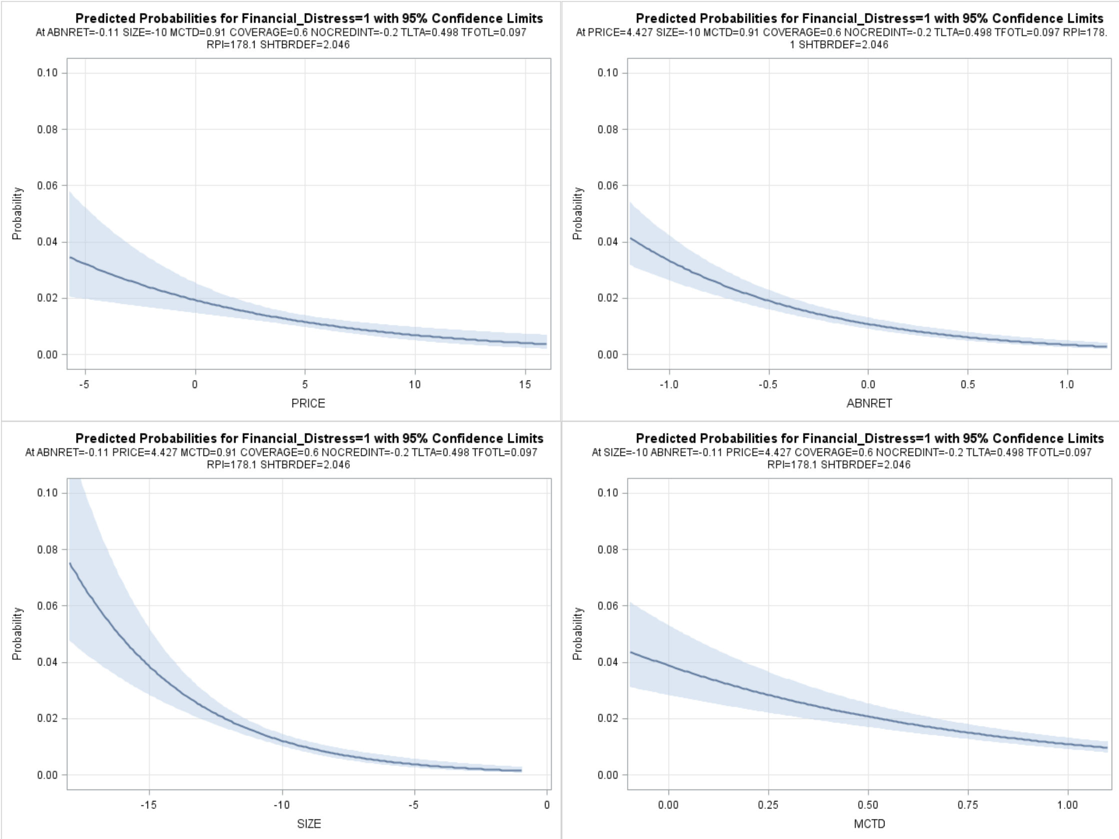

Figure 5-6 Changes in Predicted Probabilities – Market Variables

The figure plots the vectors reflecting changes in predicted probabilities (for Financial Distress = 1) at different levels of the market independent variables Share Price (PRICE), Abnormal Returns (ABNRET), the relative Size of the company (SIZE), and the ratio Market Capitalisation to Total Debt (MCTD), keeping all the other covariates constant at their mean values (TFOTL = 0.097, TLTA = 0.498, NOCREDINT = -0.2, COVERAGE = 0.6, RPI = 178.1, SHTBRDEF = 2.046, PRICE = 4.427, ABNRET = -0.11, SIZE = -10, MCTD = 0.91). The computation was made taking into account all the variables included in the 'Full' model or Model 3 (financial statement ratios, macroeconomic indicators and market variables). Predicted probabilities are estimated employing an approximate value of the minimum and maximum ranges of the independent variables. In this way, the predicted probabilities for all levels of a variable can be observed. This figure reports the predicted probabilities for the 'Full' model estimated in period *t-1*, the vectors estimated using the full model in *t-2* have very similar shapes, so they were not reported in the present study.

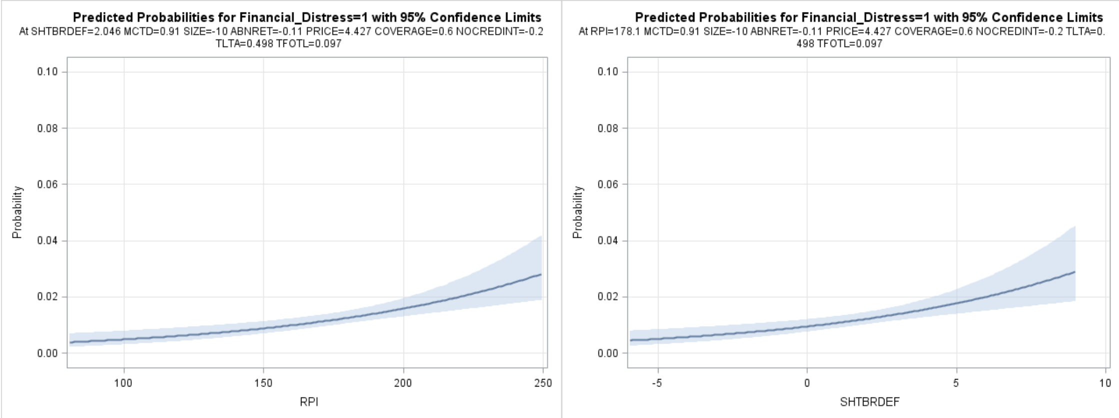

Figure 5-7 Changes in Predicted Probabilities – Macroeconomic Indicators
The figure plots the vectors reflecting changes in predicted probabilities (for Financial Distress = 1) at different levels of the macroeconomic independent variables Retail Price Index (RPI), and the proxy for interest rates, the Deflated Short Term Bill Rate (SHTBRDEF), keeping all the other covariates constant at their mean values (TFOTL = 0.097, TLTA = 0.498, NOCREDINT = -0.2, COVERAGE = 0.6, RPI = 178.1, SHTBRDEF = 2.046, PRICE = 4.427, ABNRET = -0.11, SIZE = -10, MCTD = 0.91). The computation was made taking into account all the variables included in the 'Full' model or Model 3 (financial statement ratios, macroeconomic indicators and market variables). Predicted probabilities are estimated employing an approximate value of the minimum and maximum ranges of the independent variables. In this way, the predicted probabilities for all levels of a variable can be observed. This figure reports the predicted probabilities for the 'Full' model estimated in period *t-1*, the vectors estimated using the full model in *t-2* have very similar shapes, so they were not reported in the present study.

As expected, all of the market variables show a negative relationship between variations in individual levels and predicted probabilities of financial distress. The covariate with the largest impact on the latter is SIZE, as the vector displays the steepest slope. It is followed by ABNRET, MCTD and PRICE, which is consistent with the output obtained from the calculation of marginal effects. Finally, variations in the magnitude of economic indicators are positively related to changes in the predicted probabilities of financial distress when all the other covariates are kept constant at their means. Interestingly, the vectors' slopes of the macroeconomic indicators RPI and SHTBRDEF are steeper than the financial statement ratios TLTA and COVERAGE, which could lead us to conclude that they have a larger impact on the predicted probability of financial distress than the estimates of marginal effects would suggest. However, this is hardly the case, as the ranges used to plot the slopes of the macroeconomic indicators are larger in absolute terms than those of the two financial statement ratios, which might explain the observed phenomenon.

5.5.2. Classification Accuracy Tables.

Classification accuracy tables have been used in previous works as an additional tool to measure the predictive accuracy of the default/bankruptcy prediction models. The present study, however, employs a different and more appropriate methodology to estimate proportions of correct and incorrect classifications of financially and non-financially distressed firms. In order to classify a set of binary data, previous research works employ the same observations used to fit the model to estimate the classification error, resulting in biased error-count estimates. In other words, the widely-used 2x2 frequency tables' estimates, where correctly classified observations are displayed on the main diagonal of the table, are derived using all observations to fit the model. Therefore, the results are biased, as each observation has an effect on the model used to classify itself. One way of reducing said bias is 'to remove the binary observation to be classified from the data, reestimate the parameters of the model, and then classify the observation based on the new parameter estimates[157].' Unfortunately this method is computationally demanding when using large datasets. For this reason, the present study employs logistic regression that, although is less computationally intensive still delivers high predictive accuracy and minimises type I and II error rates. Specifically, a one step approximation is applied to the preceding parameter estimates[158]. The leave-one out jack knife approach to correct for over-sampling employed in the present study helps eliminate potential biases common to analysis of classification tables that fail to use holdout samples.

In order to construct a bias-adjusted classification table, predicted financial distress event probabilities are estimated for each observation. If the predicted event probability exceeds or equals a given cutpoint value (whose real line is mapped onto [0,1]), then the observation is predicted to be in financial distress, otherwise, it is predicted to be a non-event or non-financially distressed. The probability levels chosen range from 0.020 to 0.120 in order to get high levels of Sensitivity and Specificity, combined as well as individually. The advantage of this methodology to construct classification tables is that it provides a useful tool to re-calibrate a distress prediction model with different probability cutpoints depending on the costs assigned to the Type I and II errors.

---

157 SAS Institute

158 http://support.sas.com/documentation/cdl/en/statug/63033/HTML/default/viewer.htm#statug_logistic_sect037.htm

The present study measures the accuracy of the classification through its Sensitivity (the ability of the model to predict a financial distress event correctly) and Specificity (the ability of the model to predict a non-financial distress event correctly). In Table 5-10, the 'Correct' column shows the number of observations that were correctly predicted as financially distressed and non-financially distressed, respectively. The 'Incorrect' column presents the number of non-financially distressed observations that were incorrectly predicted as financially distressed, and the number of financially distressed observations that were incorrectly predicted as non-financially distressed, respectively. The 'Percentages' column exhibits the rate of correct classifications, the proportion of financial distress responses that were predicted to be financial distress events (Sensitivity, or the ability of the model to predict financial distress correctly), and the rate of non-financial distress responses that were predicted to be non-financial distress events (Specificity, or the ability of the model to predict non-financial distress correctly), respectively.

Biased-adjusted classification tables were calculated for Model 2 (the 'Accounting plus macroeconomic indicators' model) and Model 3 (the 'Full' model) in order to assess the increase in the classification accuracy when market variables are added to a model based on financial statement ratios (Section A and section B in Table 5-10, respectively). Furthermore, Table 5-10 also exhibits a classification table for Model 3 estimated in period *t-2* in order to test whether the 'Full' model continues to be useful in predicting financial distress two years prior to the distress event, thus confirming its predictive accuracy. It can be concluded that the methodology employed was effective to confirm these two points: there is a considerable increase in classification performance from Model 2 to Model 3, meaning that market variables provide useful information not included in financial statement ratios or macroeconomic indicators. Furthermore, the improvement suggests that the three types of variables act as complementary, confirming the previous results obtained from the analysis of Areas under the Receiver Operating Characteristics Curve. The 0.060 probability level was chosen as an appropriate benchmark to perform a comparison between models for the following reasons: First, this level is equal to the rate of failed to healthy companies for which complete data made the computation of predicted probabilities possible. Second, this level produces the smallest gap between sensitivity and specificity percentages. Sections A, B, and C show that a probability level of 0.060 used as cutpoint, yields the combined highest predictive accuracy between Sensitivity and Specificity for the three models. The increase in predictive accuracy when market variables are added to the 'Accounting and macroeconomic indicators' model is equal to 5 percentage points as measured by the proportion of correct classifications in column 6 of

Table 4-10, at the 0.060 probability level as cutpoint value; from 80 to 85 per cent correct classifications in Model 2 and Model 3, respectively.

Table 5-10 Bias-Adjusted Classification Table

This table reports a biased-adjusted classification table for predicted distress frequencies at different probability levels as cut-off values for Model 2 estimated in period *t-1*, and Model 3 estimated in period *t-1* and *t-2*, in panels A, B and C respectively. The 'Correct' column shows the number of observations that were correctly predicted as financially distressed and non-financially distressed, respectively. The 'Incorrect' column presents the number of non-financially distressed observations that were incorrectly predicted as financially distressed, and the number of financially distressed observations that were incorrectly predicted as non-financially distressed, respectively. The 'Percentages' column exhibits the rate of correct classifications, the proportion of financial distress responses that were predicted to be financial distress events (Sensitivity, or the ability of the model to predict financial distress correctly), and the rate of non-financial distress responses that were predicted to be non-financial distress events (Specificity, or the ability of the model to predict non-financial distress correctly), respectively.

Probability Level	Correct		Incorrect		Percentages		
	Distressed	Non-Distressed	Distressed	Non-Distressed	Correct	Sensitivity	Specificity
Panel A: Model 2 (*t-1*)							
0.020	841	12282	4861	86	72.6	90.7	71.6
0.040	785	13602	3541	142	79.6	84.7	79.3
0.060	**762**	**13764**	**3379**	**165**	**80.4**	**82.2**	**80.3**
0.080	738	13983	3160	189	81.5	79.6	81.6
0.100	701	14275	2868	226	82.9	75.6	83.3
0.120	646	14643	2500	281	84.6	69.7	85.4
Panel B: Model 3 (*t-1*)							
0.020	685	9455	3346	43	75.0	94.1	73.9
0.040	651	10419	2382	77	81.8	89.4	81.4
0.060	**631**	**10845**	**1956**	**97**	**84.8**	**86.7**	**84.7**
0.080	608	11136	1665	120	86.8	83.5	87.0
0.100	584	11342	1459	144	88.2	80.2	88.6
0.120	563	11499	1302	165	89.2	77.3	89.8
Panel C: Model 3 (*t-2*)							
0.020	654	7793	3800	58	68.6	91.9	67.2
0.040	611	9305	2288	101	80.6	85.8	80.3
0.060	**576**	**9757**	**1836**	**136**	**84.0**	**80.9**	**84.2**
0.080	556	10013	1580	156	85.9	78.1	86.4
0.100	532	10205	1388	180	87.3	74.7	88.0
0.120	508	10356	1237	204	88.3	71.3	89.3

Furthermore, when Model 3 is estimated in period *t-2*, the rate of correct classifications decreases by only one percentage point relative to the same model estimated in period *t-1,* at the same 0.060 probability cutpoint: the correct classifications percentage is 85 in *t-1*, decreasing only marginally to 84 in *t-2*. This indicates that the 'Full' model is also very useful to predict financial distress two years prior to the event.

The present classification table also possesses the advantage of allowing a risk manager to calculate higher percentages of Sensitivity and Specificity individually. This is particularly useful as Type I and II errors are not equally weighted by practitioners. A false positive error is not as expensive as a false negative: the cost of a firm predicted as financially distressed when it is in fact healthy, is less than the cost of a firm predicted as financially healthy when it is in fact financially distressed. Therefore, if this is the case, a risk manager would be more interested in increasing the rate of correctly classified financially distressed firms (Sensitivity), choosing a lower probability level as cutpoint.[159] This would be achieved, however, only at the cost of reducing the ability of the model to predict non-financial distress events correctly (Specificity). The present study presented the rates of Specificity and Sensitivity at different probability levels as cutpoints to show the practical use of this approach to measure the accuracy of a distress prediction model and its advantages in relation to the widely employed 2x2 frequency tables that implicitly give equal weights to Type I and Type II errors.

5.5.3. Model Validation.

In order undertake validation tests for model performance, the main database was divided in two sub-periods: 2001-2006 and 2007-2011. The first one corresponds to the period after the collapse of the information technology bubble, which took place during 2000-2001, and the second one is the period following the global financial crisis of 2007 to 2011. The 'Full' model was applied to the two sub-periods in order to test whether its predictive accuracy remain acceptable as measured by the Area under the ROC Curve. Additionally, Model 3 was tested in period *t-1* and *t-2*, in order to confirm whether the predictive accuracy holds when the model is estimated one year prior to the event of financial distress. As shown in Table 5-11, the predictive accuracy decreases only marginally when the model is tested with the two sub-period data. Interestingly, the model performs better in the 2007-2011 period than in the 2001-2006 period, which might be explained by the smaller number of observations of the former, and thus the lower amount of financial distress event to predict. The same analysis applies when the model is estimated in *t-2*. Nevertheless, the model retains a very high predictive accuracy overall.

[159] In this case the predicted probability used as cut point would have to be lower than the 0.060 level.

Table 5-11 Model Validation – Areas Under the ROC Curve

This table reports the model validation results for Model 3 estimated in period *t-1* and *t-2*. The main dataset was divided in two sub-periods. The first one, 2001-2006, corresponds to the periods after the collapse of the information technology bubble, and the second one, 2007-2011, is the period that follows the global financial crisis that started in 2007. The predictive accuracy or the overall performance of the model is measured by the Area Under the Receiver Operating Characteristics Curve.

	1980-2011	2001-2006	2007-2011
Model 3 in *t*	0.9190	0.9029	0.9123
Model 3 in *t-1*	0.8918	0.8807	0.8935

5.5.4. Performance Comparison Benchmarks.

The present study also tests the robustness of the models through a comparison between the three main Models presented (Model 1, 2, and 3), the classic Altman's (1968) model estimated employing logistic regression, the widely-used Altman's (1968) Z-Score, and the comprehensive model estimated using artificial neural networks (multilayer perceptron). Three techniques for the prediction of financial distress are therefore employed to test the performance of our model. Table 5-12 presents a comparison of the performance of the 'accounting only' model, the 'accounting plus macroeconomic indicators' model, the 'full' model, Altman's (1968) model estimated using logistic regression, and the 'full' model estimated using artificial neural networks, as measured by the area under the Receiver Operating Characteristics curve (AUC), Gini rank coefficients, and Kolmogorov-Smirnov statistics.

Table 5-12 Logistic Regression and Neural Networks Performance Comparison Results

This table reports model performance statistics. Panel A shows measures for the models estimated in period *t-1,* and Panel B displays the same measures for the models estimated in *t-2*. Models 1, 2, 3 and Altman's model were estimated using the panel logit methodology. In addition, Model 3 was estimated using the neural networks methodology (multilayer perceptron). Model 1 is the 'accounting only' model, Model 2 is the 'accounting plus macroeconomic variables' model, Model 3 is the 'full' model, including market variables in addition to the variables in Model 2. The Altman Model includes the following accounting ratios: Working Capital to Total Assets, Retained Earnings to Total Assets, Earnings Before Interest and Taxes to Total Assets, Market Value of Equity to Book Value of Total Debt, and Sales to Total Assets. The first measure is a direct measure of the predictive accuracy of models estimated using the logit methodology; the area under the Receiver Operating Characteristics curve (AUC); Gini coefficients and Kolmogorov-Smirnov statistic are also presented.

Measure	Model 1	Model 2	Model 3	Altman	Multilayer Perceptron
Panel A: Models' Performance in *t-1*					
AUC	0.8718	0.8763	0.9190	0.8517	0.9250
Gini Rank Coefficient	0.7436	0.7526	0.8380	0.7034	0.8500
Kolmogorov-Smirnov	0.5949	0.6021	0.6704	0.5627	0.6800
Panel B: Models' Performance in *t-2*					
AUC	0.8523	0.8514	0.8918	0.8229	0.9120
Gini Rank Coefficient	0.7046	0.7028	0.7836	0.6458	0.8240
Kolmogorov-Smirnov	0.5637	0.5622	0.6269	0.5166	0.6592

Table 5-12 shows that when the Altman model is estimated employing the panel logit methodology, it displays a predictive accuracy similar (marginally inferior) to the 'accounting only' model (Model 1) and the 'accounting plus macroeconomic indicators' model (Model 2), as measured by the area under the ROC curve. This is as expected, as Model 1, Model 2 and the Altman model are accounting-based models, which makes the comparison appropriate. Model 2, which includes macroeconomic indicators, yields the best performance among the accounting-based models (AUC = 0.8763), followed by Model 1 (AUC = 0.8718), and Altman's (1968) model (0.8517) in *t-1*. This same pattern is reproduced when the models are estimated in *t-2*, the only difference being, as previously discussed, that Model 1 performance is marginally higher than Model 2, indicating that the information contained in accounting variables is more relevant to the prediction of failure/financial distress than the information obtained from macroeconomic variables when the model is estimated with data two years prior to the event of failure/financial distress.

Following the comparative approach between statistical methods and intelligent techniques in Olson et al. (2012), Tseng and Hu (2010), Cho et al. (2009), and Kumar and Ravi (2007), the present study also estimates Model 3 (the 'Full' model) using artificial neural networks[160] in order to perform an additional test of the performance of our model. Moreover, logistic regression is a prevalent statistical methodology employed as benchmark for comparison purposes by these authors. The present study employs the Multilayer Perceptron[161], which is the most common architecture in artificial neural networks (Alfaro et al., 2008[162]). In this regard, Table 5-12 shows that the comprehensive Model 3 estimated using artificial neural networks (multilayer perceptron) yields the highest overall performance among all models with an AUC equal to 0.9250, followed by Model 3 estimated using logistic regression with an AUC equal to 0.9190. The marginally superior performance of artificial neural networks is consistent with previous research; neural networks comprise highly complex sets of node connections and weights that can be obtained from software (Olson et al., 2012), and overcome the restrictions entailed by traditional statistical methodologies (logistic regression included) such as the assumption of linearity, normality, independence among predictor variables, for instance (Yang et al., 2011). However, Table 5-12 shows that the difference in performance is marginal; moreover, logistic regression has the advantage of providing a form that can be understood and transported quite easily, unlike neural networks, which lack 'transparency (seeing what the model is doing, or comprehensibility) and transportability (being able to easily deploy the model into a decision support system for new cases)' (Olson et al., 2012[163]).

Table 5-13 presents a biased-adjusted classification table for predicted distress frequencies at different probability levels as cut-off values when the models are estimated in period *t-1*. Models 2, 3, and Altman's model are estimated using the panel logit methodology (Panel A, B, and C respectively). In addition, Model 3 was estimated using the neural networks methodology (multilayer perceptron) in Panel D. When the 0.060 level is used as a benchmark to compare the predictive accuracy of Model 2 and Model 3 relative to the Altman model, it can be observed that Model 2 possesses a marginally higher predictive accuracy than Altman's (1968) model: the overall rate of correct predictions for the Altman model is 77.8%, following closely the predictive accuracy of Model 2, which is equal to 80.4%. On the other hand, the 'Full' model displays a rate of correct predictions equal to 86.7%, which is significantly superior to both accounting-based models.

Finally, when Model 3 is estimated using artificial neural networks (multilayer perceptron), it can be observed that it yields a very similar classification accuracy to Model

[160] For details regarding the fitting of the artificial neural network model in the present study, see the Appendix.
[161] The Multilayer Perceptron is a feedforward network that consists of an input layer, an output layer, and a number of hidden layers.
[162] P. 116.
[163] P. 464.

3 in *t-1*; with regard to the overall accuracy, Model 3 (logistic regression) shows a marginally higher performance of only 10 basis points (0.10%) approximately at the three probability levels presented. Table 5-13 also shows that, as to the performance in correctly predicting financially distressed firms, the neural networks methodology is marginally superior (by less than 1 percentage point) to the logistic regression methodology. The opposite is true as to the rate of correct classifications of healthy firms: the logistic methodology is marginally superior to the neural networks technique. Overall, it can be concluded that the performances of the logistic regression model and the neural networks model are almost identical, as the differences in predictive accuracy are very small, with the neural networks model outperforming the logit model for the prediction of failed/distressed firms, although by a very small margin (less than 1 percentage point approximately), which is consistent with the results obtained through the analysis of their respective areas under the ROC curves in Table 5-12.

Table 5-13 Bias-Adjusted Classification Table. Logistic Regression and Artificial Neural Networks Comparison

This table reports a biased-adjusted classification table for predicted distress frequencies at different probability levels as cut-off values when the models are estimated in period *t-1*. Models 2, 3, and Altman's model are estimated using the panel logit methodology (Panels A, B, and C respectively). In addition, Model 3 was estimated using the neural networks methodology (multilayer perceptron) in panel D. The 'Correct' column shows the number of observations that were correctly predicted as financially distressed and non-financially distressed, respectively. The 'Incorrect' column presents the number of non-financially distressed observations that were incorrectly predicted as financially distressed, and the number of financially distressed observations that were incorrectly predicted as non-financially distressed, respectively. The 'Percentages' column exhibits the rate of correct classifications, the proportion of financial distress responses that were predicted to be financial distress events (Sensitivity, or the ability of the model to predict financial distress correctly), and the rate of non-financial distress responses that were predicted to be non-financial distress events (Specificity, or the ability of the model to predict non-financial distress correctly), respectively.

Probability Level	Correct		Incorrect		Percentages		
	Distressed	Non-Distressed	Distressed	Non-Distressed	Correct	Sensitivity	Specificity
Panel A: Model 2 (*t-1*)							
0.040	785	13602	3541	142	79.6	84.7	79.3
0.060	**762**	**13764**	**3379**	**165**	**80.4**	**82.2**	**80.3**
0.080	738	13983	3160	189	81.5	79.6	81.6
Panel B: Model 3 (*t-1*)							
0.040	651	10419	2382	77	81.8	89.4	81.4
0.060	**631**	**10845**	**1956**	**97**	**84.8**	**86.7**	**84.7**
0.080	608	11136	1665	120	86.8	83.5	87.0
Panel C: Altman Model (*t-1*)							
0.040	1046	12584	5887	170	69.2	86.0	68.1
0.060	**944**	**14365**	**4106**	**272**	**77.8**	**77.6**	**77.8**
0.080	854	15359	3112	362	82.4	70.2	83.2
Panel D: Multilayer Perceptron (*t-1*)							
0.040	659	10390	2411	69	81.7	90.5	81.2
0.060	**640**	**10818**	**1983**	**88**	**84.7**	**87.9**	**84.5**
0.080	620	11098	1703	108	86.6	85.2	86.7

Table 5-14 shows Altman's Z-Score classification table to discriminate between healthy and financially distressed companies employing the widely-used cutoff values: a company is classified as 'financially healthy' if its Z-Score is greater than 2.99 and as 'financially distressed' if its Z-Score is less than 1.81; additionally, following Altman (2000), a company is classified as 'financially distressed' if its Z-Score is less than 2.67 (in parenthesis). From Table 5-14, it can be concluded that this method shows an impressive classification accuracy with regard to financially distressed firms. However, the Z-Score performance is less impressive to correctly classify safe or financially healthy companies, identifying a high proportion of healthy firms as distressed. Even if an error of the first kind or Type I error (false positive) is not as costly as an error of the second kind (false negative), the present analysis shows that our model for UK listed companies has some advantages over the Z-Score model. First, when comparing the predictive accuracy, it can be observed that, taking the 0.060 predicted probability level as cut-off, the 'full' model displays a superior performance for the classification of distressed firms: it correctly classified 87% of distressed companies while the Z-Score model correctly classified 81%. Second, using the same 0.060 predicted probability level as cut-off, the 'full' model displays an almost equal predictive accuracy with regard to financially healthy companies (sensitivity is equal to 85%), which makes the model reliable for the prediction of both distressed and financially healthy companies. Third, in technical terms, it is very straightforward to modify the predicted probability level employed as cut-off in order to minimise Type I or Type II errors (through a trade-off) depending on the researcher's/risk manager's objectives.

Table 5-14 Classification Table using Altman's Z-Score

This table shows the classification accuracy results for Altman's Z-score model. In order to estimate the rate of correct predictions, three different cut-offs were employed: a company was classified as financially healthy if its Z-Score was greater than 2.99, and it was classified as failed/financially distressed if its Z-Score was less than 1.81. The numbers in parenthesis represent the firms classified as failed/financially distressed when using a cut-off of 2.67, following Altman (2000).

	Predicted			
Observed	Healthy	Distressed	Total	% Correct
Healthy	9178	8278	17456	52.58%
Distressed	234	899 (997)	1133	79.35% (80.99%)
Overall Per cent				54.21%
Average Per cent				65.96%

5.6. Conclusions.

This study offers a comparison of the classification accuracy and predictive power of three types of variables (financial statement ratios, macroeconomic indicators and market variables) in a logit model for quoted companies in the United Kingdom based on a financial definition of firm distress. It contributes to the default prediction literature by, first, using a finance-based definition of distress complemented with a technical approach built using information provided by the London Share Price Database. The advantage is that the definition of financial distress presented in this study is not contingent upon its ultimate legal consequence: bankruptcy, as in most of the previous prediction literature. A wider, *ex ante* approach is employed, in order to detect early stages of financial distress with a high degree of reliability that could be useful to practitioners to avert the high costs associated with a bankruptcy filing. Second, a large dataset was built merging different types of information from data sources widely used in the academic as well as in the industry fields. Therefore, this study relies not only on independent variables used in previous research works; it applied a multi-level empirical procedure to test and select the variables with the highest contribution to the overall accuracy of the model. Furthermore, the study presents justifications for the use of each of the retained variables in the final models. The result is a model for the prediction of financial distress in the United Kingdom for quoted companies that, with a small number of variables, displays a very high classification and prediction accuracy relative to previous research works. Third, and perhaps most importantly, the study tests, for the first time in financial distress prediction models for quoted companies in the UK, the relative contributions (individual and as groups) of the three types of variables to the predictive accuracy of the model: financial, macroeconomic and market variables. Prior research has tested the ability of market variables to predict bankruptcy employing methodologies such as the Black and Scholes contingent claims or option-based approach. However, the results obtained from these models (that entail numerous restrictive assumptions) have been controversial. Many efforts have been carried out to demonstrate the superiority of market-based models over accounting-based models and vice versa. To this point, the default prediction literature is characterised by a competing approach, where there is a clear division line between market and accounting variables.

The present study adopts a different approach where the use of these types of variables is not mutually exclusive. It is tested whether the market variables (dependent, in some measure, upon the same financial information) add information that is not contained in financial statements and therefore act as complement in default prediction models. The results presented in this study clearly indicate that this is the case. The considerable increase of the area under the Receiver Operating Characteristics (ROC) curve (among several other formal measures), from 0.88 to 0.92 in a model estimated in *t-1* and from 0.85 to 0.89 in a model estimated in *t-2*, that followed the incorporation of market variables in an accounting model indicates that they contain information that is not included in financial statement ratios. A comparison of areas under correlated ROC curves performed using a non-parametric method, and the estimation of biased-adjusted classification tables confirmed these results. In addition, when a full model was estimated in *t-2* to test the real predictive accuracy of the model, three out of four market variables retained their statistical significance, the same proportion as the financial ratios, which indicates that the variables included in the model are consistent. Interestingly, Hosmer and Lemeshow goodness-of-fit tests for binary response logistic models suggest that the ‘full model’ fitted with market variables is an adequate model, unlike the ‘accounting only’ or ‘accounting plus macroeconomic variables’ model. On the other hand, results are less conclusive for macroeconomic variables, which contribute only marginally to the overall classification accuracy of the model. Finally, the estimation of marginal effects fills an important gap in the default prediction literature by presenting expected instantaneous changes in the response variable as a function of a change in a specific predictor variable while keeping all the other covariates constant, which is very useful to the interpretation of the individual effects.

5.7. Appendix.

5.7.1. Computation of Model 3 using the Neural Networks Methodology (Multilayer Perceptron).

Network information.
Input Layer Covariates: 1. TFOTL, 2. TLTA, 3. NOCREDINT, 4. COVERAGE, 5. RPI, 6. SHTBRDEF, 7. PRICE, 8. ABNRET, 9. SIZE , 10. MCTD
Hidden layers.
Number of Hidden Layers: 1
Number of Units in Hidden Layer 1 (Excluding the bias unit): 4
Activation Function: Hyperbolic Tangent
Output Layer.
Dependent Variable: Financial Distress Indicator
Number of Units: 2
Activation Function: Softmax
Error Function: Cross-entropy
Casing Processing Summary.
Training: 70.2%
Holdout: 29.8%

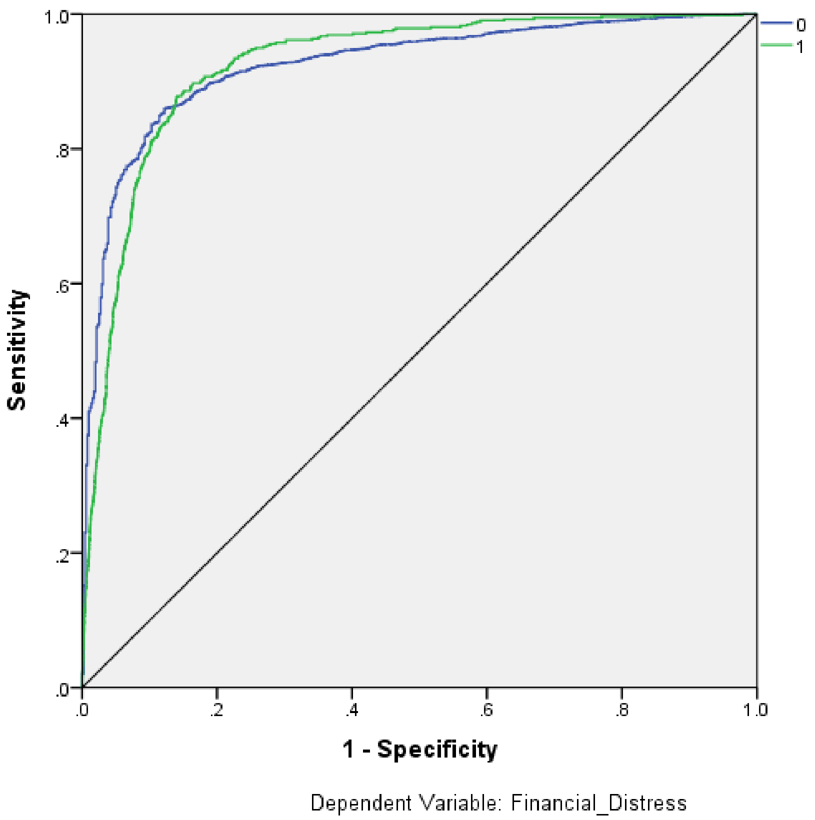

Figure 5-8 Model 3. Multilayer Perceptron – Areas under the ROC Curve
Area under the Receiver Operating Characteristics Curve when:
Financial Distress Indicator (1) = 0.925
Financial Distress Indicator (0) = 0.925

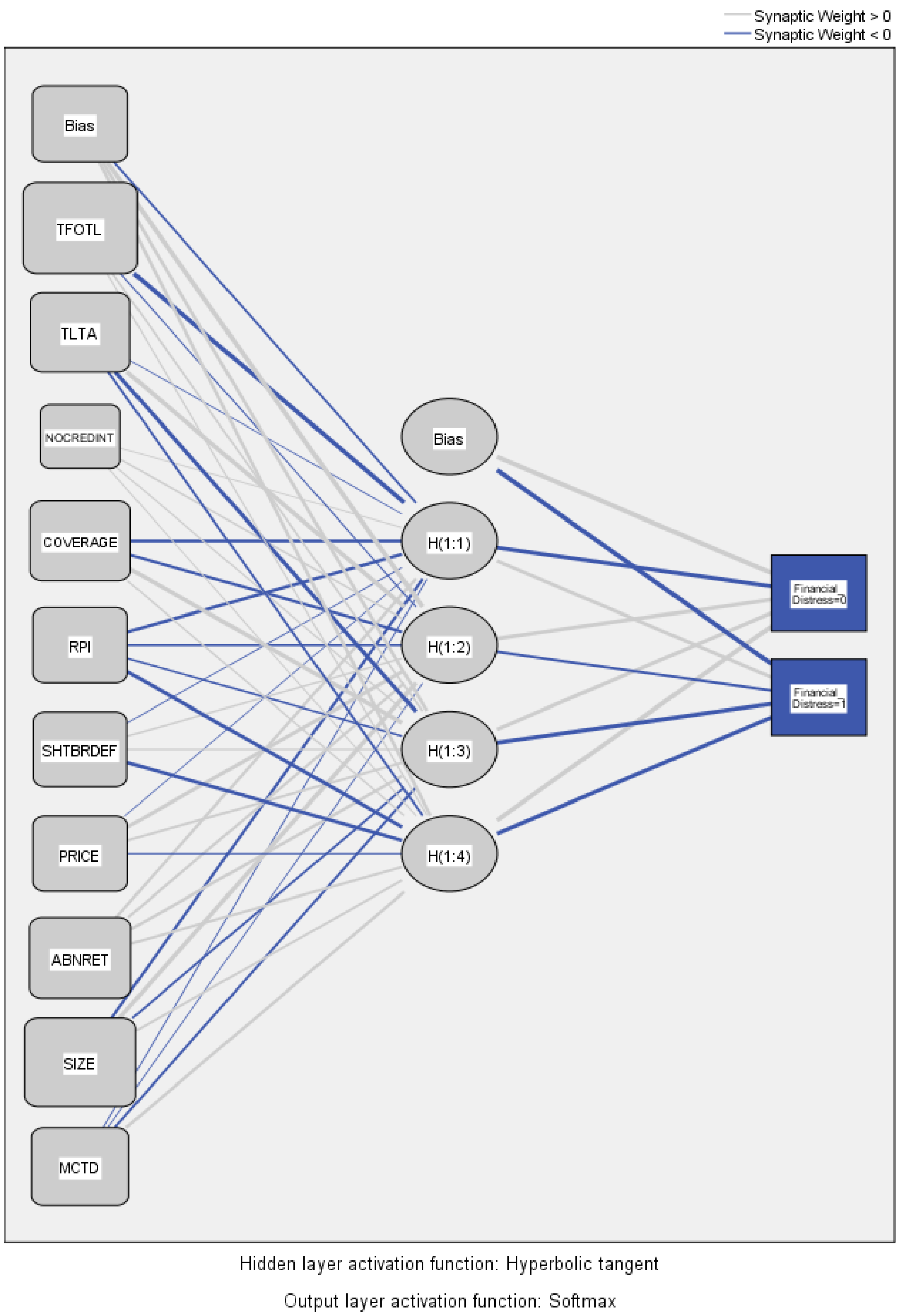

Figure 5-9 Model 3. Multilayer Perceptron Diagram

5.7.2. Estimation of Model 3 with Industry controls.

Table 5-15 Industry Code Construction

This table shows the SIC codes corresponding to the Industry classification used in the present study to control for firm sector. Four-digit SIC codes for each firm were employed for the partitioning into ten major industrial sectors. The corresponding names of the industrial groupings are presented in the last column of the table. Firm belonging to the 'Finance, Insurance and Real Estate Sector' were excluded from the analysis. Following Chava and Jarrow (2004), SIC codes were chosen for this study because they are the most widely available industry classifications for the present sample period.

Industry Code	SIC Code	Industry name
1	<1000	Agriculture, Forestry and Fisheries
2	1000 to less than 1500	Mineral Industries
3	1500 to less than 1800	Construction Industries
4	2000 to less than 4000	Manufacturing
5	4000 to less than 5000	Transportation, Communication and Utilities
6	5000 to less than 5200	Wholesale Trade
7	5200 to less than 6000	Retail Trade
8	6000 to less than 6800	Finance, Insurance, and Real Estate
9	7000 to less than 8900	Service Industries
10	9100 to less than 10000	Public Administration

Table 5-16 Logit Regression of Financial Distress Indicator on Predictor Variables – Models with Industry Dummies

This table reports results from logit regressions of the financial distress indicator on the predictor variables. The models were computed for two periods: using the accounts, market and macroeconomic data from the year prior to the observation of the financial distress event (*t-1*), and the accounts, market and macroeconomic data from two years prior to the observation of the financial distress event (*t-2*) in order to confirm their predictive ability in addition to their discriminating power. Additionally, results are also presented for a 'Market' model that incorporates market variables in *t-1* for comparison purposes. The absolute value of *z*-statistics is reported in parenthesis. * denotes significant at 10%, ** denotes significant at 5%-1%.

Variable	Model 1		Model 2		Model 3		Model 4	Model 5
	t-1	*t-2*	*t-1*	*t-2*	*t-1*	*t-2*	*t-1*	*t-1*
TFOTL	-0.8081**	-0.7355**	-0.7684**	-0.7326**	-1.1047**	-1.0056**		
	(6.67)	(6.14)	(6.31)	(6.09)	(6.62)	(6.24)		
TLTA	1.1752**	-0.0109	1.2222**	0.0347	0.6149**	-0.1022		
	(6.70)	(0.06)	(6.95)	(0.19)	(2.58)	(0.42)		
NOCREDINT	-0.2183**	-0.1766**	-0.2313**	-0.1795**	-0.1440**	-0.0968*		
	(4.87)	(3.94)	(5.16)	(4.00)	(2.65)	(1.85)		
COVERAGE	-1.3580**	-1.3124**	-1.3093**	-1.2797**	-0.9805**	-0.9885**		
	(23.20)	(22.68)	(22.31)	(21.95)	(14.25)	(14.44)		
RPI			0.0211**	0.0158**	0.0123**	0.0079**		0.0109**
			(8.78)	(6.30)	(4.38)	(2.78)		(4.37)
SHTBRDEF			0.1889**	0.2141**	0.1258**	0.1025**		0.0991**
			(6.44)	(5.68)	(3.81)	(2.43)		(3.42)
PRICE					-0.1022**	-0.0740**	-0.1650**	-0.1588**
					(3.87)	(2.88)	(6.60)	(6.28)
ABNRET					-1.1505**	-1.6262**	-1.7593**	-1.7364**
					(9.53)	(13.60)	(15.33)	(15.06)
SIZE					-0.2469**	-0.0476	-0.4484**	-0.4242**
					(7.44)	(1.55)	(15.56)	(14.55)
MCTD					-1.2621**	-0.6109**	-0.9678**	-0.9878**
					(7.26)	(3.05)	(6.87)	(6.98)
Constant	-3.9969**	-2.8718**	-8.9642**	-6.4594**	-7.2825**	-3.7900**	-19.8216	-20.4127
	(3.48)	(2.44)	(6.96)	(4.89)	(4.54)	(2.40)	(0.03)	(0.05)
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0934	0.0951	0.0977	0.0978	0.1428	0.1277	0.1027	0.1041
Max-rescaled R^2	0.2826	0.2687	0.2936	0.2743	0.4169	0.3573	0.2996	0.3009

Table 5-17 Model Performance Measures – Models with Industry Dummies

This table reports model performance statistics. Section A shows measures for the five models estimated in period *t-1* and Section B displays the same measures for all of the models estimated in *t-2*. Model 1 is the 'accounting only' model, Model 2 is the 'accounting plus macroeconomic variables' model, Model 3 is the 'full' model, including market variables in addition to the variables in Model 2, Model 4 is the 'market only' model, and Model 5 is the 'market plus macroeconomic variables' model. The first measure is a direct measure of the predictive accuracy of models estimated using the logit methodology, the area under the Receiver Operating Characteristics curve (AUC); Gini coefficients, Kolmogorov-Smirnov statistics, Cox and Snell R-squared, Nagelkerke's Max-rescaled R-squared and the models' Chi-squared are also presented. Additionally Hosmer and Lemeshow goodness-of-fit statistics are displayed.

Measure	Model 1	Model 2	Model 3	Model 4	Model 5
		Panel A: Models' Performance in *t-1*			
AUC	0.8719	0.8775	0.9194	0.8723	0.8735
Gini Rank Coefficient	0.7438	0.7550	0.8388	0.7446	0.7470
Kolmogorov-Smirnov	0.5950	0.6040	0.6710	0.5957	0.5976
Cox & Snell's R^2	0.0934	0.0977	0.1428	0.1027	0.1041
Nagelkerke's R^2	0.2826	0.2936	0.4169	0.2996	0.3009
$\chi 2$* (4, 6, 10, 4, 6)	1792.53	1857.77	2084.05	1604.07	1602.42
	(P<.0001)	(P<.0001)	(P<.0001)	(P<.0001)	(P<.0001)
		Hosmer & Lemeshow Goodness-of-Fit Test			
χ^2 (8)	76.6702	56.0823	11.0757	16.7956	14.9459
Pr> χ^2	<.0001	<.0001	0.1974	0.0323	0.0602
		Panel B: Models' Performance in *t-2*			
AUC	0.8548	0.8553	0.8922	0.8371	0.8368
Gini Rank Coefficient	0.7096	0.7106	0.7844	0.6742	0.6736
Kolmogorov-Smirnov	0.5677	0.5685	0.6275	0.5394	0.5389
Cox & Snell's R^2	0.0951	0.0978	0.1277	0.0834	0.0843
Nagelkerke's R^2	0.2687	0.2743	0.3573	0.2336	0.2333
$\chi 2$* (4, 6, 10, 4, 6)	1589.11	1616.09	1680.4646	1186.2039	1175.0079
	(P<.0001)	(P<.0001)	(P<.0001)	(P<.0001)	(P<.0001)
		Hosmer & Lemeshow Goodness-of-Fit Test			
χ^2 (8)	77.4006	36.4974	10.3433	14.7841	11.3724
Pr> χ^2	<.0001	<.0001	0.2418	0.0635	0.1815

* the parenthesis following the model's $\chi 2$ represent the degrees of freedom for each estimated model: 4 for Model 1, 6 for Model 2, 10 for model 3, 4 for Model 4, and 6 for Model 5.

6. Polytomous Response Financial Distress Models for Listed Companies using Accounting, Market and Macroeconomic Variables

6.1. Introduction.

Models for the prediction of financial distress/bankruptcy have been the object of considerable interest for academic as well as practitioners over the last four decades, which has been reflected by the number of research works in this field. In particular, the financial crisis of 2007-08 brought attention to the shortcomings of risk management practices within the lending environment and risk assessment at the micro level (PD estimation). Lenders and other investors require timely information on the default risk probability of corporates within lending and derivative portfolios. For banks, developing effective 'Internal Rating Systems' (IRB) for corporate risk management requires building probability of default (PD) models geared to the specific characteristics of corporate sub-populations (e.g. SME's, private companies, listed companies, sector specific models), tuned to changes in the macro environment, and, of course, tailored to the availability and timeliness of data. Given the importance of accurate forecasts and assessments of the likelihood of financial distress/bankruptcy to academics, practitioners, and regulators, conceptually richer, and more accurate prediction models have been developed. Furthermore, as discussed by Jones and Hensher (2004), financial distress prediction models are now widely used for a range of purposes that include: "monitoring of the solvency of financial and other institutions by regulators, assessments of loan security, going-concern evaluations by auditors, the measurement of portfolio risk, and the pricing of defaultable bonds, credit derivatives, and other securities exposed to credit risk."[164]

Several previous research works offer models that focus on the prediction accuracy of bankrupt/financially distressed companies versus financially sound firms. Therefore, a vast majority of the models advanced incorporate a binary outcome as the independent variable. In practice, the predictive accuracy of the models has been significantly enhanced, allowing risk managers to identify financial distress at an early stage and to take the necessary actions to avoid the costs associated with failure. The relative advantages of

[164] Jones and Hensher (2004), p. 1011.

binary logit models have been widely discussed since Efron's (1975) seminal theoretical paper. More recently, Jones (1987) provided a discussion on their application in the field of bankruptcy prediction, and Maddala (1991) reviewed the role of logit, probit, and discriminant analysis in accounting research. Altman et al. (2010) state that, from a statistical point of view, "logit regression seems to fit well with the characteristics of the default prediction problem, where the dependant variable is binary (default/non-default) and where the groups are discrete, non-overlapping and identifiable. The logit model yields a score between 0 and 1, which conveniently gives the firm's probability of default. Lastly, the estimated coefficients can be interpreted separately as the importance or significance of each of the independent variables in the explanation of the estimated probability of default."

The novelty of the present study lies on the fact that it considers corporate default as a dynamic process by including three possible states/outcomes in a generalised or polytomous logit regression model: a state that encloses on-going firms assumed to be in a financially sound position, a state reflecting firm Financial distress (based on a finance definition of corporate distress), and a state that represents Corporate failure (based on a technical definition built using information provided by the London Share Price Database). Next, and perhaps most importantly, this study argues that the applications to finance of the multinomial logit methodology have not been explored enough, and that the literature on financial distress and corporate failure could significantly benefit not only from the analysis of its output in the form of prediction accuracy results (of three possible outcomes), but also from the new insights that can be obtained through appropriate transformations of the multinomial function coefficients in order to provide a direct interpretation of the effects of individual covariates on the likelihood of a firm moving into one of the three possible states. Leclere (1999) argues that a potential reason for the underutilisation of these types of models "is that the interpretation of the model coefficients in a bivariate probit or logistic regression already differs substantially from OLS regression. When the models move from a dichotomous to an *n*-chotomous dependent variable, the interpretation becomes more complex. Compounding this difficulty, the typical coverage in an econometric text fails to provide readers with a systematic approach to the interpretation of model coefficients." To fill this gap in the financial distress literature, marginal effects, derived from the output of the polytomous response model, are estimated and interpreted in detail in the present study. Moreover, graphic representations of the changes produced in the vectors of predicted probabilities by a change in the level of a specific covariate (while keeping all other variables constant at their means) are presented to further analyse the individual effects of all types of variables in the models, providing thus additional insights on their patterns of behaviour as well as additional support to the interpretation of the marginal effects.

Therefore, the first objective of this chapter is to compare the multinomial function coefficients with the estimated marginal effects in order to observe the existing differences and to highlight the relevance of the latter to the interpretation of individual covariates in a polytomous response logit model. The second objective is to test whether the inclusion of accounting and market variables in a single multinomial logit model is able to outperform models based exclusively on either market or accounting information. It is investigated whether the combination of accounting and market variables enhance the goodness-of-fit of the models by estimating an 'Accounting only model,' a 'Market only' model and a 'Comprehensive' model that includes both accounting and macroeconomic data. Finally, the third objective is to provide and test a methodology to evaluate the predictive accuracy of the model using a database that is representative of the whole population of quoted companies in the United Kingdom.

The chapter is structured as follows. In the next section we discuss the literature that is relevant to our modelling approach. The database and measures of the outcome variable and set of explanatory variables are described. The estimation methodology is discussed along with analysis, results and conclusions.

6.2. Review of the Literature.

There have been a number of studies that make use of polytomous response models in areas outside the field of failure prediction: Boskin (1974), using human capital theory as analysis framework, empirically tests hypothesis about the variables influencing occupational choice. Lawrence and Arshadi (1995) analyse problem loan resolution choices using a multinomial logit model in the field of banking. Leclere (1999) develops and explains several approaches to interpreting coefficients in polytomous response models and applies them to accounting models. In the field of econometrics, McFadden and Train (2000) provide evidence suggesting that mixed multinomial logit models provide a computationally practical method for economic discrete choice that stems from utility maximisation. On the other hand, in the field of finance, Ward (1994) develops an ordinal four-state polytomous logit model to test the predictive ability of Beaver's naïve operating cash flow measure. More recently, Jones and Hensher (2004), tests the incremental ability of a three state mixed logit model to predict firm financial distress.

The above works vouch for the interest in examining the behaviour of individuals and firms through polytomous response models in several research fields (including finance), nevertheless, there is a very small number of research works that employ multinomial regression logit as the main methodology to construct financial distress models despite the fact that they could provide new insights and thus a better understanding of the financial distress/corporate failure dynamics. All of them focus exclusively on the predictive accuracy of their models relative to other research works. Occasionally, multinomial coefficient estimates are presented to infer the nature of the relationship of individual variables with respect to the probability of falling into a certain outcome. In other words, through the signs of the multinomial function coefficients, previous research works try to ascertain whether this relationship is positive or negative. To the best of my knowledge, there are no studies to date that deal with the issue of the magnitudes of individual effects on the (predicted) probabilities of falling into each of the specified outcomes.

Lau (1987) is one of the first (and very few) studies that applied the multinomial logit methodology to the field of financial distress prediction. She claims that her study extends previous binary (failing/non-failing dichotomy) corporate failure prediction models by utilising five possible states to "approximate the continuum of corporate financial health."[165] The five categories are created as follows: the first state contains financially stable firms; state 2 includes firms that have omitted or reduced dividend payments; state 2 refers to those firms that are in technical default and defaulted on loan payments; state 3 applies to firms that have filed a petition and are protected under Chapter X or XI of the Bankruptcy Act; and state 4 comprises firms in bankruptcy and liquidation. The original sample consisted of 350, 20, 15, 10, and 5 firms for each of the states, respectively. The model was tested in years 1, 2, and 3, and the multinomial function coefficients obtained were interpreted according to their respective signs. The model yielded a high predictive accuracy even though the coefficients' signs showed a number of inconsistencies. The most likely reason is that marginal effects (which do not necessarily yield the same signs as the coefficients[166]) are a more reliable measure to interpret the effects of individual covariates in a multinomial logit model.

[165] P. 127.
[166] Greene (2012).

More recently, Johnsen and Melicher (1994) develop a multinomial logit model for the prediction of corporate bankruptcy and financial distress. To the dichotomy bankrupt/non-bankrupt, they add a financially weak category in order to build a 3-state model and test the value added by multinomial logit regression methodologies. The sample used to estimate the model is composed of 157 bankrupt firms, 300 non-bankrupt firms, and 300 financially weak firms. Their study reports multinomial function coefficients and, through classification accuracy tests, finds that the multinomial model significantly reduces misclassification errors.

The previous studies that employ the multinomial logit methodology applied to the financial distress prediction field have some drawbacks that need to be addressed. First, Balcaen and Ooghe (2006), referring to the classic statistical failure prediction models, argue that if a financial distress/bankruptcy prediction model is developed for practical purposes and for use in a predictive context, the samples used in the estimation of the model should be representative for the whole population of companies. Moreover, Balcaen and Ooghe (2004) state that 'the firms in the estimation sample and new, future samples of cases, for which a failure prediction [model] is to be made, are assumed to come from the same distribution. Nevertheless, in the great majority of the classic statistical failure prediction models, the estimation of the models is based on non-random samples, whose compositions are different from the population's composition.'[167] As a matter of fact, the previous research works on financial distress/corporate bankruptcy prediction models that employ the polytomous response logit methodology use non-random samples whose compositions are highly dissimilar to the population's composition.

By contrast, the present study employs a sample for the estimation of the model that intends to reflect the distribution of the United Kingdom public company whole population. The reason for this choice is that it has been documented that if the estimation sample is not random, the function estimates as well as the predicted outcome probabilities are biased, which leads to an alteration of the overall classification accuracy (Manski and Lerman, 1977; Zmijewski, 1984). Now, the problem with non-random samples is that they can give rise to biases usually stemming from over-sampling the failing companies (Zmijewski, 1984; and Platt and Platt, 2002), from matching the number of financially sound and failed firms (Ohlson, 1980; Scott 1981; Platt and Platt, 2002), or from employing a 'complete data' sample selection criterion (Taffler, 1982; and Declerc et al., 1991),

[167] P. 26.

resulting in a misleading classification accuracy that cannot be generalised (Piesse and Wood, 1992).

Second, previous multinomial financial distress prediction models employ juridical definitions of default that are not exempt of shortcomings. For example, corporate bankruptcy can be a lengthy legal process and the legal date of failure may not represent the 'economic' or the 'real' event of failure. The previous chapter finds evidence indicating that there is a considerable time gap (up to three years or 1.17 years in average) between the period that a firm enters a state of financial distress (that caused the firm to default) and the date of legal default/bankruptcy. In line with these findings, Theodossiou (1993) reports that firms in the United States stop providing accounts approximately two years before the bankruptcy filing. Moreover, it is also possible that a firm in a state of financial distress does not change the legal status that a bankruptcy filing would entail (Balcaen and Ooghe, 2004). Referring to the classic binary default prediction models, Ooghe et al. (1995) and Charitou et al. (2004) argue that the legal definition of failure is commonly employed because, on the one hand, it provides an objective criterion to divide the sample into two distinct populations, and on the other, it allows the moment of failure to be objectively dated. In order to create a well-defined classification method that yields three financial states clearly separated from each other, the present chapter follows Barnes (1987), Barnes (1990) and Pindado et al. (2008) and presents a novel finance-based definition of firm distress that is dependent upon the level of a firm's EBITDA relative to its financial expenses and the changes in the market value of a firm over time. Additionally, the present study follows Christidis and Gregory (2010) and offers a proxy for corporate failure whose observation date reflects the economic or real event of failure: a technical definition of corporate failure based on the London Share Price Database is employed.

Finally, all of the variables included in prior polytomous response financial distress/bankruptcy prediction models include only accounting measures as independent variables. However, there is reason to believe that these models could benefit from the relevant information contained in market variables, as suggested by previous research works that have tested the utility of market variables in predicting bankruptcy by employing methodologies such as the Black and Scholes (1973) and Merton (1974) contingent claims or option based approach. Bharath and Shumway (2008), Hillegeist et al. (2004), Reisz and Perlich (2007), and Vassalou and Xing (2004) have employed the contingent claims approach to estimate the likelihood of corporate failure. More recently data on Credit Default Swaps (prices and spreads) have been used to proxy credit risk (Alexander and

Kaeck, 2008)[168]. However, the results obtained from these models (that entail numerous restrictive assumptions) have been controversial. Many efforts have been carried out to demonstrate the superiority of market-based models over accounting-based models and vice versa. To this point, the default prediction literature is characterised by a competing approach, where there is a clear division line between market and accounting variables. The present study adopts a different approach where the use of these types of variables is not mutually exclusive. It is tested whether the market variables (dependent, in some measure, upon the same financial information) add information that is not contained in financial statements and therefore act as complement in default prediction models.

6.3. Outcome Definition.

The criteria used to identify failed firms and to classify firm-years into non-financially distressed, financially distressed and failed firms in order to create an appropriate three-state panel for a polytomous-response logit analysis are as follows. A firm-year observation is classified as pertaining to the financially distressed state (DIS) whenever it meets both of the following conditions: i) its earnings before interest and taxes depreciation and amortisation (EBITDA) are lower than its financial expenses for two consecutive years, and ii) there is a negative growth of its market value for two consecutive periods. With regard to the most extreme outcome, corporate failure (FAI), a firm was classified in this category when its status in the 2012 London Share Price Database (LSPD) is one of the following[169]: suspended, in liquidation or voluntary liquidation, when its quotation has been suspended for more than three years, when the firm is being held by a receiver (in receivership), in administration or in administrative receivership, or when there has been a cancellation or suspension of the firm[170]. Finally, firm-year observations classified as non-financially distressed/failed (NFD) are those that did not display signs of financial distress according to the DIS state and that had not been classified as pertaining to the FAI state. Thus, firm-year observations that entered the NFD state are those that do not belong to either of the remaining two categories according to the established classification criteria.

[168] See the previous chapter for a detailed literature review on market based and accounting based financial distress prediction models.
[169] This definition is based on the definition of corporate failure in Christidis and Gregory (2010).
[170] The LSPD numbers and definitions in the database are: 6) Suspension / cancellation with shares acquired later. Meanwhile, may be treated under rule 163/2; 7) Liquidation (usually valueless but there may be liquidation payments; 10) Quotation suspended – if suspended for more than three years, this may lead to automatic cancellation; 11) Voluntary liquidation, where value remains, and was / is being distributed; 16) Receiver appointed / liquidation. Probably valueless but not yet certain; 20) In Administration / Administrative receivership; 21) Cancellation and assumed valueless or suspended but assumed valueless.

6.3.1. Outcome Definition

The promised analysis requires a specific definition for each of the three potential outcomes: Non-financial distress'/failure (NFD), Financial distress (DIS), and Corporate failure (FAI), which can be appropriately regarded as the outcome of a process. The present study develops *ex-ante* models for the prediction of financial distress and failure, so it is crucial to employ compelling criteria that is capable of distinctly differentiating the potential outcomes (especially in the case of financial distress and failure), as required by the polytomous response logit methodology. The main reason is that one of the main objectives of the present study is not only to provide a timely and accurate financial distress prediction model (with practical value and macro dependent dynamics that have relevance for stress testing), as in the previous chapter, but also to investigate the behaviour of the probabilities of falling into one of the three mutually exclusive states given different levels of the independent variables included in the models (accounting, market and macroeconomic indicators). Therefore, the states of financial distress and corporate failure, unlike in the previous chapter, are created as two distinct outcomes for analysis. First, in regard to the definition of financial distress (DIS), the ability of a firm to repay its financial obligations (Asquith et al., 1994) plays a special role in the present study and is in line with earlier discussions and recent papers. The present study's definition of financial distress follows Pindado et al. (2008) and employs two main conditions that need to be fulfilled in order for a firm-year observation to be classified as such: thus, a firm is classified as financially distressed [171] whenever *i) its earnings before interest and taxes depreciation and amortization (EBITDA) are lower than its financial expenses for two consecutive years and; ii) the firms suffers from a negative growth in market value for two consecutive years.*

With regard to the first condition, the reasoning is as follows: if EBITDA is lower than the interest expense on the company's debt then it can be concluded that the operational profitability of the firm is not sufficient to cover its financial obligations; on the other hand, with reference to the second condition, Pindado et al. (2008) state that the market as well as stakeholders are likely to judge negatively a firm that suffers from the operational deficit (described in the first condition) until an improvement in the financial condition is perceived again. Thus, the fall in market value for two consecutive years is interpreted as an indication that a firm is in effect in financial distress. As in Pindado et al. (2008), the study is thus introducing a dynamic approach, a novel development in existing

[171] In a general logit model a firm is considered as financially distressed in the year that immediately follows the occurrence of both events.

financial distress definitions. The variables Earnings before interest and taxes depreciation and amortization (EBITDA) and Interest expense on debt were obtained from Thomson One Banker. In order to compute the changes in market value for the companies in the database, the present study used the information available in both Thomson One Banker and Datastream[172].

Secondly, the present study's definition of corporate failure employs the information available in the 2012 London Share Price Database (LSPD) and is based on Christidis & Gregory (2010). A firm is classified as failed whenever its status is defined as suspended, in liquidation or voluntary liquidation, when its quotation has been suspended for more than three years, when the firm is being held by a receiver (in receivership), in administration or in administrative receivership, or when there has been a cancellation or suspension of the firm. Thus, a firm is classified as financially distressed when its LSPD (2012) status is equal to any of the following formal definitions (that indicate the reason why the security ceased to be quoted in the SEDOL): 6) Suspension / cancellation with shares acquired later. Meanwhile, may be treated under rule 163/2; 7) Liquidation (usually valueless but there may be liquidation payments; 10) Quotation suspended – if suspended for more than three years, this may lead to automatic cancellation; 11) Voluntary liquidation, where value remains, and was / is being distributed; 16) Receiver appointed / liquidation. Probably valueless but not yet certain; 20) In Administration / Administrative receivership; 21) Cancellation and assumed valueless or suspended but assumed valueless. In addition, the present analysis also tracks the specific date when each one of these events occurs. Finally, the state of non-financial distress is defined as those firms that did not enter either the financial distress state or the corporate failure category.

Among the total number of observations, there are 21,964 firm-years classified as non-financially distressed/failed companies, 869 firm-years identified as financially distressed, and 385 firms classified as failed. As Table 6-1 shows, the percentage of non-financially distressed/failed companies is 94.6, while that of financially distressed firm-years and failed companies is equal to 3.74 and 1.66, respectively. Finally, for simplicity and as required by the software to estimate generalized or polytomous response logit models, individual identifiers were assigned to each of the three potential outcomes of the Response variable. Accordingly, the state of Non-financial distress is denoted by the

[172] Both databases were used as some missing information on specific companies in one database could be completed by the data of the other. A merging of the databases was therefore required in order to obtain larger time series and thus a more accurate model.

identifier Response = 1, the state of Financial distress by the identifier Response = 2, and the state of Corporate failure by the identifier Response = 3.

Table 6-1 Summary Statistics of the Annual Observations. Financially and Not Financially Distressed Firms

Panel A reports summary statistics for the entire sample. NFD stands for Non-financially distressed firms, DIS for firms in a state of financial distress, and FAI indicates those firms classified as failed companies. Firms. A firm is classified as DIS when it files for bankruptcy when it meets both of the following conditions: i) its earnings before interest and taxes depreciation and amortisation (EBITDA) are lower than its financial expenses for two consecutive years, and ii) there is a negative growth of its market value for two consecutive periods. A firm is classified as FAI when its status in the 2012 LSPD is defined as: suspended, in liquidation or voluntary liquidation, when its quotation has been suspended for more than three years, when the firm is being held by a receiver (in receivership), in administration or in administrative receivership, or when there has been a cancellation or suspension of the firm[173].

Panel A: Classification of annual observations into Non-financially distressed, Financially distressed, and Failed companies.

Response	Freq.	Per cent	Cumulative Freq.	Cumulative Per cent
NFD	21964	94.60	21964	94.60
DIS	869	3.74	22833	98.34
FAI	385	1.66	23218	100.00

The previous chapter's main objective was to build more accurate and timely financial distress prediction models, using data that is routinely available. To achieve this objective, financial distressed prediction models were built employing a binary logistic regression for the analysis of the panel of data described above. The resulting logit model classification accuracy were then compared to the widely used Altman's z-score model and to the output obtained through the estimation of a multilayer perceptron model based on the artificial neural networks methodology. The results were as follows: the new binary logistic model's classification accuracy clearly outperformed the *z*-score's and displayed greater flexibility, transportability and transparency relative to the multiplayer perceptron's one. Moreover, the categorical model developed in the previous chapter displayed the advantages of providing crucial information related to the usefulness of the different types of variables as well as their individual contributions to the prediction accuracy of financially sound against financially distressed companies. The models were designed specifically to obtain more timely and accurate results compared to previous works in the academic field

[173] The LSPD numbers and definitions in the database are: 6) Suspension / cancellation with shares acquired later. Meanwhile, may be treated under rule 163/2; 7) Liquidation (usually valueless but there may be liquidation payments; 10) Quotation suspended – if suspended for more than three years, this may lead to automatic cancellation; 11) Voluntary liquidation, where value remains, and was / is being distributed; 16) Receiver appointed / liquidation. Probably valueless but not yet certain; 20) In Administration / Administrative receivership; 21) Cancellation and assumed valueless or suspended but assumed valueless.

and were constructed using a parsimonious approach since they were intended to have practical value.[174]

The present chapter, additionally, investigates the effect of the different types of variables (individually and as groups) on the outcome probabilities of falling into one of the mutually exclusive three-state Response variable. This is therefore the first study that investigates the effects of the independent variables on the changes in predicted probabilities from one state to another conditionally on a base outcome. This is also of crucial importance for academics as well as practitioners, as it provides new insights on practical and theoretical issues such as: what is the effect of a negative change of magnitude z of the accounting ratio x (while keeping the levels of all other independent variables constant) on the probability that a corporation will be in a state of failure in the future *given* that it is now in a state of financial distress (or conditionally upon being already facing a perilous financial situation[175])?; or even, what is the *magnitude* of the effect of variable x on this probability *relative* to variable y? Through the answers to this questions, practitioners could focus on the firm areas which deserve particular attention in order to prevent it from advancing to a more serious state of financial distress, with failure being the most extreme and costly outcome.

Previous research works have invariably focused on the accuracy to predict different outcomes employing multinomial logit methodologies that include almost exclusively financial statement ratios, and do not provide any insights relevant to the above central questions. The reason is that these research studies present only the coefficient estimates obtained through the fitting of generalized logit models (with a variable number of potential outcomes). Now, as it is shown in more detail in the next section of the present study, coefficients estimates of multinomial logit models, despite their relative usefulness and unlike linear regression models, do not possess an obvious and direct interpretation. The present study's aim is to fill this gap and thus contribute to the literature on polytomous response financial distress/corporate failure models by employing the appropriate transformations in order to directly interpret the models' results and thus provide straightforward and clear answers to the questions raised. To this effect, marginal effects derived from the output of the polytomous response model are estimated and shown in the present study. Furthermore, vectors of predicted probabilities are plotted to

[174] Zmijewski (1984) and more recently Pindado et al. (2008) have shown that in fact a large set of variables is not required for the models to reach their maximum level of accuracy. Pindado et al. (2008), for instance, employ a set of only three accounting variables to reach a high level of accuracy in their financial distress prediction model.

[175] Defined by two conditions: a lower level of EBITDA relative to financial obligations, and a fall in market value (both for two consecutive years), which could put the normal operations of the firm at serious risk.

confirm the effects of all types of variables in the models and to provide additional support to the interpretation of the marginal effects.

The second objective of the analysis is to test the usefulness of non-accounting variables, namely macroeconomic and market variables, with regard to their contribution to the accuracy and timeliness of financial distress/corporate failure prediction models for quoted companies. It is investigated whether the combination of accounting and market variables enhance the goodness-of-fit of the models by estimating an 'Accounting only model,' a 'Market only' model and a 'Comprehensive' model that includes both accounting and macroeconomic data (with information one and two years prior to the observation of the relevant event). There have been very few studies that analyse the performance of these types of variables in a statistical dynamic prediction model that includes controls for changes in the macroeconomic environment (thus adjusting estimated scores in relation to changes in the macroeconomic environment and providing the facility to impose stress tests scenarios). It is deemed important to investigate the potential usefulness of market variables in a generalized or polytomous response logit model since they are likely to act as a complement to the information content provided by the accounting variables, as suggested by the findings of the previous chapter. On the other hand, given the real costs associated with financial distress and corporate failure, market data is included in order to highlight the timeliness and therefore the practical value of the models.

It is also important to draw attention to the fact that data based on financial ratios can only be obtained on an annual basis, so even if the discriminating power of some previous and widely used accounting models (such as Altman's z-score model) is quite high, there is always the risk of relying on out dated information. Furthermore, through a detailed analysis of the most extreme form of financial distress, corporate failure, the present study shows that the firms that were classified as failed[176], stop providing accounting data one year on average (14 months) before the actual date of failure. Therefore, because of the continuous availability of market data, it is expected that market variables play an important role in the timeliness of the output obtained from the models by providing early warnings about financial stress (therefore allowing corporate managers to take preventive actions to avoid failure as well as corrective actions to tackle financial distress at early stages in order to avoid the costs associated with these events).

[176] See previous chapter.

Furthermore, this study provides a novel and flexible approach to measuring the classification accuracy of a three-state financial distress logit model using an unbalanced panel that is intended to approximate the real proportions of financially distressed/failed quoted companies in the United Kingdom. It is very important to highlight the fact that, almost invariably, the few previous research studies based on the multinomial logit methodology for the construction of financial distress prediction models, employed almost symmetric (or balanced) panels of data consisting of either an approximately equal number of observations for each category, or an extremely small number of total observations. Now, the number of observations as well as the proportions of the different outcomes relative to the total size of the database and to the proportions among outcomes results in alterations to individual observations' predicted probabilities (Zmijewski, 1984). The final model in this study is tested using the entire database with the original proportions of outcomes, and a novel and flexible approach for the construction of biased-adjusted classification tables based on the previous chapter is presented.

Finally, in order to take into account potential correlation problems among variables included in all the models that could cause multicollinearity issues (resulting in imprecise coefficient estimates and artificially large standard errors), correlation matrices and direct multicollinearity diagnostic tests[177] were computed and presented in Table 6-2.

[177] Multcollinearity is present when there is linear dependency among two or more independent variables in a multivariate model. This problem arises because some of them may be measuring the same concept. Consequently, when a given independent variable is a linear or a quasi-linear combination of other independent variables, the affected estimates are unstable and the standard errors inflated. Tolerance value and is reciprocal, variance inflation tests are computed as $1 - R_k^2$ and $1/(1 - R_k^2)$ respectively, where R_k^2 is the determination coefficient for regression of the *i*th regressor on all the other regressors. Freud and Little (2000), show how the instability of the coefficient estimates is increased by the existence of multicollinearity. It must be mentioned that there is not a formal criterion to establish a VIF value threshold above which multicollinearity can be ascertained; it has been argued that a VIF value greater than 10 suggests significant collinearity. The VIF values of all the regressors incorporated in the present study's models, show they are all even below 5, which indicates that multicollinearity is not present in the models and that the levels of the coefficients obtained are therefore reliable.

Table 6-2 Correlation Matrix and Multicollinearity Diagnostics Statistics

Panel A of this table reports the correlation matrix of all the variables in included in the model. It includes financial statement ratios, macroeconomic indicators and market variables. *P*-values represent the probability of observing this correlation coefficient or one more extreme under the null hypothesis (H0) that the correlation (Rho) is zero. Panel B reports the values resulting from tests intended to detect the presence of multicollinearity among all the variables incorporated in the model: Tolerance Value (TOL) and its reciprocal, Variance Inflation (VIF) are computed as $1 - R_k^2$ and $1/(1 - R_k^2)$ respectively, where R_k^2 is the determination coefficient for regression of the *i*th regressor on all the other regressors.

Panel A: Correlation Matrix

Variable	*TFOTL*	*TLTA*	*NOCREDINT*	*COVERAGE*	*RPI*	*SHTBRDEF*	*PRICE*	*ABNRET*	*SIZE*	*MCTD*
TFOTL	1.00000									
TLTA	0.17057	1.00000								
	<.0001									
NOCREDINT	-0.09720	-0.44510	1.00000							
	<.0001	<.0001								
COVERAGE	0.72613	0.02865	-0.05983	1.00000						
	<.0001	<.0001	<.0001							
RPI	-0.19100	-0.12218	0.14404	-0.19691	1.00000					
	<.0001	<.0001	<.0001	<.0001						
SHTBRDEF	0.12491	0.09343	-0.10688	0.11610	-0.81383	1.00000				
	<.0001	<.0001	<.0001	<.0001	<.0001					
PRICE	0.37131	0.05951	-0.04823	0.37641	-0.19656	0.15184	1.00000			
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001				
ABNRET	0.25785	-0.06960	0.03254	0.29870	-0.04405	-0.05138	0.28852	1.00000		
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001			
SIZE	0.36300	0.09781	-0.08105	0.40685	-0.23538	0.10799	0.58264	0.29448	1.00000	
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		
MCTD	0.08792	-0.34893	0.18940	0.13136	-0.04910	-0.00248	0.20164	0.23896	0.22630	1.00000
	<.0001	<.0001	<.0001	<.0001	<.0001	0.7461	<.0001	<.0001	<.0001	

Panel B: Multicollinearity Diagnostic Statistics

Test	*TFOTL*	*TLTA*	*NOCREDINT*	*COVERAGE*	*RPI*	*SHTBRDEF*	*PRICE*	*ABNRET*	*SIZE*	*MCTD*
TOL	0.49947	0.77183	0.87329	0.47709	0.31558	0.32067	0.60705	0.81705	0.58202	0.77601
VIF	2.00214	1.29562	1.14509	2.09603	3.16874	3.11847	1.6473	1.22391	1.71817	1.28865

6.4. Methods: Polytomous Response Logit Model Specifications.

As the sample for analysis is divided into a number of distinct groups that is higher than two, the outcome takes the form of a polytomous dependent variable. Therefore, the statistical analysis of the panel of data requires a generalisation of a binary logistic regression model in order to include more than two outcomes. A multinomial logistic methodology is appropriate for the analysis. This type of model can be referred to as a multinomial logit model because the probability distribution for the response variable is assumed to be a multinomial rather than a binomial distribution. The development of the model is as follows. Suppose that there are *J* categorical outcomes, with the running index *j* = 1, 2,…, *J*. Next, let p_{ij} be the probability that observation *i* falls into outcome *j*. The model is thus given by

$$ln\frac{p_{ij}}{p_{iJ}} = \boldsymbol{\beta}_j\mathbf{x}_i' ,$$

Where $\mathbf{x}_i'$ is a column vector of independent variables describing observation *i*, and $\boldsymbol{\beta}_j$ is a row vector of coefficients for outcome *j*. These equations are solved to yield

$$\text{Prob}(Y_i = j|\mathbf{x}_i) = P_{ij} = \frac{\exp(\beta_k\mathbf{x'}_i)}{1 + \sum_{k=2}^{J}\exp(\beta_k\mathbf{x'}_i)}$$

where *j* = 1, 2,…, *J*

Now, given that the probabilities for all *J* outcomes must sum to 1,

$$P_{ij} = \frac{1}{1 + \sum_{k=2}^{J}\exp(\boldsymbol{\beta}_k\mathbf{x}_i')}$$

therefore, in the general form of the model, only *J* parameter vectors are required to determine the *J*+1 probabilities.

Next, in a multinomial logit model, each outcome is compared to a base outcome, so assuming that there are *J* categorical outcomes and – without loss of generality – the base outcome is defined as 1 (still with *j*=1,2,…,*J*), then the probability that the response for the *i*th observation is equal to the *j*th outcome is

$$\text{Prob}(Y_i = j|\mathbf{x}_i) = P_{ij} = \begin{cases} \dfrac{1}{1+\sum_{k=2}^{J}\exp(\boldsymbol{\beta}_k\mathbf{x}_i')}, & if\ i = 1 \\ \dfrac{\exp(\boldsymbol{\beta}_j\mathbf{x}_i')}{1+\sum_{k=2}^{J}\exp(\boldsymbol{\beta}_k\mathbf{x}_i')}, & if\ i > 1 \end{cases}$$

This methodology was employed in the present study to solve the equations for different base outcomes.

The log-likelihood is derived by defining, for each individual (observation), $d_{ij} = 1$ if outcome *j* is occurring for observation *i*, and 0 otherwise, for the *J+1* possible outcomes. Thus, for each observation *i*, one and only one of the d_{ij}'s is 1. The log-likelihood is thus a generalisation of that for the binomial logit (and probit) model.

$$\ln L = \sum_{i=1}^{n}\sum_{j=1}^{J} d_{ij} \ln \text{Prob}(Y_i = j|\mathbf{x}_i)$$

where $d_{ij} = \begin{cases} 1, & if\ y_i = j \\ 0, & otherwise \end{cases}$

The present study employs the Newton-Raphson maximum likelihood optimisation algorithm.

However, the coefficient parameters of a multinomial logit model are difficult to interpret. In a linear model, the coefficients can be directly interpreted as marginal effects of the predictor variables on the outcome variable. For instance, in a linear model of the form

$$z = \beta_0 + \beta_1\mathbf{x}_1 + \beta_2\mathbf{x}_2 + \cdots + \epsilon$$

β_1 can be interpreted as the effect of a one unit increase in $\mathbf{x}_1$on z. Nevertheless, β_1 is just the marginal effect of z with respect to $\mathbf{x}_1$, following

$$\frac{\partial_y}{\partial \mathbf{x}_k} = \beta_k$$

From this equation, it can be observed that the effect of $\mathbf{x}$ on z is a derivative. Hence, the natural interpretation of a linear regression model's marginal effects through derivatives stems from the linearity of the model: in the present example the marginal effect of $\mathbf{x}_k$ on z is given by β_k. This is true regardless of the values of $\mathbf{x}_k$ or z under consideration or the values of other variables in the model.

This is not the case for polytomous response logit models. Neither the magnitude nor the sign of the parameters possess a natural meaning that can be directly interpreted. Nevertheless, the relevant estimations can be obtained using appropriate transformations of the coefficients. Therefore, in addition to the coefficient estimates computed employing the above statistical methodology, marginal effects are presented for each of the variables. The marginal effect of a predictor can be defined as the partial derivative of the event probability with respect to the predictor of interest. Marginal effects are thus a more appropriate measure to interpret the effect of the regressors on the dependent variable for discrete dependent variable models such as the multinomial logit model. Marginal effects are formally expressed as follows below.

First, for simplicity, let the probability of outcome *j* in response to a change in a specific variable $\mathbf{x}$, specific to outcome *j* be denoted by

$$\frac{\partial P_j}{\partial \mathbf{x}_j} = \left(1 - P_j\right) P_j \boldsymbol{\beta}_j$$

Next, taking into account that an identical change in the specific variable will occur for all outcomes in which the variable appears as an outcome specific variable, it is necessary to employ the cross-derivative of the probability of outcome *j* occurring in response to a change in the variable, specific to outcome *k*

$$\frac{\partial P_j}{\partial \mathbf{x}_k} = -P_j P_k \boldsymbol{\beta}_k$$

the sum over all outcomes $k \neq j$ is thus

$$\sum_{k \neq j} \frac{\partial P_j}{\partial \mathbf{x}_k} = -P_j \sum_{k \neq j} P_k \boldsymbol{\beta}_k$$

finally, the sum over all outcomes including *j* is denoted by

$$\frac{\partial P_j}{\partial \mathbf{x}_k} = P_j\left(1 - P_j\right)\boldsymbol{\beta}_j - \sum_{k \neq j} P_j P_k \boldsymbol{\beta}_k$$

$$= P_j \boldsymbol{\beta}_k - \sum_{k=1}^{J} P_j P_k \boldsymbol{\beta}_k$$

$$= P_j \left[\boldsymbol{\beta}_j - \sum_{k=1}^{J} P_k \boldsymbol{\beta}_k \right]$$

$$= P_j \left[\boldsymbol{\beta}_j - \overline{\boldsymbol{\beta}} \right]$$

where $\overline{\boldsymbol{\beta}}$ is the probability weighted average of the outcome specific variable parameters.

Notice that the marginal effect of an independent variable $\mathbf{x}_i$ on the occurrence of outcome *j* incorporates the parameters of *k* as well as the parameters of all the other outcomes: it is shown that the derivative of the probability with respect to a change in a variable is equal to the product of the probability times the amount by which the variable's coefficient for that outcome exceeds the probability weighted average variable coefficient over all outcomes. Furthermore, it is necessary to highlight that – without loss of generality – for any individual $\mathbf{x}_{ik}$, $\frac{\partial P_{ij}}{\partial \mathbf{x}_{ik}}$ need not display the same sign as $\boldsymbol{\beta}_{jk}$.

The present study tests a three-state financial distress/failure model based on a polytomous response logit regression model, where the Response possible outcomes are: NFD or Non-financially distressed companies, DIS or Financially distressed companies, and FAI or Failed firms. As required by the statistical software used to estimate this type of generalised logit model, individual identifiers were assigned to each of these three potential outcomes of the Response variable: the state of Non-financial distress is denoted by the identifier Response = 1, the state of Financial distress by the identifier Response = 2, and the state of Corporate failure by the identifier Response = 3. Thus, the analysis of the present study is based on a multinomial logit model whose response variable is composed of three mutually exclusive potential outcomes. In other words, depending upon its individual characteristics (as well as the macroeconomic environment), a firm-year observation can fall into one of the following categories: Non-financial distress, Financial distress and Corporate failure. As previously stated, the probability distribution of the response variable that was employed for this study is assumed to be a multinomial rather that a binomial distribution. Moreover, the multinomial function coefficients resulting from the three-level response logit model are supposed to reflect the effects of a specific variable on the probability of a firm-year observation falling into one of the three outcomes *conditional* upon a *base outcome* that can be selected among the options depending on the objectives of the analysis.

In order to empirically test the formal assumptions developed in this section, the present study presents, in a first stage, the multinomial function coefficients for the three possible non-redundant combinations of outcomes: Non-financial distress versus Financial distress, Corporate Failure versus Distress, and Corporate Failure versus Non-financial distress. In order to obtain the coefficient estimates, as well as average marginal effects (AMEs) for the first two pairs of outcomes, the category Financial distress was selected as the base outcome of the multinomial logit regression, as this category can be considered as a transition point between two extremes in a process. And in order to obtain the coefficient estimates (as well as AMEs) for the third pair of categories, FAI versus DIS, which further tests the ability of the variables in the model to discriminate among two potential outcomes, a second multinomial logit function was fitted specifying the category NFD as the base outcome. It is logically expected that, among these possible combinations, the model will produce better performing estimates for the prediction of pairs of outcomes that involve extreme or opposite categories. In other words, more reliable coefficient estimates (involving higher statistical significance and correct expected signs), should be expected for the pairs DIS versus NFD and FAI versus NFD than for the pair DIS versus FAI. The reason is that, concerning the latter pair of categories (where the outcomes are closer or more similar), DIS can be considered as a stage in a process that involves a deterioration of the characteristics of a firm (and a macroeconomic environment) that can ultimately lead, if aggravated to a certain point, to a most extreme outcome of the financial distress-failure process: FAI. Three sets of coefficient estimates are thus obtained for each model for the periods *t-1* and *t-2*.

Next, given that it was shown that care should be taken in interpreting the coefficient estimates obtained from this type of model (as the coefficients cannot be interpreted as the effect of a one unit change of a given covariate on the dependent variable, like those resulting from a linear regression model), this section demonstrated that appropriate transformations must be performed in order to obtain a relevant assessment of the effects of individual independent variables on the probability of a specific outcome occurring. Marginal effects, defined as the partial derivative of the event probability with respect to the predictor of interest, are thus presented as a more appropriate measure to interpret the effect of the regressors on the dependent variable (for discrete dependent variable model) and compared with the coefficient estimates. The methodology used in the present study to generate AMEs consists of outputting the individual marginal effects estimated at each observation in the dataset and then calculating their sample average in order to obtain the overall marginal effect. Additionally, standard errors (obtained employing the Delta-method), significance statistics, and 95 per cent confidence intervals are reported. In this manner, a comparison between *ex-ante* propositions/expectations, coefficient estimates, and AMEs is performed in order to provide evidence supporting the primary premise that the latter are a more appropriate measure to evaluate and interpret polytomous response logistic regression models while providing new insights on the individual effects of the independent variables. Further, the study presents biased-adjusted classification accuracy tables for all the models.

6.5. Independent Variable Specifications and Ex-ante Hypotheses.

The selection of the variables retained in the final multinomial logit models is based on previously reported results, theoretical propositions and empirical evaluations. Furthermore, the data was subject to a rigorous cleaning and testing process and a novel approach for dealing with outlying observations was tested for the first time in financial distress/corporate failure prediction models. Both univariate and multivariate procedures were employed and considerable experimentation was undertaken to arrive at the final choice of independent variables. A detailed account regarding the sources and the construction of the variables can be found in Chapter 3. This section explains the role of each variable in the models and advances their implications for the interpretation of the output obtained from the polytomous response logit regression models.

6.5.1. Accounting Ratios.

With regard to the accounting variables, four variables were retained in the final models: Total Funds from Operations to Total Liabilities, Total Liabilities to Total Assets, the No Credit Interval, and Interest Coverage. The first ratio, Total Funds from Operations to Total Liabilities (TFOTL) can be decomposed as follows: Total Funds from Operations represents the sum of net income and all non-cash charges or credits (it is the cash flow of the firm), whereas the denominator, Total Liabilities, is composed of all short and long-term liabilities acquired by the company. This ratio is intended to show the extent to which a company is able to generate funds from its operations to meet its financial obligations. Therefore, the higher the value of TFOTL, the less likely it should be for a company to be in a state of financial distress/failure. The second ratio TLTA is estimated as Total Liabilities over Total Assets of industrial firms (the addition of total current assets, long-term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets). The ratio TLTA is commonly used to measure a firm's financial leverage (and therefore financial risk) by calculating the proportion of the company's assets that have been financed using short and long-term debt. The implications of this ratio are as follows: the higher the leverage, the higher the financial risk taken by a given firm and therefore the higher its probability of financial distress/failure. The third variable, the No-credit interval (NOCREDINT) can be defined as 'an estimate of the length of time that a company could finance the expenses of its business, at its current level of activity, by drawing on its own liquid resources and on the assumption that it made no further sales.'[178] This variable was calculated using the following formula: (Quick assets minus Current liabilities) / (Daily operating expenses)[179]. The ratio is commonly used to evaluate a firm's liquidity position through the number of days that a company can finance its expenses by drawing on its own current resources. An increasing, positive value of NOCREDINT indicates an enhanced capacity of the firm to finance its business expenses (with its quasi-liquid and liquid resources given its current level of activity), and, therefore, a lower probability of financial distress/failure.

The final accounting ratio, Interest Coverage (COVERAGE), was calculated by dividing the variable Earnings before interest, taxes and depreciation (EBITDA)[180] by the variable Interest charges or Interest expense on debt that represents the service charge for the use of capital before the reduction for interest capitalized. COVERAGE measures a firm's ability to pay interest on outstanding debt[181]. An increasing value of this ratio reflects an enhanced capacity of a company to make interest payments, which should result in a lower probability of firm financial distress/failure. Further, all of the above accounting ratios were transformed using the TANH function in order to treat the problem of outlying values of the variable that could have an abnormal impact on the fitted maximum likelihood linear predictors as well as on the size of the residuals that resulted from the binary logistic regression. After the TANH transformation, the real line of the variables can be mapped onto [-1, 1].

[178] Graham (2000), P. 86.
[179] Where Quick Assets represent the assets that can be quickly and easily converted into cash or are already in cash form, Quick assets is Current Assets minus Inventories, and Daily operating expenses is equal to (Sales minus Earnings Before Interest and Taxes minus Depreciation) / 365.
[180] EBITDA measures the earnings of a firm before interest expense, income taxes and depreciation. Worldscope calculates EBITDA by taking the pre-tax income and adding back interest expense on debt and depreciation, depletion and amortization and subtracting interest capitalized.
[181] Chapter 2 provides a detailed interpretation of the possible ranges of this accounting ratio.

6.5.2. *Market Variables.*

Four market variables were retained in the multinomial logit final models of the present study in order to assess whether they contain additional information on the likelihood of financial distress and corporate failure that can increase the goodness-of-fit and performance (discriminating and predicting ability) of accounting only models[182]. The first market variable is the firm's equity price (PRICE). Market equity prices are employed as proxies for investor's expectations of future cash flows and earnings, therefore, to the extent that a firm's earnings are affected by its financial stance, it is expected that there is a negative relationship between price levels/movements and the likelihood of financial distress/failure: it is posited that a high or increasing level of PRICE will decrease the likelihood of financial distress and corporate failure.

The second market variable included in this study is the lagged cumulative security residual return (ABNRET). In order to incorporate this variable in a financial distress prediction model, each firm's past residual return[183] in year *t* was calculated as the cumulative monthly return of the twelve months prior to the year where the financial distress event was observed, minus the FTSE All Share Index cumulative monthly return for the same period (the same procedure was replicated for both periods *t-1* and *t-2*). In line with the findings of previous empirical studies[184], it is assumed that a high level of a firm's residual returns relative to those of the FTSE All Share Index will decrease the likelihood of falling into the financial distress/failure category. The third market variable incorporated to the model represents the Size of the company measured by its market capitalisation relative to the total size of the FTSE All Share Index (SIZE). It is intended to measure the magnitude of a discount in a firm's market value of equity induced by a negative investors' assessment of the firm's financial stance (while taking into account the total size of the FTSE All Share Index in order to make size static). A decline in the level of equity can systematically move towards the 'strike price' (or the value of liabilities) and eventually reach a level (below the strike price) where it is insufficient to serve the firm's financial obligations (and the firm defaults). Thus, it is predicted that a high or increasing level of

---

182 A positive finding would suggest that market variables (which already incorporate information based on financial ratios) act as complements to accounting information. In addition, they are potentially very useful to enhance the timeliness of models relying exclusively on annual accounts.

183 In order to calculate residual/abnormal returns, firms' individual returns are employed as the main input. The investment return can be defined as the total gain or loss on an investment over a given period of time. The return incorporates the change in the asset's values plus any cash distributions (dividends or interest payments). The specific Datastream datatype used in the present study is the Total Return Index (RI) which shows 'a theoretical growth in value of a shareholding over a specific period, assuming that dividends are reinvested to purchase additional units of an equity or unit trust at the closing price applicable on the ex-dividend date.'

184 See Dichev (1998), Shumway (2001), and Chapter 2.

SIZE should entail a decrease in the likelihood of firm falling into the financial distress/failure category. The final market variable that entered the final model is the ratio Market Capitalisation to Total Debt (MCTD). The denominator, Total Debt, is equal to all interest bearing and capitalised lease obligations (the sum of short and long term debt). A high value of this variable suggests that there is considerable scope for a decline in value of a firm's assets (as measured by the market value of equity) before its total debt exceeds its assets and it becomes financially distressed or insolvent. It is therefore assumed that a high level of this variable should entail a low likelihood of financial distress/failure.

6.5.3. Macroeconomic Indicators.

Two macroeconomic variables were selected (among a list of eleven macroeconomic indicators) and retained in all the models in order to incorporate macro dependent dynamics: the Retail Price Index (RPI), and the United Kingdom Short Term (3-month) Treasury Bill Rate Deflated (or the real short term Treasury bill rate), both are represented on an annual scale in the present study. The first macroeconomic variable is the Retail Price Indicator (RPI) and was taken from Datastream and the Office for National Statistics in a monthly basis and then annualised, as required by the study. This variable is used to measure the change in the prices of goods and services bought for the purpose of consumption by the vast majority of households in the UK. The *ex-ante* hypothesis in this study regarding this variable is in line with Mare (2012), who suggests that high inflation is a consequence of a generally weak macroeconomic environment, which increases the number of banking crises. It is therefore expected that a high RPI should increase a firm's probability of financial distress/failure. The second macroeconomic variable included in the model is the Short Term Treasury Bill Rate Deflated (SHTBRDEF), which represents the 'real' short-term rate of 3-month United Kingdom Treasury Bills on an annual basis. The present study included the annualised level of the 91 days (3-month) discount rate. This indicator is a proxy for interest rates, which, similar to the RPI variable, is very likely to affect industrial firms according to their capital structure. Now, taking into account that a high level of interest rates increases the cost of debt (business borrowing is perhaps the most affected) and decreases firm's expected returns on investment, it is assumed that a macroeconomic environment characterised by a high level of interest rates (a high or increasing level of SHTBRDEF) will affect positively firms' likelihood of falling into the financial distress/failure category.

6.5.4. *Implications for the Comparison of Response categories in the Models.*

The variables incorporated in the models can be further classified into those that have a negative effect on the likelihood of state NFD occurring (Response = 1) and a positive effect on the likelihood of falling into category DIS (Response = 2) and FAI (Response = 3), on the one hand, and those having the opposite effects, on the other. Consequently, in order to better understand and present the effects of individual variables on the possible combinations of outcomes (NFD versus DIS, FAI versus DIS, and FAI versus NFD) it is useful to simplify this additional classification of variables into those that decrease (negatively affect) the likelihood of falling into the financial distress (DIS) and corporate failure (FAI) categories, and those that increase (positively affect) the likelihood of falling into the DIS and FAI categories. All types of variables included, the first group is composed by: TFOTL, NOCREDINT, COVERAGE, PRICE ABNRET, SIZE, and MCTD. And the second group includes the variables: TLTA, RPI, and SHTBRDEF.

Therefore, the *ex-ante* assumptions concerning the possible pairs of outcomes are as follows: an increasing level of the variables composing the first group (TFOTL, NOCREDINT, COVERAGE, PRICE ABNRET, SIZE, and MCTD) reduces the likelihood of a firm falling into the financial distress category (Response = 2), as shown in Chapter 3. Now, given that financial distress can be considered as a stage of a process that could ultimately result in the failure of a company, then the likelihood of falling into the third (and most extreme) response level in the present study, Corporate failure (Response = 3), should also be negatively affected by a high (approaching 1) or increasing level of these independent variables. Accordingly, a low or decreasing level of these covariates should increase the likelihood of both financial distress and corporate failure. On the other hand, the second group (TLTA, RPI, and SHTBRDEF) should have the opposite effect as the first one: A high or increasing level of TLTA should positively affect (increase) the probability of a firm falling into the financial distress category as well the corporate failure category.

The implications for the multinomial function coefficients and the AMEs of the models included in the present study are as follows: With regard to the variables composing the first group, a negative sign of the coefficient estimates and AMEs is expected for the comparisons Failure (FAI) versus Distress (DIS) and Failure (FAI) versus Non-financial distress (NFD), confirming the study's *ex-ante* hypothesis that a high or increasing level of these set of covariates has a negative impact on (decreases) the likelihood of a firm falling into the corporate failure category versus falling into the financial distress category as well as the likelihood of falling into the corporate failure category versus falling into the non-financial distress category. Accordingly, the sign of the coefficient and AME for the pair Non-financial distress (NFD) versus Financial distress (DIS) is expected to be positive, suggesting that an increasing level of the covariates included in the first group positively affects (increases) the probability of a firm falling into the non-financial distress category versus falling into the financial distress category. Conversely, the opposite reasoning can be applied to the expectations regarding the directionality of the signs of the coefficients and AMEs for all the variables included in the second group: a positive sign is expected for the pairs Failure (FAI) versus Distress (DIS) and Failure (FAI) versus Non-financial distress (NFD), indicating that a high or increasing level of these set of covariates has a positive impact on (increases) the likelihood of a firm falling into the corporate failure category versus falling into the financial distress category as well as the likelihood of falling into the corporate failure category versus falling into the non-financial distress category. Accordingly, the sign of the coefficient and AME for the combination Non-financial distress (NFD) versus Financial distress (DIS) is expected to be negative, suggesting that an increasing level of the variables comprised in the second group negatively affect (decrease) the probability of a firm falling into the non-financial distress category versus falling into the financial distress category.

By advancing multinomial function coefficient estimates as well as AMEs for each of the variables in incorporated in the models, this study provides new insights not only about the *directionality* of individual effects of the covariates on the likelihood of failing into each of the three possible outcomes but also about the *magnitude* (and therefore importance) of the individual effects relative to the other covariates. This is the first study on the financial distress/failure literature that tests the theoretical assumptions of the polytomous response logit model methodology with regard to the differences between coefficients estimates and marginal effects in order to provide new information on three essential outcomes for both academics and practitioners: Non-financial distress, Financial distress, and Corporate failure. Furthermore, the study also fills a very important gap in the financial distress/failure literature by presenting comparisons of predicted probability vectors between the financial distress category and the corporate failure state for different levels of individual covariates while keeping the other independent variables constant (at their means). In this way, new insights are advanced with regard to the specific variables that have the largest (and smallest) impact on each of these two negative outcomes. Having this type of information is capital given the real costs associated with financial distress and corporate failure. Finally, this is the first study that tests the classification accuracy of a model that combines accounting and market variables (while controlling for macro dependent dynamics) applied to an unbalanced panel of data, where the proportions of non-financial distress, distressed and failed companies have a strong resemblance with the real proportions in the quoted companies sector in the United Kingdom.

Table 6-3 Summary Statistics for Model 1

This table presents summary statistics for Model 1, which includes financial statement and macroeconomic variables. It covers the Mean, Standard Deviation, Minimum and Maximum Values and the number of observations that were used in the logistic regression for the financial ratios Total Funds from Operation to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), and Interest Coverage (COVERAGE); and the macroeconomic variables Retail Price Index (RPI) and the proxy for interest rates, the 3-month Short Term Bill Rate adjusted for inflation (SHTBRDEF). Panel A contains summary statistics for the entire dataset, Panel B for financially healthy firms, Panel C for financially distressed firms, and Panel D for failed firms.

Variable	TFOTL	TLTA	NOCREDINT	COVERAGE	RPI	SHTBRDEF
Panel A: Entire data set						
Mean	0.067493	0.485921	-0.118042	0.525922	178.39851	2.048426
Std. Dev.	0.339813	0.189284	0.986466	0.822947	32.220261	2.427929
Min	-1	-0.432123	-1	-1	94.59	-4.69551
Max	1	1	1	1	235.18	7.7407
Observations	18,070					
Panel B: Non-financially distressed firms						
Mean	0.088319	0.482455	-0.109658	0.589027	177.75165	2.068698
Std. Dev.	0.325357	0.184057	0.987328	0.781256	32.427066	2.442916
Min	-1	-0.432123	-1	-1	94.59	-4.69551
Max	1	1	1	1	235.18	7.7407
Observations	17,143					
Panel C: Financially distressed firms						
Mean	-0.385525	0.524583	-0.136795	-0.866796	193.10239	1.437297
Std. Dev.	0.369959	0.279639	0.987389	0.379827	24.667725	2.117728
Min	-1	-0.302382	-1	-1	115.21	-4.69551
Max	0.99792	1	1	0.751412	235.18	7.1745
Observations	612					
Panel D: Failed Firms						
Mean	-0.185767	0.599386	-0.537879	-0.202545	185.03432	2.132532
Std. Dev.	0.33396	0.208933	0.837612	0.916257	25.739411	1.983302
Min	-1	0.005761	-1	-1	115.21	-4.69551
Max	0.796339	1	1	1	235.18	7.1745
Observations	315					

Table 6-4 Summary Statistics for Model 2

This table presents summary statistics for Model 2, which includes market and macroeconomic variables. It covers the Mean, Standard Deviation, Minimum and Maximum Values and the number of observations that were used in the multinomial logistic regression for the firm's Equity Price (PRICE), the firm's annual Abnormal Returns (ABNRET), the firm's Relative Size (SIZE), and the ratio Market Capital to Total Debt (MCTD); and the macroeconomic variables Retail Price Index (RPI) and the proxy for interest rates, the 3-month Short Term Bill Rate adjusted for inflation (SHTBRDEF). Panel A contains summary statistics for the entire dataset, Panel B for financially healthy firms, Panel C for financially distressed firms, and Panel D for failed firms.

Variable	PRICE	ABNRET	SIZE	MCTD	RPI	SHTBRDEF
Panel A: Entire data set						
Mean	4.392914	-0.111672	-10.10087	0.911268	177.87621	2.075157
Std. Dev.	1.720131	0.388324	2.238356	0.191682	32.877633	2.52962
Min	-3.912023	-0.999988	-18.762915	0.002019	94.59	-4.69551
Max	14.151983	0.999996	-2.374161	1	235.18	7.7407
Observations	14,578					
Panel B: Non-financially distressed firms						
Mean	4.495108	-0.088945	-9.965482	0.920038	177.18654	2.097117
Std. Dev.	1.646194	0.376547	2.197184	0.17782	33.115608	2.549583
Min	-3.912023	-0.999829	-18.762915	0.002019	94.59	-4.69551
Max	14.151983	0.999996	-2.374161	1	235.18	7.7407
Observations	13,780					
Panel C: Financially distressed firms						
Mean	2.652963	-0.566576	-12.605192	0.790393	192.29895	1.491971
Std. Dev.	1.982396	0.318766	1.464687	0.304776	24.90328	2.135678
Min	-3.912023	-0.999988	-16.602146	0.002877	115.21	-4.69551
Max	10.266393	0.560483	-7.427867	1	235.18	7.1745
Observations	522					
Panel D: Failed Firms						
Mean	2.580608	-0.384036	-12.118752	0.701029	184.95234	2.088227
Std. Dev.	2.012367	0.450497	1.642173	0.334435	26.553931	2.041848
Min	-3.912023	-0.996655	-16.581148	0.00588	115.21	-4.69551
Max	10.96388	0.949759	-5.641377	1	235.18	7.1745
Observations	273					

Table 6-5 Summary statistics for Model 3

This table presents summary statistics for the comprehensive model, or Model 3, which includes financial statement ratios, macroeconomic indicators and market variables. It covers the Mean, Standard Deviation, Minimum and Maximum Values and the number of observations that were used in the logistic regression for the ratios Total Funds from Operation to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), Interest Coverage (COVERAGE) the Retail Price Index (RPI), and a proxy for interest rates, the 3-month Short Term Bill Rate adjusted for inflation (SHTBRDEF), the firm's Equity Price (PRICE), the firm's annual Abnormal Returns (ABNRET), the firm's Relative Size (SIZE), and the ratio Market Capital to Total Debt (MCTD). Panel A contains summary statistics for the entire dataset, Panel B for financially healthy firms, Panel C for the firms in financial distress, and Panel D for failed firms.

Variable	TFOTL	TLTA	NOCREDINT	COVERAGE	RPI	SHTBRDEF	PRICE	ABNRET	SIZE	MCTD
Panel A: Entire dataset										
Mean	0.097363	0.497767	-0.19551	0.599672	178.08903	2.046149	4.427373	-0.108952	-10.046418	0.91036
Std. Dev.	0.27721	0.169538	0.973386	0.770045	32.874323	2.532696	1.702743	0.386299	2.22842	0.192053
Min	-1	-0.102771	-1	-1	94.59	-4.69551	-3.912023	-0.999988	-16.602146	0.002877
Max	1	1	1	1	235.18	7.7407	14.151983	0.999996	-2.374161	1
Observations	13,529									
Panel B: Non-financially distressed firms										
Mean	0.118203	0.492827	-0.184269	0.669078	177.4168	2.066005	4.526808	-0.086315	-9.913979	0.919151
Std. Dev.	0.258451	0.163083	0.975489	0.713444	33.102993	2.553595	1.630117	0.374557	2.189381	0.17828
Min	-1	-0.102771	-1	-1	94.59	-4.69551	-3.912023	-0.999829	-16.480853	0.006411
Max	1	1	1	1	235.18	7.7407	14.151983	0.999996	-2.374161	1
Observations	12,801									
Panel C: Financially Distressed Firms										
Mean	-0.332766	0.561524	-0.252689	-0.849951	192.32595	1.507206	2.708543	-0.563883	-12.555755	0.785255
Std. Dev.	0.335827	0.262972	0.963513	0.401609	25.028722	2.094824	1.964593	0.322238	1.428658	0.307795
Min	-0.999979	0.028495	-1	-1	115.21	-4.69551	-3.912023	-0.999988	-16.602146	0.002877
Max	0.724547	1	1	0.751412	235.18	7.1745	10.266393	0.560483	-7.427867	1
Observations	482									
Panel D: Failed firms										
Mean	-0.144323	0.629916	-0.668404	-0.171655	185.17427	2.068862	2.62093	-0.395512	-12.021421	0.698069
Std. Dev.	0.29425	0.187108	0.735512	0.921337	26.84074	2.07339	2.019445	0.43582	1.593138	0.331656
Min	-1	0.052458	-1	-1	115.21	-4.69551	-3.912023	-0.996655	-15.922758	0.00588
Max	0.49607	1	1	1	235.18	7.1745	10.96388	0.949759	-5.641377	1
Observations	246									

6.6. Analysis of results.

The choice of variables to include in each of the models is consistent with the objectives of the present study: on the one hand, the aim is to present new insights on the effects of the individual variables on the vectors of transition predicted probabilities of a firm reaching a particular state *conditionally* on being in a different one, as well as on the marginal effects of the variables on the probability of falling into one of the three categories; and, on the other hand, to test whether the combination of accounting and market variables in a single model is able to increase its goodness-of-fit and overall performance (to correctly discriminate and predict outcomes). Table 6-6 presents tests to assess the fitting of the model: it reports likelihood ratio tests in order to evaluate the effects of the independent covariates on the Response variable, as well as linear hypothesis tests to estimate the overall effects of all pairs of coefficients on the outcome variable for three models, all of which include macroeconomic indicators in order to account for the models' macro dependent dynamics: the 'Accounting' model (Model 1), the 'Market' model (Model 2), and the 'Comprehensive' model (Model 3) which combines accounting and market variables as well as macroeconomic indicators. The tests displayed in Table 5-6 are performed for periods *t-1* and *t-2*, using information one and two years prior to the observation of the event of interest.

Panel A, B, and C of Table 6-6 show likelihood-ratio test results to confirm the significance of the predictors to the model: the χ^2 can be interpreted as overall statistics that provide relevant information on which independent variables significantly predict the outcome category. It tests the null hypothesis that a given individual variable does not affect the outcome of the Response variable. This test shows that, in *t-1* and for all of the models, the hypothesis that all of the coefficients associated with each of the individual variables are simultaneously equal to zero can be rejected at the 99 per cent level. As for *t-2*, the tests performed on Model 3 show that the null hypothesis cannot be rejected for the accounting variable TLTA and the market variable SIZE, which is a very small proportion of the total number of variables. This is not surprising since the tests were estimated using information two years prior to the relevant event. However, given that, overall, all of the coefficients significance statistics allows the null hypothesis to be rejected, all of the variables were kept in the final models. Panel D, on the other hand, reports linear hypothesis results that test the null hypothesis that all 10 pairs of coefficients for financial distress (DIS) and corporate failure (FAI)[185] conditionally on nonfinancial distress (NFD) are equal. It yields a Wald χ^2 equal to 181.2717 with 10 degrees of freedom, producing a *p*-value equal to 0.0001. It can be concluded that the coefficients for DIS (versus NFD) and FAI (versus NFD) are not the same. Had this test produced a high *p*-value (e.g., $p > 0.05$) the null hypothesis could not have been rejected, which would have suggested that the categories of financial distress and corporate failure can be combined into a single category.

In order to test the assumptions of this study concerning the effects of individual variables on the three-state response variable, this study compares the multinomial coefficient estimates with the average marginal effects. Coefficients obtained through the multinomial logit methodology are presented in a first stage. Tables 6-7 to 6-9 present results from logistic regressions of the Response indicator on the predictor variables. As required by the polytomous response logistic regression model, firms classified as non-financially distressed (NFD) were given a value of 1, firms identified as financially distressed (DIS) were given the value 2, and failed firms (FAI) were assigned the value of 3. This classification was carried out using the previously discussed definitions developed specifically for this analysis. The present study develops three main *ex-ante* models for estimating financial distress likelihood and to test the contribution of market variables to the predictive accuracy of models based on financial statement ratios.

Table 6-7 reports results from multinomial logit regressions of the three-level Response variable on the predictor variables for Model 1 or the the 'Accounting' model, which incorporates the financial statement ratios Total Funds from Operations to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), and Interest Coverage (COVERAGE). Table 6-8 reports results from multinomial logit regressions of the three-level Response variable on the predictor variables for Model 2 or the 'Market' model, which includes each firm's Equity Price (PRICE) transformed using the logarithmic function; the firm's cumulative monthly abnormal returns on an annual basis (ABNRET), generated as the firm's excess returns minus the FTSE All Share return index for the same period of time; and the firm's relative size (SIZE) measured by the market capitalisation relative to the total size (market capitalisation) of the FTSE All Share index, in logarithmic form. Finally, Table 6-9 reports results from polytomous response logit regressions of the 3-level Response variable on the predictors for the 'Comprehensive' model or Model 3, which combines both types of

[185] The test was applied to this particular outcomes as it could be argued that, because of their potential proximity, they could be combined into a single category in order to satisfy the polytomous response logit models' requirement that the outcome categories be clearly distinct.

variables in a single logit model of financial distress/failure. Furthermore, all the three models incorporate two proxies for the macroeconomic environment in order to control for macro dependent dynamics: the Retail Price Index (RPI) and the Short Term Bill Rate adjusted for inflation (SHTBRDEF).

Table 6-6 Likelihood-ratio and linear hypothesis testing results

This table reports likelihood-ratio tests to assess the effects of the independent covariates on the Response variable for the 'Accounting plus macroeconomic indicators' model (Model 1), the 'Market plus macroeconomic indicators' model (Model 2), and the 'Comprehensive' model (Model 3) in Panel A, B and C, respectively. The likelihood ratio tests were estimated with accounting market and macroeconomic information one and two years prior to the observation of the event of interest (for periods *t-1* and *t-2*). The test is used to confirm the significance of the predictors to the model. Additionally, Panel D reports linear hypothesis testing results for the null hypothesis that all ten pairs of coefficients are equal.

Effect	DF	Chi-Square (Pr>ChiSq)	Chi-Square (Pr>ChiSq)
Panel A: Model 1		*t-1*	*t-2*
TFOTL	2	37.686 (<.0001)	31.828 (<.0001)
TLTA	2	75.154 (<.0001)	19.422 (<.0001)
NOCREDINT	2	38.460 (<.0001)	20.040 (<.0001)
COVERAGE	2	639.078 (<.0001)	652.672 (<.0001)
RPI	2	80.485 (<.0001)	40.647 (<.0001)
SHTBRDEF	2	54.266 (<.0001)	42.175 (<.0001)
Panel B: Model 2			
PRICE	2	62.548 (<.0001)	35.661 (<.0001)
ABNRET	2	313.185 (<.0001)	590.850 (<.0001)
SIZE	2	248.434 (<.0001)	102.040 (<.0001)
MCTD	2	78.609 (<.0001)	48.367 (<.0001)
RPI	2	23.085 (<.0001)	21.213 (<.0001)
SHTBRDEF	2	16.156 (<.0001)	6.738 (0.034)
Panel C: Model 3			
TFOTL	2	34.180 (<.0001)	31.695 (<.0001)
TLTA	2	13.079 (0.001)	2.655 (0.265)
NOCREDINT	2	23.849 (<.0001)	6.028 (0.049)
COVERAGE	2	304.970 (<.0001)	356.000 (<.0001)
RPI	2	20.424 (<.0001)	14.938 (0.001)
SHTBRDEF	2	18.024 (<.0001)	15.564 (<.0001)
PRICE	2	35.368 (<.0001)	23.095 (<.0001)
ABNRET	2	117.757 (<.0001)	224.161 (<.0001)
SIZE	2	63.715 (<.0001)	4.894 (0.087)
MCTD	2	59.550 (<.0001)	18.371 (<.0001)
Panel D: Linear Hypothesis Testing Results – Model 3			
ALL VARIABLES TESTED	10	181.2717 (<.0001)	

As mentioned above, the present study develops *ex-ante* models for the estimation of financial distress/failure likelihood. In practice, the date of the event of financial distress is not known and risk managers are required to employ the data that is available at the time of the analysis in order to make an estimate of the likelihood of failure or financial distress of a company. Accordingly, this study estimates the probability of financial distress/failure in the year prior to the observation of the relevant event (*t-1*) as well as two years prior to the event (*t-2*). In that way, the models provide evidence about the predictors that best discriminate between financially sound, distressed and failed companies on the one hand, and on the other, test their predictive power. Thus, for the *t-1* models, all of the accounting ratios were computed using the financial statements of the year prior to the event. Accordingly, the macroeconomic indicators were calculated with information one year prior the event: the Retail Price Index (RPI) in base 100 as well as the 3-month Bill rate (SHTBRDEF), which was annualised and deflated using the inflation rate in order to obtain a measure of the level of 'real' interest rates in the economy. As for the market variables, equity prices (PRICE) were incorporated to the model as the official closing price in *t-1*, the variable measuring abnormal returns (ABNRET) for year *t*, when the relevant event was observed, was calculated as the return of the firm in year *t-1* minus the FTSE All Share Index return in year *t-1*. Individual firms' annual returns were generated by cumulating monthly returns. With regard to the variable that measures the relative size of the firm (SIZE), following Shumway (2001), individual firms' market capitalisation was measured at the end of the year before the financial distress/failure event. Finally, as for the ratio Market Capitalisation to Total Debt (MCTD), the latter was also measured with information taken from financial statements issued in *t-1*.The same procedure was employed to estimate coefficients and average marginal effects for the period *t-2*.

6.6.1. *Multinomial Function Coefficients.*

Table 6-7 reports the resulting estimates from multinomial logistic regressions of the 3-state Response indicator on the independent variables for the 'Accounting' model. It can be observed that, as to the comparison of the Corporate failure (FAI) category versus the Non-financially distressed (NFD) category, all of the coefficients (accounting variables as well as macroeconomic indicators) in *t-1* are statistically significant at the 5%-1% level and possess the expected signs. This is in line with the study's *ex-ante* assumptions, as it displays the coefficients resulting from the comparison of the extreme outcomes contained in the Response indicator. Therefore, it is unsurprising that all of the covariates have the ability to reliably discriminate between corporate failure and financial distress. Similarly, the coefficients for the pair Non-financial distress (NFD) versus Financial distress (DIS) display the expected signs and, with the exception of NOCREDINT (which is statistically significant at the 10% level), are statistically significant at the 5%-1% level, suggesting that almost all of them are able to reliable discriminate between the pair of categories. Again, this is in line with the *ex-ante* assumptions of the study, given that, although not as extreme as the previous comparison, this pair includes two contrasting response levels. On the other hand, the results obtained from the comparison Corporate failure (FAI) versus Financial distress (DIS) are less unequivocal: two covariates - one accounting ratio and one macroeconomic indicator - lose their statistical significance. However, even if the number covariates that reliably discriminate and predict between these two outcomes is reduced, there are still three financial ratios and one macroeconomic indicator that are statistically significant. This suggests that even for similar outcomes (there is more proximity or similarity between the pair Corporate failure and Financial distress than between any of the other pairs of outcomes), the accounting model presented in this study displays a sound performance. Further, it is interesting to note that, for both pairs NFD versus DIS and FAI versus DIS, COVERAGE exhibits the highest coefficient in magnitude followed by TLTA, TFOTL, and NOCREDINT, in order of importance. This rank is not the same for the pair that compares the most extreme categories (FAI versus NFD). In this case the coefficient with the highest magnitude is TLTA, followed by TFOTL, COVERAGE and NOCREDINT, suggesting that the importance of the coefficients depends on the specific comparison pair, and that TLTA is more powerful to discriminate between extreme outcomes than COVERAGE, which performs better when the outcomes to be compared are more similar. However, the fact that the sign of the variable COVERAGE (concerning the pair FAI versus DIS) does not display the expected sign must be highlighted: in contrast with these results, it was previously posited that an increasing value of this variable would have a negative effect on the probability of falling into the Corporate failure category versus falling into the Financial distress category. Finally, the coefficients obtained when the model was estimating using information two years prior to the event of interest show a similar pattern.

Table 6-8 reports the multinomial function coefficient estimates for the 'Market' model (Model 2). The pattern reflected by the analysis of the pairs of comparisons FAI versus NFD and NFD versus DIS is similar to the one observed for the 'Accounting model': regarding the first pair, all of the market variables are statistically significant at the 5%-1% level and display the correct signs, suggesting that they are able to reliably discriminate between the most extreme potential outcomes of the Response indicator. For the next comparison, NFD versus DIS, only the macroeconomic indicator SHTBRDEF displays a decrease of statistical significance from the 5%-1% level to the 10% level.

Table 6-7 Multinomial Logit Regression of 3-Level Response Variable on Predictor Variables - Model 1 - Accounting + Macroeconomic Variables Model

This table reports results from multinomial logit regressions of the 3-level Response variable on the predictor variables for the Accounting plus macroeconomic variables Model 1. The 3-level Response variable is composed of the following states: Non-financial distress (NFD or non-failed firms), financial distress (DIS or financially distressed companies), and failure (FAI or failed firms). Model 1 was computed for two periods: using the accounts and macroeconomic data from the year prior to the observation of the relevant event (*t-1*), and the accounts and macroeconomic data from two years prior to the observation of the event (*t-2*) in order to confirm the stability over time of the displayed signs as well as the magnitude of the coefficients. The absolute value of *z*-statistics is reported in parenthesis. * denotes significant at 10%, ** denotes significant at 5%-1%.

Covariates	NFD V DIS		FAI V DIS		FAI V NFD	
	t-1	*t-2*	*t-1*	*t-2*	*t-1*	*t-2*
TFOTL	0.6103**	0.5862**	-0.3945	-0.3003	-1.0049**	-0.8865**
	(4.49)	(4.41)	(1.60)	(1.16)	(4.57)	(3.80)
TLTA	-1.1633**	0.0747	0.7940*	1.3846**	1.9573**	1.3100**
	(5.89)	(0.36)	(2.42)	(3.95)	(6.90)	(4.36)
NOCREDINT	0.1177*	0.0981	-0.3160**	-0.2021*	-0.4337**	-0.3001**
	(2.21)	(1.81)	(3.49)	(2.27)	(5.65)	(4.08)
COVERAGE	1.9453**	2.0394**	1.3069**	1.5608**	-0.6384**	-0.4786**
	(19.73)	(20.11)	(10.06)	(11.50)	(7.23)	(5.11)
RPI	-0.0202**	-0.0192**	0.00241	-0.0115*	0.0226**	0.00772*
	(6.77)	(5.96)	(0.52)	(2.44)	(6.03)	(2.13)
SHTBRDEF	-0.1431**	-0.2946**	0.1570**	-0.1994**	0.3001**	0.0951
	(4.22)	(6.02)	(2.61)	(2.76)	(5.80)	(1.71)
Intercept	8.5451**	7.9198**	-1.2830	1.7931	-9.8282**	-6.1267**
	(13.59)	(11.27)	(1.30)	(1.75)	(12.16)	(7.84)

The marginal decrease in performance (suggested by the decrease in statistical significance of the proxy for interest rates) reflects the fact that the outcomes' proximity is increased. This comparison indicates that that the market model contains useful information for the classification of financially healthy versus financially distressed companies. In contrast, three variables obtained from the comparison pair FAI versus DIS display signs that are at odds with the study's expectations, namely, ABNRET, SIZE and RPI. It was expected that an increase in both the level of residual returns and the size of the company would entail a decrease in the likelihood of the firm falling into the failure category versus falling into the financial distress category. In the case of RPI it was assumed that an increase of inflation would have a positive effect on the likelihood of failure given a current strained financial condition. From this analysis, it can be concluded that the accounting model is more reliable to discriminate between this pair of categories.

On the other hand, an analysis of the coefficients magnitudes shows that, for the pair NFD versus DIS, ABNRET can be ranked in first place followed by MCTD, SIZE and PRICE. This order is different for the pair FAI versus NFD: MCTD have the largest coefficient in absolute terms followed by ABNRET, PRICE, and SIZE, suggesting that residual returns might have an important role in discriminating between extreme outcomes.

Unsurprisingly, the statistical significance of some of the variables decreases when the model is estimating using information two years prior to the event of relevance.

Table 6-8 Multinomial Logit Regression of 3-Level Response Variable on Predictor Variables - Model 2 - Market + Macroeconomic Variables Model

This table reports results from multinomial logit regressions of the 3-level Response variable on the predictor variables for the Market plus macroeconomic variables Model 2. The 3-level Response variable is composed of the following states: Non-financial distress (NFD or non-failed firms), financial distress (DIS or financially distressed companies), and failure (FAI or failed firms). Model 2 was computed for two periods: using the market and macroeconomic data from the year prior to the observation of the relevant event (*t-1*), and the market and macroeconomic data from two years prior to the observation of the event (*t-2*) in order to confirm the stability over time of the displayed signs as well as the magnitude of the coefficients. The absolute value of *z*-statistics is reported in parenthesis. * denotes significant at 10%, ** denotes significant at 5%-1%.

Covariates	NFD V DIS		FAI V DIS		FAI V NFD	
	t-1	*t-2*	*t-1*	*t-2*	*t-1*	*t-2*
PRICE	0.0887**	0.0485	-0.2132**	-0.1859**	-0.3019**	-0.2344**
	(3.05)	(1.70)	(4.62)	(3.96)	(7.65)	(5.85)
ABNRET	2.3548**	3.0210**	1.6494**	1.6941**	-0.7053**	-1.3269**
	(15.92)	(20.34)	(7.60)	(7.81)	(4.16)	(7.97)
SIZE	0.4941**	0.2897**	0.2291**	0.1052*	-0.2650**	-0.1845**
	(13.97)	(8.95)	(4.29)	(2.07)	(6.10)	(4.48)
MCTD	0.4949**	-0.8680**	-1.3721**	-2.1018**	-1.8670**	-1.2337**
	(2.86)	(3.87)	(5.58)	(6.97)	(9.18)	(5.43)
RPI	-0.0127**	-0.0139**	-0.00238	-0.0152**	0.0103**	-0.00136
	(4.16)	(4.45)	(0.51)	(3.26)	(2.68)	(0.37)
SHTBRDEF	-0.0733*	-0.1181*	0.0926	-0.1379*	0.1659**	-0.0198
	(2.14)	(2.48)	(1.64)	(1.97)	(3.44)	(0.37)
Intercept	11.4310**	10.7512**	4.8330**	6.8700**	-6.5980**	-3.8812**
	(14.71)	(13.14)	(4.09)	(5.70)	(6.88)	(4.15)

Table 6-9 reports from polytomous logit regressions of the three-state Response indicator on the predictor variables for the 'Comprehensive' model. As expected, all of the variables coefficients resulting from the comparison FAI versus NFD (or the pair that includes the outcomes at the extremes of the financial distress/failure process) have the expected signs and display statistical significance at the 5%-1% levels, providing thus additional evidence suggesting that all of the variables contain information that is useful to discriminate between these opposite states. In other words, unambiguous differences in individual characteristics between the Corporate failure and the Non-financial distress categories can be found in every single accounting, market and macroeconomic variable incorporated in the 'Comprehensive' model. An assessment of the coefficient magnitudes reveals that, for this comparison pair, the market variable MCTD can be ranked in the first position followed by TLTA, TFOTL, ABNRET and NOCREDINT, which might indicate the order of importance of individual variables to discriminate between failed and financially sound companies. Next, with regard to the comparison NFD versus DIS, despite the fact that all of the covariates show the expected signs, only one accounting variable is statistically significant, while three out of four market variables – ABNRET, SIZE, and MCTD – and all of the macroeconomic indicators retain their statistical significance at the 5%-1% level. Furthermore, an ordering of the variables based upon the magnitude of their coefficients reveals that the top five is composed by three market variables and two financial ratios: COVERAGE, ABNRET, MCTD, TFOTL, and SIZE, in order of importance. Unlike in the previous comparison, these results confirm the importance of the effects of market variables on the likelihood of falling into category NFD versus falling into category DIS.

Unsurprisingly, the pair that combines the categories FAI and DIS yields only 6 statistically significant variables: the market variables PRICE, ABNRET, and SIZE (all of them at the 5%-1% level), and the accounting ratios COVERAGE, NOCREDINT, and TLTA (significant at the 5%-1% and 10% levels, respectively). Interestingly, when the model is estimated using information two years prior to the observation of the event of relevance, the macroeconomic indicators and the market variable MCTD become statistically significant, indicating that there is a difference in the performance (or in the amount of useful information that is relevant to the prediction of each outcome) of the variables that is dependent upon the period of analysis. Furthermore, the market variables ABNRET and SIZE and the accounting variable COVERAGE display signs at odds with this study's *ex-ante* assumptions: a negative relationship would have been expected instead for the three covariates suggesting that the higher the level of each individual variable, the lower the likelihood of falling into the FAI category versus falling into the DIS category. An analysis of the magnitude of the coefficients based on their absolute values reveals that the top five is composed by the accounting variable COVERAGE (although with the wrong sign) occupying the first place, followed by TLTA, ABNRET (also displaying the wrong sign), TFOTL and MCTD. Now, if the variables displaying the wrong signs were discarded then TLTA, TFOTL, and MCTD would be followed by NOCREDINT and PRICE.

Table 6-9 Multinomial Logit Regression of 3-Level Response Variable on Predictor Variables - Model 3 - Comprehensive Model

This table reports results from multinomial logit regressions of the 3-level Response variable on the predictor variables for the comprehensive Model 3. The 3-level Response variable is composed of the following states: Non-financial distress (NFD or non-failed firms), financial distress (DIS or financially distressed companies), and failure (FAI or failed firms). Model 3 was computed for two periods: using the accounting, market and macroeconomic data from the year prior to the observation of the relevant event (*t-1*), and the accounting, market, and macroeconomic data from two years prior to the observation of the event (*t-2*) in order to confirm the stability over time of the displayed signs as well as the magnitude of the coefficients. The absolute value of *z*-statistics is reported in parenthesis. * denotes significant at 10%, ** denotes significant at 5%-1%.

Covariates	NFD V DIS		FAI V DIS		FAI V NFD	
	t-1	*t-2*	*t-1*	*t-2*	*t-1*	*t-2*
TFOTL	0.8406**	0.8364**	-0.4411	-0.2416	-1.2817**	-1.0780**
	(4.51)	(4.61)	(1.33)	(0.74)	(4.29)	(3.67)
TLTA	-0.2855	0.0960	1.0362*	0.6839	1.3217**	0.5879
	(1.07)	(0.35)	(2.46)	(1.55)	(3.58)	(1.54)
NOCREDINT	0.0207	0.0456	-0.4177**	-0.1480	-0.4384**	-0.1936*
	(0.33)	(0.72)	(3.82)	(1.49)	(4.59)	(2.36)
COVERAGE	1.6100**	1.8016**	1.2631**	1.6784**	-0.3469**	-0.1232
	(14.45)	(15.86)	(8.67)	(11.00)	(3.42)	(1.15)
RPI	-0.0125**	-0.0141**	0.000306	-0.0153**	0.0128**	-0.00126
	(3.57)	(3.75)	(0.06)	(2.94)	(3.12)	(0.32)
SHTBRDEF	-0.1017**	-0.2107**	0.0805	-0.2383**	0.1821**	-0.0276
	(2.58)	(3.73)	(1.31)	(3.07)	(3.50)	(0.48)
PRICE	0.0356	0.0167	-0.2069**	-0.1840**	-0.2425**	-0.2007**
	(1.19)	(0.57)	(4.42)	(3.80)	(5.87)	(4.76)
ABNRET	1.5031**	1.8065**	0.9834**	0.5839*	-0.5197**	-1.2226**
	(9.96)	(12.26)	(4.44)	(2.58)	(2.91)	(6.71)
SIZE	0.3111**	-0.00848	0.1823**	-0.1044	-0.1289**	-0.0959*
	(7.45)	(0.22)	(3.08)	(1.83)	(2.77)	(2.15)
MCTD	1.1416**	0.1002	-0.4365	-1.0814**	-1.5780**	-1.1816**
	(5.36)	(0.38)	(1.50)	(3.06)	(6.58)	(4.41)
Intercept	9.3569**	6.9788**	2.5189	3.5683**	-6.8379**	-3.4106**
	(10.47)	(7.24)	(1.93)	(2.61)	(6.42)	(3.24)

The above analysis of the multinomial function coefficient was useful in order to be aware of the potentially useful predictors of the three levels of the response variables given a base outcome. It also provides hints regarding the overall performance of the model by displaying the number of variables that are statistically significant for each pair of variables. The above analysis is, nevertheless, most useful as a benchmark to make comparisons relative to what this study posited to be the most appropriate tool to interpret the individual effects of the independent variables on the different levels of the Response indicator for Polytomous response logit models: marginal effects.

Before moving on to the analysis of the average marginal effects, and in order to formally assess the goodness-of-fit of individual models, the present study employs a set of measures shown in Table 6-10.

6.6.2. Model Fit Statistics.

Table 6-10 reports model fit statistics. In order to evaluate the goodness-of-fit of each model in the study, a set of complementary measures is employed. The first of these measures, Cox and Snell's R-squared is based on the log-likelihood of the model, the log-likelihood of the original (baseline) model, and the sample size. Nagelkerke's Max-rescaled R-squared is a refinement of the former. The higher the value, the better the model's goodness-of-fit. Both can thus be considered as measuring the same concept. In general, they can be interpreted similarly (but not identically), to the R-squared in linear regression, given that they reflect the significance of the model[186]. Next, this is the first study on financial distress/failure models that employs measures based on the Akaike's information criterion and the Schwartz's Bayesian criterion in order to compare fit statistics between models[187]. These criteria are useful in cases where the main objective is to compare models (with different sets of independent variables) for the same data. The methodology used is the following: First, for both criteria (Akaike and Schwartz information criteria), statistics are estimated for an intercept only model and for a model that incorporates the relevant independent variables. Next, given that a lower value of the 'intercept plus predictors' statistic relative to the 'intercept only' statistic indicates a better fit of a given model[188], the difference is calculated and presented in the tables. Therefore, the higher this difference (shown in Table 5-10) the greater the improvement of the goodness-of-fit resulting from the inclusion of the specific model's independent variables. χ^2 Chi-square statistics, on the other hand, result of the likelihood ratio test and tests the *joint* effect (significance) of the independent variables included in the model. Thus, small *p*-values (e.g., $p<0.05$) reject the null hypothesis that all slope parameters are equal to zero ($H_0\!: \boldsymbol{\beta} = \mathbf{0}$). Finally, Deviance and Pearson statistics are also reported. For both tests, large *p*-values suggest that there is insufficient evidence for rejecting the null hypothesis that the model fits.

---

[186] See Cox and Snell (1989) and Nagelkerke (1991).

[187] In fact, the Akaike information criterion and the Schwartz's information criterion provide two distinct ways of adjusting the -2 Log L statistic for the number of terms in the model and the number of observations used.

[188] In other words, a lower value of the 'intercept plus predictors' statistic relative to the 'intercept only' statistic suggests that the model with predictors is better than the 'intercept only' model.

Table 6-10 Comparative Model Fit Statistics

This table reports model performance statistics. Panel A shows measures for the three models estimated in period *t-1* and Panel B displays the same measures for all of the models estimated in *t-2*. Model 1 is the 'accounting plus macroeconomic variables' model, Model 2 is the 'market plus macroeconomic variables' model, Model 3 is the 'comprehensive' model, including accounting, market and macroeconomic variables. The first two measures are Cox and Snell's R-squared and Nagelkerke's Max-rescaled R-squared, which provide a gauge to compare the substantive significance of the 3 models; in addition Akaike information criterion and Schwartz's bayesian criterion statistics, the models' Chi-squared, and the deviance and Pearson statistics are also presented.

Measure	Model 1	Model 2	Model 3
Panel A: models' fit statistics in t-1			
Cox & Snell's R^2	0.1071	0.1100	0.1555
Nagelkerke's Max-rescaled R^2	0.2854	0.2819	0.4028
Akaike Information Criterion	2023.246	1675.399	2247.175
Schwartz's Bayesian Criterion	1929.622	1584.352	2096.923
$\chi2$ Chi-square (12, 12, 20)	2047.246 (p<.0001)	1699.399 (p<.0001)	2287.175 (p<0.0001)
Deviance	6453.086 (p<1.0000)	5514.040 (p<1.0000)	4315.100 (p<1.0000)
Pearson	26842.865 (p<1.0000)	22898.823 (p<1.0000)	19082.679 (p<1.0000)
Panel B: models' fit statistics in t-2			
Cox & Snell's R^2	0.1122	0.0914	0.1458
Nagelkerke's Max-rescaled R^2	0.2796	0.2241	0.3617
Akaike Information Criterion	1845.295	1254.999	1899.099
Schwartz's Bayesian Criterion	1753.355	1165.015	1750.744
$\chi2$ Chi-square (12, 12, 20)	1869.294 (p<.0001)	1278.999 (p<.0001)	1939.099 (p<.0001)
Deviance	6189.397 (p<1.0000)	5713.619 (p<1.0000)	4409.522 (p<1.0000)
Pearson	24879.178 (p<1.0000)	22705.242 (p<1.0000)	17163.792 (p<1.0000)

An analysis of the measures shown in Table 6-10 indicates that, overall, the 'Comprehensive model' or Model 3, that includes the three types of variables (accounting, market, and macroeconomic), yields the best goodness-of-fit statistics: Model 3 displays the highest Cox and Snell's R-squared and Nagelkerke's Max-rescaled R-squared statistics, as well as the highest differences between the 'intercept plus predictors' statistic and the 'intercept only' statistic in both the Akaike information and the Schwartz Bayesian criteria, which indicates that Model 3 contains the set of independent variables that produces the largest improvement of goodness-of-fit statistics. Furthermore, the χ^2 statistic has a small *p*-value (p<0.0001), indicating that there is enough evidence for rejecting the null hypothesis that all slope parameters are equal to zero. In other words, it unambiguously suggests that the overall effect of the independent variables included in the model is different from zero. Moreover, with regard to the Deviance and Pearson statistics, the tests' large *p*-values (e.g., p<1.0000) suggest that there is insufficient evidence for rejecting the null hypothesis that the model fits the data well. This analysis applies when Model 3 is estimated in both periods *t-1* and *t-2*, although a marginal decrease in the levels of the statistics can be perceived, which is not unexpected, given that, in *t-2*, the models are estimated using information two years prior to the event of interest. A similar analysis of Models 1 and 2 (the Accounting and Market models, respectively) shows that there is sufficient evidence to conclude that they both have positive goodness-of-fit statistics. The differences in model fit statistics are only marginal, with Model 1 showing slightly higher levels for the first four measures (Cox and Snell's R-squared is an exception, as Model 2 displays a marginally higher value) when the model is estimated using information one as wells as two years prior to the observation of the event of relevance. Nevertheless, Model 1 shows lower magnitudes for the Deviance and Pearson statistics in both *t-1* and *t-2*, even though their respective *p*-values provide clear evidence suggesting that both models fit the data. In summary, through the comparison of the Accounting and the Market model's statistics it can be concluded that both models fit the data well; however, the evidence is insufficient to positively ascertain the superiority of one over the other.

6.6.3. Marginal Effects and Changes in Predicted Probabilities.

As previously discussed, the multinomial function coefficient estimates produced by polytomous response logit regression models (as well as binary response logit models), unlike those generated by linear regression models, cannot be directly interpreted because they do not contain useful information that fully describes the relationship between individual independent variables and the outcome (Long and Freese, 2003). Previous financial distress/failure prediction models built up using polytomous and binary response models have invariably focused on the overall discriminating and/or predictive accuracy and only very rarely do they advance insights regarding the individual effects of the variables on the probability of falling into each of the possible categories. This has been the case for research works employing binary as well as polytomous response logit models. Moreover, previous research works provide interpretations of the direction of the relationship based on the sign of the estimate. However, the coefficient estimates obtained by performing binary response models cannot explain the individual effects of variables on the model's outcomes because of their nonlinear nature. Marginal effects and predicted probabilities are appropriate analytic tools to treat this issue.

This section presents results of the computation of marginal effects of individual regressors as well as graphic representations of predicted probabilities of financial distressed companies. As previously discussed, marginal effect measurements (defined as the computation of the partial derivative of the event probability with respect to the predictor if interest) are very useful to the interpretation of the individual effects of the regressors on the dependent variable in discrete dependent variable models, or categorical response models (polytomous response logit regression in the present study). On the other hand, predicted probabilities were generated by plotting the vector reflecting the variations in the predicted probabilities of falling in to the financial distress and corporate failure categories (the predicted probability that the financial distress indicator, Response = 2 and Response = 3, respectively) when the change in an individual regressor ranges from its approximate minimum to its maximum observed value, keeping all the other covariates constant at their means.

Table 6-11 presents marginal effects (on a percentage basis) of the variables included in Model 1 and 2. Significance statistics, and standard errors obtained employing the Delta method are also presented. The analysis of marginal effects for the 'Accounting model' (Model 1) reveals that there is a strong similarity with regard to the previously reported coefficient estimates: the individual average marginal effects (AME) relative to the probability of falling into the FAI category (Response = 3) display same ranking (as the coefficients for the pair Corporate failure versus Non-financial distress) based on their absolute levels or magnitude. The same analysis can be applied to the marginal effects corresponding to the probability of falling into the NFD category (Response = 1) relative to the coefficients obtained for the pair NFD versus DIS. With respect to the marginal effects for the probability of falling into the DIS category (Response = 2) - a part from a change of ranking of the variables NOCREDINT and SHTBRDEF from the 4th and 5th places to the 5th and 4th places, respectively – there is one crucial difference to highlight: the AME for the variable COVERAGE displays the expected negative sign, in contrast with the sign displayed by the respective coefficient estimate (for the pair FAI versus DIS). Next, a similar conclusion can be obtained for the analysis of Model 2: The ranking of the variables based on the magnitude of the AMEs is very similar for the probability that Response = 1 (relative to the pair NFS versus DIS) and Response = 2 (relative to the pair FAI versus DIS). As to the probability that Response = 3, it can be observed that PRICE occupies the 1st place in the ranking followed by MCTD, ABNRET, and SIZE. But most importantly, the signs for ABNRET, SIZE, and RPI, possess the correct expected signs (negative, negative, and positive), unlike the signs of the corresponding coefficient estimates (for the pair FAI versus DIS).

Table 6-11 Marginal Effects – Model 1 and Model 2

This table reports the marginal effects (in percentages) for the 'accounting plus macroeconomic indicators' model, or Model 1 and for the 'market plus macroeconomic indicators' model, or Model 2, in panel A and B respectively. Marginal effects are intended to measure the expected instantaneous changes in the response variable as a function of a change in a specific predictor variable while keeping all the other covariates constant. Columns 2 and 3 display the individual marginal effects of each accounting variable and macroeconomic indicator on the probability that the response variable is equal to non-financial distress (*j*=1) one and two years prior to the observation of the event (*t-1* and *t-2*, respectively). Columns 4 and 5 present the individual marginal effects of each variable on the probability that the outcome variable is equal to financial distress (*j*=2) one and two years prior to the observation of the event (*t-1* and *t-2*, respectively). Lastly, columns 7 and 7 display the individual marginal effects on the probability that the response indicator is equal to failure (*j*=3) one and two years prior to the observation of the event (*t-1* and *t-2*, respectively). The methodology used in the present study to generate the marginal effects consists of outputting the individual marginal effects estimated at each observation in the dataset and then calculating their sample average in order to obtain the overall marginal effect. Standard errors, obtained employing the Delta-method, are reported in parenthesis. * denotes significant at 10%, ** denotes significant at 5%-1%.

Panel A: Model 1 – Accounting plus macroeconomic indicators model

	Pr (*j* = 1)		Pr (*j* = 2)		Pr (*j* = 3)	
	t-1	*t-2*	*t-1*	*t-2*	*t-1*	*t-2*
TFOTL	3.1273**	3.2490**	-1.5739**	-1.7531**	-1.5534**	-1.4958**
	(0.0051)	(0.0058)	(0.0039)	(0.0043)	(0.0037)	(0.0042)
TLTA	-6.0229**	-1.9115*	2.9924**	-0.4472	3.0304**	2.3584**
	(0.0071)	(0.0084)	(0.0056)	(0.0066)	(0.0049)	(0.0055)
NOCREDINT	0.9568**	0.7917**	-0.2600	-0.2694	-0.6968**	-0.5222**
	(0.0019)	(0.0021)	(0.0015)	(0.0017)	(0.0013)	(0.0013)
COVERAGE	6.1852**	7.0448**	-5.4805**	-6.5086**	-0.7051**	-0.5364**
	(0.0033)	(0.0038)	(0.0032)	(0.0036)	(0.0014)	(0.0016)
RPI	-0.0877**	-0.0716**	0.0540**	0.0609**	0.0338**	0.0108
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
SHTBRDEF	-0.8283**	-1.0601**	0.3573**	0.9361**	0.4709**	0.1241
	(0.0012)	(0.0018)	(0.0010)	(0.0016)	(0.0009)	(0.0010)

Panel B: Model 2 – Market plus macroeconomic indicators model

	Pr (*j* = 1)		Pr (*j* = 2)		Pr (*j* = 3)	
	t-1	*t-2*	*t-1*	*t-2*	*t-1*	*t-2*
PRICE	0.7002**	0.5552**	-0.1961*	-0.1175	-0.5040**	-0.4378**
	(0.0011)	(0.0012)	(0.0009)	(0.0009)	(0.0007)	(0.0008)
ABNRET	7.5441**	11.7408**	-6.8496**	-9.7677**	-0.6948*	-1.9731**
	(0.0051)	(0.0059)	(0.0047)	(0.0055)	(0.0028)	(0.0031)
SIZE	1.7596**	1.2244**	-1.4109**	-0.9261**	-0.3488**	-0.2983**
	(0.0012)	(0.0013)	(0.0011)	(0.0011)	(0.0008)	(0.0008)
MCTD	4.1821**	-0.5926	-1.0534*	3.103**	-3.1285**	-2.5112**
	(0.0061)	(0.0085)	(0.0050)	(0.0074)	(0.0038)	(0.0044)
RPI	-0.0504**	-0.0411**	0.0354**	0.0562**	0.0150*	-0.0052
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
SHTBRDEF	-0.4523**	-0.3355	0.1809	0.3950*	0.2715**	-0.0594
	(0.0012)	(0.0018)	(0.0010)	(0.0016)	(0.0008)	(0.0010)

Table 6-12 Marginal Effects – Model 3

This table reports the marginal effects (in percentages) for the 'comprehensive' model, or Model 3 that includes three types of variables: accounting, market and macroeconomic. Marginal effects are intended to measure the expected instantaneous changes in the response variable as a function of a change in a specific predictor variable while keeping all the other covariates constant. Columns 2 and 3 display the individual marginal effects of each accounting variable and macroeconomic indicator on the probability that the response variable is equal to non-financial distress (j=1) one and two years prior to the observation of the event (*t-1* and *t-2* respectively). Columns 4 and 5 present the individual marginal effects of each variable on the probability that the outcome variable is equal to financial distress (j=2) one and two years prior to the observation of the event (*t-1* and *t-2* respectively). Lastly, columns 6 and 7 display the individual marginal effects on the probability that the response indicator is equal to failure (j=3) one and two years prior to the observation of the event (*t-1* and *t-2* respectively). The methodology used in the present study to generate the marginal effects consists of outputting the individual marginal effects estimated at each observation in the dataset and then calculating their sample average in order to obtain the overall marginal effect. Standard errors obtained employing the Delta-method are reported in parenthesis. * denotes significant at 10%, ** denotes significant at 5%-1%.

	Pr (j = 1)		Pr (j = 2)		Pr (j = 3)	
	t-1	*t-2*	*t-1*	*t-2*	*t-1*	*t-2*
TFOTL	3.7638**	3.9531**	-1.8691**	-2.1635**	-1.8945**	-1.7895**
	(0.0064)	(0.0071)	(0.0048)	(0.0051)	(0.0050)	(0.0054)
TLTA	-2.5054**	-0.6939	0.3925	-0.3997	2.1127**	1.0934
	(0.0087)	(0.0101)	(0.0070)	(0.0078)	(0.0061)	(0.0069)
NOCREDINT	0.6558**	0.4331*	0.0652	-0.0894	-0.7209**	-0.3437*
	(0.0021)	(0.0022)	(0.0017)	(0.0018)	(0.0016)	(0.0015)
COVERAGE	4.2914**	4.9695**	-4.1569**	-5.1283**	-0.1347	0.1585
	(0.0031)	(0.0037)	(0.0031)	(0.0035)	(0.0016)	(0.0019)
RPI	-0.0472**	-0.0352**	0.0294**	0.0405**	0.0178**	-0.0053
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0000)
SHTBRDEF	-0.4928**	-0.5136**	0.2187**	0.6188**	0.2741**	-0.0952
	(0.0012)	(0.0018)	(0.0010)	(0.0016)	(0.0009)	(0.0011)
PRICE	0.4198**	0.3679**	-0.0276	-0.0051	-0.3922**	-0.3627**
	(0.0010)	(0.0011)	(0.0008)	(0.0008)	(0.0007)	(0.0008)
ABNRET	4.2773**	6.7551**	-3.8271**	-4.9082**	-0.4503	-1.8470**
	(0.0044)	(0.0049)	(0.0039)	(0.0040)	(0.0029)	(0.0034)
SIZE	0.9149**	0.1322	-0.7864**	0.0447	-0.1285	-0.1768*
	(0.0012)	(0.0013)	(0.0011)	(0.0011)	(0.0008)	(0.0008)
MCTD	4.887**	2.1706*	-2.5830**	-0.0352	-2.3035**	-2.1352**
	(0.0065)	(0.0086)	(0.0055)	(0.0074)	(0.0041)	(0.0050)

Table 6-12 presents marginal effects (on a percentage basis) of the variables included in Model 3, the comprehensive model. From the analysis of the average marginal effects it can be observed that the ranking, based on their absolute magnitude, is somewhat different relative to the previously reported ranking based on the multinomial function coefficient estimates. The individual average marginal effects (AME) relative to the probability of falling into the NFD category (Response = 1) are highest for the market variable MCTD, which is followed by COVERAGE, ABNRET, TFOTL, TLTA and SIZE. There is an equal number of market and accounting variables in the first six places of the ranking, with two macroeconomic variables entering the top three. Moreover, it is very important to highlight the fact that all variables display the expected signs and are statistically significant at the 5%-1% level. Next, an analysis of the average marginal effects corresponding to the probability of falling into the DIS category (or Response = 2), yields the following ranking (also based on the absolute magnitudes of the AMEs): the accounting variable COVERAGE possesses the highest value of the AME, followed by the market variables ABNRET and MCTD. TFOTL, SIZE and TLTA occupy the next places. Again, two market variables entered the top three, suggesting that ABNRET and MCTD contain a high degree of information useful to estimate the probability of a firm falling into the NFD as well as DIS categories. But above all, the procedure employed to estimate AMEs yields the correct or expected signs for all variables, with NOCREDINT being the only exception (however, the AME is not statistically significant, which provides the estimation procedure with a high degree of reliability). Moreover, seven out of ten covariates in the model are statistically significant at the 5%-1% level. Finally, with regard to the probability of a firm falling into the FAI category (Response = 3), the analysis of the absolute magnitudes of the AMEs yields the following ranking: MCTD occupies the first place followed by TLTA, TFOTL, NOCREDINT, ABNRET and PRICE. In this category there are three accounting variables in the top four, which suggests that financial ratios contain a high degree of useful information to predict FAI (corporate failure). Furthermore, six out of ten of the comprehensive model's covariates are statistically significant at the 5%-1% level, and one at the 10% level, which indicates a high degree of reliability of the AMEs estimates. Most importantly, all of the AMEs for the FAI category display the correct or expected signs.

On the other hand, all categories comprised, the resulting AMEs obtained using information two years prior to the event of interest, confirm the results of obtained when the models are estimated in *t-1*: regardless of the expected decrease of the number of covariates that are statistically significant, AMEs estimated for the period *t-2* display similar behaviour patterns to those estimated for *t-1*. Likewise, all of the individual AMEs that are statistically significant, show the expected signs, and the entirety of those few (six, all categories comprised) AMEs that display an incorrect or unexpected sign, are not statistically significant at any level. This observation provides further evidence that confirms the directionality as well as the magnitude of the effects of the estimated AMEs, which further corroborates the validity of the marginal effects estimation method and the usefulness of the AMEs reported in the present study.

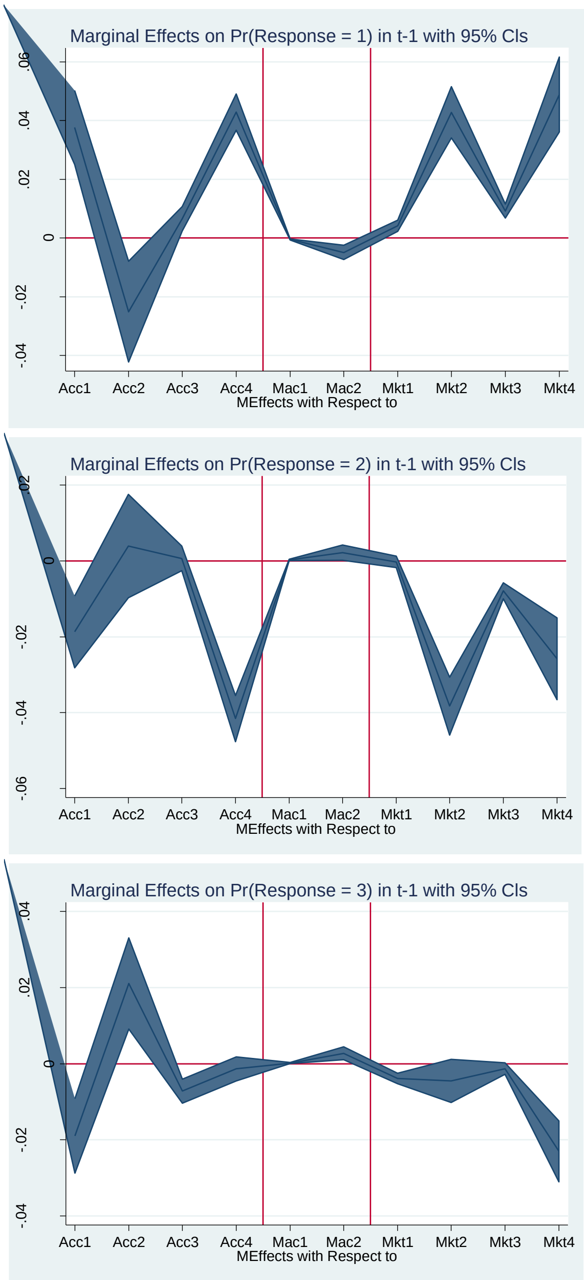

Figure 6-1 Marginal effects on the Probabilities of Non-Financial Distress, Financial Distress and Corporate Failure in *t-1*

The figure plots the average marginal effects (AME) for each variable in the comprehensive model, or Model 3, on the probability that the Response variable is equal to Non-financial distress (Response = 1), Financial distress (Response = 2), and Corporate failure (Response = 3), respectively, one year prior to the observation of the relevant event (*t-1*). The vertical lines divide the figures into Accounting (Acc), Macroeconomic (Mac) and Market (Mkt) variables, where Acc1 = TFOTL, Acc2 = TLTA, Acc3 = NOCREDINT, Acc4 = COVERAGE, Mac1 = RPI, Mac2 SHTBRDEF, Mkt1 = PRICE, Mkt2 = ABNRET, Mkt3 SIZE and Mkt4 = MCTD. The horizontal line divides the figures into positive and negative AMEs on the respective response indicator. In addition, the coloured area indicates 95 per cent confidence limits (Cls) for each level of the AME.

Figure 6-1 shows a graphical representation of the average marginal effects for each covariate included in the comprehensive model (Model 3) on the probability that the Response variable is equal to NFD (Response = 1), DIS (Response = 2), and FAI (Response = 3), respectively, in period *(t-1)*[189]. Each plot contains vertical lines dividing the figures into Accounting (Acc), Macroeconomic (Mac) and Market (Mkt) variables, where Acc1 = TFOTL, Acc2 = TLTA, Acc3 = NOCREDINT, Acc4 = COVERAGE, Mac1 = RPI, Mac2 = SHTBRDEF, Mkt1 = PRICE, Mkt2 = ABNRET, Mkt3 = SIZE and Mkt4 = MCTD. Additionally, the horizontal line divides the figures into positive and negative AMEs on the respective response indicator. The purpose of Figure 6-1 is to facilitate the analysis of the directionality and magnitude (by category) of the AMEs in Model 3 by presenting a graphic representation of the effects of individual AMEs. In this way it is possible to make a direct comparison between the effects of the individual variables incorporated in Model 3 on the three outcome categories. Furthermore, the Figure 5-1 provides 95% confidence limits (Cl) for each level of the AME.

Overall, the estimation and analysis of all covariates' AMEs incorporated in the three models provided a solution to an essential gap in the financial distress/bankruptcy models literature: the lack of a measure of the individual instantaneous effect of a change of a specific covariate on the polytomous (3-state) response variable (NFD, DIS, FAI), *while keeping all the other regressors constant*. Now, given the high costs associated with financial distress (DIS) and corporate failure (FAI), and the cost-minimisation behaviour of practitioners such as banks and investment companies, the present study presents a comparison of the vectors of predicted probabilities that reflect the impact of a change of individual specific variables on the probability of falling in the DIS and FAI categories, while keeping all the other covariates constant at their respective means. The advantage of such vector representations is that they inform practitioners as well as academics on the predicted probability of falling into one of the two categories for a level of the specific covariate that ranges from its minimum to its maximum possible values. In other words, the figures clearly show the magnitude as well as the directionality of the effect of each regressor reflected by the slope and inclination of the curves, plotted at all the possible levels of the specific independent variable.

---

[189] The graph displaying the AMEs for Model 3 estimated using information two years prior to the event of interest are not included in the present study, as they are show very similar patterns, as previously discussed.

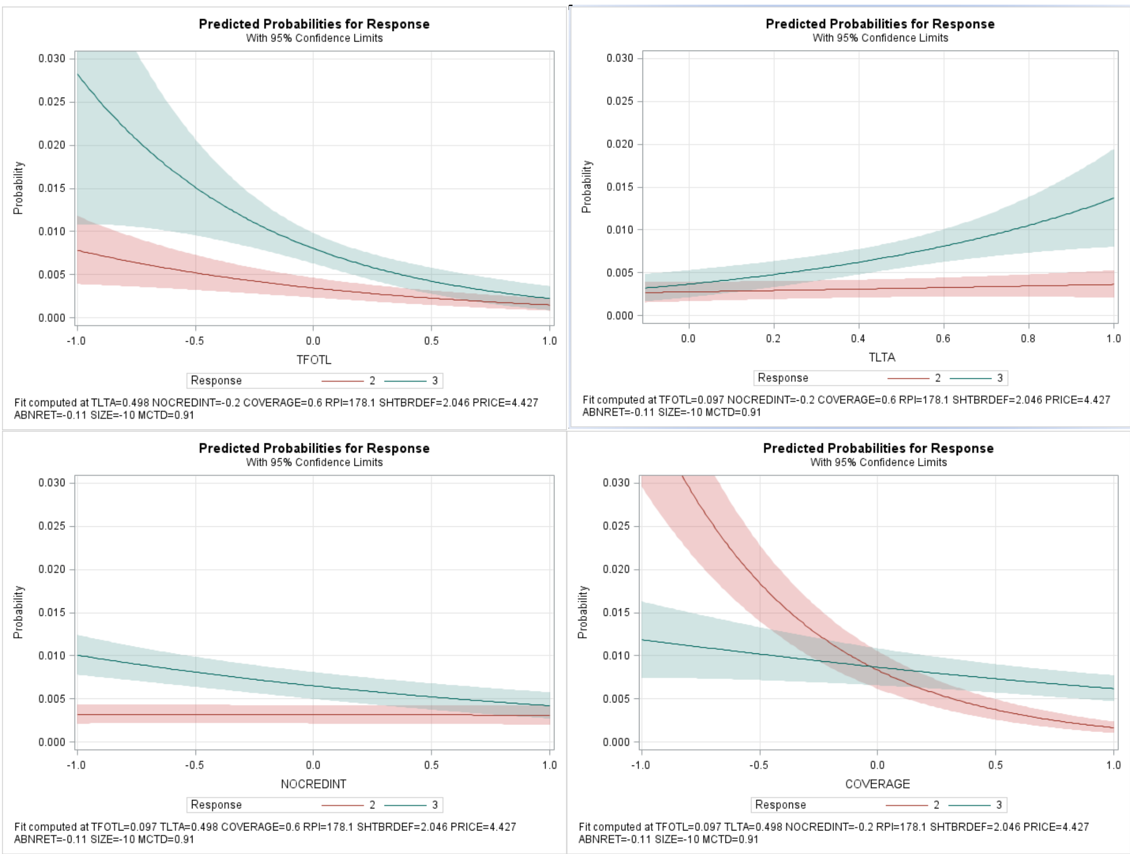

Figure 6-2 Changes in Predicted Probabilities – Financial Statement Ratios
The figure plots the vectors reflecting changes in predicted probabilities for Financial distress (Response = 2) and Corporate Failure (Response = 3) resulting from individual changes in the levels of the financial statement ratios Total Funds from Operations to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), and Interest Coverage (COVERAGE), while keeping all the other covariates constant at their mean values (TFOTL = 0.097, TLTA = 0.498, NOCREDINT = -0.2, COVERAGE = 0.6, RPI = 178.1, SHTBRDEF = 2.046, PRICE = 4.427, ABNRET = -0.11, SIZE = -10, MCTD = 0.91). The computation was made taking into account all the variables included in the 'Comprehensive' model or Model 3 (financial statement ratios, macroeconomic indicators and market variables). Predicted probabilities are estimated employing an approximate value of the minimum and maximum ranges of the independent variables. In this way, the predicted probabilities for all levels of a variable can be observed. This figure reports the predicted probabilities for the 'Full' model estimated in period *t-1*, the vectors estimated using the full model in *t-2* have very similar shapes, so they were not reported in the present study.

Figure 6-2 vectors reflect the behaviour of the predicted probabilities for financial distress at different values of each of the financial statement ratios. This figure corroborates the directionality and the magnitude of the effects of the financial ratios: The analysis shows that, concerning the DIS category (Response = 2), a positive change in the level of TFOTL, NOCREDINT, and COVERAGE results in a decreased predicted probability of falling into the financial distress category. Likewise, a positive change in the level of the proxy for leverage, TLTA, yields a positive variation (increase) in the probability of financial distress, as previously suggested by the estimation of average marginal effects. Furthermore, the accounting variable COVERAGE produces the steepest slope relative to the other financial ratios, indicating that a given change in the level of this variable should have the largest impact on the predicted probability of falling in the financial distress category. Similarly, with regard to the FAI category (Response = 3), the analysis confirms that a positive change in the magnitude of TFOTL should have the largest (negative) effect on the probability of falling in to the corporate failure category, as this accounting variable generated the steepest slope relative to the other financial ratios (especially in the range -1.0 to 0.0). Moreover, as expected, the directionality of the vectors related to the Corporate failure category follow the same directionality patterns as those related to the Financial distress category. The visible differences in magnitude, reflected by the steepness of the slopes, suggest that the same individual accounting covariates in the model have different effects on the likelihood of Financial distress and Corporate failure, which is consistent with the assumptions of the present study.

The analysis of Figure 6-3 indicates that all of the market variables show a negative relationship between the variations in individual covariate levels and the estimated predicted probabilities of the Financial distress (Response = 2) and Corporate Failure (Response = 3). The only difference lies in the magnitudes of the changes of the predicted probabilities that correspond to the changes in the covariate levels. Thus, it can be observed that, concerning the DIS category, the variable SIZE produces the vector with the steepest slope, suggesting that a positive change in the level of this market indicator should have the highest negative impact in the probability of falling into the Financial distress category, followed by ABNRET, MCTD, and PRICE. As to the vectors corresponding to the Corporate failure category, Figure 6-3 shows that the covariate PRICE generates the vector with the steepest slope, which seems to indicate that an increase (decrease) in its level should produce the highest decrease (increase) in the likelihood of a firm falling in to the Corporate failure category (particularly in the range -5.0 to 5.0). The market indicators MCTD, SIZE, and ABNRET are next in the list (based upon their respective impact on the likelihood of Corporate failure).

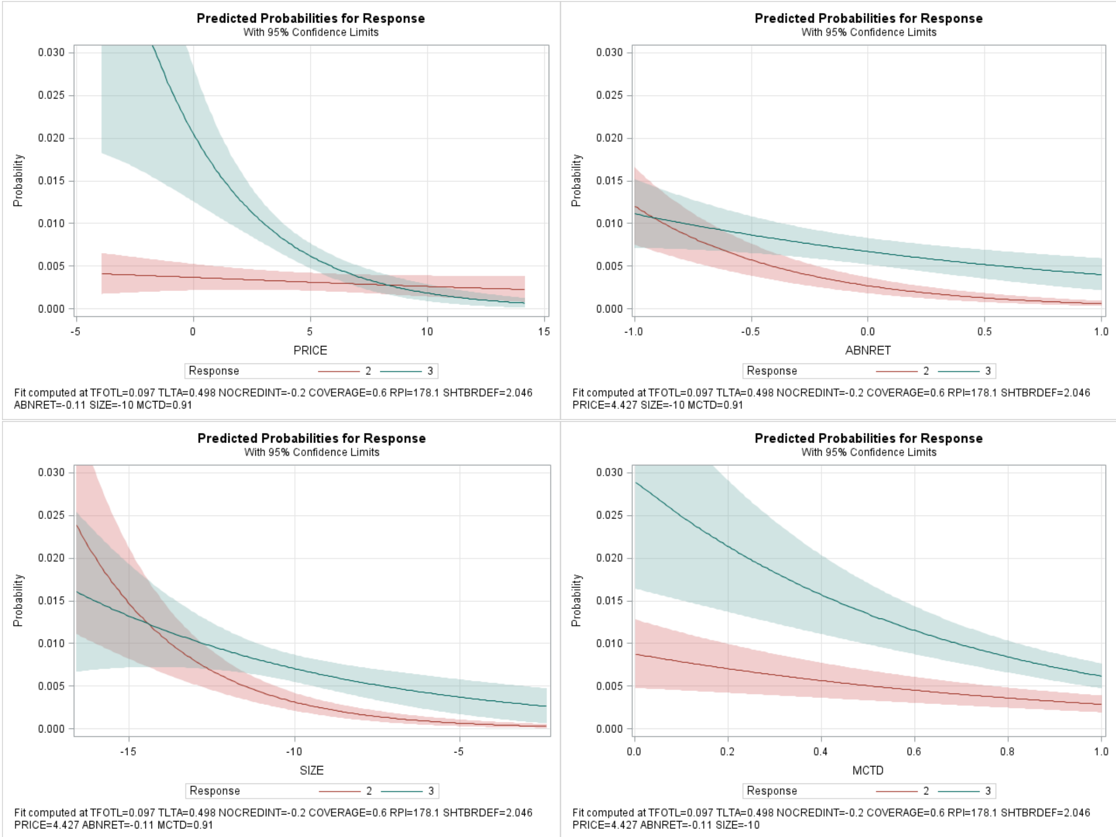

Figure 6-3 Changes in Predicted Probabilities – Market Variables

The figure plots the vectors reflecting changes in predicted probabilities for Financial distress (Response = 2) and Corporate Failure (Response = 3) resulting from individual changes in the levels of the market independent variables Share Price (PRICE), Abnormal Returns (ABNRET), the relative Size of the company (SIZE), and the ratio Market Capitalisation to Total Debt (MCTD), while keeping all the other covariates constant at their mean values (TFOTL = 0.097, TLTA = 0.498, NOCREDINT = -0.2, COVERAGE = 0.6, RPI = 178.1, SHTBRDEF = 2.046, PRICE = 4.427, ABNRET = -0.11, SIZE = -10, MCTD = 0.91). The computation was made taking into account all the variables included in the 'Comprehensive' model or Model 3 (financial statement ratios, macroeconomic indicators and market variables). Predicted probabilities are estimated employing an approximate value of the minimum and maximum ranges of the independent variables. In this way, the predicted probabilities for all levels of a variable can be observed. This figure reports the predicted probabilities for the 'Full' model estimated in period *t-1*, the vectors estimated using the full model in *t-2* have very similar shapes, so they were not reported in the present study.

Finally, Figure 6-4 presents the changes in predicted probabilities produced by the individual changes in magnitude of the two macroeconomic indicators incorporated in the models: RPI and SHTBRDEF. In line with the present study's *ex ante* assumptions, a positive change in the level both indicators should result in a positive variation in the predicted probability of a firm's likelihood of falling into the Financial distress and the Corporate failure categories. Overall, the changes in predicted probabilities are very useful as they confirm the validity of the results obtained through the estimation of marginal effects. However, it is important to highlight the fact that, the differences in ranking (based on the magnitude of the impact of individual variables on the likelihood of falling into one of the three possible categories) between marginal effects and changes in predicted probabilities stem from the specific characteristics and definitions of each. The identification of these subtle differences, far from being a disadvantage, can be instead employed by the academic/practitioner as an additional source of information to enhance their analysis.

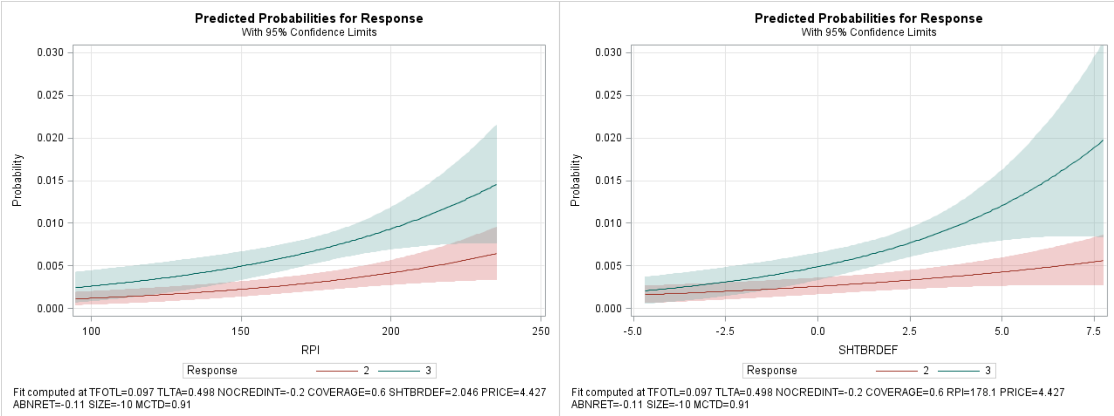

Figure 6-4 Changes in Predicted Probabilities – Macroeconomic indicators
The figure plots the vectors reflecting changes in predicted probabilities for Financial distress (Response = 2) and Corporate Failure (Response = 3) resulting from individual changes in the levels of the macroeconomic independent variables Retail Price Index (RPI), and the proxy for interest rates, the Deflated Short Term Bill Rate (SHTBRDEF), while keeping all the other covariates constant at their mean values (TFOTL = 0.097, TLTA = 0.498, NOCREDINT = -0.2, COVERAGE = 0.6, RPI = 178.1, SHTBRDEF = 2.046, PRICE = 4.427, ABNRET = -0.11, SIZE = -10, MCTD = 0.91). The computation was made taking into account all the variables included in the 'Comprehensive' model or Model 3 (financial statement ratios, macroeconomic indicators and market variables). Predicted probabilities are estimated employing an approximate value of the minimum and maximum ranges of the independent variables. In this way, the predicted probabilities for all levels of a variable can be observed. This figure reports the predicted probabilities for the 'Full' model estimated in period *t-1*, the vectors estimated using the full model in *t-2* have very similar shapes, so they were not reported in the present study.

6.6.4. Classification Accuracy Tables.

In order to evaluate the classification accuracy of the three polytomous response (three-state) logit models developed in the present study, a generalisation of the already tested biased-adjusted classification accuracy tables for the binary logistic models (introduced in the second and third chapters) is employed. This method has the advantage of testing the accuracy of the models to differentiate (and predict) among all the possible non-redundant comparison pairs of response outcomes. But most importantly, this methodology was selected to perform prediction accuracy tests as it has the advantage of being able to incorporate distinct cut-off points that allow the academic/practitioner to calibrate the model taking into account the costs associated with each outcome (financial distress, bankruptcy) in order to obtain better results for a desired outcome. Furthermore, this technique allows the inclusion of very close approximations of the actual proportions of an outcome relative to the one it is being tested against, which is very important as they can be used as cut-off points in an unbalanced panel (such as the one used in the present study, that approximates the actual proportions observed in the United Kingdom) providing thus the researcher with realistic and reliable results as well as a high degree of accuracy.

The latter point should be highlighted because, as discussed by Ooghe and Joos (1990), if a financial distress/bankruptcy prediction model is developed for practical purposes and for use in a predictive context, the samples of financially sound, financially distressed, and failed companies used for the estimation of the model should be representative for the whole population of companies. Moreover, Balcaen and Ooghe (2004) state that 'the firms in the estimation sample and new, future samples of cases, for which a failure prediction [model] is to be made, are assumed to come from the same distribution. Nevertheless, in the great majority of the classic statistical failure prediction models, the estimation of the models is based on non-random samples, whose compositions are different from the population's composition.'[190] As a matter of fact, a great majority of the previous research works on financial distress/corporate bankruptcy prediction models that employ the polytomous response logit methodology use non-random samples whose compositions are highly dissimilar to the population's composition. The methodology used in the present study incorporates an approximation of the proportions (as cut-off points) observed in the population of UK quoted companies in order to obtain a balanced (and the highest) classification accuracy for each pair of outcomes. In other words, specific weights based on the relative costs of financial distress and corporate failure are not assigned.

Classification accuracy tables have been used in previous works as an additional tool to measure the predictive accuracy of the default/bankruptcy prediction models. The present study, however, employs a different and more appropriate methodology to estimate proportions of correct and incorrect classifications of financially and non-financially distressed firms. In order to classify a set of binary data, previous research works employ the same observations used to fit the model to estimate the classification error, resulting in biased error-count estimates. In other words, the widely-used 2x2 frequency tables' estimates, where correctly classified observations are displayed on the main diagonal of the table, are derived using all observations to fit the model. Therefore, the results are biased,

[190] P. 26.

as each observation has an effect on the model used to classify itself. One way of reducing said bias is 'to remove the binary observation to be classified from the data, reestimate the parameters of the model, and then classify the observation based on the new parameter estimates[191].' Unfortunately this method is computationally demanding when using large datasets. For this reason, the present study employs logistic regression that, although is less computationally intensive still delivers high predictive accuracy and minimises type I and II error rates. Specifically, a one step approximation is applied to the preceding parameter estimates[192]. The leave-one out jack knife approach to correct for over-sampling employed in the present study helps eliminate potential biases common to analysis of classification tables that fail to use holdout samples.

In order to construct the biased-adjusted classification tables, predicted probabilities from three possible non-redundant combinations of outcomes through binary logit regressions are estimated. Thus, equation 1 computes the predicted probabilities for the pair of outcomes Non-financial distress and Financial distress, equation 2 estimates the probabilities for the pair Non-financial distress and Corporate failure, and equation 3 computes the probabilities for the pair Financial distress and Corporate failure. This procedure is performed in period *t-1* and in period *t-2*, using information one and two years prior to the observation of the event of relevance. In this way, the predictive ability of the models can be assessed. Next, from a range of probability levels, those that closely approximate the real proportions of the pairs of events and that, at the same time, minimise the difference between sensitivity and specificity, are selected for comparison. In this manner, the study provides a consistent point of comparison. Finally, the numbers of correct and incorrect classifications for each of the above equations are incorporated into a single table that reports the overall classification accuracy (in percentages) of the models built up using a panel of data that, unlike previous multinomial logit financial distress/corporate failure prediction models, is representative of the population of UK quoted companies. However, the flexibility of this methodology reflected by its ability to re-calibrate the results of the models through different choices of probability levels that, unlike the present study, take into account the costs associated with financial distress and corporate failure, must be emphasized, as it provides the present model with real practical value.

191 SAS Institute

192 http://support.sas.com/documentation/cdl/en/statug/63033/HTML/default/viewer.htm#statug_logistic_sect037.htm

Table 6-13 reports classification accuracy tables for predicted frequencies in percentages for Model 1 (the 'Accounting plus macroeconomic indicators model'), Model 2 (the 'Market plus macroeconomic indicators model'), and Model 3 (the 'Comprehensive model') using information one year prior to the observation of the event of interest. The analysis of Table 6-13 unambiguously indicates that the combination of accounting and market variables yields the highest classification accuracy among the three polytomous response logit models built in this study. Model 3 results in overall classification accuracy of 85 %, while Model 1 and Model 2 produce very similar accuracy results: 80% and 79% respectively, which suggest that the performance of accounting and market variables is not highly dissimilar: the accounting model is only marginally superior to the market model by approximately one percentage point.

Table 6-13 Bias-Adjusted Classification Accuracy Table in *t-1*

This table reports a biased-adjusted classification table for predicted frequencies in percentage for the 'Accounting plus macroeconomic indicators' model (Model 1), the 'Market plus macroeconomic indicators' model (Model 2), and the 'Comprehensive model' (Model 3, that includes the three types of variables) in Panel A, B and C, respectively. The results were obtained using information one year prior to the observation of the event of interest (period *t-1*). The first column compares the observed responses with the first row of predicted outcomes. Thus, the diagonal line (replicated in the last column 'Correct') shows the three individual models' correct predictions for non-financially distressed/failed (NFD), financially distressed (DIS) and failed (FAI) companies. In addition, this table presents overall classification accuracy percentages by model in order to compare their relative performances.

	Predicted				
Observed	NFD	DIS	FAI	Total	Correct
Panel A: Model 1					
NFD	80.83	8.15	11.02	100.00	80.83
DIS	8.42	75.25	16.34	100.00	75.25
FAI	15.56	17.62	66.83	100.00	66.83
	Overall Classification Accuracy				80.40
Panel B: Model 2					
NFD	79.25	9.65	11.11	100.00	79.25
DIS	8.48	73.81	17.71	100.00	73.81
FAI	12.64	18.13	69.23	100.00	69.23
	Overall Classification Accuracy				78.86
Panel C: Model 3					
NFD	85.45	5.46	9.09	100.00	85.45
DIS	5.39	80.29	14.32	100.00	80.29
FAI	10.98	14.02	75.00	100.00	75.00
	Overall Classification Accuracy				85.08

The classification accuracy results obtained using information two years prior to the observation of the event of relevance confirm the superiority of the predictive accuracy of the 'Comprehensive' model relative to Model 1 and Model 2 by revealing a very similar pattern to the models estimated in period *t-1*: Model 1 displays the highest overall classification accuracy (82%), followed by Model 1 (79%), and Model 2 (75%), which suggests that accounting models might perform better than market models in period *t-2*. What is more, even though the percentages decreased in period *t-2*, as expected, the models still show high classification accuracies, which confirm the robustness of the models. Unsurprisingly, the monotonic decrease in classification accuracy observed by response category can be explained by the monotonic decrease in the respective observations for each outcome, which affect accordingly the predicted probability estimations. Nevertheless, it must be emphasized that even the individual accuracies remain quite high.

Table 6-14 Bias-Adjusted Classification Accuracy Table in *t-2*

This table reports a biased-adjusted classification table for predicted frequencies in percentage for the 'Accounting plus macroeconomic indicators' model (Model 1), the 'Market plus macroeconomic indicators' model (Model 2), and the 'Comprehensive model' (Model 3, that includes the three types of variables) in Panel A, B and C, respectively. The results were obtained using information two years prior to the observation of the event of interest (period *t-2*). The first column compares the observed responses with the first row of predicted outcomes. Thus, the diagonal line (replicated in the last column 'Correct') shows the three individual models' correct predictions for non-financially distressed/failed (NFD), financially distressed (DIS) and failed (FAI) companies. In addition, this table presents overall classification accuracy percentages by model in order to compare their relative performances.

	Predicted				
Observed	NFD	DIS	FAI	Total	Correct
Panel A: Model 1					
NFD	79.39	7.90	12.71	100.00	79.39
DIS	7.74	78.18	14.09	100.00	78.18
FAI	20.45	13.75	65.81	100.00	65.81
	Overall Classification Accuracy				79.09
Panel B: Model 2					
NFD	75.74	10.15	14.11	100.00	75.74
DIS	11.39	70.46	18.15	100.00	70.46
FAI	13.75	17.47	68.77	100.00	68.77
	Overall Classification Accuracy				75.40
Panel C: Model 3					
NFD	82.26	6.04	11.71	100.00	82.26
DIS	5.92	82.35	11.73	100.00	82.35
FAI	14.64	11.72	73.64	100.00	73.64
	Overall Classification Accuracy				82.09

6.7. Conclusions.

This study presents new financial/distress corporate failure models for quoted companies in the United Kingdom using a polytomous response (three-state) logit methodology. It provides a number of contributions to the literature: first, in creates a three-state response variable that comprises a finance-based definition of the Financial distress category, a technical definition of the Corporate failure category (built using information provided by the London Share Price Database), and a category that encloses on-going firms assumed to be in a financially sound position. Further, the study, in line with the previous chapter, employs a multilevel empirical procedure to test and select the variables with the highest contribution to the overall performance of the models. Second, unlike previous research works, the present study builds up a large dataset by merging different types of information from data sources widely used in the academic as well as in the industry fields in order to estimate generalised logit models based on a sample whose distribution is representative of the whole population of quoted companies in the United Kingdom. Third, the study tests whether the inclusion of accounting and market variables in a single multinomial logit model is able to outperform models based exclusively on either market or accounting information. The reported results unambiguously indicate that this is the case: model performance statistics, tested for the first time in a financial distress/corporate failure model, invariably show a considerable increase in the goodness-of-fit of the 'Comprehensive model' relative to the 'Accounting only' model and the 'Market only' model. Additionally, novel biased-adjusted classification accuracy tables provide evidence corroborating these results: in period *t-1*, the 'Comprehensive model' yields an 85% overall classification accuracy, whereas the 'Accounting' and 'Market' models yield an overall classification accuracy of 80% and 79%, respectively. As expected, the accuracy of the models decreased when the models were estimated using data two years prior to the observation of the event of relevance; nevertheless, similar patters confirming the ascendancy of a comprehensive model can be observed. Furthermore, the classification accuracy of the models in *t-2* remains quite high: for the 'Comprehensive' model it is equal to 82%, 79% for the 'Accounting' model and 75% for the 'Market' model.

Through the estimation of marginal effects and changes in predicted probabilities, the study compared (for the first time in financial distress prediction models for quoted companies in the United Kingdom) the relative individual as well as collective contributions of accounting and market variables to the performance of the models while controlling for the macroeconomic environment. Unlike previous research works in the field, this study takes into account the difficulties of interpretation of the coefficients obtained through multinomial logistic regressions; it posited that marginal effects, defined as expected instantaneous changes in the response variable as a function of a change in a specific predictor variable (while keeping all the other covariates constant), are a more appropriate measure to assess the effects of individual covariates on the probability of falling into one of the three pre-defined financial states/outcomes. The reported results confirmed this hypothesis: a part from the advantage of their direct interpretation, the estimation of average marginal effects yielded the correct expected signs for all the variables and outcomes, unlike some of the multinomial function coefficients. In practice, these results can be used to determine the individual effects of the different covariates on the probability of a firm falling into financial distress or corporate failure with a high degree of reliability. In other words, marginal effects are an appropriate measure to determine the relative importance of individual variables based on their relative magnitudes. In this manner, practitioners are able to rank and target the specific aspects or characteristics of a company that require special attention in order to avoid the high costs associated with financial distress and bankruptcy. Finally, as a complement to these findings as well as to the usefulness and robustness of the model, the study provided graphical representations of the vectors that reflect the changes in predicted probabilities of falling into a state of financial distress or corporate failure produced by changes in the levels of individual covariates (ranging from their minimum to their maximum possible values) while keeping all the other variables constant at their means. The graphical representations, in addition, are designed to directly compare the differences in the magnitude of the effects of an individual variable on the probabilities of reaching a state of financial distress and corporate failure, respectively.

6.8. Appendix.

Table 6-15 Multinomial Logit Regression of 3-Level Response Variable on Predictor Variables - Model 4 - Comprehensive Model with Industry Effects

This table reports results from multinomial logit regressions of the 3-level Response variable on the predictor variables for the comprehensive Model 3 including industry effects. The 3-level Response variable is composed of the following states: Non-financial distress (NFD or non-failed firms), financial distress (DIS or financially distressed companies), and failure (FAI or failed firms). Model 4 was computed for two periods: using the accounting, market and macroeconomic data from the year prior to the observation of the relevant event (*t-1*), and the accounting, market, and macroeconomic data from two years prior to the observation of the event (*t-2*) in order to confirm the stability over time of the displayed signs as well as the magnitude of the coefficients. The absolute value of *z*-statistics is reported in parenthesis. * denotes significant at 10%, ** denotes significant at 5%-1%.

Covariates	NFD V DIS		BKT V DIS		BKT V NFD	
	t-1	*t-2*	*t-1*	*t-2*	*t-1*	*t-2*
TFOTL	0.8456**	0.8327**	-0.4992	-0.2574	-1.3448**	-1.0901**
	(4.50)	(4.53)	(1.49)	(0.78)	(4.43)	(3.68)
TLTA	-0.3560	0.1767	0.8912*	0.5801	1.2473**	0.4034
	(1.18)	(0.62)	(2.03)	(1.26)	(3.23)	(1.02)
NOCREDINT	0.00786	0.0504	-0.4238**	-0.1424	-0.4317**	-0.1928*
	(0.12)	(0.78)	(3.82)	(1.41)	(4.45)	(2.31)
COVERAGE	1.6147**	1.8188**	1.2508**	1.6694**	-0.3639**	-0.1494
	(14.42)	(15.97)	(8.53)	(10.89)	(3.56)	(1.38)
RPI	-0.0124**	-0.0143**	0.00138	-0.0148**	0.0138**	-0.00046
	(3.50)	(3.75)	(0.27)	(2.79)	(3.31)	(0.12)
SHTBRDEF	-0.0978*	-0.2071**	0.0873	-0.2282**	0.1851**	-0.0212
	(2.48)	(3.62)	(1.41)	(2.91)	(3.52)	(0.36)
PRICE	0.0290	0.0163	-0.2238**	-0.1943**	-0.2527**	-0.2106**
	(0.95)	(0.55)	(4.68)	(3.98)	(6.00)	(4.97)
ABNRET	1.5085**	1.8356**	0.9876**	0.5981**	-0.5209**	-1.2375**
	(9.93)	(12.27)	(4.40)	(2.61)	(2.87)	(6.71)
SIZE	0.3325**	0.00589	0.2025**	-0.0852	-0.1300**	-0.0911*
	(7.77)	(0.15)	(3.35)	(1.46)	(2.75)	(2.01)
MCTD	1.1049**	0.0575	-0.4621	-1.1491**	-1.5670**	-1.2065**
	(5.10)	(0.22)	(1.56)	(3.22)	(6.47)	(4.48)
Intercept	17.0602	15.1108	0.5096	2.6550	-16.4455	-12.2937
	(0.05)	(0.05)	(0.00)	(0.00)	(0.04)	(0.03)

Table 6-16 Marginal Effects – Model 4 with Industry Effects

This table reports the marginal effects (in percentages) for Model 4, the 'Comprehensive model' that includes industry effects in addition to the previously employed three types of variables: accounting, market and macroeconomic. Marginal effects are intended to measure the expected instantaneous changes in the response variable as a function of a change in a specific predictor variable while keeping all the other covariates constant. Columns 2 and 3 display the individual marginal effects of each accounting variable and macroeconomic indicator on the probability that the response variable is equal to non-financial distress (*j*=1) one and two years prior to the observation of the event (*t-1* and *t-2* respectively). Columns 4 and 5 present the individual marginal effects of each variable on the probability that the outcome variable is equal to financial distress (*j*=2) one and two years prior to the observation of the event (*t-1* and *t-2* respectively). Lastly, columns 6 and 7 display the individual marginal effects on the probability that the response indicator is equal to failure (*j*=3) one and two years prior to the observation of the event (*t-1* and *t-2* respectively). The methodology used in the present study to generate the marginal effects consists of outputting the individual marginal effects estimated at each observation in the dataset and then calculating their sample average in order to obtain the overall marginal effect. Standard errors obtained employing the Delta-method are reported in parenthesis. * denotes significant at 10%, ** denotes significant at 5%-1%.

	Pr (*j* = 1)		Pr (*j* = 2)		Pr (*j* = 3)	
	t-1	*t-2*	*t-1*	*t-2*	*t-1*	*t-2*
TFOTL	3.8465**	3.9369**	-1.8556**	-2.1293**	-1.9908**	-1.8076**
	(0.0065)	(0.0071)	(0.0048)	(0.0051)	(0.0051)	(0.0054)
TLTA	-2.5595**	-0.1852	0.5977	-0.5868	1.9616**	0.7719
	(0.0090)	(0.0104)	(0.0072)	(0.0081)	(0.0063)	(0.0071)
NOCREDINT	0.6144**	0.4424*	0.0957	-0.1020	-0.7100**	-0.3403*
	(0.0021)	(0.0022)	(0.0017)	(0.0018)	(0.0016)	(0.0015)
COVERAGE	4.3020**	5.0110**	-4.1370**	-5.1260**	-0.1653	0.1147
	(0.0031)	(0.0037)	(0.0031)	(0.0034)	(0.0016)	(0.0019)
RPI	-0.0481**	-0.0368**	0.0288**	0.0406**	0.0194**	-0.0039
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
SHTBRDEF	-0.4858**	-0.5091**	0.2068*	0.5917**	0.2790**	-0.0825
	(0.0012)	(0.0018)	(0.0010)	(0.0016)	(0.0009)	(0.0011)
PRICE	0.4170**	0.3814**	-0.0079	-0.0014	-0.4091**	-0.3799**
	(0.0010)	(0.0011)	(0.0008)	(0.0008)	(0.0007)	(0.0008)
ABNRET	4.2690**	6.8046**	-3.8162**	-4.9419**	-0.4530	-1.8629**
	(0.0045)	(0.0049)	(0.0039)	(0.0041)	(0.0029)	(0.0034)
SIZE	0.9619**	0.1619	-0.8371**	0.0027	-0.1249	-0.1646*
	(0.0012)	(0.0013)	(0.0011)	(0.0011)	(0.0008)	(0.0008)
MCTD	4.7632**	2.0913*	-2.4757**	0.0934	-2.2875**	-2.1845**
	(0.0066)	(0.0087)	(0.0056)	(0.0075)	(0.0041)	(0.0050)

Table 6-17 Bias-Adjusted Classification Accuracy Table – Comprehensive Model with Industry Effects

This table reports a biased-adjusted classification table for predicted frequencies in percentage for the 'Comprehensive model' or Model 4 that includes industry effects in addition to the three types of variables previously employed: accounting, market, and macroeconomic indicators. The results were obtained using information one and two years prior to the observation of the event of interest: Panel A displays the results for period *t-1*and Panel B shows the results for period *t-2*). The first column compares the observed responses with the first row of predicted outcomes. Thus, the diagonal line (replicated in the last column 'Correct') shows the three individual models' correct predictions for non-financially distressed/failed (NFD), financially distressed (DIS) and failed (FAI) firms. In addition, this table presents overall classification accuracy percentages by model in order to compare their relative performances.

	Predicted				
Observed	NFD	DIS	FAI	Total	Correct
Panel A: Estimation of the model in period t-1					
NFD	85.33	5.61	9.07	100.00	85.33
DIS	5.39	80.60	14.00	100.00	80.60
FAI	10.98	14.23	74.80	100.00	74.80
	Overall Classification Accuracy				84.97
Panel B: Estimation of the model in period t-2					
NFD	82.46	5.94	11.60	100.00	82.46
DIS	5.81	82.66	11.52	100.00	82.66
FAI	15.27	11.51	73.22	100.00	73.22
	Overall Classification Accuracy				82.29

7. Conclusions

7.1. Summary of main findings.

The thesis provided evidence on the advantages, in terms of predictive accuracy and timeliness, of combining different types of variables (accounting ratios, market variables, and macroeconomic indicators) for financial distress/prediction models for listed companies in the United Kingdom. The first chapter offered, for the first time, historical evidence on the types of variables and the information sharing mechanisms employed by American and British investors and financial institutions to assess the creditworthiness of individuals, businesses and fixed-income instruments before the emergence of modern institutions such as the credit rating agencies (or credit reference agencies) and prior to the development of complex statistical models, filling thus a crucial gap in the literature. The main findings of the three subsequent empirical chapters, where new financial distress prediction models are developed, can be summarised as follows: i) the combination of accounting and market variables in a single model, that also incorporates macroeconomic dynamics, resulted in a significant increase in the overall performance (measured by the predictive accuracy and goodness-of-fit of the models) relative to models based exclusively on either accounting or market data; ii) a finance-based definition of firm distress and a technical definition of corporate failure proved to be appropriate solutions to the disadvantages stemming from juridical definitions of bankruptcy, as the 'legal' date of failure may not represent the 'economic' or the 'real' event of failure; iii) marginal effects are appropriate transformations to interpret the individual effects of specific variables on the probability of falling into the financial distress/corporate failure category in binary choice and polytomous response logit models, and, combined with the analyses of changes in predicted probabilities, provided new insights on the behaviour of the vectors of predicted probabilities that correspond to a change in the level of a specific covariate.

7.2. Historical evidence on the types of variables and credit information sharing mechanisms in the United States and the United Kingdom.

Chapter 2 of this thesis provides pivotal historical evidence with regard to the types of variables used in order to assess the credit risk on individuals, businesses, and fixed income instruments, as well as to the first institutional forms of credit information sharing in the United States and the United Kingdom in the nineteenth century. The novelty of this chapter lies in the fact that it offered, for the first time, historical evidence on the methods employed by investors and financial institutions in order to gain useful information for the assessment of creditworthiness before the emergence of the main credit rating agencies (and the modern forms of public and private credit reference agencies), and prior to the development of modern complex statistical financial distress/scoring models and credit ratings based on payment histories, financial statements, and accounting and/or market data. Thus, through a comparative approach and employing a historical framework, Chapter 2 studied the evolution of risk assessment and credit information sharing in two of the most historically relevant financial centres in the world. The choice of the period of study was not fortuitous, as it was shown that it is precisely in the first part of the nineteenth century when the first organised forms of credit information sharing as well as the first documents that formally registered contracted financial obligations can be found. This study filled thus a crucial gap in the literature: it offered historical evidence on the input as well as on the credit information sharing mechanisms employed by credit grantors in order to evaluate risk profiles in a historical period characterised by a very large increase in trade and credit (due to the advent of the Industrial Revolution in the United Kingdom and the rapid economic development in the vast geographical area of the United States), and when accounting information was rarely available, unreliable, and incomplete.

Given the fundamental role played by information flows in the granting and pricing of credit, Chapter 2 offered, additionally, theoretical support for the development of a study focusing on the types of credit information and the information sharing mechanisms. This chapter divided credit information into three main categories that interacted in the nineteenth century (consumer credit information, trade credit information and information on corporations and securities), and showed that this categorisation is appropriate to explain the historical interrelations and therefore their contributions to the development of modern forms of credit sharing organisations such as the three main credit rating agencies. Furthermore, through a detailed historical analysis, the chapter traced the evolution of the different types of credit sharing mechanisms: the traditional letters of recommendation in support of a borrower's financial situation (extended by a supplier known by the borrower through a long-term business relationship, and based on qualitative information); the emergence of the first non-profit mutual societies for the protection of trade (employing qualitative negative information for the assessment of risk) in the United Kingdom; the hiring of private agents by the largest international merchant banks (using qualitative and quantitative information) in the United Kingdom (where the first forms of credit ratings can be found) and the United States, the profit-seeking credit reference agencies in the United States (utilising a combination of quantitative and qualitative information), and the specialised business/financial press in the United Kingdom and the United States (based on statistical data). Finally, a central contribution of this chapter to the literature is that it provided an explanation of the differences in the historical evolution of risk assessment methods and credit information sharing mechanisms that is based not only on the traditional geographical arguments but also on the different stages of development of the respective financial systems and the legal frameworks of each country.

7.3. Default prediction using accounting, market and macroeconomic variables.

Chapter 3 develops new binary logistic models for the prediction of corporate default for quoted companies in the United Kingdom calibrated based on the Christidis and Gregory (2010) definition of financial distress. The models use widely available data from the London Share Price Database (LSPD). In order to provide a 'clean' measure of the outcome (or the dependent variable), a firm was classified as failed if its status was one of the following: in liquidation, suspension, receivership, or cancellation. This definition of corporate failure was based upon the types of death available in the London Share Price Database and represents thus the last stage of financial distress: default, which can be viewed as the outcome of a process. Therefore, this chapter differed from prior studies that employed a 'legal' definition of bankruptcy in that it recognises that default can be a lengthy legal process and that the 'legal' date of failure may not represent the 'economic' or the 'real' event of failure. Most importantly, the novelty of this chapter is that it develops models, for the first time, for the prediction of corporate default that combine financial statement data, market variables, and macroeconomic indicators. Previous studies have focused on demonstrating the superiority of market-based models over accounting-based models and vice-versa, and the relevance of macroeconomic variables to the prediction of corporate default has rarely been tested. To this point, the default prediction literature is characterised by a competing approach where there is a clear division line between market and accounting variables. The present study adopted a different approach where the use of the three types of variables is not mutually exclusive. It was tested whether the market variables (dependent, in some measure, upon the same financial information) and macroeconomic indicators add information that is not contained in financial statements and therefore act as complement in default prediction models.

The results presented in Chapter 3 clearly indicate that this is the case. Five binary logistic models were developed: An 'Accounting only' model, an 'Accounting plus macroeconomic variables' model, a 'Comprehensive model' that includes accounting, market and macroeconomic variables, a 'Market only' model, and a 'Market plus macroeconomic variables' model to test the differences in performance of the three groups of variables. The results are unambiguous: the comprehensive model yielded the best performance (measured through individual areas under Receiver operating characteristics curves, Gini rank coefficients, Kolmogorov-Smirnov tests, Cox and Snell's and Nagelkerke's R-squared, and Hosmer and Lemeshow goodness-of-fit tests) in both periods *t-1* and *t-2* (when the model was estimated with information one and two years prior to the observation of the event of corporate default).

On the other hand, the results from the inclusion of market variables to an accounting-based model (that also included macroeconomic indicators) indicated that market variables contain a substantial amount of information relevant to the estimation of the likelihood of corporate default that is not included in financial statement ratios. Furthermore, when the 'Full' model is estimated in *t-2*, market variables are the most consistent set of regressors over time for the prediction of corporate default. A comparison of areas under correlated ROC curves (AUC) performed using a non-parametric method based on the theory on generalised Man-Whitney *U*-statistics, and the estimation of biased-adjusted classification tables corroborated these results. This chapter also found that, when employed in isolation, market variables seem to possess a higher explanatory power than accounting variables, as the performance of market variables closely follows the performance of the 'full' model, especially in *t-2*. Results are, nevertheless, less conclusive with regard to macroeconomic indicators, which contribute only marginally to the overall classification accuracy of the model. Finally, the estimation of marginal effects filled an important gap in the default prediction literature by presenting expected instantaneous changes in the response variables as a function of a change in a specific predictor variable while keeping all the other covariates constant. The graphical representation of changes in predicted probabilities also proved to be very useful to enhance our understanding of individual effects of individual variables included in the models.

7.4. Bankruptcy and financial distress prediction using accounting, market and macroeconomic variables.

Chapter 4 offered new binary logistic models for the prediction of financial distress and corporate failure. This chapter contributes to the literature by offering a finance-based definition of firm distress for quoted companies in the United Kingdom. Financial distress prediction models that incorporate not only the event of bankruptcy as the primary outcome, but also the time when a company fails to meet its financial obligations, were developed and tested. Taking into account that financial distress can be costly for creditors and that they would wish to take timely actions to minimise or avert these costs, Chapter 4 produces models with practical value- enhanced predictive accuracy and macro-dependent dynamics that have relevance for stress testing. Building on the corporate failure definition employed in Chapter 3, this chapter classifies a firm as financially distressed when two separate conditions are met: i) whenever its earnings before interest and taxes depreciation and amortization (EBITDA) are lower than its financial expenses for two consecutive years; ii) whenever the firms suffers from a negative growth in market value for two consecutive years. In this way, both accounting and market dimensions were accounted for in the analysis. Furthermore, this chapter offered a comparison of the goodness-of-fit, classification accuracy and predictive power of three types of variables: financial statement ratios, macroeconomic indicators and market variables. The results clearly showed the utility of combining these three types of variables in financial distress prediction models for listed companies. Moreover, the performance of the estimated models was benchmarked against models built using a neural network (multilayer perceptron) and against Altman's (1968) original Z-score specification, corroborating thus the advantages of the methodology employed in Chapter 4 and the ascendancy of comprehensive models that combine accounting, market and macroeconomic data.

In addition to the analysis of performance measures widely employed in the credit risk industry, a comparison of areas under correlated ROC curves performed using a non-parametric method, and the estimation of biased-adjusted classification tables indicated that market variables contain relevant information that is not included in financial statement ratios. Therefore, the incorporation of market variables in accounting-based model can significantly enhance the predictive power of the model. Moreover, when a comprehensive model was estimated using data two years prior to the event of financial distress, in order to test the real predictive accuracy of the model, three out of four market variables retained their statistical significance, the same proportion as the financial ratios, which indicates that the variables included in the model are consistent. Chapter 4 also found that results are less conclusive for macroeconomic variables, which contribute only marginally to the overall classification accuracy of the model. On the other hand, a comparison between the three main models developed in this chapter, the classic Altman (1968) model estimated using logistic regression, the widely used Altman (1968) Z-score and the comprehensive model estimated employing an artificial neural network (multilayer perceptron) confirmed the robustness of the models developed in this chapter. This chapter's models displayed significantly enhanced prediction accuracy results relative to the original Altman's Z-score.

Through a comparative analysis of the comprehensive logit model against the artificial neural networks model, it could be concluded that their performances are almost identical, as the differences in predictive accuracy are very small, with the neural networks model outperforming the logit model for the prediction of failed/distressed firms, although by a very small margin (less than 1 percentage point approximately), which is consistent with the results obtained through the analysis of their respective areas under the ROC curves. Nevertheless, the logit models developed in Chapter four have the advantage of providing a form that can be understood and transported quite easily, unlike neural networks, which lack transparency (seeing what the model is doing, or comprehensibility) and transportability (being able to easily deploy the model into a decision support system for new cases). Finally, Chapter 4 contributed to the literature by estimating marginal effects and presenting graphical representations of the changes in predicted probabilities, which, unlike multinomial logit function coefficients, are very useful to interpret the effects of individual covariates on the probability of financial distress.

7.5. A polytomous response logit financial distress corporate failure model.

The final empirical chapter, Chapter 5, presented new polytomous response logit models that include definitions of both financial distress and corporate failure. The novelty of the present study is that it considered corporate default as a dynamic process by including three possible states/outcomes in a generalised or polytomous logit regression model: a state that encloses on-going firms assumed to be in a financially sound position, a state reflecting firm Financial distress (based on a finance definition of corporate distress), and a state that indicates a state of Corporate failure (based on a technical definition built using information provided by the London Share Price Database). Given that there has been only a small number of prior research works that apply polytomous response models to the field of financial distress/corporate default, Chapter 5 argued that the applications to finance of the multinomial logit methodology have not been explored enough, and that the literature on financial distress and corporate failure could significantly benefit not only from the analysis of its output in the form of prediction accuracy results (of three possible outcomes), but also from the new insights that can be obtained through appropriate transformations of the multinomial function coefficients in order to provide a direct interpretation of the effects of individual covariates on the likelihood of a firm falling into one of the three possible states or outcomes. In order to empirically test these assumptions, marginal effects, derived from the output of the polytomous response model, were estimated and interpreted in detail. Moreover, graphic representations of the changes produced in the vectors of predicted probabilities by a change in the level of a specific covariate (while keeping all other variables constant at their means) were presented to further analyse the individual effects of all types of variables in the models, to provide additional insights on their patterns of behaviour as well as additional support to the interpretation of the marginal effects.

Chapter 5 provided evidence that indicates that marginal effects are an appropriate measure to assess the effects of individual covariates on the probability of falling into one of the three pre-defined financial states/outcomes in a multinomial logit model: a part from the advantage of their direct interpretation, the estimation of average marginal effects yielded the correct expected signs for all the variables and outcomes, unlike several multinomial logit function coefficients. In practice, these results can be used to determine the individual effects of the different covariates on the probability of a firm falling into financial distress or corporate failure with a high degree of reliability. In other words, marginal effects were found to be an appropriate measure to determine the relative importance of individual variables based on their relative magnitudes. In this manner, practitioners are able to rank and target the specific aspects or characteristics of a company that require special attention in order to avoid the high costs associated with financial distress and bankruptcy. Additionally, the study also found, through statistical measures used for the first time in the field of financial distress/bankruptcy models, that model performance and goodness-of-fit can be significantly enhanced by combining financial ratios and market variables in a model that also incorporates macroeconomic dynamics, providing thus additional support for the results obtained in Chapters 3 and 4.

Moreover, Chapter 5 presented a flexible classification accuracy methodology that has the advantage of allowing for the inclusion of very close approximations of the actual proportions of an outcome relative to the one it is being tested against, which is very important as they can be used as cut-off points in an unbalanced panel (such as the one used in the present study, that approximates the actual proportions observed in the United Kingdom) providing thus the researcher and practitioner with realistic and reliable results as well as a high degree of accuracy. The classification tables produced additional evidence supporting the analysis of marginal effects and changes in predicted probabilities: the comprehensive model yields the highest overall classification accuracy followed by the 'accounting only, and 'market only' models.

7.6. Directions for future research.

Given the dynamic nature of the characteristics of financially distressed/bankrupt firms over time, it is essential for regulators, practitioners, and academics, to periodically test and enhance the performance of financial distress/corporate default prediction models. This is particularly important as the areas of application of such models have been broadened to include: the monitoring of the financial situation of institutions by regulators, the evaluation of the financial viability of corporations by auditing firms, the measurement of the riskiness of portfolios, the pricing of credit derivatives and other fixed-income securities, etc. Therefore, research on financial distress/default prediction models could be further enhanced by taking into account recent methodological developments in the field of econometrics and statistics as well as the current improvements of databases that now include qualitative information. With regard to the former, new longitudinal techniques could be applied to the financial distress field in order to test whether these technical refinements are capable of enhance the overall predictive accuracy of the models and/or provide new insights as to role of individual variables and the effect of particular types of variables on the probability of failing into the financial distress/corporate default category.

Improvements to longitudinal discrete choice methodologies have not been tested in this field and it would be useful to test whether a potential gain in performance of the model is able to compensate for the increase in the complexity of such novel techniques. In fact, these advances in discrete choice modelling have alleviated questionable assumptions such as the independently and identically distributed errors assumption and allowed for unobserved heterogeneity. If these models proved to enhance the performance of prediction models, an additional question would be whether they could be adopted by practitioners given the intensiveness of resources required for their estimation. Finally, taking into account corporate finance theory, other qualitative variables such as directors characteristics could be incorporated to prediction models to test whether they enhance their performance.

Bibliography

AGARWAL, V. & TAFFLER, R. 2007. Twenty-five Years of the Taffler Z-score Model: Does it Really Have Predictive Ability? *Accounting and Business Research,* 37**,** 285-300.

AGARWAL, V. & TAFFLER, R. 2008. Comparing the Performance of Market-Based and Accounting-Based Bankruptcy Prediction Models. *Journal of Banking & Finance,* 32**,** 1541-1551.

AKAIKE, H. 1973. Information Theory and an Extension of the Maximum Likelihood Principle. *In:* PETROV, B. N. & CSÁDKI, F. (eds.) *2nd International Symposium on Information Theory, Tsahkadsor, Armenia, USSR, September 2-8, 1971.* Budapest: Akademiai Kiadó.

AKERLOF, G. A. 1970. The Market for "Lemons": Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics,* 84.

ALEXANDER, C. & KAECK, A. 2008. Regime Dependent Determinants of Credit Default Swap Spreads. *Journal of Banking & Finance*, 32, 1008-1021.

ALFARO, E., GARCÍA, N., GÁMEZ, M. & ELIZONDO, D. 2008. Bankruptcy Forecasting: An Empirical Comparison of AdaBoost and Neural Networks. *Decision Support Systems*, 45, 110-122.

ALTMAN, E. I. 1968. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *The Journal of Finance,* 23**,** 589-609.

ALTMAN, E. I., HALDEMAN, R. G. & NARAYANAN, P. 1977. ZETATM Analysis: A New Model to Identify Bankruptcy Risk of Corporations. *Journal of Banking & Finance,* 1**,** 29-54.

ALTMAN, E. I. & KAO, D. L. 1992. The Implications of Corporate Bond Ratings Drift. *Financial Analysts Journal,* 48**,** 64-75.

ALTMAN, E. I. & SABATO, G. 2007. Modelling Credit Risk for SMEs: Evidence from the U.S. Market. *Abacus,* 43.

ALTMAN, E. I., SABATO, G. & WILSON, N. 2010. The Value of Non-Financial Information in Small and Medium-Sized Enterprise Risk Management. *The Journal of Credit Risk,* 6**,** 1-33.

ALTMAN, E. I. & SAUNDERS, A. 1998. Credit Risk Measurement: Developments Over the Last 20 Years. *Journal of Banking & Finance,* 21**,** 1721-1742.

ANDERSON, R. 2007. *The Credit Scoring Toolkit : Theory and Practice for Retail Credit Risk Management and Decision Automation,* Oxford, Oxford University Press.

ANDRADE, G. & KAPLAN, S. N. 1998. How Costly is Financial (Not Economic) Distress? Evidence from Highly Leveraged Transactions that Became Distressed. *The Journal of Finance,* 53**,** 1443-1493.

ARGENTI, J. 1976. *Corporate Collapse: The Causes and Symptoms,* London, McGraw-Hill.

ASQUITH, P., GERTNER, R. & SCHARFSTEIN, D. 1994. Anatomy of Financial Distress: An Examination of Junk-Bond Issuers. *The Quarterly Journal of Economics,* 109**,** 625-658.

ATHERTON, L. E. 1946. The Problem of Credit Rating in the Ante-Bellum South. *The Journal of Southern History,* 12**,** 534-556.

BALCAEN, S. & OOGHE, H. 2004. 35 Years of Studies on Business Failure: An Overview of the Classic Statistical Methodologies and their Related Problems. *Vlerick Leuven Gent Working Paper Series,* 15.

BALCAEN, S. & OOGHE, H. 2006. 35 Years of Studies on Business Failure: An Overview of the Classic Statistical Methodologies and their Related Problems. *The British Accounting Review*, 38, 63-93.

BARNES, P. 1982. Methodological Implications of Non-normally Distributed Financial Ratios. *Journal of Business Finance & Accounting,* 9**,** 51-62.

BARNES, P. 1987. The Analysis and Use of Financial Ratios: A Review Article. *Journal of Business Finance & Accounting,* 14**,** 449-461.

BARNES, P. 1990. The Prediction of Takeover Targets in the U.K. by Means of Multiple Discriminant Analysis. *Journal of Business Finance & Accounting,* 17**,** 73-84.

BARRON BASKIN, J. 1988. The Development of Corporate Financial Markets in Britain and the United States, 1600-1914: Overcoming Asymmetric Information. *The Business History Review,* 62**,** 199-237.

BEAL, D. J. 2005. Information Criteria Methods in SAS for Multiple Linear Regression Models. *Sciences Applications International Corporation, Oak Ridge, TN*.

BEAVER, W. H. 1966. Financial Ratios As Predictors of Failure. *Journal of Accounting Research,* 4**,** 71-111.

BEAVER, W. H., MCNICHOLS, M. F. & RHIE, J.-W. 2005. Have Financial Statements Become Less Informative? Evidence from the Ability of Financial Ratios to Predict Bankruptcy. *Review of Accounting Studies,* 10**,** 93-122.

BECCHETTI, L. & SIERRA, J. 2003. Bankruptcy Risk and Productive Efficiency in Manufacturing Firms. *Journal of Banking & Finance,* 27**,** 2099-2120.

BELSLEY, D. A., KUH, E. & WELSCH, R. E. 1980. *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity,* New York, John Wiley and Sons.

BENNETT, E. Z. 1989. *Debt and Credit in the Urban Economy: London 1380-1460*. Doctor of Philosophy, Yale University.

BENNETT, P. 1984. Applying Portfolio Theory to Global Bank Lending. *Journal of Banking & Finance,* 8**,** 153-169.

BHARATH, S. T. & SHUMWAY, T. 2008. Forecasting Default with the Merton Distance to Default Model. *Review of Financial Studies,* 21**,** 1339-1369.

BLACK, F. & SCHOLES, M. 1973. The Pricing of Options and Corporate Liabilities. *Journal of Political Economy*, 81, 637-654.

BLUM, M. 1974. Failing Company Discriminant Analysis. *Journal of Accounting Research,* 12**,** 1-25.

BOOT, A. W. A. 2000. Relationship Banking: What Do We Know? *Journal of Financial Intermediation*, 9, 7-25.

BOSKIN, M. J. 1974. A Conditional Logit Model of Occupational Choice. *Journal of Political Economy*, 82, 389-398.

BREWER, E. & KOPPENHAVER, G. D. 1992. The Impact of Standby Letters of Credit on Bank Risk: A Note. *Journal of Banking & Finance,* 16**,** 1037-1046.

BROWN, M., JAPPELLI, T. & PAGANO, M. 2009. Information sharing and credit: Firm level evidence from transition countries. *Journal of Financial Intermediation*, 18, 151-172.

BROWN, M. & ZEHNDER, C. 2007. Credit Reporting, Relationship Banking, and Loan Repayment. *Journal of Money, Credit and Banking*, 39, 1883-1918.

BÜCHER, K. 1901. *Industrial Evolution*, New York, H. Holt and Company.

CAMPBELL, J. Y., HILSCHER, J. & SZILAGYI, J. A. N. 2008. In Search of Distress Risk. *The Journal of Finance,* 63**,** 2899-2939.

CANTOR, R. & PACKER, F. 1994. The Credit Rating Industry. *Federal Reserve Bank of New York Quarterly Review.*

CHANDLER, A. D. 1956. *Henry Varnum Poor, Business Editor, Analyst, and Reformer,* Cambridge, Harvard University Press.

CHARITOU, A., NEOPHYTOU, E. & CHARALAMBOUS, C. 2004. Predicting Corporate Failure: Empirical Evidence for the UK. *European Accounting Review*, 13, 465-497.

CHARITOU, A. & TRIGEORGIS, L. 2000. Option-Based Bankruptcy Prediction. *EFMA 2000 Athens*.

CHAVA, S. & JARROW, R. A. 2004. Bankruptcy Prediction with Industry Effects. *Review of Finance,* 8, 537-569.

CHIRINKO, R. S. & GUILL, G. D. 1991. A Framework for Assessing Credit Risk in Depository Institutions: Toward Regulatory Reform. *Journal of Banking & Finance,* 15, 785-804.

CHO, S., KIM, J. & BAE, J. K. 2009. An Integrative Model with Subject Weight Based on Neural Network Learning for Bankruptcy Prediction. *Expert Systems with Applications*, 36, 403-410.

CHRISTIDIS, A. & GREGORY, A. 2010. Some New Models for Financial Distress Prediction in the UK. *Xfi Centre for Finance and Investment Discussion Paper No. 10*.

CLEVES, M. A. 2002. From the Help Desk: Comparing Areas Under Receiver Operating Characteristics Curves from Two or More Probit or Logit Models. *The Stata Journal,* 2, 301-313.

COX, D. R. & SNELL, E. J. 1989. *The Analysis of Binary Data,* London, Chapman and Hall.

DAVIS, L. E. & CULL, R. J. 1994. *International Capital Markets and American Economic Growth, 1820-1914,* Cambridge, Cambridge University Press.

DAVIS, L. E. & GALLMAN, R. E. 2001. *Financial Markets and International Capital Flows. Britain, the Americas, and Australia 1865-1914*, New York, Cambridge University Press.

DAWES, R. M. & CORRIGAN, B. 1974. Linear Models in Decision Making. *Psychological Bulletin,* 81, 95-106.

DEAKIN, E. B. 1972. A Discriminant Analysis of Predictors of Business Failure. *Journal of Accounting Research,* 10, 167-179.

DECLERC, M., HEINS, B. & VAN WYMEERSCH, C. 1992. The Use of Value Added Ratios in Statistical Failure Prediction Models: Some Evidence on Belgian Annual Accounts. *Cahiers Economiques de Bruxelles*, 353-378.

DELONG, E. R., DELONG, D. M. & CLARKE-PEARSON, D. L. 1988. Comparing the Areas under Two or More Correlated Receiver Operating Characteristic Curves: A Nonparametric Approach. *Biometrics,* 44**,** 837-845.

DICHEV, I. D. 1998. Is the Risk of Bankruptcy a Systematic Risk? *The Journal of Finance,* 53**,** 1131-1147.

DICKSON, P. 1967. *The Financial Revolution in England, a Study in the Development of Public Credit, 1688-1756,* London, Macmillan.

DJANKOV, S., MCLIESH, C. & SCHLEIFER, A. 2005. Private Credit in 129 Countries. *National Bureau of Economic Research Working Paper Series No . 11078*.

DOBLAS-MADRID, A. & MINETTI, R. 2013. Sharing information in the credit market: Contract-level evidence from U.S. firms. *Journal of Financial Economics*, In press, corrected proof.

EDELSTEIN, M. 1982. *Overseas Investment in the Age of High Imperialism: the United Kingdom, 1850-1914.,* London, Methuen & Co. Ltd.

EDMISTER, R. O. 1972. An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction. *The Journal of Financial and Quantitative Analysis,* 7**,** 1477-1493.

EDWARD I. ALTMAN, BROOKS BRADY, ANDREA RESTI & ANDREA SIRONI 2005. The Link between Default and Recovery Rates: Theory, Empirical Evidence, and Implications. *The Journal of Business,* 78**,** 2203-2228.

EFRON, B. 1975. The Efficiency of Logistic Regression Compared to Normal Discriminant Analysis. *Journal of the American Statistical Association*, 70, 892-898.

EISENBEIS, R. A. 1977. Pitfalls in the Application of Discriminant Analysis in Business, Finance, and Economics. *The Journal of Finance,* 32**,** 875-900.

FERGUSON, N. 1998. *The House of Rothschild: Money's Prophets, 1798-1848,* New York, Viking.

FERGUSON, N. 1998. *The World's Banker: A History of the House of Rothschild,* London, Weidenfeld & Nicolson.

FREUND, R. J. & LITTELL, R. C. 2000. *SAS System for Regression,* New York, Chichester, Wiley, Carey.

GALINDO, A. & MILLER, M. 2001. Can Credit Registries Reduce Credit Constraints? Empirical Evidence on the Role of Credit Registries in Firm Investment Decisions. *Paper prepared for the Annual Meetings of the Board of Governors, Inter-American Development Bank and Inter-American Investment Corporation*.

GENTRY, J. A., NEWBOLD, P. & WHITFORD, D. T. 1985. Classifying Bankrupt Firms with Funds Flow Components. *Journal of Accounting Research,* 23**,** 146-160.

GODFREY, M. D. 2009. The TANH Transformation. *Information Systems Laboratory Stanford University*.

GOMBOLA, M. J., HASKINS, M. E., KETZ, J. E. & WILLIAMS, D. D. 1987. Cash Flow in Bankruptcy Prediction. *Financial Management,* 16**,** 55-65.

GRAHAM, A. 2000. *Corporate Credit Analysis,* London, Fitzroy Dearborn Publishers.

GREENE, W. H. 2012. *Econometric Analysis*, Boston, Pearson.

GREIG, C. M. 1992. *The Growth of Credit Information: A History of UATP-Infolink plc* Oxford, Blackwell.

HAMER, M. M. 1983. Failure Prediction: Sensitivity of Classification Accuracy to Alternative Statistical Methods and Variable Sets. *Journal of Accounting and Public Policy,* 2**,** 289-307.

HIDY, R. W. 1939. Credit Rating before Dun and Bradstreet. *Bulletin of the Business Historical Society,* 13, 81-88.

HILLEGEIST, S. A., KEATING, E. K., CRAM, D. P. & LUNDSTEDT, K. G. 2004. Assessing the Probability of Bankruptcy. *Review of Accounting Studies,* 9**,** 5-34.

HOPPIT, J. 1986. The Use and Abuse of Credit in Eighteenth-Century England. *In*: MCKENDRICK, N. & OUTHWAITE, R. B. (eds.) *Business Life and Public Policy: Essays in Honour of D. C. Coleman*. London.

HOSMER, D. W. J. & LEMESHOW, S. 1989. *Applied Logistic Regression,* United States of America, John Wiley & Sons.

HOUGHTON, K. A. & SENGUPTA, R. 1984. The Effect of Prior Probability Disclosure and Information Set Construction on Bankers' Ability to Predict Failure. *Journal of Accounting Research,* 22**,** 768-775.

JAFFEE, D. M. & RUSSELL, T. 1984. Imperfect Information, Uncertainty, and Credit Rationing: A Reply. *The Quarterly Journal of Economics*, 99, 869-872.

JAGTIANI, J., SAUNDERS, A. & UDELL, G. 1995. The Effect of Bank Capital Requirements on Bank Off-balance Sheet Financial Innovations. *Journal of Banking & Finance,* 19**,** 647-658.

JAPPELLI, T. & PAGANO, M. 2000. Information Sharing in Credit Markets: The European Experience. *Centre for Studies in Economics and Finance (CSEF), Working Paper No. 35, University of Naples, Italy.*

JAPPELLI, T. & PAGANO, M. 2002. Information Sharing, Lending and Defaults: Cross country Evidence. *Journal of Banking & Finance*, 26, 2017-2045.

JOHNSEN, T. & MELICHER, R. W. 1994. Predicting corporate bankruptcy and financial distress: Information value added by multinomial logit models. *Journal of Economics and Business*, 46, 269-286.

JONES, F. L. 1987. Current Techniques in Bankruptcy Prediction. *Journal of Accounting Literature*, 6, 131-164.

JONES, S. & HENSHER, D. A. 2004. Predicting Firm Financial Distress: A Mixed Logit Model. *The Accounting Review*, 79, 1011-1038.

KARELS, G. V. & PRAKASH, A. J. 1987. Multivariate Normality and Forecasting of Business Bankruptcy. *Journal of Business Finance & Accounting,* 14**,** 573-593.

KEASEY, K. & WATSON, R. 1987. Non-Financial Symptoms and the Prediction of Small Company Failure: A Test of Argenti's Hypotheses. *Journal of Business Finance & Accounting,* 14**,** 335-354.

KEASEY, K. & WATSON, R. 1991. Financial Distress Prediction Models: A Review of Their Usefulness. *British Journal of Management,* 2**,** 89-102.

KENNEDY, W. P. 1987. *Industrial Structure, Capital Markets and the Origins of British Economic Decline,* Cambridge, Cambridge University Press.

KERMODE, J. I. 1991. Money and Credit in the Fifteenth Century: Some Lessons from Yorkshire. *The Business History Review*, 65, 475-501.

KING, G. & ZENG, L. 2001. Logistic Regression in Rare Events Data. *Political Analysis*, 9, 137-163.

KUMAR, P. R. & RAVI, V. 2007. Bankruptcy Prediction in Banks and Firms via Statistical and Intelligent Techniques – A Review. *European Journal of Operational Research*, 180, 1-28.

LANGOHR, H. & LANGOHR, P. 2008. *The Rating Agencies and Their Credit Ratings: What They Are, How They Work, and Why They are Relevant*, Wiley Finance.

LAU, A. H.-L. 1987. A Five-State Financial Distress Prediction Model. *Journal of Accounting Research*, 25, 127-138.

LAUER, J. 2008. From Rumor to Written Record: Credit Reporting and the Invention of Financial Identity in Nineteenth-Century America. *Technology and Culture,* 49**,** 301-324.

LAWRENCE, E. C. & ARSHADI, N. 1995. A Multinomial Logit Analysis of Problem Loan Resolution Choices in Banking. *Journal of Money, Credit and Banking*, 27, 202-216.

LECLERE, M. J. 1999. The Interpretation of Coefficients in N-Chotomous Qualitative Response Models. *Contemporary Accounting Research*, 16, 711-747.

LO, A. W. 1986. Logit Versus Discriminant Analysis: A Specification Test and Application to Corporate Bankruptcies. *Journal of Econometrics,* 31**,** 151-178.

LONG, J. S. & FREESE, J. 2003. *Regression Models for Categorical Dependent Variables Using Stata,* College Station,Texas, Stata Press.

LOVE, I. & MYLENKO, N. 2003. Credit Reporting and Financing Constraints. *World Bank Policy Research Working Paper 3142*.

LUSSIER, R. N. 1995. A Nonfinancial Business Success Versus Failure Prediction Model for Young Firms. *Journal of Small Business Management,* 33**,** 8-20.

MADDALA, G. S. 1991. A Perspective on the Use of Limited-Dependent and Qualitative Variables Models in Accounting Research. *The Accounting Review*, 66, 788-807.

MADISON, J. H. 1974. The Evolution of Credit Reporting Agencies in Nineteenth-Century America. *The Business History Review,* 48, 164-186.

MANSKI, C. F. & LERMAN, S. R. 1977. The Estimation of Choice Probabilities from Choice Based Samples. Econometrica, 45, 1977-1988.

MALTZ, A. C., SHENHAR, A. J. & REILLY, R. R. 2003. Beyond the Balanced Scorecard: Refining the Search for Organizational Success Measures. *Long Range Planning,* 36**,** 187-204.

MARAIS, D. A. J. 1979. A Method for Quantifying Companies Relative Financial Strength. *Bank of England Discussion Paper No. 4*.

MARDIA, K. V., KENT, J. T. & BIBBY, J. M. 1979. *Multivariate Analysis. Probability and Mathematical Statistics* London, Academic Press.

MARE, D. S. 2012. Contribution of Macroeconomic Factors to the Prediction of Small Bank Failures.

MARTIN, D. 1977. Early Warning of Bank Failure: A Logit Regression Approach. *Journal of Banking & Finance,* 1**,** 249-276.

MAYS, F. E. 2004. *Credit Scoring for Risk Managers: The Handbook for Lenders*, Thomson/South-Western.

MCDONALD, B. & MORRIS, M. H. 1984. The Statistical Validity of the Ratio Method in Financial Analysis: An Empirical Examination. *Journal of Business Finance & Accounting,* 11**,** 89-97.

MCFADDEN, D. & TRAIN, K. 2000. Mixed MNL Models for Discrete Response. *Journal of Applied Econometrics*, 15, 447-470.

MCLEAY, S. & OMAR, A. 2000. The Sensitivity of Prediction Models to the Non-normality of Bounded and Unbounded Financial Ratios. *The British Accounting Review,* 32**,** 213-230.

MENSAH, Y. M. 1984. An Examination of the Stationarity of Multivariate Bankruptcy Prediction Models: A Methodological Study. *Journal of Accounting Research,* 22**,** 380-395.

MERTON, R. C. 1974. On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *The Journal of Finance,* 29**,** 449-470.

MICHA, B. 1984. Analysis of Business Failures in France. *Journal of Banking & Finance,* 8**,** 281-291.

MICHIE, R. C. 1987. *The London and New York Stock Exchanges, 1850-1914.,* London, Allen & Unwin.

MICHIE, R. 2006. *The Global Securities Market: A History,* Oxford, Oxford University Press.

MOODY, J. 1933. *The Long Road Home: An Autobiography,* New York, Macmillan.

NAGELKERKE, N. J. D. 1991. A Note on a General Definition of the Coefficient of Determination. *Biometrika,* 78**,** 691-692.

NAM, C.W., KIM, T.S., PARK, N. J., and LEE, H.L., 2008. Bankruptcy Prediction Using a Discrete-Time Duration Model Incorporating Temporal and Macroeconomic Dependencies. *Journal of Forecasting* 27, 493-506.

NEAL, L. 1990. *The Rise of Financial Capitalism: International Capital Markets in the Age of Reason,* Cambridge, Cambridge University Press.

OHLSON, J. A. 1980. Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research,* 18**,** 109-131.

OLEGARIO, ROWENA, Credit Reporting Agencies: What can Developing Countries Learn from the U.S. Experience, paper presented at the World Bank Summer Research Workshop on Market Institutions, July 17-19, 2000.

OLEGARIO, ROWENA. Credit Reporting Agencies: Their Historical Roots, Current Status and Role in Market Development, 10. Paper presented to the World Bank workshop "The Role of Credit Reporting Systems in the International Economy," Washington D.C., March 1-2, 2001, available at www.worldbank.org.

OLSON, D. L., DELEN, D. & MENG, Y. 2012. Comparative Analysis of Data Mining Methods for Bankruptcy Prediction. *Decision Support Systems*, 52, 464-473.

OOGHE, H. & JOOS, P. 1990. Failure Prediction, Explanation of Misclassifications and Incorporation of other Relevant Variables: Results of Empirical Research in Belgium. Working Paper*, Department of Corporate Finance, Ghent University*.

OOGHE, H., JOOS, P. & BOURDEAUDHUIJ, C. D. 1995. Financial Distress Models in Belgium: The Results of a Decade of Empirical Research. *The International Journal of Accounting*, 30, 245-274.

PADILLA, A. J. & PAGANO, M. 1997. Endogenous Communication Among Lenders and Entrepreneurial Incentives. *The Review of Financial Studies*, 10, 205-236.

PADILLA, A. J. & PAGANO, M. 2000. Sharing Default Information as a Borrower Discipline Device. *European Economic Review*, 44, 1951-1980.

PAGANO, M. & JAPPELLI, T. 1993. Information Sharing in Credit Markets. *The Journal of Finance*, 48, 1693-1718.

PEEL, M. J. & PEEL, D. A. 1987. Some Further Empirical Evidence on Predicting Private Company Failure. *Accounting and Business Research,* 18**,** 57-66.

PERKINS, E. J. 1973. The House of Brown: America's Foremost International Bankers, 1800-1880 *The Journal of Economic History,* 33**,** 317-320.

PIESSE, J. & WOOD, D. 1992. Issues in Assessing MDA Models of Corporate Failure: A Research Note. *The British Accounting Review*, 24, 33-42.

PINDADO, J., RODRIGUES, L. & DE LA TORRE, C. 2008. Estimating Financial Distress Likelihood. *Journal of Business Research,* 61**,** 995-1003.

PLATT, H. D. & PLATT, M. B. 1991. A Note on the Use of Industry-relative Ratios in Bankruptcy Prediction. *Journal of Banking & Finance,* 15**,** 1183-1194.

PLATT, H. D. & PLATT, M. B. 2002. Predicting Corporate Financial Distress: Reflections on Choice-based Sample Bias. *Journal of Economics and Finance*, 26, 184-199.

POOR, H. V. 1970. *History of the Railroads and Canals of the United States of America,* New York, Augustus M. Kelley Publishers.

POSTAN, M. 1928. Credit in Medieval Trade. *The Economic History Review*, 1, 234-261.

POWELL, A., MYLENKO, N., MILLER, M. & MAJNONI, G. 2004. Improving Credit Information, Bank Regulation and Supervision: On the Role and Design of Public Credit Registries. *World Bank Policy Research Working Paper 3443*.

QU, Y. 2008. Macroeconomic Factors and Probability of Default. *European Journal of Economics, Finance and Administrative Sciences*.

RAGAVAN, A. J. 2008. How to Use SASR to Fit Multiple Logistic Regression Models. *Department of Mathematics and Statistics of the University of Nevada,* Paper 369.

REES, W. P. 1995. *Financial Analysis,* London, Prentice-Hall.

REISZ, A. S. & PERLICH, C. 2007. A Market-Based Framework for Bankruptcy Prediction. *Journal of Financial Stability,* 3**,** 85-131.

SAUNDERS, A. 1997. *Financial Institutions Management: A Modern Perspective,* Illinois, Irwin, Homewood.

SAUNDERS, A. & ALLEN, L. 2002. *Credit Risk Measurement: New Approaches to Value at Risk and Other Paradigms,* New York, John Wiley & Sons. Inc.

SCOTT, J. 1981. The Probability of Bankruptcy: A Comparison of Empirical Predictions and Theoretical Models. *Journal of Banking & Finance*, 5, 317-344.

SHUMWAY, T. 2001. Forecasting Bankruptcy More Accurately: A Simple Hazard Model. *Journal of Business,* 74**,** 101-124.

STIGLITZ, J. & WEISS, A. 1981. Credit Rationing in Markets with Imperfect Information. *American Economic Review,* 71.

STOREY, D. J. 1987. *The Performance of Small Firms: Profits, Jobs and Failures,* London, Croom Helm.

SUPERVISION, B. C. O. B. 2004. International Convergence of Capital Measurement and Capital Standards. A Revised Framework.

SYLLA, R. 2001. A Historical Primer on the Business of Credit Ratings. *Stern School of Business*.

TAFFLER, R. J. 1982. Forecasting Company Failure in the UK Using Discriminant Analysis and Financial Ratio Data. *Journal of the Royal Statistical Society*. Series A (General), 145, 342-358.

TAFFLER, R. 1983. The Assessment of Company Solvency and Performance Using a Statistical Model. *Accounting and Business Research,* 13**,** 295-307.

TAFFLER, R. & TISSHAW, H. 1977. Going, Going, Gone. Four Factors Which Predict. *Accountancy,* 88**,** 50-54.

THEODOSSIOU, P. T. 1993. Predicting Shifts in the Mean of a Multivariate Time Series Process: An Application in Predicting Business Failures. *Journal of the American Statistical Association,* 88**,** 441-449.

TSENG, F.-M. & HU, Y.-C. 2010. Comparing four Bankruptcy Prediction Models: Logit, Quadratic Interval Logit, Neural and Fuzzy Neural Networks. *Expert Systems with Applications*, 37, 1846-1853.

UNIVERSITY OF LEEDS. *The Guardians: or, Society for the protection of trade against swindlers and sharpers. Established March 25, 1776*. [n.p.], [1780?]. *The Making of the Modern World*. Gale 2010. Gale, Cengage Learning. University of Leeds. 23 August 2010 Available at: http://0-galenet.galegroup.com.wam.leeds.ac.uk/servlet/MOME?af=RN&ae=U3601844161&srchtp=a&ste=14

VASSALOU, M. & XING, Y. 2004. Default Risk in Equity Returns. *The Journal of Finance,* 59**,** 831-868.

WARD, T. J. 1994. An Empirical Study of the Incremental Predictive Ability of Beaver's Naive Operating Flow Measure Using Four-State Ordinal Models of Financial Distress. *Journal of Business Finance & Accounting*, 21, 547-561.

WHITAKER, R. 1999. The Early Stages of Financial Distress. *Journal of Economics and Finance,* 23**,** 123-132.

WHITE, L. J. 2001. The Credit Rating Industry: An Industrial Organization Analysis. *NYU Ctr for Law and Business*.

WHITTINGTON, G. 1980. Some Basic Properties of Accounting Ratios. *Journal of Business Finance & Accounting,* 7**,** 219-232.

WILSON, N. 2008. An Investigation into Payment Trends and Behaviour in the UK: 1997-2007. *Department for Business Enterprise & Regulatory Reform, Credit Management Research Centre, University of Leeds.*

WRUCK, K. H. 1990. Financial Distress, Reorganization, and Organizational Efficiency. *Journal of Financial Economics,* 27**,** 419-444.

WYATT-BROWN, B. 1966. God and Dun & Bradstreet, 1841-1851. *The Business History Review,* 40**,** 432-450.

YANG, Z., YOU, W. & JI, G. 2011. Using Partial Least Squares and Support Vector Machines for Bankruptcy Prediction. *Expert Systems with Applications*, 38, 8336-8342.

ZAVGREN, C. V. 1985. Assessing the Vulnerability to Failure of American Industrial Firms: A Logistic Analysis. *Journal of Business Finance & Accounting,* 12**,** 19-45.

ZMIJEWSKI, M. E. 1984. Methodological Issues Related to the Estimation of Financial Distress Prediction Models. *Journal of Accounting Research,* 22**,** 59-82.