AN ANALYSIS OF INDUSTRIAL COMPANY FAILURE IN THE UK AND RUSSIA FOR THE 1990s

A thesis submitted for the degree of Doctor of Philosophy

by

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This is for Anna & Constantin and Valentina & Alexander

Contents

page

Acknowledgements........ v
Abstract........ vi
List of Tables........ vii
List of Figures........ ix

INTRODUCTION........ x

CHAPTER 1: BACKGROUND: DEFINITION AND CAUSES OF COMPANY FAILURE 1

1.1 Introduction........ 1
1.2 What is Company Failure........ 1
1.3 An Overview of Theories of the Firm........ 6
1.3.1 The Neo-classical Explanation: The Firm-as-Production-Function Model and Economic Inefficiency as a Failure Cause........ 6
1.3.2 The New Institutional Economics: The Role of Debt Finance in Financial Distress........ 12
1.3.2.1 The Firm as a Nexus for Contracting Relationships........ 12
1.3.2.2 The "Tax Shelter-Bankruptcy Cost" View on Debt........ 16
1.3.2.3 The Agency View on Benefits and Costs on Debt........ 21
1.4 The Institutional Framework: A Legal Mechanism for Resolving Financial Distress... 25
1.5 Corporate Finance Theories of Corporate Bankruptcy........ 29
1.5.1 Cash Management Behaviour of a Distressed Company........ 29
1.5.2 The Merton Model of Company Default........ 33
1.5.3 Scott on Theoretical Predictors of Company Liquidation........ 34
1.6 The Influence of the Macroeconomic Context........ 41
1.7 Incompetent Management Theory of Financial Failure........ 53
1.8 Conclusions........ 56

CHAPTER 2: A REVIEW OF UK AND US EMPIRICAL STUDIES MODELLING FAILURE AT THE LEVEL OF INDIVIDUAL COMPANY 59

2.1 Introduction........ 59
2.2 The Definition and Measurement of Company Failure Outcome, Data Needs and Sampling Schemes........ 61
2.3 The Choice of Candidate Variables Gauging the Factors of Company Failure........ 88
2.3.1 Firm-specific Attributes........ 89
2.3.1.1 The Rationale for and Use of Accounting Ratio-based Variables.... 90
2.3.1.2 Market Valuation Variables as Inputs in Predictive Models........ 110
2.3.1.3 Non-financial Firm-specific Attributes........ 113
2.3.2 Variables Representing External Factors........ 114
2.4 The Choice of Statistical Framework........ 117
2.4.1 Cross-sectional Data Models........ 119
2.4.1.1 Predictive Models based on Multivariate Discriminant Analysis.... 119
2.4.1.2 Logit Analysis and Explanatory Models........ 122
2.4.1.3 Neural Networks Classifiers........ 126
2.4.2 Longitudinal Data Models........ 127
2.4 Conclusions........ 129

CHAPTER 3: A LOGIT ANALYSIS OF CROSS-SECTIONAL DATA FOR UK INDUSTRIAL COMPANY FAILURE IN 1989-93 139

3.1 Introduction.......... 139
3.2 Empirical Design.......... 141
3.2.1 The Sample.......... 142
3.2.2 Independent Variables and Data Transformation.......... 150
3.2.2.1 Accounting Ratios.......... 151
3.2.2.2 Other Financial Variables.......... 158
3.2.2.3 Transformation of Financial Data.......... 161
3.2.2.4 Non-Financial Variables.......... 163
3.2.3 The Statistical Model.......... 170
3.3 Empirical Results.......... 182
3.3.1 Models Utilising Financial Ratios.......... 184
3.3.2 Models Utilising Financial Ratios and Macroeconomic Variables.......... 193
3.3.3 Models Utilising Financial Ratios and the Duration Term.......... 203
3.3.4 Models Utilising Financial Ratios, Macroeconomic Variables, and the Duration Term.......... 211
3.4 Conclusions.......... 221

CHAPTER 4: A PANEL ANALYSIS OF UK INDUSTRIAL COMPANY FAILURE 224

4.1 Introduction.......... 224
4.2 The Sample.......... 226
4.3 Independent Variables.......... 231
4.4 A Fixed Effects Binomial Logit Model for Panel Data.......... 232
4.5 Empirical Results.......... 237
4.6 Conclusions.......... 245

CHAPTER 5: A COMPARATIVE STUDY OF FAILURE DETERMINANTS FOR RUSSIAN AND UK COMPANIES 247

5.1 Introduction.......... 247
5.2 What Causes Russian Enterprise to Fail: Hypotheses.......... 249
5.3 The Sample Design and Methodology.......... 261
5.4 Empirical Results.......... 271
5.5 Conclusions.......... 280
Annex: The Bootstrap Approach Used in the Comparative Study.......... 283

CHAPTER 6: SUMMARIZING REMARKS AND SUGGESTIONS ABOUT POLICY ISSUES AND FURTHER RESEARCH 289

APPENDIX 1: Company Insolvency in England and Wales in 1988-1994.......... 301
APPENDIX 2: Variable Descriptive Statistics for the Cross-sectional Analysis of UK Company Failure.......... 302
APPENDIX 3: Variable Descriptive Statistics for the Panel Analysis of UK Company Failure.......... 318
APPENDIX 4: Variable Descriptive Statistics for UK and Russian Cross-sections Used in the Comparative Study.......... 320
APPENDIX 5: Lists of UK and Russian Companies.......... 325

References.......... 341

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Abstract

This thesis provides an examination of the key determinants of industrial company failure in the UK and Russia, for the 1990s.

For the UK, some new empirical evidence, presented for the 1990s recession period, is based on binary logit analyses of a cross-section and unbalanced panel of large quoted companies, using accounting-based indicators. Conventional for cross-sectional studies empirical design of modelling the failure determinants separately for various risk-horizons, prior to the event of insolvency, is extended here by allowing for unanticipated changes in the nominal interest rate and in the real exchange rate, and also by controlling for the firm's age effect. We find that cross-sectional models, conditioned on changes in overall economic conditions, dominate simpler models, utilising financial inputs alone, for comparisons of *ex ante*, out-of-sample classificatory accuracy. Thus, the UK data suggest that for the years before and during the 1990s recession, shifts in the real exchange rate and rises in the nominal interest rate magnified dramatically the risk of failure of highly geared firms. The estimates from the fixed effects models indicate substantial unobserved heterogeneity across members of the panel and reveal that failing UK companies were less liquid, lacked profitability, and had declining net worth.

For Russia, the evidence from binary logit is bootstrap-based and controlled by comparison with a similar random sample drawn for the UK over the recession years 1990-91. The Russian data uncover that, unlike in the UK, gearing and liquidity did not appear to explain enterprise liquidation in the mid-1990s, while lower profitability and smaller size were the key determinants of failure risk.

List of Tables

		Page
2.1	Principal Components of Empirical Design Adopted by the Core Studies into Corporate Failure at the Firm-Level	62
2.2	The Forewarning Ability of Failure Models Based on MDA	108
2.3	The Forewarning Ability of Failure Models Based on Binomial Logit	109
3.1	Sectoral Composition of the UK Company Cross-section for the Reporting Years 1988-94	146
3.2	Number of Company-years in Sets of Non-Failed Firms, Used for Random Selection of Non-Failed-Group Observations in Estimation Cross-sections	147
3.3	Financial Ratio-Based Models: Logit Results for the Cross-section of UK Companies, One and Two Years Prior to Failure	185
3.4	Financial Ratio-Based Models: Logit Results for the Cross-section of UK Companies, Three and Four Years Prior to Failure	186
3.5	Classification and Predictive Ability of Financial Ratio-Based Models, One and Two Years Prior to Failure: Logit Results for the Cross-section of UK Companies..	187
3.6	Classification and Predictive Ability of Financial Ratio-Based Models, Three and Four Years Prior to Failure: Logit Results for the Cross-section of UK Companies..	188
3.7	Models Incorporating Macroeconomic Variables: Logit Results for the Cross-section of UK Companies, One and Two Years Prior to Failure	194
3.8	Models Incorporating Macroeconomic Variables: Logit Results for the Cross-section of UK Companies, Three and Four Years Prior to Failure	195
3.9	Classification and Predictive Ability of Models Incorporating Macroeconomic Variables, One and Two Years Prior to Failure: Logit Results for the Cross-section of UK Companies	196
3.10	Classification and Predictive Ability of Models Incorporating Macroeconomic Variables, Three and Four Years Prior to Failure: Logit Results for the Cross-section of UK Companies	197
3.11	Models Incorporating the Duration Term: Logit Results for the Cross-section of UK Companies, One and Two Years Prior to Failure	205
3.12	Models Incorporating the Duration Term: Logit Results for the Cross-section of UK Companies, Three and Four Years Prior to Failure	206
3.13	Classification and Predictive Ability of Models Incorporating the Duration Term, One and Two Years Prior to Failure: Logit Results for the Cross-section of UK Companies	207
3.14	Classification and Predictive Ability of Models Incorporating the Duration Term, Three and Four Years Prior to Failure: Logit Results for the Cross-section of UK Companies	208
3.15	Models Incorporating Macroeconomic Variables and the Duration Term: Logit Results for the Cross-section of UK Companies, One and Two Years Prior to Failure	212
3.16	Models Incorporating Macroeconomic Variables and the Duration Term: Logit Results for the Cross-section of UK Companies, Three and Four Years Prior to Failure	213
3.17	Classification and Predictive Ability of Models Incorporating Macroeconomic Variables and the Duration Term: Logit Results for the Cross-section of UK Companies, One and Two Years Prior to Failure	214
3.18	Classification and Predictive Ability of Models Incorporating Macroeconomic Variables and the Duration Term: Logit Results for the Cross-section of UK Companies, Three and Four Years Prior to Failure	215
4.1	Transition within the Panel of UK Industrial Companies for 1988-93	228
4.2	Sectoral Composition of the UK Industrial Company Panel for 1988-93	229

4.3	Results from Fixed Effects Binary Logit for the Unbalanced Panel of UK Quoted Companies, the Panel Period 1988-93	238
4.4	Sets of the Key Determinants of Failure Risk for UK Quoted Companies in the Late 1980s and Early 1990s: A Comparison of Cross-sectional, Financial Ratio-based Logit Models and Fixed Effects Logit Models for the Unbalanced Panel	242
5.1	Sectoral Composition of the Russian Company Sample for 1995-96	263
5.2	Sectoral Composition of the Estimation Sample of UK Companies for 1990-91	263
5.3	Logit Results for Russian Data, 1995 Estimation Period	272
5.4	Logit Results for UK Data, 1990-91 Estimation Period	273
5.5	Logit Results for Russian Data, 1995-96 Estimation Period	278
A1.1	Company Insolvency in 1988-94, England and Wales	301
A2.1	Means and *t*-statistics - Independent Variables for the Estimation Samples used in the Cross-sectional Analysis of UK Companies, Sample Period 1988-91; One and Two Years Prior to Failure	302
A2.2	Means and *t*-statistics - Independent Variables for the Estimation Samples used in the Cross-sectional Analysis of UK Companies, Sample Period 1988-91; Three and Four Years Prior to Failure	304
A2.3	Pairwise Correlations for the Estimation Sample used in the Cross-sectional Analysis of UK Companies; One Year Prior to Failure	306
A2.4	Pairwise Correlations for the Estimation Sample used in the Cross-sectional Analysis of UK Companies; Two Years Prior to Failure	309
A2.5	Pairwise Correlations for the Estimation Sample used in the Cross-sectional Analysis of UK Companies; Three Years Prior to Failure	312
A2.6	Pairwise Correlations for the Estimation Sample used in the Cross-sectional Analysis of UK Companies; Four Years Prior to Failure	315
A3.1	Descriptive Statistics for UK Quoted Companies in the 1988-93 Panel	318
A4.1	Means and *t*-statistics - Independent Variables for the Analysis of the Russian Data: the Estimation Sample for 1995 and Pooled Estimation Sample for the Period 1995-96; One Year Prior to Failure	320
A4.2	Pairwise Correlations for the Estimation Sample of 40 Russian Companies, 1995 Sample Period; One Year Prior to Failure	321
A4.3	Pairwise Correlations for the Pooled Estimation Sample of 48 Russian Companies, 1995-96 Sample Period; One Year Prior to Failure	322
A4.4	Means and *t*-statistics - Independent Variables for the Analysis of the UK Data, The Estimation Sample for 1990-91; One Year Prior to Failure	323
A4.5	Pairwise Correlations for the Estimation Sample of 40 UK Companies, 1990-91 Sample Period; One Year Prior to Failure	324
A5.1	Company Names and Years of Entering Insolvency Regime, of UK Failed Quoted Industrials Used in the Estimation Sample for the Cross-sectional Analysis	325
A5.2	Company Names and Years of Entering Insolvency Regime of UK Failed Quoted Industrials Used in the Holdout Sample for the Cross-sectional Analysis	325
A5.3	Company Names of UK Non-failed Quoted Industrials Used in the Estimation Sample for the Cross-sectional Analysis	326
A5.4	Company Names of UK Non-failed Quoted Industrials Used in the Holdout Sample for the Cross-sectional Analysis	330
A5.5	Company Names and Years of Entering Insolvency Regime of UK Failed Quoted Industrials Used in the Panel Analysis	331
A5.6	Company Names of UK Non-failed Quoted Industrials Used in the Panel Study	332
A5.7	Company Names and Years of Entering Insolvency Regime of UK Failed Quoted Industrials Used in the Estimation Sample for the Comparative Study	338
A5.8	Company Names of UK Non-failed Quoted Industrials Used in the Estimation Sample for the Comparative Study	338
A5.9	Names, Years of Insolvency, and Accounts Years of Failed Russian Industrial Companies	339
A5.10	Names and Accounts Years of Non-failed Russian Industrial Companies	340

List of Figures

page

1.1 Company insolvencies in 1979-95 42

INTRODUCTION

A popular view held by many financial economists and accountants is that measures of traditional financial analysis play an important role in the determination of the risk of a company defaulting on its debt obligations and subsequently failing via insolvency. This thesis examines this substantive issue further by considering the determination of failure risk with company-level data for two countries, the UK between 1988 and 1993, and Russia in 1995 and 1996.

The need for better understanding the causes of corporate financial distress and failure seems significant for the following reasons.

At the microeconomic level, the key determinants of company failure are considered as an important ingredient for decisions concerned with the assessment of commercial and investment risks. Models that quantify the risk of default or detect factors, magnifying the risk of failure of an individual entity, are central to any firm's financial transactions, which involve significant credit exposures in the process of conducting business operations. Initial evaluation of default risk of an individual asset or company also lays the foundation for risk measurement systems supporting decisions in the context of corporate lending, issuing the fixed interest finance to businesses, credit derivatives pricing, and valuation and analysis of distressed firms.

At the macro level, this issue has important implications of financial stability and economic growth. Given the potential severity of the economic and social consequences of sharp rises in company failures, the knowledge of factors that increase the corporate sector vulnerability to default and insolvency, can be of practical use to banks and public bodies, monitoring the national economic situation, in their design of policies preventing and ameliorating crises.

The risk of failure via legal insolvency is the uncertainty surrounding a company's ability to service its debt and obligations. Failure risk can be broken down into three main components. The first component is associated with high gearing, the second component relates to the firm's business risk, and the third component is aggregate economy risk that depends on the state of the business and credit cycles and changes in other background macroeconomic factors such as interest and exchange rates and factor prices. Because failure is a combination of different factors and mistakes, prior to the event, there is no way to unambiguously discriminate between firms that will fail and those that will not. Thus existing commercial applications for assessing the risk of default and failure as well as analytical tools, used in academic research into failing firms' characteristics, for the most part, have not been backed by an explicit theoretical model of the failure process.* Conventional approaches to failure modelling are based on the assumption that financial statement-based measures, equity and debt market quotations, and credit ratings capture both the unique characteristics of the firm's financial profile and macroeconomic pressures on the corporate sector. That has a direct bearing on quantitative models developed for purposes of risk management or identifying failure causes. Given the problem of model uncertainty, to arrive at specifications that reflect as much of reality as possible, extant studies have heavily relied on empirical techniques that permit statistical search through a sufficiently large number of model inputs, describing the financial profile and other characteristics of the firm. However, such approaches inevitably depend on quality of data inputs and to be of practical value resultant models need to be validated and recalibrated on a continuous basis.

Numerous studies have been devoted to empirically explain the event of UK company failure. **Taffler and Tisshaw** (1977), **Marais** (1979), **Taffler** (1982), **Goudie** (1987), **Goudie and Meeks** (1991) have modelled failure as the classification problem, where the binary response variable falls into one of two classes: failed firms and non-failed firms, and the risk of failure is then quantified using discriminant analysis combined with cross-sectional data and purely accounting ratios-based covariates. Alternative approach of using logit to model a causal relationship from firm's attributes to the probability of failure was utilised in studies by **Peel, Peel, and Pope** (1986), **Keasey and McGuinness** (1990), and

* We should, however, point out to one exception. A well-known commercial application with a theoretical backing is KMV's default risk model CreditMonitor®, based on the option theoretic model due to Merton (1974). The model's implementation rests on an extensive database of historical default and bankruptcy frequencies needed to generate the measure of default risk for an individual debt issuer.

Morris (1997). The relevance of the empirically derived failure determinants was inferred from the statistical significance of individual explanatory variables and further validated by the classificatory accuracy of a model, evaluated on a out-of-sample basis. The appropriateness of detecting the important determinants of failure within the framework of traditional binary response statistical models is evidential from the true *ex ante* predictive ability of such proprietary applications for assessing quoted industrial companies as the UK-based *Z*-score model (**Taffler**, 1995) and the US-based *ZETA*® model (**Altman**, 2000). More recent UK work by **Alici** (1995), **Tyree and Long** (1995), and **Wilson, Chong, and Peel** (1995) has employed a newer analytical approach of neural networks to classify the data. These models reveal slightly improved within-sample and out-of-sample predictive accuracy when compared with conventional discriminant and logit models, however, it is worth noting that the neural network literature has not yet provided generally agreed procedures for model selection and testing (**Fairclough**, 2000). In this thesis, the apparent performance of company failure models is not the ultimate objective, but only a means for elucidating the underlying phenomena. It seems equally essential for our research to perform statistical tests of significance for modelled determinants of failure. Therefore in both parts of the thesis - in the analysis of the UK company failure determinants for 1988-93, and in a comparative study of UK and Russian firms in the 1990s - we follow the classical approach of previous UK and US work and employ logit as a methodology for statistical modelling of the relation between the risk of failure and changes in financial-ratio based explanatory variables.

Compared to past studies into UK company failure, there are two distinguishing features of our empirical work.

Firstly, in the analysis of the failure determinants using pooled cross-sectional data, we try and extend a common range of financial inputs by allowing for the non-financial factors that appeared to be important variables in the studies of the aggregate rate of business failure by **Wadhwani** (1986), **Hudson** (1987), **Young** (1995), in the macro-micro study by **Goudie and Meeks** (1991), and in the study of corporate growth and survival by **Dunne and Hughes** (1994). Specifically, we try to introduce into conventional cross-sectional analysis the "firm's age effect" and two variables reflecting changes in the macroeconomic climate. Our contribution is to better investigate the relevance of traditional financial ratio-based determinants, when the probability of failure is conditioned on unanticipated changes in the nominal interest rate and in the real effective exchange rate. We examine a relatively large unbalanced and resembling the true population proportions, cross-sectional data set of UK quoted industrial companies, covering the 1990-92 recession. To briefly anticipate our results, we find the important independent explanatory role for unexpected changes in interest and exchange rates, which are overall positively linked to the probability of failure. However, the "firm's age effect" appeared to be less pronounced when its incremental impact upon the probability of failure is judged by an improvement in the models' out-of-sample classificatory accuracy. As for accounting-based measures, we find that gearing, liquidity, and profitability determine failure of the firms in our sample.

Secondly, we explore the use of panel data and a fixed effects logit estimator, which allow us to capture both cross-section and time-series variation in financial ratio-based inputs and formally model unobserved heterogeneity across firms by controlling for unobserved firm-specific fixed effects. We utilise an unbalanced panel of UK quoted industrial companies for six years, from 1988 to 1993. Estimates of the fixed effects specifications for the "financial profile-failure risk" relationship provide an interesting comparison with estimates from our cross-sectional analysis. A robust empirical result, consistent with the observation in **Turner, Coutts, and Bowden** (1992), is that the shortage of liquidity is the main factor that discriminates between failing and non-failed firms in our samples, which implies that over the 1990s recession even some profitable, viable companies might have experienced difficulties with accessing short-term finance.

The main emphasis in this thesis is on the identification of the key failure determinants for UK quoted industrial companies, however our work also makes a contribution to the Russian transition literature by looking at the causes of industrial enterprise insolvency in the mid 1990s. It might seem unusual to examine in one piece of research the phenomena of company failure for economic, institutional, and legal settings as different as those of the UK and Russia. The reason for doing so relates to our aim to consistently apply the modelling methodology advocated in previous UK research, to the Russian case, and to contrast the two different populations of firms. To date no benchmark empirical work on Russia exists, and historical data on company failure, especially in the time dimension, are scarce. Therefore it seems sensible to use a comparative study format to investigate the important, observable from enterprise statutory accounts determinants of failure. Moreover, this format allows us to control the small sample results for Russia by indirectly inferring the Russian model performance and the relevance of explanatory variables, from a similar in empirical design, small-scale study of UK firms.

Although the small cross-sectional data set of Russian firms is still a valuable source of information about why enterprises failed via legal insolvency in the 1990s, we have to deal with an additional issue of judging model accuracy in the absence of fresh holdout observations. We follow the UK studies, based on discrete-outcome models, by **Fairclough and Hunter** (1998) and **Hunter and Komis** (2000) and attempt to solve the problem by using bootstrap simulations to evaluate the relevance of the modelled determinants of failure. We set bootstrap confidence intervals for model parameters and assess model classificatory accuracy by using the resampling scheme due to **Adkins** (1990) and procedures due to **Efron and Tibshirani** (1993).

We find that the dimensions of liquidity and financial indebtedness are not effective in explaining failure for Russian companies, whereas the measures of profitability and size appear potentially to be robust predictors. Companies of smaller size and lower profitability are more likely to become bankrupt. The Russian results are remarkably consistent with the views, expressed in **Commander and Mumssen** (1998) and **Schaffer** (1998), on the role of soft budget constraints and all-pervasive barter transactions in the Russian corporate sector.

The plan of the present thesis is as follows. We start in chapter 1 with a discussion of the UK and US literature that deals with the definitional issues, outlines a wide range of factors, associated with the process of company failure, and provides the theoretical background for empirical modelling. A basis for the analysis of company failure is given by a mix of finance, economics, law, and management literatures that offer various theoretical considerations as to the plausible causes of default and failure. Then there is a summary of the macroeconomic factors' influence uncovered by the studies of the aggregate rate of business failure. The goal of chapter 1 is to highlight the firm-level and macroeconomic characteristics driving corporate default and failure, which would seem to be desirable to capture in empirical models.

Chapter 2 presents a survey of previous UK and US empirical research concerned with explaining the causes and predicting the event of failure of industrial companies. We consider evidence in relation to failure determinants obtained with data from financial statements and market valuation information. The survey also summarises existing approaches to failure modelling by discussing the main elements of their empirical design that include: adopted sampling procedures, statistical techniques chosen, identification and selection of relevant explanatory variables to be used as model inputs, and solutions used in model validation under the limited amount of data. Theoretical considerations and previous empirical findings on the determinants of company failure allow us to suggest three research questions. In particular, as an extension to the UK firm-level research into failure causes, we wish to examine more directly the apparently missing in extant cross-sectional models link between the changes in macroeconomic conditions and failure risk for the 1990-92 recession. Further, by taking account of company unobserved heterogeneity in a panel-data analysis, we aim to develop new insights about the features of the firm's financial profile that explain UK company insolvency in this period. In addition, highlighted in previous UK and US work the value of financial ratios, as effective predictors of distress and failure, has been the source of inspiration for suggesting to carry out an exploratory study of Russian firms.

Chapter 3 deals with the cross-sectional analysis of UK quoted industrial company failure using the binomial logit estimator. In our empirical design we recognise and account for the methodological issues of non-stationarity in data and bias in the model parameter estimates, introduced by the samples non-representative of the true population proportions. The determinants of failure implied in four separate sets of models are reported, each set representing a series of time-to-failure-specific models for the four years before the event. These four sets of logit models include: (i) models based on financial inputs alone; (ii) models based on financial inputs and augmented with macroeconomic variables; (iii) models based on financial inputs and a control for firm's age; and (iv) models based on financial inputs, controlling for firm's age, and augmented with macroeconomic variables. More complete models that condition predictions on unanticipated changes in the nominal interest rate and in the real exchange rate, demonstrate the best out-of-sample classificatory accuracy over both short and long risk-horizons, indicating importance of the interrelationship between the key determinants. The contribution of this chapter is to reflect in modelling the multifactor basis of the failure process by the means of detecting financial characteristics of failing firms when the risk of failure is conditioned on the effects of changes in the macroeconomic environment, and firm's age is controlled for.

The results from the cross-sectional analysis are followed in chapter 4 by a panel-data study that uses a less conventional and sophisticated methodology of the fixed effects logit estimator. To obtain unbiased estimates for the failure determinants, we allow for unobservable permanent individual company effects in the data while exploring the relationship between the firm's financial profile and the risk of failure. The contribution of this chapter relates to the use of panel data for modelling the causes of UK company insolvencies over the 1990-92 recession.

Chapter 5 concentrates on the comparative study of failure determinants for Russian and UK firms. Based on data for enterprise insolvency in Russia for 1995-96, a model of failure risk is developed using the binomial logit estimator. The sample size is controlled by the bootstrap estimates of model statistics and by comparison with a similar random sample drawn for the UK over the recession years 1990-91. The contribution of this chapter is that we have uncovered an interesting feature in the Russian data set, specifically, we observe that profitability and size differences between failed and non-failed firms were the key discriminating variables, while, in contrast to the UK case, but not inconceivable, liquidity and financial indebtedness seemed irrelevant.

Chapter 6 concludes with a brief summary of results and suggests policy issues and research questions for future work.

CHAPTER 1: BACKGROUND: DEFINITION AND CAUSES OF COMPANY FAILURE

1.1 Introduction

Our purpose in this chapter is to provide a selective overview of the literature concerned with the nature, definitional issues and theoretical arguments for a formal representation of such diverse and chaotic phenomena as company financial distress and failure. This overview sets the scene for the subject of this thesis - empirical analysis of failure determinants for an individual company in the UK and Russia, for the 1990s. The discussion of applicable fundamental propositions made in the areas of the theory of the firm, corporate finance and management studies will be presented. It covers the dominant effects of economic inefficiency implied in poor profitability, geared capital structure, liquid asset insufficiency, declines in market capitalisation, unfavorable changes in macroeconomic conditions, and poor managerial decisions. A summary of a range of more formal models specifying the conditions for company default and liquidation is provided. The chapter also briefly describes the institutional setting for company insolvency representing a legal mechanism for resolving financial distress. Interrelations between underlying company financial collapse fundamental causes, illustrated by the published across several areas and reviewed in this chapter studies on the subject of failure, will provide guidance for structuring our empirical analysis of a complex interplay between firm-specific characteristics, environmental factors and managerial mistakes, motivating an econometric investigation reported in the last four chapters.

1.2 What is Company Failure

A voluminous literature providing stylised facts on the determinants of the company failure outcome at the firm level dates back to **Beaver** (1966) and **Altman** (1968). Despite extensive empirical research, company failure remains a vague concept and suffers definitional ambiguity. The notion of failure can be set out in a number of ways and therefore empirical investigations at the company level have explored a wide range of phenomena and provided insights into different aspects of economic and financial distress. The absence of a generic category of failure, however, complicates comparisons.

Taken to the extreme, company or business failure can be defined as closure or discontinuation of a legal entity (**Watson and Everett,** 1966). At the other end of the spectrum represented by much of the industrial economics literature on entry and exit, the semantic content of the term "company failure" usually relates to firm's exit from the product market (see, e.g., **Jovanovic,** 1982; **Mueller,** 1991; **Agarwal and Gort,** 1996; **Caves,** 1998). From this angle, failure is seen as a manifestation of the Schumpeterian "creative destruction" through which the market selects between efficient and inefficient firms (**Schumpeter,** 1942). According to neo-classical analysis, the probability of a firm's survival for a given interval of time is a function of a vector of market attributes such as, for example, growth in demand, barriers to entry, scale economies, and a vector of attributes that relate to the individual firm. Insufficient profitability is the main factor that in the long run forces the firm to reduce its presence in the market and exit the industry. Poor operating performance is not tolerated for long. Firms that do not supply the product at the competitive price-cost margins face difficulties in generating profits and exit due to the inevitable discipline of factor and product markets. Obviously, failure in the economic sense need not be accompanied immediately by financial distress arising from debt finance, liquidity shortages and external financing constraints. Market exit can simply be viewed as a set of strategic decisions made by the firm regarding the use of its inherited configuration of capital. The market exit decisions are made by the firm in response to unanticipated changes in demand and competitive conditions. Through the selection process the assets of poor performers are being reallocated to presumably better uses while the assets of good performers are retained within the firms and kept in their most efficient use. Within this framework, company failure can be viewed as a welfare-enhancing device and way of re-allocating industry-specific resources.[1] It is noteworthy that the role of a geared financial structure that exposes the firm to financial risk is usually disregarded in the embodying the economic efficiency concept models of market exit.

Financial and legal dimensions of the failure process are featured in approaches employed in the areas of financial economics, law, and the business studies. Financial distress is induced by the firm's financial structure. In high-geared firms, a small decline in operating performance will trigger financial distress. Classical research of company survivability in these areas emphasizes the importance of factoring in the capital structure considerations while the synonymous terms "corporate failure" or "company failure" is specified as the inability of a distressed company to meet debt obligations due to liquidity shortages. Under this perspective, the situation of failure subsequently involves losses incurred by the company's creditors and a need to resort to bankruptcy or insolvency mechanisms available within a legal system of the country in order to secure payment of the creditors' claims. Understanding financial failure is of great importance because firms that default on their debt affect the financial position of their creditors. That poses a threat to financial stability in the economy when an individual company failure is symptomatic of a more widespread corporate sector problem, leading to contagion, which could trigger further defaults. Since the inability to make debt payments may be resolved through liquidation and possibly acquisition of a distressed firm, financial failure is viewed as a selection mechanism leading to substantial asset reallocation away from financially distressed firms. Financial distress is often accompanied by organizational restructuring (**Wruck**, 1990; **Sudarsanam and Lai**, 2001). Comprehensive organisational changes in management, governance and structure can create value for the firm's claimholders by improving the use of resources. Financial distress frees resources to move to higher-value uses by forcing managers and directors to reduce capacity and rethink operating policy and strategy decisions. Financial distress will also create value when the firm value is the highest in liquidation and the

[1] It should be noted, however, that a firm might disappear from the industry as a result of a merger. Rivals possibly may acquire the successful firm's assets and expertise and apply it to the products of both firms. In this case exit comes from success.

management is reluctant to liquidate. However, there is little and contradictory evidence on the efficiency of financial distress and insolvency procedures while theoretical propositions on benefits of financial distress have not yet been validated and quantified in empirical studies. (see, e.g., **White**, 1989 and 1994; **Kahl and School,** 2001).

In investigating the selection process triggered by financial distress, the concept of failure has a comparatively restricted meaning, corresponding with legal usage: it usually means that a company has become involved in certain legal consequences because it defaulted on its debt obligations. Defaults can be technical and/or legal and always involve the relationship between the debtor-company and creditors. Default proper involves a missed payment of either principal or interest, i.e. it means that a debt that is due remains unpaid. Technical default is the violation of a debt covenant other[2] then one specifying principal and interest payments. The consequences will depend on the contents of the debt contract. Although in reality technical defaults can be and are renegotiated, they still signal deteriorating financial performance of the firm (**Altman,** 1993). Legal default or default proper is more serious than technical default, and may lead directly to a formal insolvency regime. If the company, unable to meet or renegotiate the cash claims upon it, exercises its right to default on payments, that usually follows by the firm's creditors instituting legal proceedings whereby all claims against the company are settled. The corporate finance literature links financial failure to the presence of long-term debt in capital structure noting however that even an all-equity-financed company may be pushed into insolvency if, for instance, it incurs a sequence of profits insufficient to meet its fixed commitments to workers and suppliers or fulfil obligations in relation to actual or potential damages from litigations.

Financial distress is not synonymous with corporate death in terms of discontinuation of a legal vehicle of the business. However, the tractable legal event of entering an involuntary insolvency regime by a debtor-firm does manifest severe financial distress. In essence, in operationalising the complex concept of company failure, the finance

[2] Such covenants can place restrictions on dividends or additional borrowing.

literature, uses a discrete variable, recording the presence in a company's history of such easily observable events of financial distress resolution as involuntary insolvency or bankruptcy (see, e.g., **Altman**, 1968; and **Taffler,** 1982 and 1995).

Although the occurrence of financial failure measured by involuntary insolvency is attributed to debt financing and the lack of liquidity, it ultimately depends on the limits of lenders' willingness to support the firm. The latter is linked to the tightness of the terms of finance. The creditors' right to liquidate can be easily exercised when lending is collateralised and concentrated in the hands of a single lender (**Armour and Frisby,** 2001). A rational secured creditor will cease supporting the firm where the returns from enforcement are greater than the returns from negotiations. The failure of a firm to meet its financial obligations does not always lead to bankruptcy because creditors can take over the distressed company or extend the maturity of the debt upon default. Often creditors forgive small shortfalls in order not to bear bankruptcy costs or transfers to other creditors (**Scott,** 1981).

The evolution of financial distress invites attention to the resolution of financial distress via quick acquisitions of poor performing firms. A financially distressed firm may become an acquisition target when the creditors observing the performance of the company in distress favour taking voting equity stakes in the firm in exchange for (partial) debt forgiveness. Therefore the literature sometimes ascribes the "negative" meaning of failure to status of those firms that lost independence in acquisitions or mergers (e.g., **Hoshi**, 1998; **Peel**, 1990; **Taffler**, 1995). **Taffler** (1995) differentiates between the outright failure of a business, an equivalent of a legal insolvency state, such as administration, receivership, or creditors' voluntary liquidation, and certain alternative events which may range from acquisitions, capital reconstructions, involving loan write-downs and debt-equity swaps, to informal government support and guarantees. This line of thinking puts on a parity liquidation and acquisition, stressing the ultimate importance for businesses to continue trading as independent firms. It may be noted that there are grounds to remain cautious when interpreting acquired firms as failures. Although financially distress cannot be excluded as a context for acquisition, corporate finance theory offers other interactive motives for acquisitions and mergers, not always associated with or explained by the causes of financial distress and debt default (see, e.g., excellent discussions in **Copeland and Weston** (1988) and **Peel** (1990)). For some insolvency-free, financially sound and fast-growing acquired companies, the acceptance of a merger or take-over invitation constitutes a strategic move and positive outcome to the owners.

The questions of existence and evolution of economic organization are dealt with in the field of the theory of the firm. Although our reading of the literature reveals no an all-purpose analytically convenient theory of the firm, features of the existing theories of the firm are useful for better understanding of a complex multidimensional phenomenon of corporate financial failure. In the next section, we sketch out some of the ideas that can be adopted for explaining survivability of economic organization.

1.3 An Overview of Theories of the Firm

1.3.1 The Neo-classical Explanation: The Firm-as-Production-Function Model and Economic Inefficiency as a Failure Cause

Neo-classical theory considers the firm mainly in technological terms, as a theoretical link to facilitate an explanation of the price system (see, e.g., **Kreps**, 1990; **Keasey and Watson**, 1993; **Hart**, 1995; **Mas-Collet, Whinston and Green**, 1995). The neo-classical model has been especially useful for analysing how the firm's optimal production choice varies with input and output prices, for understanding the aggregate behaviour of an industry, price-mediated market equilibrium and efficient social production and allocation of private goods. In the neo-classical world, the firm is run by a selfless owner-entrepreneur, who is motivated by a desire to maximise his own, exogenously determined, subjective preferences. The central concern of the neo-classical framework is that equilibrium market prices are determined by equating the supply and demand of goods by utility maximising entrepreneurs. The further assumptions of perfectly competitive markets with many market participants, homogeneous commodities with respect to quality and costless information and trade are usually made for the determination of relative prices. This implies that all arbitrage opportunities will be instantly competed away and no practical problems associated with business transactions exist.

Note that in the spirit of the neo-classical model of the firm and market structure, failure is defined as exit from the product market and serves as the means of removing inefficient firms from the industry[3]. The conditions for market exit can be established on the basis that the privately owned firm is an entity, which has an objective function, profit, which it maximizes, subject to constraints imposed by its set of technological capabilities, factor prices, and the demand curve faced by the firm. Note also that the underlying this conceptual structure economic definition of profit refers to rates of return in excess of the opportunity cost of capital employed and return to entrepreneur. An implication of the model of profit-maximising behaviour is that whatever level of output the firm chooses to produce it would do so at the minimum possible costs.

According to the firm-as-production-function theory, exit of a competitive, profit-maximising firm, operating under conditions of certainty, is implicit in its cost curves in the short and long runs. The short-run restrictions are that levels of some of factor inputs are fixed and the firm minimises costs of the variable factors or short-run variable costs, which implicitly depend on the levels of fixed costs. In the short run, the firm must always pay its variable costs, regardless of the level of output. If, in the short run situation, the total variable cost curve lies above the total revenue curve at every level of output, that is the resulting economic profit is negative, then the profit maximising firm produces nothing and loses fixed costs only. In the long run, all costs are variable and should be covered, and if the long-run competitive equilibrium price fails to cover long-run average costs, the established firm will be induced to exit from the industry. One

[3] In a classical paper, Fama and Jensen (1983) suggest that " the form of organisation that survives in an activity is the one that delivers the product demanded by customers at the lowest price while covering costs".

might expect that the firms that do not obtain best practice input-output combinations, would necessarily earn inferior profits and would, as a result of that, be forced out of the market. In this respect, in the long or medium run, failure reflects economic inefficiency. On average, the firm must earn normal profits in order to cover economic costs and any firm that fails to generate a return on capital employed comparable to that obtainable in other equally risky markets, eventually exits the market and its resources will be transferred to other uses.[4] **Buchanan** (1939; pp. 29-30; emphasis in original) put it best when he said that in the narrow economic sense the enterprise is a failure if there has been misdirected investment:

> ... failure means simply that the returns to capital invested in the opportunity, which the promotion was designed to exploit, have in fact fallen short of those expected, that, instead of the realized returns being *greater* than those elsewhere available, they have actually proven to be *less*. ... Otherwise expressed, we might say that, costs being computed on an alternative opportunity basis *at the time the enterprise began*, are in excess of returns. ... The enterprise is a failure in the sense that, had this state of affairs been anticipated, the corporation would not have been brought into being.

The neo-classical model of market exit indicates the importance of the market structure and implies that economic success can be gauged using the concepts of profitability and economic returns while economic distress is associated with inefficiency.

Writers in the area of company failure draw a distinction between financial distress and economic distress. Economic distress, being associated with inefficiency, the firm's decisions on output, entry and exit, and the market structure, manifests itself in poor operating performance in terms of sales or operating profits hence the underlying business problems might make liquidation of the company a valuable option. Financial distress is the effect of geared capital structure, when the firm has trouble with meeting the interest and principal payments on its debt and with extending credit. A firm may be

[4] This does not, of course, imply that all loss-making firms leave the industry and discontinue as legal entities, or that those that exit, will do it instantaneously. Ability to raise external finance influences the length of the failure process. Credit allows firms to smooth losses or profits over time, while financial markets permit to reduce the cost of capital.

in financial distress without being in economic distress, although the two may be linked to one another and often happen together (**Wruck,** 1990). On the other hand, a firm may experience economic distress without being in financial distress because of the absence or near absence of legally enforceable debt (**Altman,** 1983). An attempt to empirically investigate the connection and the direction of a causal relation between financial distress and economic distress has been made in **Opler and Titman** (1994), who examined corporate performance in distressed economic sectors of the US for the period of 1972-91. They implicitly assumed the exogeneity of *ex-ante* leverage ratios and measured economic distress by a decline in sales and negative stock returns. Their results seem indicative of the link from financial to economic distress since the findings show that companies with a high relative to the industry leverage ratio, tend to lose market share and experience lower operating profits during economic downturns than their more conservatively financed competitors. Opler and Titman conclude that firms in financial distress may tend to underperform. In contrast, for the UK context, **Goudie and Meeks** (1991) notice no necessary connection between legal failures and firms that are economically inefficient, because sudden changes in the macroeconomic environment such as interest and exchange rates variations or errors in government policies may eliminate economically viable enterprises.

Dixit and Stiglitz (1977), who consider market structure and exit conditions in the monopolistically competitive industry constrained on the demand side, emphasize the role of product diversification in preventing economic distress. They show that, in a monopolistically competitive industry, the equilibrium will lead to a bias against the firms supplying products that are characterized by inelastic demand and have high fixed costs and low marginal costs, as compared with a constrained Pareto optimum, where each firm must have nonnegative profit. The Dixit and Stiglitz analysis with heterogeneous consumers and social indifference curves suggests that inelastically demanded commodities are specialised products desired by a few consumers. Profit maximising firms, dealing with those products, are especially vulnerable to economic

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Although profitability is clearly a crucial factor in the process of exit form the market, it must be considered in distress and are likely to exit the industry. That results in less variety for consumers and entails distortion in allocation of resources from the social point of view. Multi-product firms might be able to stay in the industry if there would be a possibility to divest unprofitable product lines or absorb losses with cross-subsidies. The cross-subsidizing strategy would be selected if the product is in the early phase of its life-cycle and discounted expected returns over the period of production cover the costs associated with cross-subsidies. Otherwise firms who impose barriers to entry may not be forced to a part on the cost curve where losses become a significant burden.

Traditional economic models of market exit make little statements about the existence or discontinuance of the legal entity. An inefficient firm might choose to close voluntarily. Normative decisions to shut down business operations are likely to be based on expected returns and the ability of the firm to cover its variable costs. The firm should liquidate unproductive capacity when the productivity of an individual asset (i.e. a plant) falls below the firm's marginal gain from operating it. There should be a critical value of the asset's marginal product, below which the asset should be liquidated, and above which it should be retained. Liquidation may take two different forms, closure when demand is low and selling out to more productive users when demand is high. Thus a firm's decision to liquidate a plant will depend on its productivity and also on industry and macroeconomic conditions, although inefficient transfers by bankrupt firms are likely to be severe in times of industry downturns.

We note the failure of the neo-classical model to utilise the importance of the financing mix for explaining exit of an economic organisation due to financial distress. First, by assuming an ideal world of perfect and complete capital markets, neo-classical theory renders financing decisions irrelevant because the value of the firm can be solely determined by its ability to generate positive cash flows (**Modigliani and Miller,** 1958 and 1963). Since the firm's ability to generate cash flows is independent of the financing decision, its value will be irrelevant to how the cash flows are split between

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combination with capitalisation variables.

different capital suppliers. Therefore, the choice of capital structure will not affect the value and thus survivability of the economic organisation. In reality, capital markets are imperfect and geared firms facing severe liquidity problems and externally imposed capital rationing may be unable to avoid negotiating their debt contracts with creditors in legal insolvency proceedings. Bankruptcy caused by debt default can be effective in forcing firms to scrap assets when demand is low. However, when demand is low, both the value of the assets and the difference in value between efficient and inefficient firms is also likely to be lower. Therefore the value of bankruptcy in weeding out inefficient firms might not be high. It is also obvious that failure in the economic meaning of an excess of average cost above average revenue need not to be accompanied at once by financial difficulties resulted from the geared capital structure and subsequent inability to meet debt obligations as they mature.

Second, the neo-classical set-up ignores incentive problems within the firm and incomplete and costly contracts between agents. Neo-classical theory supposes that all transactions, including employment relations, ownership rights and financial structures, are contingent contracts that can be costlessly negotiated and perfectly enforced without legal disputes. The neo-classical model ignores the costs incurred by agents in solving a set of problems from initially making a contact with potential buyers and sellers through to obtaining restitution should one party default on an agreement. Even when the neo-classical theory incorporates some separation of ownership from control it supposes that managers will always make decisions that are in the best interest of owners (or shareholders) since information is symmetric. The once orthodox view that the firm is a production function has been re-thought in the new institutional economics literature, which preserves a role for financial instruments in explaining survivability of the firm.

1.3.2 The New Institutional Economics: The Role of Debt Finance in Financial Distress

In relation to establishing the consistent relationships underlying the process of company failure, the contributions made by the studies in the new institutional economics suggested a new perspective on the implications of capital structure decisions and gearing levels for financial distress. We summarise below the relevant to our present concerns ideas grown out of the new institutional economics work.

1.3.2.1 The Firm as a Nexus for Contracting Relationships

Approaches, abandoning the concept of the entrepreneur-owner and the firm-as-production-function model, have been developed in the new institutional economics literature, in particular under the rubrics of "transaction cost theory" and "agency theory" which have many applications in corporate finance. This literature focuses on the effects of information and the structure of ownership and financial claims in controlling and rewarding conflicting agents. The main approach in investigating behavioural implications of individual property rights is to consider the firm as a set of contracts among factors of production, with each factor motivated by its self-interest. Transaction cost economics posits that due to uncertainty about the future states and information asymmetry, writing an internal or external contract, specifying an incentive scheme, is difficult and costly. Therefore contracts are not comprehensive, being revised and renegotiated as the future unfolds. The primary reason is that, under uncertainty, it is costly to plan for various contingencies, difficult to negotiate about these plans, and hard and costly to write these plan down in such a way that in the event of a dispute, an outside authority can simply enforce the contract. As a result, contracts contain gaps and missing provisions, which the parties can fill as they go along. It is important to note, that the re-negotiation process imposes *ex post* costs, incurred at the re-negotiation stage itself, and others are *ex ante* costs, incurred in anticipation of re-negotiation. This theme of transaction costs lies at the heart of the large transaction cost literature, which started in a classic work by **Coase** (1937) on the existence of the firm and firm-market boundaries.

Coase's thinking about the firm suggests that the organisational forms that are able to deal effectively with transaction and agency costs are able to survive and prosper at the expense of others. Assuming that significant transaction costs are incurred in organising economic activities, Coase insists that the firm and the market are alternative modes for organising the very same transactions. The main reason why it is profitable to establish a firm is a cost of using the price mechanism of spot-markets. Thus, the firm is viewed as an institutional device whereby transaction costs can be reduced and factors can be hired on incomplete contracts. The property of an incomplete contact permits the subsequent direction of recourses to their most profitable uses as circumstances change.

Incomplete contracts are inconsistent with neo-classical market equilibrium. In reality, in many markets, there is neither a clearly defined commodity nor a clear-cut price. On the contrary, the relationships between the parties may need to be renegotiated in ways not fully anticipated at the stage of the initial contract. Thus, administrative intervention is needed to complement or replace the operation of market forces, not merely to enforce contract terms. However, even if re-negotiation proceeds smoothly, the outcome may depend on the *ex post* bargaining strengths of the parties rather on economic efficiency.

A radical contribution to understanding the economic nature and financial structure of the firm has been made by the writers in the agency tradition (see e.g., **Jensen and Meckling** 1976; **Fama and Jensen** 1983; **Jensen** 1986; **Agnion and Bolton,** 1992). Originated in financial economics, the "principal-agent problem" literature recognises that financial contracts - including debt contracts - are inherently and unavoidably incomplete but focuses upon the crucial role played by information and the structure of ownership and financial claims in controlling and rewarding conflicting and opportunistic agents in the environment of contractual incompleteness. Information is a subject that has obvious connections to the incentives and opportunities that exist for moral hazard (contractual non-performance) and transactions. The agency view suggests that agents do not give up their own self-interests just because they have entered into an economic relationship. As mentioned above, moral hazards and opportunism, particularly under the conditions of uncertainty and costly and asymmetrically distributed information, render fully state-contingent contracts impossible or excessively costly to draw-up, monitor and enforce. Having pointed out that the *firm is not an individual* and the personalisation of the firm seems a misleading approach, **Jensen and Meckling** (1976) assert that firms are *legal fictions*, which serve as a *nexus for a set of contracting relationships among individuals*. The value of debt arises from the contingent control allocation it induces. Most investment projects are sufficiently complex that it is difficult or very costly for the contracting parties – the entrepreneur and the financier - to make contracts contingent directly on the future states of nature and describe *ex-ante* precisely the most desired schedule of corresponding actions. Even if we abstract from the issue of bargaining under asymmetric information assuming that the contracting parties can perfectly identify which state of nature will occur, important future variables have to be left out of the contract as they are difficult to verify initially. However contracts can be made contingent on a publicly verifiable signal about the state of nature at some future date. Such signals may represent a variable of short-term performance (or profits) or a default-no-default event.

Debt financing is a natural way of implementing contingent control allocations of a particular kind. If the signal represents a default-no-default event then the entrepreneur gets control as long as he does not default on debt obligations but the creditor gets control in the event of default.

This view of the firm emphasises the important role the legal system plays in the organisation of economic activity. Law sets bounds on the kinds of contracts into which individuals and organisation can enter, while the powers of the state are used to enforce performance of contracts. Insolvency (bankruptcy) refers to the court-supervised process for breaking and rewriting the contracts. Liquidation refers to the sale of the firm's assets and distribution of proceeds to claimants. In relation to the financial distress resolution, insolvency law works alongside the institutional framework for the market of corporate control, providing distressed firms with mechanisms for exit through insolvency or acquisition.

It is necessary to note that these developments in the agency literature have been based on the assumption that the relevant unit of analysis of the enterprise behaviour is a large publicly traded quoted firm with dispersed power of many small shareholders who may find it difficult to exercise control. The firm has ready access to external capital markets for equity and debt finance. It is further assumed that the firm's equity shares are liquid, there are strong financial and regulatory incentives to obtain and process information on the firm, and that the capital market is efficient in processing this information. Fama and Jensen's model, which is now firmly established in the finance literature, emphasises the minimising of transaction and agency costs as the major motivation behind the choice of external market contracting (**Fama and Jensen**, 1983). According to Fama and Jensen, agency theory of the firm has several aspects. The most important contractual arrangement is the contracts that specify which agents have the right to any residual income (ordinary shareholders) and which agents are responsible for day-to-day control of the firm (managers). Control consists of two distinct decision processes, namely, the initiation and implementation of decisions, undertaken by professional managers, and the ratification and monitoring of decisions, overseen by the board of directors directly elected by the shareholder group. One type of agency problem arises from a potential conflict between control (managers) and ownership (equity holders), which leads to nontrivial monitoring costs the owners will incur in order to keep the agents (managers) in line. Furthermore, in a public company, dispersed power of shareholders creates a free-rider problem. An individual shareholder does not have an incentive to expend substantial resources to monitor the behaviour of managers since the gains from improved management are enjoyed by all shareholders, whereas the costs are borne only by those who are active. Because of the free-rider problem, the managers of a public company may have a fairly free hand to pursue other than the shareholders' wealth maximisation goal, including empire-building or enjoyment of perquisites. Consequently the owners face a trade-off between monitoring costs and forms of compensation that will cause agents to act in the interests of the owners. If the managers' compensation were all in the form of shares in the firm, the monitoring costs will be zero. But this is practically impossible since the agents will always be able to receive some compensation in the form of non-pecuniary benefits. The owners therefore would have to incur inordinate agency costs in order to ensure that the agents always make the decisions the owners would prefer. Especially relevant to the question of financial failure is the power of agency theory to shed light on the choice made by a modern corporation with dispersed ownership as to a particular debt-to-equity mix. It is convenient at this juncture, if, before outlining the factors proposed in the agency theory literature in relation to financing strategies as a means to overcome the agency problem between the owners and top management of the firm, we detour slightly to discuss a basic model of capital structure determination which weighs up the relative advantages and disadvantages of long-term debt finance and has important implications for understanding company failure in the form of insolvency.

1.3.2.2 The "Tax Shelter-Bankruptcy Cost" View on Debt

The "standard" theories of capital structure conclude that as far as company survival is concerned, gearing and financial risk are the primary causes of default and bankruptcy but there are both advantages and disadvantages to the presence of debt in capital structure. Capital structures of companies can be separated into two types. Companies can have either a capital structure, which consists entirely of equity capital, or a mixed capital structure where capital with a fixed rate of return (such as loan capital and preference share capital) and equity capital are held in varying proportions. Viewed more broadly, apart from debt and equity securities, financing arrangements to fund operations also include other claims that also promise fixed payoffs, issued to employees, managers, and suppliers. For the modern public corporation, the mixed capital structure is more common.

Financial gearing levels, indicating the proportion of debt capital in the firm's overall capital structure, are choice variables, arising from the budget constraints, therefore the capitalization of a company is a risk and return trade-off. The firm takes on the risk of fixed financing costs, anticipating that higher returns will accrue to equity holders at higher levels of demand. The effect of financial gearing is that, for a financially geared company, any increase in profit before interest and tax will result in a more that proportionate increase in the return to the shareholders after taxes. Assume that the basic earning power of the firm is given by the return on assets (ROA) that compares earnings before interest and tax with total assets. The basic earning power, being invariant to capital structure and the way the firm is taxed, is a measure of profitability, which is of utmost importance from the operating point of view. The relation between the return on shareholders' equity (ROE) and the return on assets (ROA) is a function of the proportion of debt used for financing and the cost of that debt finance. Introducing (FC) as the average interest rate on debt and (t) as the effective tax rate on the firm, we can write ROE as:

$$ROE = ROA + (ROA - FC(1-t))\frac{\text{Debt}}{\text{Equity}}. \tag{1.1}$$

As long as the basic earning power (ROA) is greater than the cost of debt (FC), debt financing will magnify the profitability contribution of the earning power. The magnification factor is the capital gearing ratio. The higher the degree of gearing, the greater the profits, so long as trading income exceeds the costs of servicing the debt. The amount the earning power could fall before the shareholders will be hurt by financial gearing is given by the term $(ROA - FC)$, which measures the excess returns on the firm's assets over the cost of debt. Relation (1.1) implies that higher returns may offset some of the negative effect of high gearing on the risk of debt default.

An efficient mix of debt and equity in the capital structure of a company reduces the price of long-term capital thus increasing net economic returns, which ultimately increases the firm's value. Fixed interest capital has an advantage of being cheaper to raise than equity while interest payments are allowable against profits for tax purposes by most tax systems. Equity is costlier to shareholders because, in liquidation, creditors are paid first. Preferences for having debt in the long-term capital structure may also stem from the shareholders' unwillingness to accept outside equity into the business, because of the dilution of control.

The theory recognizes that financial risk is attached to debt finance. Increased corporate debt in relation to equity, assets, or cash flows, entails a possibility of non-repaying interest and principal as promised in the debt contract, and is likely to lead to a greater probability of financial distress and bankruptcy (**Auerbach**, 1985; **Davis**, 1995; **Rees**, 1995; **Andrade and Kaplan**, 1998; **Crosbie**, 1998). A number of factors directly influence the ability of a firm to meet debt obligations. The key factors include: (i) profit stability determined in turn by the nature of the firm's product, the competitive structure of the industry, cyclical fluctuations and other aspects of the macroeconomic environment; (ii) the ability of the firm to generate cash flows; (iii) a level of fixed costs of production, which have to be paid irrespective of the level of sales and profits; and (iv) the market value of the firm's assets defining the relative burden of the firm's contractual obligations and default risk.

As discussed above, one advantage to having debt in capital structure debt relates to the tax deductibility of interest payments. These benefits, existing for companies in tax paying positions, are counterbalanced by costs associated with financial distress and bankruptcy. The inclusion of bankruptcy costs alongside the tax deductibility of interest payments, extended the pioneering work by **Modigliani and Miller** (1958) on capital structure irrelevancy by arguing that a value maximising firm may choose optimal capital structure consisting of both debt and equity (see, e.g., **Baxter**, 1967; **Myers**, 1977; **Brennan and Schwartz**, 1978; **Chen and Kim**, 1979; **Myers**, 1993). Research differentiates between the direct and indirect costs of bankruptcy to a distressed firm (see, e.g., **Giammarino**, 1989; **Altman**, 1993). Direct costs are out-of-pocket cash expenses directly related to bankruptcy filing and administration. Indirect bankruptcy costs of a firm in distress are expenses or economic losses that result from bankruptcy, but are not cash expenses on the process itself. These relate to the lost-profit component and include the diversion of management time while bankruptcy is underway, the impact on the firm's reputation, lost sales during and after bankruptcy, and the loss of key employees after a firm becomes bankrupt. **White** (1989 and 1994) adds to indirect costs those losses that are generated by inefficient decisions in relation to continuing, reorganising or liquidating; for instance, the value of forgone investment opportunities during bankruptcy procedure and the lost value of funds that are tied up during bankruptcy and incurred by the creditors and the economy. White considers bankruptcy costs as the "deadweight" economic costs of firms going bankrupt. **Armour and Frisby** (2001) present recent evidence from interviews conducted with UK insolvency practitioners that debtor goodwill would suffer through adverse publicity associated the commencement of insolvency proceedings.

The link between the level of gearing and the probability of failure is implied in the "tax shelter-bankruptcy cost" (TS-BS) theory, discussed in **Castanias** (1983), where financial failure is defined as a revenue outcome which is insufficient to cover promised, the end of period payments to debt holders. The probability of failure is endogenously determined by the choice of the level of debt, and given by the following basic model:

$$F = \int_{-\infty}^{B} g(E,R)\,dE \qquad (1.2)$$

where
B = face value of debt;
E = earnings before interest and taxes;
R = business risk parameter of earnings probability distribution (e.g., the variance);
$g(E,R)$ = probability of earnings level E, given R.

The TS-BC hypothesis predicts that a shift in the earnings probability distribution implies an increase in the probability of financial failure (relative to the level of leverage prior to the earnings distribution shift) and simultaneously raises the expected marginal default costs and lowers the expected marginal tax savings. Empirical tests conducted in Castanias (1983) support that firms choose shareholders' value maximising mixes of debt and equity on account of bankruptcy costs and the tax deductibility of interest payments.

In the TS-BS framework, the risk of financial distress is a function of both operating and financing risk. Business risk captures all elements of uncertainty of the income stream of the firm resulting from other than financing transactions. Included in this category would be such considerations as the firm's competitive position, the determinants of demand for its products, and the structure of its costs. One implication of TS-BS theory is that all companies, whether they be geared or all-equity financed, face the probability of being forced into bankruptcy. This fact is just one component of the concept of business risk and is allowed for in the required expected return on equity capital. Financial risk is linked to the element of uncertainty arising from inclusion of fixed-commitment debt financing in the firm's capital structure. The act of gearing up by a company has the effect of positively adding to the probability of the company's bankruptcy, due to the fact that if the company is unable to meet its fixed debt interest payments, then the debt holders have the legal right to liquidate the company in order to repossess their capital and unpaid interest. Therefore it is reasonable to expect companies with higher gearing and thus greater financial risk to run a higher risk of financial distress. However, the risk of distress and default will vary with the risk position of the debt issuer and the shape of the economy. Since the likelihood of debt default is a function of both operating and financing risk, one would expect companies with high operating risk to use less debt.

1.3.2.3 The Agency View on Benefits and Costs on Debt

Agency theory can explain capital structure without relying on taxes or costs of bankruptcy and draws attention to incentive alignment properties of debt finance. The agency view helps to support the case of debt finance, pointing out to the control and efficiency enhancing, positive effects of debt. Attempts to resolve information asymmetries and conflicts of interests between equity holders and managers can serve as explanations of observed in practice preferences for having in capital structure of the firm both debt and equity. Furthermore, agency theory assumes a conflict between managers (shareholders) and debt holders, which along with asymmetric information explains such contracting features as restrictive debt covenants that give rise to an agency cost of debt. **Jensen and Meckling** (1976) argue that an optimal level of debt finance can be obtained by trading off the agency cost of debt against the benefit of debt. Each of the two facets of the agency problem of debt is now considered in turn.

First, it seems desirable to have two different financial instruments such as debt and equity because of non-tax, organisational, and incentive benefits of a debt contract. Assume that the equity holders are wealth-constrained but they can raise new funds from outside investors. One possibility is to raise new equity finance, which means that new investors will take controlling interest in the firm. Another possibility is to borrow money from suppliers of debt finance and promise to make certain payments. A simple debt contract implies that if the firm does not make the payments, control shifts to debt holders raising the prospects for liquidation and reallocation of assets. It is useful to recall at this juncture that default is an attribute of any debt contract such as a bond or a loan. As **Davis** (1995) points out, debt contracts are incomplete financing contracts which do not specify the behaviour of the borrower in every eventuality, therefore it is uncertain whether or not a limited liability company will fulfill its promise to pay a debt. The outcome of corporate insolvency is simply the legal consequences of the event of default and inability of a company to pay its debts (**Scott**, 1981; **Brown**, 1996; **Goode**, 1997). Hence, a debt contract granting debt holders a fixed periodic payment and contingent control rights is a natural way of implementing contingent control allocations – debt holders cannot exercise control unless default has occurred[5].

A clear advantage of debt financing over equity financing is that non-payment of debt triggers a shift in control. By giving creditors a legal right to demand restructuring, a debt contract provides a specific type of discipline and monitoring of the managers' behaviour that is not available to an all-equity firm. The model due to **Agnion and Bolton** (1992) demonstrates that in the environment of contractual incompleteness, when equity holders are wealth-constrained, it may be optimal to transfer control from this party to debt holders. In an independent but related study, **Wruck** (1990) claims that default associated with debt finance, serves as a catalyst for organisational change. Where operating performance and the firm's value are deteriorating as a result of poor management decisions and weak governance, an earlier default can preserve value by increasing the likelihood that the firm will reorganise quickly and efficiently. Note that viewed in this light, default is not synonymous with liquidation, but it may result in either restructuring of claims or liquidation. However, this benefit of value preservation disappears when the primary cause of corporate defaults is exogenous shocks responsible for the removal of economically viable firms.

The agency theory way of thinking suggests that the "automatic" incentive devise provided by a geared capital structure may actually prevent economic and thus financial distress. Debt indirectly restricts non-value-maximising behaviour by corporate managers. By promising lenders a fixed stream of payments, the debt contract effectively links managerial rewards closely to the performance of the firm. **Jensen**

[5] The key difference between the equity and debt securities is the design of the control rights. Equity differs form debt by its cash flow claims and control rights. Equity holders are granted the unconditional right to dismiss the managers.

(1986) argues that high leverage aligns managerial incentives and minimises the inefficient use of "free cash flows". Default removes assets from managers' hands and thereby terminates any perquisites, which they can derive from the control of the firm. Where creditors have the right to replace the managers, the threat of dismissal induces the managers to perform better. It follows that debt financing gives managers an incentive to maximise expected returns and therefore a more efficiently run firm may have a reduced probability of financial distress. The incentive concept of debt expressly implies that, at the extreme, one may expect to find the inverse relationship between levels of debt and the risk of financial distress. However, Jensen's argument will work best when most of the variation of cash flow is idiosyncratic to the firm. When most of the risk is common across firms and debt is costly to negotiate, Jensen's theory may lose its appeal.

Second, the agency view explores further the disciplinary aspects of debt finance when it focuses on the conflict between debt providers and owners. The debt contract gives shareholders and managers the opportunity of wealth transfer from debt holders by investing sub-optimally in very risky projects. This aspect of agency theory supports the use of protective provisions in lending agreements with shareholders. Protective covenants are imposed by debt finance suppliers who are concerned with the riskiness of their position in situations where the management raise finance for a supposed investment in a low-risk project but, once the debt is issued, they use the funds to invest in a high-risk project (**Simpson and Anderson,** 1957). In these circumstances, debt holders might suffer because there is insufficient equity capital to carry the risk. Thus the expected rate of return for debt holders would not properly reflect the risk of their investment. In order to avoid this sort of situation, debt suppliers might impose covenants on loan agreements that constrain managers' freedom of action. Debt covenants may carry restrictions on subsequent financing, on dividend policy or may prohibit disposing of major fixed assets without the debt holders' agreement. All this implies an agency cost to the firm of using debt finance. A violation of a debt covenant represents technical default, which may not necessarily lead directly to a formal insolvency (bankruptcy), but nonetheless signals the deteriorating financial performance of the firm and increasing chances that the company's cash flow will not be sufficient to meet these fixed debt interest payments. Because the management of a company hold "undiversified portfolios" as far as their labour is concerned, to them the cost of bankruptcy is very substantial - they lose their employment. Therefore, management are given an incentive to take actions that reduce gearing and the probability of bankruptcy so as to avoid the very substantial agency costs involved.

A great deal of insight into the link between the financing mix, unanticipated redistribution of wealth from debt holders to shareholders, and the likelihood of default has been obtained by applying the Black-Scholes approach to option pricing in analysis of capital structure choices. The option theory story of the conflict between equity holders and debt holders seems to fit well with the agency cost ideas. **Black and Scholes** (1973) and **Merton** (1974) suggest that the equity in a geared firm, organised as a limited liability company, can be thought of as a call option. When equity holders issue debt that is equivalent to selling the assets of the firm, but not the control over the assets, to debt holders in return for proceeds from the debt issue and a call option. Assume for simplicity, that the firm issues zero coupon bonds secured by its assets, there are no transaction costs or taxes, there is a known non-stochastic, risk-free rate of interest, and there are homogeneous expectations about the stochastic process that describes the market value of the firm's assets. The value of the equity holders' position is equal to the discounted value of the bonds and a call option. If on the bonds' maturity date, the value of the firm exceeds the face value of the bonds, the shareholders will exercise their call option by paying off the debt and keeping the excess. But, if the market value of the firm is less then the face value of the bonds, the equity holders will default on the debt by deciding not to exercise their option. It should be realised however that option pricing theory assumes the possibility of unanticipated redistributions of wealth. However, debt holders can protect themselves from anticipated redistributions of wealth by charging an adequate rate of return or by writing debt covenants restricting the actions of shareholders.

This section has discussed seminal theories of the firm that contribute to understanding the causal processes underlying financial distress and financial failure of companies. The traditional, firm-as-production-function model of the firm relating survival to profitability shows that market exit of inefficient firms heightens the efficiency of asset allocation. However, the traditional technological model does not deal with the financial risk factor and largely ignores the genuine differences in relative risks of distress attributed to geared long-term capital structures. Differences in financial instruments and their role in the evolution of economic organisation have been accounted for in the models of the firm displayed in the studies from new institutional economics. In this field, several theories, combining arguments from corporate finance and economics, have been put forward to explain the relation between the observed in practice financing mix types and failure in the form of involuntary insolvency triggered by debt default. The logic of new institutional economics sheds light on the differences between economic and financial distress. The main import from the theories of transaction cost and agency relationships is that capital structure measures should be regarded as an important independent factor defining the likelihood of financial failure due to default on debt payment. However, the state of modern theory of the firm does not allow to devise a unified analytic framework for empirical analysis of the determinants of company failure in the form of involuntary insolvency.

1.4 The Institutional Framework: A Legal Mechanism for Resolving Financial Distress

In discussing the selection process triggered by financial distress, it is desirable to consider the institutional framework that shapes exit of firms via the bankruptcy route. Insolvency (or "bankruptcy", in the US context) is a public policy aimed at the promotion of general welfare, which could be served by the protection of creditors and efficient asset reallocation as well as by the rehabilitation and organisational survival of debtors. The usefulness of insolvency (bankruptcy) proceedings as a mechanism to resolve financial distress of companies requires strong creditor rights and judicial efficiency. Creditors are more likely to undertake the costs of bankruptcy if they are able to effectively use courts in case of default.

Bankruptcy law determines the allocation of power between the firm and its financiers. UK and US bankruptcy procedures are different. US law imposes significant restrictions on the contractual rights of lenders in the event of default, especially the liquidation rights of senior lenders (see, e.g, **Franks and Torous** (1994), **Suarez and Sussman,** 1999; **Franks and Sussman** (2002)). In the US, Chapter 11 of the 1978 Bankruptcy Act includes a lengthy automatic stay, the exclusive right of the debtor to remain in control of the company, to submit a reorganisation plan, and to raise new supra priority financing. Within the US legal framework for bankruptcy, courts are accorded much discretion about the extent of the company's relief from its creditors. In contrast, the UK approach to insolvency has been characterized by the strict enforcement of creditors' contractual rights, including the litigation rights of secured creditors. In sum, UK insolvency law tends to concentrate power in the hands of the secured creditors, whereas US bankruptcy law favours the company and unsecured creditors.

When a company fails to pay a debt on its due date, the lender is entitle to avail himself of all the rights and remedies given to him by the debt contract and insolvency laws, including the institutions of legal proceedings against the borrower. However, the company's inability to pay debts does not automatically give rise to legal consequences for the company unless a formal insolvency procedure is commenced. For instance, a petition to compulsorily wind up a company can be presented if it is unable to pay its debts, or an administrative receiver can be appointed. At this point, under the 1986 UK Insolvency Act, two primary tests of insolvency may be applied for the purpose of relevant statutory provisions (**Goode**, 1997). The first test is a short-term measure of insolvency that is the company's inability to pay its debts as they fall due (unless the debt is disputed), and is known as the *cash flow*, or *going-concern*, or *commercial insolvency test*. The company may be cash-flow insolvent and unable to pay its way in the conduct of business, but yet still have sufficient non-liquid assets, so that on the long-term view it is solvent. The second alternative test is the *balance sheet* or *assets test* which employs a wider expression of the term *debt* and establishes whether the company's assets are insufficient to discharge its liabilities,[6] taking into account prospective and contingent liabilities. A cash-flow based definition of insolvency means that a firm is unable to meet current cash obligations, while the balance-sheet based definition indicate the firm's negative economic worth. It is possible that a firm may be insolvent on a balance-sheet basis but solvent on a cash-flow basis and in this case the firm's creditors have little power as their claims are paid to date (**Wruck,** 1990). Both tests require an analysis of the debtor-company's financial position and involve an element of projection, the cash flow test because the court looks to see whether the company's inability to pay its debts as they fall due is purely temporary, and the balance sheet test because it is required to take into account prospective and contingent liabilities. Proving either test to the satisfaction of the court is sufficient for the purpose to attract statutory insolvency proceedings against the company.

In the UK, there are five distinct legal regimes for handling a failing company, namely: administrative receivership; administration; winding-up (liquidation); statutory compromises, compositions and arrangements with creditors; and reorganisations (*workouts*[7]), which are arranged contractually outside the framework of corporate insolvency law (**Goode,** 1997). Administrative receivership is a creditor-oriented procedure. There was an opinion that in the early 1990s, the large number of administrative receivership (Table A1.1 of appendix 1) represented precipitate behaviour of secured lenders (banks), causing viable companies to fail. (Insolvency Service (2001): *Insolvency - A Second Chance*)). Though winding up is the fate of the most insolvent companies, it is not that every insolvency leads to liquidation. The

[6] There is a difference between the legal and the accounting concept of assets and liabilities. Both law and accountancy distinguish between capital transactions, in which an asset is acquired for a price, and revenue transactions, in which rent is paid for the use of another's assets, or some other revenue expenditure is incurred. But the law concentrates on the *location of title*, whereas accounting standards focus on *economic substance* (Goode, 1997).

[7] A workout is the restructuring of debt. Workouts usually involve lower direct costs than receiverships or administration, because the time, spend in informal reorganisation, is generally much shorter (Chatterjee, Dhillon, and Ramirez, 1996).

introduction of company voluntary arrangements (within or outside the administration procedure) and the use of non-statutory bank-led workouts, facilitated by the London Approach,[8] aimed at increasing scope for business rescues.[9]

As mentioned above, the legal criteria for company failure are used in the world of business by practitioners.[10] For instance, credit management systems of banks and credit agencies in defining the default event apply criteria of importance, transparency, and lack of ambiguity. Commonly used as the nominated default event are clear events of financial distress (formal insolvency regimes as well as rating downgrades) and payment defaults on obligations above a nominated threshold after the expiration of a specific period. Insolvency-based events are most easy to ascertain, because the presentation of bankruptcy petition or the winding up order is a matter of public record, and the event and the date it occurs is relatively easy to establish. For other quasi-insolvency events timing and occurrence issues are less clear cut (**Brown and Chance,** 1998). For instance, defaults to banks might be negotiable - it is sometimes up to the bank to decide when a borrower has problems. Unless forced, it might not be in the bank's interests to do so, because its shares would be hammered. Debt reschedulings and restructurings that frequently undertaken to avoid payment default or legal insolvency are affairs that can run for many years. Loans may be non-performing for several years without being called into default. The consequence of such definitional imprecision is that academic research into causes of corporate distress and failure commonly choose the state of legal insolvency as an operational proxy for the event of failure.

[8] London Approach restructurings used during the early 1990s' recession by a small number of very large companies, are orginised by banks and aim to maximise value for creditors by avoiding unnecessary collapse of potentially viable enterprises as a result of disagreements between creditors (Kent, 1994; Belcher, 1997).

[9] In the 1990s, most notably in the USA and France, a so-called "rescue culture" of rehabilitation of the enterprise has been identified. The proposed reforms of UK insolvency laws place great importance on both formal and informal rescue regimes to reverse actual or to avert imminent insolvency of the enterprise (Brown, 1996; Belcher, 1997; Goode, 1997). As a result of rescue procedures attempting a "turnaround", the failing company may restore solvency and profitability and continue trading. In this sense company failure associated with temporary distress would not lead to liquidation.

[10] For instance, *business failure*, the term adopted by Dun & Bradstreet, a leading supplier of relevant statistics on businesses, applies to the following firms: (i) those that cease operations following assignment or bankruptcy; (ii) those that cease with loss to creditors after such actions as executions, foreclosure, or attachment; (iii) those that voluntary withdraw, leaving unpaid obligations; (iv) those that have been involved in court actions such as receivership, reorganisation, or arrangement; and (v) those that voluntary compromise with creditors. In 1990, the business failure total in the USA, reported by Dun & Bradstreet, was slightly less than the number of business bankruptcy filings (Altman, 1993).

In relation to the distinction between financial and legal dimensions of failure, **Brown** (1996) draws attention to the fact that even liquidation does not necessarily connote failure of the business (commercial enterprise) as opposed to its legal vehicle, the company. The business of the company may be saved by a sale, or the assets being hived down to a new subsidiary established for this purpose.

1.5 Corporate Finance Theories of Corporate Bankruptcy

As mentioned earlier, company failure research at the firm level does not rest on a unified, coherent analytical model linking together the factors underlying company failure. The major implications of models proposed in the area of theory of the firm for company failure research have been considered in section 1.3. The aim of the present section is to review the developments that have been used in the field of corporate finance to explain in a more formal way the process of financial failure. We begin with a brief description of the theoretical approach employed in **Laitinen and Laitinen** (1998), who are interested in the impact the cash management behaviour makes upon company liquidity during an early phase of financial distress. Then the discussion turns to the treatment of company default by Merton's model (**Merton**, 1974) and to theoretical predictors developed in **Scott** (1981) for the final stage of distress represented by liquidation of an individual company. Scott (1981) derived his analytical models with the purpose to discover the logic underlying the forecasting success claimed by some commercial models of long-term (balance-sheet) solvency.

1.5.1 Cash Management Behaviour of a Distressed Company

The cash management approach uses a dynamic theoretical framework of reserve (inventory) cash management models to depict the behaviour of a financially distressed firm and to predict failure. Constituting financial failure events of legal insolvency, bond default, an overdrawn bank account, or non-payment of a preferred stock dividend are originated in the failure to fulfill the cash balance requirements (**Beaver,** 1966). Therefore, it is reasonable to assume that the cash management model of a financially distressed firm will systematically differ from one of a "healthy" firm and that the difference may be useful in explaining failure.

Laitinen and Laitinen (1998) advanced a dynamic model of the cash management behaviour and attempted to empirically test whether the parameter estimates of cash management models had additional explanatory and predictive power when these variables were utilised alongside conventional accounting-based determinants in modelling distress. Failure of short-term management of corporate cash balances refers in their model to an imbalance between cash inflows and outflows, which leads to illiquidity or the inability of the firm to pay its financial obligations as they come due. The Baumol-Tobin cash reserve (inventory) framework and its extensions (**Baumol,** 1952; **Tobin,** 1956)[11] was chosen as a model of demand for money. Assuming the firm's demand for money depends on the volume of transactions, the objective of the model, subject to cash balance requirements, is to minimise the costs of cash management. The transaction (liquid) assets consist of two types: cash and a secondary asset which is interest bearing. The cash management problem in this framework deals with the apportionment of the transaction assets between these two types. Each transaction between the asset types causes a lump sum (fixed) cost (a) and a variable cost (b) proportional to the volume of transaction (transaction costs), and an opportunity cost of holding cash because of foregone interest earnings (at the rate of interest i). The total volume of transactions to cash (S) is needed to finance the difference between (periodic and instantaneous) cash inflows and cash outflows (occurring at a constant rate) in a fixed period (t). At the beginning of the period, this amount is invested as a secondary asset, and will be transferred to cash in equal parts (A) during the period. This leads to the average cash balance of ($A/2$) and to the opportunity cost of ($i(A/2)$). The

[11] The theoretical background of demand for money has been developed by macro economists like Fisher, Pigou, Marshall, Keynes and Friedman. Keynes (1936) classified the factors affecting the demand for money in three categories: transaction, precaution, and speculative motives. The transaction motive is caused by the lag between cash inflows and outflows, which leads to the need for cash as a buffer. The view of the firm as a reservoir of liquid assets, which serves as a buffer against variations in the flows, formed the core of the approach adopted by Beaver (1966), in one of the early empirical studies of the determinants of failure.

number of transactions during the period (t) is ($N=S/A$). Thus the total cost of cash management is the sum of opportunity and transaction costs:

$$C = i(A/2) + a(S/A) + bS \ . \tag{1.3}$$

The size of transferred optimal volume A minimising total costs is:

$$A^{*} = (2aS/i)^{0.5} \, . \tag{1.4}$$

That leads to the following optimal long-term average cash balance:

$$M^{*} = A^{*}/2 = (aS/2i)^{0.5} = (aN/i)^{0.5} \, . \tag{1.5}$$

Expression (1.5) gives 0.5 for the elasticity of optimal cash balance with respect to the rate of fixed costs (e_a), to the volume of transactions (e_S), and to the number of transactions (e_N) as well as –0.5 for the elasticity with respect to the rate of interest (e_i).

Assuming (a) is a constant, the simple static model of the actual cash balance of a firm in period (t) can be given in the logarithmic form by a multiplicative function of (S) and (i):

$$\ln M(t) = \ln D + e_s \ln S(t) + e_i \ln i(t) + u(t) \, . \tag{1.6}$$

where (t) refers to the period, (D) is a scale constant and ($u(t)$) is a random variable.

Within the Baumol-Tobin framework, the financial distress behaviour is based on the analysis of how the values of the parameters of specification (1.6) react to the peculiar cash management behaviour, when the firm is in financial distress. Distress means that the firm has a shortage of cash and, as a result, the maximum attainable cash balance ($M_U(t)$) is very close to the cash balance leading to the liquidity crisis ($M_L(t)$), therefore, for a distressed firm, the difference ($M_U(t) - M_L(t)$), or the range, in which the cash balance can vary, is small. This means that generally only a small, if any, proportion of the cash is available with respect to the motive factors $S(t)$ and $i(t)$. Thus, expression (1.5) for a financially distressed firm would yield the lower absolute values of elasticities of cash balance ($M(t)$) with respect to the volume of transactions (e_s) and to the rate of interest (e_i), than the values for a similar "healthy" firm.

Further, in order to describe the distress behaviour, the dynamic cash management model introduces an adjustment process, according to which the actual cash balance tends to adjust towards the optimal balance. Total adjustment costs ($C(t)$), consisting of both the costs due to imbalance between the optimal and actual cash balance and the costs due to the adjustment towards the optimal cash balance, are approximated by squared functions as follows:

$$C(t) = \alpha(M(t)) - M^*(t))^2 + \beta(M(t) - M(t-1))^2, \tag{1.7}$$

where (α) is the rate of imbalance cost and (β) the rate of adjustment cost.

This leads to a partial adjustment model given by:

$$M(t) - M(t-1) = y(M^*(t) - M(t-1)) . \tag{1.8}$$

The adjustment is assumed to take place at a constant rate, periodically, and (y) measures the speed of adjustment:

$$y = \alpha/(\alpha + \beta) . \tag{1.9}$$

If β=0, then y=1 and the actual cash balance is immediately adjusted to the optimal balance because there are no adjustment costs.

For a firm in financial distress, ($M(t-1)$) may be less than ($M^*(t)$), and due to financial distress, the change may take place downwards so that ($M(t)$) is below ($M(t-1)$). Consequently, imbalance costs after the change, are greater than in the previous period (t-1) since ($M^*(t) - M(t) > M^*(t-1) - M(t-1)$). The behaviour of a distressed firm may lead to the situation as if the rate of imbalance cost (α) is negative and the rate of adjustment cost (β) positive. The negative values of (α) might be such that ($|\alpha| > \beta$) would result in a value of (y) greater than unity, and may exceed the rate for the similar "healthy" firm. It follows that, the larger the differences in estimates of the adjustment rate between a distressed firm and its counterpart, the shorter is the time for bankruptcy.

The cash management behaviour framework implies the importance of liquidity and cash management factors for explaining and modelling company failure. The upshot of the argument made by Laitinen and Laitinen is that the model demonstrates the direct link between environmental changes, captured in their model by the interest rate, and switches in the cash management behaviour[12].

1.5.2 The Merton Model of Company Default

The work published by Merton in 1974 has extended the approach by Black and Scholes (1973) and Merton (1973). Merton infers the probability of default for a quoted company from the valuation of assets and liabilities of the company. The model states that a company is in default when the market value of the company's assets falls below the book value of its liabilities. The original variant of the model assumes that the event of default occurs only at the maturity of the debt, but in later versions this assumption has been relaxed. The event of default depends on the volatility of a company's assets, as measured by the standard deviation. Merton's approach posits that if there is a great variation in the change in the value of the firm's assets over time, the range of possible values may include a default point. However, if the value of the debt is fixed and the value of the firm's assets grows with time then that in itself will reduce the likelihood of default. The financial distress evolution is represented by the standardised *distance to default*, given by the difference between the expected value of the company's assets and the book value of debt at that point in time, divided by the standard deviation of the value of the assets. To derive the underlying value of a company's assets from the value and volatility of its equity and the book value of its liabilities Merton then applies option

[12]A test of the Baumol-Tobin framework consistency and explanatory value for failure prediction of the parameters that enter static and dynamic equations for the cash management behaviour, has been performed in Laitinen and Laitinen (1998) with data on 82 Finnish distressed firms. Empirical results from multivariate logit showed that a model based on the cash management variables only, achieved poor classification accuracy on the estimation sample. When used in combination with traditional financial determinants, the cash management variables from the static model again did not provide information incremental over the benchmark financial variables. On the estimation sample, the dynamic model was clearly outperforming the static model in failure prediction as the estimates for the scale elasticity of cash in the dynamic model provided information that had incremental value. The classification error rates of the combined model for the year one before failure had slightly, by about 6 per cent, been reduced. Apparently, the theory did not agree well with the data examined.

pricing techniques (see **Black and Scholes** (1973) and **Merton** (1973)). Assuming the probability of default follows a standard normal distribution, the probability of default of an individual quoted company can be easily evaluated.

1.5.3 Scott on Theoretical Predictors of Company Liquidation

A Single-period Model

The single-period model of bankruptcy (**Scott**, 1981) is based on a firm that lasts for two periods. Its securities are traded in the current period and it will be liquidated next period. If (V_1) is a random variable representing the market, end-of-period value of a hypothetical firm and if (D_1) denotes the amount owed to creditors, then the firm will go bankrupt, in the sense of having negative net worth or being long-term insolvent, if

$$V_1 < D_1. \tag{1.10}$$

Assuming that (V_1) has a two-parameter probability distribution with parameters (μ_v) and (σ_v), we can standardise both sides of inequality (1.10) and obtain the following condition for bankruptcy:

$$\frac{V_1 - \mu_v}{\sigma_v} < \frac{D_1 - \mu_v}{\sigma_v}. \tag{1.11}$$

Now, if $F[\cdot]$ represents the cumulative distribution function for $(V_1 - \mu_v)/\sigma_v$, then the probability of failure equals $F[(D_1 - \mu_v)/\sigma_v]$.

Notably, this model favours as empirical predictors of liquidation both the market value of equity and the estimates of liabilities from financial accounts. As formula (1.11) contains only stock variables, namely the next debt payment (principal and/or interest) and the expected market value of the firm (debt plus equity) at the next debt payment, and no flow variables, the model does not capture factors linked to illiquidity and hence failes to explain the power of existing empirical predictors represented by flow accounting values and earnings variables.

A Gambler's Ruin Model

The gambler's ruin models (e.g., **Borch,** 1967; **Wilcox,** 1976; **Santomero and Vinso,** 1977) assume that the firm has a given amount of capital, (K), and that changes in (K) are random. Positive changes in (K) result from positive cash flows from the firm's operations. Losses require the firm to liquidate assets. Implicitly this model assumes the firm is completely cut off from security markets and can not raise funds via debt or equity issues. When (K) becomes negative, the firm is declared bankrupt.

Assume that accounting values can serve as surrogates for liquidation values. If (K) is the liquidation value of shareholders' investment, measured by the book value of equity, and (Z) is the change in (K), represented by the change in retained earnings, then in terms of standardised variables the firm goes bankrupt if

$$\frac{Z-\mu_z}{\sigma_z} < \frac{-(\mu_z + K)}{\sigma_z}. \tag{1.12}$$

Both a stock variable and a flow variable appear in the gambler's ruin model. The stock variable represents the gambler's stake, and is measured by the liquidation value of the firm's physical assets. The flow variable is represented by the next period change in retained earnings (net income minus dividends and equity repurchases).

Dividing the terms of expression (1.12) by the value of total assets yields the following theoretical predictor:

$$\frac{\mu_z / TA + K / TA}{\sigma_z / TA}. \tag{1.13}$$

Scott (1981) pointed out the correspondence between the variables in model (1.13) and some empirically derived determinants of failure represented in the risk evaluation model *ZETA*®[13] described in **Altman, Haldeman, and Narayanan** (1977). Like

[13] In the analysis by Scott (1981), *ZETA*® was viewed as a benchmark empirical model of commercially proven predictive ability. Altman (2000) reports that, in the late 1990s, the *ZETA*® model based on the liner discriminant function was still being used by practitioners throughout the world. The *ZETA*® variables include: a size measure

ZETA®, the gambler's ruin model contains stock variables, which reflect the financial position at a point in time, as well as flow variables that involve estimates of the firm's future cash flow distributions. For instance, the ratio of retained earnings over total assets in *ZETA*® is close to the ratio of shareholders' equity over total assets, (*K/TA*), in (1.13). The ratio of earnings before interest and tax over total assets in *ZETA*® is similar to (μ_z / TA). The standard error of the ratio of earnings before interest and tax over total assets is close to (σ_z / TA). However, the *ZETA*® model includes the additional determinants which are absent from the gambler's ruin model (1.13).

A Model with Perfect Access to External Capital

The idea of this model is similar in spirit to the option pricing model by **Black and Scholes** (1973) and **Merton** (1973). The option pricing framework recognises equity as a call option which is written on the value of the geared firm. Limited liability implies that equity holders have the right, but not an obligation to pay off debt holders and take over the remaining assets of the firm. The firm is essentially owned by the holders of other liabilities until those liabilities are paid off in full by equity holders. Thus, equity is the same as a call option on the firm's assets with a strike price equal the book value of the firm's liabilities. Default or bankruptcy occurs when asset value falls below the values of the firm's liabilities.[14] The risk of a firm going bankrupt depends critically on the beginning market value of the firm's assets relative to its external debt as well as the volatility of the market value of the firm's assets.

In the model with perfect access to external capital a firm has a potentially infinite life and can meet losses by selling debt or equity in an efficient market without incurring

given by the log of total tangible assets; profitability and earnings stability measures expressed by the level and standard deviation of the ratio of earnings before interest and tax divided by total assets; the current ratio measuring liquidity; the ratio for debt service expressed as the log of earnings before interest and tax divided by total interest payments; the ratio of cumulative profitability expressed by retained earnings over total assets; and the ratio of the market value of common stock over the market value of total capital (Altman, 1993). We discuss the *ZETA*® model in chapter 2.

[14] KMV Corporation, the market consultancy, presents empirical evidence from a sample of several hundred companies, which suggests that, in general, firms do not default when their asset value reaches the book value of their total liabilities (see Crosbie, 1998). Many firms continue to trade and service at this point because the long-term

flotation costs (**Scott**, 1976 and 1977). The model assumes that the secondary market for real assets is imperfect and the firm's initial level of assets is optimal. The firm can also sell assets but does not choose to do so. It remains solvent as long as shareholders' wealth, measured in terms of market value, remains positive.

Formally, the firm fails if

$$S + X < 0, \tag{1.14}$$

where (X) represents the next period earnings (loss), and (S) the optimal value of equity in the next period (ignoring the loss).

The determination of whether a given loss will bankrupt the firm is based on the following scenario. First, shareholders ignore the loss and determine the optimal asset and debt structure and a financial plan to achieve that structure. They then observe what the value of their equity would be, given the optimal plan and ignoring the loss. If this optimal value exceeds the loss, they avoid bankruptcy by first carrying out the plan and then selling just enough additional equity to pay off the loss. If the optimal value of their equity is less than the loss, the firm fails. Thus, this theory is dynamic in the sense that it assumes that management act optimally when faced with solvency-threatening losses.

In terms of standardised variables, the bankruptcy condition is:

$$\frac{X - \mu_x}{\sigma_x} < \frac{-(\mu_x + S)}{\sigma_x}. \tag{1.15}$$

If a group of firms shares the same two-parameter probability distribution for earnings, $F[\cdot]$, then $F[-(\mu_x + S)/\sigma_x]$ equals a firm's probability of failure. The higher the $((\mu_x + S)/\sigma_x)$, the lower the probability of failure.

The transformation of (1.15) with scaling the terms by total assets and multiplying by minus one yields the following predictor:

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nature of some of their liabilities provides them with a breathing space. KMV Corporation finds that the asset value, at which the firm will default, lies generally between total liabilities and short-term liabilities (Crosbie, 1998).

$$\frac{\mu_x / TA + S / TA}{\sigma_x / TA}. \tag{1.16}$$

All of the variables in model (1.16) are likened to the $ZETA^{®}$ variables in **Altman, Haldeman, and Narayanan** (1977) and affect the probability of bankruptcy in the same direction. For instance, the ratio of earnings before interest and tax over total assets in $ZETA^{®}$ is close to (μ_x / TA), whereas the standard error of earnings before interest and tax to total assets is similar to (σ_x / TA).

Unlike the single-period and gambler's ruin models, the perfect-access model bases the prediction of bankruptcy on both the internal earnings variables (μ_x, σ_x) and the external stock market variable (S). The presence of a market valuation variable is an important practical advantage, because a low stock market value does not just predict bankruptcy it actually increases the probability of bankruptcy. The market value of a firm's stock determines the amount of external capital the firm can raise to avoid going bust (**Beaver,** 1968). Thus, the lower the market value, the lower the borrowing capacity and potential for survival.

The gambler's ruin model and perfect-access model have generally agreed with empirical predictors, for example, with commercial applications reported in **Altman, Haldeman, and Narayanan** (1977) and **Crosbie** (1998).

A Model with Imperfect Access to External Capital

For the more realistic case of imperfect external markets, **Scott** (1981) derived a criterion that contains both a liquidation value of the firm's existing assets, as in the gambler's ruin model, and the present value of the firm's future cash flows, as in the perfect-access model.

To change the perfect access model into a model with imperfect access, Scott allows that a firm must pay flotation costs, there are no personal taxes, and securities are efficiently priced. Real assets can be bought and sold in perfect secondary markets. For simplicity, it is assumed that the firm has no debt but can issue equity. Investors are risk averse with homogeneous expectations; and future single-period interest rates are constant and certain.

Suppose that there are three distinct points of time, denoted 0, 1, and 2. The current period is period 0. A firm can exist until period 2, at which time it will be orderly liquidated.

To write the expression for the probability that the firm will go bankrupt at period 1 Scott introduces the following variables. Shareholders' equity at period (i) is given by (K_i). ($X_i[K_{i-1}]$) is income of the firm when i=(0,1), and the value the firm would have in an orderly liquidation when i=2.(X_i) is a random variable that can take any real value. Each realisation of this random variable is an increasing, concave function of (K_{i-1}). Net investment at period (i), a decision variable, is denoted by (I_i); so ($K_i = K_{i-1} + I_i$). The market value of the firm's equity at period (i) is given by ($S_i[I_i]$); (r) is the rate of interest, and (c) is flotation costs per unit of equity sold.

Shareholders' wealth at period 2 will equal $\max[X_2[K_1], 0]$ because equity has limited liability. Since investors are risk neutral, the market value at period 1 is given by

$$S_1[I_i] = \frac{E_0[X_2[K_0 + I_1]]}{1+r}, \tag{1.17}$$

where (E_0) represents the partial Lebesque-Stieltjes expectations operator with a lower limit of integration equal to zero.

Due to flotation costs, the optimal level of (I_1) and thus (S_1) will depend on the level of income ($X_2[K_0]$).

Let shareholders' wealth at period 1 be denoted by (*SW*), then

$$SW = \begin{cases} S_1[\bar{I}_1] + X_1[K_0] - \bar{I}_1 & \text{if } X_1[K_0] \geq \bar{I}_1 \\ S_1[X_1[K_0]] & \text{if } \bar{I}_1 \geq X_1[K_0] \geq \underline{I}_1, \\ S_1[\underline{I}_1] + (1+c)(X_1[K_0] - \underline{I}_1) & \text{if } \underline{I}_1 \geq X_1[K_0] > \underline{I}_1 - S_1[\underline{I}_1]/(1+c). \end{cases} \tag{1.18}$$

In (1.18) ($\bar{I}_1$) is the optimal level of investment when income is sufficiently high and investment is funded from income, while ($\underline{I}_1$) is the optimal level of investment in the case when income is low and the firm must use the externally-raised funds.
According to (1.18) the bankruptcy takes place when shareholders' wealth reaches zero:

$$S_1[\underline{I}_1] + (1+c)(X_1[K_0] - \underline{I}_1) \leq 0. \tag{1.19}$$

A financially distressed firm maximises its value by setting ($I_1 = \underline{I}_1$) The difference ($S_1[\underline{I}_1] - (1+c)\underline{I}_1$), which is the maximum of the present value of future earnings less current investment, can not be negative, because ($S_1[\underline{I}_1] \geq 0$) by limited liability, and ($I = 0$) is a feasible investment decision. Therefore, bankruptcy requires that ($X_1[K_0]$) be negative. If ($S_1[\underline{I}_1]$) is insufficiently large the firm goes bankrupt at period 1.

Defining ($\underline{K}_1 = K_0 + \underline{I}_1$) and rewriting (1.19) in terms of standardised variables we obtain:

$$\frac{X_1[K_0] - \mu_x}{\sigma_x} \leq \frac{-\mu_x - (K_0 - \underline{K}_1) - S_1[\underline{I}_1]/(1+c)}{\sigma_x}. \tag{1.20}$$

Then, given that the firm is faced with earnings losses, the term ($K_0 - \underline{K}_1$) can be interpreted as the amount of assets it is optimal for a distressed firm to sell, and the term ($S_1[\underline{I}_1]/(1+c)$) represents the maximum amount of equity (after flotation costs) a financially pressed firm making optimal decisions can sell.

The bankruptcy criteria of the gambler's ruin and perfect-access models (1.12) and (1.15) are special cases of (1.20), i.e. as ($c \to \infty, S_1[\underline{I}_1]/(1+c) \to 0$), and the firm is forced to meet all earnings losses with sales of assets. If ($c \to 0$, $\underline{I}_1 \to \bar{I}_1$), the firm will rely more heavily on the equity market to cover losses and the imperfect access model approaches the perfect access model. If, in addition, the firm has already achieved its optimal capital stock, then at the optimum, ($I_1 = 0$). Under these conditions, (1.20) is identical to the perfect access criterion (1.15).

Condition (1.20) implies that the firm's income, initial levels and changes in market values of shareholders' equity, and the rate of interest are factors that might be relevant for empirical examination of insolvency.

1.6 The Influence of the Macroeconomic Context

Company survivability is influenced by the environmental factors. The links between the changes in overall economic conditions and aggregate rates of corporate liquidations have been in the focus of a large number of studies based on economy-wide-level information. The examples of investigations answering the question about the rate of company liquidations include **Bernanke** (1981), **Altman** (1983), **Wadhwani** (1986), **Turner, Coutts and Bowden** (1992), **Davis**, (1995), **Young** (1995), **Cuthbertson and Hudson** (1996), **Robson** (1996), **Assadian and Ford** (1997), and **Gray** (1999). Work on aggregate liquidations has found that the important among the environmental factors are cyclical swings in economic activity, shifts in factor prices, credit availability, changes in real and nominal interest rates, and movements in exchange rates. Research results in the macro-level strand of the company failure literature have merits for potentially explaining regularities observed at the level of individual firm.

Bankruptcy risk is a counter-cyclical variable (**Bernanke**, 1981; **Altman**, 1983). Sales and earnings of companies are directly related to overall business activity with most defaults occurring during or immediately after recessions, which are often coincident with periods of monetary and fiscal constraints. The link from recession to bankruptcy is influential in imperfect capital markets, which prevent companies from being able to borrow as much as they would to cover cash flow shortages resulting from a fall in demand for their products and services.

Figure 1.1 illustrates what happened to the UK corporate sector when the 1990-92 recession set in. Company insolvencies rose steadily from 1980 to 1985, by which time the overall number had roughly doubled. Then they fell back sharply to the level of 1982 between 1986 and 1988 and began to accelerate in 1990. The 1992 figure is roughly three times that of 1989. However it should be borne in mind that, in the UK, in the mid-1980s company formation was unusually rapid, and the failure rate could be expected to rise during the recession.

At the time, failures were located primarily in the South-East outside London, Scotland and the South-West, indicating a higher failure rate among companies

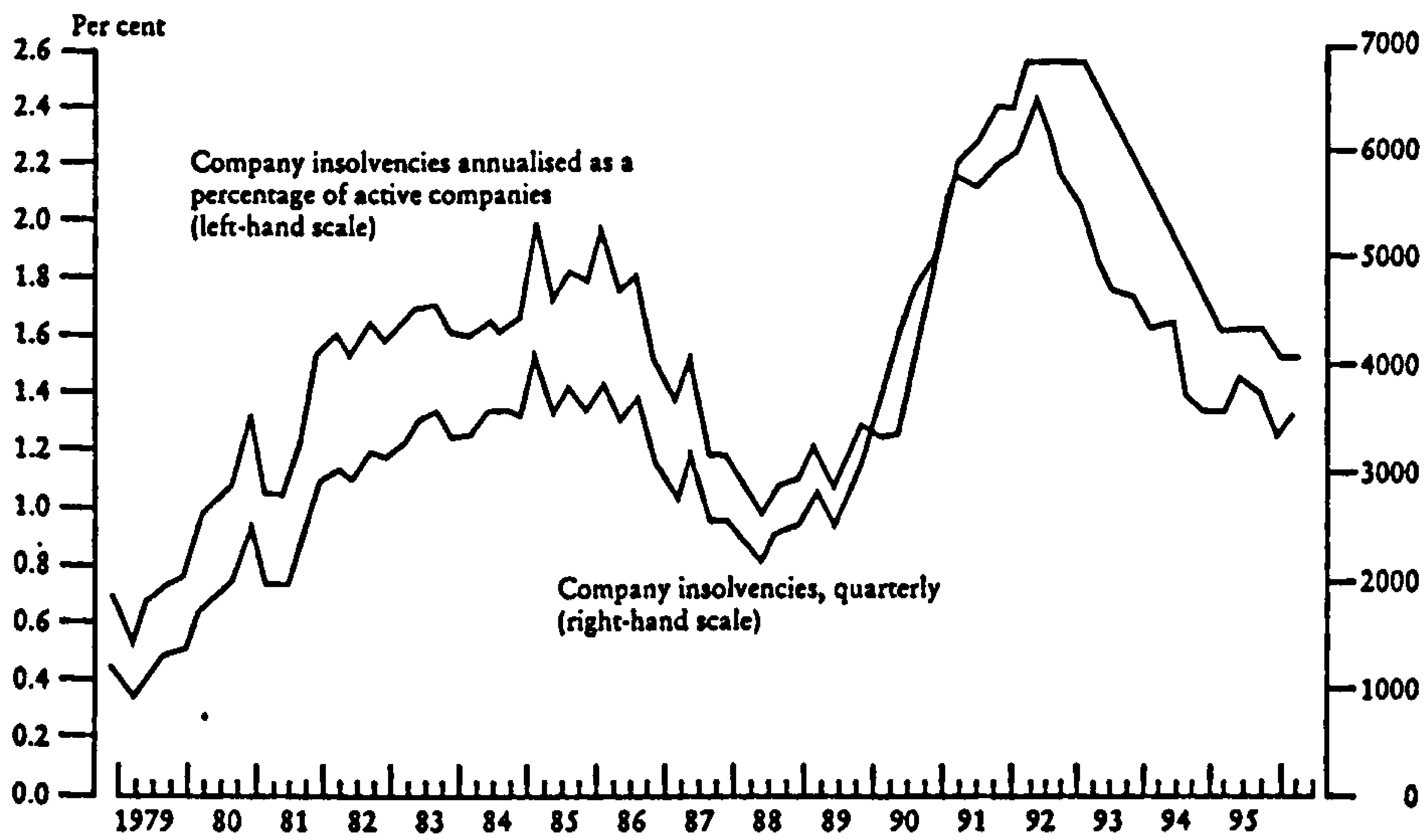

Figure 1.1 Company insolvencies in 1979-95 (adopted from "Understanding the UK Economy", 1997).

formed in the late 1980s. A credit crunch existed throughout the 1990s recession, when the banks became unwilling to lend to the companies that got into trading difficulties. Not only the banks widened the gap between the interest, at which they could borrow, and the rate, at which they lent, but also they disposed of their collateral when payments secured by that collateral cease to be made, and shut down companies, which, in better times, they would have been willing to support ("Understanding the UK Economy", 1997).

In recessions, firms are severely affected by a collapse in demand, which creates financial distress by narrowing the margin between cash flows and debt service. **Bernanke** (1981) suggested a link between the economy-wide level of bankruptcy risk and the propagation of recessions. In the period of recession, the initial fall in national income may be propagated through the economy via a multiplier mechanism. Given costly bankruptcy, there would be a general attempt to ensure solvency. Even given the assumption, that, at the outset of recession, only a few were at zero liquidity or going bankrupt, the need to guard against the risks of low liquidity would be a factor in the economic behaviour of most agents. Consumers and firms would be careful to retain sufficient liquid assets to meet fixed expenses. Lenders would tighten credit by both charging the interest rate that includes a premium compensating for the increased risk of default, and setting loan sizes below what borrowers would like. That leads to a reduced demand for consumer and producer durables – which in turn generates further income reductions. One profound implication of this theory is that company failure is industry sector-specific. The largest impact on company survival is predicted to occur in sectors producing long-lived, illiquid goods.

Altman (1983) empirically tested the impact of diminishing GDP activity on the US business failure rate for 1950-79 by including the percentage change in real GDP in the set of explanatory factors. Other macroeconomic factors affecting companies' financial position included credit and liquidity constraints as defined by the nation's monetary stock M2, investor expectations, and changes in business formation. The results indicate the negative effect of changes in real GDP on the rate of business failures but, somewhat counter-intuitively, did not support the link from the rises in interest rate to the propensity of firms to fail.

In contrast, econometric studies by **Wadhwani** (1986), **Young** (1995), **Davis** (1995), **Cuthbertson and Hudson** (1996), where a careful look at the aggregate rate of company liquidations in the UK was taken, produced evidence suggestive of a strong link between the changes in the real and nominal interest rates and company failure incidences.

Wadhwani (1986) presents theoretical considerations that declining profitability and interest rates are the key determinants of corporate insolvencies when debt is not indexed and capital markets are imperfect. Price inflation has a significant effect on the aggregate bankruptcy rate and default premia, independent of real interest rates. It is well known that high inflation is detrimental to companies as it rises nominal interest charges. Under these circumstances, firstly, the company would become reluctant to raise long-term capital even if there is a need for investment, and, secondly and more importantly, lenders might be reluctant to accommodate the firm with cash flow problems. If one assumes that the short-run cash flow factors determine failure than the nominal rather than real rate of interest might have an important role in explaining failure. Another possible link is that rising inflation may engender expectations of a subsequent tightening of macroeconomic policy, leading to a decline in business confidence.

In Wadhwani (1986) the bankruptcy condition is specified for an individual, quoted firm and then tested with aggregated quarterly UK data for total liquidations covering 1965-81. First, Wadhwani looks at the perfectly competitive case and ignores inflation. The firm is a price-taker and chooses the level of employment (*L*) to maximise expected profits net of expected bankruptcy costs, which depend on the probability of bankruptcy denoted $\mu(\cdot)$. The firm has a borrowing constraint and the budget constraint. The firm has borrowed the amount (*D*) at the real, risk-free rate of interest (ρ). Should the firm fail to meet the current obligations, it can raise external finance up to ($S = MV - D$), where (*MV*) is the expected present value of the future earnings and (*S*) is the value of shares. The only source of uncertainty is the output price ($\tilde{p}$), which is a random variable with the known distribution with the mean and variance ($\bar{p},\sigma$). Denoting money wage by (W) the bankruptcy condition is given by:

$$\tilde{p}F(L) - WL - \rho D + S < 0. \tag{1.21}$$

Second, Wadhwani augments the model by introducing the effects of inflation and allowing the firm to compete a'la Cournot-Nash. Given that the borrowing limits are determined by the expected present values of earnings, a firm with debt exceeding its borrowing limit, will have to survive on generated cash flows. But if debt is not indexed and at a variable rate, inflation erodes cash flows. This is because for any positive real interest rate, a given rise in inflation leads to the greater proportionate increase in the nominal interest rate (r) than the proportionate increase in the nominal value of its operating profits, thereby increasing the probability of bankruptcy. Wadhwani also points out that inflation reduces the firm's chances in obtaining new loan finance because inflation negatively affects interest cover, the ratio of profits to nominal interest payments, limits for which might be set in loan covenants by using nominal interest rates.

If there is a steady inflation of ($\dot{p}$), and the real rate of interest is replaced by the nominal rate of interest, $r = \rho + \dot{p} + \rho\dot{p}$, the firm goes bankrupt when:

$$(1+\dot{p})[\tilde{p}F(L) - WL - \rho D + (MV - D)] < 0. \tag{1.22}$$

Under Cournot-Nash competition, a firm chooses the output to maximise profits net of expected bankruptcy costs, taking other firms' output as given. Assuming that employment is affected by aggregate demand (AD), the general expression for the probability of bankruptcy under imperfect competition would be:

$$\mu(\cdot)_{IPC} = \mu(W, \rho, D, MV, \bar{p}, \sigma, AD). \tag{1.23}$$

Relation (1.23) implies that bankruptcy risk is linked to debt, the market value of equity, the real interest rate, factor and output prices, and aggregate demand. However, while his theoretical framework suggests the use of the real interest rate (ρ) and the rate of inflation ($\dot{p}$), in empirical modelling Wadhwani experiments with both the nominal interest rate (r) and the real interest rate (ρ). He reports that the use of the real interest rate was rejected by tests, but the nominal interest rate was a highly significant variable over the 1965-81 analysis period, implying that inflation raises bankruptcy rates.

A similar theoretical base with the focus on the link between current profits, credit rates, inflation, and the likelihood of bankruptcy, was used by **Simmons** (1989) who explored the factors determining the bankruptcy rate amongst small unincorporated UK businesses. His findings, therefore, are not directly comparable with the aggregate results of Wadhwani (1986). Simmons found that demand variables and real wage costs were the significant key determinants of failure, but, in sharp contrast to the findings of Wadhwani, rises in interest rates reduced bankruptcy rates in retailing, road haulage and construction.

General specification (1.23) has been used in the study of major OECD countries, reported in **Davis** (1995). For the context of the UK in 1969-90, Davis registered that inflation (whose influence was implicit in the positively signed coefficient for the nominal interest rate and the negatively signed coefficient for the real interest rate), the business cycle (recession), and factor prices were as important for explaining business failure rates as corporate gearing. Results on the influence of macroeconomic factors on UK business dissolutions in 1980-90, reported in **Robson** (1996), support the findings of Wadhwani although point to the especial importance for explaining business deregistrations of the changes rather than levels of the real interest rate. Since levels of the interest rate may be to some extent anticipated, then only an unanticipated component represents new information, which matters for explaining the process of company failure.

In the UK study for 1977-92, **Young** (1995) explicitly distinguishes between the expected and unexpected changes in nominal and real interest rates. Young demonstrates empirically that is was macroeconomic instability, associated with high inflation and sharp, unanticipated movements in real interest rates and demand, that led to a higher liquidation rate of the sample companies. Young has also discovered that the firm's response to changes in interest rates will depend on the composition of its debt contract.[15] Companies financed by variable-rate debt are adversely affected by the unexpected increase in real interest rates as that reduces the market value of their capital, but does not affect the value of variable-rate debt, causing the firm's net worth to fall. Firms financed at fixed nominal interest rates would be vulnerable to the unanticipated reduction in inflation. Results from Young's model suggest that a rise in nominal interest rates may either increase, decrease or have no effect on the rate of business failure, depending on whether it corresponds to a rise in real interest rates or inflation, is anticipated or unanticipated, and debt is at fixed rates or variable rates.

Cuthbertson and Hudson (1996) in their empirical design followed Wadhwani's (1986) general specification for the probability of failure (see expression (1.23)) too, but they examined only compulsory liquidations among UK companies over the period 1972-89. Their model specification controlled for the "age-structure" effect proxied by the number of company "births", and included a profit margin variable to capture the individual cost variables of Wadhwani (1986). In their model, it is an increase in income gearing, which increases insolvencies. Cuthbertson and Hudson (1996) explained this finding by creditors being myopic and relying in their assessment of the probability of

[15] Interest rates on loan finance may be either floating or fixed. A floating rate means that the rate of return payable to lenders will rise and fall with market rates of interest, although it is possible for a floating rate loan to be issued, which sets a maximum rate of interest and/or a minimum rate of interest payable. The market value of the lender's investment in the business is likely to remain fairly stable over time. The converse will normally be true for fixed interest loan capital. The interest payments will remain unchanged with rises and falls in market rates of interest, but the value of the loan investment will fall when interest rates rise, and rise when interest rates fall. A company that has borrowed at a floating rate of interest, may find that interest rate rises will place real strains on cash flows and profitability. Conversely, a company that has a fixed rate of interest will find that when interest rates are falling it will not enjoy benefits of lower interest charges. To reduce or eliminate the risk, a company may enter into a hedging arrangement, such as forward rate agreements, interest rate guarantees (options), interest rate swaps. However, unanticipated movements in interest rates can present a significant issue for companies that have high levels of borrowing.

insolvency of a debtor on the debtor recent performance. However, this result also implies that, after a time, firms may be able adapt to high nominal interest rates by reducing borrowing and, in the long run, by cutting input costs. Increases in real unit labour costs and real input prices influenced profit margins and these changes in profit margins caused an increase in compulsory liquidations for the sample period. As for interest rates, they had a direct effect on gearing and indirectly affected the earning power via changes in real output and hence profit margins.

The short-term view creditors tend to take as to distressed companies prospects is evident in the results form a macro-study of the effect of the Thatcher government on UK company liquidations by **Turner, Coutts, and Bowden** (1992). Their work covering 1951-89 empirically tested two alternative theoretical conditions for liquidation. The first condition is linked to value maximising theory. This theory implies that the probability of a company being placed into liquidation depends on the assessment by the company creditors/members of the company's liquidation value today relative to the discounted present value of the expected future net revenues and the expected future liquidation value. They consider a firm that has purchased capital equipment of the value (K) and expects to receive a stream of future net revenues on this capital given by (π_t ($t = 1,\ldots,T$)), where (π_t) is the net expected revenue in period (t), and (T) is the liquidation time. If the firm decides to abandon production and to sell its capital instead, it can do so but at a discount rate equal to (δ). The real interest rate (ρ) equals the nominal rate (r) minus the expected rate of inflation (Δp^e).

The firm will go into liquidation if the return from selling off its capital exceeds the present value of the stream of the expected net future revenues and the expected future liquidation value (L_T):

$$K(1-\delta) > \sum_{t=0}^{T} \frac{\pi_t}{(1+\rho)^t} + \frac{L_T}{(1+\rho)^T}. \tag{1.24}$$

Inequality (1.24) specifies the condition for a firm's creditors to choose liquidation when capital markets are perfect, that is the firm has a free choice of the amount it can borrow at the going interest rate. Liquidation of the company is determined here by its long-term profitability prospects, rather than short-term fluctuations in cash flow due to micro and macro factors. Condition (1.24) fails to take account of capital structure, although it does take in a factor external to the firm, the interest rate.

An alternative constraint suggested by Turner, Coutts, and Bowden for specifying firm's survival, implicitly introduces debt and assumes that: (i) there are restrictions on the maximum amount (B) the firm can borrow at the current interest rate, and (ii) given a free choice, the firm will continue to trade. The constraint is the following:

$$rK - B > \pi_0 \; . \tag{1.25}$$

Inequality (1.25) seems relevant when it is expected that short-term factors have a much stronger impact upon company failure. Firstly, condition (1.25) implies that the current cash flow of the firm is insufficient to meet its fixed costs, which in this case are the interest payments on its capital. Secondly, its borrowing capacity is insufficient to make up any shortfall. The determinants of the borrowing capacity of the firm will depend on the banks' attitude towards risk and their willingness to extend short-term credit on the basis of the anticipated long-term profit potential. Condition (1.25) concurs with the explanation put forward by Wadhwani (1986), who asserts that the nominal rate of interest rather than the real rate of interest is the appropriate explanatory variable in the company failure process.

By combining factors from conditions (1.24-1.25), Turner, Coutts, and Bowden introduce appropriate macroeconomic measures as independent variables to explain in an econometric specification, the aggregate failure rate. Their macroeconomic variables included the nominal rate of interest, the rate of price inflation, the rate of growth of money stock, reflecting credit market constraints, and the rate of company formation that captures the age structure of companies. The empirical evidence appeared consistent with liquidation condition (1.25), giving importance to the cash flow interpretation of company liquidation and pointing to creditors' miopia. Econometric results also indicated sensitivity of company liquidations to the effects of the cycle, which were channeled via company profitability.

Goudie and Meeks (1991) attempted to assess *ex post* the response of the potential failure rates to movements in a key macroeconomic variable, the effective exchange rate. Their examination of the impact of variations in the exchange rate upon the potential failure rate among the top 100 UK companies in 1984-89 showed an asymmetric and irregular relationship. The results from a macro-micro model suggested that failure could be a penalty for producing exports (or importing material inputs) at a time of a soaring exchange rate, especially if the rise is combined with the relative price increase leading to a disastrous loss of competitiveness.

Increased attention, in the recent financial economics literature, has been directed to a complementary analysis of micro and macro linkages such as a relation between the "health" of the corporate sector as a whole and a country's macroeconomy, especially in the light of the Asian Crisis of 1998. A recent study by **Gray** (1999) bridges the gap between the corporate finance concept of illiquidity and macroeconomic analysis of insolvency. Gray's framework is based on the notion of "economic value added", which is tied to the creation of shareholder wealth and economic growth. The author puts forward a model for corporate sector "vulnerability" defined as the sharp decline in equity below a threshold that triggers widespread default for a significant part of the corporate sector.

Gray's model implies that vulnerability to default in the corporate sector is high if: (i) equity value is sensitive to changes in exchange rates, interest rates, and investment; (ii) the level of liquid assets held by corporations is low; (iii) corporations are highly leveraged with the low level of equity; (iv) there is a high level of short-term debt and concentration of a few lenders in the corporate sector, which could stop financing or rolling-over short-term debt; and (v) there is the potential for investment to drop by a large amount and even to turn negative in a short period of time creating a short-term financing constraint.

The empirical research by **Takala and Viren** (1996) that deals with the macroeconomic problem of bankruptcies in Finland over the period 1923-94, show that company failures are strongly related to the business cycle, indebtedness, real interest rates, and asset prices. Excessive indebtedness easily causes a wave of bankruptcies when an economy is hit by a recession with a fall in demand, output, and asset prices and with an increase in real interest rates.

An attempt to theoretically link interest rates and bankruptcies has also been made in a recent, macro study of US firms. **Assadian and Ford** (1997) adopted a theoretical model that assumed a direct relation between negative profits and the probability of business failure. They re-specified the traditional profit maximisation model by changing, in line with agency and managerial theories, the decision variable of the firm, from the level of output to the rate of growth of output. The rationale for introducing an alternative decision variable is based on the managerial utility theory for modern corporations with separate ownership and control. The managerial utility theory implies that managers of such firms are typically concerned with the growth of the firm and not with the level of output at any given point in time. The size of the firm is represented by the present value of the total money capital invested by the firm (I). They consider perfectly competitive input and output markets, and the linear and homogeneous production function assuming that both total costs and total revenues increase more than proportionately with higher rates of growth of output. The profit growth function (Π) depends on the firm's initial net revenue at time zero (A), the firm's cost of capital, proxied by the interest rate (i), the rate of growth of output (g), and the present value of the firms expansion costs, (C):

$$\Pi = A[(1+i)/(1-g)] - C \ , \qquad (1.26)$$

where it is assumed that $i > g$.

The first and the second order conditions for maximisation are written as:

$$\Pi_g = A[(1+i)/(i-g)2] - C_g = 0 \ ,$$
$$\Pi_{gg} = 2A[(1+i)/(i-g)3] - C_{gg} < 0. \tag{1.27}$$

Supposing that the rate of growth (g) depends on the firm's size, expressed as the present value of capital invested (I), and on the initial net revenue (A), and assuming further that the cost of capital impacts both total revenues and total costs, the general expression for profits becomes

$$\Pi = \Pi(\overset{(?)}{A}, \overset{(-)}{i}, \overset{(?)}{I}). \tag{1.28}$$

Assadian and Ford pointed out an apparent limitation of the chosen economic structure (1.28) as a basis for empirical research. Model (1.28) fails to define the direction of the impact the independent variables would have on profits, with the exception of the finding that the firm's cost of capital (i) would have a negative effect. Empirical results showed a bipolar relation. The expected positive link between the interest rate and insolvencies was documented for the firms with large liabilities (over $100,000), but a negative effect was present for the group of firms with smaller liabilities (under $100,000). With respect to the latter group, these results appear to have some similarity with those obtained in Simmons (1989). Much of the literature sampled above clearly implies that managerial ability to forecast and react adequately to changes in the business environment is crucial for company survival and calls for a joint examination of important, internal and external to the firm factors. We turn our attention now to what has been said in the literature about the role of managerial factors.

1.7 Incompetent Management Theory of Financial Failure

The literature, explaining business failure by managerial inadequacies, seldom uses rigorous statistical methods and tend to rely on evidence from case studies and practical experiences of management consultants and insolvency experts involved in failing companies (e.g., **Argenti,** 1976; **Slatter,** 1984; **Altman,** 1993; *The SPI Survey,* 1996).

The Society of Practitioners of Insolvency (SPI) have been undertaking regular surveys of corporate insolvency in the UK since October 1991. Their reports have come to be acknowledged as the principal source of qualitative information on the state of British industry and of the reasons for and significance of company insolvency. The surveys have identified the following interdependent factors leading to insolvency:

- Loss of Market
- Management Failure
  - Fraud
  - Over-Optimism in Planning
  - Imprudent Accounting
  - Lack of Management Information
  - Erosion of Margin
  - Product Obsolescence / Technical Failure
  - Overgearing
- Bad Debt
- Finance
  - Loss of Long-term Finance
  - Lack of Working Capital / Cash Flow
- Knock-on
  - Knock-on from the Failure of an Another Group Company
- Other
  - Excessive Overhead
  - New Venture / Expansion / Acquisition

The Fifth SPI Survey (1996) was based on 1,660 insolvency cases - 9.5 per cent of the total number of insolvencies during July 1994 and June 1995 - and dealt only with the particular insolvency regimes, such as administrations, company voluntary arrangements, receiverships, compulsory liquidations, creditors' voluntary liquidations. The analysis suggested that most failures were not caused by external effects or economic conditions alone. The difference between similarly troubled firms that survived, and those that did not, appeared to be the relative quality and prudence of management.

The Fifth Survey stresses that weaknesses in management had a great influence, with around 22 per cent of the companies in the sample failing due to this reason. Finance factors were responsible for 21.5 per cent of insolvencies. The interesting result is that fraud depends on company size and less of threat to smaller companies, many of whom are managed by their owners. The proportion of failures due to fraud was only 1.5 per cent for small businesses (turnover less than £1m), while among companies with higher turnover, fraud was listed as a primary factor in 7 per cent of insolvencies. In the opinion of many practitioners, loss of market, which caused 31.5 per cent of failures, and finance problems were themselves due usually to the failure of management to react to market conditions, rather then exceptional, external, and unforeseeable occurrence.

Managerial theory of company failure was in the focus of the two well-known earlier studies by **Argenti** (1976) and **Slatter** (1984). The authors assert that one can trace virtually all the causes for failure back to "bad management", arguing that either poor decisions or inaction on the part of management is the principal default factor. Even where the cause of distress is primary due to changes in environmental characteristics of the business, which are beyond directors' control, one could argue that management should forecast such events and plan accordingly. Often, quantitative managerial factors are not easy to operationalise for modelling which might have constrained their use as explanatory variables in company failure research.

Argenti (1976) believes that features associated with company failure can be separated into three categories - inherent defects in the actual organisation and financial structure of the company, management mistakes, and symptoms of deterioration. He describes (Argenti, 1976; p.122; emphasis in original) 12 major inter-linked elements:

> If the *management* of a company is poor then two things will be neglected: the system of *accounting information* will be deficient and the company will not respond to *change*. (Some companies, even well managed ones, may be damaged because powerful *constraints* prevent the managers making the responses they wish to make.) Poor managers will also make at least one of three mistakes: they will *overtrade*[16]; or they will launch a *big project* that goes wrong; or they will allow the company's *gearing* to rise so that even *normal business hazards* become constant threats. These are the chief causes, neither fraud nor the bad lack deserves more than a passing mention. The following symptoms will appear: certain *financial ratios* will deteriorate but, as soon as they do, the managers will start *creative accounting*, which reduces the predictive value of these ratios and so lends greater importance to *non-financial symptoms*. Finally the company enters the characteristic period in its *last few months*.

Slatter (1984), who studied a sample of forty UK public companies in turnaround situations, adopted and tested Argenti's argument. Slatter derived a list of principal factors similar to those of Argenti's, and concluded that lack of financial control in terms of cash flow forecasts, costing systems, budgeting, and incompetence of management personnel were clearly the major causes of failure for the firms in the sample. Notably, overtrading did not appear to be a discriminating dimension. Thus, Slatter concluded that failure was most likely to occur when a firm, already weakened by poor management, inadequate financial control, and economic inefficiency, was affected by adverse changes in market demand due to cyclical fluctuations, and by problems resulting from big projects, of both a capital and revenue nature.

In the turnaround literature, corporate failure is often attributed to poor managerial responses to performance decline. **Jensen** (1993) stresses the key role of information in

[16] Overtrading occurs where a company operates at the level of activity that cannot be supported by the amount of finance, which has been committed. Overtrading results in permanent liquidity problems, which might lead to failure unless the level of operations is cut back in line with available finance.

managing exit from the market efficiently. In making decisions about exit, firms often are faced with the lack of information regarding their own costs and the costs of their competitors. It is often unclear to managers that they are the high-cost firm and should reduce the firm's presence in the market and exit the industry. When managers exercise poor judgement, resisting the adjustment actions of shutting down, restructuring, or liquidating the firm because that creates uncertainty and interrupts management careers, and continue to invest in the losing operations, the firm may inevitably face financial difficulties and fail.

Although somewhat short on rigorous statistical analysis, arguments expressed by Argenti, Jensen, and Slatter have been influential in the use in models of company failure of non-financial indicators, either alone or in conjunction with financial ratios. For the UK, **Peel, Peel and, Pope** (1986), **Keasey and Watson** (1987) and **Peel and Peel** (1988) attempted to incorporate factors, reflecting managerial capabilities, however, their modelling results did not indicate strong explanatory power of managerial variables. But the key and valid point, made by the models based on managerial theories of failure, is that in trying to understand the process of failure it is important to allow for mispredictions or mistakes by firms' managers in forecasting their market environment and the macroeconomic conditions.

1.8 Conclusions

We have presented a selected survey of the important literature, from the UK and the US, concerned with the theoretical background of models of company distress and failure. We note that so far research in this area has not produced a complete representation of a unified analytical framework, which can be validated in empirical work and then used for predicting the phenomenon of company failure. All the more, financial, economic, and legal meanings of distress and failure differ. The industrial economics literature associates failure with company exit from the market, which results from negative economic profits. Another way to characterize failure in the strict economic sense is to equate failure of a firm with inefficiency defined as the firm's revenues being less than its alternate revenues would be if its capital were invested in the best alternate use. Neoclassical theory of the firm and transaction and agency costs theories advanced in new institutional economics, provide a conceptual basis for understanding the causes of economic and financial distress for the case of a public corporation with diffused ownership. Concepts of capital structure, illiquidity and insolvency takes on added importance in the modern corporate finance literature. Company financial failure is broadly defined as inability to pay debts as they come due, which is caused by: (i) lack of cash flow or liquid assets and (ii) absence of new inflow of external financing, for instance, in the form of debt or equity, necessary to overcome illiquidity. The firm's failure is linked to indebtedness and triggered by debt default explained by insufficiency of liquid assets due to a fall in operating profits and inability to rollover the debt. Deteriorating profitability, being sensitive to both aggregate and idiosyncratic risks, might result from cyclical or competitive reasons; from rapid growth with subsequent overtrading; from over-expansion; from shifts in exchange rates causing a drop in competitiveness; and from excessive gearing which together with unanticipated changes in interest rates impinges upon the firm's ability to service borrowings. As the evolution of the market value of equity depends on the firm's profits net of interest payments to lenders, short-term illiquidity develops into long-term insolvency with entrepreneurial equity (net worth) falling below zero. When creditors have instituted legal proceedings against a company, which failed to meet its debt obligations, the company might eventually discontinue as a legal entity via the rout of formal insolvency.

Theoretical frameworks for analysing the evolution of financial distress and determining conditions for liquidation, offered in **Merton** (1974), **Scott** (1981), **Wadhwani** (1986), **Turner, Coutts, and Bowden** (1992), **Laitinen and Laitinen** (1998), and **Gray** (1999), motivate out choice of explanatory variables in empirical modelling. The conditions for company failure derived analytically, usually imply that the risk of debt default and subsequent insolvency can be explain by two groups of factors. The first group represents firm-specific attributes that correspond to the dimensions financial analysis traditionally uses in describing the firm's financial profile, with liquidity, the level of indebtedness or gearing, and changes in market valuation being of utmost importance. The second group is the contextual factors usually represented by the macroeconomic environment changes modifying firm's financial performance and altering distressed firms' access to external finance. The conceptual frameworks that establish that failure risk is determined both by firm-specific characteristics and by macroeconomic factors have a strong implication for empirical research. These models suggest that a possible way of enhancing the predictive and explanatory power of traditional models, relying on financial statement-based inputs alone, is to include controls for such macroeconomic influences as the phase of the cycle and unanticipated changes in nominal and real interest rates, exchange rates, and inflation.

Finally, the literature refers to the incompetent management theory, linking corporate collapse in the form of insolvency to managerial mistakes and fraud. Clearly, this theory is not naturally expressible in pure economic or finance categories. A rigorous statistical test of this theory, being impossible from publicly available information, would require data from case studies or surveys, specially designed and carried out.

The confrontation of economic and financial theories with the observable phenomenon of company financial distress and failure is the objective of empirical research. Therefore chapter 2 summarizes features of the core econometric studies of the financial failure question the firm-level, examining data on UK and US firms. Our exploration of the determinants of financial distress and failure of large quoted companies presented in chapters 3-5 adopts a traditionally accepted in the finance theoretical literature, clear but narrow meaning of the company failure outcome associated with the state of involuntary insolvency arising from debt default.

CHAPTER 2: A REVIEW OF UK AND US EMPIRICAL STUDIES MODELLING FAILURE AT THE LEVEL OF INDIVIDUAL COMPANY

2.1 Introduction

Company failure research from both the UK and the US, contains many dozens of observational retrospective studies that purport to show that the process of failure can be analysed at the level of individual firms. There are perhaps two major strands in the literature. Benchmark studies forecast failure with accounting and market information and claim acceptable levels of predictive accuracy of developed statistical models at classifying failures and survivors over time horizons ranging from one to four years. Despite being usually reliant on relatively small data sets, this strand seems successful in establishing the link between failure caused by financial distress and observable from publicly available data changes in company performance and financial position. These studies report set of accounting-based predictors usually measuring profitability, gearing, liquidity and financial efficiency, but, taken as a whole, the findings from these investigations do not demonstrate consistency with respect to the predictive power of particular accounting measures. This is not entirely unexpected in the situation of small-scale statistical examinations where the choice between the models is made on empirical grounds, dependent on model fit, and that approach render inference sample-sensitive. It would seem implausible to locate a "correct" unique set of predictive constructs because accounting variables by their very nature tend to be imperfect measures of notions of profitability, indebtedness, liquidity and financial efficiency. More importantly, there is also likely to be some variation in accounting practices across the populations of studied firms, across industry sectors and over time. This inconsistency may also result from the modifying impact of macroeconomic conditions on the interrelations between failure risk and accounting and economic variables. A number of studies in this first strand, attempting to detect failure of quoted firm with market-based indicators, have produced predictive models based on the ideas from option theory. This approach quantifies the chances of the adverse outcome commonly proxied by debt default or involuntary insolvency by looking at the changes in the level of indebtedness and at the evolution of market value of the firm's equity. Although a stereotype predictive model is usually set as the classification problem, implying a causal mechanism, much of the studies in the first strand concern short-term prediction and usually do not make direct claims of exploring and quantifying plausible causal relationships between financial failure and the underlying firm-specific and contextual factors.

More recent studies, forming the second strand, have been conducted with substantially larger data sets and explicitly sought to develop explanatory models at the firm level by expanding the "dimensionality" of the statistical relationship and covering the influence of environmental factors. These examinations assess how the interactions between firm-specific, industry-level and economy-wide factors help to explain failure outcome in their data. For the purposes of the present thesis, we are reviewing below some exemplary studies representative of the two strands.

Our purpose in this chapter is to identify from current research some baseline ideas concerning the empirical design for an analysis of company failure at the firm level. Given the lack of the unifying theoretical framework, an appropriate choice of components of empirical design is of great significance for isolating the empirical determinants of company failure. We review design choices in relation to the sample selection, statistical techniques for modelling, and the link between the two in the light of the literature from the United Kingdom and the United States, which has pioneered the retrospective observational design in the area[17]. Many papers were written by distinguished authors or groups of authors and have achieved a prominent place in the debate about corporate financial failure. Our purpose in reviewing the empirics from the

[17] Both countries provide the financial environment ideal for building successful statistical models for monitoring company financial "health" and have a long history of failure prediction research. This success of prediction models in these two countries may be attributed to: (i) relatively higher incidences of corporate insolvency which serves as a common exit route for distressed firms; (ii) corporate financial data are readily available; (iii) failure is easier to identify because of the existence of bankruptcy/insolvency laws and banking infrastructures; and (iv) the sophisticated regulation of companies to protect investors.

UK and the US, is not to challenge the validity of particular accounting predictors and classificatory performance of the extant models. Rather our aim is to appreciate a valuable contribution of the previous literature towards the empirical design of company failure analysis in terms of the interrelated components of data, candidate variable selection and statistical methodology. Yet we will summarise some difficulties with applying the empirical design typical of the literature, concerning predominantly with prediction, for our particular investigation of the determinants of company failure for the UK and Russia. Both the limitations and the valuable contributions of the current literature motivate the choice we make in the present thesis in relation to statistical settings for explanatory models of failure, data sampling, and variable selection so that the determinants of company failure may be rigorously examined.

2.2 The Definition and Measurement of Company Failure Outcome, Data Needs and Sampling Schemes

The traditional empirical methodology for conducting an investigation into company failure causes at the firm level is econometric analysis, and the tools used by researchers are statistical. The case study method, an alternative to econometric modelling, suffers serious drawbacks such as the lack of generalizability and selectivity because single cases are not usually selected at random and form samples that are too small to support generalizations about the company failure phenomenon. When one is interested in average tendencies manifesting themselves in a wide range of settings, econometric work seems more appropriate, and that is the course we pursue in the present thesis.

Econometric modelling of the failure process involves important choices and judgements regarding the appropriate empirical design. A short summary of approaches towards empirical design adopted in the core papers dealing with the problem of modelling company failure at the firm level is provided in Table 2.1. The problem of modelling failure at the firm level involves the estimation of the association between hypothesised risk factors and the adverse outcome on the basis of a postulated causal

Table 2.1 Principal Components of Empirical Design Adopted by the Core Studies into Corporate Failure at the Firm-Level

Study and Country	*Definition of Failure Outcome and Type of Response Variable*	*Sampling Unit and Sampling Method*	*Explanatory Variables*	*Statistical Method and Validation Strategy*
1	2	3	4	5
1. Beaver (1968) US	Legal insolvency, Bond default, Overdrawn bank account Nonpayment of preferred stock dividend, Failed / Non-failed Dichotomy	Industrial corporation, Cross-section data, State-based sample, observations matched on industry and size	Financial statement ratios	Univariate approach of dichotomous classification tests performed with mean financial ratios , Validation on an *ex-post* holdout
2. Altman (1968) US	Bankruptcy Filing, Failed / Non-failed Dichotomy	Manufacturing corporation, Cross-section data, State-based sample, observations matched on industry and size	Financial statement ratios	Multivariate discriminant analysis; Validation on an *ex-post* holdout
3. Altman, Haldeman and Narayanan (1977) US	Bankruptcy Filing, Failed / Non-failed Dichotomy	Firm in retail or manufacturing, Cross-section data, State-based matched sample	Financial statement ratios, Measure of earnings stability	Multivariate discriminant analysis; Validation on an *ex-post* holdout and by using the Lachenbruch jackknife method
4. Taffler and Tisshaw (1977) UK	Corporate insolvency, Failed / Non-failed Dichotomy	Large company quoted on the London Stock Exchange, Cross-section data, State-based sample, observations matched on industry and size	Financial statement ratios	Multivariate discriminant analysis; Validation by using the Lachenbruch jackknife method and in a follow-up study

Table 2.1 – *Continued*

1	2	3	4	5
5. Taffler (1982) UK	Corporate insolvency, Failed / Non-failed Dichotomy	Quoted industrial firm, Cross-section data, State-based equal share sample, No matching procedure	Financial statement ratios	Multivariate discriminant analysis; Validation on an *ex-ante* holdout and by using the Lachenbruch jackknife method
6. Bank of England (Marais (1979)) UK	Corporate insolvency, Failed / Non-failed Dichotomy	Listed industrial company, Cross-section data, State-based unbalanced sample, matching by the timings of accounts	Financial statement ratios	Multivariate discriminant analysis; Validation on an *ex-ante* holdout
7. DATASTREAM (1980) UK	Corporate insolvency, Failed / Non-failed Dichotomy	Listed company, Cross-section data, State-based unbalanced sample, matching by the timings of accounts	Financial statement ratios	Multivariate discriminant analysis; Validation on an *ex-ante* holdout
8. Bell and Belhoul (1987) UK	Corporate insolvency, Failed / Non-failed Dichotomy	State-based unbalanced sample, Cross-section data, No matching procedure	Financial statement ratios; Levels and standard deviations	Multivariate discriminant analysis; Validation on an *ex-post* holdout and by using the Lachenbruch jackknife method
9. Goudie (1987); Goudie and Meeks (1991) UK	Voluntary liquidation or receivership, Failed / Non-failed Dichotomy	Manufacturing or distribution company, Cross-section data, State-based equal-share sample, No matching procedure	Financial statement ratios	Multivariate discriminant analysis; Validation on an *ex-ante* holdout

Table 2.1 – *Continued*

1	2	3	4	5
9. Ohlson (1980) US	Bankruptcy Filing, Failed / Non-failed Dichotomy Binomial response	Listed industrial company, Cross-section data, State-based unbalanced sample, Randomly selected observations on control group of firms	Financial statement ratios	Logit No holdout test
10. Zavgren (1985) US	Bankruptcy Filing, Failed / Non-failed Dichotomy, Binomial response	Industrial corporation, Cross-section data, State-based equal-share sample, observations matched on industry and size	Financial statement ratios	Logit Validation on an *ex-ante* holdout
11. Platt and Platt (1990) US	Bankruptcy Filing, Failed / Non-failed Dichotomy, Binomial response	Publicly traded company, Cross-section data, State-based equal-share sample, observations matched on industry and size	Financial statement ratios, industry-adjusted values	Logit Validation on an *ex-ante* holdout and by using the Lachenbruch jackknife method
12. Lau (1987) US	Omission or reduction of dividend payments, technical default and default on loan payments, filing for bankruptcy, and liquidation, Multinomial response	Quoted company, Cross-section data, State-based unbalanced sample, No matching procedure	Financial statement ratios	Logit, Validation on an *ex-ante* holdout
13. Johnsen and Melicher (1994) US	Bankruptcy filing, Standard & Poor's debt ratings of below average and lower quality Multinomial response	Quoted company, Cross-section data, State-based unbalanced sample, No matching procedure	Financial statement ratios	Logit, Model validation using a follow-up study

Table 2.1 – *Continued*

1	2	3	4	5
14. Richardson, Kate and Lobingier (1998) US	Bankruptcy filing, Binomial response	Listed firm, Cross-section data, State-based unbalanced sample, No matching procedure	Financial statement ratios and dummies controlling for recession	Logit, Validation by using the Lachenbruch jackknife method
15. Mossman, Bell and Turtle (1998) US	Bankruptcy filing, Binomial response	Non-financial firms, Cross-section data, State-based equal-share sample	Financial statement ratios, Cash-flow statement measures, Market-adjusted returns and variance of market returns	Logit, Validation by using the Lachenbruch jackknife method
16. Peel, Peel and Pope (1986); Peel and Peel (1988) UK	Creditors' voluntary liquidation, receivership or winding up by the court order, Binomial response	Listed company, Cross-section data, State-based unbalanced sample, No matching procedure	Financial statement ratios, lag in reporting accounts and number of directors resignations and appointments	Logit, Validation on holdout data
17. Keasey and McGuinness (1990); 19. Keasey, McGuinness and Short (1990) UK	Insolvency, Binomial response, Multinomial response	Quoted industrial firm, Cross-section data, State-based, equal-share sample, matching by industry, net assets size and the timings of accounts	Financial statement ratios	Logit, Validation on an *ex-post* holdout sample
20. Morris (1997) UK	Receivership or winding up by the court order, Failed / Non-failed Dichotomy, Binomial response	Listed company, Cross-section data, State-based, equal-share sample	Financial statement ratios, Share price returns, non-financial indicators,	Logit, Neural networks Validation on an *ex-post* and ex ante holdout samples
21. Wilson, Chong and Peel (1995) UK	Receivership or winding up by the court order, Distressed acquisition, Failed / Non-failed Dichotomy, Failed / Non-Failed/Distressed Acquisition Polychotomy	Industrial company quoted on the London Stock Exchange, Cross-section data, State-based sample	Financial statement ratios, Dummy for going concern qualification, Industry sector controls	Neural networks, Validation by using the Lachenbruch jackknife method

Table 2.1 – *Continued*

1	2	3	4	5
22. Pastena and Ruland (1986) US	Bankruptcy filing / Merger, Binomial response	Manufacturing firm, Cross-section data, State-based unbalanced sample	Financial statement ratios, Measure of ownership concenration	Probit, No holdout test or jackknife approximation
23. Alici (1995) UK	Receivership, liquidation or administration, Failed / Non-failed Dichotomy	Manufacturing firm, Cross-section data, State-based, equal-share sample, observations matched on industry, size and the year of accounts	Financial statement ratios	Neural networks, Validation on an *ex post* holdout
24. Diacogiannis (1996) UK	Liquidation or winding up by the court order	Quoted industrial firm, Time –series data, State-based sample containing failed firms alone	Marker valuation variables (share returns) and macroeconomic indicator (inflation meaasure)	Profile analysis: failed company share performance vis-a-vis the market index
25. Lindsey and Campbell (1996) US	Bankruptcy filing, Failed / Non-failed Dichotomy, Binomial Response	Industrial corporation, Time-series and cross-section data, State-based, equal-share sample, observations matched on industry	Financial statement ratios, and chaos statistics derived from stock returns	Univariate discriminant analysis based on chaos statistics alone, Multivariate discriminant analysis based on financial ratios and chaos statistics, Validation on an *ex post* holdout
26. Hill, Perry and Andes (1996) US	Bankruptcy filing and cumulative negative earnings over three-year period, Failed / Non-Failed/Distressed firm Polychotomy	Industrial corporation, Longitudinal data set, State-based unbalanced sample	Financial statement ratios, Economic indicators (unemployment rate and prime rate), Qualified audit opinion	Event history analysis, Validation on the estimation data points

link between the two. The *observational retrospective design* plays an important role in inferring causation from association in company failure analysis. However, in contrast to the macro-level studies of company failure, where aggregate failure rates are observable - by recording, for instance, the rate of corporate liquidations - at the level of individual firms, we can only record whether or not the event of failure occurs and cannot observe the probability of failure. In a retrospective study at firm level, a sample of firms is chosen according to failure outcomes in the analysis period and the analysis then investigates what values of potential explanatory factors had previously existed in firms' history. Measurement of explanatory variables for the intended analysis, are usually taken at specified times prior to failure in accordance with the principle of *temporal precedence* with respect of the putative causes and the adverse outcome.

Two major and interrelated elements of empirical design in observational studies are the data and the associated statistical methodology and these must be chosen in a way allowing for their interdependence. Econometric inference can be no better than the suitability, relevance, and completeness of the data on which this inference is based. Therefore relevance of derived empirically determinants of failure depends heavily on the quality of the underlying data. On the other hand, the choice of both the analysis method and the model structure has considerable impact on the form and content of the data to be used. A statistical analysis of observations on firms can be conducted on cross-section, time-series and panel data. While static cross-sectional studies aim to assess the variation in failure determinants across firms, time-series analysis allows evaluation of the association between the temporal variation in characteristics of failing firms over time. An inclusion of a panel element in empirical design is desirable. It generates extra data points, which allow for the incorporation of dynamic elements to an explanatory model and exploration of more complex relationships between the outcome of failure and firm-level and environmental variables. On the other hand, the specification of the type and structure of the data determines a range of appropriate candidate multivariate analysis techniques for developing the desired model. The formulation of prior postulates of the failure process, on the basis of stylised facts and theory, is also important as it provides needed guidance on the choice of data structure and statistical framework.

A data set for an econometric work on company failure is defined by the *sampling unit*, *sampling frame*, and *sampling procedures*. Individual independent companies are used as sampling units because information on failure outcomes and accounting variables is usually recorded at this level. The sampling frame specifies every unit of the population from which the sample is taken. The choice of the sampling frame affects sample size and the extent of the data, which in turn influences the subsequent statistical analysis. It appears from the literature that in order to obtain a representative and sufficient sample of data to conduct an econometric analysis, sampling frames pertain to fairly broad populations of companies. The bulk of prior research focuses on large quoted companies since these firms release into the public domain more detailed primary data about their performance and operating activity and are better covered by the data bases researchers have assess to.

In creating the sample, a primary consideration should be given to the definition of the adverse outcome and its timing. Failure is modelled by using a categorical response variable and the researcher uses a certain rule in making his judgement on the observed outcome. The importance of careful definition of company failure in the process of setting the sampling frame cannot be over-stressed since an inadequate criterion may lead to observing the wrong phenomenon or taking measurements on the wrong unit of analysis. As discussed in chapter 1, failure has often been used as a rubric for very different degrees of financial distress and this definitional variation is apparent in empirical studies. Prior empirical studies identified the event of company failure by using such measures as negative operating profit over several consecutive years (e.g., **Hill, Perry and Andes,** 1996), debt default(s) (e.g., **Beaver,** 1966), or legal insolvency – involuntary bankruptcy initiated by creditors (e.g., **Altman,** 1968, **Taffler,** 1982). Negative operating profits have the virtue of concentrating attention on the phenomenon of economic distress since they are natural response measures to identify the causes of economic inefficiency. However, the use of a negative operating profit-based definition is likely to result in small sample size as information on firms, showing persistent operating losses, may be difficult and expensive to collect. When the phenomenon of interest is financial failure, than negative operating profits is an inherently noisy measure because not all firms experiencing a period of negative operating income will necessarily default on debt and collapse into insolvency. The use of this measure also gives rise to the problem of defining the timing of failure as in this case the adverse outcome can be related to any period in the interval of negative operating profits.

As far as the use of debt default is concerned, this event can be observed from publicly available records and unambiguously signals financial distress but the operational use of this measure also involves a judgement about the timing of failure. Over the analysis period, the firm may have a history of multiple defaults, probably of dissimilar importance in terms of involved amounts of missed principal and interest payments. Since information about "minor" defaults may be neglected, the use of debt default as a failure indicator raises the problem of selectivity with respect to the presence of the adverse outcome. Therefore the rules on identifying the appropriate timing amongst the observed default times should be stated. In contrast, the criterion of legal insolvency is less ambiguous and regarded in the literature as a strong indicator of severe distress and failure. This measure narrows down the meaning of company failure, focusing the analysis on the outcome characterised by serious consequences, including a possible discontinuation of the legal vehicle and disappearance of the business.

Econometric modelling is concerned with unbiased estimates of failure determinants, and this aim dictates the choice of *sampling procedures*. Usually it is unfeasible to base the desired analysis on all elements of the population of firms defined by the sample frame and the required information is obtained from a representative sample. A certain degree of error is inherent in the process of sampling since some information on the population will never be obtained. The sampling error increases as the sample size decreases, while the adherence to the principle of random sampling process ensures that the systematic component of error is minimized. As mentioned above, at the level of individual firms we observe the outcome of failure and, in general, assume the existence of sub-populations of failing and surviving firms. Most studies employ the assumption that important determinants can be identified by comparing attributes of the companies in whose history the adverse outcome is present with characteristics of the continuing firms and therefore use a dependent categorical variable for describing the failure outcome. In practice, a truly random sample of defined by the sample frame observational units each having an equal probability of being selected, is not usually appropriate due to paucity of failed company cases in the population. Under this circumstance, a more complex method of sampling - called *state-based sampling* - seems to assist the analysis of association between explanatory variables and the outcome of failure. In the context of the simplest dichotomous outcome, naturally proxied by a binomial response, modelling methods involve classification, comparing failing firms with a group of non-failed firms. A *case-control design* with independent sampling for groups of failed and continuing firms fulfills the sample structure requirements for an econometric analysis of failure at the firm level. State-based sampling involves identifying and including in the case group of a data set the firms, where failure has occurred, and selecting either randomly or through a certain matching procedure the control group of firms where the adverse outcome is absent. However, separate sampling of each category in the data set entails an important issue about the determination of group proportions.

Equal-share samples with firms in the case and control groups matched on industry, size and the time of measurement of explanatory variables are common in the literature, although given the generally low yearly rates of corporate failures serious drawbacks of this approach become obvious immediately. Matching by the timing of records on explanatory variables seems appropriate since this procedure controls both for changes in the financial profile of the distressed firm over the period preceding failure and for temporal differences in the business and regulatory environments modifying failure risk. To facilitate isolation of firm-specific explanatory variables it appears necessary to synchronize their measurements in the case and control categories so as to alleviate the confounding effect of time-varying environmental factors. However, matching by industry and size appears less desirable in models explaining company failure. Firstly, these con-founders can themselves be important explanatory variables and secondly matching procedures yield smaller samples, reducing the generalisability of inference on failure determinants and giving rise to substantive problems in applying the findings at a practical policy level. A related issue arising from equal-share sampling is the overrepresentation of the failed category compared to the proportions, which purely random sampling would give. When the estimation method does not involve a correction procedure, an implication of ignoring the expected population proportions are the biased estimates of model parameters (see, e.g., **McFadden,** 1984; **Palepu,** 1986). We return to the issue of disproportionate sampling in chapter 3 where disproportionate sampling is discussed in greater detail. In general, the use of an unbalanced sample presents an alternative and practical way of obtaining unbiased parameter estimates. In an unbalanced sample, the share of failed firms is set according to the hypothesized rate of failure in the population or on the basis of the prior probability of the adverse outcome. Relatively few studies have ignored matching and construct *unbalanced samples* approximating the population shares of failed and non-failed firms.

Another advantage of unbalanced sampling is that it alleviates the problem of small sample size. Studies, which favour equal-share sampling, suffer from the problem of insufficient sample size and that necessitates the use of a rigorous statistical methodology for obtaining reliable statistical inference. In company failure modelling, the sample size is affected not only by the selection process, but often depends on the need to set aside a number of observations to explore the aspect of model robustness with respect to the model predictive power at classifying the status of fresh observations on firms. It is important to emphasize that when the analysis question is that of explaining failure (as it is in the present thesis) we are concerned with isolating the predictors or determinants, which are stable across firms in the population of interest and over time. Researchers are usually sensitive to this issue and the general principle employed in the literature states that to give confidence in predictors, the model has to be validated on data points (observations), which have not been used for calibrating. Such procedures, termed in the literature *holdout sample tests*, entail the partitioning of the full set of available collected data into the estimation and holdout samples, inevitably reducing the number of data points over which the model is estimated. The literature on company failure risk especially stresses the importance of validating the inter-temporal stability of the model on an *ex ante* holdout sample containing fresh observations on new firms, taken from the post-estimation time period. An early example of this approach to validation can be found in **Taffler** (1982). Other examples of *ex ante* holdout tests in the UK work include **Taffler** (1985) and **Peel and Peel** (1988). Although the importance of satisfying the principle of the "out-of-estimation-sample" validation is recognised in the literature, limited availability of fresh data often precludes "true" *ex ante* tests. A widely used but rather unsatisfactory substitute is an *ex post* holdout created by dividing the full data set, at times at random (e.g., **Altman, Haldeman, Naranayan,** 1977), into estimation and holdout subsets. In the UK literature, **Keasey and McGuinness** (1990) and **Alici** (1995) support their interpretations of powerful predictors by such *ex post* holdout tests. One can argue quite generally in favour of *ex ante* holdout, suggesting that conclusions obtained with *ex post* holdouts should be treated cautiously because the resulting overlap between the time periods of the initial and secondary data sets takes away confidence in inter-temporal stability of the model. However, both approaches to model validation using holdout samples can be criticized as wasteful of data. A method particularly appropriate for model choice and checking and, at the same time, allowing to preserve the size of the estimation sample in situations of data scarcity is based on the principle of predictive cross-validation and involves a re-sampling of calibration data points. The Lachenbruch jackknife test (**Lachenbruch,** 1967[18]) has been particular popular with researchers (e.g., **Taffler and Tisshaw,** 1982; **Altman, Haldeman, Naranayan,** 1977, **Taffler,** 1992; **Platt and Platt,** 1990; **Wilson Chong and Peel,** 1995; **Mossman, Bell and Turtle,** 1998; **Richardson, Kane and Lobingier,** 1998). However, compared with an *ex ante* holdout method, weaker levels of evidence regarding model stability attach to the Lachenbruch "leaving-one-observation-out" procedure. Alternative and versatile computational solutions for approximating model parameters such as the bootstrap have

[18] The approach of approximating the expected actual error rate for discriminant functions originally suggested in Lachenbruch (1967) is a form of jackknife method for small samples. The procedure involves omitting one single observation at a time, reestimating the discriminant function and then classifying the data point left out with the obtained model. An almost unbiased estimate of the expected error rate is calculated from the number of classifications done for all data points.

not received much attention in the modelling methodology debate which having been taken place in failure studies.

Below we discuss the examples of approaches to creating data sets for company failure modelling employed in the literature. We think that there is a distinction to be drawn between company failure models for predictive purposes and models, which give the description of the underlying phenomenon. Since in the present study we wish to investigate the determinants of failure, our main purpose in reviewing empirical designs adopted by prior studies is to indicate varying strength and as well as shortcomings of these approaches for developing explanatory models of failure.

A univariate analysis of association between changes in accounting ratios, describing company financial performance, and failure risk has been undertaken by **Beaver** (1966) for the US context, with a cross-sectional sample covering 1954-64. Beaver argues that financial statement ratios, devised by credit analysts to monitor the financial position and performance of firms, must signal financial distress and failure. Using the concept of dichotomous response taking on just two values, "failure" and "non-failure" and a "coarse" definition of failure, Beaver includes in the failed category those companies that unable to pay financial obligations as they become due. The selection criteria of legal insolvency, bond default, an overdrawn bank account or non-payment of a preferred stock dividend yield a sample representative of various stages in the process of failure. A formal analysis, set as the classification problem, reveals best predictors by assessing individual discriminating power of a number of financial ratios. Favouring equal-share sampling, Beaver constructs a data set comprising 158 firms that are matched by industry and asset size. As Beaver primarily focuses on the ability of changes in financial statement ratios to predict failure risk, his matching procedures appears justified by the need to control for the variation in risk caused by the contextual effects reflected in sectoral and size differences. In the context of a different analysis question, where the researcher is interested in isolating the potential determinants of failure, matching by variables that represent important risk factors seems as a less reasonable sampling treatment. Matching on "confounding" factors precludes any quantification of the influence of the "con-founders", affecting the reliability of inference about the "regularly" reproduced relations between changes in financial ratios and failure risk. Another serious pitfall of the empirical design in **Beaver** (1966) is the choice of overlapping time periods for estimation and holdout samples, which weakens evidence on the predictive power of ratios. Combined with matching, the *ex post* holdout approach makes Beaver's conclusions peculiar to the particular small sample of firms.

Our reading of the literature shows that most of the post-Beaver (1966) studies that developed multivariate empirical models of failure tend to employ narrower definitions of failure, using the state of legal insolvency (or bankruptcy in studies of US corporations) as a measure of the adverse outcome. However, matching by industry sector and company size has been a characteristic feature of sampling plans for predictive models. One example is the sampling scheme adopted for the well-known Z-score model in **Altman** (1968) who popularised the multivariate discriminant function for predicting the failure outcome. Altman (1968) defines the failure event as a filing for bankruptcy and works with cross-sectional data on large US manufacturing corporations for 1946-65. An equal-share sample of 132 firms, matched by industry and asset size is used but cases in the non-failed category are stratified randomly, to obtain predictors representative of the generality of large corporations. Altman also constructs an *ex post* holdout for testing the model's classificatory power on a sample of new observations.

An analogous with Altman's (1968) design is adopted in **Altman, Haldeman and Narayanan** (1977) for developing a commercial variant known as ZETA® credit risk model for predicting bankruptcies in retail and manufacturing. A multivariate discriminant function is derived from a pair-matched sample of 106 large industrial corporations, taken from 1960-75. The sample frame excludes corporations in banking, finance, real estate and railroads to avert the influence of possibly confounding factors related to differing accounting practices and bankruptcy environments. The classification accuracy of the model and implied relevance of risk factors are evaluated on a secondary sample of *ex post* holdout data pertaining to 1974-83. Given the small size of the estimation sample, the study uses an alternative solution for model testing and carefully approximates expected error rates of classification with a "leaving-one-observation-out" re-sampling of estimation data points in line with the jackknife procedure devised by **Lanchenbruch** (1967). This aspect of methodology in Altman, Haldeman and Narayanan (1977) addresses the concerns of misinterpreting the apparent error rate relating to the calibration data as a measure of predictive ability of their model.

Whereas most studies conducted in the Sixties and Seventies focus on the US context, in 1977 **Taffler and Tisshaw** publish results on the first predictive model of UK firm failure for the situation of 1969-76. It is worth nothing that the empirical design of their study adopts approaches implemented in the work of Altman and colleagues. In **Taffler and Tisshaw** (1977), the sample frame is restricted to large, listed on the London Stock Exchange companies. Failure is gauged with indicators of severe financial distress such as receivership, creditors' voluntary liquidation, compulsory winding up by the court order, or bailing out by the government. A matched equal-share sample of 92 firms is created for estimating a discriminant function. Matching criteria include industry and size, but observations on failed and non-failed categories were not matched by the timing of accounts. One can question the appropriateness of non-matching the sample firms by the time of measurement of financial and economic variables. Non-matching by the time of measurement, in general, implies that the structure of association between explanatory factors and the adverse outcome remains stable over the time, giving a time-invariant model that assumes the "average" macroeconomic conditions. Since macroeconomic instability does alter failure risk and, more importantly, impacts upon different companies in different ways, non-matching by the timing of accounts seems a rather untenable approach. It is easy to imagine that, for instance, the extent to which changes in interest rates may alter the cost of capital to the firm depends on the firm's capital structure. It is also clear that ignoring the matching by the timing of accounts cannot ameliorate the sensitivity of the discriminant function to the observations used in estimation because the sampling procedure in Taffler and Tisshaw's study uses matching by industry and size. Thus, the potential gains of developing a more general and stable over time model by ignoring matching on the timing of accounting records might well be negated by the effect of controlling for industry and size. An interesting feature of empirical design in the Taffler and Tisshaw paper is a follow-up study, demonstrating their adherence to the principle of evaluating the model predictive power and predictor relevance on the "out-of-estimation-sample" basis. A follow-up study has a great advantage for interpreting the power of models intended to be predictive, but this component of empirical design is rarely adopted in the literature, the only exception being a study by **Johnsen and Melicher** (1994). In addition, Taffler and Tisshaw (1977) follow Altman and colleagues' cue and employ a usual simple solution of assessing expected error rates of classification by the Lachenbruch "leaving-one-out" method applied to estimation sample observations.

The predictors of UK quoted industrial firm failure relevant for a later period 1968-73 are examined in **Taffler** (1982), where matching by industry or size of the sample firms is abandoned so as to obtain a more general predictive model. More importantly, unbalanced sampling is used for creating a small estimation data set of 23 insolvent and 45 continuing firms. The adequacy of the developed multivariate discriminant function – the UK Z-score - is tested both by the Lachenbruch procedure for estimation data points and by fitting the model to data points pertaining to the post analysis period of 1974-76.

Most of the UK post-Taffler (1982) literature displays empirical design similarities, following methodological ideas exemplified in the work by Taffler (1982) and Altman and colleagues (1977). Company failure is modelled with cross-section data as the classification problem with a binary/binomial indicator describing the dichotomous outcome. The methodology of discriminant analysis of state-based – and most often equal-share – data samples is used to find associations permitting classification of the population into groups of failing and continuing firms. The lack of secondary holdout data for conducting rigorous checks of models is a frequently arising situation, so it becomes convenient to use an alternative for results robustness checks and generate the estimates of expected error rates via the Lachenbruch computational procedure for the primary calibration data. The best performing discriminatory variables help to predict failure risk, pointing to common patterns in performance and position of failing firms.

A small unbalanced sample of 38 insolvent and 53 non-failed firms is used in a study of UK listed manufacturing and distribution companies in 1973-77, which was carried out at the Bank of England (**Marais**, 1979). Non-failed category was selected at random, and although observations are not matched by the time of measurement of accounting variables, stratification over the analysis period controls for short-term cyclical effects. The performance of the Bank of England model is evaluated on a out-of-estimation-sample basis, by using *ex ante* holdout data from 1978 to classify a small secondary sample of 10 failed and 19 non-failed firms.

The Z-score model developed in 1980 by DATASTERAM (cited in Taffler (1974)) is based on the operational definition of failure and sampling procedures similar to those employed in **Taffler** (1982). A listed company represents the sampling unit in the DATASTREAM study to ensure that the constructed commercial model is applicable across a wide range of manufacturing, distribution, service and transport sectors. The classificatory power of the DATASTREAM discriminant function is assessed on a secondary sample of fresh observations.

In setting the sample for a development of a discriminant model, **Bett and Belhoul** (1987) also use a legal definition of failure. They construct an unbalanced sample for the period 1974-79, not attempting any matching of firms from failed and healthy groups by size, industry or by the timing of accounting records. The model classificatory power is approximated by the Lachenbruch method as well as being supplemented by a further evaluation on an *ex post* holdout sample.

Using data from 1960-74, **Goudie** (1987) and **Goudie and Meeks** (1991) have constructed a micro-macro model of corporate failure that incorporates a predictive discriminant function as a final tier. The unit of analysis in their study is a listed company operating in manufacturing or distribution. The authors restrict the meaning of failure to voluntary liquidation or receivership and favour the equal-share sampling plan, but, to obtain more general inference, they select cases into the non-failed category randomly. To assess the inter-temporal stability of model classificatory power and the predictor relevance, Goudie and Goudie and Meeks conduct both the *ex post* (within-the-estimation-sample-period) and the *ex ante* (out-of-estimation-sample-period) model testing.

The studies, which have been discussed so far in this section, with the exception of Beaver's (1966) seminal paper, use multivariate discriminant analysis as a devise for modelling the association between the firm-level characteristics and the failure outcome. Another popular methodology applied in examination of the failure process is logit, a conditional probability model for discrete outcome. A conditional probability model generates the probabilities of failure occurring as a non-linear function of explanatory variables, but can also be used as a classification tool for forecasting. Logit analysis of data on US corporate failure is employed in, e.g., **Ohlson** (1980), **Zavgren** (1985), **Platt and Platt** (1990), **Johnsen and Melicher** (1994), **Richardson, Kane, and Lobingier** (1998), **Mossman, Bell, Swartz, and Turtle** (1998). Logit results regarding the association between firm attributes and failure risk are abound in the UK company failure literature too, being reported in **Peel, Peel, and Pope** (1986), **Keasey and Watson** (1987), **Peel and Peel** (1988), **Keasey and McGuinness** (1990), **Keasey, McGuinness, and Short** (1990), **Morris** (1997). As with discriminant analysis, state-based samples are particularly suitable for examining failure risk determinants using a conditional probability model.

Ohlson (1980) questions the appropriateness of equal-share sampling design and investigates bankruptcy of US listed industrial corporations in 1970-76 using a large, state-based, unbalanced sample. Ohlson argues that a sufficiently large sample size represents an essential condition for valid statistical inference regarding failure risk causes. To prevent possible confounding of results by differing across sectors bankruptcy regulations, the sample frame covers only firms operating in a similar bankruptcy environment. Sampled observations give three-year records on 105 failed firms and 2,058 company-year records on control, non-failed cases, with the latter category being drawn randomly from the COMPUSTAT population of firms. Because all available at the time of the analysis cases have been used for calibration, no holdout tests are conducted, but the "in-sample" stability of classificatory power of the model is evaluated with the apparent error rate computed across a wide range of cutoff probability values. The variant of empirical design adopted by **Ohlson** (1980) illustrates the problem of finding an acceptable compromise between the two conflictive objectives of sampling plans. Namely, estimation sample size needs to be increased for reliable inference but reduced on the pragmatic grounds of preserving some observations for "out-of-sample" holdout tests. Ohlson asserts that classificatory accuracy evaluated with a larger estimation sample - as compared to small sample sizes typical for UK and US academic research into failure predictive models in the 1970s and 1980s - should approximate well the *ex ante* predictive ability of his model. However, this contention is open to question as the apparent error rate produced by fitting the model to the calibration data points yields a generally optimistic estimate of the expected error rate in predicting future observations (see, e.g., **Lachenbruch**, 1977; **Efron**, 1986). In the absence of fresh secondary data, the two conflicting objectives can be reconciled by approximating the expected error rate with a jackknife-type resampling procedure or with other more advanced techniques of numerical simulations.

Following Ohlson's paper, applications of logit to state-based samples became as popular in the literature dealing with company failure prediction as analyses based on discriminant functions. **Zavgren** (1985) favours logit but she also modifies the experimental design centred on a single model predicting failure one- to two-years ahead. Zavgren employs a sample of repeated cross-section data on US firms with measurements of explanatory variables taken at several pre-specified time-horizons. The rationale for using a design based on repeated cross-sections is that it provides "time-to-failure" specific logit functions, useful for our understanding of the evolution of failure symptoms over time. Zavgren's paper turns on the premise that as the firm approaches failure, defined as bankruptcy, the relative importance of failure factors changes. The problematic element of the sampling plan in Zavgren relates to the matching on industry and size, which is employed for creating a comparison group of non-bankrupt firms. In Zavgren, this procedure reduces the estimation sample size to just 90 firms from 1972-78, while data on 16 failed firms from 1979-80 are set aside for holdout tests. As noted earlier, a serious limitation of matching is the increased sensitivity of obtained parameter estimates to the data points used for model development, that weakens the model predictive power and can render inferences on the key drivers of failure invalid. It seems fair to argue that unlike Ohlson's inference based on a larger sample, Zavgren's interpretation of failure symptoms, backed up by standard asymptotic tests on a relatively small, equal-share and matched sample, appears less convincing.

The unit of analysis in a study by **Platt and Platt** (1990) is a US publicly traded company filing for bankruptcy in 1972-86. They employ an equal-share sample of 114 firms matched by industry sector, asset size and the timing of financial records. The predictive power is validated by using jackknife tests and by fitting the model to fresh observations from 1986-87. Since the estimation and holdout time periods are not distinctly different, the test results in Platt and Platt (1990) are likely to suffer from a bias, overstating the model predictive power.

Almost all studies envisage just two mutually exclusive and exhaustive outcomes in justifying the sufficiency for company failure analysis of the conventional dichotomy between failed and non-failed firms. Extensions of the design with a categorical dependent variable consider more complex structures and can be used in describing a multi-stage process of failure or for analysing more than one adverse outcome. In the background of the former problem is the proposition that some variables exist that can explain and predict the different and distinct stages of failure process. In other words, we think that one should be concerned here with regression models linking an *assessed categorical response* variable with a set of predictor or explanatory variable. An assessed categorical variable is generated by an assessor (or maybe by the researcher) who processes some amount of information before providing his judgement of the degree of financial distress and corresponding grades of the categorical variable. For instance, one can judge the severity of distress in firms by the 4-point scale: "none", "mild", "moderate" or "severe". This approach to failure analysis effectively dictates the use of an assessed ordered categorical response as a dependent variable.

However, it appears that in some studies (e.g., in **Lau**, 1987) the naturalness of a qualitative ordered response is ignored and the ordered categorical regression problem has been replaced by the problem of multinomial response. As a consequence these studies use multinomial response models which assume exclusive and exhaustive states in the outcome space. As one would expect, sampling approaches adopted in this context, involve state-based procedures for separate sampling of each outcome. The first paper on corporate failure modelling, which discretises the continuum of company financial health is a study of large quoted US firms in the 1970s by **Lau** (1987). Lau assumes the following five stages of the evolution of financial position of a quoted company: financial stability, an omission or reduction of dividend payments, technical default and default on loan payments, filing for bankruptcy, and liquidation. For isolating factors explaining each of the outcomes, Lau uses a large, state-based, unbalanced estimation sample of 400 companies, with the prevailing proportion of healthy firms. *Ex ante* holdout tests are performed on a taken from a later time period sample of comparable size and structure. An objection to the empirical design in Lau is that to describe the relationship it combines unsuitably the ordered outcome with an inappropriate for this situation logit model of the multinomial variety. The major difficulty with creating a sample for modelling the failure process as a categorical response relates to defining adequate indicators that measure unobservable stages of financial distress. Overlapping categories violate the underlying the multinomial and ordinal model methodology assumptions of the categories associated with the set of outcomes being mutually exclusive and exhaustive, which obviously leads to a rather poor identification of failure determinants. A range of proxies used in Lau seems unsuitable for defining non-overlapping categories, therefore one may have some reservations in relation to the validity of Lau's interpretations of stage-specific factors of financial distress.

An analysis of failure with a multinomial dependent variable is conducted in a recent paper by **Johnsen and Melicher** (1994), who study US firms in 1970-83. Their empirical design suffers shortcomings similar to those that we have just identified in the paper by Lau (1987), although the number of states of the outcome space has been collapsed to three. In order to locate bankrupt, financially weak and non-bankrupt companies, the authors use the records of bankruptcy filings along with Standard & Poor's rankings of stock quality. A large state-based sample consists of 112 bankrupt firms, 293 non-bankrupt firms and 255 financially weak firms, but the observations comprising the two latter groups are drawn randomly, to facilitate generalizability of results. To prevent the confounding influence of contextual factors relating to industry differences, utilities and firms in financial and service sectors are not included in the sample, in line with the treatment applied in Altman, Haldeman and Narayanan (1977) and Ohlson (1980). The model fit, assessed on estimation data points, is additionally validated in a follow-up study whereby the predictive performance is monitored by tracking both financial position and changes in status of the sample firms over a five-year period after the year of the initial classification in the estimation sample.

A recent paper from the US by **Richardson, Kane and Lobingier** (1998), is concerned with development of an explanatory model of failure. Their empirical design, centred on the dichotomy between bankrupt and non-bankrupt firms, addresses the issue of appropriate sample proportions in explanatory models of failure, which employ the binary dependent variable. A large unbalanced sample of 2,218 listed firms resembling the population proportions of failed and non-failed firms, is used for calibrating a binomial logit model. No holdout data set is created for "out-of-sample" tests, but the relevance of failure risk factors is inferred from the assessment of the model predictive power in the Lanchenbruch tests.

In the late 1990s, studies from the US, exploring aspects of company failure, started to employ larger and unbalanced samples to address the pertinent problem of reflecting the population proportions in the data sets used for model development. Since information on company status performance and financial position has become widely available from established electronic data bases, it became possible to use correct, from the statistician point of view, random sampling procedures for constructing the comparison category of non-failed firms. Notwithstanding these improvements in data availability, there are examples of recent analyses favouring a problematic equal-share sample design, that is constrained further by matching on factors which can be considered as causes of failure. This problematic approach to sampling can be found in a comparative study of model sensitivity to alternative sets of financial-based model inputs, conducted by **Mossman, Bell and Turtle** (1998). Adhering to the empirical design typical of the early literature, they construct an equal-share sample of non-financial firms by matching them on size and industry, and obtain inference regarding the model classificatory power by using the jackknife procedure due to Lanchenbruch.

Peel, Peel and Pope (1986) in their investigation of UK listed companies work with binomial logit and a sample of 78 firms, 34 of which failed in 1971-82. The failure outcome is defined as creditors' voluntary liquidation, receivership or winding up by the court order, and no matching is used in creating the sample. From the perspective of model validation, an obvious flaw of Peel, Peel and Pope's approach relates to the limited usefulness of an *ex post* holdout, taken from the estimation time-period. This method of constructing the holdout sample introduces a bias in the estimates of model predictive accuracy and lessens the validity of results as to the stability of the effects of explanatory variables. The same criterion of failure and analogous sample structure shape the empirical design in the logit analysis of UK company failure in 1978-82 in **Peel and Peel** (1988). However, a holdout sample containing observations from a post-estimation time period 1983-85 seems more suitable for checking the sensitivity of evaluation results to the estimation sample data points.

A narrower meaning of the failure outcome, whereby a company is considered as a failure if it is declared insolvent, is employed by **Keasey and McGuinness** (1990) **and Keasey, McGuinness and Short** (1990) who investigate UK industrial company failure in 1976-84. Relatively small repeated cross-sectional samples (just 86 firms are studied in **Keasey and McGuinness** (1990) and 80 firms in **Keasey, McGuinness and Short**

(1990) are created using matching on industrial sector, size, and the year of accounting records. While **Keasey and McGuinness** (1990) analyse the conventional dichotomy between failure and non-failure with a set of year-prior-to-failure specific binomial logit models, employing the design approach similar to **Zavgren** (1985), **Keasey, McGuinness and Short** (1990) create a multinomial response variable measuring respectively one "healthy" state and five "year-to-failure-specific" stages in the failure process. They then proceed in a manner similar to Lau (1987) applying multinomial logit approach for isolating important financial-ratio based predictors over the five time horizons, corresponding to failure occurring in one- to five-years time. Their methodological approach seems to suffer from the mentioned above flaw of neglecting the intrinsically categorical nature of successive stages in the failure process. These inappropriate assumptions made in their work may result in some problematic effects such as biased coefficients, inefficient estimates and spurious statistical inference on financial variable effects. For an ordered outcome variable a more appropriate option may be the use of the proportional odds model or other methods for ordered categorical responses (**Agresti**, 1996). Aside from that, an equal-share sampling plan, with tests relying on *ex post* holdouts, is most likely to produce biased logit inference regarding the important causes of failure in their sample. A questionable design employing overlapping estimation and holdout samples do not provide a good basis for assessing validity of the results as to the empirically isolated determinants.

Morris (1997) tests the relationship between financial ratios and the failure outcome with an equal-share data set of UK listed companies, taken from 1973-83, by conducting binomial logit analysis and then by training neural networks. Morris defines failure as receivership or wound up order by the court. One part of his data set is used for model validation, which is conducted on an *ex post* holdout of failing firms pertaining to the estimation period and on an *ex ante* holdout of continuing firms from a later time period.

There has also been some interest in modelling a broader concept of corporate failure, equating an adverse outcome with the event of discontinuation, when the firm loses its status of a separate independent organisation. In this situation, exit through insolvency can be seen as an alternative to exit through acquisition because a financially distressed firm may well become an acquisition target. One example of modelling more complex exit structures is provided in **Wilson, Chong and Peel** (1995) who train a neural networks model for classifying three mutually exclusive outcomes of legal insolvency, distressed acquisition, and survival in UK quoted firms. The sampling frame defines a distressed acquired firm as a company, when the two conditions of separate outcomes are being satisfied: the firm was taken over and had reported either negative working capital, or negative pre-tax profit, or accounts' qualification. A state-based, equal-share sample of 112 firms, with the non-failed category selected randomly, is constructed by Wilson, Chong and Peel for training a neural net. No holdout data points were set aside for further assessments, and estimates of classificatory accuracy of the trained neural network are generated in standard jackknife tests. An earlier US paper by **Pastena and Ruland** (1986) also uses a broad definition of company failure but is distinctive in that it assumes the dichotomy between merger and bankruptcy, working with a sample of distressed firms from 1970-83. Firms in early stages of financial distress were identified by a screening procedure based on the Altman Z-score (Altman, 1968). The legal meaning of bankruptcy is used for constructing their small data set of 110 firms, which has the prevailing share of merged companies. The absence of holdout tests represents a serious limitation of the empirical setting, casting doubt on the reliability of inference in Pastena and Ruland.

Alici (1995) discusses the case of using neural networks classifiers for untangling the effects of changes in financial ratios on the risk of failure of UK firms. Failure is defined as a company being in receivership, liquidation or administration and modelled using the conventional dichotomous response. An equal-share, training sample of 92 manufacturing firms falling into insolvency during 1987-92 is selected using matching by industry sector, size and the year of accounts. The predictive performance of the neural net is then evaluated with randomly drawn holdout observations on 590 firms, but the overlap in holdout and estimation time periods limits the reliability of tests of the importance of individual predictors.

In a time-series analysis of the relation between movements in returns on a firm' equity share and subsequent failure, carried out with a sample of UK companies, **Diacogiannis** (1996) defines failed firms as those that were liquidated, wound up by the court order or placed into receivership. The data set is made of failed firms alone because the approach adopted uncovers the behaviour of share returns of listed failing firms by contrasting these returns with returns on the market over the analysis period. A broad market index is used to establish the benchmark performance. The primary sample from 1975-83 and the secondary validation sample for a later time period 1986-93 are constructed, both containing failed firms from the same industry category. In Diacogiannis (1996), matching by industry was necessary for minimising the distorting effects of sectoral trends on share return time-series.

A study by **Lindsey and Campbell** (1996) uses the time series estimates of stock returns variability obtained within the chaos systems framework as inputs for a classification model of failure amongst US firms in 1983-92. The purpose of their work is to establish the potential of chaos statistics of stock returns for improving performance of conventional univariate and multivariate failure prediction models. Failures are located using the bankruptcy criterion while a case-control equal-share sampling is used in creating the full data set of 158 firms matched by industry. The full data set is randomly divided to set aside one third of observations for *ex-post* holdout tests. The samples are sub-divided further to allow a comparison of chaos measures over the two observational windows: 7-5 years prior and 3-1 years prior to bankruptcy.

The choice of statistical method determines the sampling plan used in **Hill, Perry and Andes** (1996). The rationale for a longitudinal data set relates to the aim of conducting a more complex, event history analysis, which introduces a time dimension in the data and permits to explore the effects of both firm-specific and economy-wide factors in financial distress and bankruptcy of US industrial firms in 1977-87. Event history analysis uses so-called survival-time data, a variant of cross-sectional time-series data, which contain information on firm duration. The sample frame excludes financial companies, transportation firms and utilities, to obtain a more homogeneous data set. Taking the cue from Lau (1987) and Johnsen and Melicher (1994), **Hill, Perry and Andes** (1996) model the failure process as evolving in three distinct stages: the stable state, state of financial distress and bankrupt state. Firms with cumulative negative earnings over any three consecutive years in the sample period are assigned the status of financially distressed, while involuntary bankruptcy indicates the bankrupt state. The resulting longitudinal data set contains 381 firms followed over 11 years, including 75 bankrupt cases. A rotating panel design ensures that the panel is balanced: as failed firms drop out of the data set, they are being replaced by fresh cases. Although the models are intended to be explanatory only, the authors employ 'in-the-estimation-sample' classification tests for evaluating the overall fit of the model built.

This section provided a discussion on data needs and sampling plans that are characteristic of the extant literature. All the studies reviewed above focus on an individual company as the unit of analysis. As data necessary for setting the samples are usually obtained from commercial data-bases that rarely include financial records on smaller firms. We have seen that most studies use data on large quoted companies in their examination of the company failure phenomenon.

These past investigations usually utilise the retrospective case-control design for a micro-level analysis of failure within the classification framework and with state-based and often equal-share samples. Most micro level studies from the UK and the US, rely on cross-section data, the exceptions being multivariate time-series data analysis of share returns in **Diacogiannis** (1996), the use of time-series estimates in **Lindsey and Campbell** (1996) and a longitudinal study in **Hill, Perry and Andes** (1996). A binary indicator is a natural choice for modelling the dichotomy between "failure" and "survival", while legalistic criteria for identifying the failure outcome are considered as more practical because the event and timing of legal bankruptcy is easy to track with publicly available information. Favouring the notion of several distinct stages in the failure process, some studies attempted to modify financial distress analysis with classification models handling a multinomial response. The recurring flow in these multinomial studies is that they ignore the ordinal nature of individual stages in the failure process. Assuming distinct, mutually exclusive and non-overlapping grades in the scale measuring financial distress these studies introduce imperfect proxies for grades such as omissions of dividend payments, technical default, default on loan payments, rankings of stock quality by credit agencies and cumulative negative earnings. Our standpoint is that there is no merit to fit a multinomial regression to the response variable, which is putatively categorical. At the other end of the spectrum, financial failure by insolvency is modelled as one of the possible exit routes and compared with an alternative of losing independence through acquisition.

An important issue of empirical design, which has a connection to sampling problems discussed above, concerns the choice of relevant causal variables for an explanatory model. In a retrospective observational study, firm-specific attributes, which measure explanatory variables, should be identifiable in the sample. The degree of consistency of records on the variables of interest affects sample sizes and determines the completeness of the data for the desired statistical analysis. The next section reviews approaches adopted in the prior literature towards selection of explanatory variables and potential predictors.

2.3 The Choice of Candidate Variables Gauging the Factors of Company Failure

The problem of variable selection in company failure studies arises from the coincidence of model uncertainty and parameters' heterogeneity. Such features as the definitional ambiguity of failure, absence of a clear conceptual structure and need for an integrated analysis of macroeconomic and firm-level factors place a burden on empirical research. Company financial distress depends on the firm's ability to meet payment obligations or renegotiate and restructure its debt, and this ability is determined by a multitude of potentially interacting internal and external factors. Econometric investigations of company failure are viewed as a search for empirical regularities, not as a set of exercises in structural estimations. Our reading of the literature suggests that the orientation of company failure research is exploratory and descriptive, rather than a stringent test of structural relationships. The goal of a typical study is to identify internal and external to the firm characteristics, which are positively or negatively associated with failure and to explore their relative importance.

Nonetheless, empirical models - even the models developed for predictive purposes only - have generated useful economic insights. The lack of a unifying analytical model does not appear to imply that the derived empirically failure predictors render their economic interpretation invalid. Previous studies of the failure phenomenon have explored a variety of predictors or explanatory variables including a number of firm-specific attributes that are based on accounting information, non-financial disclosures and market valuation as well as on indicators of the corporate business environment.

2.3.1 Firm-specific Attributes

Financial distress is a complex, high-dimensional phenomenon and plausible explanatory variables should ideally reflect the whole context of the failure process. Company failure is not a sole domain of finance. Although the empirical literature, offering stylised facts on the risks of failure, stresses the critical role of financial performance and position for the company's robustness to external shocks, the literature also recognises an important influence of economic efficiency, productivity, firm size and age, managerial competence and corporate governance. In the long term, the primal causal forces affecting the firm's performance and survival are its superior competitive ability and the growth potential, which result in profits, larger cash flow, and easier access to external finance. Abundantly supplied by the current literature accounting ratio-based predictive models are driven by intuitions that financial statement measures should reflect the impact of deep causal factors because ratios are widely used by credit analysts to judge credit risk of firms. That gives the rationale for the use of financial statement-based explanatory variables, which can be thought of as the observable indices of changes in the deeper latent variables that constitute the conditions for failure. The operational models of failure risk, initiated by **Altman** (1968) and **Taffler** (1982), show that failing companies can be identified with data from company accounts capturing shifts along dimensions of profitability, gearing, liquidity, and financial efficiency. It follows therefore that the scholar may be able to say something about the conditions for failure by looking at the relationships that exist between accounting ratio-based observables and the adverse outcome. In other words, unobserved changes in primary factors will be recorded in observed consequences.

2.3.1.1 The Rationale for and Use of Accounting Ratio-based Variables

In financial analysis, an examination of company performance and financial position with data from financial statements involves a comparison of summary measures in ratio form. The prominence of financial ratio analysis for comparing performance is a response to the need to compress the large informational content of accounts, controlling at the same time for the effect of firm size. The rationale for the wide-spread use of ratios is to measure the non-size related variation in the accounting variable of interest either across companies or on the time-series basis. Although accounting practices in relation to specifications of individual items and the ways ratio components are calculated vary, numerous financial ratios proposed in the literature can be classified into broad categories of profitability, gearing, liquidity and financial efficiency[19], in accordance with the important dimensions of company performance and financial position. By construction, ratios within each category can considerably overlap in the information they provide, with the implication that a representative of each category set of ratios can convey much of the information contained in the accounts of a firm. The choice of particular sets of ratios for empirical work on company failure has been often justified by some evidence on their particular relevance reported in past studies, but at times this choice is simply predetermined by the coverage of account items in the data-bases used by researchers.

Financial analysis holds that the embedded in a geared firm potential risk of debt default, which may carry the danger of bankruptcy and liquidation, results from unfavourable changes along the dimensions of short-term liquidity and long-term

[19] Note that in the literature, efficiency ratios can also be termed "turnover" or "activity" ratios.

solvency. Observable from company accounts measures of profitability and gearing encapsulate the conditions of long-term solvency, while liquidity and efficiency ratios facilitate assessment of short-term financial risk.

Theoretical considerations link changes in profitability and the risk of liquidation. The liquidation event may occur when the market value of the firm's assets does not cover the book value of its liabilities (**Merton**, 1974; **Scott**, 1981). Profitability determines the changes in the asset value of the firm and therefore seems a natural determinant of failure. Accounting measures of the concept of profitability reflect the relationship between income and expense. The ability to control expense in relation to income enhances earning power essential for the firm's ultimate existence. The two most frequently used profitability ratios are returns on investment and profit margins. A generic ratio and the primary test of profitability is return on capital, which expresses the relationship between profits and the investment required to generate them. Several levels of profit and diverse measures of investment result in different forms of rates of return illustrating different aspects of investment and performance. In equilibrium, the after-tax return on investment is expected to be equal to the real interest rate on the risk-free asset plus a risk premium, which in turns depends on the business risk of the firm. An alternative way of expressing profitability is by calculating profit margins which state profit as return on turnover. In general, higher margins assist firm survival, however, many firms face a trade-off between profit margins and turnover. It may be possible to achieve a higher profit margin by charging higher prices but the level of sales will fall. The level of profit margins may be determined by industry sector and reflect the market power of the firm (**Machin and Van Reenen**, 1993).

Financial risk in a firm is captured by gearing and liquidity ratios. Capital gearing measures the long-term default risk implied by the firm's financial structure. It captures the balance between the two sources of long-term finance – funds invested by ordinary share capital holders and those invested by lenders. The presence of debt in capital structure of the firm involves fixed obligations in the form of interest and principal payments and therefore generates default risk. But a certain amount of gearing is attractive to shareholders as interest expenses on debt are tax deductible, and that should have the effect of raising the average return on equity. Capital gearing is concerned with the relation between the basic earning power, which can be measured by return on total assets or by return on equity[20].

Given that default risk is an attribute of debt, an analysis of underlying indebtedness is a crucial component in a joint examination of the extent to which the firm's long-term solvency can be affected by absolute levels and relative changes in gearing ratios. Capital gearing ratios relating debt to equity help to assess whether the firm can pay back the principal on the outstanding debt. However, various constructs of capital gearing ratios are inevitably arbitrary and the choice of the components entering the numerator and denominator of a ratio depends on how one defines liabilities and equity for the analysis. Some variants of the debt to equity ratio combine preference capital under the *debt* label, while other exclude short-term debt from calculations with the rationale that short-term debt is transitory and may not contribute to financial stress. The literature draws attention to a problem of measuring company assets, arising from the use of capital gearing ratios in financial position analysis (**Foster**, 1986). Capital gearing is a stock variable and where the debt to equity ratio uses book values it is likely to provide an inadequate picture of underlying indebtedness. While the balance sheet value of debt is approximate, the balance sheet value of equity is grossly inaccurate. There are variants of debt ratios that use market values instead of book values to reflect the fact that some firms have a significantly greater capacity to borrow than their book values of equity might indicate. The increases in debt levels may be matched by an increase in the market value of equity due to higher expectations of future profits or due to the presence of intangible assets, which are not capitalised in the balance sheet. Finally, it seems still appropriate to use market value-based debt ratios in examining the companies who do not have publicly traded debt since deviations of market values of equity from respective book values are likely to dominate in debt ratio calculations.

[20] We discuss this relation in chapter 1.

Capital gearing captures only one part of the effect one would like to attribute to indebtedness. The second group of gearing measures, called income-gearing ratios and based on items from the profit and loss account, gauge the combined effects of indebtedness and profitability, allowing for the important influence of changes in interest rates on financial position of the firm (**Nickell and Nicolitsas**, 1999). Income gearing ratios that concern with the relation between pre-interest profit and post-interest profit for a given amount of interest indicate the firm's capacity to make interest payments from earnings. Unlike capital gearing, income gearing is a flow variable and avoids the problems arising from measurement of company assets.

A joint analysis of changes in capital and income gearing ratios is of great importance as it helps to understand the extent of financial distress. A firm with low capital gearing but with a relatively high income gearing caused possibly by unfavourable changes in interest rates or temporary declines in profits, may be able to resolve debt sustainability problems by raising new external finance, thereby avoiding outright default. The situation of high income gearing being accompanied by high capital gearing makes the problem of temporary illiquidity more challenging. This situation can lead to a crisis of solvency because it might be impossible to rapidly evaluate the firm's long-term prospects and to implement a necessary restructuring of financial claims relatively cheaply. By reducing borrowing capacity, excessive gearing affects the firm's access to external finance and increases risk of failure. **Stead** (1995) emphasises that in covenants for their lending, bankers would normally consider a range of gearing indicators including equity or shareholders' funds value, the debt to equity ratio and interest cover (the reciprocal of income gearing). A violation of debt covenants results in technical default under the loan agreement, making the debt due immediately. If waivers from lenders are not obtained, the event of debt default might be followed by the firm's creditors initiating legal insolvency proceedings.

Profitability and capital gearing are important factors affecting the viability of a company in the long run. However, as implied by the concept of income gearing, the firm's inability to meet its interest payments and other short-term financial commitments can become an overriding issue since continually developing illiquidity is a terminal condition. Short-term liquidity risk arises primarily from the need to finance working capital, with poor liquidity leading to financial distress. Evidence from surveys conducted by the *Society of Practitioners of Insolvency* (1996) suggests that failing companies refer to the lack of working capital and non-paying debtors as the primary reasons for their financial distress. However, one can argue that, given equal capital gearing, short-term liquidity risk will be determined by the interaction of liquidity and profitability since the firm short of ready cash but generating good profits may be able to get the right backing and continue to trade. To avoid the potential shortfalls of liquidity the firm may keep more liquid assets on its balance sheet as a buffer.

Accounting measures of liquidity are usually derived from the balance sheet. Current assets liquidity, as defined by the current ratio, gives a view of cash circulating in the working capital area of the company, measuring the relation between current assets and current liabilities. In a more conservative check of current assets, liquidity can be measured by the cash ratio that restricts liquid assets to only cash or cash and marketable securities. In addition to the on-balance sheet liquidity indicators, a related set of cash flow measures can be constructed with items from cash flow statements and funds of flow. The especial relevance of cash flow statement-based ratios for evaluating a company's liquidity position is emphasised in **Beaver** (1966). For analysing financial health, Beaver introduces the reservoir analogy, thinking of the firm as a reservoir of liquid assets supplied by cash inflows and drained by cash outflows. However, one potentially troubling feature of cash flow measures is that they reflect working capital movements, masking movements relevant to liquid assets. The serious problem of adequately measuring depreciation also arises in the operational use of cash flow measures. The literature observes the volatility of constructed cash flow ratios, which often precludes their use as explanatory variables in empirical models of failure (**Altman**, 1968; **Taffler**, 1982).

A firm's working capital requirements and its liquidity position tend to vary with changes in management of working capital or financial efficiency. Efficiency (or turnover) ratios are important for describing short-term liquidity risk because they are driven by sales activity and capture the effects of changes in inventories and debtors. The debtor turnover ratio can be particularly relevant as it can throw some light on the possibility of the domino effect should the company's clients experience liquidity problems. Overall, greater operational efficiency leads to a shorter financing period for the firm to fund working capital needs and reduces the likelihood of financial distress.

Evidence from the industrial economics literature emphasises the need to control for size when examining the firm exit process. The empirical research in the field of market exit indicates clear links between age, size, subsequent growth and exit of firms. The learning process might induce the most efficient firms to expand and the least efficient firms to contract or exit. One benchmark model - the "passive learning" model due to **Jovanovic** (1982) - implies that new firms do not initially position themselves at a unique optimal size and learn about levels of their costs and efficiency over time. The inverse relationship between size and exit risk is supported in empirical work by **Marcus** (1967), **Dunne, Roberts, and Samuelson** (1988), **Dunne and Hughes** (1994), and **Mata and Portugal** (1994). In the extant finance literature, the preferred explanation of the size effect is that larger firms have greater market power, their earnings stability is expected to be greater, they therefore may be more successful in negotiating debt rollovers and financial restructurings, which provides them with an easier access to new external funds. The size effect also supports the view that within any given industry, small firms are more likely to be marginal suppliers and therefore could be highly sensitive to declines in industry demand and recessions. Special rescue actions by the government to resolve distress problems in larger firms seem more likely because large firm bankruptcies can be more costly to the economy in general as compared with failures of small firms. To the extent that size of a distressed company serves as an additional incentive for its creditors to co-operate in negotiating a corporate workout at the pre-insolvency stage this may partly explain higher incidences of insolvency amongst smaller firms.

Marcus (1967) reports the importance of size and age effects for variations in aggregate rates of firms' mortality. For US data from 1951-60, Marcus finds that the exit rate measured as a proportion of firms experiencing losses is explained by the effects of young age and small size, common to all industries. Markus argues that the higher probability of losses for small firms, given identical market risks, is linked to the fact that the cost of capital is higher for smaller firms, which in turn might imply lower profitability. In addition, Markus argues that the observed inverse relationship between failure and firm size is in line with the migration hypothesis, according to which profitable firms experience, on average, positive growth rates and subsequently migrate into larger size groups.

The financial accelerator literature suggests that recessions, monetary tightening, and increased interest rates should have a differential effect on net worth and solvency of borrowers because the severity of the agency cost problem faced by firms depends on firm size. When the need for external funds is rising, credit flows away from harder-to-monitor, low-net-worth borrowers to high-net-worth borrowers. Large firms should have lower agency costs per unit of external finance because of their greater diversification, longer track records, and because of economies of scale in collecting and processing information about their situation. This gives rise to the agency problem in credit markets for smaller firms who experience reduced access to credit relative to other borrowers and therefore reduce their spending and production earlier and more sharply than other firms. Using firm-level data for US manufacturing companies, **Bernanke, Gertler, and Gilchrist** (1994) present strong empirical evidence on the "small size effect" being explained by the flight to quality in recessions.

The "small size effect" is observed in **Dunne and Hughes** (1994), who investigate the relationships between asset size, age, growth and death for the large sample of UK quoted and unquoted companies in 1975-85. Their analysis adopts a wide definition of exit including takeovers, voluntary and compulsory liquidations, receiverships, losses of quotation, company reconstructions and reorganisations. In their analysis, they find a non-linear, inverted U-shape relationship between exit and size, measured by net assets.

For companies with over £1 million in size in 1980, liquidation rates peak at 5.1 per cent in the £4m-£8m category and then fall to 1.3 per cent for the firms with net assets greater than £64m. The authors also observe the turbulence of small firms' growth, and the tendency for younger smaller firms to have a greater propensity to fail.

Firm size can be defined in a number of ways – in terms of employment, product market share, turnover (or net sales), book value of total (or net) assets, and, for quoted companies, by market capitalisation. Company accounts generally provide adequate measures of these variables, although the information on product market shares available from accounts may be inconsistent and lacking detail. In predictive models of company failure, firm size has often been measured by turnover (e.g., **Ohlson**, 1980; **Wilson, Chong and Peel**, 1995) or by assets (e.g., **Altman, Haldeman and Narayanan**, 1977; **Marais**, 1979; **Peel, Peel and Pope**, 1986).

The heterogeneity of the failure process can also stem from differing ages of firms going into insolvency. **Altman** (1968) recognises the importance of age and uses an indirect proxy of cumulative profitability in his discriminant model, but such an approach seems simplistic. In much modelling of corporate failure at the firm level, essentially static cross-sectional empirical designs preclude incorporation of a time dimension. Despite the fact that the importance of the age factor has been registered by empirical work in the field of industrial economics (see, e.g., robust results in **Dunne and Hughes** (1994)), models of failure as an inter-temporal process, with firm duration entering as an independent explanatory variable, are virtually non-existent in a large body of UK empirical literature.

In modelling failure, the choice of appropriate financial ratios to proxy the factors of interest can be justified by references to theory, especially when one is interested in providing further evidence on the explanatory role of indebtedness, cash flow, size, and age. However, the multitude of ratio specifications, ratio collinearity and concerns not to omit possibly important variables often induce the researcher to justify the choice of accounting-based explanatory variables by evidence on their predictive power reported by past studies. This modelling strategy has serious limitations. Empirical results can be ratio-construct-sensitive as well as sample-sensitive, inhibiting a comparison of the usefulness of particular predictors, while the underlying causes of failure may vary across firms, sectors, and over time, depending also on institutional arrangements for insolvency or bankruptcy. In the absence of a clear theoretical framework, an alternative way of revealing the important determinants is to rely on statistical selection procedures conducted with a wide range of ratio-based inputs, reflecting company performance and financial position.

For a univariate analysis of US companies, **Beaver** (1966) uses thirty financial ratios which are selected on the basis of their popularity with financial analysts, performance in past studies and ability to reflect the cash flow position of the firm. Using an equal-share sample, Beaver compares mean values of ratios for failing and continuing firms as a profile analysis over a five-year period prior to failure, identifying general associations between changes in ratios and the adverse outcome. Based on results from dichotomous classification tests conducted on a univariate basis and for various prediction horizons, Beaver concludes that the ratio of cash flow to total debt discriminates best between failing and continuing firms. Less powerful predictors included cash flow to total debt, net income to total assets, total liabilities to total assets, working capital to total assets, current ratio, and ND credit interval [21]. The most important dividend of Beaver's univariate study is evidence that financial ratios, or more generally, accounting data from which they are derived, have the information content that allows to predict failure for at least five years prior to the event.

A standard example of a ratio-based multivariate discriminant model for failure prediction is the Altman Z-Score model for US manufacturing corporations (**Altman**, 1968). An initial set of twenty two popular in the finance literature ratios was used in model development, but the ratio of cash flow to debt, the most important measure in Beaver (1966), was not possible to include in the model because of the lack of

[21] ND stands for Net defensive assets. ND credit interval = [(cash + marketable securities-current liabilities)/(operating expenses-depreciation-depletion-amortisation)].

consistent depreciation data. The final specification of Z-Score function encompasses a comprehensive set of ratios, covering all main dimensions of financial analysis. Liquidity is represented by working capital to total assets; cumulative profitability and long-term solvency by retained earnings to total assets and by earnings before interest and taxes to total assets; gearing by market value of equity to book value of total liabilities and efficiency by sales to total assets. In offering the rationale for including cumulative profitability, Altman argues that this variable has an important additional function of being an indirect proxy for age. A relatively young firm had less time to build up its cumulative profits and therefore would show a lower ratio of retained earnings to total assets. Cumulative profitability measures, however, should be used with care as their usefulness as an indirect control for age can be restricted by manipulation via corporate quasi-reorganisations and declarations of stock dividends.

A commercial application of the Altman Z-Score, the ZETA® credit risk model, developed to predict failure both in retail and manufacturing, is reported in **Altman, Haldeman, and Narayanan** (1977)[22]. The range of explanatory factors has been expanded by adding measures of asset size, market capitalisation and earnings stability, and by using income gearing instead of capital gearing. The seven discriminating ratios included earnings before interest and taxes over total assets (overall profitability), the logarithm of total tangible assets (size), the current ratio (liquidity), earnings before interest and taxes over total interest payments (income gearing), retained earnings over total assets (cumulative profitability), market value of common stock over market value of total capital (market capitalisation) and the normalised measure of the standard error of estimate around a ten-year trend in the overall profitability variable (earnings stability). By allowing in the model specification for volatility in the firms' earnings, Altman, Haldeman, and Narayanan take a more dynamic view on bankruptcy risk.

Both models - the Z-Score and ZETA® - are still being used by practitioners throughout the world, illustrating that accounting ratios perform reasonably well as indicators of

[22] The *ZETA®* model is a proprietary model for subscribers to *ZETA* Services, Inc. (Hoboken, NJ).

corporate financial health (**Altman**, 2000). The UK earlier work on company failure prediction generally followed the methodology of modelling failure risk as a function of financial ratios. The work by Altman and colleagues seemed to provide an important modelling principle, transferable into the context of a country with different accounting and bankruptcy environments, that both long-term solvency and short-term liquidity should be represented in an appropriate specification of a predictive model. It should be noted that differences in accounting standards and accounting measure definitions make it impractical if not impossible to exactly mimic ratios employed by prior studies for different contexts, and the extant literature uses a wide range of different and often not directly comparable measures.

The first applications of the ratio-based classification model for screening financial health of UK listed industrial companies are reported in classical work by **Taffler and Tisshaw** (1977) and **Taffler** (1982). The choice of ratios employed by **Taffler and Tisshaw** (1977) is determined by the ratios' interpretability in terms of financial analysis dimensions, evidence on their effectiveness in prior empirical modelling and expert opinions given by financial analysts. Profitability is expressed as profit before tax to current liabilities, liquidity is given by current assets over total liabilities and by no-credit interval[23], while the ratio of current liabilities to total assets reflects gearing. The ratios entering the predictive function in **Taffler** (1982) broadly fall into the categories of profitability, liquidity, gearing, and efficiency. The information on changes along these dimensions is provided by a five-variable set, containing the ratio of earnings before interest and taxes to opening total assets, the ratio of total liabilities to net capital employed, the ratio of quick assets to total assets, the ratio of working capital to net worth and by stock inventory turnover. Taking the cue from Beaver (1966), who argues that models containing cash flow-based predictors should have better predictive power, Taffler experimented with ratios derived from the funds flow statement, but generated cash flow measures exhibited intertemporal instability, and did not enter the final specification of the predictive function. Taffler's paper establishes "stylised facts"

[23] The "no-credit interval" is akin to the acid-test ratio, and defined as the period of time, for which the company can finance its continuing operations from its immediate assets if all other sources of short-term finance are removed.

regarding UK company failure as well as makes causal claims. The author observes the particular importance of profitability and gearing, noting the consistency of this observation with the view that short-term illiquidity and inadequate working capital management are less important in determining the viability of a firm than the magnitude of the firm's liabilities and its earning power. This result lends support to the hypothesis that long-term considerations will prevail when trade creditors, bankers and debenture holders decide on foreclosure of a defaulted debtor with temporary cash flow difficulties. Taffler's data also show that over the analysis period 1968-73, basically sound enterprises could usually borrow their way out of temporary difficulties or reschedule the debt payments.

The appropriateness for multivariate modelling of favoured by Beaver cash flow measures is also investigated in the Bank of England study of listed UK industrials reported in **Marais** (1979). The Bank of England model includes flow of funds ratios alongside more conventional measures from the balance sheet and profit and loss account. It was found that the pre-specified ratio constructs adopted from Beaver (1966) and Taffler and Tisshaw (1977) performed on the Marais sample rather poorly, implying that the explanatory power of particular ratios can be sample-sensitive. Marais also investigates the usefulness of an alternative set of inputs, modelling the effects of profitability, size, liquidity, and cash flow. A cash flow measure was defined as the sum of pre-tax profit and depreciation. The final discriminant function relies on the following measures: the ratio of cash flow to current liabilities, the reciprocal of gross total assets, the ratio of current assets to gross total assets and the ratio of funds generated from operations and adjusted for the net increase in working capital to total debt. The model was inaccurate at classifying non-failed firms in an *ex ante* holdout, with error rates in the order of 50 per cent. The poor performance of the model might be partly attributable to the particular ratios but the small size of the estimation sample also likely to limit the robustness of predictors.

It seems self-evident that a carefully selected set of accounting ratios is necessary for successful empirical analysis. Econometric models of company failure are predicated on the identification of a candidate set of model inputs, say of dimension ζ. In the absence of a clear theoretical guidance and resource constraints in modelling the total number of possible models is 2^{ζ}, and, at this juncture, the objective of the researcher is reduce the total number of possible specifications upon which to base the selection of the model with adequate fit. Much of models of failure for the US and UK firms have been shaped by a purely statistical search. In selecting the preferred set of explanatory variables for the final model, it is common to begin modelling with an initial variable set, containing a wide range of financial measures and representative of the underlying causes of failure suggested by theory. With large sample sizes and in the absence of multicollinearity, a stepwise method employing standard statistical procedures of backward elimination or forward selection yields a subset of the key predictors. However, the combination of small sample size with highly correlated ratios is a regular feature of data available for company failure research, and that limitation makes alternative approaches more attractive. One procedure that aids the variable selection is to perform a preliminary univariate analysis of the relations between individual ratios of interest and the indicator describing failure risk, and then choose the model inputs based on their relative explanatory power. Another approach uses the methods of factor analysis or principal-component analysis for manipulating data prior to developing models. These methods serve as a means to reduce a large number of accounting measures (possible collinear) to a small number of largely uncorrelated salient characteristics, capable of describing company performance and condition. A typical example of applying exploratory factor analysis at the preliminary stage of examination of financial statement data is work by **Chen and Shimerda** (1981). This paper reports that the diversity of factors represented in financial ratios can be attributed to differences along basic financial dimensions of profitability, gearing, efficiency, cash position, liquidity and working capital management. Given high multicollinearity of financial ratios, Chen and Shimerda recommend the inclusion into the variable set for statistical modelling of failure the minimum number of representative ratios. The development of DATASTREAM Z-score model (described in Taffler (1974)) illustrates the use of principal-component analysis for reducing the initial set of forty financial ratios to only four variables representative of profitability, liquidity, gearing and efficiency. It would be fair to argue however, that in using the techniques of reformulating a set of observed financial and economic variables into a new, fewer in number, set of independent variables, one of the major difficulties the researcher encounters is the interpretative ambiguity of components (or factors) obtained. When the purpose of the model is to predict future observations, these methods of manipulating the data seems inappropriate as they convey little information to the model user.

In deciding which ratios to include in a discriminant model, **Goudie** (1987) **and Goudie and Meeks** (1991) rely on the notion that an appropriate set of ratios should reflect traditional dimensions of financial analysis, including the cash flow position of the firm. These two studies model the influence of profitability, liquidity, income gearing, changes in capital gearing and cash flow, with the cash flow ratio being measured by the sum of retentions and depreciation over net assets. The model based on these measures suggested that cash flow, income gearing and profitability play the dominant role in predicting failure for the sample firms.

As discussed above, Altman, Haldeman and Narayanan made an attempt to augment a financial ratio-based discriminant function with a measure of earnings stability, to reflect the long-term solvency prospects. The hypothesis about the strong association between failure risk and variability in the key performance indicators was subsequently tested for the US by **Dambolena and Khoury** (1980) and for the UK by **Betts and Belhoul** (1987). In Betts and Belhoul (1987), an initial set of twenty-nine financial ratios was reduced via stepwise statistical selection to just six measures reflecting the degree of gearing and the levels and standard deviations for both profitability and liquidity. However Betts and Belhoul fail to provide any justification for thinking that standard deviations based on just three of time-series observations is an adequate measure of financial ratio volatility. It is easy to see how fragile is the authors' assertion that the adopted measures of ratio stability enhance their model performance. However, their analysis highlights the need for more dynamic approaches in studies of failure.

Ohlson (1980) supports the use of standard accounting items in measuring factors of failure risk. The use of standard ratio constructs averts the potential difficulties of obtaining the data needed for creating measures replicating "handcrafted" ratio-constructs. In addition, for a predictive model to be useful in a decision-making context, it should be based on conventional, standard for the particular environment ratios. In a large-scale study of US listed company bankruptcies over the period 1970-76, Ohlson uses a standard set of accounting items available from COMPUSTAT. The probability of failure is modelled as a function of asset size, gearing, changes and levels of net income, liquidity, cash flow, and balance sheet solvency. An interesting innovation of his study relates to the use of proxies for long-term solvency, which is measured both in terms of negative net income over the latest two-year period and in terms of balance sheet solvency. Ohlson registers that changes in asset size, gearing, current liquidity and performance played the key role in the sample firms' bankruptcies. In discussing the empirical results, Ohlson makes an important methodological point regarding the inherent incomparability of statistical models of failure based on differing data sets and predictor-variables. Since data sources used for modelling are rarely standardised, it is difficult to ensure "like with like" comparisons of resultant models. Ohlson notes that given differences in specification of individual accounting predictors, the researcher should shift the focus of the comparison of findings to the question about the relevance of the main drivers which these predictors represent, and to the overall conformity of empirical evidence.

Practical considerations influence the choice of explanatory variables in **Zavgren** (1985), where the ratios, representing return on investment, leverage, short-term liquidity, cash position, and operational (financial) efficiency, reflect major financial dimensions. The logit analysis of data on US companies from 1972-78, suggests that at shorter risk horizons - one and two years before failure due to bankruptcy- higher levels of indebtedness and liquidity shortages signal failure. Lower levels of efficiency seem to indicate a failure event occurring in three-year time or four-year time, while changes in profitability – notably in a sharp contrast with Ohlson's results from a large-sample study - are not associated with failure risk.

The literature recommends raw values transformations to improve empirical properties of ratio-based covariates and to strengthen predictive power of models. In particular, **Platt and Platt** (1990) address the methodological problem of inter-sectoral instability of accounting ratios in their analysis of US firms in the period from 1972 to 1986. As dimensions of company performance and financial position, Platt and Platt employ profitability, efficiency, leverage, liquidity and size. Platt and Platt introduce the use of industry-adjusted, centred values of accounting ratios in a logit model of failure. They record predictive accuracy improvements in *ex ante* holdout tests, the result, in their view, entirely attributable to the use of the transformed values. This finding is, of course, consistent with the general recommendation from statistical modelling that normality improving transformations or adjustments of continuous (or quasi-continuous) variables improve the overall fit of a resulting model. While the logarithmic and square root transformations can be used for the ratios defined in the positive area, standardised or centred ratio values can also be employed to improve statistical properties. Therefore when evaluating the results in Platt and Platt it seems impossible to separate out the improvements obtained due to the standard statistical procedure of centering and the effects of the centring ratio values on the industry-level averages. However, **Altman** (1993) argues that in the situation where a model is intended for prediction, transformation of values of new observations by applying sectoral averages may be not possible in a consistent way as many firms operate simultaneously in different industries or switch industries over time. More importantly, sectoral differences are not the sole factor affecting stability of accounting ratios and power of company failure prediction models. Changing economic conditions reflected in indicators measuring inflation, interest rates, credit availability, and the business cycle also impact on company financial performance and position.

A substantial body of work examines inter-temporal and inter-industry stability of financial ratio constructs (see, e.g., **Dambolena and Khoury,** 1980; **Mensah,** 1984; and **Sudarsanam and Taffler,** 1995). Empirical evidence from these studies suggests that ratios exhibit both non-proportionality and non-normality in the ratio component relationship, which may render the distribution of the resulting ratio skewed and non-normal. The proportionality assumption that implicit in the transformation of accounting variables into the ratio form, is not maintained when data from company accounts represent different industry sectors and recorded for different phases of the business cycle. There is also evidence that the relationship between ratio components changes over time within a particular industry sector. This issue cannot be ignored in the context of company failure modelling because stereotype statistical methods often necessitate variable normality while data sets are heterogeneous due to unavoidable pooling of data across different years and industries to obtain sufficient sample sizes. One would expect that structure and accuracy of empirical models of company failure risk, estimated over untransformed accounting ratio values, differ across different business environments. However, current research seems to lend support to the following viable solution to this empirical issue. An appropriate, normality improving transformation of ratio values such as a simple standardisation of annualised values using parameters of the respective annual distributions for the sample years, can improve the behaviour of financial ratios, strengthening model stability.

In recent work, the choice of particular accounting ratios has been primarily justified by the availability of comprehensive arrays of readily available accounting items offered by large commercial databases. A major benefit of using standard ratio constructs, adjusted for changes in accounting treatments and practices, is convenient access to several years of observations on broad cross-sections of firms, which allows to create large samples needed for valid inference. But reliance on commercial databases in turn inevitably pre-determines the sample frame, restricting analyses to the population of large quoted actively traded firms. Illustrations of the use of 16 standard ratios supplied by DATASTREAM are two studies of UK non-financial large quoted firms in 1976-84 by **Keasey and McGuinness** (1990) and **Keasey, McGuinness and Short** (1990). The purpose of these investigations was to examine the importance of profitability, efficiency, gearing and liquidity as indicators of financial health of large firms. Obtained logit estimates broadly imply that profitability and efficiency ratios are important explanatory variables in the short term, in the years immediately prior to failure. A more recent example of the use of standard ratio constructs is the study by **Morris** (1997), where the EXTAT database is used as a source of accounting data for analysis of UK firm failure in 1973-83. Morris finds that profitability, gearing, liquidity and size are important in explaining the risk of failure. Accounting-based measures of profitability, risk, cash flow, liquidity, gearing and working capital held on MICROEXSTAT are employed for developing classifiers based on neural networks in **Alici** (1995). Over one hundred standard accounting ratios were included in the initial set, which was then reduced through stepwise elimination procedures to several smaller sets of best discriminating variables. Alici finds that classification accuracy in holdout tests tends to improve when a large number of ratios are used for training neural networks classifiers. This finding has a profound implication for company failure research that a desirable specification should be based on a wider range of explanatory variables because sparse models may fail to reflect high heterogeneity amongst companies and irregularities in financial ratios, associated with their stochastic nature.

The widespread use of accounting ratios as input variables is particularly significant in company failure research but there is a problem of having too many possible ratios. Similar predictive power of reported in past studies models with specifications based on different combinations of ratios, seems to imply that no dominant or unique set of accounting variables with respect to corporate performance and financial position can be established (see Tables 2.2 and 2.3). Despite difficulties of selecting an appropriate set amongst a large number of candidate sets of ratios and relatively weak economic and finance theories, in terms of predictive power, resultant models seem to differ marginally. However, as direct comparisons of the levels of model accuracy seem inappropriate due to differing data samples, more formal assessments of differential influences of alternative sets of ratios on model predictive power have been conducted. In a recent paper, **Mossman, Bell, Swartz, and Turtle** (1998) test the sensitivity of logit model classificatory power to the variable set choice. Their investigation complements a well-known work published by **Hamer** in 1983, who finds no evidence that the predictive accuracy of discriminant and logit models varies when the dimensions of profitability, liquidity and leverage are being represented by alternative

Table 2.2 The Forewarning Ability of Failure Models Based on MDA

	US Studies		UK Studies			
Years Prior to Failure	Altman[24] (1968)	Deakin[25] (1972)	Taffler[26] (1982)	Goudie (1987)		Betts and Belhoul[27] (1987)
	Error Rate (percentage)					
	Type I	Type I+II	Mispredictions of Firms at Risk	Type I	Type II	Type I+II
1	6	22	4	n/a	n/a	19.1
2	28	6	39	0	1.0	47.1
3	52	12	52	16.7	5.3	76.5
4	71	23	65	25.0	5.2	76.5
5	64	15	n/a	30.0	11.1	87.5

[24] Altman (1968) classifies companies from the estimation sample, using one-period function.
[25] Deakin (1972) reports cross-validation results, using *n*-period functions.
[26] Taffler (1982) reports the results for the 23 failed companies in his estimation sample, however, he applies the one-period model to the data from accounts for the years prior to the last set of financial statements. Entries denote percentages of failing firms, which were not identified as being at risk. Taffler stresses that this classification does not constitute a test of the model's predictive ability. It only states the error rate in identifying the firms subsequently going bankrupt.
[27] The validation sample results demonstrated by the linear discriminant function containing stability measures and developed for one year prior to failure.

Table 2.3 The Forewarning Ability of Failure Models Based on Binomial Logit

Years Prior to Failure	US Studies										UK Studies					
	Zavgren (1985)		Richardson, Kane, and Lobingier (1998)		Mossman, Bell, Swartz, and Turtle (1998)[28]						Peel and Peel[29] (1988)		Keasey and McGuinness[30] (1990)		Morris (1997)[31]	
	Error Rate (percentage)															
	Type I+II		Type II		Type I	Type II	Type I	Type II	Type I	Type II	Type I	Type II	Type I	Type II	Type II	
															1983-84	1993-94
	Ex post	*Ex ante*	(a)[32]	(b)[33]	Financial Ratios		Cash Flow		Market Returns		*Ex post*		*Ex post*		*Ex ante*	
1	18	31	62.6	55.6	20	28.9	28.9	31.1	33.3	42.2	8.6	6.8	44	30	4 (54)	25 (78)
2	17	31	n/a	n/a	41.9	41.9	41.9	39.5	55.5	39.5	8.6	6.8	22	29	n/a	n/a
3	28	31	n/a	n/a	51.3	55.3	50.0	36.8	39.5	42.1	8.6	6.8	27	44	n/a	n/a
4	27	31	n/a	n/a	48.3	58.6	62.1	37.9	69.0	44.8	n/a	n/a	32	38	3 (63)	14 (86)
5	20	31	n/a	n/a	40.4	46.2	57.7	42.3	42.3	26.9	n/a	n/a	39	69	n/a	n/a

[28] Mossman, Bell, Swartz, and Turtle obtained discrimination accuracy results using a quasi-jackknife procedure, a cutoff probability value was set at 0.5. The classificatory accuracy is reported for the sample composed by the "Size-primary" matching procedure.
[29] The binomial logit models' classification accuracy on the estimation sample, at the 0.5 cutoff.
[30] The *ex post* holdout results.
[31] The results are for two *ex-ante* holdout samples, taken from the periods of 1983-84 and 1993-94. Estimates are obtained assuming the prior probability of failure equal 0.5. Figures in parentheses are given for the prior probability of failure set at 0.02.
[32] The Lachenbruch test results at the 0.02 cutoff, for the base model utilising accounting ratios only.
[33] The Lachenbruch test results at the 0.02 cutoff, for the model with recession controls.

comprehensive sets of ratio constructs. Hamer therefore recommends that the researcher should consider a variable set that minimises the cost of data collection. **Mossman, Bell, Swartz, and Turtle** (1998) extended the investigation of model sensitivity to differing variable sets by adding stock market returns to a representative set of accounting ratio-based predictors. Four sets were constructed with the inputs used by **Altman** (1968) for representing financial analysis dimensions in Z-Score model, cash flow variables employed in **Aziz, Emanuel, and Lawson** (1988), and market valuation variables from the studies by **Clark and Weinstein** (1983) and **Aharony, Jones, and Swary** (1980). A comparison of results, derived from the four alternative sets, reiterates the conclusion that a comprehensive set of accounting ratios captures best the changes in company performance and position. Altman's set of ratios shows the best discriminatory power in the short term, while the set of cash flow measures does not provide gains in discriminatory power. The logit model based on independent variables derived from stock returns was the weakest in terms of classificatory power. However, this reduction in predictive power is not unexpected and should not be over-interpreted. The aggregation of time-series data on stock returns in order to use these measures within a cross-sectional statistical framework, fails to capture the information on the variance between the distributions of stock returns for failed and non-failed firms over time.

2.3.2.2 Market Valuation Variables as Inputs in Predictive Models

For the purpose of generating the estimates of the likelihood of insolvency, the rationale for the use of market valuation measures arises out of the perceived limitations of financial statements recording the past and therefore backward looking. In contrast, the market value of an individual company synthesises views of many investors about the firm's ongoing business, future growth and earnings prospects, and risk. In an efficient market, the value of a firm is being constantly revised and thus incorporates the information the market judges to be relevant to financial distress, given that the market's reactions irrelevant to insolvency are random. Changes in performance and financial position of a firm caused by the entry of a new competitor with lower-cost manufacturing plants or likely movements in interest and exchange rates should be factored into share prices of the firm. Data on share prices and market returns, are publicly available and represents an alternative type of information which can be used for inferring the probability of failure at the company level within appropriate statistical frameworks for time-series data analysis. An array of academic studies that have experimented with market valuation variables include **Beaver** (1966), **Aharony, Jones, and Swary** (1980), **Theobald and Thomas** (1982), **Clark and Weinstein** (1983), **Diacogiannis** (1996), **Lindsay and Campbell** (1996), and **Morris** (1997). Recent proprietary models of implied corporate default probability based on gearing, market prices of equity, and asset value volatility are discussed in **Crosbie** (1998). An important advantage of having market-based model inputs is that this type of variables facilitates modelling within a dynamic framework allowing for a "natural" incorporation into the model of time-varying variables capturing the important influence of the business environment. It should be noted that the object of the strand of literature just mentioned is prediction of the event of failure over different time horizons, not isolation of deep-seated causes of failure. Market valuation measures seem to be less useful as independent variables in explanatory models of failure. As discussed in chapter 1, company failure is a somewhat ambiguous concept and both definitions and measurements of failure differ across studies. It is self-evident that for a geared firm, the evolution of the market value of assets contains a lot of information on the firm solvency because the firm is insolvent when the asset value falls below the face value of debt. From the perspective of explaining failure, one can perhaps wish to consider a dramatic decline in the market value as a variable being predicted, in other words, a response variable or alternative proxy for the adverse outcome of failure.

One example of time-series analysis of share price returns and the outcome of failure is the study of UK quoted companies for 1975-93 by **Diacogiannis** (1996). Cumulative average residuals are employed in a profile analysis of the behaviour of quarterly time series of returns on a failing company's shares. The residual was defined in the usual fashion, as the difference between the realised return on security, and the return obtained from the estimated market equation, where a market proxy was represented by the FTSE-500 Share Index.

The predictive worth of market valuation variables using a profile analysis has also been checked in **Morris** (1997). He analyses the behaviour of monthly returns over a 60-month interval prior to failure with the purpose to establish how long it is before insolvency that the market on average marks down the shares of financially distressed firms that went into receivership or liquidation in the period 1973-83. In contrast with the results in Diacogiannis, who observes the 50 per cent error rates when isolating failing firms in an *ex ante* holdout, Morris optimistically claims that return-based measures demonstrate strong predictive power for the sample companies. He concludes that, in relative terms, the market marks down share prices of failing firms two-three years prior to failure.

Market-based model inputs alongside financial statement information are used in a related area of research on credit risk assessment. One of the best-known proprietary models of the percieved default risk, based on the option pricing framework due to **Merton** (1974) is CreditMonitor® by KMV (**Crosbie,** 1998). The CreditMonitor® approach is dynamic and uses market prices of equity and the book value of liabilities to derive the expected value and the standard deviation of the process that drives the value of the firm's assets. In this model, the standard deviation of the asset value represents business and industry risk. These estimates are then used to calculate the distance to default and evaluate, using an empirical distribution of incidents of default, a default probability.

Overall, there is no doubt that market valuation measures contain information on the perceived risk of failure. But it is difficult to escape the conclusion, when reviewing this strand of the literature, that market-based indicators are useful in quantifying the likelihood of company default rather than in isolating the underlying causes of failure.

2.3.2.3 Non-financial Firm-specific Attributes

Since the **Argenti** (1970) paper that put forward a proposition that the risk of failure is a function of management qualities and capabilities, there has been an interest in isolating empirically non-financial causes of financial distress. In Argenti's view, corporate failures are caused by weaknesses and defects in organisational and governance structures, resulting in costly mistakes on the part of companies' management. Argenti argues that associated with modelling failure risk financial variables such as ratios from company accounts or market-based measures, cannot fully explain the phenomenon of failure since financial variables merely record symptoms of distress. Moreover, Argenti contends that financial measures give rather unreliable predictors since the failing company management would appear to be able to manipulate or "manage" important accounting information to hide the poor financial conditions from the firm's financiers. In the current literature, a common empirical strategy for investigating the information content of non-financial variables is to develop a conventional classification model that uses non-financial variables alongside conventional financial ratios, and then to test the predictive power of a hybrid model. The augmentation of a model with non-financial inputs seems particularly relevant in the context of small firm failure research, primarily due to the need to give attention to the important role the entrepreneur (owner-manager) plays in survival of a small firm. Experiments with various non-financial indicators in small firm failure models can be seen as an attempt to overcome limitations of the information content of small company accounts related to less detailed, as compared to large quoted firms, disclosure (**Keasey and Watson,** 1987).

For UK large companies, an examination of non-financial variable predictive power has been conducted in **Peel, Peel and Pope** (1986) and in **Peel and Peel** (1988). In their work, a set of added variables included the submission lag in reporting accounts, the number of directors' resignations and appointments, and directors' shareholdings. The conclusion as to the incremental value of these additional non-financial predictors reached in **Peel, Peel and Pope** (1986) and **Peel and Peel** (1988) is merely suggestive of the need for a further in-depth investigation of the role of managerial factors in the failure process. Following these two studies, **Wilson, Chong and Peel** (1995) also expand a set of accounting predictors by including a number of indicators controlling for managerial factors, namely, for directors' shareholdings, lag in submitting the annual accounts and qualified audit opinion. **Keasey and Watson** (1987) carried out a logit analysis of the explanatory role of non-financial factors with a sample of UK 146 small businesses. They tested the influence of five variables relating to management characteristics; these included average lag of accounts submission, number of directors, bank secured loans, and prior and current year audit qualifications. Keasey and Watson assert that classificatory performance of logit models has been improved by the addition of the non-financial variables to a set of accounting ratios and interpret this result as supportive of Argenty's views on the primary role in company failure of managerial inadequacies and mistakes.

We note that studies of the extent the variables measuring management competence explain variations in failure risk are rare and offer findings that not as conclusive as evidence presented by the more traditional accounting-based investigations but they have an important implication for identifying further research avenues. More empirical work needs to be directed towards examining more explicitly the importance in the company failure process of ownership, corporate governance, management structure, top managers' competence and managerial practices. Here traditional observational studies with publicly available data may have to be supplemented by investigations going inside the conventionally defined boundaries of public disclosures, in the form of case studies or by using questionnaire survey data.

2.3.2 Variables Representing External Factors

An analysis based solely on financial historical statements and other firm-specific attributes gives an incomplete picture of the relations underlying the failure process. To describe more accurately the phenomenon of failure, the literature examines the role of macroeconomic conditions for survival (**Audretsch and Mahmood,** 1995). External shocks resulting from uncertainty regarding trading conditions, business and credit cycles and other macroeconomic influences affect the volatility of cash flows and clearly condition the risk of debt default. Current research suggests that a better approximation of complex interrelations between factors influencing the failure process can be achieved by incorporating the business environment variables into traditional, accounting ratio-based models of failure.

In the UK, the first paper to incorporate a macroeconomic indicator into a firm-level cross-sectional model of failure prediction was work by **Goudie and Meeks** (1991) who register the critical role of currency risk in a predictive model of corporate failure. Their analysis links failure risk to the degree of transaction exposure suggesting that company failure can be a penalty for producing exports at a time of a soaring exchange rate, especially if the rise is combined with relative price increases leading to a disastrous loss of competitiveness. The inclusion of changes in inflation in a time series analysis of UK company insolvency improves the predictive ability of a market return-based model in **Diacogiannis** (1996), implying that inflation is a relevant explanatory factor. Results from the event history analysis conducted in **Hill, Perry, and Andes** (1996) indicate the importance of the business cycle and the interest rate in explaining distress and bankruptcy in a sample of US quoted companies from 1977-87. The relevance of the accounting-based factors, modelled in Hill, Perry, and Andes depends on the stage of financial distress. Variables reflecting liquidity, leverage, size, a proxy for qualified audit opinion, and the prime rate are statistically significant for the financially distressed firms, which are still at the pre-bankruptcy stage. For the group of bankrupts, significant variables include profitability, leverage, size, a proxy for qualified audit opinion, the business cycle, and the prime rate.

The key role of the business cycle motivates a hybrid model, reported **by Richardson, Kane, and Lobingier** (1998), that includes conventional, accounting-based variables and two indicators controlling, respectively, for failures occurring over recession periods and for accounts reporting operating results for recessionary periods. Although the separate time-specific fixed effects of the recession indicators have not been evaluated, logit inference indicates that the relative importance of firm-specific attributes changes considerably over the cycle. If a recession period was anticipated, the ratio of net income to total assets alongside the ratio of cash to total assets were significant predictors of failure. On the other hand, if data reflected operations during a recession period, significant predictors included the ratio of current assets to total assets, the current ratio, and the leverage ratio of long-term debt to total assets. If the operations supporting the data occurred during a non-recession period, the relevant predictors were the ratio of net income to total assets, the ratio of current assets to total assets, the current ratio, the ratio of cash to total assets, and the leverage ratio.

Commercial applications of company failure models also imply the strong explanatory power of economy-wide factors. During the 1990s, a number of credit risk methodologies, integrating macroeconomic factors into models of default risk, have been proposed. For instance, McKinsey, a leading consultancy firm, has developed a CreditPortfolioView, a discrete time, multi-period model **(Crouhy, Galai, and Mark,** 2000). The model is used to simulate the joint conditional distribution of default and migration probabilities for various credit rating groups in different industries. The probabilities are conditional on macroeconomic factors, driving the credit cycle in the economy, which include the unemployment rate, the rate of growth in GDP, the level of long-term interest rates, foreign exchange rates, government expenditures and the aggregate savings rate.

In sum, our overview in this section of various categories of plausible variables used as inputs in failure models seems to indicate that accounting-based explanatory variables are useful predictors of failure at the firm level, signalling changes in the underlying unobservable factors. Precise comparisons of explanatory power of ratio variants from different studies are vitiated by differences in sample frames, time periods, and accounting practices. No "uniquely correct" set of accounting ratios has been established in the literature. Nevertheless, it is noteworthy that investigations into sensitivity of models predictive power to alternative specifications of ratio-based explanatory variables usually conclude that an appropriate set of ratios for a predictive model should be representative of the main dimensions of financial analysis such as gearing, profitability, liquidity and financial efficiency. Being indirect proxies of distress, market-valuation variables appear powerful predictors, though they present less attractive candidates for independent variables in an explanatory model of failure. Failure is a multifaceted phenomenon. In most cases there is much about the failure process for which financial ratio-based and market-valuation variables do not account. One group of possible omitted influences interacting with financial ratios and intruding on past results may relate to the effects of age, size, and managerial capabilities and other non-financial characteristics of the firm. Although most of extant studies utilise only micro-level data, permitting detailed attention to attributes of individual firms, the literature offers empirical evidence on the important role of environmental factors in explaining and predicting failure process. The effects on the failure process of macroeconomic factors and of firm age merit further enquiry and chapter 3 of the present thesis reports our empirical findings on the role of these factors.

2.4 The Choice of Statistical Framework

One of challenging problems in empirical work on determinants of company failure involves the choice of statistical setting in which to observe the processes that generate the data and to control for a whole variety of internal and external variables. The work on financial distress prediction started with univariate analysis of the individual accounting ratio potential to signal the event of failure (e.g., **Beaver,** 1966) and later adopted more powerful multivariate techniques, enabling one to model the ways different factors affect the viability of a company. Multivariate analyses of company failure data have been conducted with cross-section, time-series and panel data. As discussed above, the choice of appropriate statistical methodology is linked to the research question, choice of data, sampling schemes and explanatory variables. While most of past studies work with cross-section data and develop static models (see, e.g., the benchmark studies by Altman (1968) and Taffler (1982)), a dynamic approach based on a longitudinal data set has been employed in a US recent study by Hill, Perry and Andes (1996). Examples of profile analysis with time-series samples, testing the capability of market return variables to signal failure are reported in Diacogiannis (1996) and Morris (1997). Below we highlight the relative merits of the current statistical approaches for a causal multivariate analysis of the company failure determinants.

In company failure research, statistical analyses usually distinguish between the response or dependent variable and explanatory or independent variables[34]. To simplify the problem, the researcher views the population of firms as consisting of two distinct groups of failing and surviving units. The introduction of the dichotomy between failing and continuing companies allows one to employ two nominal categories for measuring the dependent variable such as "failure" and "non-failure". When it is assumed that the order of listing these two categories is irrelevant, the statistical analysis does not depend on this ordering. Such categorical variable is referred to as qualitative to distinguish it from numerical-valued or quantitative variables. Response variables having two categories are called binary or binomial response, while response variable having several non-ordered categories of outcome are termed multinomial responses. Explanatory variables, which can be also termed as covariates or predictors, represent putative causes or symptoms of failure and may be continuous or categorical. Company failure research uses standard statistical methods, which include basic ways of assessing the association between the response describing the event of failure and explanatory variables of interest. For the classification setting, these include multivariate discriminant analysis, neural networks classifiers and the conditional probability models, namely, logit and probit. The findings reported in the failure prediction

[34] This taxonomy implies a strict unidirectional causality and might not be completely adequate, particularly for the more complex cases of the reverse causality.

literature, testing applications of these statistical techniques for the purpose of classifying companies into various categories, suggest comparable predictive power.

2.4.1 Cross-sectional Data Models

2.4.1.1 Predictive Models based on Multivariate Discriminant Analysis

For both the USA and the UK, most of earlier work on multivariate modelling of failure risk seeks a best predicting model and is usually based on multivariate discriminant analysis (MDA), whereby a discriminant function for the two categories of "failure" and "non-failure" is derived from a combination of discriminating predictors (see, e.g., **Altman**, 1968; **Altman, Haldeman and Narayanan**, 1977; **Taffler and Tisshaw**, 1977; **Taffler**, 1982; **Goudie**, 1987; **Goodie and Meeks**, 1991, **Marais**, 1979; **Bell and Belhoul**, 1987).

The problem of assigning a firm into one of two discrete, defined and mutually exclusive groups is a specific case of the multi-group classification problem but the essence of the method is contained in the two-group case. In particular, if $\mathbf{y}$ is a binary response variable and $\mathbf{x}$ is a vector of continuous explanatory covatiates describing attributes of firms, MDA as well as binomial logit are alternative means of characterizing the joint distribution of $(\mathbf{y},\mathbf{x})$. Company failure studies have been primarily concerned with the discriminating power of accounting ratio-based variables, most of which can be classed as continuous or quasi-continuous. We observe the *k*-dimensional vector $\mathbf{x}$ and must assign the individual firm, whose characteristics are given by $\mathbf{x}$, to one of the groups. We can construct an assignment rule by using samples from the two sub-populations. Discriminant analysis focuses on the distribution of the $\mathbf{x}$ covariates conditional on $\mathbf{y}$. It is important to note that an analysis of company failure with linear multivariate discriminant functions involves the restrictive assumption of multivariate normality and homoscedasticity of the two sub-populations with respect to covariates [35]. In derivation of the discriminant function, it is almost always assumed that the distribution of $\mathbf{x}\,|\,\mathbf{y}$ is multivariate normal with a common covariance matrix. For linear discrimination, the assignment rule is based on a linear function $\lambda'\mathbf{x}$, which is obtained from two samples of companies representing two groups, corresponding to, say, $\mathbf{y}=1$ (failure) and $\mathbf{y}=0$ (non-failure). The coefficients λ are chosen so that the variance of $\lambda'\mathbf{x}$ between the groups is the maximum relative to its variance within the groups. The standard MDA classification rules have been derived from minimising loss functions of a form that takes into account the prevalence rates, which are called *a priori* probabilities of group memberships (π_g and π_h), and costs of misclassification ($C(g\,|\,h)$)[36] **(Eisenbeis, 1977).**[37] Then, the classification rule for the two-group case is:

assign a new observation with a profile vector $\mathbf{x}_0$ to group 1 if

$$\lambda'\mathbf{x}_0 - \frac{1}{2}\lambda'(\bar{\mathbf{x}}_1 + \bar{\mathbf{x}}_2) \le \ln\frac{C(1\,|\,2)\pi_2}{C(2\,|\,1)\pi_1}\,. \tag{2.1}$$

The rule is optimal if the data are multivariate normal, the covariance matrices of the two groups are equal, and the *a priori* probabilities, π_1 and π_2, are known. If the analysis ignores both the *a priori* probabilities and the misclassification costs, a cutoff point is given by $\frac{1}{2}\lambda'(\bar{\mathbf{x}}_1 + \bar{\mathbf{x}}_2)$.

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[35] As discussed above, only appropriately transformed values of accounting variables give normal data. However, the use of untransformed ratios for estimating linear discriminant structures has not been uncommon. Various other discriminant analysis techniques deal with non-normal data (Lachenbruch, 1977), but it appears that no discriminant analysis results obtained with the methods handling non-normal covariates have been published.

[36] Despite the fact that statisticians have specified the optimal cutoff score, little attempt has been made to explicitly incorporate misclassification costs into the models of failure prediction.

[37] $C(g\,|\,h)$ is the cost of misclassifying an observation as a member of group g given that it came from group h.

A numerical *Z*-score for a company can be calculated from the discriminant function. Using the cutoff, the discriminant function can then be used for sorting companies into those companies that are likely to fail and those that are likely to survive. Supposing that failure is denoted $y = 1$, the firm with a score below the empirical cutoff is expected to fail, while the company with a score above the cutoff can be thought of as financially sound. The predictive power is measured in terms of performance of the discriminant function on new (future) observations and that can be evaluated using the criterion of error (misclassification) rates. There are two possible classification errors: unexpected failures, i.e. companies classified as survivors that failed (Type I errors) and unexpected survivors, i.e. companies classified as failures that survive (Type II errors). Multivariate discriminant analysis is designed to find an optimal frontier, trading off one type of error against another. Estimates of the expected error rates, can be generated using a number of methods: by conducting holdout tests, whereby fresh observations, drawn from the same population, are classified, by resampling the observations used for calibrating the function, or by calculating the apparent error rates on the estimation sample. In applied contexts, one can adjust the cutoff point depending on what matters to the user of the classification tool. For instance, an investor avoiding investments in risky companies may set the cutoff at a low level, to reduce Type I errors. Apart from ranking companies according to their riskiness, the obtained discriminant scores can also be used to generate the probability of failure, assuming that estimated scores are normally distributed.

From a statistical point of view, the problem with multivariate discriminant analysis for modelling failure relates to the often-violated assumptions of multivariate normality and homoscedasticity of the two sub-populations in terms of model covariates. Deviations from the normality assumption in studies, dealing with accounting and economic variables, are usually true. Many conventional accounting ratios have a lower bound of zero but possess no theoretical upper bound. For instance, the gearing ratio of total debt to shareholders' equity exhibits this property. Furthermore, coefficients of a discriminant function are not unique and therefore the relative importance or substantive significance of discriminating variables can be only assessed up to the constant of proportionality. The tests used for the significance of individual predictors, such as the *F* test, may be unreliable as they depend on the same restrictive assumptions with the implication that the methodology is not well suited for isolating and quantifying the influence of specific variables (**Eisenbeis**, 1977). Notwithstanding these drawbacks, the commercial success of discriminant models for failure prediction is a strong argument for the use of this statistical setting when the research question concerns prediction.

2.4.1.2 Logit Analysis and Explanatory Models

Simple cross-sectional conditional probability models for discrete choice circumvent some of the problems with discriminant analysis. Various authors have considered conditional probability models as an appropriate statistical setting for modelling company failure. The examples of this approach include **Ohlson** (1980), **Zavgren** (1985), **Peel, Peel and Pope** (1986), **Peel and Peel** (1988), **Keasey and McGuinness** (1990), **Platt and Platt** (1990), **Johnsen and Pedersen** (1994), **Morris** (1997), **Richardson, Kate and Lobingier** (1998). It should be noted that researchers using discriminant analysis are interested in finding a relationship which permits classifying company populations into subgroups of failed and non-failed companies. Discriminant models are intended to be predictive, with the modelling purpose being to find certain distinct properties of the subgroups that will permit prediction. Since validity of a predictive model must also involve causality, in other words the direction of "effect" of plausible factors of failure (measured by firm-specific attributes) should be correctly specified, findings from discriminant analyses in respect of important predictors seem important for any new examination of company distress. Unlike discriminant analysis, binomial response models appear to have at least two applications in company failure studies. First, this methodology can be used as an alternative to MDA to develop a classification predictive model, and, second, and particularly relevant to the research question of the present thesis, this methodology overcomes the limitations of MDA and permits developing an explanatory model incorporating external environmental factors alongside firm-level attributes. When the analysis question concerns testing the hypotheses about the significance of firm-specific attributes and some external factors that modify the influence of these attributes, as well as involves an evaluation of the magnitude of factors' influence, the choice of a conditional probability model seems more appropriate.

In contrast to MDA, a conditional probability model involves the distribution of $\mathbf{y}$ conditional on $\mathbf{x}$. The starting point for statistical analysis of a binary response variable $\mathbf{y}$ is often a linear regression model extended to binomial response by introducing an intermediate unobserved (latent) variable $\mathbf{y}^*$ with:

$$\mathbf{y}^* = \boldsymbol{\beta}'\mathbf{x} + \boldsymbol{\varepsilon}, \tag{2.2}$$

and an indicator function

$$y_i = z(y_i^*) = \begin{cases} 1, & \text{if } y_i^* > 0, \\ 0, & \text{if } y_i^* \le 0, \end{cases} \tag{2.3}$$

where $\mathbf{x}$ is a vector of explanatory variables, $\boldsymbol{\varepsilon}$ is unobserved disturbance, and $i = 1,\dots,n$ indexes sample observations.

If $F(\boldsymbol{\varepsilon} \mid \mathbf{x})$ is the cumulative distribution function of the disturbances, then the model is characterised by the conditional distribution of $\mathbf{y}$ given $\mathbf{x}$

$$\begin{aligned} \text{Prob}(\mathbf{y} = 1) &= \text{Prob}(z(\mathbf{y}^*) = 1 \mid \mathbf{x}) \\ &= \text{Prob}(\mathbf{y}^* = \boldsymbol{\beta}'\mathbf{x} + \boldsymbol{\varepsilon} \ge 0) \\ &= F(\boldsymbol{\beta}'\mathbf{x} \mid \mathbf{x}), \end{aligned} \tag{2.4}$$

and also termed the response probability.

The most common binomial models, which assume ε independent of $\mathbf{x}$, are logit with

$$F(\boldsymbol{\beta}'\mathbf{x}) = \frac{e^{\boldsymbol{\beta}'\mathbf{x}}}{1+e^{\boldsymbol{\beta}'\mathbf{x}}} \\ = \Lambda(\boldsymbol{\beta}'\mathbf{x}), \tag{2.5}$$

and probit with

$$F(\boldsymbol{\beta}'\mathbf{x}) = \int_{-\infty}^{\boldsymbol{\beta}'\mathbf{x}} (2\pi)^{-1/2} \exp(-\frac{1}{2}z^2)dz \\ = \Phi(\boldsymbol{\beta}'\mathbf{x}). \tag{2.6}$$

Both models are derived from distribution functions with thin tails, though the logistic distribution is heavier in tails than the standard normal distribution. Therefore, for intermediate values of $\boldsymbol{\beta}'\mathbf{x}$ the two distributions tend to give the similar probabilities. The logistic distribution tends to give larger probabilities to $\mathbf{y}=0$ when $\boldsymbol{\beta}'\mathbf{x}$ is extremely small (and smaller probabilities to $\mathbf{y}=1$ when $\boldsymbol{\beta}'\mathbf{x}$ is very large) than the normal distribution.

In general, when the multinomial logit model is adopted to handle $J+1$ responses which proxy stages or states of failure (see, e.g., **Lau**, 1987; **Keasey, McGuinness and Short**, 1990), the probability that any of them is observed is given by the following formula:

$$\text{Prob}(Y=l) = e^{\beta_l' \mathbf{x}_i} / \sum_{j \in J} e^{\beta_j' \mathbf{x}_i} \qquad \text{for } l = 0, \ldots, J. \tag{2.7}$$

The binomial logit, well established in company failure studies, is the special case for which $J=1$.

If we model the binary response y_i which independently equals 1 or 0 with probabilities π_i or $1-\pi_i$, then the maximum likelihood estimate of the parameter vector $\hat{\boldsymbol{\beta}}$ gives estimates $\hat{\pi}_i$ by substitution in (2.7). The $\hat{\pi}_i$ is considered as predicting whether an observation with the covariate vector $\mathbf{x}_i$ will be a failed firm or a non-failed firm, by using the realised prediction rule $\hat{\eta}$:

$$\begin{cases} \hat{\eta}_i = 1 & \text{if } \hat{\pi}_i > C_0, \\ \hat{\eta}_i = 0 & \text{if } \hat{\pi}_i \leq C_0, \end{cases} \tag{2.8}$$

for some cutoff point C_0.[38]

As a general proposition, the question of the appropriate density is unresolved. In discussing the question of choice of alternative distributions, **Greene** (1997) points out that one should expect different predictions from two models if the sample contains: (i) very few responses (y_i equals to 1) or very few non-responses (y_i equals to 0), and (ii) very wide variation in an important independent variable, particularly if (i) is also true.

Ohlson (1980; p.118) notes that in the absence of a positive theory of bankruptcy, there is no easy solution to the problem of selecting an appropriate class of probability functions:

> As a practical matter, all one can do is to choose on the basis of computational and interpretative simplicity.

In discussing the choice of statistical setting, **Efron** (1975) shows that if the normality of $\mathbf{x} \mid \mathbf{y}$ does obtain then MDA is considerably more efficient than logit. Nevertheless, if normality does not obtain, then the normal MDA estimator is inconsistent whereas the logit estimator maintains its consistency under a wide class of alternative joint distributions of $(\mathbf{y}, \mathbf{x})$. Logit requires less restrictive statistical assumptions, and provides explicit probabilistic predictions facilitating interpretation of empirical results in decision-making. Unlike discriminant analysis, logit permits the statistical

[38] We use the definitions and notations that are given in Efron (1986).

significance of each of the variables in the model to be evaluated independently. Further, the non-linear shape of a logit function is appealing. Unlike a linear model that changes the dependent variable by the same increment in response to equal changes in an explanatory variable, a logit model has a greater impact per unit change in an explanatory variable in the mid range of the logistic distribution. Near the tails of the distribution, there is a smaller incremental effect. Hence, the underlying logistic distribution implies that an extremely "healthy" (distressed) firm must experience a larger proportionate downturn (upturn) to significantly deteriorate (improve) its condition. For these virtues, recent research, examining bankruptcy, favoured logistic regression.

A notable contribution to the investigation of the problem of the suitable statistical model for the context of corporate failure has been made by **Lo** (1986). Lo presented a specification test for the conditional normality of the attributes $\mathbf{x}$ and hence a test for appropriateness of applying normal discriminant analysis under the maintained hypothesis of logistic conditional response probabilities. He concluded that, for his sample, the null hypothesis of MDA and logit being equivalent, may not be rejected. Thus his findings help explain the fact that both MDA and logit have been accepted in commercial applications of company failure prediction. A more detailed discussion of inference with binomial logit with respect to failure modelling using both cross-sectional and panel data is presented in chapters 3 and 4.

2.4.1.3 Neural Networks Classifiers

An alternative classifier of companies into failing and surviving, that had a relatively rapid diffusion in failure modelling in the 1990s is a model based on neural networks (see, e.g., **Alici**, 1995; **Tyree and Long**, 1995; **Wilson, Chong and Peel**, 1995; **Morris**, 1997). A neural network is a collection of simple interconnected computational units called neurons, which are organised in layers and can be constructed hierarchically. The connections between neurons have weights attached to them. A neuron can receive inputs from the preceding layer or from the external environment. Each connection between neurons has a weight, which models the influence of an input neuron on an output neuron. The output is computed by a non-linear transformation of inputs, for which a logit squashing function can be used. The number and pattern of interconnections of neurons in a network determine the classification task the network is capable of performing. The neurons in the output layer each form linear combinations of their inputs and apply a nonlinear transformation before sending the output signal. The network learns connection weights during a training process in which training data sets consisting of inputs and associated outputs are presented to the network. In the context of classification model of company failure, attribute data on a particular firm activate the input neurons, and this activity feeds through the layers of neurons to the outputs which represent the group membership of this firm. The output is then compared with the appropriate target values. Any errors in classification are then used to alter the interconnection weights. The training set is processed repeatedly until a measure of network performance based on prediction errors for the whole training set reaches an acceptable level. An important attraction of neural networks is that that they can cope with the mass of ratio variables and the problem of ratio selection is thus avoided. However, there is no strong evidence that neural networks outperform the classification capabilities of multinomial discriminant analysis or conditional probability models.

2.4.2 Longitudinal Data Models

One problem with cross-sectional studies based on MDA, logit or probit, is that these models presuppose a steady state for the failure process. Statistically it means that the distribution at any given point in time is only informative if the underlying process remains stable over time. That assumption is often violated. Secondly, logit and probit do not give any estimate of the time to failure. This means that, the dynamic nature of the failure process has simply been unused in failure prediction. Empirical settings discussed so far deal with cross-sectional samples and can be criticised for the lack of dynamic approach. However, our overview of the literature identifies one dynamic study from the US, reported recently in **Hill, Perry and Andes** (1996) who conduct event history analysis of longitudinal data on corporate bankruptcy. By introducing a time dimension, this methodology permits more complex modelling of the failure process. Event history analysis uses the information on inter-temporal variation of explanatory variables, allowing the use of time-varying covariates, and controls for censored cases or companies surviving the analysis period. Under the event history framework, each firm is assigned a "spell" for every year while the progression of spells represents the history over time. A spell is defined by the dependent variable called the transition rate - the unobserved rate at which failure occurs - and the associated time-varying independent variables, measuring the firm's characteristics[39]. The effects of the explanatory covariates on the transition rate are modelled with a log-linear link function. Similar to logit (and to probit), the estimated parameters from the model identify significant characteristics related to changes in a firm's status.

As a final point in reviewing statistical settings used in company failure modelling, we should mention survival data models. These methods take account of time to failure or duration, use the time series information of the explanatory covariates and - in the simplest case of a single exit route - provide probability estimates of the binomial response variable defining the failure outcome. Complex models of survival data have recently been used in studies investigating industrial dynamics, including problems of survival, market exit, growth, corporate insolvency, acquisition, and takeover (see, e.g., **Luoma and Laitinen**, 1991; **Mata and Portugal**, 1994; **Helwege**, 1996; **Henebry**, 1996; **Lee and Urrutia**, 1996; **Dickerson, Gibson and Tsakalotos**, 1998; **Harhoff, Stahl, and Woywode**, 1998; **Laitinen and Kankaanpaa**, 1999). Techniques for survival data inolve estimating the parameters of the function that defines the hazard rate - the number of failures per time period given the number of companies at risk. An

[39] The probability that a firm will occupy a particular state at time t+1, given that the firm does not occupy the state at time t, is given by: $p_{jk}(t_1,t_2) = prob[Y(t_2) = k \mid Y(t_1) = j]$, where j, k = 0,1,2, the alternative states.
The transition rate is given by: $r_{jk}(t) = \lim_{\Delta t \to 0}[p_{jk}(t,t+\Delta t)/\Delta t]$.
The transition rate depends on the characteristics of firm i, $\mathbf{x}_i$: $r(t) = \exp(\beta' \mathbf{x}_i)$.

alternative interpretation of the information in the hazard function is the survival function – the length of time until failure occurs. Thus, one way of viewing the application of this methodology to modelling the determinants of company failure is to estimate the impact of factors that caused a large number of failures in a given period. Another aspect is that the estimates of the hazard function reveal which factors led to shorter or longer life spans among the various companies. The hazard rate is a measure of the probability of failure, but unlike logit or probit, the estimation procedure focuses on the conditional probability of failure – conditional on not having failed in an earlier time period. The use of survival analysis avoids some of the problems associated with the classical cross-sectional design in failure modelling. In contrast to studies developing a series of logit models for different time-horizons (see, e.g., **Zavgren,** 1985; **Keasey and McGuinness,** 1990), the hazard function takes into account previous years' data in making use of the current data, and particularly makes use of the fact that the firm did not fail in the earlier years. Survival analysis does not assume failed and non-failed firms as belonging to the different non-overlapping populations, but, being based on the rationale that at some stage all firms are at risk, treats non-failed firms as censored observations. However, one difficulty, which arises in application of survival analysis for modelling failure of large quoted company, is that of finding an appropriate proxy for the date of company birth (**Morris,** 1997). Our review of the existing company failure studies has identified two papers - by **Luoma and Laitinen** (1991) and by **Laitinen and Kankaanpaa** (1999) - which apply the hazard model in failure prediction but both use data on Finnish industrial firms.

2.5 Conclusions

This chapter has reviewed the empirical literature that studies company failure modelling, from primarily the UK and the US. Since this thesis looks at the determinants of failure risk at the firm level, we have focused on the particular components of empirical design employed for firm-level research.

We have seen that, ostensibly at least, that much of the literature has opted for prediction as opposed to explanation and description. The micro-level empirical work conducted in academia and by practitioners, has been aiming for a powerful predictive model for large, quoted companies, that may be useful as a forecasting tool or screening device operating with publicly available accounting data. This area of research has provided important methodological principles for developing commercial applications of predictive models of company failure. The concentration of effort, in both UK and US studies, on identifying the best predicting accounting ratios, reliably signalling default and insolvency in the short run for the population of firms analysed, has resulted in neglecting another avenue of company failure research - the problem of developing an adequate explanatory model to inform policy choices.

Early studies from the UK and the US are practically undistinguishable in that a typical statistical setting for modelling the conventional dichotomy between failing and continuing firms had been the multivariate classification problem. When the research question comes down to classification, the focus of analysis is shifted from the examination of the detailed causes underlying the high-dimensional process of distress and failure to the isolation of a small number of observable indicators most symptomatic of and closely associated with the insolvency outcome. These indicators are then used as components of a composite index of company vulnerability. The index provides a warning signal of impending failure by classifying future observations on firms into failing and surviving, on the basis of the latest available records on predictor-variables. By providing the high abstraction of the analysis, classification model methodologies made it possible to proceed with developing successful diagnostic tools without calling for a more detailed knowledge of the actual phenomenon and interrelations between failure "drivers". This may seem extraordinary, given the implications of corporate failures for financial stability and economic growth, but can partly be explained by the absence of a unifying analytical framework facilitating the motivation for explanatory model specifications.

In the absence of a clear analytical structure, the power of a model is often set by the sophistication of empirical design and depends upon decisions made by the researcher on the design components. The UK and US literature discusses various aspects of retrospective observational design in a firm-level econometric analysis, namely, sample frames, the definition of failure, data needs and sampling plans, justifications for selecting particular right hand-side variables, statistical settings for the discrete outcome, and the means of checking the modelling results robustness.

In much of the published work from the UK and the US, a large quoted industrial company represents a unit of study, probably because data on this type of companies is available in assessable databases. Under the reason of obtaining more homogeneous samples, sample frames tend to concentrate on manufacturing firms while sectors that are subject to regulatory differences in terms of accounting practices and the insolvency arrangements environment, are often excluded.

Any econometric study of company failure requires decisions on how to define the phenomenon of interest and how to proxy the associated dependent variable. Many of UK and US applied studies have employed purely legalistic definitions, equating failure of a financially distressed company with involuntary insolvency (bankruptcy for the US context). The primary dependent variable here as a limited dependent or discrete variable indicating whether there has been in the firm's history an event of failure associated with financial distress such as defaults on public debt, defaults on bank loans, and involuntary insolvency. Empirically, failure has almost always been gauged with a binomial (binary) indicator, reflecting the dichotomy between failing and continuing firms. Attempts to introduce finer distinctions within each of the "failing" categories have been made in a rather informal way since the naturalness of ordering of a multi-stage process of failure was entirely ignored by the employed statistical settings for nominal responses. Various indicators were used to define the intermediate stages of distress at the pre-bankruptcy phase including technical and proper debt defaults, an omission of dividends, and negative operating profits. Designs based on a polychotomous response presented scholars with purely practical difficulties in collating a representative sample of sufficient size, since it is not straightforward to locate companies in various, distinct, non-overlapping stages of financial distress.

The specific feature of empirical design in company failure research, characteristic both of UK work and of US work, is the use of a state-based sample, which contains the case and control groups. In the two-category case, a state-base sample includes observations on failing firms, always selected non-randomly, since observations on failed companies can be available only on a limited basis, and observations on the control group of non-failed firms, which can be - and in some studies have been - drawn at random. We would like to point out that reliance on equal-share samples unrepresentative of the population proportions of the studied firms has been a shortcoming of cross-sectional design, which led to the problem of reduced sample sizes and therefore undermined inference. Another problematic treatment is the use of pair-matched sampling plans, involving matching of observations on firms from the two categories by some confounding factor, e.g. by industry sector or firm size. Such matching neglects the possibility that the "confounders" may be important for explaining failure. Pair-matched sampling plans results in smaller sample sizes and increase the sensitivity of inference to data points used in model development. The advantages of non-matching on industry and size, in terms of improvements in inference generalizability, have been appreciated by more recent empirical studies from the US, that are based on larger unbalanced samples resembling the true population proportions with the prevailing share of the "survivors" at the end of the analysis period. Paucity of failed cases is the major reason for the widespread use of pooled, multi-time-period, cross-sectional samples. Considering the consequences of pooled-sample design for the reliability of inference, current research recommends to proceed with circumspection in the use of inter-temporally unstable accounting variables when modelling over pooled samples. Normality and stationarity improving transformations of data are recommended by both the UK and the US studies, as a means of improving stability of model structures. Another particular feature of sample design is the use of repeated cross-sections that is almost always motivated by the aim to incorporate a time dimension in developing cross-sectional models of failure. Repeated cross-sectional design is thought of as being helpful for isolating the changes in the importance of individual, time-horizon-specific determinants. The use of pooled repeated cross-sections seems especially advantageous for developing explanatory models of failure, but may provide an inappropriate structure of relating predictors to the response, since inconsistent signals generated by time-specific models impair the models' usefulness for a decision-maker. The literature also points to the importance of matching the observations in the case and control groups by the years of economic and accounting variable records. Recent studies from the US argue that matching by timing of microeconomic information is important for controlling the changes in the firm attributes caused by the business cycle and environmental shocks.

Techniques used for evaluating predictive power of models have impact on sampling plans and samples sizes. It appears that a common approach is to set aside a part of the available data and then evaluate the stability of an estimated model over these "new" holdout data points. In other words, the available data set is usually divided into estimation and holdout samples. Resultant small estimation sample sizes – often in the order of less than two hundred observations – have posed a serious problem for statistical modelling of company failure. One alternative to holdout tests, which allows to adopt a sampling plan preserving all available data points for estimation, and to which prior research from the UK and the US, has often turned to is jackknife validation methods. Jackknife procedures provide additional support to statistical inference obtained with small estimation samples. Given the limited number of observed failure cases, bootstrapping approaches and other numerical simulation methods would appear to be a suitable means for tackling the problem of small estimation samples size. However, results from applying appropriate - and economical in the use of data - techniques of statistical sampling for generating statistically valid pictures of the company failure process so far have not been reported in the UK and US academic literature.

Empirical design for analyzing company failure involves the selection of potential explanatory variables or predictors. This is a difficult task related to a more general problem of model uncertainty. Often researchers restrict the rationale for their choice by conclusions as to predictive success of particular measures, reported in past studies. However, the strategy of using pre-specified in this way indicators of failure may not be always appropriate for empirical work because studies based on data from differing countries, company populations and time periods, produce results that are sample sensitive and incomparable at this level of detail. The extant literature has explored the potential predictive power of a huge variety of candidate measures representing putative factors including combinations of firm-specific attributes and contextual variables. The empirics of company failure - consistent with theoretical predictions - seems to agree that the likelihood of financial distress and subsequent insolvency (or bankruptcy) is broadly associated with indebtedness, size, profitability, liquidity and financial efficiency. In UK and US studies, accounting-based measures in the form of financial statement ratios have been used as convenient proxies for these economic concepts. However, as one would expect, research evidence on the appropriateness of particular ratio constructs has been conflicting and no "unique", "correct", or "best predicting" set of accounting-based measures has been isolated. For explanatory model development that implies that a statistical reduction of a wide comprehensive set of ratios representative of the main dimensions of company performance and position seems an appropriate modelling strategy. In is conventional to argue that to counteract the effects of non-normality of financial ratios and to accelerate the estimation of models it is necessary to apply appropriate transformations of ratio values.

Another interesting feature of the extant literature from the UK and the US is that past time-series studies of quoted companies attach particular predictive power to the levels and volatility of market value of equity, consistent with analytical models of debt default due to Merton (1974). Market valuation and failure risk are highly correlated. Furthermore, for a publicly traded company, the concept of financial failure can be thought of in terms of rapidly declining value of its equity. It follows that the erosion in market value can itself serve as a measure of failure. If it is thought to be important to reveal the underlying deep-rooted causes, a model specification approximating different aspects of explanatory factors by the direct path from changes in the market value to the risk of failure may not be very helpful. Therefore, in modelling the determinants of corporate collapse, market valuation variables need be combined with other company performance attributes and indicators of exogenous macroeconomic shocks. Amongst macroeconomic indicators, the business cycle, interest and exchange rates, and inflation were shown as robustly related to the probability of financial failure. The value of having macroeconomic indicators amongst the predictor variables is also demonstrated by the commercial success of proprietary models of credit risk.

If financial failure is a result of management incompetence and mistakes, then the adequate set of explanatory variables should allow the measurement of this impact on company survival. Few studies from the UK attempt to augment accounting ratio-based models with management-related variables, utilizing accounts submission lags, number of directors and other non-financial measures. Inference regarding the incremental explanatory value of such non-financial indicators has been rather inconclusive and this aspect of company failure merits further investigation with questionnaire survey data. While studies from the industrial economics literature have documented the important role for survival of firm age, in line with theoretical models of learning, it appears that age has not been directly tested as an explanatory variable in traditional specifications used for firm-level models.

In respect of statistical techniques for developing cross-sectional models intended for predicting failure or screening financial health of companies, multivariate discriminant analysis and binomial logit have been by far the most popular both in academic studies and in commercial applications. Classifiers based on neural networks have also been used for formalizing the problem of classification. Although being based on different statistical assumptions, the three techniques appear to demonstrate comparable levels of predictive accuracy at short-term horizons - one- or two- years ahead - with no material gains registered for neural networks classifiers. Our reading of the literature suggests that conditional probability models such as logit are adequate as a statistical setting for the explanatory type of models. From a purely statistical point of view, logit analysis has important advantages in that it averts the restrictive assumptions of multivariate discriminant analysis and, unlike neural networks classifiers, permits a sounder theoretical basis for a rigorous evaluation of the magnitude and significance of the effects of explanatory variables.

In macro-level analyses of both time-series and longitudinal data, attention has been given to a formal representation of a time dimension in a model of failure. A more comprehensive assessment of factors underlying company propensity to fail calls for more complex modelling approaches able to simultaneously utilise cross-sectional and time series components of information that firm-specific explanatory covariates contain. As of the time of submitting the present thesis, in May 2000, our search of the literature has identified just one study of US company failure, which explores advantages of cross-sectional time series data in explaining failure (see **Hill, Perry and Andes**, 1996). However, it appears that no longitudinal studies of UK companies have been conducted so far.

A group of studies concerned with developing prediction tools emphasizes the crucial role of adequate approaches for evaluating model predictive performance. The stereotype solutions suggested in the literature include tests over *ex ante* holdout samples, follow-up studies, and approximations based on jackknife resampling. Recent computationally intensive methods available for evaluating parameter estimates have not been popular. The Monte Carlo statistical philosophy and its particular elegant variant - the bootstrap - seem to be able to provide a wide scope for making robust inference about model parameters and to uncover the real factors and their complicated interrelations affecting company failure risk.

The current empirical literature from the UK and the US, on predictive and explanatory models of failure offers an impressive array of general methodology advice but few stylized facts. In the following three chapters we endeavour to build on the existing research and provide an investigation of company failure determinants with new primary, cross-section and panel data for the UK and Russia. Our search of the literature identifies the lack of studies conducted with UK data pertaining to the period from the late 1980s to early 1990s, which contains the lowest point in the recent UK economic cycle. In a cross-sectional analysis, the objective will be to examine the causes of company failure by constructing more complete models of binomial response that are based on accounting ratios, control for firm's age, and condition failure risk on changes in the macroeconomic climate. We intend to extend this analysis of failure causes by utilising a panel data-set that introduces the time series component of covariate information, enabling us to formally allow for unobserved heterogeneity across firms, which is of great importance for generating more reliable and robust inference on estimates of model parameters. The panel analysis offers a holistic way of evaluating the interrelationships between the probable causes and failure outcome.

We also intend to provide a contribution to the literature by conducting an examination of Russian company insolvency over a transitional period of the 1990s with accounting ratio-based explanatory variables. We motivate our study of Russia by the findings reported in the UK and US literature that broad measures of indebtedness, profitability, liquidity and efficiency determine corporate financial distress. That in turns implies that to the extent accounting ratios from Russian company accounts capture changes along these dimensions, one should be able to develop a conventional cross-sectional model, adding to our understanding of failure determinants. We take account of the problems associated with empirical design in past studies on company bankruptcy outcome, and, given the limited availability of data on Russian firms leading to the issue of small sample inference, support our conclusions by the bootstrap. As an additional means of verification of our findings on Russia we then contrast the Russian results with those obtained from a UK study of similar size within an inter-country comparative framework.

CHAPTER 3: A LOGIT ANALYSIS OF CROSS-SECTIONAL DATA FOR UK INDUSTRIAL COMPANY FAILURE IN 1989-93

3.1 Introduction

This chapter offers empirical evidence based on cross-section data and the binomial logit estimator, relating to the determinants of UK industrial company failure in the form of insolvency, for the late 1980s and early 1990s. The conventional cross-sectional approach in this retrospective observational study identifies the key financial characteristics that reflect deterioration in company performance over several years prior to the event. Here the empirical design draws upon methodological principles developed in previous research yet an attempt is made to refine cross-section models, firstly, through introducing a control for company duration and, secondly, by accounting for changes in the macroeconomic climate that modify the corporate sector vulnerability. The risk of failure through insolvency can be decomposed into three components: financial risk associated with highly geared capital structure, business risk, inherent in the firm's operations, and aggregate economy risk. At the firm level, conventional quantitative analysis of failure risk involves a detailed examination of a firm's balance sheet, profit and loss account and cash flow statement, assuming that information on financial and business risks is reflected in financial accounts. However, an analysis of historical financial statements alone may present an incomplete picture of the relations underlying the failure process. Aggregate economy risk, arising from macroeconomic uncertainty, affects the volatility of cash flows and thus clearly conditions the risk of corporate failure. Given that the risk of default varies with changes in the economic environment and may be dramatically magnified in highly geared companies, it appears important to incorporate into a modelling framework the effects of macroeconomic factors so as to achieve a better approximation of complex interrelations underlying the failure process. Most defaults and bankruptcies occur during or immediately after recessions, so we focus our analysis on the recession period 1990-92, during which a considerable number of UK companies became insolvent (see Table A1.1 in appendix 1). Covering this period, company-level data analysed here are taken from a reliable data-source, DATASTREAM.

Failure determinants are revealed by estimating and then assessing the predictive performance of four separate sets of binomial logit models. The prediction functions of the first group are based on the input variables that are purely financial. The second group yields both financial predictors and two macroeconomic variables, measuring unanticipated changes in the real exchange rate and nominal interest rate. Then in developing the third group of models we incorporate a proxy for time duration (or age) of the firm, and, lastly, the models of the fourth group make use of financial ratios, the two macroeconomic variables and the duration variable.

A single set of models is a series of individual logit functions estimated with data specific to four risk-horizons, ranging from one to four years prior to failure. The obtained models yield the determinants explaining the propensity of a quoted industrial company to fail over the specified time horizons. Although in terms of individual ratio significance and overall predictive accuracy, the findings of this cross-sectional study are not directly comparable with the evidence from previous research due to differing data sets and model specifications, the results are intuitively appealing. We find a strong association between gearing, liquidity, profitability, and the probability of failure. The relevance of unexpected changes in exchange rates and interest rates to company failure in the early 1990s is evidenced by an improvement in predictive performance of models in holdout tests, when predictions are conditioned on changes in these two macroeconomic variables. The significance of coefficients for the duration term, judged in isolation, implies the importance of the age factor. We also find that when the duration term enters models based on financial and macroeconomic variables, the resulting specifications for risk horizons of one, two, and three years before failure demonstrate no improvement in out-of-sample predictive performance as compared with simpler models with no duration term. Conversely, when the forecasting performance of the model for the three-year horizon, which includes the two macroeconomic variables and firm age, is considered, it appears that the duration term contributes to correct predictions. Overall the addition of the duration term to models based on a wide set of financial ratios, has little impact on failure predictability, implying that a separate control for this factor is of limited importance for our data.

3.2 Empirical Design

We follow a cross-section approach employed in studies by **Zavgren** (1985) and **Keasey and McGuinness** (1990) and estimate logit models specific to each of the four years before failure. Sets of *n*-period prediction models depict the failure process, described by significant predictors, and, in comparison with one-period prediction functions, permit a temporal aspect to appear in the explanation of company failure. Yet the approach has been criticised in the literature because predictive models based on such data structures may give contradictory results regarding the failure probabilities and this inconsistency impedes the practical value of such sets of models (see, e.g., **Altman,** 1970). Another shortcoming of previous cross-sectional research is that it often disregards changes in the macroeconomic environment when developing a series of time-horizon-specific functions (**Goudie,** 1987). In an attempt to address the latter problem, this study explores macro-to-micro linkages by incorporating into models unanticipated changes in the nominal interest rate and real exchange rate. In the analysis of cross-sectional data we also control for corporate age, the factor being suggested as important in explaining company failure (e.g., **Hudson,** 1987; **Altman,** 1993; **Dunne and Hughes,** 1994).

The unit of our retrospective observational study is a British large quoted industrial company. The sample design is driven by the objective of a cross-sectional study that aims at developing a series of models specific to each of the four years prior to failure. Therefore we create and estimation and holdout cross-sections repeated for four years prior to failure. The choice of the DATASTREAM database as a source of accounting data made it possible to compile an estimation cross-section of 421 company-years based on 53 failed companies and 316 non-failed companies. This estimation sample is larger in size in comparison to data sets analysed in UK academic studies of large industrial firms (e.g., just 86 companies were used for estimation in **Keasey and McGuinness** (1990), whereas the models in **Wilson, Chong, and Peel** (1995) were derived with data on 112 quoted companies). We include in the sample industrial companies quoted on the London Stock Exchange, failing in the period 1989-93 and satisfying the constraint that for every observational unit, the company accounts data were available for all four years preceding failure. At the same time, in constructing the estimation data set, we take account of the issue of disproportionate sampling (**Palepu**, 1986; **Maddala**, 1992; **Greene**, 1997). Specifically, to get as close as it was feasible with the continuous data, available on observational units, to the true population proportions, we designed for model estimation an unbalanced cross-sectional sample. In the sample, the failed group represents 12.6 per cent of the total observations and non-failed company-years were drawn at random. We note that in the constructed cross-section, the resultant proportion of failed firms is similar to a 9.1 per cent estimate of the prior probability of insolvency suggested by a stockbroker firm for one of Taffler's studies of quoted UK companies (see **Taffler**, 1982).

We utilise the sturdy statistical methodology of binomial logit model to avoid problems associated with multivariate discriminant analysis.[40] Aside from providing probabilistic predictions, binomial logit permits one to test both the overall statistical significance of the model and the significance of individual predictors, which is crucial for isolating company failure determinants. To achieve more realistic evaluation of models' predictive power we perform *ex-ante* holdout tests as well as approximate analytically the downward bias in the apparent error rate by using the formulation due to **Efron** (1986).

3.2.1 The Sample

We take a large quoted industrial company as the unit of analysis. In binomial logit, the model posits that a company is in one of two observed states: in state 1 if it is failing and in state 2 otherwise; correspondingly, sample observations represent two groups – the failed firms and non-failed firms. The construction of estimation and validation samples requires: (i) a definition of failure and (ii) a specification of the population from which companies are drawn. In the present study, we have adopted the traditional failed/non-failed dichotomy based on a purely legalistic criterion.[41]

[40] We discuss the assumptions of MDA and the issue of choice of the statistical methodology in chapter 2.
[41] Past studies from the UK and the US, which used the state of bankruptcy to measure the event of distress include, e.g., Ohlson (1980), Taffler (1982), Keasey and McGuinness (1990), Richardson, Kane and Lobingier (1998).

We equate company failure with the event of entering a formal (involuntary) insolvency regime, such as administrative receivership, administration, and winding-up (liquidation). The population boundaries are set by the following criteria towards the sampling unit: (i) the period 1989-93, which is defined here in terms of the calendar year of the formal announcement of insolvency of a sample company; (ii) the equity of the company has to be listed; (iii) the company must be classified as an industrial on the DATASTREAM database; (iv) the company must have four years of financial data prior to bankruptcy, retrievable from the DATASTREAM database. The first criterion reflects the problem with the definition of recession as, for instance, the boundaries of 1990-92 designated in *The Economic Briefing*, published by the HM Treasury, simply correspond to the period of falling output (The UK Recession 1990-92, *The Economic Briefing* 6 (February 1994)). Therefore, in order to play it "safe" and to account for a certain degree of judgement involved in deciding what constitutes a recession, we have included 1989, the year preceding the low point of the business cycle. The endpoint of 1993 is chosen because of a long (up to twenty months) lead-time between the fiscal year end in the last relevant records and the date of the formal announcement of insolvency for our sample firms. The second criterion excludes small or privately held companies thus allowing us to use the "live" list of firms, covered by DATASTREAM at the time of this analysis, as a source for constructing a sub-set of non-failed (solvent) firms. The third requirement removes from the sample financial services companies, transportation, and petroleum companies. Companies in these industries are structurally different and have different taxation regimes, accounting conventions, and insolvency environment. The sectoral composition of UK company cross-sections for the reporting years 1988-94 can be seen in Table 3.1. The fourth criterion, followed from the principle of temporal precedence, is necessary for constructing repeated pooled cross-sections.

It is important to notice that due to a usually small number of insolvency cases in any single year, the observations forming a pooled cross-section are drawn from a number of consecutive calendar years, a design common in most failure studies. We started by constructing a single cross-section of failed firms with data corresponding to the years when the last sets of accounts were published. Then we extended this cross-section by including company-years of the non-failed group. In compiling company-years for the non-failed group, we randomly pick data points from the reporting years identified by the last public records on the failed group. Finally, we collected records for the companies in the resultant pooled cross-section for each of the four years prior to the respective insolvency times of the failed firms. The sampling procedure yields a temporal sequence of pooled cross-sections, which enable us to estimate n-period models. One advantage of pooled cross-section data is that it permits a relatively large sample. Further, a temporal dimension is of great importance for isolating the influence of macroeconomic factors on failure risk. Annualised values of major financial items were collected for a four-year period prior to insolvency so as to allow for temporal precedence in revealing the determinants of failure occurring in one, two, three and four years. Thus, the sample companies are subject to availability of at least four consecutive years of complete accounting records. On the other hand, a pooled cross-section design may lead to the problem of temporal distortion whenever time-series data are analysed as cross-sections. We shall describe a way of standardizing the data to reduce the impact of non-stationarity in section 3.2.2.3.

Names of quoted failed companies and their insolvency dates have been taken from the London Stock Exchange Official YearBooks for years 1988-97. The list of non-failed company names has come from the DATASTREAM files of UK equities.

First, we complied a list of 53 quoted industrial companies entering insolvency in 1989-93, all those companies have satisfied a requirement of having four consecutive years of complete accounting records available on the DATASTREAM database in 1997.[42] Insolvent company names and years of insolvency can be seen in Table A5.1 in appendix 5. These companies had terminated financial reporting twelve to twenty months before the insolvent state was announced via a suspension/cancellation of the listing of shares or appointment of the official receiver.[43] When analysing company accounts data, it is important to ascertain the timing of company failure. Companies

[42] The initial list of companies, entering the state of insolvency in 1989-93, consisted of more than one hundred companies quoted at the London Stock Exchange, but only 53 firms satisfied the sample inclusion criteria.
[43] Most insolvent UK companies end up in liquidation, but there is a slight possibility, that insolvent companies selected for the present study might have resumed financial reporting if they were successful in turning-around their businesses. However, because the DATASTREAM database, considering such companies as "dead stocks", listed them no longer, we were not able to trace their fortunes after they had entered the insolvency state.

put into insolvency terminate financial reporting. Given a considerable lag between the issuance of the last accounts and the formal announcements, it seems appropriate to proxy the first year prior to failure by the calendar year of the last accounts. As a consequence, the time frame of the estimation samples spans four calendar years, namely, 1988-91. Accounting data for estimation sample firms were collected for this period. Out of 53 failed firms, 6 companies published their last accounts in 1988, 18 in 1989, 17 firms in 1990, and 12 in 1991. Consequently, the sub-set of failed firms in the estimation sample for one year prior to failure consists of 6 firms with accounts for 1988, 18 firms with accounts for 1989, 17 firms with accounts for 1990, and 12 firms with accounts for 1991. The sampling scheme for the failed group is *state-based*, because by including all companies that met criteria of data completeness and consistency, we aim at enriching informationally the estimation sample. As in the population, the number of insolvent companies is smaller than the number of solvent firms, a random selection scheme would have led to very few failed firms in the estimation sample and inefficient estimates.[44] Second, we constructed a *random* sub-sample of non-failed (control) firms to be used in estimation. A list of non-failed firms was generated using the following steps. A primary list of non-failed firms was tabulated from the DATASTREAM list of UK " live" quoted industrials[45] that consisted of 1,330 equities as of 13 February 1997. We took account of the methodological problem of state-based sampling for model estimation, which leads to biased and incorrect inferences in logit (see, e.g., **Palepu,** 1986) and used all available, continuing in independent existence, non-failed companies with complete and consistent DATASTREAM records over the period 1985-95. We did not match failed and non-failed companies on industry sector or size, but we viewed matching on timings of records as important and accordingly drew accounting data for non-failed cases from the period 1988-91. The end points of this interval were arrived at in the process of collating the failed company set.

[44] Manski and McFadden (1981) show that an appropriate state-based sample provides more efficient estimates compared to a random sample of the same size.
[45] The DATASTREAM code for this list of equities was "UKQI".

Table 3.1 Sectoral Composition of the UK Company Cross-section for the Reporting Years 1988-94, Breakdown of Observational Units by Economic Groups (Percentages in parentheses)

	FT-SE Economic Groups											
	Mineral Extraction		General Industrials		Consumer Goods		Services		Utilities		Total	
Panel A: Estimation Sample, 1988-91												
Non-Failed	1	(0.3)	173	(54.7)	35	(11.1)	106	(33.5)	1	(0.3)	316[46]	(100)
Failed	-	-	24	(45.3)	5	(9.4)	24	(45.3)	-	-	53	(100)
Panel B: Holdout Sample, 1992-94												
Non-Failed	2	(2.3)	40	(46.5)	15	(17.4)	29	(33.7)	-	-	86	(100)
Failed	-	-	7	(70.0)	1	(10.0)	2	(20.0)	-	-	10	(100)

[46] The figure excludes double-counting as in the UK cross-section, the sub-sample of non-failed firms consists of data on 368 company-years represented by 316 live companies, on which the accounts data on four consecutive years were available.

Thus, in the estimation cross-section for one year before failure, the non-failed group contains company-years (data points) pooled across 1988, 1989, 1990, and 1991. The four sets of company-years pertinent to each of the four-year period needed to be constructed to allow random selection of non-failed cases. To that end, we reduce the list of non-failed firms by excluding from the DATASTREAM list of UK "live" quoted industrials: (i) those firms that had no accounts prior to 1995 and (ii) the firms with incomplete records over a seven year period prior to 1992. We have also checked information about the companies on the resulting list against various editions of the London Stock Exchange Official YearBook to ensure they had been "free" of involuntary insolvency up to 1995. Table 3.2 displays the number of company-years in four sets from which we draw at random data point for non-failed firms.

Table 3.2 Number of Company-years in Sets of Non-Failed Firms Used for Random Selection of Non-Failed-Group Observations in the Estimation Cross-sections

	Year of the Last Set of Accounts			
	1988	1989	1990	1991
Non-failed Group: Number of Company-years	675	736	815	898

The final sub-set of non-failed observations in the pooled estimation cross-section is made up of 368 company-years randomly drawn, without replacement, from the four sets. These 368 company-years are based on the records of 316 non-failed companies (their names can be seen in Table A5.3 of appendix 5). The temporal composition of company-years for the non-failed group, which are used in the cross-sectional estimation sample for year one prior to failure, is as follows. Of 368 non-failed cases, 98 company-years have accounts for 1988; 88 company-years for 1989; 88 company-years for 1990; and 94 company-years have accounts for 1991. The non-failed company-years in the estimation cross-sectional samples for years two, three, and four before failure simply represent repeated observations for earlier years.

The sampling approach yields an unbalanced sample with a 12.6 per cent sampling frequency for failed companies in each of the four years before failure. It is impossible to access how accurately the sample mix approximates the proportions of failed and non-failed firms in the underlying population of large quoted industrials, as the necessary data have been hard to acquire.[47] However, under limited access to data sources, we attempt to attain a sample structure, which alleviates well-known methodological problems (**Palepu**, 1986; **Maddala**, 1992; **Greene**, 1997) arising from the use of state-based cross-sections in logit.

Lastly, we constructed year-prior-to-failure-specific holdout samples that contain data on firms entering insolvency in 1992-95. Notice that in terms of timing of last published financial statements, the holdout observations span the period 1992-94. The pooled holdout was constructed using criteria and procedures similar to those employed in the estimation sample design. Of 10 failed firms, used in the holdout, 4 firms reported their last accounts in 1992; 5 firms in 1993; and 1 in 1994. The corresponding observations on non-failed firms are distributed over the period 1992-94. Of the 86 holdout non-failed observations, 58 company-years were selected from 1992; 14 company-years from 1993; and further 14 company-years from 1994. Names and respective years of insolvency for the holdout companies can be seen in Tables A5.2 and A5.4 in appendix 5. The holdout sample is also unbalanced, containing a 10.4 per cent share of failed firms and being representative of the quoted company population proportions for failed and non-failed categories.

With regard to robustness of prediction model and validation of results, prior research recommends the use of post-estimation-sample holdouts, taken from a period distinctly different from the interval chosen for the estimation sample. Clearly, the holdout sample for 1992-94 is not distinctly different from our

[47] To our knowledge, comprehensive time series on the number of UK quoted companies suffering financial distress or being placed into formal insolvency regimes have not been reported systematically, and only rough and even arbitrary estimates have been used in previous research. Estimates of population proportions for failed and continuing firms vary. Letza (1994) refers to Dun & Bradstreet's estimate of the long run average failure rate of companies in England and Wales at 0.85 per cent. Taffler (1982) drew on subjective estimates of the investment analysts and used an odds ratio (based on the prior probabilities for a failed and non-failed firm) of 1:10. Focusing on the period of 1968-73, his study of UK company failure was concerned with industrial enterprises quoted on the London Stock Exchange, and failure was defined as formal insolvency. Dunne and Hughes (1994) examine death rates over the period of 1980-85 in the sample of 2,149 UK firms that includes all

estimation sample, especially noting the fact that 62 firms came from 1992 because of data incompleteness. As a consequence, validation on such holdout data probably overstates predictive power of built models. This shortcoming arises from the insolvent company data "constraint" as the incidence of liquidation and receivership is counter-cyclical. At the time of constructing the data set for this study, in 1997-98, we included in our primary list all records on large quoted company failures in 1992-95, available from London Stock Exchange Official YearBooks. However, we try and take account of data with these characteristics and address the problem of holdout reliability by supplementing validation of logit model with Efron's formulation (**Efron**, 1986) for approximating the bias in the apparent error rate.

We should emphasise the limitations of our sample representative of the population of companies covered by the London Stock Exchange Official Yearbooks and monitored by DATASTREAM. First, the sample frame for a cross-sectional examination of this chapter, is predetermined by the population of large long-established companies, operating internationally. This represents a relatively small slice, towards the larger end of the scale, of the total population of incorporated businesses. In 1998, there were about 1.14 million UK companies registered at Companies House, but only 2,450 or so companies have their shares publicly traded on the London Stock Exchange (DTI: *Modern Company Law for a Competitive Economy* (1998)). An immediate consequence of our choice of data source is limited generalisability of empirical results. Inference presented in the present chapter as well as in chapters 4 and 5 cannot be extended to the populations of private companies and small and medium-sized enterprises. Second, DATASTREAM retains and provides historical records on the firms that failed ("dead" firms) only the for a limited period of time after their failure, which caused difficulties in collecting time series data on most failed cases. Unavailability of longer time-series in turn restricted the number of repeated pooled cross-sections to just four. As a result the evolution of company failure is analysed in terms of four risk-horizons, namely, for one, two, three, and four years prior to the outcome. In future work, a more comprehensive examination, which can be based on a longitudinal survey data,

quoted and large unquoted companies, and find that, on average, liquidations or receiverships accounted for 3.7 per cent of sample firms.

should allow an examination of changes in financial attributes of firms and the macroeconomic environment on failure risk over longer risk-horizons. Third, accounting-based, firm-specific attributes stored on the DATASTREAM database do not cover other, likely to underlie the financial causes, dimensions such as corporate governance and managerial independence, practices and capabilities, important for understanding of the failure process of publicly traded large company.

3.2.2 Independent Variables and Data Transformation

As discussed in chapter 2, the existing empirical literature on financial failure at the firm level, which analyses cross-sections of companies, explains the risk of default by factors relevant to business prospects of a firm, its financing arrangements, and macroeconomic conditions. The most obvious source of publicly available information about the business' performance and financing is its financial reports that are traditionally used by credit analysts to judge whether or not the firm is a poor credit risk given the possible developments in the economy. For a quoted company, market prices for equity and debt, present an alternative source of information for modelling failure as the behaviour of market prices reflects the company's prospects.[48]

In the present chapter, we base models of failure on information, contained in financial accounts. In doing so we follow the well-known UK studies by **Taffler** (1982, 1995), **Keasey and McGiunness** (1990), and **Wilson, Chong, and Peel** (1995). We also try and explore the role of other factors, such as company age and macroeconomic conditions. For these variables, measures, based on financial statements and market valuation, might be rather unconvincing proxies. Here we augment standard, accounting ratio-based statistical models by adding to model inputs, measures of firm's age and unanticipated changes in the macroeconomic climate, which the literature links to corporate financial distress. The macroeconomic aspect is represented by two policy variables - the real exchange rate and the nominal interest rate. We now turn to a more detailed description of the three

[48] In general, the predictive ability of models utilising these two groups of explanatory variables is comparable.

categories of the explanatory variables used here for cross-sectional modelling of UK company failure: financial variables, firm's age, and macroeconomic variables.

3.2.2.1 Accounting Ratios

Information from annual audited and published accounts is seen in the literature as a critical input to empirical models of company failure. Ideally, financial statements reflect the company's performance, especially profitability, and changes in its financial position (**Rees**, 1995). The financial position is affected by the economic resources the company controls, by its financial structure, liquidity and solvency, and capacity to adapt to changes in the market environment, in which it operates. The significance of accounts' numbers comes from their comparison with other firms' performance. However, it is also important to notice that ratios based on accounts' items reflect the past and suffer from the limitations of accounting statement numbers.[49]

In reviewing the annual accounts to assess the overall "health" of a firm there are certain key things to measure. It is fairly conventional to group ratios in accordance with the major dimensions of the firm's performance, such as profitability, turnover, gearing (capital structure, or financial risk), and liquidity. One problem that arises from the use of ratios as model inputs, relates to the choice of ratio constructs. It should be emphasised that many different ratios are in common usage in the financial analysis literature and that for each ratio there may be more than one acceptable specification. Consequently, no dominant or unique ratio set with respect to corporate performance exists in the literature on failure modelling. Empirical results from a study by **Hamer** (1983) of comparative power of failure prediction

[49] Rees (1995) points out that the accounting reporting system might periodically experience failure. For instance, that happens when a substantial firm fails even though its latest accounts show an apparently healthy situation. He refers to examples of UK firms, namely, BCCI, British and Commonwealth, Coloroll, Maxwell Communications, Mirror Group Newspapers as the cases where accounting information gave no indication of impeding problems. In a way, this example of inability of accounts' ratios to indicate failure might not be that surprising given the fact that, when calculated at book values, ratios from accounts are likely to be backward looking. It is interesting to note here that Coloroll and Maxwell Communications are amongst the estimation sample companies we use in the cross-sectional analysis of the present chapter. The relatively simple financial ratio-based models of section 3.3.1 accurately predicted failure for Maxwell Communications, one and two years ahead, but were unsuccessful in forecasting the failure outcome for Coloroll.

models,[50] show that there is no significant difference in the reported classification error rates, which can be attributed to differences in the variable sets as long as the sets of ratios are *comprehensive* and represent the major dimensions used in financial analysis of company performance. Hence, in the present thesis, when modelling the determinants of failure of UK industrial firms, we employ the standard items of accounting and capital market information contained in the DATASTREAM database. Specifically, we use accounting ratios and capital market-based ratios as defined in "Company Accounts Definitions Manual, Issue 5" (1994) and "DATASTREAM Definitions Manual, Issue 2" (1995). For each firm in our sample we have initially collected data on 31 accounting ratios, readily available for UK industrials, which are grouped into six DATASTREAM categories of rates of return, profit margins, turnover ratios, gearing, liquidity, and tax position. To capture the influence of firm's size, solvency, and dividend policy, we then added to this set total net sales, the net tangible assets index, and the dividend payout ratio. In addition to these standard measures of the firm's profile, variants of the two ratios due to **Altman** (1968) were generated using company accounts' items provided by DATASTREAM: a ratio, measuring cumulative profitability, and a liquidity ratio of the net current assets to the total assets employed. [51] As discussed in chapter 2, the empirical literature suggests that a set of input variables for a debt default prediction model shall combine information from financial statement with market valuation information. For instance, independent variables based on market values of common equity are employed in **Altman,** (1968), **Altman, Haldeman, and Narayanan** (1977), and **Crosbie** (1998). To take account of the market-synthesised view on the growth prospects and risk of an individual company we supplement the list of inputs, measured at book value, with the ratio of market capitalisation to net assets. However, not all of the 38 potential determinants have been used for general specifications in statistical modelling, as some covariates were perfectly collinear.

[50] In a paper about sensitivity of failure prediction models' accuracy to alternative variable sets and statistical techniques, Hamer (1983) maintains that four reasonably comprehensive sets of variables associated with failure models - those that were suggested by Altman (1968), Deakin (1972), Blum (1974), and Ohlson (1980) - perform comparably on a pair-based sample of 88 firms. Ratios appeared in their sets can be broadly classified into six categories: profitability, liquidity, leverage (financial risk), turnover, variability, and size. These variable sets have also survived the test of time as strong predictors, and some were employed in recent studies, e.g. Johnsen and Melicher (1994), Letza (1994), Mossman, Bell, Swartz, and Turtle (1998).
[51] In the UK studies by Keasey and McGuinness (1990), Keasey, McGuinness, and Short (1990), individual predictors of failure are based on standard ratios from DATASTREAM.

Consequently, we now turn to a more specific description of the 25 ratio-based, candidate variables employed in model development.

Profitability Ratios

The concept of profitability in our analysis is measured by returns and profit margins. The *return on shareholders' capital* reflects the performance of shareholders' funds and is shared between the ordinary shareholders and preference shareholders. The computation of this ratio relates the after-tax profit to the total of share capital and reserves. However, this ratio does not reflect profitability of the firm as a whole.

The *return on capital employed* takes account of the proportion of the firm, which is financed by fixed interest capital other than preference shares. Total interest charges and pre-tax profit (including associates) are included in the numerator, and total capital employed and borrowings repayable within one year are included in the denominator. This ratio tests whether the business is generating a worthwhile return on the capital used regardless of gearing and tax considerations.

The *return on net fixed assets* details further the structure of the performance of the business for the equity-holders by looking at the performance of net of depreciation fixed assets in generating sufficient net profits, after the deduction of tax, minority interest and preference dividends, for the ordinary shareholders. The fixed assets exclude the assets leased out. One can see this ratio as a way of testing adequacy of the net profits for the ordinary shareholders.

The *cumulative profitability* measure is expressed as a ratio of the revenue reserves for the parent company and its subsidiaries, to the total assets employed defined as the sum of all assets less total current liabilities. As pointed out in chapter 2, similar measure of profitability, namely, the ratio of retained earnings to total assets, was found to be the most important determinant of company failure in the *ZETA*® study (**Altman, Haldeman, and Narayanan,** 1977), where it was introduced for the first time to impute firm's age.

The relation between profits and sales is reflected in profit margins. One ratio that represents the core of earnings for shareholders – a crucial area for financial analysis - is the *operating profit margin*, which standardises operating profit by total net sales.

Other key measure of profitability is the *pre-tax profit margin*, which standardises pre-tax profit by total net sales. The objective of this ratio is to try to assess the repeatable profits of the business rather than one-off events. This is the case that the special items are figuratively sidelined as largely irrelevant to understanding of likely future performance. The numerator of this ratio excludes interest and non-recurring items or items of very irregular amount such as exceptional/extraordinary items, non-operating provisions, and exchange profit/losses.

Finally, the overall profit margin shows how much income is earned for all shareholders from each pound of revenue. It is net of all expenses including tax, and adjusted for items that do not relate to normal trading activities of the firm. The *net profit margin* standardises after-tax profit before minority interests and preference dividends by total net sales.

Turnover Ratios

It is in the interest of the firm, all other things being equal, for it to maximise the output generated for a given level of investment.

The *fixed assets turnover* shows the efficiency of long-term capital investment, i.e. how effectively the firm manages its fixed assets. This ratio is calculated as total net sales divided by total fixed assets net of depreciation. However, some shortcomings of this construct of the turnover ratio are noted in **White, Sondhi, and Fried** (1998). This ratio does not give a measure of actual efficiency as the simple accumulation of depreciation expense leads to higher turnover because the carrying value of assets has been reduced. Also, the behaviour of this ratio is erratic as it is affected by characteristics of its constituents – sales growth is continuous, albeit at varying rates, whereas increases in capacity to meet that sales growth are discrete, depending on the addition of new plants, and so forth. Compounding such issue is the fact that management often has discretion over the method, timing, and form of financial reporting of the acquisition of incremental capacity.

The ratio of *net current assets turnover* relates total net sales to net current assets. It is conventional to decompose this overall measure of net current assets efficiency into several measures for investment in working capital, by constructing separate items for stocks, debtors, and creditors. The detailed analysis is based on the principle that stocks, debtors, and trade creditors are basically driven by sales activities. Credit sales create debtors and the need to order more stocks and to carry out more work, and the purchase of stocks creates more trade creditors. Failure to manage working capital investment efficiently is very common in business, since it requires continuous vigilance in management of stocks and/or debtors, in which capital is invested. As a result, firms frequently have to borrow. Slowdowns in turnover of stocks may indicate reduced demand for a firm's product or sales to customers whose ability to pay is less certain. A slowdown in debt collection may indicate liquidity problems among customers or may suggest lapsed credit control efficiency, while a slowdown in payment to creditors may reflect liquidity problem in the firm being analysed and possibly also a desire to window dress at the financial year end (**Stead, 1995**). An interpretation of declining turnover ratios usually requires a parallel analysis of company profitability and liquidity. We utilise here three DATASTREAM ratios that relate total net sales and working capital items – the *stock turnover*, *debtors turnover*, and *creditors turnover*.

Gearing Ratios

Gearing ratios are concerned with the level of debt and its burden to the company. With regard to most ratios mentioned above there is a clear view that, all other things being equal, a firm's financial profile is "healthier" if the ratio moves in a particular direction. For instance, higher values of fixed assets turnover, profit margin, or return on capital are better than lower values. In contrast, the financial analysis literature gives no obvious good or bad interpretation of gearing (leverage or capital structure[52]). Financial debt takes many forms - short-term such as overdrafts and commercial paper; medium-term such as hire purchase, leasing, term loans and bonds; and long-term such as capital bonds, debentures, and convertibles.[53] The significance of debt is that it is repayable, bears interest or the equivalent, and may be secured and/or subject to covenants, thus affecting the firm's ability to obtain new external funds. The level of debt, which is safe for a firm to borrow, depends on various factors. They include the size of the firm, the particular nature of the debt (one example here is exchange losses), the cost of debt relative to operating profits or cash flows from operations, and the business climate.[54] As far as the mix of publicly-traded debt and equity securities or capital structure is concerned, the recent empirical research, summarised in **Megginson** (1997), suggests that capital structures have pronounced industry patterns. Certain industries such as transportation companies and those composed mainly of mature capital-intensive firms are characterised by high publicly traded debt-to-equity ratio, while other industries, for example, service firms, employ little or no long-term debt financing. Companies rich in collateralizeable assets, such as commercial real estate and transportation equipment, are able to tolerate far higher publicly traded debt-to-equity ratios than companies whose principal values are human capital of its employees or intangible assets. Furthermore, regardless of the industry in question, the most profitable companies may borrow the least (see **Myers,** 1993).

In the present work, the gearing ratios used are the DATASTREAM specifications. *Capital gearing* is computed as the ratio of all long, medium, and short-term debt, including the preference capital, divided by total assets net of intangibles and future income tax benefits. It should be noted that capital gearing is measured here in terms of book value of equity plus book value of debt.

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[52] It should be noted that in corporate finance the phrase "capital structure" is usually applied strictly to the relative mix of debt and equity securities in the long-term financial structure of a firm as contrasted with more general measures of the firm's total indebtedness.

[53] Some sources would (see e.g. the definitions of gearing ratios used by PRIMARK DATASTREAM) include preferred shares as debt as it behaves as if it were debt.

[54] In the end of the 1980s and early 1990s, British companies were particularly sensitive to the high level of debt, since interest rates have tended to be relatively high and volatile. On the other hand, the relative amount of debt carried by the UK companies tends to be lower than in America and most European countries (Stead, 1995).

Income gearing is calculated as total interest charges divided by the sum of operating profit and total non-operating income. Interest charges are calculated on loans, bonds and debentures, leasing finance and hire purchase including dividends/interest payments of redeemable preference shares described as participative loans.

The *borrowing ratio* relates the sum of subordinated debt and total loan capital including borrowings repayable within one year to the sum of equity capital and reserves and deferred tax adjusted for intangibles.

To help further with the analysis of the debt situation of the company we use the ratio of the *gross cash flow over total liabilities*, which includes shareholders' funds and calculated in regard to only tangible values. This concentrates attention on the adequacy of operational cash flows and the affordability of debt, as a low value of this ratio could signal the long-term solvency problem. The strength of this ratio is that it is responsive to changing circumstances in the business.

Additional insight into debt levels can be gained by examining loan capital in relation to tangible shareholders' base expressed by the amount of equity and reserves net of intangibles. This ratio of *loan capital to equity and reserves* concentrates on over-one-year horizons for repayments by excluding loans with under-one-year maturity. A joint analysis of the borrowing ratio and the loan capital to equity and reserves ratio helps address the impact of the general profile of debt maturity, as distant horizons for repayment are generally more attractive than fast approaching repayment dates, which create potential liquidity problems.

Liquidity Ratios

The issues of profitability and financial indebtedness are important financial factors for a company. However, the question of liquidity can become an overriding issue when the organisation is in financial distress, since continually developing illiquidity is a terminal condition. Also, even in a profitable business, poor liquidity can expose the company to serious risks. A firm, which is short of ready cash but is generating good profits, with the right backing, will usually continue to trade. But one, which is short of cash and unprofitable, will find difficulty in getting the backing it needs and may therefore fail, before profit-making capacity can be restored.

The most common measures of liquidity are derived from information available in the balance sheet. Current assets liquidity gives a view of cash circulating in the working capital areas of the company, and can be measured on separate levels, from cash or its shortfall through to the whole of the current assets and current liabilities.

The first liquidity measure, the *quick assets ratio*, contrasts quick assets with current liabilities. Quick assets are the current assets, which are currently in the process of producing cash or are already cash, cash equivalents, or short-term investments. Total stock and work in progress are excluded.

The second measure, the familiar *working capital ratio* of total current assets over total current liabilities, gives a broader view of liquidity, assuming that all current assets may be used to pay off liabilities. An alternative specification measured by *net current assets relative to total assets employed* is also considered. A similar ratio was employed in Altman's *Z*-score model (**Altman**, 1968). This alternative construct helps to overcome the well-known problem with the quick and working capital ratios, as both may be distorted by window dressing – if the numerator and denominator in the ratio are not equal in size then any switching between them changes their proportionate relationship. Also, a firm experiencing consistent operating losses will find current assets relative to total assets employed shrinking.

3.2.2.2 Other Financial Variables

Controlling for firm's size is considered important in failure studies (see e.g., **Foster,** 1986; **Marcus** (1967); **Bernanke, Gertler, and Gilchrist,** 1994; **Dunne and Hughes,** 1994).

The studies of company failure usually take the logarithm of total assets or logarithm of total sales as the means of determining " bigness". The main problem with the choice of assets as a basis for categorisation is that the balance sheet values of total assets could be heavily influences by the limitations of accounting numbers. The assets of the firm pass through a market – and therefore are properly valued – only when the firm is actually sold. In this respect annual sales may provide a more reliable measurement. Therefore to control for firm's size in modelling UK company failure, we utilise the *logarithm of total sales net of trade discounts*. The logarithm of sales as a measure of size has been employed in prior empirical studies of failure by **Pastena and Ruland** (1986), **Betts and Belhoul** (1987), **Wilson, Chong, and Peel** (1995), **Lindsay and Campbell** (1996), **Hill, Perry, and Andes** (1996), **Laitinen and Laitinen** (1998) and **Richardson, Kane, and Lobingier** (1998).

As discussed in chapter 1, due to inadequate liquid assets, a firm may suffer phases of relative illiquidity or inability to meet and pay its debt obligations promptly, yet still have sufficient non-liquid assets to discharge its liabilities. Such problems of temporary illiquidity can be sometimes resolved outside the framework of corporate insolvency law, for instance, the firm may use new overdraft facilities. However, when the company assets are insufficient to discharge its liabilities the company is insolvent or its net worth is negative. A very crude indicator of solvency can be provided by changes in the book value of tangible shareholders' funds or net tangible assets in the balance sheet. The net book worth is commonly used in the assessment of the prudential level of borrowing and may affect the company's ability of raising external finance despite the fact that book values are historically oriented and affected by changes in accounting conventions and thus may cause the unrealistic presentation of the company (**Stead,** 1995). To reflect this aspect of the firm's performance and financial stability we employ here the *index of net tangible assets* that uses the year of the first accounts as the base year. Net tangible assets are derived from the balance sheet and defined as equity capital and reserves less total intangibles.

As discussed above, the finance literature, concerned with theoretical and empirical aspects of failure risk modelling, suggests that only the equity market value provides a good measure of the value of the ongoing business of the firm, because it changes as market participants revise the firm's future prospects, reassesing the firm's viability (see, e.g., **Altman,** 1968; **Altman, Haldeman, and Narayanan,** 1977;

Scott, 1981; **Crosbie**, 1998; **Gray**, 1999). Therefore it seems essential to include in the vector of company descriptors, as a proxy for the firm's asset value, the ratio of the *market value to book value* of the ordinary shares, which is also called *premium* or *discount to net tangible assets*. This ratio allows one to appraise the degree of the difference between the future and market oriented valuation and historically oriented book value of the ordinary shareholders' capital. The literature emphasises that the perceived relative effectiveness of the management of assets might be a fundamental cause of differences between companies when compared on the basis of this measure (**Stead**, 1995). If problems of accounting measurement are disregarded for the moment, it is mainly profitability as measured by the return on assets, which the managers can achieve, dictates the size of premium the investors are prepared to pay, relative to the reported assets value. However, the market value of shareholders' funds also depends on a number of factors that are outside the control of the company. Most importantly these external factors include interest rates and current supply and demand for shares. The inclusion of the ratio of market-to-book value in the vector of failure predictors can also be based on the argument that as the market valuation reflects the expected future cash flows and interest rates, it also captures the effects associated with macroeconomic factors. It should be noted, however, that in models described in this chapter we attempt to explicitly model the impact of some contextual factors on failure risk by adding into our financial ratio-based models measures of unanticipated movements in the interest rate and exchange rate.

In modelling failure, we also include in the initial set of independent variables the *tax ratio*, which shows the relationship of published tax to published accounting pre-tax profit. However, it must be recognised, that the tax charge can vary depending on many factors unconnected with the current year performance. A selection of such factors, affecting the tax charge and hence the post-tax profits of firms is listed in **Stead** (1995). These include: (i) previous years' tax losses and/or investment allowances being utilised; (ii) sister companies' tax losses and/or investment allowances being utilised; (iii) the nature and extent of capital investment in the year; (iv) the nature and extent of capital investment in previous years; (v) dividend policy and the interaction of dividend payments with the extent of overseas earnings (i.e. problems of unrelieved surplus advance corporation tax); (vi) the extent and rate of overseas taxes, and also the possibility of unrelieved double taxation.

The *payout ratio* measures the proportion of earnings paid out as dividends. This ratio is the reciprocal of dividend cover. All modern dividend theories assign an information revelation role to payout ratio changes (**Megginson, 1996**). On the one hand, a low payout ratio shows how much leeway was available for the last dividend, and the company commitment to investment and growth, suggesting that the company retains its earnings for investment into the business – rapidly growing firms hoard cash and might select a very low dividend. On the other hand, dividend decreases may imply declining earnings prospects. As British firms generally rely on capital market financing and compete for funds, they might pursue ambitious dividend policies even in a period of poor profits (**Stead, 1995**). Firms generally are unwilling to cut dividends; any significant decrease in dividends is likely to signal either financial distress or expected poor cash-flow performance in the future. Almost all firms maintain constant nominal dividend payments per share, even in the face of temporary net losses, therefore negative dividend cover might be taken as a sign that a company is in an especially difficult position.

3.2.2.3 Transformation of Financial Data

Methodological issues arising from empirical properties of accounting-based variables and, in particular, financial statement ratios have been indicated and discussed in the finance literature (e.g. **Foster**, 1986; **Ezzamel, Brodie, and Mar-Molinero,** 1987; **Platt and Platt,** 1990; **Platt, Platt, and Pedersen,** 1994; **Rees,** 1995; **Sudarsanam and Taffler,** 1995). As discussed in chapter 2, empirical evidence shows: (i) that underlying the use of ratios the numerator-denominator relationship is inconsistent with the specific strict proportionality assumption between the numerator and denominator;[55] (ii) that distributions of financial ratios depart from normality; (iii) that there is a substantial variation between ratio components over time; and (iv) that instability of ratios over time along with the use of research samples, which pool data points across different periods, violate the stationarity condition necessary to produce accurate forecasts. The conclusions from this strand of the literature suggest that accuracy and structure of multivariate financial ratio-based models can be improved by using transformed financial variables to remove non-stationarity. Here, to better approximate normality and to alleviate the temporal instability problem, we apply a normalisation procedure to observations in the estimation and holdout samples. Aside from that, standardised data are more appropriate for a non-linear method.

For the estimation sample, the normalised value of the individual observation r_{it} on firm i pertaining to year t is calculated using the respective values for the sample mean $\bar{r}_t$ and standard error se_t, obtained for the sample of observations taken from year t alone:

$$\text{Normalised Ratio} = \frac{(r_{it} - \bar{r}_t)}{se_t} \quad . \tag{3.1}$$

However, as there are fewer observations in the holdout sample, 96 as opposed to 421 used in the estimation cross-section, we normalise holdout observation values with respect to the means and standard errors of three different, larger cross-sections created for 1992, 1993, and 1994 - for the three years, corresponding with the time period of the holdout sample. These cross-sections, containing 493, 488, and 487 observations, respectively, are used in a panel of UK quoted industrial firms, which we analyse in chapter 4. Tables A2.1-A2.6 of appendix 2 display covariate descriptive statistics calculated from the normalised values of 25 financial variables employed in cross-sectional model development, including, means for the failed company group and non-failed company group, related test statistics and pairwise correlations for each of the four years prior to failure.

[55] The strict proportionality between the numerator and denominator assumed both in comparison of ratios across firms at a point in time and in time-series analysis of ratios. However, for a particular ratio, the actual relation might imply a constant term or be non-linear.

3.2.2.4 Non-Financial Variables

The Duration Variable

The important explanatory role of company age, suggested by the model of market exit in a duopoly (**Lambrecht**, 1999), is consistent with stylised facts obtained from research into company failure determinants, which documented a negative relationship between age and failure risk. For instance, in the failure prediction model *ZETA*® (**Altman, Haldeman, and Narayanan**, 1977) corporate age was indirectly proxied by a cumulative profitability factor that had a large influence on failure risk. A number of studies, investigating the aggregate incidence of company insolvency and corporate growth and survival (**Marcus**, 1967; **Hudson**, 1987; **Turner, Coutts, and Bowden**, 1992; **Altman**, 1993; **Dunne and Hughes**, 1994), also have shown the importance of the age structure of companies.[56]

Hudson (1987) reports evidence on the age structure of UK company liquidations, obtained from the sample of 1,830 firms liquidated between 1978 and 1981. The age of the firm was proxied by the number of months between the company being incorporated and the liquidator or, in the case of a compulsory liquidation, the official receiver being appointed. Hudson finds that for the two categories of liquidations, involving insolvency, namely, winding up orders following petitions to the court by creditors and creditors' voluntary liquidations, newly incorporated companies prevail. In his sample, companies experienced difficulties in becoming established, which led to higher risk of becoming insolvent during their first nine years. Further, the firms that went into compulsory liquidations, stemming from winding up orders, were younger than the companies being placed into creditors' voluntary liquidations. His analysis also revealed variation of this age structure of liquidations across regions and industries. Those industries that had seen greatest increases in unemployment, were characterised by a larger proportion of older firms amongst those being liquidated. The pattern changed with the cycle - as the recession deepened the proportion of old established firms going into liquidation began to rise.

[56] Altman (1993, 2000) refers to a failed US firm age statistics compiled by Dun & Bradstreet for the 1990s. The data give evidence that a young undercapitalised firm has a far greater propensity to fail than its old counterpart. In 1990, about 50 per cent of all failures were firms less than five years old, and nearly 10 per cent of firms failed in their first year.

It follows that age is a distinct factor that merits a separate analysis in company failure prediction research. Here the age of the firm is proxied by the length of time its records have been kept by the DATASTREAM database, and termed a duration variable. We recognise that the measure of duration, defined this way, can be only viewed as a very crude approximation of the age of a public limited company, but the reason this basis has been chosen is its practicality. Using the sources of public records we have had access to, it was hard to "exactly" establish the age in each particular instance, mostly due to changes in the legal type of incorporation of the business. A value for the duration variable is calculated by subtracting the year from which DATASTREAM holds information about a company (the base date for equity records), from the accounts' year of the record used in the cross-section constructed for year one prior to failure. In the cross-section created with the data for one year prior to failure, the mean and median values of the duration variable equal 12.7 years and 11 years for the failed company group, and 19.5 years and 23 years for the non-failed company group.

Further, we have scaled the duration variable by expressing it in relative terms. For both the estimation and holdout sets, the respective maximum values have been chosen as bases to obtain relative values.

Macroeconomic Variables

If the factors leading to insolvency were internal to all companies, the rise in failures in slump periods would be inexplicable. The actual occurrence and timing depends on changes in firm-specific characteristics due to economic events, which exacerbate financial constraints on firms. This suggests that characteristics of the macroeconomic environment might be helpful explanatory variables in firm-level models of failure. The current firm-level models reviewed in chapter 2 include variables representative of various aspects of the macroeconomic environment (see, e.g., **Hill, Perry, and Andes** (1996) and **Richardson, Kane, and Lobingier** (1998)). Theoretical considerations for company liquidation, link individual company vulnerability to default to changes in interest rates and exchange rates (see, e.g., **Wadhwani,** 1986; **Scott,** 1981; **Turner, Coutts, and Bowden,** 1992; **Bartov**

and Bodnar, 1994; **Davis,** 1995; **Crosbie,** 1998; **Gray,** 1999). For modelling company failure with cross-sectional data, we have chosen these two indicators as the prime candidates for potentially relevant macroeconomic determinants.[57]

The literature suggests that the principal channels, through which real and nominal interest rates impact listed company failure risk, are: (i) the market value of equity that has direct bearing on long-term solvency and determines the relative burden of debt, altering the firm's borrowing capacity and ability to restructure and reschedule outstanding short-term debt obligations; (ii) variations in risk premia and the cost of capital, which might also influence the company's ability to raise new funds;[58] and (iii) sales and profit levels as well as interest expenses on outstanding obligations, which all impact on cash flows and the short-term liquidity position of the company. For the firms involved in international activities, for instance, exporters, importers, or firms with foreign operations that have current or future cash flows denominated in foreign currency, the linkages could be more complex. The extend to which interest rates affect equity values of such firms will also depend on their shares of foreign and domestic components of outstanding debt, on export intensity and the proportion of operations abroad. Movements in the exchange rate result in direct changes in the relative prices of domestic and foreign goods, which influence both the current and future expected cash flows and revenues of firms with international operations. A rise in the real exchange rate is associated with a loss of international competitiveness in the traded sector, whereas a fall brings an improvement in competitiveness. Another dimension to how exchange rate movements affect the value of firms is given by the relation between the exchange rate and the domestic currency value of foreign currency-denominated fixed assets and liabilities. However, the impact of a change in the exchange rate on company performance, assets and liabilities is complicated by firms' "unobservable" activity to hedge

[57] We have also attempted to follow Platt, Platt, and Pedersen (1994) who attributed an improvement in predictive power of failure models based on logit for US petroleum companies to the explanatory role of inflation. However, in our study, a proxy for an unanticipated change in inflation, seems to be inconsistent with the initial set of model inputs that includes financial statement-based variables and two measures proxying changes in the nominal interest rate and real exchange rate.

[58] The discussion in Nickell and Nicolitsas (1999) suggests two effects on the costs of external funds, of the general rise in interest rates. Assuming that a large part of the firm's net worth is determined by the present value of future profits, there would be a direct effect, because the risk-free interest rate has risen, and an indirect effect, because net worth falls. The indirect effect reinforces the direct effect and is more important the higher is the initial level of debt relative to net worth.

foreign currency exposures. Therefore a complete market response to the impact of past changes in the exchange rate on the market value of a company is delayed until information regarding past performance, assets, and liabilities of the company, is released (**Bartov and Bodnar**, 1994).

A number of empirical studies for the UK (e.g., **Wadhwani**, 1986; **Goudie**, 1987; **Goudie and Meeks**, 1991; **Young**, 1995; **Diacogiannis**, 1996), and commercial models of default risk (see a description of the CreditPortfolioView approach from McKinsey in **Crouhy, Galai, and Mark** (2000)), explicitly allow for the effects of interest rates, exchange rates, and inflation. Therefore, we follow the similar route in the cross-sectional analysis of UK company failure during the 1990s recession. Specifically, we seek to augment cross-sectional, financial ratio-based models of failure risk by introducing proxies for effects of changes in such important and observable prices in the economy as the nominal interest rate and the real exchange rate. The literature (see, e.g., **Wadhwani**, 1986) emphasises the influence of the nominal interest rate, which also encapsulates expected inflation rates, on the risk of failure.

The particular relevance of changes in these indicators to survival of the sample companies follows from the fact that in the period post-1986, the UK experienced an inflationary episode associated with excess aggregate demand that was pushed up by a number of factors. These factors included financial liberalisation, a relaxation of monetary policy, rising asset prices, tax cutting budgets in 1987 and 1988, growing consumer confidence, and buoyant world demand. The excess demand caused inflation to rise - the Retail Price Index increased from the annualised rate of 4.14 per cent in 1987 to the annual rate of 9.46 per cent in 1990. The tightening of monetary policy in late 1988 taken in conjunction with the need to defend a higher exchange rate to keep the pound within the Exchange Rate Mechanism meant that the authorities felt unable to reduce interest rates below 10 per cent. In the spring of 1990, despite persistent inflation, the real interest rate, as expressed by a three-month lending rate less inflation, was also high - for instance, the relevant estimate for the UK was 7.5 per cent and for the US - 3.0 per cent ("Understanding the UK Economy", 1997).

It appears, therefore, that by the end of 1989, the shocks from changes in the interest rates and exchange rate had been strong enough to influence default risk of highly geared companies by causing both short-term liquidity problems and a reduction of the market value of equity. As the recession of 1990-92 began and profits declined further, an increased number of companies suspended payments to creditors and subsequently entered insolvency procedures.

The potential for allowing in a model estimated with cross-sectional data for the effects of changes in the two macroeconomic indicators comes from the structure of our repeated pooled cross-section sample. By pooling data points across several consecutive years, we provide a time dimension, allow for variation of financial covariates over time, and comply with an important for our analysis principle of temporal precedence because no cause can precede its effect. Different macroeconomic conditions are contained in data on accounting ratio-based and market valuation-based inputs. The resulting temporal dimension of our data permits us to explicitly model changes in economic conditions over the sample period. From a positive economic standpoint, the estimated relations might help to understand how these macroeconomic variables condition the probability of failure of a firm. It might be assumed that unfavourable changes in the nominal interest rate and real exchange rate had adverse effects on those companies that would consequently fail, thus a macroeconomic dummy variable is constructed that equals 1 for failed companies and 0 for non-failed firms. This dummy is then used in interactions with each macroeconomic variable. It follows that the predictions from the model will be conditional on the *mistakes* over macroeconomic forecasts made by the firm, the effect of which is measured from their impact on the failed firms. Hence, we are looking at the risk of failure conditional on a poor response to changes in macroeconomic conditions.

In modelling the influence of the two macroeconomic variables we follow **Young** (1995) in assuming that only unanticipated changes (surprises) in interest rates and exchange rates will affect the firm's solvency, as in a perfect capital market prices fully and correctly reflect available information. According to Young, this is because anticipated changes are reflected in initial business decisions in a way that unanticipated changes are not. Further, we assume the delayed effect of the macroeconomic variables upon the firm's performance and financial position. Due to the certain extent of inertia, it is the last year's mistakes and miss-predictions, which may be critical as a financial distress trigger. The failure process might well be driven by a sequence of such mistakes. Accordingly, in modelling, we utilize one-year lagged unanticipated changes in the annualised values of macroeconomic variables corresponding with the timings of financial records for the sample firms.

Unanticipated changes in macroeconomic variables are directly unobservable, therefore they must be proxied. The simplest path to follow is to assume that the macroeconomic series of interest evolve as a random walk.[59] To measure the underlying economic risks affecting failure, we make an assumption that a process for the y_t series of observations of a macroeconomic variable is generated by a naive (driftless) random walk:

$$y_t = y_{t-1} + \varepsilon_t; \quad \varepsilon_t \sim \mathrm{IID}(0,\sigma^2); \quad t = 1,\dots,n \ , \tag{3.2}$$

where y_t is a value of the variable at time t; and ε_t is a random disturbance, not predictable from the history of the process.

Then the conditional mean and variance of the variable at date t, conditional on the initial value y_0 at date 0, is:

$$E(y_t \mid y_0) = y_0 + 0 \tag{3.3}$$

$$Var(y_t \mid y_0) = \sigma^2 . \tag{3.4}$$

[59] As for the nominal interest rate process this assumption is a gross simplification. However, stylised facts concerning time series for the major exchange rates (under floating exchange rate regimes) are that exchange rates are hard to distinguish empirically from a simple random walk (Mussa, 1984; Taylor, 1995). Meese and Rogoff (1988) report that their regression forecasts of log real exchange rates are never significantly better than the driftless random walk.

That implies that the unanticipated change in the macroeconomic variable equals $(y_t - E(y_t))$, that is the entire change is unanticipated. From (3.2) - (3.4) it is apparent that one can approximate the "surprise" by the one-year lagged change in the macroeconomic variable.

Accordingly, we construct the one-year lagged logarithmic change in the real exchange rate, which influences competitiveness in the traded goods sector, and the one-year lagged logarithmic change in the nominal interest rate, which directly impacts on the burden of debt and capacity to raise finance. If financial statement-based independent variables describing an individual firm in the cross-section pertain to year *t*, then the two macroeconomic variables are measured as follows:

$$\text{One-year Lagged Change in the Real Exchange Rate} = [\ln RER(t-1) - \ln RER(t-2)], \quad (3.5)$$

where the real effective exchange rate, $RER(t)$, is given as an index,[60]

$$\text{One-year Lagged Change in the Nominal Interest Rate} = [\ln IR_n(t-1) - \ln IR_n(t-2)], \quad (3.6)$$

where the nominal interest rate, IR_n, is given by the 3-month sterling interbank rate measured as the annualised percentage rate.[61]

An additional advantage of specifying these macroeconomic measures in differences is that the resulting variates are also stationary, complementing the correction made for financial statement-based variables.

It is important to observe that the expected value of the two macroeconomic variables is zero, implying on average zero response to either the interest rate change or the exchange rate change. One can argue that unanticipated rises both in the exchange rate and in the interest rate had the adverse impact on those companies that would consequently fail. Thus to capture the influence of changes in the business climate, a macroeconomic dummy variable is constructed that is equal to 1 for failed

[60] The index is the DATASTREAM item "UKOCREXC".

companies. This dummy is used in interactions with each macroeconomic variable. It follows that the predictions from the model will be conditional on the mistakes in macroeconomic forecasts, the effect of which is measured from their impact on failed firms. Hence, we are looking at the risk of failure conditional on a poor response to changes in macroeconomic conditions.

As a final point, we should also comment on a potential methodological problem of measuring the impact of aggregate macro variables on micro units, when a strategy of merging aggregate data with cross-sectional data is employed (**Moulton**, 1990). Using an example of the linear model, **Moulton** cautions that ignoring the correlation of errors within groups, which used to merge aggregate with micro data, can result in spurious downward bias of the usual OLS standard errors, the resulting inflation of test statistics and incorrect inference. It is worth noting that in the present study, the logit specifications[62] that condition the probability of failure on changes in the two macroeconomic variables do not account for the within-group disturbance correlation. It is important to emphasise that in our empirical design no aggregate measure is being used as we combine with financial statement data on firms such economic indicators as the nominal interest rate and the real exchange rate. Aside from that, it was necessary to allow for the influence of macroeconomic factors as current empirical models, developed to explain company financial distress and failure, refute any "single cause" explanation. Moreover, the cost of omitting relevant explanatory variables is inconsistency. Nonetheless, we recognise that in further research it might be desirable to investigate further the implications and solutions of this potential problem when a range of macroeconomic variables used in logit models of failure is expanded by the addition of aggregate macro variables.

3.2.3 The Statistical Model

The Discrete Binary Dependent Variable

The phenomenon of company failure we seek to examine is discrete, and in the case of a conventional, failed/non-failed dichotomy, the depended variable describing

[61] Young (1995) employed the same measure of the nominal interest rate.
[62] These models are described below in sections 3.3.2 and 3.3.4.

outcomes is a binary response, which means that we equate the event of "failure" with 1 and the event of "non-failure" with 0. We view an outcome as a reflection of an underlying regression, which links the discrete dependent variable to a set of explanatory and control variables representing major dimensions of financial analysis, firm age, and macroeconomic variables. Changes in accounting variables and business conditions will result in various degrees of "financial health" of a firm, and this might, in principle, be measured on a continuous scale. But given the problems of defining distinct stages in the continuum of "financial health", which we have discussed in chapter 1, it seems more expedient and sufficient for the purpose at hand, to observe merely, whether the firm is broke or survives. Therefore, the discrete character of the dependent variable is somewhat imposed by the purpose of our analysis of company failure. In modelling, such an idea can implemented by using the latent variable specification described and chapter 2 and revisited below.

The Binomial Logit Model

We utilise in this study logit - the non-linear estimator common in studies of company failure prediction (e.g., **Ohlson**, 1980; **Zavgren**, 1985; **Peel, Peel, and Pope**, 1986; **Keasey and McGuinness**, 1990; **Platt and Platt**, 1990; **Platt, Platt, and Pedersen**, 1994; **Richardson, Kane, and Lobingier**, 1998).

For logit we believe that a set of predictor-variables, gathered in a vector $\mathbf{x}$, explains company failure. The latent hypothesis is captured by a linear combination of the independent variables $\boldsymbol{\beta}'\mathbf{x}$. This linear combination is then transformed into a probability using the log-link. The use of the logit link here is to simply ensure that the mean is mapped from the real line to the unit interval required since the indicators are dichotomous. Thus the probability for a company to fail is given by the following expression:

$$\text{Prob}(Y = 1\,(\mathit{Failure})) = \frac{e^{\boldsymbol{\beta}'\mathbf{x}_i}}{1 + e^{\boldsymbol{\beta}'\mathbf{x}_i}}. \tag{3.7}$$

Here the y_i independently equals 1 or 0 with probabilities π_i or $1-\pi_i$. The maximum likelihood estimate of the parameter vector $\hat{\boldsymbol{\beta}}$ generates estimates of $\hat{\pi}_i$.

By using the realised prediction rule $\hat{\eta}$ for some threshold point C_0, the model predicts the failure outcome for an observation with the covariate vector $\mathbf{x}_i$:

$$\begin{cases} \hat{\eta}_i = 1 \ \text{ if } \hat{\pi}_i > C_0, \\ \hat{\eta}_i = 0 \ \text{ if } \hat{\pi}_i \le C_0. \end{cases} \tag{3.8}$$

The estimation of the logit model is based on the likelihood function. Each observation is treated as a single draw from a Bernoulli distribution (binomial with one draw). The model with response probability $F(\boldsymbol{\beta}'\mathbf{x})$ and independent observations leads to the joint probability or likelihood function:

$$L = \prod_{i \in F} \left[\frac{e^{\boldsymbol{\beta}'\mathbf{x}_i}}{1+e^{\boldsymbol{\beta}'\mathbf{x}_i}}\right] \prod_{j \in N} \left[\frac{1}{1+e^{\boldsymbol{\beta}'\mathbf{x}_j}}\right], \tag{3.9}$$

where F defines the subset of failed companies in the sample, and N reflects the subset of sampled non-failed companies. Taking logs we obtain for the sample of n observations, where $n = F + N$, the log-likelihood function:

$$\ln L = \sum_{i=1}^{n} [y_i \ln F(\boldsymbol{\beta}'\mathbf{x}_i) + (1 - y_i)\ln(1 - F(\boldsymbol{\beta}'\mathbf{x}_i))]. \tag{3.10}$$

The first order conditions for maximisation require:

$$\frac{dL(.\mid \boldsymbol{\beta})}{d\boldsymbol{\beta}} = \sum_{i=1}^{F+N} \mathbf{x}_i'\hat{\varepsilon}_i = 0, \tag{3.11}$$

where $\hat{\varepsilon}_i = y_i - \hat{\pi}_i$; $\hat{\pi}_i = \dfrac{e^{\hat{\boldsymbol{\beta}}'\mathbf{x}_i}}{1+e^{\hat{\boldsymbol{\beta}}'\mathbf{x}_i}}$, and $\hat{\boldsymbol{\beta}}$ is the maximum likelihood estimate of the parameters.

If $\mathbf{x}_i$ contains the intercept, the first-order conditions imply that the average of the predicted probabilities must equal the proportion of 1s in the sample.

The coefficient in the logit model is the change in the log of the odds ratio associated with a unit change in the covariate. It is easy to see that

$$\pi_i = \frac{e^{\boldsymbol{\beta}'\mathbf{x}_i}}{1+e^{\boldsymbol{\beta}'\mathbf{x}_i}} \tag{3.12}$$

and

$$1-\pi_i = \frac{1}{1+e^{\boldsymbol{\beta}'\mathbf{x}_i}} \tag{3.13}$$

so that the logarithm of the odds ratio is linear in $\mathbf{x}$ and in the parameters $\boldsymbol{\beta}$

$$\ln\left(\frac{\pi_i}{1-\pi_i}\right) = \boldsymbol{\beta}'\mathbf{x}_i . \tag{3.14}$$

Any linear function of relevant covariates can thus be inserted in the logistic function; its argument may be treated exactly like a regression equation. It should as a rule include a dummy constant "1" with an intercept α as its coefficient. Just as in a regression function covariate values can be appropriately transformed, for instance, by taking logarithms or centring, while qualitative factors can be represented by categorical variables.

Since the cumulative distribution function $F(\cdot)$ is non-decreasing, the logit model in equation (3.7) is consistent with the intuitive principle that failure becomes near certainty at the high levels of the log odds ratio (which shows how much the outcome 1 is "nearer" than the alternative outcome 0). The rate of change in the probability that outcome 1 results, given a change in the k-th covariate, is

$$\frac{d\pi_i}{dx_{ik}} = \frac{d\Lambda(\boldsymbol{\beta}'\mathbf{x}_i)}{dx_{ik}} = \Lambda'(\boldsymbol{\beta}'\mathbf{x}_i)\frac{d(\boldsymbol{\beta}'\mathbf{x}_i)}{dx_{ik}} = f(\boldsymbol{\beta}'\mathbf{x}_i)\beta_k , \tag{3.15}$$

where $f(\boldsymbol{\beta}'\mathbf{x}_i)$ is the probability density function of a logistic random variable evaluated at the point $(\boldsymbol{\beta}'\mathbf{x}_i)$ and β_k is the k-th parameter in the vector $\boldsymbol{\beta}$.

In interpreting logit results it is important to remember that the probability density function $f(\boldsymbol{\beta}'\mathbf{x}_i)$ is always positive, thus the sign of β_k indicates the direction of the relationship between the explanatory variables and the probability π_i. If $\beta_k > 0$ than an increase in x_{ik} increases the probability that $y_i = 1$; and if $\beta_k < 0$ than an increase in x_{ik} reduces the probability that $y_i = 1$. The magnitude of the change in the probability, given a change in x_{ik}, is determined by the magnitude of β_k and the magnitude of $f(\boldsymbol{\beta}'\mathbf{x}_i)$.

Inference in the Logit Model

Since maximum likelihood estimators of binomial logit model fit within the general large sample theory for non-linear models, statistical inference is conventional for large sample tests.[63] An important advantage of the chosen logit methodology is its suitability for implementing a traditional econometric approach for addressing the problem of evaluating particular specifications under the condition of model uncertainty posed by the absence of a unifying theoretical framework and parameter heterogeneity. Here we built a parsimonious model by testing down an initial general specification and eliminating covariates using a sequence of asymptotic t-tests and independent Likelihood Ratio tests. The resulting model should essentially contain a satisfactory proportion of information conveyed by the original general specification, while also being much more parsimonious[64].

For testing hypotheses about individual coefficients, usual t-tests and Likelihood Ratio tests are used.

When the sample size n is large the maximum likelihood estimator $\hat{\boldsymbol{\beta}}$ for the logit model has a sampling distribution that is approximately normal:

$$\hat{\boldsymbol{\beta}} \sim N[\boldsymbol{\beta}, \mathrm{cov}(\hat{\boldsymbol{\beta}})]. \tag{3.16}$$

Consequently,

[63] As a rule of thumb, sample sizes, which yield less than thirty responses per alternative, produce estimators, which can not be analysed reliably by asymptotic methods. Monte Carlo studies and second-order asymptotic approximations suggest that in many qualitative response models with sample sizes of a few hundred and more, first-order approximations are moderately accurate (McFadden, 1984).

$$t = \frac{\hat{\beta}_k - \beta_k}{se(\hat{\beta}_k)} \sim N(0,1). \tag{3.17}$$

Given the null and alternative hypotheses

$$\begin{aligned} H_0 &: \beta_k = 0 \\ H_1 &: \beta_k \neq 0 \end{aligned} \tag{3.18}$$

the t-statistic is $t = \dfrac{\hat{\beta}_k}{se(\hat{\beta}_k)}$.

If the null is true, the t-statistic has a normal distribution (approximately) in large samples, and the critical values for the test may be taken from the standard normal distribution or the t_{n-K} - distribution (K gives the number of explanatory variables including the intercept).

Therefore, the appropriate standard errors for the model can be calculated by taking the square roots of the diagonal elements of the empirical analogue of the covariance matrix, $\text{cov}(\hat{\boldsymbol{\beta}})$, which can be obtained by evaluating the Hessian matrix of second-order derivatives at the maximum likelihood parameter estimates.

General and joint hypotheses about the parameter values can be tested by using the Likelihood Ratio tests. The null and alternative hypotheses will be stated as

$$\begin{aligned} H_0 &: R\boldsymbol{\beta} = \mathbf{r} \\ H_1 &: R\boldsymbol{\beta} \neq \mathbf{r}. \end{aligned} \tag{3.19}$$

The Likelihood Ratio test compares the value of the log-likelihood function, $\ln L$, evaluated at the maximum likelihood estimator $(\hat{\boldsymbol{\beta}})$, to the restricted maximum likelihood estimator $(\hat{\boldsymbol{\beta}}^*)$ that results when the log-likelihood function is maximised subject to the restrictions $R\boldsymbol{\beta} = \mathbf{r}$ being true.

[64] For a discussion of model selection see, e.g., Davidson, Hendry, Srba, and Yeo (1978) and Hendry, Muellbauer, and Murphy (1990).

The Likelihood Ratio test statistic,

$$LR_r = 2[\ln L(\hat{\beta}) - \ln L(\hat{\beta}^*)] \tag{3.20}$$

has a $\chi^2_{(J)}$ distribution if the null hypothesis is true, where J is the number of independent restrictions being tested. If the data do not support the null hypothesis then the value of the test statistic becomes large, and the null is rejected if $LR_r \geq \chi^2_{(J)}$.

A number of overall fit measures for the logit model have been suggested. To test specifications, that is to make a judgement about the goodness of fit of a model and to evaluate different models fitted to the same sample, even if they are not nested, the maximised values of log-likelihood functions at convergence, $\ln L_M$, for the alternative models can be compared (**Cramer,** 1991; **Greene,** 1997), although it varies in proportion with the sample size n and increases with the number of fitted parameters K.

A common test of the "overall" significance of a particular logit model, when we wish to test the null that all the slope coefficients are zero, is given by comparing the log-likelihood evaluated at the maximum and the corresponding baseline log-likelihood of the baseline model with a constant only. The corresponding Likelihood Ratio test statistic is:

$$LR_r = 2[\ln L(\hat{\beta}) - \ln L_0], \tag{3.21}$$

which has a $\chi^2_{(K-1)}$ distribution.

An analog to the coefficient of determination R^2 in a conventional regression model, is the Likelihood Ratio Index (**McFadden,** 1974):

$$LRI = 1 - \frac{\ln L(\hat{\beta})}{\ln L_0}. \tag{3.22}$$

The result of model estimation is a maintained probability model with accepted parameter estimates. But in practice the aim is to use these results in forecasts and policy formulation. The explanatory power of a model, fitted to the estimation data points, and hence the relevance of the obtained determinants of insolvency outcome is judged by the model's classification accuracy and ability to predict the response value for the observations that lie outside the estimation range and period. Notice that these predictions offer probability statements, not a single value of a point estimate, as with a linear regression. So it will be useful to think of a pseudo-R^2 for assessing the fit of a binomial logit model in terms of classificatory accuracy (**Maddala,** 1992).

Thus we define classificatory accuracy as the proportion of the correct predictions of the realised prediction rule $\hat{\eta}$ (3.8), which attaches 0 or 1 to $\hat{y}_i$ on the basis of the probabilities of these values:

$$\text{count R}^2 = \#\{y_i = \hat{\eta}_i\} / n. \tag{3.23}$$

In general, a prediction rule of the form (3.8) will make two types of errors. It will incorrectly classify responses as non-responses (Type I error) and non-responses as responses (Type II error). Changing the cutoff probability value C_0 will always reduce the probability of one type of error while increasing the probability of the other. However, there is no correct answer as to what is the best cutoff value to choose, because the classification errors are usually asymmetric in the costs that result. Therefore, the appropriate cutoff value will depend on the decision context given by the criterion function upon which the prediction rule depends. The usual threshold value for C_0 in (3.8) is 0.5, and in this case we have the maximum probability rule "predict the most probable state".[65] If the sample is unbalanced, with

[65] This point has been illustrated by BarNiv (1990) in the study of the association between market- and cash-flow-based data and the ability to classify and predict insolvency in the insurance industry. BarNiv selects a

many more non-responses than responses, than the obvious adjustment is to reduce the cutoff value C_0.

It is common to assess the classificatory power of a model, fitted to the estimation sample, by the apparent error rate:

$$\bar{\mathrm{e}}\mathrm{rr} = \#\{y_i \neq \hat{\eta}_i\}/n. \tag{3.24}$$

In other words we use the apparent error rate as an estimate of the true error rate of the model. However, because $\mathbf{y}$ was used for both constructing and assessing the prediction rule $\hat{\eta}$, $\bar{\mathrm{e}}\mathrm{rr}$ will usually be biased downwards: a new binary outcome might not be predicted as nearly as accurately by the old $\hat{\eta}$.

The bias (or the optimism) is the difference between the true error rate and the apparent error rate, hence the purpose of estimating the bias is the constructing of estimates of the true error rate, better than the apparent error rate. The literature suggests several, frequently used solutions of the problem of assessing the *ex ante* predictive power of the realised prediction rule. These include: (i) the use of a holdout sample of new observations, which should be temporally distinct from the estimation sample; (ii) bootstrapping approaches for approximating the bias in the apparent error rate in logit; and (iii) Efron's formula for approximating the bias in the apparent error rate analytically (**Efron**, 1986). As far as the bootstrap is concerned, **Jeong and Maddala** (1993) note that, in parametric binary response models, bootstrapping may not be useful unless the sample size is small. Since for the cross-sectional study of the present chapter, we use a sample of 421 observations, which may be viewed as a reasonably large sample, we do not employ

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cutoff value that minimises the expected costs of misclassifications in the estimation sample (ECM): $ECM = p_1 c_1 n_1 / N_1 + p_2 c_2 n_2 / N_2$, where c_i = misclassification costs for type i error; n_i = the total number of type i misclassifications; N_i = sample size of the i-th group; p_i = prior probability of the i-th group.

Ohlson (1980) discussed the issue and made no attempt of specifying a decision context by the priors and costs of misclassification. He merely presented Type I and Type II errors for different values of the cutoff probability within the range from 0 to 1. The cutoff value of 0.5 is used in Keasey and McGuinness (1990).

Richardson, Kane and Lobingier (1998) reduce the cutoff value to 0.02, a choice reflecting a large differential between Type I error costs and Type II error costs.

the bootstrap procedures.[66] However, we handle the problem by providing alternative, analytic estimates of the optimism in the apparent error rate (**Efron**, 1986). The analytic estimate of the expected downward bias in the apparent error rate is added to the apparent error rate so as to obtain an improved estimate of prediction error, and to infer how well a model predicts the response value of a future observation.

An analytic estimate of the bias for logit is obtained by calculating:

$$\omega(\hat{\pi}) = \frac{2}{n}\sum_{i=1}^{n}\hat{\pi}_i(1-\hat{\pi}_i)\phi\left(\frac{\hat{c}_i}{\sqrt{\hat{d}_i}}\right)\sqrt{\hat{d}_i}\,, \tag{3.25}$$

where $\phi(z) = (2\pi)^{-1/2}\exp(-\frac{1}{2}z^2)$,

$$\hat{c}_i = \ln\left(\frac{C_0}{1-C_0}\right) - \hat{\boldsymbol{\beta}}'\mathbf{x}'_i, \tag{3.26}$$

$$\text{and } \hat{d}_i = \mathbf{x}'_i\hat{\Sigma}^{-1}\mathbf{x}_i,\ \ \hat{\Sigma} \equiv \sum_{j=1}^{n}\hat{\pi}_j(1-\hat{\pi}_j)\mathbf{x}_j\mathbf{x}'_j. \tag{3.27}$$

The matrix $\hat{\Sigma}^{-1}$ is the usual estimate for the covariance matrix of $\hat{\boldsymbol{\beta}}$. The resulting estimate is a nearly unbiased estimator and has a small standard deviation.

The Problem of Disproportionate Sampling

One methodological problem, which often arises in applications of the binomial logit models, relates to non-random, disproportionate sampling (that is when two groups are sampled at different rates), which is employed in conjunction with estimators and inference procedures that assume random sampling (see, e.g., **McFadden** 1984; **Palepu**, 1986; **Maddala**, 1992; **Greene**, 1997; **Cramer**, 1999; **Bayldon and**

[66] The bootstrap computation of prediction error, which is adopted from Efron and Tibshirani (1993), and the relevant resampling plan from Adkins (1990) is employed in chapter 5 for models derived from small samples for the comparative study of company failure in the UK and Russia. The bootstrap procedures used in the present thesis are detailed in the annex to chapter 5.

Zafiris, 1999). For instance, usually all available observations on firms failed during the chosen for analysis period are included in the sample, but only a small percentage of non-failed firms in a population is sampled. There is a valid econometric justification for preferring a state-based selection of failed cases over random sampling of this group, as a random sample would be likely to include very few failed firms leading to relatively imprecise parameter estimates (**Palepu**, 1986). On the other hand, the use of equal-share samples, with equal shares of failed and control groups, leads to biased estimates of the model parameters and to overstating the model's ability to predict failed firms.

Consider a firm i in the population with a probability p of being a failure (become insolvent). Let p' be the probability that the firm i in the sample is a failure. Using Bayesian formula for conditional probability,

$$p' = \frac{p \times prob(i \text{ is sampled} \mid i \text{ is a failure})}{[p \times prob(i \text{ is sampled} \mid i \text{ is a failure}) + (1-p)prob(i \text{ is sampled} \mid i \text{ is non-failure})]} \quad (3.28)$$

Under the case of random sampling, the probability of firm i being sampled is the same whether it is a failure or non-failure: $p' = p$.

When an equal-share sample is used, the sample likelihood yields an unbiased estimate of p'. But under equal-share sampling $(p'-p)>0$ since usually the number of failed companies in the population is much smaller than the number of non-failed companies. In this case, the simple maximum likelihood procedure of maximising the sample likelihood function leads to the overstated true values of the probabilities of failure. Consequently, the observed error rate understate the model's true error rate in predicting failures and overstate the true error rate in predicting non-failures, although the net effect on the overall error rate is determined by the cutoff probability employed and the prior probabilities of the firms in the sample (**Palepu**, 1986).

To address the problem of determining an appropriate for *ex ante* classification cutoff, **Palepu** (1986) makes an assumption that the costs of Type I and Type II errors are equal and then uses the minimisation of error criterion. The errors are at their minimum where the conditional marginal probability densities for two groups (failed firms and non-failed firms) are equal, that corresponds with the point where the plotted distributions of the estimated probabilities of failed and non-failed firms intersect.

In discussing the problem of appropriate cutoff, **Maddala** (1992) points out that it is only the constant term that is affected by the unequal sampling rates, implying that for inference as to the effects of explanatory factors, the usual logit model can be used without any adjustment even with unequal sampling. If the estimated model is going to be used for prediction purposes, the constant term needs to be decreased by $(\ln p_1 - \ln p_2)$, where p_1 and p_2 are the sampling rates of the two groups for which $y=1$ and $y=0$, respectively. However, these sampling rates are difficult to estimate. **Greene** (1997) suggests a simpler treatment of adjusting the cutoff probability C_0 in (3.8) to take into account the bias introduced by the unbalanced sample.

Cramer (1999) discussed the issue further and considers the unavoidable asymmetry in the estimated by maximum likelihood within-sample probabilities when a standard binary logit is fitted to a sample with the unequal shares of the two outcomes. For instance, if $y_i = 1$ refers to the outcome with the larger share, then inequality of sample proportions by itself leads to a high overall level of the estimated probabilities (unadjusted for disproportionate sampling) for the outcome, to high log-likelihoods, and to the good prediction of prevalent states. Assuming that the company failure outcome is normalised, it follows that in the company failure studies with representative samples where the share of non-failed group is relatively large, the inequality of sample proportions influences all the estimated probabilities downwards while higher sampling rates for the failure event influence the estimated probabilities for the failure state upwards. Cramer contends that to allow for unequal sample sizes in assessing the within-sample performance of the fitted model, the cutoff value reflecting the improvement of the obtained specification over the baseline model in predicting the outcome for the particular observation *i*, is a cutoff point which is set at the average of the estimated probability of the outcome $y_i = 1$

(failure state). The solution advocated by Cramer, receives further support in **Bayldon and Zafiris** (1999), who examine the bias of disproportionate sampling and the consequences resulting from highly unequal sampling proportions in company failure modelling. Bayldon and Zafiris argue that the cutoff probability that is equal to the sampling frequency for the failure outcome, is the correct one to use in assessing the fit of the model, irrespective of population size, sample size and sampling rates. Obviously, this cutoff value is neutral with respect to relative misclassification costs, and may not be optimal for prediction in actual decisions. If the costs of misclassifying a failed company are higher than the costs of misclassifying a non-failed company, than the cutoff should be set lower than the average rate of failures in the sample.

Given a large degree of subjectivity involved in making assumptions as to the prior probability of quoted industrial firm insolvency over a particular period and about relative misclassification costs, we follow **Ohlson** (1980) and will assess the predictive performance of UK logit models at various cutoff probability values ranging from 0.1 to 0.875.

3.3 Empirical Results

Here the failure outcome is normalised and, therefore, the binary dependent variable takes a value of 1 if the firm is failed. We interpret the estimated models as describing the conditional expectation of the failure outcome $\mathbf{y}$ given the selected explanatory variables $\mathbf{x}$. A model building approach utilised here is a backward elimination. To produce a parsimonious model, the modelling approach starts with a very general and fairly unrestricted specification, which is subsequently reduced in size by testing restrictions, imposed on individual variables. A sequence of independent Likelihood Ratio tests is used to eliminate covariates. A resultant model should essentially contain a satisfactory proportion of the information from the original general specification, while also being much more parsimonious. As follows from the overviews of chapters 1 and 2, there is little coherent theory of company failure upon which to base the choice of explanatory variables from a vast array of potentially useful candidate-variables. The literature essentially suggests that the relevant variables are those that measure firm-specific and external factors, which might affect the firm's performance and financial position and influence its propensity to default on debt. At this juncture, we take a usual route to proceed and include into an initial general specification a wide set of variables derived from observable financial reports, so as not to omit any important financial attribute. The spectrum of potential determinants has been complemented by a control for firm's age and by two macroeconomic variables that were seen important by past studies into aggregate incidence of liquidation and bankruptcy.

Because performance measures deteriorate as a failing company approaches insolvency, models are estimated for four risk horizons, ranging one to four years, with pooled cross-sections data taken from four successive reporting years before failure. A single series of logit results consists of four functions, each being year-prior-to-failure specific. The results, however, are not attributable to any particular annual/calendar period, but, being representative of observations pertinent to 1988-91, give a broad picture of accounting indicators of failure for the whole four-year period. Four individual series of models estimated here include: (i) basic models, employing financial variables alone; (ii) models employing financial statement-based inputs and two macroeconomic variables; (iii) models employing financial variables and a proxy for firm's age; and (iv) models employing financial variables, two macroeconomic variables, and a proxy for firm's age. Specifications, presented below in Tables 3.3, 3.4, 3.7, 3.8, 3.11, 3.12, 3.15, and 3.16, are risk-horizon specific parsimonious models based on a wide range of 25 financial variables, for which appendix 2 gives descriptive statistics. Values for pairwise correlations (see Tables A2.3-A2.6 of appendix 2) suggest that potential financial predictors are not highly correlated. The variables entering final parsimonious models have been selected on a stepwise basis by using asymptotic *t*-tests and Likelihood Ratio tests as criteria for elimination.

A description of logit estimation results is shown in two groups of tables. The first group reports the coefficient estimates and the goodness of fit measured by the log-likelihood at convergence, Likelihood Ratio test statistic, and Likelihood Ratio Index. Measures of the goodness of fit, which are given by within-the-estimation-sample classificatory accuracy and the power to predict fresh, holdout observations, are displayed in the second group of tables. Alternative estimates of models' prediction error are provided by adjusting the overall apparent error rate generated on estimation samples for the downward bias approximated with Efron's formulation (as given by expressions 3.25-3.27). The choice of the relevant cutoff probability value influences to a great extent the classification results. Given that the differential in the relative costs of Type I error (when a failing firm is misclassified) and Type II error (when a non-failing firm is misclassified) depends on the decision context, which is unknown, here we assume symmetrical costs and provide classificatory and predictive accuracy for a wide range of cutoff probability values.

3.3.1 Models Utilising Financial Ratios

We now turn to a description of a series of logit functions estimated with the data on financial ratios. A general specification for these models is solely based on the 25 financial inputs, capturing various aspects of financial performance and position. The overall fit for the parsimonious models for each of the four years prior to failure (Tables 3.3 and 3.4) is acceptable as the χ^2 statistics for the joint significance of model parameters exceed respective critical values at the 0.1% level. The one-year prior model shows the best fit in terms of the Likelihood Ratio Index (Table 3.3). As indicated above, the results for one year prior to failure (Table 3.3) correspond to the information contained in the last accounts a failing company releases. These results, therefore, record the state of severe (and thus, possibly, easily identifiable) financial distress and are usable for up to one-year predictions only. One-year results suggest that all obtained empirical determinants are significant at the level of 5% and better. A turnover measure, given by creditors turnover, capital gearing, the liquidity factor, represented by the working capital ratio, and the payout ratio have expected signs, suggesting that a company with relatively lower creditors turnover, higher gearing, lower liquidity, and a smaller proportion of earnings, paid out as dividends, is more likely to fail. The signs of profitability ratios indicate that nearer the point of entering an insolvency regime, failing firms in our sample have negative operating profits, which might be interpreted as a symptom of economic distress, do not generate

Table 3.3 Financial Ratio-Based Models:

Logit Results for the Cross-section of UK Companies,
One and Two Years Prior to Failure; 1988-91 Estimation Period,
53 Failed Companies and 368 Non-failed Company-years (n=421)

Dimension / *Variable*	One Year Prior to Failure: Coefficient (two-tailed p-value of asymptotic t-statistic)		Two Years Prior to Failure: Coefficient (two-tailed p-value of asymptotic t-statistic)	
Constant	-3.249	(0.000)	-2.517	(0.000)
Size				
Log Total Sales			-0.455	(0.022)
Profitability				
Return on Shareholders' Capital	1.370	(0.006)		
Return on Capital employed	-1.244	(0.001)		
Operating Profit Margin	-0.813	(0.017)		
Pre-tax Profit Margin				
Net Profit Margin				
Cumulative Profitability				
Turnover				
Turnover/Net Current Assets				
Debtors Turnover				
Creditors Turnover	-0.450	(0.048)		
Gearing				
Capital Gearing	0.667	(0.001)		
Income Gearing				
Borrowing Ratio				
Gross Cash Flow/ Total Liabilities			-0.705	(0.000)
Loan Capital/Equity and Reserves				
Liquidity				
Working Capital Ratio	-1.789	(0.000)	-1.124	(0.000)
Quick Assets Ratio				
Working Capital / Assets Employed				
Other Financial Variables				
Payout Ratio	-1.312	(0.020)	-0.800	(0.056)
Assets Index				
Tax Ratio				
Log-Likelihood at Convergence	-103.55		-125.85	
χ^2 statistic of LR Test (p-value)	111.61 (0.000)		67.00 (0.000)	
Likelihood Ratio Index	0.325		0.179	
n	421			
Per cent Failed	12.6			

Table 3.4 Financial Ratio-Based Models:

Logit Results for the Cross-section of UK Companies,
Three and Four Years Prior to Failure; 1988-91 Estimation Period,
53 Failed Companies and 368 Non-failed Company-years (n=421)

Dimension / *Variable*	**Three Years Prior to Failure** Coefficient (two-tailed p-value of asymptotic t-statistic)		**Four Years Prior to Failure** Coefficient (two-tailed p-value of asymptotic t-statistic)	
Constant	-2.263	(0.000)	-2.458	(0.000)
Size				
Log Total Sales	-0.804	(0.000)	-1.020	(0.000)
Profitability				
Return on Shareholders' Capital				
Return on Capital employed				
Operating Profit Margin				
Pre-tax Profit Margin				
Net Profit Margin				
Cumulative Profitability				
Turnover				
Turnover/Net Current Assets	0.225	(0.017)		
Debtors Turnover				
Creditors Turnover				
Gearing				
Capital Gearing	0.828	(0.000)		
Income Gearing	0.865	(0.023)		
Borrowing Ratio			0.937	(0.007)
Gross Cash Flow/ Total Liabilities			-0.439	(0.005)
Loan Capital/Equity and Reserves			-1.312	(0.002)
Liquidity				
Working Capital Ratio			-0.701	(0.001)
Quick Assets Ratio				
Working Capital / Assets Employed				
Other Financial Variables				
Payout Ratio				
Assets Index			0.368	(0.007)
Tax Ratio			-0.796	(0.050)
Log-Likelihood at Convergence	-134.65		-125.02	
χ^2 statistic of LR Test (p-value)	49.39 (0.000)		68.64 (0.000)	
Likelihood Ratio Index	0.122		0.185	
n	421			
Per cent Failed	12.6			

Table 3.5 Classification and Predictive Ability of Financial Ratio-Based Models, One and Two Years Prior to Failure:

Logit Results for the Cross-section of UK Companies,
1988-91 Estimation Period
(53 Failed Companies and 368 Non-failed Company-years);
1992-94 Holdout Period
(10 Failed and 86 Non-failed Companies).

Panel A: One Year Prior to Failure: Correct Classification, Percentage						
Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample						
Non-failed	73.6	79.1	92.7	97.8	99.2	99.5
Failed	90.6	79.2	54.7	45.3	18.9	9.4
Overall	75.8	79.1	87.9	91.2	89.1	88.1
Overall Error Rate Bias Estimated by Efron's Formula	1.9	2.4	3.9	5.2	6.2	6.5
Estimate of Prediction Error	26.1	23.3	16.0	14.0	17.1	18.4
Holdout Sample						
Non-failed	73.3	77.9	90.7	96.5	96.5	96.5
Failed	100.0	100.0	60.0	40.0	30.0	30.0
Overall	76.1	80.2	87.5	90.6	89.6	89.6

Panel B: Two Years Prior to Failure: Correct Classification, Percentage						
Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample						
Non-failed	67.7	75.8	93.2	98.4	99.2	99.7
Failed	86.8	77.4	45.3	18.9	7.5	3.8
Overall	70.1	76	87.2	88.4	87.6	87.6
Overall Error Rate Bias Estimated by Efron's Formula	2.1	2.6	4.1	5.1	5.5	5.7
Estimate of Prediction Error	32.0	26.6	16.9	16.7	17.9	18.1
Holdout Sample						
Non-failed	59.3	65.1	88.4	96.5	98.8	100
Failed	80.0	70.0	50.0	20.0	10.0	0.0
Overall	61.5	65.6	84.4	88.5	89.6	89.6

Table 3.6 Classification and Predictive Ability of Financial Ratio-Based Models, Three and Four Years Prior to Failure:

Logit Results for the Cross-section of UK Companies,
1988-91 Estimation Period
(53 Failed Companies and 368 Non-failed Company-years);
1992-94 Holdout Period
(10 Failed and 86 Non-failed Companies).

Panel A: Three Years Prior to Failure: Correct Classification, Percentage						
Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample						
Non-failed	62.8	75.5	92.4	98.4	99.7	99.7
Failed	83.0	73.6	34	9.4	3.8	3.8
Overall	65.3	75.3	85	87.2	87.6	87.6
Overall Error Rate Bias Estimated by Efron's Formula	1.8	2.3	3.8	5	5.3	5.4
Estimate of Prediction Error	36.5	27.0	18.8	17.8	17.7	17.8
Holdout Sample						
Non-failed	27.9	29.1	34.9	38.4	40.7	40.7
Failed	50.0	40.0	30.0	30.0	30.0	30.0
Overall	30.2	30.2	34.4	37.5	39.6	39.6

Panel B: Four Years Prior to Failure: Correct Classification, Percentage						
Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample						
Non-failed	67.9	75.3	90.2	98.6	100	100
Failed	77.4	69.8	39.6	24.5	9.4	1.9
Overall	69.1	74.6	83.8	89.3	88.6	87.6
Overall Error Rate Bias Estimated by Efron's Formula	2.1	2.6	4.2	5.6	6.3	6.5
Estimate of Prediction Error	33.0	28.0	20.4	16.3	17.7	18.9
Holdout Sample						
Non-failed	60.5	65.1	83.7	94.2	95.3	95.3
Failed	80.0	80.0	50.0	0.0	0.0	0.0
Overall	62.5	66.7	80.2	84.4	85.4	85.4

sufficient return on capital used, but might show a positive return on shareholders' capital. This counterintuitive, positive relation between returns on shareholders' capital and failure risk could simply be due to the DATASTREAM specification of the ratio used. It is possible, that in the last reporting year, combinations of negative numbers for after-tax profits and negative values for shareholders' funds result in a positively signed ratio.

Failure determinants for earlier years, are revealed by models for two, three, and four years prior to failure. All predictors in the models for two through to four years prior to failure, except the turnover ratio in the model for three years prior (Table 3.4), have signs that are logically acceptable. Reinforcing the stylised fact that smaller firms exit first (see e.g. Dunne, Roberts, Samuelson, 1989), size measured by the logarithm of net sales appears indicative of insolvency in years two through to four prior to failure. The coefficient of the size variable is significant at the 5% level and better and negatively related to failure. The model based on accounts for two years prior to failure (Table 3.3), gives a strong indication that failing firms generate insufficient cash flow from operations (the ratio of gross cash flow to total liabilities is significant at the 0.1% level) and have inadequate current assets (the working capital ratio is significant at the 0.1% level). Failing firms also seem to pay out as dividends a smaller proportion of their earnings if compared with non-failing firms, however, the payout ratio is significant only at the 10% level. The three-year prior model (Table 3.3) indicates that, over this risk-horizon, high gearing, measured by capital and income gearing, distinguishes the likely to fail firms from the healthy ones. A positive relationship is also observed between current assets turnover and the probability of failure. This problematic sign might be consistent with the view that highly geared and fast growing companies fared least well during the 1990-92 recession. The model derived from financial statements for four years prior to failure (Table 3.4) strongly suggests that failing companies seriously lack liquidity in the earlier years. When compared with a healthy company profile, failing firms appear to have comparatively less debt repayable in more than one year, but borrow more from short-term sources to compensate for insufficient current assets and low levels of their gross cash flow relative to total liabilities. This is implied by the positively signed borrowing ratio and the negatively signed ratio of loan capital to equity and reserves, which jointly signal the failing company's reliance on borrowings with less that one year maturity. The failing companies' reliance on borrowings with less that one year maturity, is also consistent with the negative coefficients on the ratio of gross cash flow to total liabilities and on the working capital ratio. The four-year prior model suggests the importance of changes in the value of net tangible assets – the coefficient of the assets index is positive and indicates that failing firms are likely to demonstrate higher assets growth (in terms of book values), which probably increases their borrowing capacity, facilitating access to credit. In the four-year prior model, the tax ratio has a negative sign, indicating that for the case of failing firms, tax payments represent a lower proportion in pre-tax profits. As mentioned in section 3.2.2.2, the tax charge is subject to factors unconnected with the current year performance. Therefore, to understand which factors brought about a negative relation between the tax ratio and the risk of failure, one will need more detailed information about tax payments, profits, investment, and dividend policy during the years preceding insolvency. However, the spectrum of financial attributes in our data set is insufficient to examine in greater detail the causes of the negative sign on the tax variable.

As far as the classification and predictive ability of obtained accounting ratio-based models is concerned, the question of interest is of finding to what extent the results are coherent. Models, predicting within one and two years (Table 3.5), generate relatively robust, across a wide range of cutoff probability values, estimates of the overall error rate adjusted for the bias evaluated by Efron's formulation (expressions (3.25)-(3.27)). Prediction error estimates vary from 14 per cent to 26.1 per cent for year one prior (Panel A in Table 3.5), and lie between 16.7 per cent to 32 per cent for two years prior (Panel B in Table 3.5). Roughly similar accuracy is demonstrated in holdout tests, the exception being a 0.1 cutoff, at which the two-year prior model incorrectly identifies 38.5 per cent of observations as compared with the 23.9 per cent estimate of the overall error rate from one-year predictions. Noticeably, at cutoff values of 0.25 and greater, models for one and two years prior to failure perform better at predicting non-failures than failures, demonstrating high rates of Type I error. This finding can be explained by the sample design, which results in the non-failed group representing 87.4 per cent of estimation sample observations and 89.6

per cent of holdout sample observations. Therefore, the overall classification rate is influenced by the relatively low sample frequency. As Table 3.5 shows, applying a cutoff point of 0.875 generates high, within-sample overall classification rates of 88.1 per cent for one year before failure and 87.6 percent for two years before failure, however, the success rate for the failure outcome drops to 9.4 per cent and 3.8 per cent, respectively. On the estimation sample observations representing failing firms, the highest accuracy of 90.6 and 86.8 per cent is achieved at a conservative cutoff point of 0.1, for one- and two-year horizons, respectively; while the cutoff value of 0.125 that closely corresponds with the estimation sample proportion of failed companies equal to 12.6 per cent, returns correct classification rates of 79.2 per cent and 77.4 per cent. As discussed in section 3.2.3, the recent literature (see, e.g., **Cramer**, 1999) suggests that for assessing the within-sample performance of a model derived from an unbalanced sample, the cutoff probability taken from sample frequencies is the appropriate one to use. Holdout tests show that at 0.1 and 0.125 cutoff values, the one-year prior model still retains the classificatory accuracy, demonstrated on the training sample, identifying all failed firms and correctly predicting 73.3 per cent and 77.9 per cent of solvent companies. Raising a cutoff value further to 0.25 results in a rapid decline of the correct classification rates for failed companies in both estimation and holdout samples: models for time-horizons of one and two years correctly predict 54.7 and 45.3 per cent of failing firms, respectively, while holdout tests classify correctly 60 per cent and 50 per cent of failing firms.

Table 3.6 describes the classificatory and predictive ability of accounting ratio-based models for three and four years before failure. The performance of the four-year prior model, in terms of overall prediction error magnitudes and robustness on both estimation and holdout observations, is remarkably similar to that of the one-year model and two-year model, detailed in Table 3.5. However, when the three-year model is considered, the overall correct classification rate from the holdout test achieves 30.2 per cent at the 0.1 cutoff and climbs only to 39.6 per cent at the 0.875 cutoff, thus being in sharp contrast with the holdout results for other years and indicating an overfitted model. In the model for three years prior to failure, the poor approximation of the holdout data corresponds to the lowest goodness of fit amongst the four models – the respective values for the likelihood at convergence and the Likelihood Ratio Index are -134.65 and 0.122 (Table 3.4). However, if accuracy is judged by the criterion of the adjusted apparent error rate, the three-year prior model is likely to forecast no worse than models for other risk-horizons - the estimates of prediction error lie between 17.7 and 36.5 per cent (Panel A in Table 3.6).

It is not easy to compare predictive performance of models and the importance of obtained accounting-based predictors, with results from earlier UK work, as it appears that only one study, **Alici** (1995), reports evidence from 1987-92. Alici documents that a logit model and neural networks derived from an unbalanced sample of firms, which contains accounting data for one year prior to failure, misclassify, respectively, 34 per cent and 26 per cent of holdout observations. Thus the holdout approximation in **Alici** (1995) is roughly similar to accuracy levels observed in the present study for one, two, and four years prior to failure.[67] Alici's logit model indicates the importance of the profitability dimension (measured by profit before tax to total capital employed), the liquidity position (proxied by ratios of quick assets to current liabilities and working capital to total assets), and the degree of gearing (measured by the ratio of equity to total assets). Broadly defined, these dimensions are reflected in the model estimated here for one year prior to failure (see Table 3.3), although it is impossible to infer the usefulness and performance stability of individual ratio constructs as the determinants of failure. When compared to logit results in **Keasey and McGuinness** (1990), who also use the standard ratio constructs from DATASTREAM for their analysis of UK company failure for 1976-84, the models, presented here, seem to demonstrate more stable classification accuracy at the critical probabilities that minimise the overall error rate. For instance, at a cutoff of 0.5, the downward bias-adjusted estimates of the overall error rate, for years one through to four, are 14 per cent, 16.7 per cent, 17.8 per cent, and 16.3 per cent, whereas unadjusted (and therefore downward biased) primary sample error rates reported in Keasey and McGuinness (1990) are 14 per cent, 18.5 per cent, 23.5 per cent, and 30 per cent for years one to four before failure. As for the significance of individual variables, our results differ from a quite

[67] The basis for comparison and generalisations is also restricted by the lack of details on cutoff values used in Alici (1995).

incoherent pattern of importance of company performance dimensions in Keasey and McGuinness (1990), who also measure financial performance and position with DATASTREAM ratios. In sum, our models in Tables 3.3 and 3.4 paint the following picture. Gearing is a quite robust empirical determinant and important for all four years, size mearured by net sales has a reasonable degree of explanatory power for two through to four years prior to failure, liquidity is important for years one, three, and four prior, and profitability being insignificant over longer risk-horizons is important for year one prior to failure.[68] Finally, our results do not appear to be in line with the evidence for the earlier period 1968-73, presented in **Taffler** (1982). Although we observe a similar noticeable independent role of gearing both over shorter and over longer risk-horizons, our modelling with the financial ratio data for the early 1990s does not support the strong link from low profitability to failure, reported in Taffler's work. In contrast to the studies documented a strong explanatory power of market valuation variables (e.g., Morris, 1997), the market to book ratio, a proxy for the future prospects of the firm, has not been selected as a key predictor by the econometric modelling procedures adopted in this chapter.

3.3.2 Models Utilising Financial Ratios and Macroeconomic Variables

Tables 3.7 and 3.8 contain estimates for a series of four models that incorporate financial ratios alongside one-year lagged, unanticipated changes (or "surprises") in the real effective exchange rate and nominal interest rate. The starting specification being tested down to produce this series of models is richer than that used for the series of basic models of the previous section, based on financial ratios alone. The crude modelling assumption made here is that time series for both the nominal interest rate and the real exchange rate follow a random walk, implying that the entire change in a macroeconomic indicator is unanticipated. It is important to notice that we assume a lagged relation between the changes in a macroeconomic variable and their full economic impact on the firm's performance as reflected in financial accounts and market valuation. The effect of changes in economic conditions on

[68] Profitability was not found to be a significant distinguishing characteristic in the US study documented in Zavgren (1985).

Table 3.7 Models Incorporating Macroeconomic Variables:[69]

Logit Results for the Cross-section of UK Companies,
One and Two Years Prior to Failure; 1988-91 Estimation Period,
53 Failed Companies and 368 Non-failed Company-years (n=421)

Dimension / *Variable*	**One Year Prior to Failure** Coefficient (two-tailed p-value of asymptotic t-statistic)		**Two Years Prior to Failure** Coefficient (two-tailed p-value of asymptotic t-statistic)	
Constant	-5.481	(0.000)	-2.682	(0.000)
Size				
Log Total Sales			-0.540	(0.010)
Profitability				
Return on Shareholders' Capital	3.895	(0.000)		
Return on Capital employed	-3.778	(0.000)		
Operating Profit Margin				
Pre-tax Profit Margin				
Net Profit Margin				
Cumulative Profitability				
Turnover				
Turnover/Net Current Assets				
Debtors Turnover				
Creditors Turnover				
Gearing				
Capital Gearing	1.641	(0.000)		
Income Gearing				
Borrowing Ratio			0.548	(0.030)
Gross Cash Flow/ Total Liabilities			-0.727	(0.001)
Loan Capital/Equity and Reserves				
Liquidity				
Working Capital Ratio			-0.980	(0.002)
Quick Assets Ratio				
Working Capital / Assets Employed	-1.222	(0.018)		
Other Financial Variables				
Payout Ratio				
Assets Index				
Tax Ratio				
Non-financial Variables				
Change in Real Exchange Rate	190.452	(0.002)	35.066	(0.000)
Change in Nominal Interest Rate	31.230	(0.000)		
Log-Likelihood at Convergence	-25.90		-115.69	
χ^2 statistic of LR Test (p-value)	266.90 (0.000)		87.31 (0.000)	
Likelihood Ratio Index	0.831		0.246	
N	421			
Per cent Failed	12.6			

[69] Models include a macroeconomic dummy interacted with the two macroeconomic variables.

Table 3.8 Models Incorporating Macroeconomic Variables:[70]

Logit Results for the Cross-section of UK Companies,
Three and Four Years Prior to Failure; 1988-91 Estimation Period,
53 Failed Companies and 368 Non-failed Company-years (n=421)

Dimension / *Variable*	**Three Years Prior to Failure** Coefficient (two-tailed p-value of asymptotic t-statistic)		**Four Years Prior to Failure** Coefficient (two-tailed p-value of asymptotic t-statistic)	
Constant	-2.519	(0.000)	-3.243	(0.000)
Size				
Log Total Sales	-0.651	(0.001)	-0.621	(0.028)
Profitability				
Return on Shareholders' Capital				
Return on Capital employed				
Operating Profit Margin			1.441	(0.045)
Pre-tax Profit Margin			-1.683	(0.034)
Net Profit Margin				
Cumulative Profitability				
Turnover				
Turnover/Net Current Assets				
Debtors Turnover				
Creditors Turnover				
Gearing				
Capital Gearing	0.867	(0.000)		
Income Gearing	0.751	(0.043)		
Borrowing Ratio			1.126	(0.025)
Gross Cash Flow/ Total Liabilities				
Loan Capital/Equity and Reserves			-1.374	(0.021)
Liquidity				
Working Capital Ratio			-0.699	(0.036)
Quick Assets Ratio				
Working Capital / Assets Employed				
Other Financial Variables				
Payout Ratio				
Assets Index				
Tax Ratio			-1.478	(0.009)
Non-financial Variables				
Change in Real Exchange Rate	32.773	(0.000)	-122.365	(0.000)
Change in Nominal Interest Rate	-26.655	(0.000)	21.104	(0.000)
Log-Likelihood at Convergence	-118.31		-81.04	
χ^2 statistic of LR Test (p-value)	82.08 (0.000)		156.63 (0.000)	
Likelihood Ratio Index	0.228		0.472	
N	421			
Per cent Failed	12.6			

[70] Models include a macroeconomic dummy interacted with the two macroeconomic variables.

Table 3.9 Classification and Predictive Ability of Models Incorporating Macroeconomic Variables:

One and Two Years Prior to Failure,
Classifications and Predictions Conditioned on Interactive Effects between Macroeconomic Variables and Failure.

Logit Results for the Cross-section of UK Companies,
1988-91 Estimation Period
(53 Failed Companies and 368 Non-failed Company-years);
1992-94 Holdout Period
(10 Failed and 86 Non-failed Companies)

Panel A: **One Year Prior to Failure: Correct Classification**, Percentage

Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample						
Non-failed	97.6	98.6	99.2	99.5	99.5	100
Failed	94.3	94.3	92.5	90.6	84.9	83
Overall	97.1	98.1	98.3	98.3	97.6	97.9
Overall Error Rate Bias Estimated by Efron's Formula	1.1	1.2	1.4	1.7	2.1	2.3
Estimate of Prediction Error	4.0	3.1	3.1	3.4	4.5	4.4
Holdout Sample						
Non-failed	98.8	98.8	98.8	98.8	98.8	98.8
Failed	20.0	20.0	20.0	10.0	10.0	10.0
Overall	90.6	90.6	90.6	89.6	89.6	89.6

Panel B: **Two Years Prior to Failure: Correct Classification**, Percentage

Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample						
Non-failed	73.1	79.9	95.4	98.6	99.2	99.7
Failed	75.5	73.6	56.6	39.6	17.0	9.4
Overall	73.4	79.1	90.5	91.2	88.8	88.4
Overall Error Rate Bias Estimated by Efron's Formula	2.1	2.5	3.7	4.7	5.3	5.6
Estimate of Prediction Error	28.7	23.4	13.2	13.5	16.5	17.2
Holdout Sample						
Non-failed	29.1	38.4	68.6	93.0	97.7	98.8
Failed	100.0	80.0	50.0	50.0	10.0	0.0
Overall	36.5	42.7	66.7	88.5	88.5	88.5

Table 3.10 Classification and Predictive Ability of Models Incorporating Macroeconomic Variables:

Three and Four Years Prior to Failure,
Classifications and Predictions Conditioned on Interactive Effects between Macroeconomic Variables and Failure.

Logit Results for the Cross-section of UK Companies,
1988-91 Estimation Period;
(53 Failed Companies and 368 Non-failed Company-years),
1992-94 Holdout Period
(10 Failed and 86 Non-failed Companies)

Panel A: **Three Years Prior to Failure: Correct Classification**, Percentage						
Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample						
Non-failed	78.2	84.5	96.5	99.2	99.5	100.0
Failed	84.9	79.2	56.6	41.5	18.9	5.7
Overall	79.1	83.8	91.4	91.9	89.3	88.1
Overall Error Rate Bias Estimated by Efron's Formula	2.1	2.6	3.7	4.7	5.4	5.8
Estimate of Prediction Error	23.0	18.8	12.3	12.8	16.1	17.7
Holdout Sample						
Non-failed	38.4	38.4	39.5	43.0	43.0	45.3
Failed	40.0	40.0	40.0	30.0	30.0	30.0
Overall	38.5	38.5	39.6	41.7	41.7	43.8

Panel B: **Four Years Prior to Failure: Correct Classification**, Percentage						
Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample						
Non-failed	87.8	92.7	96.2	100.0	100.0	100.0
Failed	83.0	83.0	77.4	67.9	52.8	41.5
Overall	87.2	91.4	93.8	96.0	94.1	92.6
Overall Error Rate Bias Estimated by Efron's Formula	2.4	2.6	3.5	4.4	5.0	5.4
Estimate of Prediction Error	15.2	11.2	9.7	8.4	10.9	12.8
Holdout Sample						
Non-failed	80.2	80.2	81.4	81.4	83.7	83.7
Failed	60.0	60.0	60.0	60.0	60.0	60.0
Overall	78.1	78.1	79.2	79.2	81.3	81.3

failure risk is modelled by employing an interactive dummy variable, which equals unity for failing companies. This dummy variable is used in interactions with each of the two macroeconomic variables. This is an essential and novel feature of the specification capable to account for the influence the contextual factors when modelling failure at the firm level. Clearly, if in estimation the macroeconomic dummy were set to unity for all observations, then the resultant model could not discriminate and identify the macro effects as the mean value would be the same for failed firms as well as for non-failed firms. As discussed in section 3.2.2.4, one can argue that non-failed firms forecast the future environmental conditions more accurately, being able to better, faster and at low costs react to "surprises" in the macroeconomy. Hence, in modelling, we assume that performance and survival of industrial firms are sensitive to one-year lagged unanticipated changes because of the failing firms' inability to adequately assess the impact of the changes and alter their activities in response to the new trading conditions. We judge the relevance of changes in the environment as measured by the two macroeconomic variables by examining both the significance of individual coefficient estimates and the accuracy of conditional predictions on primary and holdout observations. The predictive impact of the macroeconomic variables is identified in this way so that outside of sample it can be used to predict failure in all firms. In holdout tests, outside the estimation period, we assume that all firms are at risk of failure and set the macroeconomic dummy to unity for both failing and non-failed firms.

Results presented in Tables 3.7 and 3.8 indicate that all four models for years one through to four before the event of failure show acceptable overall performance with the Likelihood Ratio χ^2 statistics being significant at the 0.1% level. In terms of the log-likelihood at convergence and Likelihood Ratio Index, the two best models are the model for one year prior (the respective values are -25.9 and 0.831) and the model for four years prior (-81.04 and 0.472, respectively). The two external factors, approximating trading risks, appear significant explanatory variables of failure risk. For the firms in our sample, failure risk depends on the changes in competitiveness imposed by shifts in the exchange rate. The coefficient for the unanticipated change in the real exchange rate is significant at the 1% level and better, over all four years preceding failure, being positively signed in models for years one, two, and three prior to failure, but being negative in the model for four years prior. Overall, this indicates that increases in the real exchange rate precipitated company failure during the 1990s recession. To help interpreting this positive influence it might be important to recall that the pattern for the real exchange rate was actually quite volatile from 1986 to the beginning of 1991 (see, e.g., "Understanding the UK Economy", 1997). The real effective exchange rate showed a rising tendency from 90.6 in 1986 to 97.3 in 1988, was falling to 96.6 in 1989 and rising again to 102.0 in 1991.[71] In general, if firms with direct international operations are considered, then exporters and firms with foreign operations that have current or future cash inflows denominated in foreign currency will benefit from depreciation, while importers of final products or inputs to production, as well as users of domestically available inputs, whose prices are determined in international markets, will benefit from appreciation. But, these are only direct consequences of the changes in the exchange rate on the revenue and cash flow position of companies, and their ability to meet debt obligations. The second indirect impact relies on the fact that exchange rate changes are likely to result in changes in other macroeconomic variables such as interest rates. Therefore, the unexpected exchange rate movements are also likely to have impact on firms that have no direct international activities. However, due to the limited range of company characteristics described by the data available for the present study, it is impossible to identify the sampled firms' linkages to international conditions and account for this factor in modelling.

Nevertheless, this element of changes in the interest rate, induced by movements in the exchange rate, is controlled in our analysis, because the models presented in Tables 3.7 and 3.8 capture the unanticipated changes in the nominal interest rate. Overall, the nominal interest rate effect is adverse and positive, exacerbating financial constraints and leading to a higher risk of failure. During the downturn in the late 1980s, the unanticipated rises in the nominal interest rate might have been especially harmful for firms dependent on the home market, while exporters were less affected by the domestic recession. This interpretation seems to be reconcilable with the evidence from a large-scale survey of UK leading firms reported in **Geroski**

[71] Annual averages; 1990=100.0.
Source: PRIMARK DATASTREAM.

and Gregg (1996), that export oriented firms and foreign owned firms fared better during the 1990s recession. Therefore, one possible interpretation of the positive relation between the unanticipated rise in the real exchange rate and the probability of failure, detected in the sample, could be a loss of competitiveness in the domestic market due to the overvalued currency. The second possible explanation of the positive effect of the exchange rate "surprises" is via the link to the rises in domestic prices and short-term interest rates, which adversely affected highly geared, distressed firms predominantly dependent on the domestic market.

Turning now to a more detailed description of the impact of interest rates, the models for years one, three, and four before failure yield as an important determinant the change in the nominal interest rate, which is significant at the 0.1% level (Tables 3.7 and 3.8). We have discussed in chapters 1 and 2 the notion that high nominal interest rates translate into high failure rates. High interest rates raise costs of business borrowing, increase unit costs, signal inflation, and might induce recession. Moreover if long-term interest rates are high, then an increased cost of capital might entice firms into shifting their preferences towards riskier investment projects associated with higher rates of expected return required to afford debt finance. In other words, rises in nominal interest rates are unlikely to better the failure risk profile of industrial firms. Obviously, in analysing the effects of increases in nominal interest rates on the cost of capital, account should be taken of the contemporaneous rise in the rate of inflation. The positively signed coefficients for the variable representing unanticipated changes in the nominal interest rate in models for years one and four prior to failure are consistent with this contention. Unexpected increases may apply with particular force to the companies in our sample, which pertain to the early 1990s. A report by The Bank of England suggested that in the early 1990s, subdued equity issues and a fall in short-term interest rates following the stock market crash of October 1987, encouraged companies to issue long-term debt and increase short-term borrowing. The capital gearing of UK industrial and commercial companies rose significantly over the early 1990s being about three times higher than in 1980s (*Bank of England Quarterly Bulletin*, August 1993). A sharp rise in interest rates from 1988 increased companies' debt service costs while the subsequent recession lowered companies' ability to service debt.

In the model for three years prior to failure (Table 3.8) the coefficient of the interest rate variate is "incorrectly" signed suggesting the negative relation between high nominal interest rates and the probability of failure. A similar "empirical anomaly" has been observed in the UK study by **Simmons** (1989) and in the US study by **Assadian and Ford** (1997).

The inclusion of the two macroeconomic variables in model development alters the relative importance of major financial dimensions demonstrated by the basic models reported in section 3.3.1. Similarly to the results from the series of financial ratio-based models, the coefficient for the size variable is significant at the level of 5% and better, for years two, three, and four before failure, indicating the ultimate importance of the ability to generate revenues. An interesting result is that profitability measures are now important over both short and longer risk-horizons, with such measures as rates of return, the pre-tax profit margin, and the operating profit margin entering models for one year prior and for four years prior to failure. The model for one year prior to failure (Table 3.7) suggests, that the directions, in which profitability ratios (significant at the 0.1% level) influence the probability of insolvency, match the pattern revealed by the model based on financial ratios alone (see Table 3.3). The rate of return on shareholders' capital retains its positive sign and the rate of return on capital employed is again negatively signed. In the four-year prior model (Table 3.8), profitability measures, significant at the 5% level, imply that failing firms have lower pre-tax profit margins (exclusive of interest and non-recurring items) despite the fact that their operating profit margins are higher as compared with non-failing firms, suggesting the absence of economic distress. Therefore, it appears that failing firms in our sample exhibit profitability problems as early as four years before insolvency. Models with macroeconomic variables appear to reiterate the key role of the geared capital structure in all four years preceding failure, as gearing measures are all correctly signed and significant at the 5% level and better (Tables 3.7 and 3.8). Precipitating failure, relatively lower liquidity ratios are important in years one and four before failure (the respective coefficients are significant at the 5% level). As with the models based only on financial variables, lower tax ratios are associated with a higher probability of failure in four years time

(Table 3.8). Lastly, none of the models indicates that turnover helps explain the failure probability.

Evaluation of the obtained failure determinants by way of assessing model performance in terms of correct and incorrect predictions is described in Tables 3.9 and 3.10.

Predictions, generated by applying the one-year prior model to the estimation sample (Panel A in Table 3.9), indicate that conditioning on the effects of macroeconomic variables improves correct classification rates for failed and non-failed firms as compared to the financial ratio-based model for the one-year horizon (Panel A in Table 3.5). An improvement across different cutoff probability values is consistent with the decreased level of the overall prediction error, adjusted for the downward bias using Efron's formula, which is now 4.5 per cent and better (Panel A in Table 3.9). However, the results of predicting holdout firms reveal the model's poor performance in detecting failed firms and hence a less stable relationship between the changes in incorporated macroeconomic variables and failure risk for the short risk-horizon. For instance, the Type I error rate reaches 90 per cent, although the overall error rate is low, ranging from 9.4 per cent to 10.4 per cent (Panel A in Table 3.9).

Predictive performance of the model for two years prior to failure (Panel B in Table 3.9) is somewhat dissimilar from that of the one-year prior model. First, we should point out a deterioration in the holdout approximation at cutoff values of 0.1 and 0.125, as compared to the financial ratio-based model performance (Panel B in Table 3.5). When cutoff probability values of 0.1 and 0.125 are used, Type I error rates fall to zero and 20 per cent, respectively. But the overall accuracy declines to the levels of 36.5 and 42.7 per cent, being much worse than the correct prediction rate of 61.5 per cent and better shown by the basic, financial ratio-based model constructed for this time-horizon (Panel B in Table 3.5).

The importance for modelling failure risk over longer time-horizons of the macroeconomic factors is suggested by the classificatory and predictive ability of models built for pre-insolvency years three and four (Table 3.10). In comparison to the basic model, utilising financial ratios only (Panel A in Table 3.6), the three-year prior model, augmented with proxies for changes in macroeconomic conditions, demonstrates slightly improved accuracy in classifying observations on both the estimation sample and the holdout across all cutoff probability values. For instance, on the estimation sample, at the 0.1 cutoff, the Type I error rate is reduced from 17 per cent to 15.1 per cent, whereas the overall error rate falls from 34.7 per cent to 20.9 per cent. Despite the reduction in misclassification rates generated with holdout observations - at the 0.1 cutoff, the Type I error rate falls by 10 per cent while the overall error rate declines by 8.3 per cent as compared to the financial ratio-based model. The overall predictive power of the three-year prior logit function is again poor when judged by the overall error rates, reaching the levels of 56.2 per cent and higher (Panel A in Table 3.10).

An examination of classificatory and predictive power of the four-year-period logit function gives a picture of better performance. As compared to the results from the basic model based solely on financial variables (Panel B in Table 3.6), the four-year-period logit function classifies more accurately failed and non-failed firms in estimation and holdout samples. Notably, accuracy gains, evidencing the relevance of the two macroeconomic variables for the four-year risk-horizon, are present across a wide range of cutoff values and consistent with the alternative estimates of prediction error adjusted for the downward bias, of 15.2 per cent and better. This is also in line with the predictions generated with holdout observations, which produce the overall error rate of 21.9 per cent and better, with 40 per cent of failing firms being incorrectly classified. A possible interpretation of this improvement in predictive performance of the four-year-period logit function is that unanticipated rises in the nominal interest rate and unanticipated falls in the real exchange rate affected viability of companies in our sample with a delay.

3.3.3 Models Utilising Financial Ratios and the Duration Term

Tables 3.11 and 3.12 display the estimation results for a series of logit models when a duration variable is added to the general specification based on a wide array of 25 candidate measures based on financial statement items, to assess an impact of company age on failure risk.

Judging by overall fit, parsimonious models are well determined, with covariates being jointly significant at the 0.1% level. The best fit is shown by a model for year one prior to failure, which, amongst the four models, has the highest log-likelihood at convergence of –92.11 and the Likelihood Ratio Index of 0.399. The backward selection results in all models containing the duration variable that is negatively signed and significant at the 0.1% level. On this criterion alone, the age factor helps explain insolvency risk, suggesting that younger firms are more prone to failure. This negative relationship between firm's age and failure risk for the examined here 1988-91 cross-section concurs with the findings from the previous research into aggregate rates of company bankruptcy and firm's survival by **Hudson** (1987), **Turner, Coutts, and Bowden** (1992); **Altman** (1993), and **Dunne and Hughes** (1994). The relationship seems to be robust across all four years preceding insolvency. Furthermore, given the theoretical and empirical evidence on the inverse age-growth relationship (see, e.g., **Jovanovic,** 1982; **Evans,** 1987; **Dunne and Hughes,** 1994) the observed negative effect of age might, in part, be explained by firm's growth. That notion has been supported by the findings for the UK reported by **Geroski and Gregg** (1996) and **Morris** (1997) that fast growing, especially via acquisitions, firms coped worse with the 1990-92 recession. A negative impact of growth via acquisition on UK industrial firms have been registered by **Dickerson, Gibson, and Tsakalotos** (1997) in a study for 1948-77. Disadvantages of this type of growth are linked to a number of factors, which tend to delay or reduce the returns on the investment. First, there is a possibility that by purchasing existing plant the firm may not get exactly what it would prefer had it begun the investment from scratch. Secondly, the acquired firm might not have been without its own sets of problems, one of which is financial distress. Third, even if the acquired firm has no problems, there might be difficulties integrating it with the existing organisational structure of the acquirer. In addition to that, the use of debt to finance acquisition is

Table 3.11 Models Incorporating the Duration Term:

Logit Results for the Cross-section of UK Companies,
One and Two Years Prior to Failure; 1988-91 Estimation Period,
53 Failed Companies and 368 Non-failed Company-years (n=421)

Dimension / *Variable*	**One Year Prior to Failure** Coefficient (two-tailed p-value of asymptotic t-statistic)		**Two Years Prior to Failure** Coefficient (two-tailed p-value of asymptotic t-statistic)	
Constant	-1.805	(0.000)	-0.871	(0.012)
Size				
Log Total Sales				
Profitability				
Return on Shareholders' Capital	1.411	(0.006)		
Return on Capital employed	-1.236	(0.002)		
Operating Profit Margin	-0.939	(0.013)		
Pre-tax Profit Margin				
Net Profit Margin				
Cumulative Profitability				
Turnover				
Turnover/Net Current Assets				
Debtors Turnover				
Creditors Turnover	-0.529	(0.041)		
Gearing				
Capital Gearing	0.683	(0.001)		
Income Gearing				
Borrowing Ratio				
Gross Cash Flow/ Total Liabilities			-0.908	(0.000)
Loan Capital/Equity and Reserves				
Liquidity				
Working Capital Ratio	-1.071	(0.042)	-1.014	(0.001)
Quick Assets Ratio	-1.234	(0.037)		
Working Capital / Assets Employed				
Other Financial Variables				
Payout Ratio	-1.078	(0.062)		
Assets Index				
Tax Ratio				
Non-financial Variables				
Duration	-2.813	(0.000)	-2.602	(0.000)
Log-Likelihood at Convergence	-92.11		-121.62	
χ^2 statistic of LR Test (p-value)	134.48 (0.000)		75.47 (0.000)	
Likelihood Ratio Index	0.399		0.207	
n	421			
Per cent Failed	12.6			

Table 3.12 Models Incorporating the Duration Term:

Logit Results for the Cross-section of UK Companies,
Three and Four Years Prior to Failure; 1988-91 Estimation Period,
53 Failed Companies and 368 Non-failed Company-years (n=421)

Dimension / *Variable*	**Three Years Prior to Failure** Coefficient (two-tailed p-value of asymptotic t-statistic)		**Four Years Prior to Failure** Coefficient (two-tailed p-value of asymptotic t-statistic)	
Constant	-0.576	(0.104)	-0.543	(0.197)
Size				
Log Total Sales	-0.418	(0.048)	-0.678	(0.009)
Profitability				
Return on Shareholders' Capital				
Return on Capital employed				
Operating Profit Margin				
Pre-tax Profit Margin	-0.479	(0.020)		
Net Profit Margin				
Cumulative Profitability			0.391	(0.052)
Turnover				
Turnover/Net Current Assets				
Debtors Turnover				
Creditors Turnover				
Gearing				
Capital Gearing	0.724	(0.001)		
Income Gearing	0.767	(0.047)		
Borrowing Ratio	0.407	(0.070)	1.723	(0.006)
Gross Cash Flow/ Total Liabilities			-0.724	(0.000)
Loan Capital/Equity and Reserves			-2.042	(0.002)
Liquidity				
Working Capital Ratio			-0.464	(0.027)
Quick Assets Ratio	-1.234	(0.037)		
Working Capital / Assets Employed				
Other Financial Variables				
Payout Ratio				
Assets Index			0.408	(0.008)
Tax Ratio			-1.129	(0.014)
Non-financial Variables				
Duration	-2.825	(0.000)	-3.242	(0.000)
Log-Likelihood at Convergence	-123.06		-110.76	
χ^2 statistic of LR Test (p-value)	72.58 (0.000)		97.19 (0.000)	
Likelihood Ratio Index	0.198		0.278	
n	421			
Per cent Failed	12.6			

Table 3.13 Classification and Predictive Ability of Models Incorporating the Duration Term, One and Two Years Prior to Failure:

Logit Results for the Cross-section of UK Companies,
1988-91 Estimation Period
(53 Failed Companies and 368 Non-failed Company-years);
1992-94 Holdout Period
(10 Failed and 86 Non-failed Companies)

Panel A: **One Year Prior to Failure: Correct Classification**, Percentage

Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample						
Non-failed	79.6	82.6	91.8	97.0	99.2	99.7
Failed	90.6	86.8	66.0	43.4	22.6	15.1
Overall	81.0	83.1	88.6	90.3	89.5	89.1
Overall Error Rate Bias Estimated by Efron's Formula	2.0	2.3	3.8	5.5	6.3	6.7
Estimate of Prediction Error	21.0	19.2	15.2	15.2	16.8	17.6
Holdout Sample						
Non-failed	70.9	72.1	84.9	94.2	95.3	95.3
Failed	100	90.0	80.0	40.0	30.0	30.0
Overall	74.0	74.0	84.4	88.5	88.5	88.5

Panel B: **Two Years Prior to Failure: Correct Classification**, Percentage

Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample						
Non-failed	69.6	77.2	90.8	98.4	99.2	99.2
Failed	88.7	79.2	56.6	17.0	9.4	3.8
Overall	72.0	77.4	86.5	88.1	87.9	87.2
Overall Error Rate Bias Estimated by Efron's Formula	1.7	2.1	2.1	4.7	5.1	5.2
Estimate of Prediction Error	29.7	24.7	15.6	16.6	17.2	18.0
Holdout Sample						
Non-failed	52.3	59.3	81.4	96.5	98.8	100.0
Failed	90.0	80.0	50.0	20.0	10.0	10.0
Overall	56.3	61.5	78.1	88.5	89.6	90.6

Table 3.14 Classification and Predictive Ability of Models Incorporating the Duration Term, Three and Four Years Prior to Failure:

Logit Results for the Cross-section of UK Companies, 1988-91 Estimation Period (53 Failed Companies and 368 Non-failed Company-years); 1992-94 Holdout Period (10 Failed and 86 Non-failed Companies)

Panel A: **Three Years Prior to Failure: Correct Classification**, Percentage						
Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample						
Non-failed	69.8	75.5	89.1	98.4	99.2	99.7
Failed	81.1	69.8	52.8	17.0	3.8	3.8
Overall	71.3	74.8	84.6	88.1	87.2	87.6
Overall Error Rate Bias Estimated by Efron's Formula	2.1	2.5	4.1	5.9	6.5	6.7
Estimate of Prediction Error	30.8	27.7	19.5	17.8	19.3	19.1
Holdout Sample						
Non-failed	26.7	29.1	40.7	44.2	46.5	52.3
Failed	80.0	80.0	60.0	40.0	30.0	30.0
Overall	32.3	34.4	42.7	43.8	44.8	50.0

Panel B: **Four Years Prior to Failure: Correct Classification**, Percentage						
Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample						
Non-failed	72.0	76.6	91.0	99.2	99.7	100.0
Failed	79.2	75.5	50.9	26.4	18.9	9.4
Overall	72.9	76.5	86.0	90.0	89.5	88.6
Overall Error Rate Bias Estimated by Efron's Formula	2.1	2.6	4.3	6.1	6.8	7.0
Estimate of Prediction Error	29.2	26.1	18.3	16.1	17.3	18.4
Holdout Sample						
Non-failed	59.3	65.1	79.1	88.4	94.2	95.3
Failed	100.0	40.0	30.0	0.0	0.0	0.0
Overall	63.5	62.5	74.0	79.2	84.4	85.4

likely to increase gearing levels and financial risk.[72] We should note at this juncture that in future work, an investigation of the impact of past acquisitions on failure risk of the sample companies can provide an interesting extension to the cross-sectional analysis reported in this chapter.

Once the age factor has been controlled for, it appears that size has negative effect on failure risk over longer time-horizons since it enters the models for three and four years before failure (Table 3.12). Profitability ratios (significant at the 10% and better) are of importance over short and longer risk-horizons, which is indicated by the models for years one, three, and four (Tables 3.11 and 3.12). In year one prior to failure, creditors turnover is important and inversely related to failure, but the efficiency related ratios are absent from models for two, three, and four years. The dimensions of gearing and liquidity are captured by all models and would appear to be important for all the four risk-horizons, with the respective coefficient estimates being significant at the 5% level and better. The payout ratio, reflecting a dividend decrease, is important in the year immediately preceding failure (Table 3.11), although its coefficient is significant at the 10% level. The lower tax ratio is associated with the higher risk of failure in the four-year prior model. It is of interest to notice that the model for year one prior to failure (Table 3.11) includes profitability, turnover, gearing, and payout ratios, whose coefficient magnitudes and signs, roughly match the parameters of the model based on regular financial ratios alone (Table 3.3). In addition, relatively lower liquidity of failing firms is highlighted by the working capital ratio and quick assets ratio, both significant (at the 5% level) and correctly signed (Table 3.11). The model for two years prior again shows insufficient cash flow and persistent liquidity problems of failing firms. The coefficients of the ratio of gross cash flow to total liabilities and the working capital ratio are highly significant (at the 0.1% level) and correctly signed. The results from the model, predicting failure in three years' time (Table 3.12), indicate that size,

[72] Davis (1995) and Geroski and Gregg (1996) point out to a period of intense takeover activity in 1983-90, as an important cause of heightened gearing in the UK corporate sector in the period prior to the 1990s recession. Takeovers can be financed by internal funds or by raising funds externally via issuing debt or equity. Debt finance might be particularly attractive because of the tax subsidy to debt due to deductibility of nominal interest payments. This motive for using debt finance can also be strengthened by expected inflation because inflation is likely to reduce the real cost of borrowing. However, it is hard to precisely ascertain from the literature how indebtedness of UK companies was quantitatively affected by takeover activity in the period prior to the recession of the early 1990s.

profitability, gearing, and liquidity are the important determinants of failure, when the age effect is controlled for. The set of estimates establishing predictive relationships by the model for four years prior to failure (Table 3.12), suggests that in the early years failing firms may well be profitable, which is implied by the positive coefficient of the cumulative profitability variable, significant at the 10% level. In comparison with the non-failed group, failing firms have higher gearing, lack liquidity, and exhibit faster assets growth measured by the index of net tangible assets.

Classification and prediction results for specifications, which include the age variate, are presented in Tables 3.13 and 3.14. Noticeably, the accuracy pattern is qualitatively comparable with the predictive ability of the models displayed in Tables 3.5 and 3.6, which are based on a general specification employing only financial ratios. The addition of the duration term improves the fit. All models with the duration variable are slightly better at classifying non-failing firms on primary samples, demonstrating a Type II error rate not exceeding 30.4 per cent and the prediction error estimate of 30.8 per cent or better (Tables 3.13 and 3.14). This estimate of prediction error is roughly similar to an estimate of 36.5 per cent and better obtained for simpler financial ratio-based models (Tables 3.5 and 3.6). However, the holdout approximation does not appear to be clearly suggestive of an independent explanatory role of the introduced duration term. When a cutoff probability value is set at 0.1, then the models for time-horizons of one, two, and four years, discriminate between holdout failed and non-failed firms no better then the logit functions based on financial ratios alone. The model for three years prior to failure performs equally poorly, although at the 0.1 cutoff it reduces slightly the overall error rate from 69.8 per cent to 67.7 per cent (Panel A in Table 3.6 and Panel A in Table 3.14). Thus, the holdout results indicate that the inclusion of the duration term into a set of traditional financial determinants is likely to deliver no improvement in the out-of-estimation-sample performance of the time-period-specific models of company failure. It would appear that the provided by the duration proxy information has already been captured by a quite wide range of measures derived from financial reports. However, conceptually there is a clear advantage in having a model specification that contains both financial variables and a duration term since it becomes possible to separately assess the independent effects of the firm's financial performance and age on the risk of failure.

3.3.3 Models Utilising Financial Ratios, Macroeconomic Variables, and the Duration Term

Tables 3.15 and 3.16 present estimates of the independent variable coefficients and accompanying statistics for each of the four, time-horizon-specific models of failure risk, incorporating financial ratios, macroeconomic variables, and a proxy for the age of the firm. The reported values for the log-likelihood at convergence, Likelihood Ratio statistics, and Likelihood Ratio Index indicate the acceptable fit and jointly significant covariates (at the 0.1% level) for all four models, however the models for years one and four prior to failure are slightly better performers on those criteria. The parsimonious models in Tables 3.15 and 3.16 are based on a rich general specification represented by the 26 firm-specific and 2 macroeconomic variables. As expected, these models show better values for the measures of fit than the three series of models based on fewer variables (discussed above and displayed in Tables 3.3-3.4; 3.7-3.8; 3.11-3.12). When compared with the models from Tables 3.7 and 3.8, where we also explicitly allow for the effects of macroeconomic indicators, a remarkable feature of the models with the control for age, is that the significance and direction of the macroeconomic variable effects do not practically change when the duration term enters the models. However, the key financial determinants differ. We shall just remark that this suggests no bias introduced by possible endogeneity. The results appear robust to adding the duration term into the general specification with the implication that the data from the early 1990s support the link between failure risk and unanticipated shifts in the real exchange rate and nominal interest rate. The unanticipated change in the real exchange rate is significant (at the 1% level and better) in all models and has the expected positive sign in the models for time-horizons of one, two, and three years. Similar to findings from the series of models, combining financial ratios with macroeconomic variables (Tables 3.7 and 3.8), unanticipated changes in the nominal interest rate are highly significant (at the 1% level) and thus important for explaining failure in one, three, and four years prior to

Table 3.15 Models Incorporating Macroeconomic Variables and the Duration Term:[73]

Logit Results for the Cross-section of UK Companies, One and Two Years Prior to Failure; 1988-91 Estimation Period, 53 Failed Companies and 368 Non-failed Company-years (n=421)

Dimension / *Variable*	**One Year Prior to Failure**		**Two Years Prior to Failure**	
	Coefficient (two-tailed p-value of asymptotic t-statistic)		Coefficient (two-tailed p-value of asymptotic t-statistic)	
Constant	-3.302	(0.000)	-1.062	(0.005)
Size				
Log Total Sales				
Profitability				
Return on Shareholders' Capital	3.960	(0.000)		
Return on Capital employed	-4.102	(0.000)		
Operating Profit Margin				
Pre-tax Profit Margin			-0.889	(0.000)
Net Profit Margin				
Cumulative Profitability				
Turnover				
Turnover/Net Current Assets				
Debtors Turnover				
Creditors Turnover				
Gearing				
Capital Gearing	2.211	(0.000)		
Income Gearing				
Borrowing Ratio			0.544	(0.012)
Gross Cash Flow/ Total Liabilities				
Loan Capital/Equity and Reserves				
Liquidity				
Working Capital Ratio			-0.741	(0.021)
Quick Assets Ratio				
Working Capital / Assets Employed				
Other Financial Variables				
Payout Ratio				
Assets Index				
Tax Ratio			-0.189	(0.051)
Non-financial Variables				
Change in Real Exchange Rate	129.658	(0.003)	35.177	(0.000)
Change in Nominal Interest Rate	28.885	(0.000)		
Duration	-3.965	(0.014)	-2.772	(0.000)
Log-Likelihood at Convergence	-24.81		-107.10	
χ^2 statistic of LR Test (p-value)	269.08 (0.000)		104.50 (0.000)	
Likelihood Ratio Index	0.838		0.302	
n	421			
Per cent Failed	12.6			

[73] Models include a macroeconomic dummy interacted with the two macroeconomic variables.

Table 3.16 Models Incorporating Macroeconomic Variables and the Duration Term:[74]

Logit Results for the Cross-section of UK Companies,
Three and Four Years Prior to Failure; 1988-91 Estimation Period,
53 Failed Companies and 368 Non-failed Company-years (n=421)

Dimension / *Variable*	**Three Years Prior to Failure** Coefficient (two-tailed p-value of asymptotic t-statistic)		**Four Years Prior to Failure** Coefficient (two-tailed p-value of asymptotic t-statistic)	
Constant	-0.798	(0.032)	-1.013	(0.033)
Size				
Log Total Sales				
Profitability				
Return on Shareholders' Capital				
Return on Capital employed				
Operating Profit Margin			2.212	(0.001)
Pre-tax Profit Margin	-0.523	(0.016)	-3.739	(0.000)
Net Profit Margin			1.127	(0.006)
Cumulative Profitability				
Turnover				
Turnover/Net Current Assets				
Debtors Turnover				
Creditors Turnover				
Gearing				
Capital Gearing	0.615	(0.004)		
Income Gearing	0.730	(0.051)		
Borrowing Ratio	1.547	(0.011)	0.942	(0.048)
Gross Cash Flow/ Total Liabilities				
Loan Capital/Equity and Reserves	-1.047	(0.013)	-1.115	(0.051)
Liquidity				
Working Capital Ratio				
Quick Assets Ratio				
Working Capital / Assets Employed				
Other Financial Variables				
Payout Ratio				
Assets Index				
Tax Ratio			-1.819	(0.002)
Non-financial Variables				
Change in Real Exchange Rate	35.084	(0.000)	-122.708	(0.000)
Change in Nominal Interest Rate	-26.325	(0.000)	20.680	(0.000)
Duration	-2.955	(0.000)	-3.654	(0.000)
Log-Likelihood at Convergence	-107.02		-73.24	
χ^2 statistic of LR Test (p-value)	104.65 (0.000)		172.23 (0.000)	
Likelihood Ratio Index	0.392		0.522	
n	421			
Per cent Failed	12.6			

[74] Models include a macroeconomic dummy interacted with the two macroeconomic variables.

Table 3.17 Classification and Predictive Ability of Models Incorporating Macroeconomic Variables and the Duration Term,

One and Two Years Prior to Failure:
Classifications and Predictions Conditioned on Interactive Effects between Macroeconomic Variables and Failure.

Logit Results for the Cross-section of UK Companies,
1988-91 Estimation Period
(53 Failed Companies and 368 Non-failed Company-years);
1992-94 Holdout Period
(10 Failed and 86 Non-failed Companies)

Panel A: **One Year Prior to Failure: Correct Classification**, Percentage						
Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample:						
Correct Classification						
Non-failed	95.7	97.3	98.6	99.5	100.0	100.0
Failed	94.3	94.3	94.3	90.6	86.8	84.9
Overall	95.5	96.9	98.1	98.3	98.3	98.1
Overall Error Rate Bias Estimated by Efron's Formula	1.0	1.1	1.4	1.8	2.1	2.3
Estimate of Prediction Error	5.5	4.2	3.3	3.5	3.8	4.2
Holdout Sample:						
Correct Classification						
Non-failed	98.8	98.8	98.8	98.8	98.8	98.8
Failed	30.0	30.0	30.0	30.0	20.0	20.0
Overall	91.7	91.7	91.7	91.7	90.6	90.6

Panel B: **Two Years Prior to Failure: Correct Classification**, Percentage						
Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample:						
Correct Classification						
Non-failed	76.9	80.4	93.8	98.1	99.5	99.7
Failed	79.2	77.4	58.5	41.5	24.5	7.5
Overall	77.2	80.0	89.3	91.0	90.0	88.1
Overall Error Rate Bias Estimated by Efron's Formula	1.9	2.2	3.4	4.6	5.4	5.7
Estimate of Prediction Error	24.7	22.2	14.1	13.6	15.4	17.6
Holdout Sample:						
Correct Classification						
Non-failed	48.8	58.1	74.4	90.7	97.7	98.8
Failed	80.0	80.0	80.0	50.0	10.0	10.0
Overall	52.1	60.4	75.0	86.5	88.5	89.6

Table 3.18 Classification and Predictive Ability of Models Incorporating Macroeconomic Variables and the Duration Term:

Three and Four Years Prior to Failure,
Classifications and Predictions Conditioned on Interactive Effects between Macroeconomic Variables and Failure.

Logit Results for the Cross-section of UK Companies,
1988-91 Estimation Period
(53 Failed Companies and 368 Non-failed Company-years);
1992-94 Holdout Period
(10 Failed and 86 Non-failed Companies)

Panel A: **Three Years Prior to Failure: Correct Classification**, Percentage						
Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample:						
Correct Classification						
Non-failed	76.6	82.1	94.3	99.2	99.7	100.0
Failed	83.0	79.2	73.6	41.5	24.5	15.1
Overall	77.4	81.7	91.7	91.9	90.3	89.3
Overall Error Rate Bias Estimated by Efron's Formula	2.1	2.4	3.7	5.2	6.0	6.4
Estimate of Prediction Error	24.7	20.7	12.0	13.3	15.7	17.1
Holdout Sample:						
Correct Classification						
Non-failed	74.4	74.4	74.4	74.4	75.6	76.7
Failed	50.0	50.0	50.0	50.0	50.0	40.0
Overall	71.9	71.9	71.9	71.9	72.9	72.9

Panel B: **Four Years Prior to Failure: Correct Classification**, Percentage						
Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample:						
Correct Classification						
Non-failed	86.7	89.9	97.3	99.2	100.0	100.0
Failed	83.0	83.0	79.2	73.6	56.6	43.4
Overall	86.2	89.1	95.0	96.0	94.5	92.9
Overall Error Rate Bias Estimated by Efron's Formula	2.0	2.3	3.2	4.0	4.8	5.3
Estimate of Prediction Error	15.8	13.2	8.2	8.0	10.3	12.4
Holdout Sample:						
Correct Classification						
Non-failed	80.2	80.2	81.4	81.4	81.4	87.2
Failed	60.0	60.0	60.0	60.0	60.0	60.0
Overall	78.1	78.1	79.2	79.2	79.2	84.4

failure. Models for one and four years prior to failure return an expected positive sign for the change in the nominal interest rate, yet the model for three years prior reiterates the negative relation between the interest rate "surprise" and the probability of failure. Similar to the reported above results of section 3.3.2, changes in the nominal interest rate do not enter the final model for two years prior to failure. Taken together, the findings suggest that unanticipated rises in the real exchange rate and nominal interest rate had a detrimental - especially over longer time-horizons - effect on the probability of failure of the sample firms.

The relevance of the duration variable is again indicated by all four models, the respective coefficients are significant at the 5% level and better, and negatively signed, implying that younger firms more prone to failure. In contrast to more simple model specifications considered above (see Tables 3.3-3.4; 3.7-3.8; and 3.11-3.12), the size variable is absent from all four models, whereas profitability measures become particularly important for every of the four years (the estimates for profitability ratio coefficients are significant at the 5% level and better). This is an interesting finding as it shows that, at least for the analysis period, the fundamental of profit is important to company survival. Turnover appears to be an unimportant factor when firm's age and unanticipated changes in the two macroeconomic variables are taken into account. Gearing ratios are important determinants of failure over all four years, whilst liquidity distinguishes failing firms from non-failing firms only in the two-year prior model. Lastly, the negative tax ratio explains failure in two years time and in four years time. Overall, in this series of models, the pattern of coefficient signs is found to be highly congruous with *a priori* expectations although two exceptions should be pointed out. The first difficulty is concerned with the positive sign on the rate of return on shareholders' capital that appears in the model for one year prior to failure (Table 3.15). One way of explaining this "problematic" sign for the return on shareholders' capital, which has been already suggested in section 3.3.1, is to simply attribute the "counterintuitive" sign to possibly negative numbers of ratio constituents and small absolute values of divisors. The second problem arises in interpreting the directions of the relation between profitability measures and failure risk. In the four-year prior model (Table 3.16), the negatively signed pre-tax profit margin appears together with the positively signed net profit margin. This combination would seem to accord with the evidence displayed by the models for two and four years prior to failure that failing firms have the tax ratio lower as compared to non-failed firms. Given the fact that in our sample tax charges may well be driven by factors unconnected with the current year performance it is likely that failing firms might be characterised by lower pre-tax profit margins but relatively higher net profit margins.

Tables 3.17 and 3.18 report model validation results, describing the classificatory and predictive power of estimated logit functions. On primary (estimation) samples, as one would expect, financial ratio-based models conditioned on unanticipated changes in the exchange rate and interest rate, and controlling for firm's age, demonstrate a better fit then the fit of models based on general specifications containing fewer variables. As compared to the results from the "basic" model, utilising financial predictors alone (Panel A in Table 3.5), the one-year prior logit function identifies more accurately both failed and non-failed companies, demonstrating at cutoff values of 0.25 and greater, the misclassification rate of 15.1 per cent and better for the failed firm category, a reduction by more than 40 per cent in Type I error rates (Panel A in Table 3.17). The overall accuracy is also higher, reaching 95.5 per cent at a conservative cutoff of 0.1; this estimate is consistent with the observed small magnitudes for the downward bias, which range from 1 to 2.3 per cent. However, the one-year prior to failure model with added macroeconomic characteristics (Table 3.9) performs on the estimation sample just as well, which once more indicates that the addition of the duration term gains no additional classificatory power. The two-year prior model, containing the two macroeconomic variables and duration term (Panel B in Table 3.17), slightly improves on the correct classification rates that are shown for failed firms in the estimation sample by the model incorporating the macroeconomic variables (Panel B in Table 3.9). For every cutoff probability value, except 0.875, Type I error rates have been reduced by 1.9 per cent and more. However, the two-year prior model that includes the macroeconomic variables and duration term, still mispredicts more than 41.5 per cent of failing firms at cutoff probability values of 0.25 and greater (Panel B in Table 3.17).

The three- and four-year horizon models with added macroeconomic variables and the duration term (Panels A and B in Table 3.18) show the primary sample classificatory accuracy similar to that generated by the three- and four-year functions with no duration control (Panels A and B in Table 3.10). The three-year prior model classifies failing firms slightly more accurate, for instance, at 0.25 and 0.75 cutoff values, Type I error rates have fallen by 17 per cent and by 5.6 per cent, respectively (Panel A in Table 3.18). The model also does not reduce the overall error rate on the estimation sample. Similar classificatory accuracy on the estimation sample, with Type I error rates being reduced by 1.8 per cent and more, is achieved by the four-year prior model (Panel B in Table 3.18).

However, the usefulness of more complete models and the explanatory power of extra variables, are judged by the ability of a model to correctly classify new firms from the population that produced the estimation sample. It is this data analysis step that gives us the answer as to how well the series of augmented models captures the phenomenon of UK company failure in the late 1980s and early 1990s. In our study, the holdout data, used to validate models, represent new firms for the post-estimation time period. Hence, in model validation, the focus is on the holdout results. Predictive accuracy, assessed by holdout tests, indicates that the models for the time-horizons of three and four years prior to failure appear to do better in capturing factors influencing company insolvency. The strongest results are produced by the three-year prior model (Panel A in Table 3.18). In classifying both categories of firms, this model outperforms a less comprehensive, with no duration term model across all cutoff probability values (Panel A Table 3.10). Type I error rates have declined to 60 per cent and better, meaning a reduction in the misclassification rate for failing firms by 10 per cent and more. It should be noted, that the model would permit 40 per cent (at the 0.875 cutoff value) or 50 per cent (at cutoff values ranging from 0.1 to 0.75) of failing firms to be predicted correctly, demonstrating the accuracy levels that compare favourably with random selection. Note that our holdout cross-section contains 10 failed and 86 non-failed firms, therefore for a holdout failing firm the expected rate of predictive accuracy, based on chance, is 10.4 per cent. The model also classifies more accurately holdout non-failed firms, bringing down Type II error rates to 25.6 per cent and better, a reduction by 30 per cent and more.

However, the models for one, two, and four years prior to failure that are augmented with the two macroeconomic variables and duration term (Panels A and B in Table 3.17; Panel B in Table 3.18), have produced less impressive improvements in the predictive power. For instance, the holdout performance of the four-year prior model (Panel B in Table 3.18) is fairly similar to the predictive accuracy of the model augmented with macroeconomic variables (Panel B in Table 3.10). Both models predict correctly 60 per cent of failed firms and more than 80.2 per cent of non-failed firms, demonstrating stable performance across all cutoff probability values. This is a striking result, as we observe a quite high overall accuracy of 78.1 per cent and better for four-year-period logit functions (Panels B in Tables 3.10 and 3.18). Both models appear to identify failed firms as far back as four years prior to failure, remarkably better than random selection. A comparison with the much weaker results, shown on holdout observations by the model based on financial ratios alone, which achieves at a conservative cutoff point of 0.1 the overall correct classification rate of 62.5 per cent (Panel B in Table 3.6), implies that the models, incorporating the macroeconomic variables, best capture factors determining failure risk. This finding suggests that unanticipated changes in the exchange rate and interest rate explain a great deal of the probability of company failure over the recession period of the late 1980s and early 1990s. However, the similar predictive ability in holdout tests of the two models for the four-year horizon, which both condition the probability of failure on changes in the macroeconomy, seems to lend further support to our interpretation that the effect of firm's age, captured by the duration term, is unlikely to improve the classificatory accuracy. We recognise that this result seems to point to a rather weak information content of the used here proxy for age, which is measured by the period of time covered by the DATASTREAM records for a quoted firm, reflecting a limitation of our data source. In future work, the empirical modelling of the influence of firm's age can be sharpened by employing alternative measures based on the sources of public records of dates of incorporation and flotation.

The relative unimportance of the duration term is further confirmed by more complete models, constructed for one- and two-year horizons (Panels A and B in Table 3.17), which do not demonstrate on holdout observations the predictive power substantially superior to that of the simpler models with the two macroeconomic variables and no control for firm's age (Panels A and B in Table 3.9). For instance, although the one-year prior model is slightly better at detecting holdout failed firms, improving, across all cutoff probability values, the Type I error rate by at least 10 per cent, 70 per cent of failed firms are still mispredicted.

Finally, as compared to the financial ratio-based model performance, the predictive, out-of-estimation-sample accuracy of the model for two years prior to failure, incorporating the unanticipated change in the exchange rate and the duration term, is somewhat weaker, with higher rates of Type II and overall errors when the conservative cutoff probability values of 0.1, 0.125 and 0.25 are used (Panel B in Table 3.17 and Panel B in Table 3.5). However, the model detects better failing firms, reducing the Type I error rate by 10 per cent and more, at cutoff probability values ranging from 0.125 to 0.875. When compared with the model augmented with the unanticipated change in the exchange rate (Panel B in Table 3.9), a more complete, two-year prior model (Panel B in Table 3.17) again better predicts holdout non-failed firms, reducing, at the cutoff value of 0.1, the Type II error rate by 19.7. Note, that the Type I error rate has risen by 20 per cent at the 0.1 cutoff and we register no gain in the overall accuracy at the cutoff values greater than 0.25. It should be noted that unlike the models constructed for time-horizons of one, three, and four years, the unanticipated change in the nominal interest rate does not enter parsimonious specifications for two years prior to failure.

Out-of-estimation-sample performance of the models allowing for macroeconomic effects and firm's age, also reveals a general "pattern" of variations in predictive accuracy demonstrated at risk-horizons changing from one year to four years before insolvency. The one-year prior model returns the overall error rate of 9.4 per cent or better, whereas the long-term accuracy of models for three and four years prior to failure, is described by the overall error rate of 20.8 per cent and better.[75] In contrast, at the lower cutoff probability values of 0.1 and 0.125, the two-year prior model's performance on the holdout sample is characterised by a big drop in the overall accuracy with the error rate being in the vicinity of 40 per cent. The models, constructed from the financial statement data pertaining to two annual accounting periods prior to failure, seem to be the worst performers at approximating holdout observations. In general, one would expect, on an *a priori* basis, that as the forecast horizon increases, the relative predictive power of models would diminish. However, accuracy of models derived from our data seems to improve as the lead time increases from two years prior to failure to three and four years prior to failure. In the case of the risk-horizon of two years, the logit functions are overfitted, as regardless of what general specification is used for modelling, the error rates, generated in holdout tests, are markedly and persistently higher than for other forecast horizons. The likely explanation of the problem associated with getting the adequate *ex ante* predictive accuracy for the two-year-prior models might relate to some important omitted firm-specific variables that are not reflected in the general specifications used for model development.

3.4 Conclusions

The objective of this chapter was to re-examine the determinants of company failure in the form of insolvency by looking directly at the contribution of the environmental, macroeconomic factors and firm's age to the likelihood of failure measured at the firm-level in a sample of UK large quoted industrials taken from the early 1990s. The data used in the empirical models of this chapter came from DATASTREAM. The contribution of this study is that macroeconomic indicators were incorporated into cross-sectional models of failure risk. The motivation was to better understand how the changes in the economy modify the risk of insolvency modelled at the firm-level. We aimed to extend the company failure empirical literature to help inform forward-looking policies of banks and public bodies on preventing sharp rises in company failures. The employed in this chapter empirical

[75] The three and four-year prior accuracy, achieved in holdout tests by the constructed here logit models is similar to the *ZETA*® model's accuracy of 70 per cent for five years prior to bankruptcy (see Altman, 2000).

design based on repeated pooled cross-sections addressed the need of reflecting a temporal dimension, to allow in firm-level modelling for the effects of the important macroeconomic indicators. The essential feature of our approach towards the empirical design is that we assume a lagged relation between the changes in the contextual factors and failure risk. To examine the complex interplay between firm's age and failure risk, highlighted in work by **Jovanovic** (1982) and **Dunne and Hughes** (1994), we attempted augmentation of models with a duration term. We assessed effects of the shifts in the two macroeconomic indicators and the influence of age on the probability of insolvency by fitting time-to-failure specific logit models to pooled across several years cross-section data. Specifically, we obtained the determinants over the risk horizons ranging one to four years before insolvency. Availability of time-series observations on large, quoted at the London Stock Exchange, industrial companies, which were put into insolvency during the UK 1990s recession, constrained the maximum length of risk-horizon for our modelling the determinants of failure. We assessed model adequacy and inferred the importance of the contextual, macroeconomic factors and the duration term from the significance of coefficient estimates and classificatory and predictive accuracy of the models.

The main findings are as follows.

For the analysis period, the effects of the macroeconomic factors are quite strong. Lagged yearly, unanticipated changes in the nominal interest rate and in the real effective exchange rate are significant variables in explaining failure. Aggregate economy risk arising from macroeconomic instability and uncertainty regarding trading conditions clearly conditions the risk of failure for the firms in our sample. Although the duration term enters significantly indicating that younger firms are prone to failure we register no qualitative improvements in out-of-estimation-sample performance when the models are augmented with age, which seems to imply that age has no independent explanatory role in financial distress of the sample companies.

The important finding is that models incorporating the macroeconomic indicators exhibited lower prediction errors assessed on an out-of-sample basis. The best predicting models, augmented with the two macroeconomic variables, demonstrated stability and the adequate fit on the out-of-sample data points. In holdout tests, the overall accuracy of 90.6 per cent and better was achieved over the one-year risk horizon, and of 71.9 per cent and better over the risk horizons of three and four years. The achieved accuracy compares favourably with a weaker approximation of the holdout observations by the basic models based on financial ratios alone.

The empirical relation between increases in the probability of failure and unanticipated changes in the real exchange rate and nominal interest rate appeared stable over the four-year period before failure, indicating the importance of macroeconomic stability. Obtained empirical predictors suggested that during the 1990s recession, unanticipated increases in the real exchange rate and rises in the nominal interest rate were associated with a higher propensity of UK quoted industrial company to fail. The results seemed to confirm the links to declining liquidity, to a loss in competitiveness for the firms relying on exports, to a possible decline in performance via reported equity values for the firms with assets denominated in foreign currency, and to the detriment of inflation for highly geared firms.

Being remarkably robust to the model augmentation with macroeconomic indicators, the pattern of significance of financial statement-based determinants assessed for the four-year period prior to failure, provided evidence on the key roles of gearing, liquidity and profitability, corroborating earlier results on UK company failure reported in Taffler (1982), Keasey and McGuinness (1990) and Alici (1995). At the firm-level, financial crisis preventing policies should be aimed at reforms forestalling problems of excessive gearing and insufficient liquidity in the corporate sector.

CHAPTER 4: A PANEL ANALYSIS OF UK INDUSTRIAL COMPANY FAILURE

4.1 Introduction

In this chapter we report an empirical investigation of the determinants of company failure for the last UK recession, based on a panel data on 539 large quoted industrial firms observed over the period 1988-93. The vast empirical literature has documented an association between measures of company performance and failure. Studies, employing cross-sectional data and independent variables derived from accounts, provided models useful for identification of problem-companies with financial profiles similar to the firms that due to severe financial distress were placed into a legal insolvency regime. Chapter 3 has reported results on the financial ratio-based determinants of UK company failure from a retrospective observational study based on the combination of binary logit with a temporal sequence of pooled repeated cross-sections, where we control in modelling for the influence of macroeconomic factors and firm's age. Covering the period of the 1990s recession, findings of the previous chapter appeared to be generally consistent with conclusions of earlier UK research. For instance, gearing was found to be of particular relevance and positively associated with failure at the risk-horizons, ranging from one to four years, whereas profitability and liquidity were negatively related to the probability of insolvency. The models presented in the previous chapter imply a strong, lagged relation between changes in macroeconomic variables and failure risk and therefore point to the importance of adopting more dynamic approaches to modelling company failure determinants.

In the present chapter we attempt to enrich company failure research by departing from a standard, static cross-section design and analysing a panel data on UK quoted companies, taken from 1988-93. This extension to panel data is based on **Chamberlain's** (1980) conditional logit model with a binomial response. Our panel of UK industrial firms permits to observe on several occasions the dichotomous (binary) response, which measures the adverse outcome of formal insolvency. We should emphasise a great advantage of panel study that relates to its potential of providing larger numbers of observations, which is necessary for alleviating the cross-sectional problem of over-sampling the failed category with respect to the actual proportion of failed companies in the population. A panel study measures changes with greater precision than does a series of cross-sections of the same sample size. Another very useful property of observational design in the form of panel, which provides the rationale for our choice of this empirical methodology, is that the analysis of change in serial measurements over individual firms is fundamental in the examination of financial distress and in understanding its *causal* mechanism. Unlike pooled repeated cross-sections, examined in chapter 3, in the panel of UK quoted industrial firms, the data on failing firms are synchronised with the data on companies that survived the economic downturn of 1990-92. A panel study provides evidence on the temporal ordering of variables, an important factor in causal analysis. A cross-section study may show an association between the two variables of interest but it would not indicate which comes first, while panel data help to distinguish between the possible explanations of the association between failure risk and a plausible cause. Furthermore, the accumulation of information over both times and firms allows to take account in estimation for *permanent effects* that are not identifiable from cross-sectional analysis or from repeated cross-sections but nonetheless are likely to influence company performance and may be correlated with observable variables.

In other words, a cross-sectional model of financial distress risk is limited to considering the impact of observed predictors on the outcome. A panel model successfully overcomes this limitation of the cross-section design, giving better scope to account for the role of more or less constant *unobserved heterogeneity* across firms, which may be difficult to capture with observable, firm-level variables. The promise of panel data lies in their ability to control and allow for additive individual effects. Many company characteristics might tend not to vary over time, especially over short periods. Individual company effects might reflect the firm's business risk, share of exports in sales,[76] organisation and ownership structure,[77]

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[76] Exports continued to grow during the 1990-92 recession (HM Treasury, *Economic Briefing*, 6, 1994) and export-oriented firms fared better during the economy downturn (Geroski and Gregg, 1996).
[77] Using data generated from a large-scale survey of how UK firms coped with the 1991 recession, Geroski and Gregg (1996), identify an association in the data between organisation and ownership structure and vulnerability

corporate governance characteristics, technological and managerial qualities, "know-how" stock, industry-specific influences,[78] aspects of the business location, industrial union power,[79] as well as vulnerability to external shocks explained by a particular type of long-term debt finance that can be issued, for instance, either at fixed rate or at variable-rate.[80] The existence of firm-specific effects seems to be consistent with the view that selection effects of recessions are unevenly spread amongst firms (see e.g. **Geroski and Gregg**, 1996; **Morris**, 1997). It is important to realise that unobserved heterogeneity or differences between firms in their baseline levels of the outcome of failure may be interpreted as unobserved differences that impact on the outcome and reflect stable unmeasured characteristics of individual companies. Control for unobserved heterogeneity is then the basis for obtaining consistent estimates of the systematic part of the logit model, involving observable predictors. Not controlling for these unobservable incidental parameters, leads to bias in the resulting parameter estimates, which might be equivalent to omitted variable bias. In the context of model uncertainty in the form of a lack of unifying theoretical model and parameter heterogeneity, our panel data set may be more robust to incomplete model specifications.

4.2 The Sample

As with the cross-sectional study described in chapter 3, we define company failure as the event of entering a legal insolvency regime (administrative receivership, or administration, or winding-up, i.e. liquidation). That allows us to employ in model development a binary response describing the failure outcome, which takes the value 1 in the year the failing company published the last set of accounts. The data for the present panel study of company failure consist of company accounts' items and

to the recession. Holding companies and firms with highly dispersed share ownership tended to be a little more vulnerable to recessionary pressures than functionally organised and divisionalised firms with a dominant owner (such as foreign owned firms).

[78] See Dickerson, Gibson, and Tsakalotos (1997).

[79] Machin and Van Reenen (1993) employ an explicit measure of industrial unionism in their panel study of UK firms' profitability.

[80] Young (1995) discusses how the types of debt contract might have influenced aggregate company liquidations in the UK in the early 1990s, because a variable-rate debt is a good hedge against inflationary shocks whereas fixed-rate debt is a good hedge against real interest rate shocks. His empirical findings from the time-series study support two reasons for the rise in compulsory and creditors' voluntary liquidations over the early 1990s. The first reason has been an unexpected rise in real interest rates in the late 1980s, and the more important second factor has been that, over the period from the mid-1970s to early 1990s, variable-rate debt was heavily used.

market valuation information for the six-year period 1988-93 and were extracted from the DATASTREAM database in 1997.

Any empirical analysis involves choices made regarding the sample composition. It is worth pointing out at this juncture to a considerable overlap - especially with respect to the group of failed firms - between individual observational units in our panel and the companies contained in our pooled cross-sections, the composition of which is detailed in section 3.2 of chapter 3 and in appendix 5. Unfortunately, due to missing and incomplete records on the DATASTREAM files it was impossible to construct a cross-section sample totally identical in size and observed companies with the panel data set. The same problem of incomplete records resulted in the starting point of the panel being set in 1988, although, naturally, an earlier starting point would be desirable, providing more data for inference. Since a larger unbalanced panel sample with a prevailing share of non-failed firms can lead to more precise inference, it considered inappropriate to reduce the number of firms in the panel as such a reduction would have distorted the sample frequency.

The data set is a moderately-sized unbalanced panel, constituting 539 individual quoted industrial companies, 56 of which are failed firms that went into involuntary insolvency over the analysis period and discontinued publishing financial records in 1988-93. A short and wide panel created for the purpose of this study appears common of data employed in microeconomic research (see, e.g., **Greene**, 1997), where a relatively large number of individual units is being observed over the quite small number of periods. Our panel is unbalanced because in the present thesis we equate the date of failure with the fiscal year, in which, according to the DATASTREAM records, the failing company issues the last set of accounts. Therefore, this calendar year is considered as the firm's last year in the panel. In our sample, a failed company terminates reports twelve to twenty months before insolvency proceedings commence, while a choice of the particular sample period of 1988-93, is a reflection of those lead times. The years of sample data were arrived at by identifying the dates of release of the last accounts for: (i) firms, where formal

Table 4.1 Transition within the Panel of UK Industrial Companies for 1988-93

(Failure is determined as the time of release of the last accounts)

	Unbalanced Panel: 1988-93					
	1988	1989	1990	1991	1992	1993
Total	539	539	521	505	493	488
Companies "live" in the current year and subsequent years of the panel	483	483	483	483	483	483
Companies failing over the current and subsequent years of the panel	56	56	38	22	10	5
Cumulative total of companies failed in preceding years and in the current year	-	18	34	46	51	56
Companies failing in the current year *t*	-	18	16	12	5	5
Companies failing in the current year *t*, per cent	-	3.34	3.07	2.38	1.01	1.02

Table 4.2 Sectoral Composition of the UK Industrial Company Panel for 1988-93, Breakdown of Observational Units by Economic Group (Percentages in parentheses)

	FT-SE Economic Groups											
	Mineral Extraction		General Industrials		Consumer Goods		Services		Utilities		Total	
	Unbalanced Panel: Distribution across 1988-93 (N=539)											
1988 Non-Failed	1	(0.19)	307	(56.96)	80	(14.84)	150	(27.83)	1	(0.19)	539	(100)
1988 Failed	-	-	-	-	-	-	-	-	-		0	(100)
1989 Non-Failed	1	(0.19)	299	(57.39)	78	(14.97)	142	(27.26)	1	(0.19)	521	(100)
1989 Failed	-	-	8	(44.44)	2	(11.11)	8	(44.44)	-	-	18	(100)
1990 Non-Failed	1	(0.20)	289	(57.23)	77	(15.25)	137	(27.13)	1	(0.20)	505	(100)
1990 Failed	-	-	10	(62.50)	1	(6.25)	5	(31.25)	-	-	16	(100)
1991 Non-Failed	1	(0.20)	285	(57.81)	77	(15.62)	129	(26.17)	1	(0.20)	493	(100)
1991 Failed	-	-	4	(33.33)	-	-	8	(66.67)	-	-	12	(100)
1992 Non-Failed	1	(0.20)	282	(57.79)	77	(15.78)	127	(26.02)	1	(0.20)	488	(100)
1992 Failed	-	-	3	(60.00)	-	-	2	(40.00)	-	-	5	(100)
1993 Non-Failed	1	(0.21)	279	(57.76)	76	(15.73)	126	(26.09)	1	(0.21)	483	(100)
1993 Failed	-	-	3	(60.00)	1	(20.00)	1	(20.00)	-	-	5	(100)

insolvency was concurrent with the 1990-92 recession, and (ii) companies, where failures might have resulted from operations during the recession, even though the recessionary phase had actually ended before the date of insolvency.

Transition of companies within the unbalanced panel can be seen in Table 4.1. Since failing companies exit the panel, the sub-panel of failed firms is unbalanced. In contrast to the failed company category, 483 non-failing firms are being followed over the whole six-year period of the panel, meaning that the resulting sub-panel of non-failed firms is complete and rectangular. Names of 56 quoted industrial companies that entered insolvency state in the early 1990s, have been identified by using various editions of the London Stock Exchange Official YearBook. Non-failed company names were taken from the DATASTREAM "live" list of quoted industrials[81] as of 13 February 1997.

We intended to base a panel analysis upon a fixed effects estimator, inferences from which are with respect to permanent effects that are within the sample. Therefore it was essential to make the best use of the DATASTREAM data and include in the data set all quoted industrials with consistent available records for the period. Although it was not possible to attain a panel inclusive of all firms available on the DATASTREAM database list of "live" industrials, the sampling range had been significantly widened, as compared with the composition of pooled cross-sections, examined in chapter 3. We selected 483 non-failed firms with continuos records over the late 1980s and through to mid 1990s. Again, as in the cross-sectional study, the non-failed category is deliberately "oversampled" to resemble the actual incidence of insolvencies in the population. In the constructed panel, annual rates of failures vary from 1.01 to 3.34 per cent (Table 4.1), being close to the overall rate of 1.2-3.0 per cent observed for the corporate sector in 1989-94 (Table A1.1 in appendix 1). It would appear that the sample proportions closely resemble the actual population proportions of failed and non-failed industrial companies. In similar vein to the cross-sectional study of chapter 3, we restrict the population boundaries by

[81] The DATASTREAM code for this equity list was "UKQI".

excluding petroleum, transportation, and financial services firms. The names[82] of firms in the panel are listed in Tables A5.5 and A5.6 of appendix 5 and their broad industrial classification can be seen in Table 4.2. More than 80 per cent of non-failed and failed firms come from manufacturing and services sectors.

4.3 Independent Variables

We use in the development of a panel data model, 24 financial statement-based and equity valuation items reported by DATASTREAM for UK quoted industrial firms. The rationale behind financial ratio-based empirical models of failure, and the definitions of accounting ratios have been outlined in chapters 2 and 3 (see especially sections 2.3.1.1 and 3.2.2). We did not introduce any extra variables in addition to the measures used in the cross-sectional study, and are simply proceeding here with the analysis of information contained in financial accounts by combining the different, panel type of data and a fixed effects logit estimator to explicitly model unobserved heterogeneity of the sample firms. As in chapter 3, the set of 38 standard measures of financial performance, based on DATASTREAM items, has substantially been reduced at the preparatory stage so as avoid multicollinearity. The list of financial variables for the general model specification totals 24 candidate variables, which proxy plausible determinants. Note that the initial set of candidate variables based on accounting ratios differs from that used in the cross-sectional analysis of chapter 3 because the ratio of net current assets to total assets employed has been excluded due to multicollinearity. Standard financial ratios represent the key dimensions of financial analysis, namely, profitability, turnover, gearing, and liquidity. We also proxy size by net sales; market valuation of the firm by the ratio of market value to book value (premium or discount to net tangible assets), and dividend policy by the payout ratio (a reciprocal of dividend cover). Further, to proxy the firm's net worth, we also included an index for the book value of ordinary shareholders' funds computed as the sum of share capital and reserves less intangibles. This so called "net tangible assets index" is defined as a percentage of the assets figure obtained from the first (in terms of DATASTREAM records)

[82] As both the cross-sectional study of chapter 3 and the panel study of the present chapter examine failure of British industrial companies over the same period of time and using the same DATASTREAM lists, there is an

accounts; it is often used for solvency control, and therefore might be important in determining the risk of default. To the company, as a corporate identity, shareholders' funds are usually the only source of funds, other then liabilities, which it can use to finance assets. Changes in ordinary shareholders' funds also matter because a borrower's financial position is a key determinant of the cost of external finance. However, net worth at book values represents a rather crude estimate of the firm's value, because the assets shown in the balance sheet are usually recorded at historic cost (less depreciation) and may differ greatly from their current market values. Finally, the ratio between published tax and published pre-tax profit is used to proxy the tax position of the company. The comprehensive range allows us to implement a statistical procedure of backward elimination or reduction, based on conventional asymptotic tests, so as to identify the financial performance variables, explaining failure risk for our data set. Names and descriptive statistics of independent variables employed in modelling are displayed in Table A3.1 of appendix 3. To handle the problem of non-stationarity in data, the original DATASTREAM values were normalised with respect to means and standard errors of relevant cross-sections for each calendar year of the panel, that is each observation is relative to the year mean and therefore centred on zero.

4.4 A Fixed Effects Binomial Logit Model for Panel Data

As in the cross-sectional case, the model with a binary dependent variable can be formulated in terms of an underlying latent variable. Typically, for a possibly unbalanced panel we would specify:

$$y_{it}^{*} = \alpha_i + \boldsymbol{\beta}'\mathbf{x}_{it} + \varepsilon_{it}, \tag{4.1}$$

where we observe $y_{it} = 1$ if $y_{it}^{*} > 0$, and $y_{it} = 0$ otherwise.

In (4.1) we index all variables by an i for the individual cross-sectional unit $(i = 1,...,N)$ and a t for the time period $(t = 1,...,T)$. There are K explanatory

inevitable significant overlap in terms of names of individual firms.

variables (financial determinants) in $\mathbf{x}_{it}$, which are observed, not including a constant. This means that effects of a change in $\mathbf{x}$ are the same for all units and all periods, but the average level for individual i may be different from that for unit j.

The α_i captures the effects of those variables that are peculiar to the $i-$th individual member of the panel and that are assumed as being constant over time. Two basic approaches for modelling unobserved heterogeneity are a fixed effects treatment and a random effects treatment. The fixed effects approach takes α_i to be a group specific constant term and ε_{it} is assumed to be independent and identically distributed over individuals and time with mean zero and variance σ_ε^2:

$$y_{it}^* = \alpha_i + \boldsymbol{\beta}'\mathbf{x}_{it} + \varepsilon_{it}, \quad \varepsilon_{it} = \mathrm{IID}(0, \sigma_\varepsilon^2). \tag{4.2}$$

A random effects framework specifies that α_i are different but that they can be treated as group specific disturbances, similar to ε_{it}, except for each group there is but a single draw that enters the regression identically in each period. The essential assumption is that these drawings are independent of the explanatory variables in $\mathbf{x}_{it}$. That leads to the random effects model where individual specific constant terms are randomly distributed across cross-sectional units. The error term in this model thus consists of two mutually independent components, which are also independent of $\mathbf{x}_{js}$, namely, a time-invariant component α_i and a remainder component v_{it} that are uncorrelated over time. If we specify that $\varepsilon_{it} = \alpha_i + v_{it}$, the random effects model can be written as

$$y_{it}^* = \mu + \alpha_i + \boldsymbol{\beta}'\mathbf{x}_{it} + v_{it}, \quad \alpha_i = \mathrm{IID}(0, \sigma_\alpha^2); \quad v_{it} = \mathrm{IID}(0, \sigma_v^2). \tag{4.3}$$

The fixed effects approach is contrasted with the random effects one. Whether to treat the individual effects α_i as fixed or random can make a difference to the estimates of the $\boldsymbol{\beta}$ parameters when T is small and N is large relative to T (**Verbeek**, 2000). A distinction is that under a fixed effects approach we condition on the α_i's, so that their distribution plays no role. This interpretation makes sense if the individuals in the sample are "one of a kind", such as large quoted companies of the present study, and cannot be viewed as a random draw from some underlying population (**Greene**, 1997). The fixed effects model is thus considered as applying only to cross-sectional units in the sample and, therefore, inferences are with respect to the effects that are in the sample. A random effects approach invokes a distribution for α_i, and individual specific constant terms are viewed as randomly distributed across cross-sectional units. This is appropriate if we believe that sampled cross-sectional units are drawn from a large population.[83] Thus the random effects approach allows one to make inference with respect to the population characteristics. However, even if one is interested in the larger population of individual units, and a random effects framework seems appropriate, the fixed effects estimator may still be preferred. The reason for this is that it may be the case that α_i and $\mathbf{x}_{it}$ are correlated, in which case the random effects approach, ignoring this correlation, leads to inconsistent estimators due to omitted variables.

Two techniques have been commonly used for modelling unobserved heterogeneity on panel data with a binary dependent variable: a fixed effects logit model based on a conditional likelihood approach due to **Chamberlain** (1980) and a random effects probit model that is often referred to as **Butler and Moffitt's** (1982) "equicorrelated" model. Given that both categories of firms in the panel, the failed firms and the non-failed firms, represent a rather large proportion of equities, followed by the DATASTREAM database, and were not sampled randomly, we would expect the fixed effects approach to have some intuitive appeal. More specifically, the 489 non-failed firms in the panel represent 36.8 per cent of equities that were on the "live" DATASTREAM list as of February 1997, while the 56 failed companies account for 50.9 per cent of those quoted companies, that according to the London Stock Exchange Official Year Book entered the insolvency state over the period 1988-93. The list of firms selected for the panel analysis was compiled by excluding transportation, petroleum, and financial services companies because of

[83] Appropriate scaling will help to alleviate such problem, as the differences associated with size, for example, are less pervasive when the data are standardised. However, the micro units in the sample may differ for other reasons, such as industry sector, export sensitivity, etc.

their specific taxation and accounting policies, and then through unavoidable filtering of companies due to the usual requirement of record completeness and continuity for the period of the analysis. The above might well have resulted in non-random selection of both the failed companies and the non-failed companies. Further, in the present study we expect that unobserved individual-firm-specific effects, such as, for instance, managerial quality, industry-specific influences, industrial union power, organisational structure, ownership and corporate governance structures, are likely to be correlated with observable characteristics of firm performance, captured by financial statement-based and equity market valuation measures. Therefore it would appear reasonable to assume that the fixed effects logit model would yield an appropriate specification for the present panel study.

We specify a fixed effects logit model that accounts for unobserved heterogeneity as:

$$\text{Prob}(Y = 1\,(Failure)) = \frac{e^{\alpha_i + \boldsymbol{\beta}'\mathbf{x}_{it}}}{1 + e^{\alpha_i + \boldsymbol{\beta}'\mathbf{x}_{it}}}. \tag{4.4}$$

If we treat α_i in (4.4) as fixed unknown parameters, we essentially including N dummy variables in the model. Maximising the log-likelihood function with respect to $\boldsymbol{\beta}$ and α_i (i=1,...,N) results in a consistent estimator provided that the number of time periods T goes to infinity. For a short and wide panel, with fixed T and $N \to \infty$, the estimators are inconsistent. The reason is that for fixed T, the number of parameters grows with the sample size N, which results in an "incidental parameters" problem arising in any fixed effects model. That is, any α_i can be only estimated consistently if we have a growing number of observations for individual i, thus we have T tending to infinity. In general, the inconsistency of $\hat{\alpha}_i$ for fixed T will carry over to the estimator for $\boldsymbol{\beta}$.

Chamberlain (1980) suggested an approach to estimating a panel data model with a binary dependent variable, where N is large and T is small. He considers the set of T observations for unit i as a group, and then use the likelihood function conditional upon a set of statistics t_i that are sufficient for α_i. This means that conditional upon

t_i, an individual's likelihood contribution no longer depends on α_i but still depends upon β.[84] In the fixed effects logit model, $t_i = \bar{y}_i$ is a sufficient statistic for α_i, and consistent estimation is possible by conditional maximum likelihood. That is we discard alternative sets for which $\sum_t^T y_{it} = 0$ or $\sum_t^T y_{it} = T$, because these cross-sectional units never change states and thus contribute zero to the likelihood function. The conditional distribution of $y_{i1},\ldots,y_{iT}$ is degenerate if $t_i = 0$ or $t_i = 1$. The conditional likelihood function is written as

$$L^c = \prod_{i=1}^{N} \text{Prob}(Y_{i1} = y_{i1}, Y_{i2} = y_{i2}, \ldots, Y_{iT} = y_{iT} \mid \sum_{t=1}^{T} y_{it}). \tag{4.5}$$

Maddala (1987) provides an illustration for the case of T=2, where we have to consider the sets $\sum_t^T y_{it} = 1$. For the logit model given by (4.4)

$$\text{Prob}(0,1) = \frac{1}{1+e^{\alpha_i+\beta' x_{i1}}} \cdot \frac{e^{\alpha_i+\beta' x_{i2}}}{1+e^{\alpha_i+\beta' x_{i2}}}, \text{ and } \text{Prob}(1,0) = \frac{e^{\alpha_i+\beta' x_{i1}}}{1+e^{\alpha_i+\beta' x_{i1}}} \cdot \frac{1}{1+e^{\alpha_i+\beta' x_{i2}}}.$$

Since (1,0) and (0,1) are mutually exclusive,

$$\begin{aligned}\text{Prob}\,[(1,0) \mid (1,0) \text{ or } (0,1)] &= \frac{\text{Prob}\,(1,0)}{\text{Prob}\,(1,0) + \text{Prob}\,(0,1)} \\ &= \frac{e^{[\beta'(x_{i1}-x_{i2})]}}{1+e^{[\beta'(x_{i1}-x_{i2})]}},\end{aligned}$$

and

$$\text{Prob}\ [(0,1) \mid (1,0) \text{ or } (0,1)] = \frac{1}{1+e^{[\beta'(x_{i1}-x_{i2})]}}.$$

[84] In the panel data model with a binary dependent variable, the existence of a minimal sufficient statistic depends upon the functional form of $F(\cdot)$, that is, depends on distribution of ε_{it}. If a sufficient statistic t_i exists, this means that there exists a statistic t_i such that the probability mass function does not depend on α_i, that is $f(y_{i1},\ldots,y_{iT} \mid t_i, \alpha_i, \beta) = f(y_{i1},\ldots,y_{iT} \mid t_i, \beta)$. For a probit model no sufficient statistic for α_i exists. Thus in applying the fixed effects models to discrete dependent variables based on panel data, the logit model and the log-linear model seem to be the only choices (Maddala, 1987).

The α_i's have been eliminated and we have a standard logit model to estimate, in which changes in the x_{it}'s are used to explain changes in the binary dependent variable. For general T, we have to consider the sets $\sum_{t}^{T} y_{it} = 1,2,...,(T-1)$.

With homogeneity $(\alpha_i = \alpha)$, the model can be estimated as a binomial logit model. In order to test the null hypothesis of the homogeneity restriction a Hausman-type test[85] based on the difference between Chamberlain's conditional maximum likelihood estimator (*CMLE*) and the usual logit maximum likelihood estimator (*ML*), ignoring the individual effects, is performed.

Constructing the difference $\hat{\mathbf{q}} = \hat{\boldsymbol{\beta}}_{CMLE} - \hat{\boldsymbol{\beta}}_{ML}$

with the variance $V(\hat{\mathbf{q}}) = V(\hat{\boldsymbol{\beta}}_{CMLE}) - V(\hat{\boldsymbol{\beta}}_{ML})$,

$$m = \hat{\mathbf{q}}'[\mathrm{V}(\hat{\mathbf{q}})]^{-1}\hat{\mathbf{q}} \tag{4.6}$$

can be used as a $\chi_K{}^2$ statistic under the null, where K is the dimensionality of $\boldsymbol{\beta}$. Whether the null hypothesis of homogeneity is true or not, Chamberlain's conditional maximum likelihood estimator is consistent, but inefficient under the null, because it fails to use the homogeneity restriction. The usual maximum likelihood estimator is consistent and efficient only under the null of homogeneity and inconsistent under the alternative.

4.5 Empirical Results

Table 4.3 presents the results from the logit analysis for three parsimonious models derived from a more general specification that includes the 24 financial variables. Covariates were eliminated using a sequence of independent Likelihood Ratio tests. The failure outcome is denoted by 1 and the opposite state is assigned 0, therefore a

[85] Hausman (1978).

Table 4.3 Results from Fixed Effects Binomial Logit for the Unbalanced Panel of UK Quoted Companies, the Panel Period 1988-93

Alternative Specifications of Fixed Effects Binary Logit
For the Unbalanced Panel of UK Quoted Companies, for 1988-93,
Failure Times are Defined as Years the Last Accounts Released,
N=539, T=6, Sample Size 3,085 [(488×6)+(5×5)+(12×4)+(16×3)+(18×2)],
56 Failed Companies

Financial Dimension *Accounting Variable*	**Model 1**		**Model 2**		**Model 3**	
	Coefficient (two-tailed p-value of asymptotic t-statistic)					
Profitability						
Cumulative Profitability	0.314	(0.060)	0.302	(0.075)		
Operating Profit Margin	0.755	(0.155)	0.765	(0.147)		
Pre-tax Profit Margin	-3.484	(0.028)	-3.754	(0.018)	-2.766	(0.070)
Net Profit Margin	2.858	(0.036)	3.107	(0.023)	2.666	(0.061)
Turnover						
Turnover /Net Current Assets	-0.747	(0.166)				
Debtors Turnover	-3.914	(0.059)	-3.697	(0.067)	-2.902	(0.087)
Liquidity						
Quick Assets Ratio	-3.603	(0.011)	-3.568	(0.009)	-2.622	(0.016)
Net Worth						
Assets Index	-92.028	(0.002)	-99.200	(0.001)	-100.789	(0.001)
Log Likelihood at Convergence	-30.84		-32.28		-34.25	
χ^2 statistic of LR Test[86]	65.71		62.83		58.91	
(p-value)	(0.000)		(0.000)		(0.000)	
Hausman Fixed Effects Test χ^2 statistic	53.58		33.37		13.01	
(p-value)	(0.000)		(0.000)		(0.023)	
n			3,085			
Per cent Failed			1.8			

[86] Note that here the Likelihood Ratios are only a function of the slope parameters and not the fixed effects themselves, which are never estimated.

positive (negative) coefficient indicates that the factor, expressed by the covariate positively (negatively) correlated with the outcome of company failure. As with cross-sectional models, the diagnostics indicate that the panel data models have good overall fit – the Likelihood Ratio test statistics are significant at the 0.1 per cent level for all three models. In all Models 1, 2, and 3, based on the Hausman χ^2 statistics, the null hypothesis of homogeneity of intercepts is rejected at the 5% level and better. As discussed above, this implies that control for the firm-specific effects is necessary and that, therefore, the cross-sectional results may be biased. Regarding the importance of individual dimensions of company performance, the absence of gearing measures from all the three models is noteworthy. This contrasts sharply with the cross-sectional models of chapter 3, where the negative effect of gearing was evident in all models and for each of the four years before failure. With regard to other dimensions of company performance, profitability, turnover, liquidity, and changes in net worth (measured by the index of net tangible assets at book value) have a strong effect on the probability of failure for the firms in the panel. When the influence of ratios, expressing a profitability factor, is examined, at first glance, the estimate coefficients in Models 1, 2, and 3 seem not all to have the correct sign. For instance, the coefficient for the cumulative profitability ratio and the coefficient of the operating profit margin (in Models 1 and 2) have contra-intuitive positive signs.

The essential implication of positively signed coefficients for the cumulative profitability ratio, significant at the 10% level, is that failing companies are characterised by a greater ratio of revenue reserves relative to total assets employed.

Aside from that, Models 1 and 2 link a greater likelihood of failure to higher operating profit margins, and judging by the sign of the coefficient on operating profit margin no economic distress is detected by these models, but this variable is insignificant. Positive coefficients for the net profit margin (significant at the 10% level and better in Models 1, 2, and 3) appear to provide further support to a "teasing" positive relationship between profitability and the risk of failure. However, coefficients for the pre-tax profit margin (significant at the 10% level and better) are negative.

One possible explanation of the signs of these explanatory variables stems from the definitions of ratios adopted by DATASTREAM. For example, the operating profit margin is calculated before both interest expenses and losses on termination of operations. On the other hand, the pre-tax profit margin ignores pre-tax and after-tax profits of associated companies and undertakings, whereas the net (after-tax) profit margin takes account of amounts of associates' profits attributable to the parent company. Therefore, the fact that the pre-tax profit margin is negative, but the net profit margin is positive, might have to do with the equity method, used in financial reporting of companies, which have subsidiaries, and where financial results of subsidiaries are significant in their overall impact. Under the equity method, the parent company often shows in consolidated accounts proportional profits of its associates attributable to the group. Since profits are attributed it is possible that little or nothing has been received by the group, and its liquidity position has not been improved. In other words, higher profitability as measured by the net profit margin might have no bearing on the liquidity of the business. For further investigation of the "incorrectly" signed net profit margin, more detailed information of cash flow reports and relevant notes is needed, however, the range of financial characteristics covered by our data preclude our pursuing this aspect of analysis further. As far as the ambiguous sign for the measure of cumulative profitability is concerned, it might be explained by the possible impact that accounting policies might have on the accounting values of retained profits, because attributable revenue reserves of subsidiaries are included into revenue reserves of a parent company, in line with the equity accounting method. Moreover, the positive sign of the operating profit margin, considered together with the negatively signed coefficient for the pre-tax profit margin ratio, might be an indication that failed companies in the sample were productive and economically valuable as they would still be trading and generating revenues in the years preceding insolvency. At the same time, they are equally likely to suffer greater losses from terminating operations and incurring greater interest expenses as compared with the non-failing group. That tentative interpretation of the subtle interplay between the four profitability ratios, in our view, might reflect certain underlying factors such as shifts in the corporate sector indebtedness combined with high nominal interest rates before the 1990-92 recession, such that the high gearing effect is captured by the incidental parameters.

Further, "conflicting" signs of profit margins and the cumulative profitability ratio are consistent with the fixed effects specification, as they would appear to accord with the fact that, in the failed category of our panel, many firms are organised as a group or a holding company, and this organisational feature might also have been captured by the firm-specific fixed effects.

All three models suggest an appropriate negative relationship between turnover measures and failure risk. The ratio of turnover to net current assets is insignificant in Model 1, while the debtors turnover ratio is significant at the 10% level in all three models, reflecting that before failure there is either a slowdown in trade, due to a fall in demand, or a decline in debtors quality resulting in bad debts, not recognised by provisions. The liquidity dimension is captured by the significant at the 5% level and better quick assets ratio that deals with the most liquid assets and is regarded as the best guide to short-term solvency. In all three models, the quick assets ratio suggests the expected negative influence of liquidity on the risk of failure. Lastly, all models yield the net tangible assets index as a key determinant of failure, significant at the 5% level and better. As shown in Table 4.3, a company is more likely to fail if its index of net tangible assets is declining. This result is intuitively logical as the borrower's net worth represents a buffer or a crude margin of long-term solvency between the assets and the liabilities, although, being based on book values and hence historically oriented, this measure depends upon accounting conventions. Moreover, the strong influence of the assets index should be treated with caution as financial reporting policies and practice, which affect book values, might have been inconsistent across the companies as well as over the years followed by the panel. It is interesting to note the contrast with the cross-sectional, financial ratio-based model for four years prior to failure (displayed in Table 3.4 in section 3.3.1), which has suggested a positive relation between the net tangible assets index and failure risk at the longer risk-horizons of three or four years.

To provide an overall comparison between the cross-section results of chapter 3 and the results from the fixed effects model, we summarise the key determinants of company failure in Table 4.4. Results displayed in Table 4.4 relate to the logit

Table 4.4 Sets of the Key Determinants of Failure Risk for UK Quoted Companies in the Late 1980s and Early 1990s: A Comparison of Cross-sectional, Financial Ratio-based Logit Models and Fixed Effects Logit Models for the Unbalanced Panel (The Coefficient Signs for Explanatory Variables are in Parentheses)

DIMENSION OF FINANCIAL ANALYSIS	THE EXPLANATORY VARIABLES AND THEIR COEFFICIENTS' SIGNS		
	LOGIT MODELS BASED ON FINANCIAL VARIABLES AND CROSS-SECTIONAL DATA: 1988-91 ESTIMATION PERIOD		THE FIXED EFFECTS LOGIT MODEL FOR THE 1988-93 UNBALANCED PANEL
	1 AND 2 YEARS PRIOR TO FAILURE	3 AND 4 YEARS PRIOR TO FAILURE	
(1)	(2)	(3)	(4)
SIZE:	• **Log Total Sales (-)**	• **Log Total Sales (-)**	
PROFITABILITY:	• **Return on Shareholders' Capital (+)** • **Return on Capital Employed (-)** • **Operating Profit Margin (-)**		• **Cumulative Profitability (+)** • **Pre-tax Profit Margin (-)** • **Net Profit Margin (+)**
URNOVER:	• **Creditors Turnover (-)**	• **Turnover/Net Current Assets (+)**	• **Debtors Turnover (-)**
EARING:	• **Capital Gearing (+)** • **Gross Cash Flow/Total Liabilities (-)**	• **Capital Gearing (+)** • **Income Gearing (+)** • **Borrowing Ratio (+)** • **Gross Cash Flow/Total Liabilities (-)** • **Loan Capital/Equity and Reserves (-)**	
IQUIDITY:	• **Working Capital Ratio (-)**	• **Working Capital Ratio (-)**	• **Quick Assets Ratio (-)**
DIVIDEND PAYOUT:	• **Payout Ratio (-)**		
NET WORTH (at book value):		• **Assets Index (+)**	• **Assets Index (-)**
TAXATION OF PROFITS:		• **Tax Ratio (-)**	

functions constructed using common financial ratio-based inputs. The key predictors of failure detected with the cross-section data set are supplied by a series of four, year-prior-to-failure specific logit functions, where only financial ratio-based explanatory variables are used (these cross-sectional logit models can be seen in Tables 3.3 and 3.4 of chapter 3). Although both sets of modelling results are intended to explain the risk of failure for UK quoted companies in the late 1980s and early 1990s, Table 4.4 points to the differences between the two sets of significant explanatory variables obtained from modelling with the cross-sectional and panel data. The preference should be given to the results produced by the panel estimator, as cross-section estimates of company failure determinants may suffer from the problem of omitted variable bias. First, the features of estimators and differing dimensions of the data could account for the discrepancies revealed by the comparison of pooled cross-section and panel estimates. Further, despite the same source of primary data used to construct the samples, there is an inevitable mismatch in terms of individual firms and calendar years as the panel includes more individual companies than pooled cross-sections used in estimation (539 as opposed to 369). The discrepancies might also arise from slightly differing initial sets of potential predictors adopted for general specifications. As discussed in chapter 3, in our cross-section analysis, a general, comprehensive specification for the series of four, year-prior-to-failure specific logit models includes the 25 financial variables, whereas the panel study utilises a reduced set of 24 financial variables, because the ratio of net current assets to assets employed is excluded due to collinearity. Under these limitations of comparability of the results, we offer in Table 4.4 a rather broad description of the three sets of the key explanatory variables and their respective coefficient signs: (i) those that are important at shorter risk-horizons, as suggested by cross-sectional, financial ratio-based logit models derived from the data for one and two years prior to failure (Column 2 in Table 4.4); (ii) those that are important at longer risk-horizons, as suggested by cross-sectional, financial ratio-based logit models estimated with the data for three and four years prior to failure (Column 3 in Table 4.4); and (iii) those that explain the event of failure in the panel, when the unobservable heterogeneity in individual characteristics of firms is controlled for (Column 4 in Table 4.4).

Based on evidence from both the cross-sectional analysis and the panel-data analysis, the turnover and liquidity dimensions seem to be strongly associated with failure at all risk-horizons (Table 4.4). It is remarkable that analyses of different data sets yield the negative signs of the coefficients for liquidity ratios, implying that insufficiency of liquid assets determines failure of firms in our samples. The sign pattern for coefficients on turnover ratios is more complicated. For instance, the cross-section model that gives a three-year early warning of failure, suggests that the ratio of turnover to current assets positively relates to failure, which may be interpreted as that, in earlier years, overtrading increases the risk of failure (Column 3 of Table 4.4). However, the fixed effects logit models return a negative sign for the ratio of debtors turnover (Column 4 of Table 4.4), implying that a slowdown in the sales activity signals failure. That seems to be plausible and in conformity with the negative relation implied by the coefficient sign for the creditors turnover ratio in the model one year prior to failure (Column 2 of Table 4.4). As for other principal financial dimensions, the pattern of their importance in terms of significance and signs of explanatory variable coefficients is somewhat contradictory. For instance, the fixed effects logit models indicate that profitability factors are associated with failure, while the cross-section logit model that generates the probability of failure at the risk-horizon of one year, suggests that such association exists only in the later years. In the same vein, the negative and highly significant coefficient for the net tangible assets index in models for panel data records a deterioration in solvency of failing firms, which is evidential of the independent explanatory role of a decline in the balance sheet value of ordinary shareholders' funds. In contrast, modelling the risk of failure with pooled cross-section data restricts the importance of changes in net worth to the longer risk-horizons of three and four years, yielding the positively signed coefficient for the net tangible assets index, which seems to link failure risk to faster growth in early years.

In summary, the results, conditioned on the firm-specific effects, broadly confirm the relevance of failure determinants obtained in chapter 3 with the cross-sectional data pertinent to the same time period.

4.6 Conclusions

This chapter presented empirical results on financial ratio-based determinants of company failure obtained with panel data on UK large quoted industrials for 1988-93. This panel study contributes towards the empirical literature on company failure by addressing the problem of unobserved heterogeneity across firms in empirical models of the determinants of failure. The panel data used here provided an extension to previous UK research that, to our knowledge, had been based on cross-section, pooled repeated cross-section, or time-series data. We employed an estimation technique that controlled for the unobservable permanent differences across companies, which were likely to affect the propensity to failure of an individual industrial firm. We found strong evidence of considerable heterogeneity across companies in the panel, which suggests that the panel data estimates are preferable to the cross-sectional estimates. In an unbalanced panel we follow 539 companies of which 56 firms exit the panel due to severe financial distress problems resulted in formal insolvency. The structure of the panel constructed resembles the actual population proportions of the examined categories of failed and non-failed firms

As for the individual determinants, our analysis provides the following findings. When the unobservable fixed individual effects are controlled for, our results with regard to important financial dimensions, suggest that narrowly defined liquidity, profitability, turnover, and changes in net worth (measured as the book value of net tangible assets) are the key determinants of failure for firms in our panel data set. Moreover, modelling with the panel data captures changes in both short-term liquidity and long-term solvency. The documented importance of the liquidity dimension emphasises that the current cash flow considerations, rather than the economic value of the firm based on the future free cash flows, are more pertinent to the explanation of company failure in our panel. That result is consistent the findings reported in the time-series study of the aggregate rate of company insolvency by **Turner, Coutts, and Bowden** (1992), who argue that failure of the banks to extend to distressed companies short-term credit on the basis of the long-term potential is an important structural weakness of the British economy. The results also show that the event of failure is associated with lower pre-tax profit margins. However, unexpectedly, the analysis also identifies a concurrent and of roughly equal magnitude, positive link between the net profit margin and insolvency risk, which, under the equity method used in financial reporting of groups, might be linked to that fact that profits of associates are attributable to the parent company. This observation appears to be in line with evidence from **Geroski and Gregg** (1996) that holding companies had fared less successfully in the 1990-92 recession. In contrast to previous cross-sectional studies and the cross-section results of chapter 3, we do not detect in our panel an association between gearing and the probability of insolvency, when models of failure are conditioned on the fixed effects. Lastly, being based on a fixed effects estimator, inference presented in the present chapter must be viewed as being applicable only to the companies in the study, not to the additional firms outside the sample.

The panel analysis, presented in this chapter, is an exploratory study, providing basis for a more exhaustive empirical design of future work, where panel estimation and analysis of pooled cross-section data will have identical sample frames, based on the same analysis units (quoted companies) observed over a period longer than the covered here six-year period. Obviously, a cross-section of companies for this more exhaustive analysis will contain observations on failed and non-failed companies, coming from every year of the corresponding panel. This future work will also enable an interesting comparison of the determinants of failure over the risk-horizons longer than four years.

CHAPTER 5: A COMPARATIVE STUDY OF FAILURE DETERMINANTS FOR RUSSIAN AND UK COMPANIES

5.1 Introduction

In this chapter, based on principles accepted in the UK empirical literature on failure modelling, we try and investigate the accounting-based determinants of company failure for Russian industrials, specific for the early transition years of the mid-1990s. Our purpose in this chapter is purely empirical: to clarify what was happening with distressed firms which were put into bankruptcy. We try to extract the key factors so as to deepen understanding of company failure and better inform judgements about the enterprise fortunes in the transitional economy, whether at the level of the agent or at the level of national policy on the Russian enterprise sector. In Russia, corporate bankruptcy is a relatively new phenomenon, as the legal provision for that mechanism of resolving financial distress and reallocation of resources of inefficient firms only became available since 1992. It follows that the statistical modelling of failure risk is constrained by the availability of data. To permit robust conclusions as to failure determinants, a research strategy, based on a *comparative analysis*, is adopted. We indirectly assess the model usefulness and information content of Russian data by imposing similar "experimental" restrictions on a parallel analysis of UK company failure. A small *random* sample of UK companies that entered a legal insolvency regime in the recession years of the early 1990s is employed to construct a model of failure and test its *ex ante* predictive performance. In the UK case, we can compare the empirical determinants of failure with the findings of previous research as well as with the large sample results for 1989-93, reported in chapters 3 and 4 of the present thesis. In comparison, empirical work into the nature of Russian company failure remains scarce.[87] Therefore, in this

[87] We are aware of the two papers which have reported empirical evidence on corporate failure for Russia.

In the paper by Kasatkin (1995), the main interest is to develop an accounting-based model for a company in the petroleum sector. Kasatkin evaluates failure risk on the implicit assumption that the structure and covariates of the US *Z*-Score model due to Altman (1968), are applicable to the Russian case for the 1990s. No empirical investigation has been carried out to establish what particular financial attributes of an enterprise would convey information credibly about corporate failure risk in the economic and institutional environment different from the US conditions in the 1960s. The dicsriminant function (we discuss Altman's *Z*-Score in section 2.2.2.1) is replicated from the corporate accounts data taken for Russian petrochemicals, however, the model performance is not reported.

study, a numerical analysis based on bootstrap simulations, is implemented to validate the Russian model. Firstly, in model assessment we construct bootstrap confidence intervals for model parameters, using the resampling plan due to **Adkins** (1990). Secondly, aside from assessing by the bootstrap procedure the model's classificatory accuracy for a wide range of cutoff classification points, we also provide alternative, analytic approximations of the downward bias of the apparent error rate (**Efron**, 1986).

In accord with the larger sample studies of UK firms, reported in chapters 3 and 4, the empirical design for modelling failure is based upon the much-favoured in the binary response literature, binomial logit methodology combined with traditional for company failure research at the firm level independent explanatory variables, measuring profitability, liquidity, gearing (indebtedness), turnover, and company size. Unlike larger sample studies of chapters 3 and 4, here we concentrate rather narrowly on those financial variables that are observable from the publicly available statutory balance sheet and income statement. As noted earlier in chapters 1 and 2, economic and financial theory of company failure does not provide a unified framework for selecting particular ratios, therefore, we address the predictor selection problem by starting with the widest possible range of ratios and then allowing good failure predictors to emerge from the analysis. We find that the dimensions of liquidity and gearing are not effective in explaining failure for Russian companies declared insolvent in 1996-97 and subsequently liquidated, whereas the measures of profitability, size, and turnover appear to be robust predictors. Companies of smaller size, lower profitability, and slower turnover are more likely to become bankrupt. The Russian results are remarkably consistent with recent developments in the transition economics literature. The obtained determinants agree with the logic of studies into soft budget constraints (**Schaffer**, 1998) and into the all-pervasive barter transactions in the Russian enterprise sector

A study of Russian bankruptcy by Lambert-Mogiliansky, Sonin, and Zhuravskaya (2000) contributes to a separate strand of the literature, concerned with federalism in Russia and economics of bankruptcy procedures. In their analysis of inefficiency of the Russian bankruptcy law of 1998, an attempt is made to explain a ruling of the regional arbitrage court judge, as to whether to rehabilitate or liquidate an insolvent enterprise, by integrating a game theoretic approach and statistical model. The authors argue that the regional arbitrage courts, being captured by the political power, permit the regional governors in alliance with managers of large regional enterprises to employ financial rehabilitation as a vehicle for effective expropriation of the

(Commander and Mumssen, 1998). Moreover, our results, explaining company failure in the context of the first 1992 bankruptcy law, do not appear to contradict the assertions in **Lambert-Mogiliansky, Sonin, and Zhuravskaya** (2000), regarding inefficiency of bankruptcy institutions stipulated by the 1998 new insolvency law. More specifically Lambert-Mogiliansky, Sonin, and Zhuravskaya contend that discretion of judiciary in the regions, results in the opportunistic use of the external management procedure, assisting certain technically insolvent, albeit profitable, large companies to avoid federal tax payments and debt payments to creditors outside the region. As for the UK firms, our logit results indicate the importance of profitability, gearing, and liquidity in explaining the event of failure, as one would expect from relevant UK research.

In the following section we introduce the basic background relevant to the specific, enterprise-level and macroeconomic conditions, in which a Russian industrial firm operates, and specify hypotheses on Russian company failure. The chapter goes on to outline the sample design and some methodological problems it entails, with the remainder containing the discussion of empirical results and some concluding remarks. Finally, the annex displays a description of the bootstrap used to produce inference in the comparative study.

5.2 What Causes Russian Enterprise to Fail: Hypotheses

The defining characteristic of industrial company performance in post-communist Russia appears to be dramatic growth of loss-making and illiquid enterprises. According to Goskomstat, in a single calendar year between 1995 and 1996, the share of enterprises, reporting net losses, rapidly increased from 26.4 to 43.5 per cent, constituting the majority of large and medium-sized firms in the economy. That was accompanied by large-order accumulation of enterprise arrears. In 1996, for companies in manufacturing and fuel and energy sectors, the total of accounts receivable reached 54 per cent of the total accounts payable, which was two times more when compared with 1995. The phenomena of negative net profits, inability to

federal government and the outside investors. Using a trivariate logit they found that of debtor-enterprises, larger, in terms of employment, firms go into rehabilitation and smaller firms are liquidated.

meet debt obligations, arrears to trade creditors, non-payments of taxes and wages common to Russian enterprises in transition, has been widely described in the literature on post-communist economies under the generic term of "enterprise bankruptcy" or "financial distress".

However, failure of Russian private industrial enterprise differs from company financial distress in market economies due to: (i) the different role of the state in economic activities and resource allocation and (ii) the existence in a market economy, of the functional financial system and institutional, regulatory, and legal arrangements necessary for sustaining financial discipline in the corporate sector and for providing a mechanism for managing financial distress.

As discussed in chapter 1, the finance literature, broadly defines financial distress as the company's inability to pay debts as they come due, which is caused by the lack of liquid assets and absence of new external finance. Illiquidity leads to payment defaults. Financial distress is a situation where cash flow is insufficient to cover current obligations. These obligations can include unpaid debts to suppliers and employees, actual or potential damages form litigation, missed principal or interest payments under borrowing agreements. Bankruptcy refers to the court-supervised process for breaking and rewriting the contracts, while liquidation refers to the sale of the firm's assets and distribution of proceeds to claimants. We should again emphasise that there is bound to be some uncertainty as to the conditions under which creditors can initiate bankruptcy proceedings (see, e.g, **Armour and Frisby** 2001).

In market economies, the number of illiquid firms is constrained by the existence of institutions facilitating their timely exit or financial restructuring, and corporate bankruptcy (insolvency) provides one of a number of possible solutions for resolving financial distress. However, the literature in the area of economics of bankruptcy (e.g., **White** (1989 and 1994), **Wruck** (1990), **Opler and Titman** (1994)) argues that economic distress and financial distress do not necessarily go hand in hand. Poor economic performance is not tolerated for long and there should be a substantial asset reallocation from poorly performing, inefficient firms, but negative consequences of the selection process of bankruptcy relate to a possibility that an economically viable enterprise can be put into insolvency as a result of debt default and discontinue as a legal entity. As discussed in chapter 1, such manifestation of distress as corporate bankruptcy results from a complex interaction of various firm-specific and external factors affecting the company's indebtedness, profitability, cash flows, market values of its assets, and hence its ability to meet or renegotiate debt obligations. The usefulness for modelling failure risk of data from company accounts, reflecting performance and financial position, is viewed as self-evident from the success of practical applications of accounting ratio-based empirical models in managing financing risk (see, e.g., **Altman**, 2000).

In the analysis of Russian enterprise distress and illiquidity, it appears necessary to use the concept of *soft budget constraints* due to **Kornai** (1980), especially relevant in the context of a economy in transition from plan to market. The soft budget constraint is defined in the literature as a subsidy paid *ex post*, typically by the paternalistic state, to loss-making firms to guarantee their survival regardless of whether or not they are economically viable (**Schaffer**, 1998). The consequences of soft budget constraints are that: (i) debt is not associated with the disciplining of the management of poorly performing firms, and (ii) performance *per se* is not a condition for the injection of finance. In contrast, in a market economy, the private firm should face hard budget constraints, which means that if it made losses it would not normally be rescued by the state.[88]

Now we delineate why a representative manufacturing firm had become financially distressed as the old economic system was demolished, and ascertain from the literature why, in the 1990s, a large number of loss-makers persisted in the Russian industry, impeding the exit of economically non-viable enterprises. In what follows we describe some macroeconomic and institutional factors, shaping the degree of hardness of budget constraints, and then proceed to outline the survival routes the enterprise sector and the state have invented and employed to avoid mass exit.

[88] However, public firms may have relaxed budget constraints as they cannot go bankrupt (Bertero and Rondi, 1997).

Change in Supply and Demand

Economic and financial distress of Russian firms is not simply a by-product of the competitive process and natural selection as it is in mature market economies. In modern Western societies, institutions of markets and exchange provide a mechanism to co-ordinate activities of individual agents, who pursue their own interest. Out of the process of market exchange come the prices, wages and profits that serve to determine the allocation of the economy's resources and the distribution of income. Competition drives each and every agent to search for more profits and more production and, given infinite wants of consumers, economic growth and sustained improvement in human welfare are delivered. The market paradigm points the road towards affluence and a sustainable future. However, the proper functioning of markets requires clear profit-oriented incentives and financial discipline, which flow from defined property rights. Self-regulating market systems based on market exchange and competition are subordinated to law. Company law and bankruptcy law lie at the heart of the economy and fundamental to facilitating competitiveness, growth, and investment. Efficient, performing better producers are selected through competition, via interrelated processes of industry entry of new firms and exit of unviable firms, and, in the case of inability of the enterprise to meet debt obligations, by the disciplining mechanism of bankruptcy (or insolvency) [89]. There is, however, a dilemma: during downturns or periods of macroeconomic instability, default by many companies on their debt can produce a domino effect, generating excessive bankruptcies, posing a risk to financial stability of the economy as a whole, and entailing social costs. One of the central and unanswered questions, posed by work of the students of bankruptcy economics, is the efficiency of the selection mechanism of bankruptcy. When the selection process is inefficient it might create a situation where creditors put economically viable firms into bankruptcy (and even "automatically" liquidate efficient firms). Hence it is important to also look at the desirable properties of bankruptcy law that can guarantee efficient reallocation of resources. Understanding the causes of the process leading to bankruptcy is important for preventing severe financial distress in the enterprise sector and has implications for economic policy and bankruptcy reform.

Since 1992, radical reforms have brought about major changes. The liberalisation of prices, foreign trade, exchange rates and other transactions, the collapse of former regional and domestic trading arrangements represented a combination of transition-related, structural changes for enterprises. Macroeconomic shocks have resulted from the fall in the public and private demand for enterprises' output and from the disappearance of trade between the former Soviet Union countries, and markets of the former Soviet Bloc. Structural shocks derived from the shifts in the pattern of demand and profitability have followed from the reduction of the state orders[90] and the opening of the domestic market to foreign competitors. Those factors led to changes in the structure of relative prices that have been moving towards the structure of international prices, and had imposed a double shock upon firms: firstly, in their production costs and, secondly, in the value of their product. The effect of the move from the planned economy to the market economy was a fundamental disequilibrium associated with the excess output, energy and material use, and overmanning in many firms. On the supply side, the prices on material inputs, such as energy and raw materials, have increased relatively to the prices of labour and manufactured goods. The disappearance of the economic area of the former Soviet Union, led to input dislocation for some companies making it impossible for the purchasers of intermediate inputs to complete their output and to sell their product. Removal of product-related, budgetary subsidies increased costs of inputs. On the demand side, the seller market vanished and the buyer market emerged. The power of foreign competition and consumers affected the prices of enterprises' output. This shock was differentiated across the Russian enterprise sector. Energy and raw materials producers saw an increase in demand, whereas heavy industrial goods producers, who used to supply specialised products and were dependent on the state orders, suffered a negative demand shock and revenue losses. Competitiveness of the enterprise sector was also affected by the significant depreciation of the rouble during the transition and a fall in the real exchange rate.

[89] At the extreme, recessions can be viewed as an integral part of the process by which economies grow and develop. An analysis by Saint-Paul (1993) supports an argument that recessions are associated with productivity-improving activities.

Bank Credit Squeeze and Collusive Trade Credit

Initially, in the first phase of reforms, there were massive extensions of directed credit to state-owned and some privatised enterprises. That fuelled the sharp increase in inflation,[91] but from 1994-95, the tight monetary measures of stabilisation focused on containing the inflationary consequences, later the state subsidies had fallen, the supply of liquidity through directed credit was significantly reduced,[92] and strict credit ceilings were imposed on the enterprise sector. There was very limited lending by banks to the private sector.[93] Banks had strongly shifted their portfolios to financing the government (towards GKOs - rouble short-term government debt). The nominal and real interest rates remained at more than 100 per cent per annum with the high spreads, thus making banking credit prohibitively expensive for enterprises. The high nominal interest rate caused cash-flow problems because borrowers were forced into accelerated and premature amortisation of their debt, in real terms, whenever they were not able to add to their borrowings an amount equal to the reduction in the real value of the rouble due to inflation. With no access to bank credit to finance working capital, an enterprise's output collapsed even if the enterprise was economically viable. Furthermore, the credit squeeze stopped any change in obsolete capital stock, necessary to make radical improvements in techniques of production to respond to price movements. Poorly developed banking and financial systems along with the unstable macroeconomic and regulatory environment, constrained the use of equity and debt instruments to finance investment.

However, financial discipline via an initial credit squeeze is not easily established in an economy in transition. The excessively tight credit policy aimed at inducing firms to restructure can generate the potential for a collusive creation of financial arrears, arising from the temptation, even for profitable reformable firms, to resist by inertia

[90] State-orders are defined as orders from the government to the private companies, including orders from public sector enterprises.

[91] In 1994, inflation reached 200 per cent leading to high relative price variability and unpredictability of the firm's revenues. When inflation is high, enterprise decisions predicated on the relative prices prevailing at the time of making decisions, may be well translated into the production processes that are no longer financially viable at the *ex post* relative price configuration. An uncertain revenue stream increases the possibility of default.

[92] By the middle of 1998 directed credits have been phased out, and explicit subsidies to the enterprise sector diminished to no more than 2 per cent of GDP (Commander and Mumssen, 1998).

any retrenchment, necessary to overcome a shortage of liquidity (**Khan and Clifton,** 1992; **Perotti,** 1999). Given an inflexible, highly monopolistic trading structure, inherited from central planning, and a significant proportion of unsalvageable value-subtractors, firms with no alternative markets to redirect the output from illiquid buyers, tend to extend unforceable trade credit to non-creditworthy clients. This in turn ensures the availability of trade credit to the better, reformable firms, which postpone the internal costs of restructuring because their behaviour is likely to be determined by insider ownership[94] and effective control over assets by managers, who are able to derive benefits from an opportunistic use of assets. Good firms become entangled with bad ones. Moreover, the enterprise sector expect that the *ex post* unconditional bail-outs will result from the political pressure caused by a massive chain of trade arrears and the confusion between the subsidy and credit channels, because the performance and prospects of individual enterprises are blurred by involuntary and strategic collusive trade credit. That lack of discrimination between firms in the bail-out process prevents unsalvageable enterprises from closures and introduces a perverse external influence on firms that are capable of restructuring, but prefer to take refuge in collusive illiquidity. In the Russian context, the potential for collusion could explain the explosive growth of trade arrears. Net arrears of the enterprise sector, the gap between overdue payables and receivables, rose from zero in 1994 to around 15 per cent of GDP in 1998 (*IMF*, 1999).

Tax and Payments Systems

The fall in output and inflation had adversely affected the tax revenues that declined with high inflation as enterprises delayed the settlement of tax liabilities. Since taxes are generally not indexed to inflation, late payments were seen as a "sensible" way of reducing the real value of payments. In the 1990s, to protect tax revenues in the inflationary environment the government ceaselessly redesigned the tax code, introducing punitive and emergency taxes and penalties, hence the stock of the tax

[93] As Popov (1998) reports, by the end of 1996, total bank credit outstanding fell to about 10 per cent of GDP while total long-term credit shrank to less than 1 per cent. In contrast, in the UK, the relative size of domestic bank credit was 125.7 per cent of GDP in 1995.
[94] Majority ownership by managers and employees has emerged as a result of Russia's mass privatisation programme, and as early as in 1994 these forms prevail in over 70 per cent of privatised firms (Earle, Estrin, and Leshchenko, 1996).

arrears of an enterprise could grow to a level, at which it was impossible to pay tax debts out of the current revenues.[95] Unpredictability and high real tax rates have tended to be a specific feature of the Russian transition. The second institutional characteristic has been an integration of enterprise banking and tax collection, which resulted in effective state control over enterprise withdrawal of funds. Those tax related factors along with, as **Hendley, Ickes, and Ryterman** (1999) point out, a legal culture in which firms could question fairness and legitimacy of tax payments, reduced the usefulness of bank accounts for enterprise payments and receivables.

Tax Arrears and Non-Monetary Transactions as a Route of Softening Budget Constraints

Analytical and empirical research has emphasised that tax arrears and deferrals to the state[96] and quasi-fiscal institutions like utilities and railways, represent the main route a Russian firm takes to "soften" the cash constraint (**Commander and Mumssen,** 1998; **Gaddy and Ickes,** 1998; **Grigoriev and Kuznetsov,** 1998; **Schaffer,** 1998). The route is made possible by constant creation and injection of liquidity to the enterprise sector and by the practice of the state, of accepting tax payments in kind and issuing tax offset papers in return for purchases of goods for public procurement. These quasi-fiscal credits are then reallocated across the enterprise sector by using a complex system of non-monetary transactions and intermediaries, designed to avoid the banking system altogether, which encompasses barter trade,[97] promissory notes, in kind or late payments of wages, taxes, and utility bills. The underlying reasons for the growth of the net infusions of indirect subsidies into the enterprise sector have been associated in the literature with a substitution of indirect credit from the state and workers for direct subsidies and bank credit (**Commander and Mumssen,** 1998). A kind of financial transfer from the state to a continuing firm takes place where a flow of tax and utility arrears is not getting paid at all, or is being written off, or is being paid in kind at overvalued prices, which

[95] In 1995, there were some 200 identified taxes in Russia, with the corporate profit tax in the range of 25-42 per cent and pension tax of 42 per cent *(OECD,* 1998; *EBRD,* 1994; Shama and Merrell, 1997).

[96] Schaffer (1998) reports growing stocks of tax arrears in Russia from 1.5 percent of GDP to 6.5 per cent during 1995, and to 12.0 per cent of GDP in 1996.

[97] Hendley, Ickes, and Ryterman (1999) refer to the *Russian Economic Barometer* and *World Bank-Russian Academy of Science* survey estimates that, between the first quarter of 1995 and 1997, barter increased as a share of industrial sales from under 20 per cent to 43 per cent, which indicates the thickness of barter market.

means that failing firms are being *ex post* indirectly subsidised, hence the soft budget constraint.[98]

The Soft Bankruptcy Constraint

The nascent bankruptcy process generally did not provide an effective hard budget constraint on illiquid enterprises. Nevertheless, legal insolvency is possible and might constitute a final event of company exit (the discontinuation of the legal entity) - the number of distressed enterprises recognised insolvent by arbitrage courts on the national level, grew from 50 in 1993 to 1,035 in 1996, and to around 4,000 in 1998. (*Bulletin of the High Court of Arbitration of the RF*, 1997; *IMF*, 1999).[99]

[98] The growth in tax arrears over the period 1995-98 implies an implicit fiscal annual subsidy to the enterprise sector of 5 per cent of GDP (*IMF*, 1999).

[99] The first 1992 insolvency law provided creditors with three alternative structures for dealing with financially distressed enterprises: (i) reorganisation via external management or rehabilitation, (ii) liquidation, and (iii) amicable settlement. The main problem with the first 1992 law was that it required a somewhat high threshold for the declaration of bankruptcy, this is because the definition of bankruptcy combined the two, illiquidity and solidity, indicia of insolvency: non-payment of debt and debt in excess of assets, at book values. However, net worth of a privatised, but formerly owned by the state, enterprise is likely to differ greatly from the true market value assessments. That is because valuation of assets is likely to be subjective, especially for firms where balance sheet values were set at arbitrary levels at the time of privatisation and later several times readjusted for inflation.

In March 1998, the first insolvency law was replaced by the 1998 Federal Law on Insolvency which is currently in force. The 1998 law has simplified initiation of bankruptcy by a creditor. A creditor with three months overdue claims amounting to 500 times the ongoing minimal monthly wage (e.g. less than US$5,000 in 1999) can file for bankruptcy. Next, the debtor-enterprise is placed by the arbitrage court in temporary management to prevent stripping of assets by incumbent managers, and to organise a creditors' meeting, where the creditors choose between liquidation or external management (rehabilitation). As the 1998 law was motivated by preventing inefficient liquidations, it allows creditors to make a decision on external management before the court conducts the hearing to determine whether the enterprise is indeed bankrupt, and in such cases the court will approve creditors' decision. However, the law also gives discretionary powers to judges, to impose external management in cases when the creditors' meeting proposes liquidation. It is important to notice, that the incumbent manager can be appointed as an external manager, and that, by creating a possibility of fraudulent bankruptcy, might impede restructuring of the distressed firm.

An important non-judicial, administrative extension of reorganisation and restructuring of state-owned companies is organised under the umbrella of the Federal Service of Russia on Insolvency and Financial Rehabilitation (initially called the Federal Insolvency Administration), the state agency. In particular, the Federal Service is tasked with handling financial distress in enterprises with the state ownership of 25 per cent or more, by monitoring financial performance at the micro level, as well as with decision-making on solvency and relative merits of reorganisation or liquidation. In accordance with the 1998 Insolvency Law, the Federal Service analyses solvency of large economically and socially important organisations (Tal, 1999). In practice, the Federal Service efforts have been partly related to tax collection, for instance, in 1996, 936 court insolvency cases against non-paying enterprises was initiated by the Federal Service (*OECD*, 1998).

Prima facie the federal agency have always recognised the need of evaluation and *ex ante* classification of enterprises according to estimates of chances of their survival. Stemming from the importance that traditional financial analysis places on company liquidity in market-based economies, a set of liquidity criteria had been designed, and their lower bounds were recommended and widely used in extensive monitoring of the enterprise sector (Federal Insolvency Administration, 1994). Non-compliance with the liquidity criteria triggered intervention by the federal agency, following insolvency procedures. Other important aspects of viewing liquidity, such as profitability and cash flow patterns, were ignored. Such a simplified approach was limited by the very essence of liquidity ratios, which can be subject to "window dressing". Also, in a market-based economy, liquidity measures may decline in size as a result of increased efficiency, rather than a result of cash flow difficulties. In contrast, in the transition economy case, hyper-inflation and the diminishing purchasing power of money create incentives for businesses to lower the level of cash holdings, and to resort to barter transactions. However, the set of liquidity ratios had outlasted the 1992 old law and still was operational in September 1999 (see e.g. Vladimirov, 1999), one year after the 1998 Federal Law on Insolvency came into

However, the persistence of indirect subsidies, collusive arrears, and expectation of bail-outs resulted in *creditor passivity* (**Mitchell**, 1993; **Hoshi**, 1998; **Hoshi, Mladek, and Sinclair**, 1998), which accounted for the relatively small rate of court insolvency cases given the scale of enterprise negative net profits and illiquidity.[100] Further, unlike in Western countries, where company directors are under legal obligations to declare insolvency and enter bankruptcy proceedings,[101] managers of Russian companies had little incentive to commence the process voluntarily, which implied informational asymmetries. This in turn restricted the ability of creditors to screen and monitor firms, setting a limit to future borrowing and increasing the costs of funds raised externally. In the circumstances, the most frequent use of insolvency proceedings was as a device by the fiscal authorities to collect tax (**Mirsky**, 1999; *IMF*, 1999).

The notion of the soft bankruptcy constraint receives further theoretical and empirical support in **Lambert-Mogiliansky, Sonin, and Zhuravskaya** (2000), who address the issue of efficiency of rehabilitation in bankruptcy, in terms of managerial incentives to restructure and creditor protection. A game theoretic model of a regional arbitrage court which is either politically influenced by the regional governor or corrupt, shows how the present bankruptcy institutions in Russia tend to fail to protect creditor rights or induce restructuring, and external management is likely to be opportunistically used as a tool to avoid federal taxes and debt repayments to creditors outside the regions. This is an additional route of "softening" budget constraints in technically insolvent, large enterprises. The authors maintain that their theoretical model is consistent with the empirical evidence they present on the economic and political factors that determine the likelihood of an enterprise being in an external management regime, liquidation, or escaping these two bankruptcy states. Lambert-Mogiliansky, Sonin, and Zhuravskaya utilise a trivariate

effect. Insufficiency of a single dimension of liquidity for solvency monitoring and a necessity of employing more sophisticated approaches based on probabilistic predictions, was recognised in the interview with the senior officials of the Federal Service of Russia on Insolvency and Financial Rehabilitation (Samonis, Vitryanski, and Postyshev, 1998).

[100] In market economies, creditors when faced with a default debtor react promptly and aggressively, any sign of passivity reflects badly on the creditors and undermine their position via financial markets.

[101] In the UK, to encourage more risk-averse behaviour by company directors the concept of wrongful trading is introduced in the 1986 Insolvency Act. A director who knows that a company is insolvent can be held liable for

logit to examine the effect of enterprise-specific characteristics on these three levels of enterprise financial distress. Their model inputs include cash flows given by the cost per unit of output, technical efficiency measured by labour productivity, restructuring efforts prior to insolvency, defined in terms of the logarithmic change in labour productivity, and size given by employment. The empirical micro-model also incorporates industry-wide aggregates for the firm-level variables and controls for a number of region-wide factors such as the extent the governor politically controls the regional economy and tension of her/his relations to the federal centre; federal tax arrears, cash tax collections; and the regional product per capita. Based on 17,475 data points for 1997-99, their model suggests that having greater costs per unit of output and lower technical efficiency increases the probability of external management or liquidation, whereas successful restructuring prior to insolvency staves off liquidation. Further, the model indicates the relevance of industry-wide factors. For instance, being in an industry with relatively large costs per unit of output, reduces the probability of external management and increases the probability of liquidation, while prior efforts of restructuring undertaken in the sector reduce the risk of falling into either of those states. Finally, the strength of the governor in the regional economy, tension of her/his relation to the regional centre, federal tax arrears in the region, and the opacity of the tax collection system increase the probability of external management. Overall, the authors argue that these empirical findings imply the dependence of judiciary on regional authorities and, consequently, bankruptcy institution failure to harden budget constraints on large company managers.

Hypotheses

Soft finance and non-monetary instruments impact on the pattern observed in the literature concerned with market-based economies, of how changes in traditional financial analysis ratios reflect the risk of company failure. Quasi-fiscal credits and a thick non-cash market blur the true position of company profitability and, consequently, short-term liquidity and long-term solvency. Firstly, it is likely, that the short-term liquidity characteristics that are centrally crucial for company survival

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the extra losses sustained by carrying on in business and can be disbarred from holding directorships in the future for a fixed period (Cuthbertson and Hudson, 1996).

in market economies will be unhelpful in distinguishing between failed and non-failed Russian companies. Illiquidity and soft finance are not incompatible with enterprise survival. The firm may be able to repeat the operating cycle and generate revenues on the continuous basis with the lower level of cash reserves. Reduced flows of cash and non-monetary transactions would limit the usefulness of the analysis of the enterprise cash position for determining failure. Although in financial statements debtors represent sales, they do not represent cash amounts due from customers. Similarly, creditors may not represent levels of future cash outflows. Therefore, both failed and non-failed enterprises are unlikely to have consistent differences between liquidity ratios. Hence, it is anticipated for the Russian case that:

H1: The liquidity position will be irrelevant for the purpose of discriminating between the failed and non-failed Russian enterprises.

As far as financial gearing[102] is concerned, in market economies, debt imposes conditions that can trigger default, because higher debt is expected to result in higher fixed financing costs and, therefore, increased financial risk for the same level of variance with respect to a particular level of sales. The firm with higher debt will represent a poor bankruptcy risk. On the other hand, the theory of debt and managerial ownership points to the role of high leverage in imposing financial discipline on company managers and enchancing performance (see e.g. **Aghion and Bolton**, 1992; **Jensen**, 1986, 1989 and 1991). However, in 1990s' Russia, long-term debt does not play a significant role in capital structure, and short-term debt seems not to discipline the management of poorly performing companies due to the existence of soft budget constraints. Therefore, there is unlikely to be a significant difference in levels of indebtedness, measured by debt ratios, between the failed and non-failed Russian firms. Our second hypothesis proposed for examining the Russian enterprise financial distress, is:

H2: The gearing position will be irrelevant for the purpose of discriminating between failed and non-failed Russian enterprises.

[102] We use here a more general meaning of financial gearing as a measure of a company's total indebtedness as contrasted with the "strict" definition of financial gearing as capital structure, which is applied to the relative mix of debt and equity securities in the permanent capital.

Third, general financial performance of a company may be assessed by its ability to generate income. The effect of erosion of earning power on an enterprise entails its inability to serve its debts. In order to continue trading the enterprise must be able to sell its goods and services at prices that exceed the costs of production, therefore profitability is expected to be a significant predictor of failure. Higher turnover (activity) of assets improves profitability and therefore should have a negative effect on the probability of failure. For a Russian firm, a negative relation between turnover and failure is expected to outweigh the opposite impact of overtrading, which might be caused by rapid expansion of trade. According to **Geroski and Gregg** (1996) this appears to have occured in the UK over the period of the early 1990s. It is anticipated that:

H3: *A Russian enterprise will fail because of its relatively poor financial performance in terms of turnover and profitability.*

In what follows we attempt to obtain a clearer, yet practical understanding of Russian company failure by investigating empirically the relationship between the risk of formal insolvency and the accounting variables. To control for the size of the Russian sample we contrast the results with a similar sized study of the UK.

5.3 The Sample Design and Methodology

The Russian Company Sample

Following previous UK research we proxy the event of corporate failure by the state of legal insolvency. A sampled, failed Russian company is an industrial enterprise, organised as a joint stock company,[103] which was declared insolvent in 1996 or 1997 by courts of arbitration, and subsequently compulsory liquidated, i.e. failure equals discontinuation of the legal entity. Thus we focus on just two states of financial "health": failure, where the firm is determined as insolvent by the court, and non-failure otherwise. The definition of failure as legal insolvency allows us to be consistent in separating out the loss-making companies that despite being in payment

[103] During the 1992-94 corporatisation, the vast majority of state enterprises (22 thousands by the end of 1994 (Boycko, Shleifer, and Vishny, 1995) were corporatised, i.e. re-registered as joint-stock companies with equity capital, a corporate charter and a board of directors. Transformed ex-socialist enterprises were removed from

arrears continued trading in 1996-97, and those enterprises that had eventually failed and exit the market over these two years. It should be noticed that our operational definition of Russian company failure is narrower than that we have employed in identifying failed cases for the UK study used as a control for Russian results.[104] A more strict notion of failure seems appropriate for Russia in the late 1990s, as many illiquid Russian debtor-enterprises have been provided with soft finance and bailed out by the state, or were considered as being "solvent" because of "satisfactory results" from "the balance sheet structure" test.[105] Moreover, occurrence and the dates of legal insolvency are easy to ascertain, because information about Russian enterprises, declared insolvent by courts, is systematic and publicly available, which is crucial for timing the failed firms' accounts for the years preceding failure.

The overall sample contains 21 insolvent companies and 27 solvent firms.[106] Insolvent companies were identified from the list of court insolvency cases published in 1996-97 in the periodical *The Bulletin of the High Court of Arbitration.* A list of sampled, failed companies can be seen in Table A5.9 of appendix 5. Selection criteria for including an insolvent firm in the sample were the following. Firstly, the firm should be organised as a joint-stock company as those firms were likely to be of medium or large size, and play an important role in the economy in terms of output and employment. Second, the sectors were defined using the failed company list and their respective industry codes available from the State Committee on Statistics. For consistency in accounts and similar experience of the transition process only manufacturing, retail, and construction companies were included. The non-failed company names listed in Table A5.10 of appendix 5 were selected randomly from the relevant sectoral lists of joint-stock companies at the State Committee on Statistics. The breakdown of the Russian company sample by economic sector (Table 5.1) shows that manufacturing firms prevail with

their dependence on the old branch ministries and become governed by commercial law common to both public and private organisations.

[104] Throughout the present thesis, in modelling UK company failure with both cross-sectional and panel data, a wider definition of failure as the event of entering insolvency proceedings is employed.

[105] However, net worth at book value, when distorted by inflation and periodic revaluations, required by the government to adjust for the impact of inflation, is likely to be a poor indicator of long-term solvency.

[106] The relatively small number of company insolvency cases in the mid-1990s, coupled with the absence of free of charge available company accounts, explains the small size of the Russian firm sample we obtained for this study. To alleviate the problem of model accuracy arising due to the small sample size, we support inference with the bootstrap.

Table 5.1 Sectoral Composition of the Russian Company Sample for 1995-96 (Percentages in parentheses)

	Economic Groups									
Sample	General Industrials		Consumer Goods		Services		Telecom-munications		Total	
Panel A: Sample Split into Estimation Sample (n=40, 1995) and Holdout (n=8, 1996)										
Estimation Sample										
Non-Failed	15	(75.0)	1	(5.0)	-	-	4	(20.0)	20	(100.0)
Failed	17	(85.0)	2	(10.0)	1	(5.0)	-	-	20	(100.0)
Holdout Sample										
Non-Failed	5	(71.4)	1	(14.3)	1	(14.3)	-	-	7	(100.0)
Failed	1	(100.0)	-	-	-	-	-	-	1	(100.0)
Panel B: Pooled Sample (n=48, 1995-96)										
Estimation Sample										
Non-failed	20	(74.1)	2	(7.4)	1	(3.7)	4	(14.8)	27	(100.0)
Failed	18	(85.7)	2	(9.5)	1	(4.8)	-	-	21	(100.0)

Table 5.2 Sectoral Composition of the Estimation Sample of UK Companies for 1990-91 (Percentages in parentheses)

	FT-SE Economic Groups									
Estimation Sample	General Industrials		Consumer Goods		Services		Utilities		Total	
Non-Failed	10	(50.0)	4	(20.0)	6	(30.0)	-	-	20	(100.0)
Failed	9	(45.0)	2	(10.0)	9	(45.0)	-	-	20	(100.0)

approximately 75 per cent of non-failed companies and 85 per cent of failed firms. The selected Russian firms seem also to be representative of the population in terms of size measured by employment: the mean and median values are 1 034 and 8 50 employees for the failed group, and 2216 and 1579 for the non-failed group.[107]

The State Committee on Statistics was the source of statutory financial statements, from which the accounting measures were drawn. Since publicly available records began in 1995, the failed company data one year prior to legal insolvency,[108] are based on accounting measures calculated from end-of-year financial accounts for 1995 and 1996. Similarly, non-failed companies were assigned from the same time-segment, a "year" to collect financial statement information.

The available data points were initially split into an estimation sample and a holdout sample with the intention of validating the model using fresh observations. There are 20 failed and 20 non-failed companies in the first estimation sample with data pertaining to 1995, and 1 insolvent and 7 solvent firms in the holdout, which uses accounting data for 1996 results. Additionally, in an attempt to take into account all available information, we utilise all 48 observations in model estimation.

The UK Company Sample

For the UK model, we equate company failure with the firm being placed on a formal insolvency regime: administrative receivership, or administration, or winding-up. We construct estimation and holdout samples of UK firms, by drawing observations randomly from the data set employed in chapter 3, a much larger cross-section. The names of failed companies were identified from various editions of the London Stock Exchange Official YearBook, and names for the non-failed category were on the "live" list of quoted industrials in the DATASTREAM database as of 13 February 1997. We aimed to achieve the closest possible correspondence with the Russian data set in terms of sample size and proportions of failed and non-failed companies. We also took account of the time frame by selecting macroeconomic

[107] Boeva and Dolgopiatova (1994) defined a medium-sized industrial enterprise as a firm with 500-600 employees for 1992 conditions.

conditions equivalent for the UK to the transitional depression state that has influenced enterprise failure in Russia. For comparison, we sample UK observations from the time period of a full-blown recession. However, as there exists no universally accepted definition of a recession, in deciding on the years to sample UK observations from, the annual unemployment rate (an aggregate business cycle variable) was used. Firstly, employment and unemployment typically respond with a lag to fluctuations in the level of economic activity. Second, according to PRIMARK DATASTREAM figures, the years 1991-93 saw a steady increase in unemployment. The unemployment rate was 8.0 per cent in 1991, 9.7 per cent in 1992, and 10.3 per cent in 1993. Assuming a one-year lag, we determined the period 1990-91 to draw accounts for UK companies. Twenty failed companies chosen for the estimation sample, issued their last accounts in either 1990 or 1991, and similarly, accounts of twenty non-failed companies were obtained for the same years. Lists of UK cases in the estimation sample for the comparative study can be found in Tables A5.7 and A5.8 in appendix 5.

Since holdout tests are employed for validating the UK model, we construct for the UK 25 random holdout samples each including 1 failed and 7 non-failed firms to resemble the structure of the Russian holdout. The holdouts pertaining to 1992-94, are random draws, without replacements, from the holdout observations employed in the cross-sectional study of chapter 3 (the company name lists, from which the observations have been drawn, can be seen in Tables A5.2 and A.5.4 of appendix 5). As for the sectoral composition, the UK sample is somewhat similar to the Russian data set: 50 per cent of non-failed firms and 45 per cent of failed firms in the randomly selected training sample, came from manufacturing (see Table 5.2).

Independent Variables

As discussed in chapter 2, models of company failure constructed for Western economies typically link a set of independent accounting ratio-based variables and a discrete dependent variable describing different states of company financial health. Ratio-based prediction models have enjoyed the relative success, proving that public

[108] Short history of financial records on individual companies, available in the public domain, precludes use of the analytical framework that chapter 3 employs, where completely different models are constructed for

accounts capture and quantify both the unique financial characteristics of the specific firm and macroeconomic pressures on the corporate sector, thus reflecting information sufficient for *ex-ante* identification of distressed firms (**Altman**, 1982). However, even a country with developed stock-markets, such as the UK, where the system of financial reporting seeks to serve the informational requirements of investors, financial statement ratios as failure determinants are bound to have certain limitations as they are computed by means of a set of accounting conventions based on judgements and opinion. The key examples of the subjectivity would relate to depreciation and stock valuation, accounting for convertible debt, classification of items under appropriate headings by nature and in terms of liquidity, historical cost accounting and accounting for inflation. Despite the trend towards standardisation, changes in accounting practice impact on values of accounting items and can cause inconsistency in data, affecting both the relevance of a particular measure to the conceptual variable of interest and the accuracy of failure risk prediction. An alternative route, taken to avoid those troublesome problems, is the use of equity market-based and non-financial indicators as model inputs.[109] Unfortunately, it is not feasible to implement this approach for the study of Russia, as equity market data do not exist for sampled companies,[110] therefore we take as a point of departure accounting ratio-based predictors.[111] In doing so we follow UK research by **Taffler and Tisshaw** (1977), **Marais** (1979), **Taffler** (1982 and 1995) **Goudie** (1987), and **Goudie and Meeks** (1991), where classification models rely on pure public accounts information.

It should be noted that the meaning of financial statements is conditional on the environment and that Russian accounting standards differ significantly from the Anglo-American tradition. At the time of compiling the data, statutory reports did

prediction horizons of one, two, three, and four years prior to failure.

[109] Several instances of studies, exploring non-financial indicators, are briefly reviewed in chapter 2. In modelling the event of failure with larger data sets of UK firms in chapters 3 and 4, to capture the influence of a wider range of factors, we add to the range of financial ratio-based covariates, a firm's duration term and macroeconomic variables.

[110] In 1996 (this year is covered by our sample for the study of Russian enterprises) the Russian stock market was thin with only about 80 equities quoted (*Rossiysky Credit Bank*, 1996). Listed industrials were predominantly represented by revenue-rich, in comparison with the rest of the economy, exporters, or natural monopolists from petroleum, metal, telecommunications, energy, extractive sectors, and also by distillers, enjoying trade in the protected domestic market.

not seem to satisfy the informational needs of creditors and investors. Supplementary reports based on international GAAP and audited, were virtually non-existent. However, the statutory set comprising the balance sheet and income statement, provided us with a consistent albeit basic information set necessary to identify and calculate a range of principal accounting ratios. Such ratios have been widely applied in the Russian financial analysis literature to assess enterprise performance and solvency (e.g. **Astakhov**, 1996).

As discussed in chapter 3, in terms of reported classification accuracy, a dominant ratio set does not appear to exist (**Hamer**, 1983). Also, there are no unique specifications of particular ratios or their components. The investigation of failure determinants is often exploratory due to the lack of substantive theories, and the researchers are trying to empirically identify useful discriminating ratios. In such situations it is common to start with a ratio set as comprehensive as feasible, representing the major financial dimensions. We have selected for the analysis of Russian company failure a set of 12 accounting ratios[112] along with the log of total assets, to control for enterprise size. This combination represents a relatively wide variety of covariates to capture dimensions of a firm's financial stance. The profitability dimension is given by the pre-tax profit margin, return on the long-term capital, and return on the net fixed assets. Turnover (or activity) indicators include stock turnover, shareholders' funds turnover, and the ratio of sales to total assets. Gearing, or an enterprise's total indebtedness, is proxied by three ratios. Firstly, capital gearing is obtained as a sum of the long-term debt and one year borrowings, divided by the value of the total assets net of intangibles. Second, we use a measure specific to the Russian practice of financial analysis, the cover for current assets out of shareholders' funds, (providing that fixed assets have been equity financed).[113] Thirdly, the ratio of total liabilities divided by total assets is considered. There also is a separate ratio of total debtors divided by total assets, which is used in Russia for

[111] It should be noted that in chapter 3 and 4 we use the phrase "financial ratio-based" models because initial sets of ratios for specifications, estimated in these chapters, include constructs with components based on equity market values.
[112] All Russian accounting ratios are unadjusted for inflation, as such adjustments require more detailed information on items from balance sheets and profit and loss accounts. In 1996, the annual inflation rate had fallen to 21.8 per cent (Source: *Russian Economic Trends*, 23 September 1997).
[113] For instance, this measure is utilised in Federal Insolvency Administration Materials (1994), and in Astakhov (1996).

the analysis of assets structure. Lastly, we utilise two liquidity ratios: the ratio of quasi-cash assets defined as a sum of cash, short-term investments and debtors divided by the short-term liabilities, and the current ratio.

Tables A4.1, A4.2, and A4.3 in appendix 4 present mean values and pairwise correlations of thirteen accounting-based explanatory variables for two estimation samples of Russian companies - for the sample of 40 enterprises and for the pooled sample of 48 enterprises. Univariate analysis of failed and non-failed groups (Table A4.1 of appendix 4) reveals that the significant differences between the categories of failed and non-failed enterprises arise from the following dimensions: size, profitability, and turnover. That provides support for the hypotheses about the irrelevance of liquidity and leverage in discriminating between failed and non-failed enterprises. Interestingly, the pattern of significance is similar for both estimation samples - for the sample of 40 companies and the sample of 48 companies. Pairwise correlation analysis for the Russian data (Tables A.4.2 and A4.3 in appendix 4) suggest that the potential explanatory variables are not highly correlated with each other. Hence, no variable may be viewed as redundant and as a result there is little evidence that multicollinearity may be a problem.

For the UK model, we utilised a standard set of accounting ratios available from the DATASTREAM database for quoted industrials. The set includes a size measure, which in the UK case is given by the logarithmic net sales, and 12 accounting ratios. Profitability is given by return on shareholders' equity, return on net fixed assets, and the pre-tax profit margin. Turnover is described by the ratio of net sales divided by fixed assets, stock turnover, debtors turnover, and creditors turnover. Gearing is measured by capital gearing and income gearing, and common ratios are employed for liquidity: the working capital (current) ratio, the quick assets ratio, and the ratio of stock and work in progress to current liabilities. We report the group means and correlations of covariates selected for the UK model in Tables A4.4 and A4.5 of appendix 4. For all financial dimensions, group means are significantly different for the failed and non-failed categories. It appears from the UK sample that, on average, relative to non-failed firms, solvent companies are typified by larger size, higher profitability, higher creditors turnover, lower gearing, and higher liquidity, thus confirming the results from the previous UK studies (see **Taffler,** 1982 and 1995; **Peel, Peel, and Pope,** 1986).

Methodological Problems Associated with Small Sample Estimation

To model the dependence of the response variable, proxying the event of failure, and the covariate vector, containing accounting ratios, logit is employed - the non-linear estimator common in studies of company failure (e.g. **Ohlson,** 1980; **Zavgren,** 1985; **Peel, Peel and Pope,** 1986; **Keasey and McGuinness,** 1990). Since we discuss the general format of binomial logit in section 3.2.3 of chapter 3, it seems sufficient here just to reiterate some methodological problems that might arise from small size and equal-share sampling of the Russian data set and similarly designed data set of UK firms.

A small and equal-share sample is likely to be a factor limiting the reliability of inference about model classificatory and predictive accuracy and as a result about the identified key determinants of financial distress. However, corporate failure studies often involve small sample sizes and independent variables that are skewed, collinear, and non-stationary, i.e. suffer from distributional problems of accounting ratios.[114]

First, the small size of the estimation sample results in a small number of observations from the response group per independent variable, that leads to the a model being overfitted and thus to less reliable parameter estimates and downward bias in the apparent error rate of classificatory accuracy. In the comparative study, we attempt to approach the evaluation of how well logit models estimated on small number of observations, capture the failure process, by employing three alternative solutions: an *ex ante* holdout sample test, bootstrap procedures, and Efron's formula[115] for estimating the bias in the apparent error rates in logit (**Efron,** 1986).

[114] Altman and Narayanan (1997) refer to a number of carried out in developed and developing countries classification studies into company failure, which, apparently viewed small paired samples as adequate, despite barely having sufficient number of cases of failed companies and publicly available data on them. For instance, only 21 failed and 21 surviving companies are used in the Australian study (Castagna and Matolcsy, 1982); 18 "sick" and 18 "healthy" companies formed a sample for the study of financial distress in India (Bhatia, 1988); and the Malasian study (Bidin, 1988) relied on paired sample of 21 distressed and 21 financially sound companies.

[115] Efron's formulation for the bias in the apparent error rates in logit, is presented in section 3.2.3 of chapter 3.

Several Russian samples are constructed to this end. Initially, the insolvent and solvent groups were each split into an estimation sample of data pertaining to 1995 financial reports, and a holdout sample taken from accounts for 1996. The narrow time frame for sampling leads to a holdout set that may not be sufficiently distinct in terms of time period from the primary sample, and as a result such holdout set risks overstating the forecasting power of the estimated model. The obvious alternative is to improve precision of the model by "sacrificing" the holdout data in order to increase the estimation sample size. In the second sample, all 48 data points are used to estimate the logit model. We account for the problem of small sample bias and size distortions in asymptotic tests by drawing inference from bootstrap distributions. Parameters and test statistics for logit are calculated by bootstrapping; the details of the bootstrap can be seen in the annex to the present chapter.

Second, as discussed in section 3.2.3, under equal-share sampling, the maximum likelihood estimation procedure for a binary logit model does not yield an unbiased estimate of the population probability of failure. It understates the model true error rate in predicting failed firms and overstates the true error rate in predicting "healthy" companies. Given that in Russia, in 1996 and 1997, the number of legally insolvent industrial enterprises, going into compulsory liquidation, was much smaller than the number of non-failed firms, one can conclude that the two categories have been sampled at different rates. Solutions, suggested in studies based on binary logit, include: (i) a correction procedure for the constant term of the model using the prior probabilities of the two outcomes and the sample proportions (**Palepu**, 1986), and (ii) the adjustment of the cutoff probability point to take into account the bias introduced by the unbalanced sample (**Eisenbeis**, 1977; **Taffler**, 1982; **Maddala**, 1992; **Altman**, 1993; **Greene**, 1993). Both methods require the estimates of prior probabilities for the populations of failed and non-failed firms. The obvious proxy for the prior probability of failure is the annual rate of enterprise insolvencies, however such data are not available for the Russian study, therefore the classificatory and predictive performance of logit models described below, is analysed by applying different cutoff probability values.

5.4 Empirical Results

The logit results for one year prior to failure, for both countries, are reported in Tables 5.3, 5.4, and 5.5. It is important to realise that the comparison with the UK model is used to validate the small sample results obtained for Russian companies. Failed companies form the response category and are assigned a 1, whereas non-failed companies were assigned a 0. That implies that a negative coefficient indicates that an increase in the ratio would reduce the probability of failure, and a positive coefficient suggests that a rise in the ratio increases failure risk. In modelling we start from 13 covariates and test down to the specific models. Variables were eliminated by using sequential Likelihood Ratio tests.

The Russian model R-$1_{L,}$ estimated on 40 data points (Panel A of Table 5.3), produces a somewhat disappointing result. It indicates that the ratio measuring return on the net fixed assets is insignificant, and the further three covariates, such as the pre-tax profit margin, return on the long-term capital, and stock turnover ratio are significant only at the 10% level, whereas the shareholders' funds turnover ratio is significant at the 5% level. The coefficients for significant variables have signs suggesting that failed firms are less profitable, have lower turnover and higher ratio of accounts receivable to total assets. The poor significance of the covariates might be attributed to the poor information content of the small Russian sample or to some collinearity amongst variables, though the overall performance is acceptable. However, standard inference, given the large sample criteria, may not be relied upon in this case.

Results for the UK model UK_L derived from 40 data points are reported in Table 5.4. The turnover ratio of net sales over fixed assets has an ambiguous positive sign, which could point to overtrading as a factor determining corporate failure for our data, although this variable is insignificant. The three covariates that are significant at the 5% level show expected signs consistent with previous UK work, indicating that lower profitability, higher gearing, and lower liquidity are likely to be the important determinants of the probability of insolvency. The similar association

Table 5.3 Logit Results for Russian Data, 1995 Estimation Period, Equal-Share Sample (n=40), One Year Prior to Failure

Panel A: **Logit Model R-1$_L$** (n=40)

Financial Dimension *Accounting Variable*	Coefficient (two-tailed p-value of asymptotic t-statistic)	
Constant	5.041	(0.041)
Profitability		
Pre-tax Profit Margin	-31.796	(0.056)
Return on Long-term Capital	52.810	(0.092)
Return on Net Fixed Assets	-23.568	(0.240)
Turnover		
Stock Turnover	-1.105	(0.059)
Shareholders' Funds Turnover	-3.327	(0.050)
Assets Structure		
Debtors/Total Assets	131.969	(0.060)

Log-Likelihood at Convergence	-8.13
χ^2 statistic of the log-likelihood ratio (p-value)	39.20 (0.000)
Likelihood Ratio Index	0.707

Panel B: **Classification and Predictive Ability**, Percentage

Cutoff Value	**0.125**	**0.25**	**0.5**
Estimation Sample			
Correct Classification			
Failed	95.0	95.0	95.0
Non-failed	60.0	80.0	95.0
Overall	77.5	87.5	95.0
χ^2 test for differences in probabilities[116]	18.14[a]	27.69[a]	37.18[a]
Overall Error Rate Bias Estimated by Efron's Formula	70.6	73.6	77.8
Holdout Sample[117]			
Correct Classification			
Failed	100.0	100.0	100.0
Non-failed	0.0	0.0	0.0
Overall	12.5	12.5	12.5
χ^2 test for differences in probabilities	0.0	0.0	0.0

[a] Significant at 0.001, 2-tailed.

[116] This χ^2 statistic (Conover, 1971, pp. 141-154)) tests whether there is a significant difference between the classification accuracy of a model and the naive model in which all firms classified as failed.
[117] The holdout sample includes accounting data on 1 failed and 7 non-failed Russian companies, for 1996.

Table 5.4 Logit Results for UK Data, 1990-91 Estimation Period, Equal-Share Sample (n=40), One Year Prior to Failure

Panel A: **Logit Model UK_L** (n=40)				
			Bootstrap Confidence Intervals for a Coefficient, 5000 Replications	
Financial Dimension Accounting Variable[118]	Coefficient	(two-tailed p-value of asymptotic t-statistic)	90% Confidence Interval	95% Confidence Interval
Constant	-2.219	(0.247)	(-99.512, 12.608)	(-283.665, 60.942)
Profitability				
Pre-tax Profit Margin	-0.240	(0.022)	(-11.590, -0.065)	(-29.686, -0.061)
Turnover				
Turnover / Fixed Assets	0.350	(0.131)	(-0.286, 14.076)	(-0.041, 38.107)
Gearing				
Capital Gearing	0.083	(0.028)	(0.008, 3.477)	(0.008, 8.284)
Liquidity				
Stock & Work in Progress/ Current Liabilities	-7.473	(0.026)	(-340.736, -1.065)	(-842.846, -0.592)
Log-Likelihood at Convergence			-10.18	
χ^2 statistic of the log-likelihood ratio (p-value)			35.10 (0.000)	
Likelihood Ratio Index			0.633	

Panel B: **Classification and Predictive Ability**, Percentage			
Cutoff Value	**0.125**	**0.25**	**0.5**
Estimation Sample			
Correct Classification			
Failed	100.0	95.0	85.0
Non-failed	70.0	70.0	85.0
Overall	85.0	82.5	85.0
χ^2 test for differences in probabilities	21.54^a	22.56^a	32.81^a
Overall Error Rate Bias Estimated by Efron's Formula	2.9	5.2	9.8
Bootstrap Estimates of the Expected Error Rate Bias, 300 Replications			
Failed	4.1	5.1	6.9
Non-failed	4.6	5.4	6.9
Overall	4.6	5.5	7.0
Holdout Sample[119]			
Correct Classification			
Failed	100.0	100.0	100.0
Non-failed	50.3	71.9	82.6
Overall	56.5	75.5	84.8
χ^2 test for differences in probabilities	3.82†	7.78^b	7.78^b

^{a} Significant at 0.001, 2-tailed.
^{b} Significant at 0.05, 2-tailed.
† Insignificant

[118] The pre-tax profit margin and capital gearing are expressed in per cent.
[119] The UK holdout results are the averages for 25 samples, which are randomly selected from the data set of chapter 3, specific to year one prior to the event of failure, and correspond to the period 1992-94. The mix of each random sample mimics the proportions of the Russian holdout sample, i.e. each UK random holdout includes 1 failed and 7 non-failed firms.

between changes along these three dimensions of financial analysis and the failure outcome is confirmed by the seven-variable model from the large cross-section of chapter 3 (see Table 3.3 of section 3.3.1). This seems to be a remarkable result, but it can simply be ascribed to the tremendous merits of random sampling employed in the UK model development in this chapter. The UK model, derived by applying a sturdy methodology of logit to a small-size but truly random sample, works because characteristics of all of the various types of firms in the population have a variability much closer to zero than to plus infinity, and hence the sampling units (firms) have a high degree of redundancy.

Turning to the analysis of classificatory and predictive power, which is used as a performance measure, then we find that both Russian and UK models perform comparatively well at correctly classifying observations in the training sample. Using different cutoff values, [120] overall accuracy varies from 77.5 per cent to 95 per cent for the Russian model R-1_L, and ranges between 82.5 percent and 85 per cent for the UK model UK_L (Panel B of Table 5.3 and Panel B of Table 5.4).

However, on the holdout observations, taken from outside the training sample time frame, the model R-1_L demonstrates no predictive ability. Obtained analytically by Efron's formula, estimates of the bias in the apparent error rate for the model R-1_L are consistent with the holdout test, as the bias values range from 70.6 per cent to 77.8 per cent indicating overfitting. The UK model UK_L forecast performance, when assessed on 25 random holdouts, mimicking the mix of failed and non-failed cases in the Russian holdout set, contrasts sharply with the Russian results, as the UK model appear to have some predictive power when, on average, it correctly classifies from 56.5 per cent to 84.8 per cent of holdout firms. The analytical estimates of the overall error rate bias vary from 2.9 per cent to 9.8 per cent also pointing out the predictive ability of the UK model derived from the small random sample. To see the sensitivity of inference, we also provide bootstrap estimates of prediction error. Estimates of optimism in the apparent error rate for the UK model, based on 300

[120] Classification errors are assumed to be equally costly in this study, and accuracy is given for a range of cutoff probability values. Raising the cutoff value increase Type I errors of misclassifying of a failed firm, whereas reducing the cutoff value increases Type II errors of misclassifying a non-failed firm.

bootstrap samples,[121] can bee seen in Panel B of Table 5.2. The downward bias in the overall error rate equals 4.6 per cent, 5.5 per cent, and 7.0 per cent for cutoff probability values of 0.125, 0.25, and 0.5, respectively, which is close to the range of values obtained from the Efron approximation. Then we can adjust the apparent error rate of the UK model by adding the estimated bias. Choosing the maximum values for optimism produced using the bootstrap and the Efron approximation, the improved estimates of the true overall error rate are 19.6 per cent, 23.0 per cent, and 24.8 per cent corresponding to 0.125, 0.25, and 0.5 cutoff values, respectively.[122] This assessment of the UK model overall accuracy is consistent with the results obtained from the holdout test when 0.25 and 0.5 cutoff values are used for classification. However, at the 0.125 cutoff probability, the inference differs from that based on the bootstrap and the analytical approximation, as the overall error rate of classifying holdout observations sharply rises to 43.5 per cent, indicating the poor predictive power.

The evaluation of the stability of the UK model predictive performance, via comparison between holdout and bootstrap results suggest that similar approach may aid a more developed analysis of Russia, although feasibility of such assessment would obviously require adequate holdout data. In summary, on the basis of the results for the model validation using bootstrap procedures, holdout tests, and the analytical approximation of the apparent error rate bias, one can conclude, that the important financial dimensions for distinguishing between failed and non-failed UK companies, are likely to be: profitability as measured by the pre-tax profit margin, gearing proxied by the capital gearing ratio, and liquidity shown by the ratio of stock and work in progress over current liabilities. These results are remarkably similar to other work on the UK both in the sense of forecasting performance and in terms of the isolated determinants of company failure (see e.g. **Alici**, 1995; **Taffler**, 1995). Furthermore, an interesting and important result is that a set of the discovered determinants conforms with the key dimensions of performance and financial

[121] Efron (1986) and Efron and Tibshirani (1993) state that 300 replications is an appropriate number of bootstrap replications to approximate prediction error for classification problems.
[122] The seven-variable model for one year prior to failure that is presented in chapter 3 and based on a larger cross-section of 421 company-years, demonstrates roughly the same predictive power judged by estimates of the overall prediction error. For the seven-variable model, the estimates of the true error rate vary from 14 per cent to 23.3 per cent, depending on the cutoff (see Panel A in Table 3.5 of chapter 3).

position, which are important for explaining failure risk in the firms included in a larger cross-section of chapter 3 (Table 3.3 in chapter 3). We note that the remarkable performance of the UK small sample points towards the success of the adopted here empirical design, highlighting benefits of recent techniques of iterative sampling methods in company failure modelling.

As indicated above, we attempt to improve the information content of the training sample for the Russian logit model by using all available 48 data points in estimation. The resulting logit model R-2_L can be seen in Table 5.5. The covariates defining the second Russian model R-2_L, reveal the financial characteristics crucial for identifying failed enterprises. As expected, liquidity and gearing ratios are absent from the final specification thus supporting hypotheses *H1* and *H2* that in terms of liquidity and gearing there exist no significant difference between Russian failed and non-failed industrial companies, for the analysis period.[123] The final set of three determinants includes the log of total assets (significant at the 5% level), the pre-tax profit margin (significant at the 1% level), and a ratio of shareholders' funds turnover (significant at the 10% level). The negative signs of the coefficients are consistent with the directions suggested by hypothesis *H3*, that failure is associated with lower profitability and slower turnover. The model also yields enterprise size, measured by the logarithmic total assets, as an additional failure predictor, implying that smaller firms have higher incidence of failure. Enterprise size might be important for a number of reasons. One is that larger firms provide employment and the social safety net and, therefore, they are likely to have more bargaining power in obtaining soft finance, because the cost to the society of large enterprise failures. Another reason is that larger enterprises might have easier access to short-term loans when approaching credit institutions, or stand a better chance in overcoming illiquidity problems by arranging debt for equity swaps. In addition to that, large firms might have more diversified operations and therefore have greater potential to succeed in the barter trade. However, we would not wish to overly stress the importance of the ratios found to be statistically significant as compared to the non-importance of the insignificant ratios as the latter may depend on the constructs of ratios selected and definitions of ratio components. In addition, the results seem to show a pattern broadly consistent with conclusions offered in **Lambert-Mogiliansky, Sonin, and Zhuravskaya** (2000), who find for Russia that such factors as firm's size and profitability of the industry[124] are inversely related to the probability of liquidation in bankruptcy.

As no new holdout observations are available to test the second Russian model, we set bootstrap confidence intervals for the parameters, based on 5000 replications[125] and constructed using the modified percentile method **(Davidson and MacKinnon,** 1993). For the purpose of comparison, we also estimated bootstrap confidence intervals for parameters of the UK model UK_L. Looking at the bootstrap results for Russia (Panel A in Table 5.5) we can see that the 90% confidence interval for the pre-tax profit margin coefficient, emphasises the statistical significance of profitability in explaining company failure, although, the 95% confidence interval indicates greater variation of the coefficient. Confidence intervals for the turnover ratio and the log of total assets say that their coefficients either closely approach or even include zero values thus indicating a much weaker relation between the covariates and the event of failure.

An interesting finding is that confidence intervals for the UK model parameters (Panel A in Table 5.4) also show large variability of coefficients for all ratios and do not rule out zero values, thus suggesting that financial measures, proxied by the covariates, might have no association with the event of failure. That revelation contradicts the UK model's performance in holdout tests making generalisation of such results less conclusive. We also use the bootstrap to assess the second Russian model's predictive performance to supplement classification accuracy as measured by the apparent error rate obtained from the training sample. The correct classification rate for the final Russian model $R\text{-}2_L$, obtained on the estimation

[123] It follows that the set of liquidity ratios, the Federal Service of Russia on Insolvency and Financial Rehabilitation have heavily relied upon in monitoring the enterprise sector (Federal Insolvency Administration Materials, 1994), would appear to be insufficient in diagnosing the risk of failure of an individual firm.

[124] But to the extent that profitability can be captured by cash flows approximated in Lambert-Mogiliansky, Sonin, and Zhuravskaya (2000) by costs per unit of output.

[125] We use here 5000 bootstrap replications, which appears to be an adequate number for obtaining bootstrap confidence intervals (see e.g. Efron and Tibshirani, 1993).

Table 5.5 Logit Results for Russian Data, 1995-96 Estimation Period, 21 Failed and 27 Non-failed Companies (n=48), One Year Prior to Failure

Panel A: **Logit Model R-2$_L$** (n=48)

Financial Dimension *Accounting Variable*	Coefficient (two-tailed p-value of asymptotic t-statistic)		Bootstrap Confidence Intervals for a Coefficient, 5000 Replications: 90% Confidence Interval	95% Confidence Interval
Constant	3.116	(0.024)	(0.737, 8.804)	(0.205, 11.443)
Size				
Log of Total Assets[126]	-0.544	(0.049)	(-1.452, 0.086)	(-2.097, 0.044)
Profitability				
Pre-tax Profit Margin	-12.529	(0.007)	(-28.991, -5.765)	(-38.946, -4.877)
Turnover				
Shareholders' Funds Turnover	-0.680	(0.072)	(-2.710, -0.087)	(-4.060, -0.069)

Log-Likelihood at Convergence	-14.39
χ^2 statistic of the log-likelihood ratio (p-value)	37.02 (0.000)
Likelihood Ratio Index	0.563

Panel B: **Classification and Predictive Ability**, Percentage

Cutoff Value	**0.125**	**0.25**	**0.5**
Estimation Sample			
Correct Classification			
Failed	95.2	85.7	85.7
Non-failed	59.3	74.1	92.6
Overall	75.0	79.2	89.6
χ^2 test for differences in probabilities	23.76[a]	35.00[a]	49.72[a]
Overall Error Rate Bias Estimated by Efron's Formula	3.7	6.1	9.6
Bootstrap Estimates of the Expected Error Rate Bias, 300 Replications			
Failed	6.3	5.1	1.8
Non-failed	4.0	3.2	0.7
Overall	5.2	4.2	1.3

[a] Significant at 0.001, 2-tailed.

[126] Total assets are measured in billions of roubles.

sample, varies from 75.0 per cent to 89.6 per cent (Panel B in Table 5.5), and might be unrealistically high as the same observations are used both for building and for assessing the model.

The bootstrap estimates of the downward bias in the apparent error rate range from 1.3 to 5.2 per cent, whereas Efron's approximation yields higher values from 3.7 to 9.6 per cent. When we correct for the bias in the apparent error rate, the estimated true error rate for the Russian model R-2_L forms an interval from 20.0 per cent to 30.2 per cent depending on chosen cutoff probability points. The assessed accuracy is analogous to the UK model UK_L, which yields the estimates of the true overall error rate from 19.6 per cent to 24.8 per cent. In summary, the R-2_L model validation on the basis of error rates obtained via bootstrapping and analytical approximation, supports the conclusion that profitability, turnover, and company size are likely to be the key indicators of failure risk, even given the small cross-section of Russian firms analysed.

In summary the results seems to suggest that the underlying structure of enterprise financial crisis may be changing through time and different across countries, especially when one compares a developed market economy vis-à-vis a transition country. Russian enterprise reforms, although extensive, were not coherent. We would inclined to think the Results onn Russia obtained in this chapter can be explained by the regime of transfers and subsidies characteristic of this transition country in the 1990s. Such traditional dimensions as liquidity and gearing will become relevant to financial distress and bankruptcy risk for Russian enterprises - as for UK firm they have been and are - once inter-enterprise arrears have been removed by market forces and the government have implemented programmes eliminating such cushions as bank credits on easy terms and arrears in payments due to government for taxes, custom duties, and social security. Bankruptcy as a mechanism of distress resolution will play a role in recourse reallocation when creditors become important agents of restructuring. Getting creditors to play this role in the Russian transition takes financial incentives, adequate information, and legal powers in debt collection.

5.5 Conclusions

We have constructed and compared the performance of failure prediction models for two countries: the UK and Russia. The resulting models implied the following determinants of failure: for the UK, measures of profitability, gearing, and liquidity; and for Russia, measures of enterprise size, profitability, and turnover. The classification and forecasting results are related to the year prior to failure. The strategy adopted in the comparative study allows for comparison of performance of Russian and UK models, in terms of their explanatory power and predictive ability. Firstly, we applied the principles accepted in the UK literature on failure modelling, to empirical research into Russian company financial distress. Account is taken of the specific micro and macroeconomic conditions relevant to the current position of Russian industrial enterprises. Secondly, given the small size and narrow time frame of the available Russian data set, we performed the UK study under similar conditions. A similar sized random sample of UK industrial companies is employed to permit correct comparison of the test statistics and diagnostics. Third, we conducted our empirical investigation of Russian enterprise failure using robust statistical techniques based on the well-known logit estimator supplemented by the bootstrap. Estimation and validation results from the Russian model were statistically significant and did not reject our hypotheses, that liquidity and financial indebtedness were unimportant in identifying failure for the specific environment associated with 1995-96, while profitability and turnover seemed to be important predictors. The model demonstrated acceptable classification accuracy and small apparent error rate biases. This is an interesting research outcome as it supports the potential use of models of Russian enterprise failure based on inputs derived from financial statements, to back-up more judgmental analysis. The Russian model results also support the theory that a Russian industrial enterprise has soft budget constraints, and emphasises the clear differences with the determinants of UK company failure where liquidity and gearing along with profitability are important in identifying corporate financial distress. The UK results performed well when compared with relevant UK models based on larger data sets.

It should be noted, that although the approach to model validation employed here makes the most use of the data available, evaluation results, based on just two years of data, must be interpreted with care, since they reflect the macroeconomic conditions and policy environment prevalent at the time of the analysis. A fresh holdout for Russia with more years of out-of-sample observations will provide for a sterner evaluation of enterprise failure model forecast accuracy and of the relevance of failure determinants. Subject to the obvious limitation of the sample used, the results presented here suggest that low profitability is the key indicator of failure. Liquidity measures, which even in the UK can be manipulated, are not relevant and that is not surprising given soft budget constraints. Size in the context of the Russian case provides a shield against failure, large firms would seem less likely to be allowed to fail. Turnover, which has no designation for sign, is the least important variable to differentiate the UK from the Russian case. Clearly, traditional failure risk measures, based on UK and US data and variables, are not valid for the analysis or prediction of failure risk at this still early stage of transition of Russia to the market.

The exploration of the experience of Russian enterprises vis-à-vis UK firms, undertaken in this chapter, makes a point that it is essential not to over-generalise because country differences can profoundly affect the relative importance of financial analysis dimensions. It seems that the current economic system of Russia makes the factors of indebtedness and liquidity irrelevant for enterprise survival. In the long run, on completion of stabilisation of what now looks as a relatively liberalised economy, through freeing Russia from macroeconomic instability and creating the essential institutions that foster competition, support far-reaching enterprise reforms, impose financial discipline and strengthen the tax system, the key factors of gearing and liquidity may do their work in explaining and evaluating bankruptcy risk of Russian private firms.

Accurate failure prediction is of use to exporters, to investors, and owners of interests in Russia. Furthermore, the Russian government might employ this type of methodology to calculate how sensitive the Russian enterprise sector might be to failure. Such analysis would appear preferable even on small samples to an analysis based on models from studies of the UK and the US.

Annex: The Bootstrap Approach Used in the Comparative Study

This annex explains the bootstrap procedures of chapter 5 by demonstrating how they are used in evaluating the relevance of the determinants of failure, and overall predictive performance of classification models derived from small samples. Specifically, bootstrap procedures are employed to: (i) construct confidence intervals for binomial logit model parameters and (ii) assess the bias in the error rate, or the difference between the true and apparent error of the prediction rule based on a logit function.

Widely used in the context of empirical work for model estimation, validation and hypotheses testing, bootstrap methodology[127] invented by **Efron** is an alternative to conventional asymptotic approximations, which, unless the sample size is very large, might not be sufficiently precise to allow to interpret model results with confidence. As **Veall** (1998, p. 419 and p. 423) puts in his survey:

> The bootstrap method may be regarded as a simulation study that is tailored to the actual data being studied, with the results used either to fill in statistical gaps that do not yield easily to analytical methods (such as providing standard errors or confidence intervals when they are otherwise unavailable) or to adjust the original statistical estimates in an attempt to improve finite-sample accuracy. ... the bootstrap does not create any additional information. It is simply a computational device to utilise information already in the original sample.

The bootstrap uses the single available data set to implement a sort of Monte Carlo experiment in which the data themselves are used to approximate the distribution of the error terms or other statistics in the model. It is based on the idea that the available sample is a good representation of the underlying population and the random quantities of interest are drawn not from an assumed distribution, such as normal, but rather from the empirical distribution of their sample counterparts.

[127] For the class of discrete response data, the paper by Fairclough and Hunter (1998), on *ex ante* classification of takeover targets using neural networks, uses a bootstrap pairs sampling algorithm, and a residual-based sampling algorithm to generate alternative standard errors and confidence intervals. Another recent example of applying the bootstrap tool for inference in a semi-parametric, discrete response model is in the study of UK mergers and acquisition activity by Hunter and Komis (2000).

Suppose a random sample $\mathbf{x} = (x_1, x_2, ..., x_n)$ from the unknown probability distribution F has been observed and we wish to estimate some statistic of interest $\theta = t(F)$ on the basis of $\mathbf{x}$. For that purpose one can calculate an estimate $\hat{\theta} = s(\mathbf{x})$. One way to obtain whatever features of the distribution of θ is to bootstrap the available set of data. **Efron and Tibshirani** (1993) use the following notion of a bootstrap sample. Let $\hat{F}$ be the empirical distribution function, putting probability $\frac{1}{n}$ on each of the observed values x_i. A bootstrap sample is defined to be a resampled version of $\mathbf{x}$ or a random sample of size n drawn with replacements from $\hat{F}$: $\mathbf{x}^*(i) = (x_1^*(i), x_2^*(i), ..., x_n^*(i))$, $\hat{F} \to (x_1^*(i), x_2^*(i), ..., x_n^*(i))$. Corresponding to a bootstrap data set $\mathbf{x}^*(i)$ is $\theta(\mathbf{x}^*(i))$, which represents a bootstrap replication of θ. B independent bootstrap samples yield B statistics $\theta(\mathbf{x}^*(i))$ and one can approximate the distribution of θ by the bootstrap distribution. The bootstrap as just described is called the non-parametric bootstrap for it is based on $\hat{F}$, the non-parametric estimate of the population F.

The resampling scheme adopted here is a variant of the parametric bootstrap used in **Adkins** (1990) for generating bootstrap samples for a binary response in a probit model, based on normal distribution.[128] Here we applied Adkin's variant to a binomial logit model, also a parametric binary response model. **Jeong and Maddala** (1993) stress that the benefits from bootstrap methods, in most cases of parametric binary response models, is only for small sample properties. In large samples, the parametric bootstrap does not outperform the maximum likelihood estimation, which gives asymptotically efficient estimators.

Applying Adkins' scheme to logit, defined as:

$$y_i = \frac{e^{\beta' \mathbf{x}_i}}{1 + e^{\beta' \mathbf{x}_i}} + \varepsilon_i, \tag{5.1}$$

[128] The residual resampling standard bootstrap is not appropriate for the discrete dependent variable case since the residuals have an incomplete distribution (Jeong and Maddala, 1993).

where ε_i is IID and has a logistic distribution, y_i takes values 0 and 1,

one can resample the response variable $\mathbf{y}^*$ and hence generate a bootstrap data set $(\mathbf{y}^*, \mathbf{x})$ by fist generating a vector of uniform random numbers $\boldsymbol{\varepsilon}^* \sim [0,1]$, and then calculating

$$\begin{cases} y_i^* = 1 \text{ if } 0 \le \varepsilon_i^* \le \Lambda(\hat{\boldsymbol{\beta}}' \mathbf{x}_i), \\ y_i^* = 0 \text{ if } \Lambda(\hat{\boldsymbol{\beta}}' \mathbf{x}_i) < \varepsilon_i^* \le 1. \end{cases} \tag{5.2}$$

A bootstrap data set $(\mathbf{y}^*, \mathbf{x})$ is then used to compute bootstrap replications of the quantity of interest: $\hat{\theta}^* = s(\mathbf{y}^*, \mathbf{x})$.

As mentioned above, in the comparative study, based on small samples, we are concerned with approximating confidence intervals of model parameters and estimating prediction errors of derived models of company failure.

First, we discuss one possible bootstrap tool to form confidence intervals. It is worth to emphasise the appropriateness of the construction of bootstrap confidence intervals based on the bootstrap distribution of a statistic, as compared to the approach of setting the endpoints by using the bootstrap standard errors. According to **Jeong and Maddala** (1993) the latter procedure is not sufficient because even if the asymptotic and bootstrap standard errors agree, there can be large differences in the corresponding confidence intervals if the bootstrap distribution is sufficiently skewed, thus producing different confidence intervals. One usual solution to this problem is to set confidence intervals using bootstrap percentiles (**Efron and Tibshirani**, 1993). Let $\hat{G}$ be a cumulative distribution function of a model parameter $\hat{\beta}^*$. The lower limit and the upper limit of the $1-2\alpha$ percentile interval are defined by the α and $1-\alpha$ percentiles of $\hat{G}$:

$$[\hat{\beta}_{\%lo}, \hat{\beta}_{\%up}] = [\hat{G}^{-1}(\alpha), \hat{G}^{-1}(1-\alpha)]^{129}. \tag{5.3}$$

Since by definition $\hat{G}^{-1}(\alpha) = \hat{\beta}^{*(\alpha)}$, the $100 \cdot \alpha$th percentile of the bootstrap distribution, one can rewrite the percentile interval as

$$[\hat{\beta}_{\%lo}, \hat{\beta}_{\%up}] = [\hat{\beta}^{*(\alpha)}, \hat{\beta}^{*(1-\alpha)}]. \tag{5.4}$$

For some finite number of bootstrap replications B, let $\hat{\beta}_B^{*(\alpha)}$ be the $100 \cdot \alpha$th percentile of the $\hat{\beta}^*(b)$ values, that is, the $B \cdot \alpha$th value in the ordered list of the B replications of $\hat{\beta}^*$. Similarly, let $\hat{\beta}_B^{*(1-\alpha)}$ be the $100 \cdot (1-\alpha)$th empirical percentile. The approximate $1-2\alpha$ percentile interval is

$$[\hat{\beta}_{\%lo}, \hat{\beta}_{\%up}] = [\hat{\beta}_B^{*(\alpha)}, \hat{\beta}_B^{*(1-\alpha)}]. \tag{5.5}$$

If the empirical distribution function of the parameter is asymmetric it is no longer optimal to omit the same number of $\hat{\beta}_b^*$ from each end of the empirical distribution function. One can follow **Davidson and MacKinnon** (1993) and **Johnston and DiNardo** (1997) in using the modified percentile approach, which tends to move the confidence interval away from the longer tail of the distribution, thus allowing to find the shortest interval that includes $100 \cdot (1-\alpha)$ per cent of the $\hat{\beta}_b^*$. As given in **Davidson and MacKinnon** (1993) the modified percentile interval is constructed by minimising the quantity:

$$\frac{1}{2}\left(\hat{\beta}^{*(l+(1-\alpha)B)} + \hat{\beta}^{*(l+(1-\alpha)B+1)}\right) - \frac{1}{2}\left(\hat{\beta}^{*(l-1)} + \hat{\beta}^{*(l)}\right), \tag{5.6}$$

with respect to the positive integer $l < \alpha \cdot B$.

[129] The value α is the significance level for the one-sided hypotheses that the true parameter is greater (less) than β. Also, hypothesis tests can be carried out by constructing a confidence interval and then checking whether the null value is in the interval.

We turn now to the description of the bootstrap procedure due to **Efron and Tibshirani** (1993) used here for estimation of prediction error. In classification problems, prediction error is commonly defined as the probability of an incorrect classification: $PE = \text{Prob}(\hat{y} \neq y)$, where y is a future response and $\hat{y}$ is its prediction from the model. PE is also called the misclassification rate.

Let the data $(y_1, x_1),...,(y_n, x_n)$ be an IID sample from the multidimensional distribution F, where y_i indicates a class membership of the ith observation. We apply a prediction rule to the training sample and form the realised prediction rule $\hat{\eta}$, given by expression (3.13).[130] Let $Q[y_0, \hat{\eta}(x_0)]$ be the criterion that measures the error between an observed value y_0 and prediction $\hat{\eta}(x_0)$. The true error of the realised prediction rule $\hat{\eta}$ is defined as the expected error that $\hat{\eta}$ makes on a new observation (y_0, x_0) from F:

$$\text{err}(\hat{F}, F) \equiv E_{0F}\{Q[y_0, \hat{\eta}(x_0)]\}. \tag{5.7}$$

A possible estimate of prediction error is the proportion of errors that the realised prediction rule $\hat{\eta}$ makes when applied to the original observations $\mathbf{x}$, or the apparent error rate.

The apparent error rate is quantified by

$$\overline{\text{err}}(\hat{F}, \hat{F}) = E_{0\hat{F}}\{Q[y_0, \hat{\eta}(x_0)]\} = \frac{1}{n}\sum_{1}^{n} Q[y_i, \hat{\eta}(\mathbf{x}_i)], \tag{5.8}$$

because $E_{0\hat{F}}$ simply averages over the n observed cases of the data. The apparent error rate underestimates the prediction error. The difference between the true prediction error and the apparent error rate is defined in **Efron and Tibshirani** (1993) as the optimism in the apparent error rate:

[130] In section 3.2.3 of chapter 3 we discuss the prediction rule for logit.

$$\Omega(\hat{F},F)=\mathrm{err}(\hat{F},F)-\overline{\mathrm{err}}(\hat{F},\hat{F}). \tag{5.9}$$

The expected optimism is

$$\omega=E_{\hat{F}\sim F}\Omega(\hat{F},F), \tag{5.10}$$

where the expectation is taken over $\hat{F}$, which is obtained from the sample generated by F. To correct for the downward bias one can employ the bootstrap. A bootstrap replication of the downward bias is computed as

$$\omega_b^*=\frac{1}{n}\sum_{i=1}^{n}Q[y_i,\hat{\eta}^*(\mathbf{x}_i)]-\frac{1}{n}\sum_{i=1}^{n}Q[y^*{}_i,\hat{\eta}^*(\mathbf{x}_i)]. \tag{5.11}$$

The bootstrap approach in **Efron and Tibshirani** (1993) estimates the bias in the apparent error rate as an estimator of the prediction error. To approximate the final estimate of prediction error, the apparent error rate is corrected by adding the downward bias:

$$\frac{1}{n}\sum_{1}^{n}Q[y_i,\hat{\eta}(\mathbf{x}_i)]+\frac{1}{B}\sum_{b=1}^{B}\omega_b^*. \tag{5.12}$$

CHAPTER 6: SUMMARIZING REMARKS AND SUGGESTIONS ABOUT POLICY ISSUES AND FURTHER RESEARCH

The substance of the present thesis is two studies, contained in chapters 3-5. The first study examines the determinants of industrial company failure in the UK for the late 1980s and early 1990s, and the second study is concerned with a comparative analysis of the industrial company failure determinants for Russia and the UK in the 1990s. Both analyses explore the relationship between the characteristics of the company's financial profile and the outcome of failure, which is proxied here by the state of involuntary insolvency. The UK company failure analysis with firm-level data, allows also for the effects of the macroeconomic factors.

Presented in chapters 1 and 2 overviews of the literature, concerned with economic and financial aspects of company distress and seeking to isolate the failure determinants, appeared to indicate the lack in most company-level empirical investigations of a unified analytical framework, which relates the risk of the adverse outcome to variables derived from company accounts. In past research based on company-level data, there appeared to be no agreement about which accounting-based measures can explain the failure outcome best and, therefore, previous studies employed variables reflecting main dimensions of financial analysis, such as profitability, liquidity, gearing and efficiency (turnover). The literature, which deals with the aggregate rate of insolvencies, points to the important independent explanatory role in company survival of the changes in macroeconomic conditions. Given model uncertainty in relation to accounting-based explanatory measures, in the present thesis, we isolate empirically the firm-specific determinants of company failure using a conditional probability model. Such framework has often been employed in past firm-level research to discover the determinants of failure by examining the associations between failure risk and a wide range of indicators, based on publicly available information from financial accounts and market prices of equity and debt. This modelling approach, which depends on the assumption that company accounts and market valuation variables capture tendencies in both the firm's characteristics and in the market environment, has been accepted by academics and recognised by practitioners because of satisfactory predictive power of empirical models. Specifically, for both cross-sectional and panel data, we use familiar binomial logit estimators allowing us to detect the key determinants of failure, interpret their relative importance, and validate the results by assessing out-of-sample predictive power of parsimonious models. Empirical design reflects developments in the UK and US literatures on involuntary insolvency (bankruptcy) prediction, on models for discrete dependent variables, and on the bootstrap, in particular, in work by **Chamberlain** (1980), **Ohlson** (1980), **Zavgren** (1985), **Efron** (1986), **Palepu** (1986), **Peel, Peel, and Pope** (1986), **Peel and Peel** (1988), **Adkins** (1990), **Keasey and McGuinness** (1990), and **Efron and Tibshirani** (1993). In the UK study, we base empirical evidence on a relatively large, resembling the true population proportions of failing and non-failed firms, cross-section sample and a panel, covering the UK recession of the early1990.

As one would expect, the results for Russia, provided in chapter 5, stand in contrast with the results for the UK, therefore, findings from the two studies appear to have some value taken individually. Firstly, this is because of obviously different economic, institutional, and regulatory settings in which an individual, private firm exits via the route of legal insolvency. Secondly, the limitation of a small Russian data set led us to opt for the comparative analysis format in order to interpret better broad tendencies as to the key determinants of Russian industrial enterprise failure, detected in the data. Sample size and time-period have a big effect on the choice of plausible explanatory factors, which can be modelled, and on the comparability of results from econometric analysis, across the two countries.

Accordingly, for the Russian study, we modelled failure for the one-year risk-horizon and restricted the variety of possible model inputs to 13 measures observable from statutory accounts, while in a large-scale, cross-sectional analysis of UK firms, where failure was modelled over longer risk-horizons - up to four years before the event - 25 financial statements-based inputs were supplemented by firm's age and macroeconomic indicators. Moreover, it was important to explore how well a model, derived from a small sample of Russian firms, would detect the linkages between explanatory variables and the probability of failure. Thus, in the absence of fresh holdout observations, we felt that the format of comparative study would provide a complementary means for validating the results for Russia. We indirectly control for the Russian sample size, by applying a binomial logit model to a small, equal-share, selected at random data set of UK firms. It appeared that the UK model, derived from this small sample, did capture the essence of reality, as it yielded a set of correctly signed predictors and performed satisfactorily at classifying *ex ante* new holdout firms, broadly conforming with the evidence from the UK studies based on larger data sets. The estimate of prediction error for this UK model, at a conservative cutoff probability value of 0.125 was 19.6 per cent. This performance supported the explanatory power of the pre-tax profit margin, the capital gearing ratio, and the ratio of stock and work in progress over current liabilities, which, in turn, implied that the dimensions of profitability, gearing, and liquidity discriminated between failing and non-failed UK firms at the one-year risk horizon. It follows that modelling the failure determinants with a modest in size, random sample might produce fairly interpretable results, thus lending further indirect support to the significant central factors of enterprise insolvency implicit in the model for Russia.

An interesting and novel feature of our Russian work is the use of bootstrap procedures to infer the significance of model parameters and predictive ability. Setting the cutoff probability value at 0.125, the estimate of prediction error, generated by the Russian model, was 30.2 per cent, roughly analogous to accuracy rates reported in the UK study by **Alici** (1995), who examined corporate failures in the early 1990s. Based on bootstrap estimates, perhaps the most important result of our comparative work is that the Russian model implies no association between the risk of legal insolvency and changes in variables, reflecting the liquidity position and level of indebtedness. This finding supports the proposition that, at least over the analysis period, Russian firms faced soft budget constraints and extensively relied on barter. Moreover, the results show fairly clearly that profitable and large Russian firms were more likely to survive the state of severe illiquidity and financial distress, which would appear to suggest that the actual implementation of Russian bankruptcy laws staved off imminent insolvency of large and potentially valuable enterprises.

We should also add that, as yet, no similar work on modelling the Russian enterprise insolvency determinants with data from statutory financial statements has been reported in the literature. Therefore, while it might not be difficult to believe that our results for Russia are true, they still should be treated circumspectly. Due to limited resources available for this Russian work, the time period, over which we traced the failure determinants for Russian firms, is rather short. Undoubtedly, a larger sample of enterprises observed over a longer period of time is necessary to see how robust our results are to the sample period. Larger data sets will permit to model the more subtle effects that changes in the firm's financial performance might have on the risk of failure over the transition from plan to market. Further, to provide a broader view to inform the policies of the government, domestic and foreign investors, and international agencies involved in economic reforms in Russia, it would seem important to move the research focus away from mere changes in enterprise performance towards investigating more directly the role in enterprise survival of such factors as characteristics of ownership, corporate governance, managerial flexibility, industry sector, regional location, and employment.

In contrast, for the UK, to permit an exploration of the finer aspects of the failure process and to examine the influence of non-financial factors, we created a decent-sized cross-sectional sample and, in addition, constructed a panel data set, both covering company failures during the recession that occurred in the UK in 1990-92. Our UK work, which is reported in chapters 3 and 4, focuses on large quoted industrials and complements the empirical results provided by previous firm-level studies of UK company failure. We have introduced the following two extensions to the UK past literature. First, inference from research into aggregate rates of company insolvency led us to examine, within a traditional for cross-sectional data studies framework, a more complete model of the determinants of company failure by adding to a set of accounting-based indicators the two variables, which capture aggregate economy risk. To allow macroeconomic influences to feed through company financial results within a year or so, we considered annual, unanticipated changes in macroeconomic variables, using one-year lagged interaction terms. Reported in chapter 3 cross-sectional models condition the risk of failure upon changes in the nominal interest rate and in the real exchange rate. Second, in chapter 4, when modelling the failure determinants with panel data we allowed for unobserved heterogeneity across firms.

In the cross-sectional analysis of UK firms, presented in chapter 3, to permit a temporal aspect to appear in explanation of causes of failure, we constructed several series of time-to-failure-specific logit models and isolated the failure risk determinants for each of the four years prior to failure. We have started with a set of time-to-failure-specific cross-sectional models, based on 25 financial covariates, representing traditional dimensions of financial analysis. This general specification was then augmented by adding a control for firm's age and the terms, representing unanticipated shifts in the nominal interest rate and in the real exchange rate. To reveal the important determinants we estimated and then assessed the out-of-sample classificatory accuracy of the four sets of parsimonious models. These included: (i) basic models based on financial variables alone; (ii) models based on financial variables and one-year lagged unanticipated changes in the exchange rate and interest rate; (iii) models based on financial variables and a proxy for firm's age; and (iv) models based on financial variables, a proxy for firm's age, and one-year lagged unanticipated changes in the exchange rate and interest rate.

All estimated with the cross-sectional data logit models were found to be highly significant and being capable of producing predictions, which compared favourably with random selection for a wide range of cutoff probability values. We stress that this result can be taken as indicative of the relevance of the modelled determinants. Across all models, the estimate of the overall prediction error, obtained from Efron's approximation, was in the vicinity of 30 per cent. However, when models were confronted with the most severe test – out-of-sample classificatory ability - more complete models performed better on holdout samples. In particular, the predictive power of models, constructed for identifying failure in three-year time and four-year time in the future, appeared to be enhanced by incorporating macroeconomic variables. Remarkably, in holdout tests, the four-year-prior model that conditioned predictions on unanticipated changes in the two macroeconomic variables, approximated both failed and non-failed firms more accurately, than a simpler, financial ratio-based model. Specifically, it demonstrated stable rates of correct predictions across a wide range of cutoff probability values, improving on the overall accuracy by 15.6 per cent at a conservative cutoff classification point of 0.1.

This gain in accuracy over *ex ante* holdout tests, considered together with highly significant coefficients for the two macroeconomic variables, appears to suggest that for the years before and during the 1990s recession, shifts in the real exchange rate and rises in the nominal interest rate were associated with a higher propensity of a large industrial company to fail, thus indicating the links to a loss in competitiveness and the effect of high gearing. The finding that this "outperformance" was shown for the risk-horizons longer than two years, points to the importance of relationships between changes in the macroeconomic environment and the risk of bankruptcy, signalling the need to promote macroeconomic stability to contain default risk. Our results highlight that changes in macroeconomic conditions should be an important ingredient of any extension of empirical models of company failure determinants.

To better capture factors influencing company failure, an attempt was also made to control for firm's age, the factor that, as was concluded by previous studies of the UK, inversely relates to the probability of failure. The models, based on financial ratios, two macroeconomic variables, and age, demonstrated stable rates of overall accuracy across the whole range of cutoff values, achieving the in-sample correct classification rate of 90.6 per cent and better for the one-year risk-horizon, and 71.9 per cent and better for horizons of three and four years. However, prediction did not improved. We found that, with the exception of the three-year horizon, the out-of-sample classificatory ability of most of the models that contain both the two macroeconomic variables and the control for duration, was rather similar to that of the simpler models, the specifications allowing for the macroeconomic effects but without the duration term. These results did not seem to be indicative of the particular usefulness of a duration control in financial ratio-based models of company failure. It appeared that for our data set, the proxy for firm's duration did not contain new information not already captured by a wide range of covariates derived from financial statements.

As far as the financial ratio-based determinants of failure are concerned, our overall results from the cross-sectional analysis show a strong positive association between gearing and the probability of failure; this effect of high gearing was robust to augmenting model specifications by non-financial variables. Coefficient estimates of gearing ratios are significant in all specifications and over all years preceding failure. The strong influence of changes in the nominal interest rate, combined with the observed strong effect of gearing, seems to indicate that the companies that went bust over the period 1988-91 had severe problems in meeting their debt obligations. The capital gearing of UK industrial and commercial companies rose significantly over the early 1990s, being about three times higher than in the first Thatcher recession of 1980-81 (*Bank of England Quarterly Bulletin*, August 1993). In the early 1990s, companies experienced a sharp decline in the growth of orders, subdued equity issues, and were affected by a fall in short-term interest rates following the stock market crash of October 1987. That encouraged companies to issue long-term debt and increase short-term borrowing with the unhealthy reliance on overdrafts and other short-term lending. A drawback to short-term finance is that a failure to rearrange the agreement can be devastating for the borrower. A sharp rise in interest rates from 1988 increased companies' debt service costs while the subsequent recession lowered companies' ability to service debt.

If firm's age and unanticipated shifts in the two macroeconomic variables were uncontrolled for, then liquidity negatively related to the probability of failure for most of risk-horizons, whereas the profitability variables had a negative effect on failure risk at the shortest, one-year horizon. However, when model specifications were controlling for firm's age and predictions were conditioned on the changes in the macroeconomy, the liquidity dimension became unimportant, but profitability differences between failing and non-failed firms were evident both over the shorter horizons and over the longer horizons. The effect of turnover was implicit in models unconditioned on macroeconomic factors. The pattern of signs of coefficients on turnover measures was unstable over the risk-horizons analysed and appeared to suggest that, in the earlier years, fast growth and overtrading were associated with the risk of failure, whilst in the last year before failure lower turnover pointed to low efficiency and higher failure risk. It is also worth stressing that since our data cover only one recession, the UK results reported in this thesis are likely to be specific to the late 1980s and early 1990s.

To examine more rigorously the impact of changes in corporate performance on the risk of failure, in chapter 4 we modelled the failure determinants for a panel of UK large quoted firms observed over the period 1988-93. We emphasise that the panel element of our study is of tremendous importance. The main advantage of modelling with panel data was that this empirical design allowed us to correct for unobservable, firm-specific, time-invariant factors, which were likely to be associated with failure risk. The corporate finance literature suggests the potential explanatory power of such factors as ownership characteristics, corporate governance, technological and managerial qualities, industry-specific influences, business location, market position and export intensity, however previous empirical studies failed to address the problem of allowing in modelling financial distress for the effects of these factors. Given the nature of our panel data, which contains only large quoted industrial firms, we adopted a fixed effects approach and allowed for fixed unobserved parameters by using Chamberlain's conditional binomial logit model.

We found a noticeable degree of unobserved heterogeneity across companies in the panel, which implies that the panel data estimates were preferable to the cross-sectional estimates. As one would expect, the results from the panel data yielded the set of key explanatory variables and corresponding, broader dimensions that somewhat disagreed with the pattern implied in our cross-sectional models. The major difference lies in the absence of gearing variables amongst the key determinants of failure, although this finding can be explained by the possibility that the gearing factor is captured by individual-specific, permanent effects. Further, our panel results showed that, after controlling for unobserved firm-specific factors, lower liquidity, measured by the quick assets ratio, and slower turnover, proxied by the ratio of debtors turnover, were linked to the higher risk of insolvency over the 1990-92 recession. The fixed effects models also suggest that profitability played an important independent role, although the observed pattern of the coefficient signs of profitability proxies is rather puzzling, as all models feature a positive coefficient on the net profit margin and a negative coefficient on the pre-tax profit margin. We attempted to offer a tentative interpretation that the positive sign of the coefficient on the net profit margin could reflect an accounting treatment of associates in consolidated accounts of the company that has subsidiaries and where subsidiaries' profits impact significantly the overall performance of the group. Under the equity accounting method, a holding company or group might have showed a higher net profit margin but a lower pre-tax profit margin, simply because the consolidated profit and loss account of the group must report proportional profits of its associates attributable to the parent company by reason of its shareholding. It is worth noting that profits of associates, attributable to the group, do not indicate accessibility or cash flow, but rather a fair share allocation. However, more future research with additional and more detailed data will be needed to see what has caused the observed here mixed performance of profitability measures.

In contrast to cross-sectional models, the panel data analysis clearly demonstrated that failing firms were not only illiquid but also insolvent since all models record a meaningful negative association between the probability of failure and changes in net worth, proxied by the index of net tangible assets. Overall, when we contrast the two types of evidence, obtained in this thesis with the cross-sectional and panel data, the bottom line seems to be that the major dimension discriminating between failed and non-failed firms in our samples was liquidity. This result was found to be very robust, supporting the evidence from the study by **Turner, Coutts, and Bowden** (1992) who contend that the current cash-flow considerations, rather than the future prospects of the firm, determined company failures over the 1990s recession. The potential for the robust predictive performance of the failure determinants points to the importance of creating a framework for encouraging lenders to employ on a greater scale empirical measures of credit risk of their borrowers so as to analyse and monitor the financial position of firms regularly and more closely. Early detection by the lender of the danger of distress of the borrower should result in more successful restructurings and preserve financial stability.

We have tried to show that empirical modelling of the determinants of failure is useful for understanding the process of financial distress at the company-level and therefore may be of some assistance in informing responsible lending by banks and authorities' economic policies, aimed at maintaining stability. However, our study left for future work a number of other important questions.

We did not attempt to explain the role in the failure process of the structure of short- and medium-term debt finance and, in particular, the role of trade credit that due to cheapness and flexibility makes up an important part of the funding needs of UK companies. In future work, the link between company survival and the degree of reliance on a simplest and "free" short-term source of trade credit should be examined in greater detail and in combination with some kind of industry adjustment in the empirical analysis.

Granting trade credit is, in effect, the granting of a loan. The credit provider usually relies on an assessment of credit risk provided by a credit reporting agency who make the their judgement or assessment as to the trade partner or borrower creditworthiness, based on information from company accounts and macroeconomic forecasts. Similar to insolvency announcements, credit rating downgrades represent clear events of distress and were used in past analyses of company failure to operationalise the concept of failure and derive the probability of default (see, e.g., **Johnsen and Melicher** (1994), **Crouhy, Galai, and Mark** (2000)). But there is also an obvious way to extend the scope of analysis of UK company distress by seeking an explanation of how perceived assessments of creditworthiness in the form of credit quality spreads could modify the risk of corporate failure. This future work will require an extended version of the used in the present study data sets of UK firms.

This thesis has provided the first panel-data documentation of the effects that the accounting-based, company-level characteristics had on distress risk of UK firms during the 1990s recession. Given a relatively short sample period, it was not possible to allow in our panel model for the business cycle influence and for the factors underlying the banks' unwillingness to extend debt maturities of distressed firms, which lead to high liquidation rates in the early 1990s. The question, which merits further investigation, is how the relative importance for company survival of firm-specific, accounting ratio-based factors would change if an analysis, similar to that undertaken in the present thesis, were performed with the data representative of the first Thatcher recession of the early 1980s. The panel data methodology, which reinforces information on trend, has good potential to provide an empirical answer to this question. This future work can assess the impacts both of recessionary climate and of changes in banks' behaviour, by allowing in modelling for external economic, credit and industry conditions, which will require additional, going back to the late 1970s, macroeconomic and company accounts data.

Lastly, the story that the models built in this study tell about the key role in failures of the sample companies, of insufficient liquidity and gearing, seems consistent with the fact that, over the analysis period, administrative receivership - a creditor-oriented regime in the 1986 UK Insolvency Act - represented the dominant proportion of UK total company insolvencies. The institutional framework for insolvency affects the determinants of financial failure and creditors' myopia, implied in our models, is the research result that has important implications for the debate about further policy reforms on insolvency in the UK. The procedure of administrative receivership seemed to provide the banks with an incentive to be lazy in planning for a possible slow-down in the economy, in monitoring financial health of firms and in pre-empting debt repayment problems. Therefore one of the central questions about financial distress of UK companies, is how creditor-oriented insolvency provisions affect the efficiency of financial distress resolution. It should be noted, however, that the ability of secured lenders to appoint a receiver is fundamental to the operation of the market system. As a contractual solution to the conflicts of interest, administrative receiverships have provided major benefits in terms of speed, flexibility, and control in enforcing performance of debt contracts.

Over the recent decade, the procedure of administrative receivership has been subject to criticism because of its tendency to disregard the economic value and potential to restructure of the debtor-firm (see, e.g., **Armour and Frisby** (2001), **Franks and Sussman** (2002)). In case of default, an administrative receiver, appointed by the holder of the floating charge (the bank), has, without considering the interests of other stakeholders, in particular unsecured creditors, full discretion over whether to realise the firm's assets by selling the firm as a going concern or to liquidate it piece meal. Banks effectively take control of the debtor-firm and may be careless with respect to the indirect costs of bankruptcy. When the firm's economic value exceeds its liquidation value, such concentration of control rights in the hands of one lender was seen as a shortcoming of the insolvency provisions available in the 1990s. Collateralised and concentrated in the hands of one lender lending was viewed as a factor, which encouraged precipitate behaviour on the part of banks, causing companies to fail unnecessary in the early 1990s and imposing a barrier to enterprise, productivity, and innovation (Insolvency Service (2001): *Insolvency - A Second Chance*)). Furthermore, the available mechanisms, intended to promote a rescue culture by providing the economically efficient firm with temporary protection from creditors' actions such as administration and company voluntary arrangement procedures, have not functioned well since the holder of the floating charge (the bank) had the power to veto both procedures and appoint a receiver instead. The new Enterprise Act 2002 has tried to implement more debtor-oriented approaches by amending administrative receivership and thus promoting a corporate rescue culture.

One way to guard against the threat of inefficient liquidations of companies and to inform a judgement about the overall efficiency of insolvency law as a financial distress resolution device, is to establish to what extent liquidations of economically efficient companies are influenced by the insolvency law orientation. The question can be investigated empirically, although the empirical design will need to address the problem of the absence of a clear benchmark of economic efficiency. Clearer implications for the discussion and debate about the efficiency of UK insolvency law can be generated in a large longitudinal study which will compare the determinants both of involuntary insolvency and of economic distress of the UK large quoted firms with the causes, underlying company failure, in countries with a more debtor-oriented bankruptcy code, such as the US. Given that existing evidence of the efficiency of the selection process, triggered by financial distress, is mixed and limited (**White**, 1989 and 1994; **Kahl and School**, 2001) it would be important to create a panel of firms containing a group of economically but not financially distressed firms alongside another group of the financially distressed firms. This important extension to the work, presented in this thesis, will also help to highlight the role of debt in the reallocation of assets.

APPENDIX 1: COMPANY INSOLVENCY IN ENGLAND AND WALES IN 1988-94

Table A1.1 Company Insolvency in 1988-94, England and Wales
(*Source*: Department of Trade and Industry, 1997)

TYPE OF INSOLVENCY	1988	1989	1990	1991	1992	1993	1994
Company Insolvencies - England and Wales							
Total	9,427	10,546	15,051	21,827	24,425	20,708	16,728
Compulsory Liquidations	3,667	4,020	5,977	8,368	9,734	8,244	6,597
Creditors' Voluntary Liquidations	5,760	6,436	9,074	13,459	14,691	12,464	10,131
Proceedings Related to Insolvency - England and Wales							
Receiverships	1,094	1,706	4,318	7,515	8,324	5,362	3,877
Administrator Appointments	198	135	211	206	179	112	159
Voluntary Arrangements	47	43	58	137	76	134	264
Companies on Register, England and Wales, thousands							
	864,4	1075,9	1115	1125,1	1117,9	1074,6	1058,6
Overall Rate of Insolvencies and Proceedings Related to Insolvencies,[131] percentage							
	1.2	1.2	1.8	2.6	3.0	2.4	2.0

[131] Insolvencies and proceedings realed to insolvencies relative to the number of companies on the Register.

APPENDIX 2: VARIABLE DESCRIPTIVE STATISTICS FOR THE CROSS-SECTIONAL ANALYSIS OF UK COMPANY FAILURE

Table A2.1 Means and *t*-statistics - Independent Variables for the Estimation Samples used in the Cross-sectional Analysis of UK Companies, Sample Period 1988-91, 53 Failed Companies and 368 Non-failed Company-Years, One and Two Years Prior to Failure

Financial Dimension	One Year Prior Mean (n=421) (Normalised Values)			Two Years Prior Mean (n=421) (Normalised Values)		
Accounting Variable	Failed	Non-failed	*t*-value	Failed	Non-failed	*t*-value
Size						
Log of Total Sales (Net of Trade Discounts)	-0.330	0.094	3.70***	-0.451	0.077	4.18***
Profitability						
Return on Shareholders' Capital	0.200	-0.002	1.05	-0.414	0.043	2.65***
Return on Capital Employed	-0.526	0.069	4.61***	-0.367	0.026	2.94***
Return on Net Fixed Assets	-0.442	0.046	3.97***	-0.398	0.002	2.83***
Cumulative Profitability	0.227	-0.005	1.06	-0.237	0.026	1.73*
Operating Profit Margin	-0.334	0.063	4.11***	-0.564	0.048	4.81***
Pre-tax Profit Margin	-0.443	0.078	5.07***	-0.724	0.067	5.03***
Net Profit Margin	-0.407	0.099	4.32***	-0.705	0.072	4.46***
Turnover						
Turnover / Fixed Assets	-0.090	-0.016	0.52	-0.069	-0.022	0.35
Turnover / Net Current Assets	-0.258	-0.050	2.54**	-0.018	-0.022	0.05
Stock Turnover	-0.036	-0.041	0.04	-0.103	0.050	2.16**
Debtors Turnover	-0.148	0.017	1.08	-0.075	0.010	1.10
Creditors Turnover	-0.362	0.090	3.04***	-0.320	0.059	2.73***

*** Significant at 0.01.
** Significant at 0.05.
* Significant at 0.10.

Table A2.1 - *Continued*

Financial Dimension	One Year Prior Mean (n=421) (Normalised Values)			Two Years Prior Mean (n=421) (Normalised Values)		
Accounting Variable	Failed	Non-failed	*t*-value	Failed	Non-failed	*t*-value
Gearing						
Capital Gearing	0.662	-0.035	5.49***	0.147	-0.14	0.61
Income Gearing	0.459	-0.046	1.97*	0.073	0.005	0.63
Borrowing Ratio	-0.125	-0.009	0.34	0.464	0.020	2.15**
Gross Cash-flow / Total Liabilities	-0.734	0.089	5.61***	-0.760	0.072	6.66***
Loan Capital / Equity and Reserves	0.267	0.008	0.93	0.320	0.026	1.71*
Liquidity						
Working Capital Ratio	-0.640	0.069	9.44***	-0.428	0.040	5.20***
Quick Assets Ratio	-0.552	0.048	4.25***	-0.346	0.024	2.88***
Net Current Assets / Total Assets Employed	-0.180	0.021	-0.47	-0.184	0.038	2.27*
Other						
Market Value/Book Value	-0.385	-0.028	2.76***	-0.061	-0.010	0.47
Payout Ratio	-0.300	0.023	2.71***	-0.284	0.078	2.07*
Assets Index	0.125	0.031	0.47	0.125	0.017	0.35
Tax Ratio	-0.200	0.100	1.54	-0.640	0.044	2.36*

*** Significant at 0.01.
** Significant at 0.05.
* Significant at 0.10.

Table A2.2 Means and *t*-statistics - Independent Variables for the Estimation Samples used in the Cross-sectional Analysis of UK Companies, Sample Period 1988-91, 53 Failed Companies and 368 Non-failed Company-Years, Three and Four Years Prior to Failure

Financial Dimension	Three Years Prior Mean (n=421) (Normalised Values)			Four Years Prior Mean (n=421) (Normalised Values)		
Accounting Variable	Failed	Non-failed	*t*-value	Failed	Non-failed	*t*-value
Size						
Log of Total Sales (Net of Trade Discounts)	-0.490	0.062	4.56***	-0.577	0.033	5.17***
Profitability						
Return on Shareholders' Capital	-0.231	0.076	1.68*	-0.235	0.040	2.38**
Return on Capital Employed	-0.179	0.028	1.41	-0.279	0.086	2.41**
Return on Net Fixed Assets	-0.133	0.044	1.40	-0.396	0.085	2.79***
Cumulative Profitability	-0.058	0.033	0.46	0.139	-0.026	0.62
Operating Profit Margin	-0.305	0.056	2.82***	-0.249	0.070	2.13**
Pre-Tax Profit Margin	-0.401	0.085	3.77***	-0.394	0.082	3.24***
Net Profit Margin	-0.345	0.077	3.35***	-0.304	0.043	2.61***
Turnover						
Turnover / Fixed Assets	0.089	-0.013	0.73	0.096	0.027	0.45
Turnover / Net Current Assets	0.346	0.007	1.90*	0.029	-0.003	0.20
Stock Turnover	0.333	-0.034	1.43	-0.012	0.057	0.39
Debtors Turnover	0.018	0.037	0.11	-0.081	0.053	0.85
Creditors Turnover	-0.103	0.022	0.61	-0.086	0.020	0.69

*** Significant at 0.01.
** Significant at 0.05.
* Significant at 0.10.

Table A2.2 - *Continued*

Financial Dimension	Three Years Prior Mean (n=421) (Normalised Values)			Four Years Prior Mean (n=421) (Normalised Values)		
Accounting Variable	Failed	Non-failed	*t*-value	Failed	Non-failed	*t*-value
Gearing						
Capital Gearing	0.483	-0.089	3.19***	0.576	-0.096	3.16***
Income Gearing	0.195	-0.038	2.13**	0.074	-0.017	0.60
Borrowing Ratio	-0.031	-0.043	0.11	-0.123	-0.033	0.40
Gross Cash-Flow / Total Liabilities	-0.429	0.069	3.46***	-0.520	0.128	4.30***
Loan Capital / Equity and Reserves	-0.170	-0.055	0.45	-0.195	0.010	1.61
Liquidity						
Working Capital Ratio	-0.279	0.060	2.88**	-0.314	0.104	2.36**
Quick Assets Ratio	-0.197	0.036	1.70*	-0.229	0.103	1.84
Net Current Assets / Total Assets Employed	-0.221	0.013	1.29	-0.086	0.028	0.44
Other						
Market Value/Book Value	0.297	0.003	0.97	-0.271	-0.036	1.16
Payout Ratio	-0.064	0.012	0.34	-0.286	0.029	2.17**
Assets Index	0.148	-0.027	0.59	0.077	-0.039	0.47
Tax Ratio	-0.231	-0.023	2.35**	-0.294	0.081	1.89*

*** Significant at 0.01.
** Significant at 0.05.
* Significant at 0.10.

Table A2.3 Pairwise Correlations for the Estimation Sample used in the Cross-sectional Analysis of UK Companies, Sample Period 1988-91, 53 Failed Companies and 368 Non-failed Company-Years, One Year Prior to Failure

	Return on Shareholders' Capital	Return on Capital Employed	Return on Net Fixed Assets	Cumulative Profitability	Operating Profit Margin	Pre-tax Profit Margin	Net Profit Margin	Turnover / Fixed Assets
Log of Total Sales	0.037	0.183	0.080	-0.076	0.139	0.097	0.068	-0.019
Return on Shareholders' Capital		0.196	0.148	0.359	0.124	0.113	0.072	-0.113
Return on Capital Employed			0.506	-0.229	0.366	0.345	0.296	0.118
Return on Net Fixed Assets				-0.232	0.288	0.298	0.464	0.317
Cumulative Profitability					0.023	0.031	0.001	-0.012
Operating Profit Margin						0.866	0.645	-0.067
Pre-tax Profit Margin							0.747	-0.064
Net Profit Margin								-0.036

Table A2.3 - *Continued*

	Turnover / Net Current Assets	Stock Turnover	Debtors Turnover	Creditors Turnover	Capital Gearing	Income Gearing	Borrowing Ratio	Gross Cash-flow / Total Liabilities	Loan Capital / Equity and Reserves
Log of Total Sales	0.027	-0.038	0.232	-0.032	0.145	-0.060	-0.009	0.185	0.020
Return on Shareholders' Capital	-0.002	0.020	0.002	-0.094	0.020	0.039	-0.313	0.325	-0.303
Return on Capital Employed	0.052	0.058	0.043	-0.112	0.289	0.068	-0.068	0.667	-0.167
Return on Net Fixed Assets	0.062	0.040	0.141	-0.108	-0.072	0.003	-0.075	0.480	-0.169
Cumulative Profitability	-0.002	0.005	0.020	0.033	-0.187	-0.012	-0.215	-0.061	-0.075
Operating Profit Margin	0.028	0.039	0.006	-0.218	-0.069	0.028	-0.018	0.593	-0.038
Pre-tax Profit Margin	0.024	0.057	0.002	-0.155	-0.149	-0.046	-0.048	0.603	-0.109
Net Profit Margin	0.021	0.043	-0.011	-0.152	-0.128	-0.040	-0.039	0.501	-0.088
Turnover / Fixed Assets	-0.006	-0.008	0.072	0.195	0.040	0.041	0.081	-0.075	0.065
Turnover / Net Current Assets		-0.005	-0.029	0.037	-0.021	0.017	0.026	0.027	0.011
Stock Turnover			-0.010	-0.012	-0.018	-0.008	-0.065	0.075	-0.028
Debtors Turnover				0.211	-0.051	0.005	0.000	0.052	-0.008
Creditors Turnover					-0.165	-0.001	0.049	-0.025	0.039
Capital Gearing						0.014	-0.019	-0.240	0.044
Income Gearing							0.047	-0.020	0.099
Borrowing Ratio								-0.113	0.733
Gross Cash-flow / Total Liabilities									-0.206

Table A2.3 - *Continued*

	Working Capital Ratio	Quick Assets Ratio	Net Current Assets/Total Assets Employed	MTBV	Payout Ratio	Assets Index	Tax Ratio
Log of Total Sales	-0.190	-0.211	-0.058	0.032	0.144	0.149	0.097
Return on Shareholders' Capital	-0.080	0.024	0.111	0.044	0.002	0.015	0.011
Return on Capital Employed	0.010	0.097	-0.096	0.279	0.026	-0.161	0.076
Return on Net Fixed Assets	0.214	0.109	-0.067	0.214	0.084	0.046	0.062
Cumulative Profitability	0.022	-0.002	0.269	-0.141	-0.032	0.005	0.020
Operating Profit Margin	0.071	0.038	-0.020	0.165	0.022	0.047	0.055
Pre-tax Profit Margin	0.328	0.345	0.044	0.186	0.035	0.067	0.080
Net Profit Margin	0.240	0.276	0.009	0.150	0.028	0.050	0.063
Turnover / Fixed Assets	0.152	-0.031	0.129	0.015	0.046	-0.028	0.043
Turnover / Net Current Assets	0.008	0.002	0.011	0.159	0.079	-0.006	0.052
Stock Turnover	-0.024	0.078	-0.002	0.023	-0.013	-0.019	-0.004
Debtors Turnover	-0.091	-0.184	-0.076	0.037	-0.024	0.249	0.044
Creditors Turnover	0.251	0.169	-0.005	-0.016	-0.029	0.095	0.059
Capital Gearing	-0.254	-0.211	-0.093	-0.211	-0.017	-0.341	-0.074
Income Gearing	-0.030	-0.046	0.022	0.002	-0.080	-0.004	0.111
Borrowing Ratio	0.024	-0.049	0.195	0.389	-0.015	0.008	-0.025
Gross Cash-flow / Total Liabilities	0.126	0.221	-0.051	0.337	-0.005	0.052	0.083
Loan Capital / Equity and Reserves	-0.002	-0.073	0.016	0.173	-0.041	0.029	-0.099
Working Capital Ratio		0.785	0.171	0.022	-0.022	0.027	0.038
Quick Assets Ratio			0.100	0.035	-0.017	-0.020	0.021
Net Current Assets/Total Assets Employed				0.240	0.001	-0.016	-0.016
Market Value/Book Value					0.020	0.054	0.001
Payout Ratio						0.017	0.290
Assets Index							-0.023

Table A2.4 Pairwise Correlations for the Estimation Sample used in the Cross-sectional Analysis of UK Companies, Sample Period 1988-91, 53 Failed Companies and 368 Non-failed Company-Years, Two Years Prior to Failure

	Return on Shareholders' Capital	Return on Capital Employed	Return on Net Fixed Assets	Cumulative Profitability	Operating Profit Margin	Pre-tax Profit Margin	Net Profit Margin	Turnover / Fixed Assets
Log of Total Sales	0.117	0.219	0.047	-0.034	0.155	0.146	0.152	-0.010
Return on Shareholders' Capital		0.420	0.247	0.360	0.387	0.430	0.434	0.067
Return on Capital Employed			0.362	0.024	0.467	0.508	0.468	0.137
Return on Net Fixed Assets				0.113	0.386	0.408	0.483	0.355
Cumulative Profitability					0.091	0.128	0.092	0.022
Operating Profit Margin						0.928	0.793	-0.067
Pre-tax Profit Margin							0.848	-0.056
Net Profit Margin								-0.047

Table A2.4 - *Continued*

	Turnover / Net Current Assets	Stock Turnover	Debtors Turnover	Creditors Turnover	Capital Gearing	Income Gearing	Borrowing Ratio	Gross Cash-flow / Total Liabilities	Loan Capital / Equity and Reserves
Log of Total Sales	0.046	-0.007	0.183	0.019	0.127	-0.025	0.050	0.201	0.125
Return on Shareholders' Capital	0.034	0.175	0.031	0.002	-0.020	-0.054	-0.197	0.573	-0.009
Return on Capital Employed	0.066	0.183	0.035	-0.076	0.172	-0.024	-0.096	0.636	-0.083
Return on Net Fixed Assets	0.010	0.102	0.117	-0.012	-0.067	-0.027	-0.112	0.404	-0.110
Cumulative Profitability	0.001	0.020	0.008	0.047	0.021	-0.132	-0.111	0.254	-0.091
Operating Profit Margin	-0.029	0.047	0.001	-0.140	-0.012	-0.045	-0.120	0.685	-0.073
Pre-tax Profit Margin	-0.018	0.080	0.005	-0.058	-0.089	-0.081	-0.180	0.754	-0.116
Net Profit Margin	-0.004	0.057	-0.005	-0.040	-0.074	-0.019	-0.160	0.700	-0.099
Turnover / Fixed Assets	0.031	0.097	0.100	0.157	-0.015	0.022	0.023	-0.043	-0.032
Turnover / Net Current Assets		-0.023	-0.037	-0.005	-0.007	-0.014	-0.024	0.051	0.003
Stock Turnover			-0.015	0.055	-0.011	-0.046	-0.003	0.136	-0.015
Debtors Turnover				0.232	-0.041	0.030	-0.028	0.067	-0.022
Creditors Turnover					-0.118	0.020	-0.046	0.073	-0.003
Capital Gearing						0.068	0.192	-0.112	0.110
Income Gearing							0.108	-0.085	0.087
Borrowing Ratio								-0.209	0.632
Gross Cash-flow / Total Liabilities									-0.114

Table A2.4 - *Continued*

	Working Capital Ratio	Quick Assets Ratio	Net Current Assets/Total Assets Employed	MTBV	Payout Ratio	Assets Index	Tax Ratio
Log of Total Sales	-0.188	-0.202	-0.138	0.043	-0.013	0.147	0.091
Return on Shareholders' Capital	0.001	0.040	0.088	0.243	-0.006	0.032	0.105
Return on Capital Employed	-0.018	0.050	0.033	0.208	-0.028	-0.131	0.109
Return on Net Fixed Assets	0.175	0.080	0.258	0.049	0.006	0.070	0.056
Cumulative Profitability	0.051	0.036	0.372	0.039	0.022	-0.008	0.071
Operating Profit Margin	0.105	0.045	0.061	0.126	-0.009	0.089	0.112
Pre-tax Profit Margin	0.256	0.237	0.127	0.119	0.028	0.102	0.123
Net Profit Margin	0.198	0.195	0.082	0.085	0.032	0.099	0.113
Turnover / Fixed Assets	0.154	-0.049	0.313	0.089	-0.027	-0.016	0.034
Turnover / Net Current Assets	-0.033	-0.017	0.019	0.085	0.018	-0.005	0.029
Stock Turnover	0.005	0.114	-0.056	0.008	-0.015	-0.029	0.016
Debtors Turnover	-0.073	-0.190	-0.104	0.047	-0.040	0.302	0.015
Creditors Turnover	0.243	0.188	0.067	-0.059	-0.030	0.084	0.062
Capital Gearing	-0.153	-0.125	-0.240	0.014	-0.010	-0.217	0.040
Income Gearing	-0.105	-0.128	-0.150	-0.014	-0.014	-0.024	0.007
Borrowing Ratio	-0.140	-0.128	-0.203	0.224	-0.045	-0.013	-0.004
Gross Cash-flow / Total Liabilities	0.072	0.149	0.046	0.169	-0.016	0.055	0.103
Loan Capital / Equity and Reserves	-0.071	-0.090	-0.128	0.317	-0.044	0.012	0.012
Working Capital Ratio		0.793	0.426	-0.028	0.031	0.029	0.077
Quick Assets Ratio			0.237	-0.015	0.054	-0.017	0.035
Net Current Assets/Total Assets Employed				-0.026	0.010	-0.021	0.094
Market Value/Book Value					0.003	0.020	-0.009
Payout Ratio						-0.019	0.065
Assets Index							-0.025

Table A2.5 Pairwise Correlations for the Estimation Sample used in the Cross-sectional Analysis of UK Companies, Sample Period 1988-91, 53 Failed Companies and 368 Non-failed Company-Years, Three Years Prior to Failure

	Return on Shareholders' Capital	Return on Capital Employed	Return on Net Fixed Assets	Cumulative Profitability	Operating Profit Margin	Pre-tax Profit Margin	Net Profit Margin	Turnover / Fixed Assets
Log of Total Sales	0.065	0.150	-0.002	-0.021	0.096	0.064	0.069	-0.026
Return on Shareholders' Capital		0.367	0.068	0.352	0.071	0.080	0.056	0.087
Return on Capital Employed			0.483	0.047	0.505	0.516	0.442	0.160
Return on Net Fixed Assets				-0.006	0.390	0.423	0.457	0.567
Cumulative Profitability					0.004	0.008	-0.021	0.011
Operating Profit Margin						0.933	0.826	-0.114
Pre-tax Profit Margin							0.880	-0.098
Net Profit Margin								-0.091

Table A2.5 - *Continued*

	Turnover / Net Current Assets	Stock Turnover	Debtors Turnover	Creditors Turnover	Capital Gearing	Income Gearing	Borrowing Ratio	Gross Cash-flow / Total Liabilities	Loan Capital / Equity and Reserves
Log of Total Sales	0.041	-0.042	0.185	0.016	0.115	-0.028	0.038	0.141	0.077
Return on Shareholders' Capital	-0.057	0.288	-0.012	-0.060	0.038	-0.030	0.024	0.168	0.152
Return on Capital Employed	-0.005	0.230	0.016	-0.003	-0.079	-0.042	-0.125	0.766	-0.135
Return on Net Fixed Assets	-0.017	0.048	0.084	0.045	-0.155	-0.039	-0.053	0.457	-0.091
Cumulative Profitability	-0.015	-0.007	-0.014	0.021	0.218	-0.030	-0.189	0.080	-0.005
Operating Profit Margin	-0.039	0.005	-0.030	-0.125	-0.159	-0.063	0.024	0.677	0.033
Pre-tax Profit Margin	-0.038	0.004	-0.038	-0.064	-0.295	-0.108	0.003	0.689	0.016
Net Profit Margin	-0.028	-0.003	-0.047	-0.081	-0.253	-0.082	0.014	0.609	0.023
Turnover / Fixed Assets	0.023	0.134	0.083	0.211	0.052	-0.036	-0.069	-0.034	-0.100
Turnover / Net Current Assets		-0.015	-0.042	-0.006	0.023	-0.032	0.052	0.009	0.031
Stock Turnover			0.034	0.025	0.100	0.095	-0.065	0.089	-0.082
Debtors Turnover				0.188	-0.028	0.116	-0.001	0.026	-0.010
Creditors Turnover					-0.124	-0.088	-0.018	0.092	-0.045
Capital Gearing						0.059	-0.190	-0.275	-0.203
Income Gearing							0.056	-0.093	0.062
Borrowing Ratio								-0.014	0.932
Gross Cash-flow / Total Liabilities									-0.022

Table A2.5 - *Continued*

	Working Capital Ratio	Quick Assets Ratio	Net Current Assets/Total Assets Employed	MTBV	Payout Ratio	Assets Index	Tax Ratio
Log of Total Sales	-0.195	-0.225	-0.056	-0.003	0.005	0.149	0.083
Return on Shareholders' Capital	-0.072	-0.027	0.146	0.288	0.022	0.015	0.027
Return on Capital Employed	-0.053	0.017	0.023	0.333	-0.006	0.016	0.336
Return on Net Fixed Assets	0.244	0.106	0.184	0.116	-0.032	0.044	0.258
Cumulative Profitability	0.036	0.009	0.732	-0.076	0.009	-0.015	-0.011
Operating Profit Margin	0.086	0.065	0.010	0.193	0.032	0.140	0.257
Pre-tax Profit Margin	0.273	0.294	0.053	0.215	0.037	0.124	0.342
Net Profit Margin	0.223	0.269	0.022	0.159	0.080	0.122	0.305
Turnover / Fixed Assets	0.095	-0.030	0.183	0.086	-0.062	-0.034	0.061
Turnover / Net Current Assets	-0.057	-0.042	-0.028	-0.001	-0.034	-0.002	0.004
Stock Turnover	-0.100	0.012	-0.056	0.137	-0.047	-0.022	0.063
Debtors Turnover	-0.111	-0.206	-0.106	0.037	-0.053	0.130	0.064
Creditors Turnover	0.240	0.162	0.082	0.276	-0.023	0.035	0.113
Capital Gearing	-0.290	-0.272	-0.031	-0.017	-0.040	0.016	-0.145
Income Gearing	-0.099	-0.086	0.001	0.014	0.089	-0.047	-0.068
Borrowing Ratio	-0.064	-0.069	-0.056	0.091	0.073	0.052	0.053
Gross Cash-flow / Total Liabilities	0.036	0.095	0.052	0.230	0.018	0.067	0.349
Loan Capital / Equity and Reserves	-0.041	-0.042	0.065	0.028	0.062	0.061	0.027
Working Capital Ratio		0.801	0.338	0.030	-0.005	0.003	0.211
Quick Assets Ratio			0.202	0.055	0.055	-0.020	0.201
Net Current Assets/Total Assets Employed				-0.063	0.003	-0.005	0.085
Market Value/Book Value					-0.007	-0.029	0.082
Payout Ratio						0.003	0.038
Assets Index							0.028

Table A2.6 Pairwise Correlations for the Estimation Sample used in the Cross-sectional Analysis of UK Companies, Sample Period 1988-91, 53 Failed Companies and 368 Non-failed Company-Years, Four Years Prior to Failure

	Return on Shareholders' Capital	Return on Capital Employed	Return on Net Fixed Assets	Cumulative Profitability	Operating Profit Margin	Pre-tax Profit Margin	Net Profit Margin	Turnover / Fixed Assets
Log of Total Sales	0.057	0.022	-0.054	-0.149	-0.015	-0.022	0.006	-0.051
Return on Shareholders' Capital		0.639	0.346	0.225	0.361	0.377	0.355	0.031
Return on Capital Employed			0.463	0.070	0.550	0.569	0.527	0.148
Return on Net Fixed Assets				0.037	0.352	0.382	0.392	0.500
Cumulative Profitability					0.059	0.034	0.015	-0.027
Operating Profit Margin						0.950	0.878	-0.102
Pre-tax Profit Margin							0.930	-0.075
Net Profit Margin								-0.079

Table A2.6 - *Continued*

	Turnover / Net Current Assets	Stock Turnover	Debtors Turnover	Creditors Turnover	Capital Gearing	Income Gearing	Borrowing Ratio	Gross Cash-flow / Total Liabilities	Loan Capital / Equity and Reserves
Log of Total Sales	0.070	-0.054	0.241	-0.010	0.125	0.003	0.052	0.061	0.056
Return on Shareholders' Capital	-0.029	0.152	-0.004	-0.023	-0.156	-0.064	0.190	0.563	0.195
Return on Capital Employed	-0.114	0.296	0.026	-0.012	-0.240	0.016	0.026	0.815	-0.016
Return on Net Fixed Assets	-0.051	0.134	0.130	0.059	-0.246	0.010	-0.002	0.423	-0.030
Cumulative Profitability	-0.014	0.059	0.008	0.090	0.090	0.000	-0.081	0.070	0.028
Operating Profit Margin	-0.103	0.075	-0.052	-0.147	-0.216	0.033	0.050	0.681	0.024
Pre-tax Profit Margin	-0.105	0.097	-0.034	-0.081	-0.353	0.031	0.058	0.707	0.008
Net Profit Margin	-0.143	0.111	-0.047	-0.095	-0.324	0.050	0.079	0.672	0.026
Turnover / Fixed Assets	0.027	0.070	0.124	0.158	-0.055	-0.009	0.002	-0.041	-0.035
Turnover / Net Current Assets		0.007	-0.044	0.044	0.046	-0.012	0.005	-0.088	-0.003
Stock Turnover			-0.031	-0.027	-0.093	-0.004	-0.009	0.143	-0.003
Debtors Turnover				0.173	-0.024	0.028	0.020	0.023	0.010
Creditors Turnover					-0.156	0.009	0.050	0.059	0.036
Capital Gearing						-0.033	-0.257	-0.348	-0.178
Income Gearing							0.216	0.047	0.031
Borrowing Ratio								0.117	0.896
Gross Cash-flow / Total Liabilities									0.060

Table A2.6 - *Continued*

	Working Capital Ratio	Quick Assets Ratio	Net Current Assets/Total Assets Employed	MTBV	Payout Ratio	Assets Index	Tax Ratio
Log of Total Sales	-0.223	-0.247	-0.247	0.034	0.066	0.172	0.065
Return on Shareholders' Capital	-0.046	0.017	0.138	0.181	0.032	0.048	0.066
Return on Capital Employed	-0.092	-0.004	0.063	0.281	-0.033	0.014	0.088
Return on Net Fixed Assets	0.180	0.092	0.301	0.151	0.035	0.022	0.040
Cumulative Profitability	0.025	-0.002	0.550	-0.031	-0.018	-0.009	-0.027
Operating Profit Margin	0.007	0.016	0.058	0.270	0.033	0.126	0.072
Pre-tax Profit Margin	0.123	0.158	0.064	0.274	0.039	0.122	0.081
Net Profit Margin	0.104	0.153	0.025	0.255	0.083	0.141	0.063
Turnover / Fixed Assets	0.129	0.053	0.270	-0.003	-0.028	-0.034	-0.023
Turnover / Net Current Assets	-0.050	-0.049	0.005	-0.053	0.016	0.020	-0.046
Stock Turnover	-0.062	0.041	-0.011	-0.261	-0.002	-0.012	0.020
Debtors Turnover	-0.082	-0.177	-0.157	0.029	-0.024	0.139	-0.017
Creditors Turnover	0.299	0.229	0.117	0.013	0.039	0.044	0.012
Capital Gearing	-0.344	-0.331	-0.091	-0.236	-0.122	0.019	-0.021
Income Gearing	0.008	-0.004	0.029	-0.011	0.062	0.003	0.019
Borrowing Ratio	0.005	-0.009	-0.117	0.341	0.093	0.050	0.003
Gross Cash-flow / Total Liabilities	-0.018	0.065	0.006	0.337	0.002	0.065	0.062
Loan Capital / Equity and Reserves	-0.021	-0.026	-0.037	0.368	0.084	0.056	-0.002
Working Capital Ratio		0.869	0.408	0.000	-0.003	-0.010	-0.015
Quick Assets Ratio			0.268	-0.004	0.040	-0.014	0.003
Net Current Assets/Total Assets Employed				-0.027	-0.045	-0.050	-0.021
Market Value/Book Value					0.049	0.022	-0.044
Payout Ratio						-0.004	0.065
Assets Index							0.011

APPENDIX 3: VARIABLE DESCRIPTIVE STATISTICS FOR THE PANEL ANALYSIS OF UK COMPANY FAILURE

Table A3.1 Descriptive Statistics for UK Quoted Companies in the 1988-93 Panel, 483 Non-failed Companies and 56 Failed Companies with a Maximum of 6 Years of Data on Each Company, Sample Size 3,085 [(488×6)+ (5×5)+ (12×4)+ (16×3)+(18×2)]

	Mean	St. Dev.	Annual Means					
	Levels		Levels					
	Full Sample 3,085 obs.		539 cases	539 cases	521 cases	505 cases	493 cases	488 cases
	1988-93		1988	1989	1990	1991	1992	1993
Financial Dimension								
Accounting Variable								
Size								
Total Sales ()	546.116	1405.888	424.586	501.920	549.124	565.561	601.056	651.352
Profitability								
Return on Shareholders' Capital (percentage)	10.510	101.743	17.024	16.563	8.034	14.951	9.791	-4.566
Return on Capital Employed (percentage)	15.502	48.046	21.096	21.093	12.131	12.019	12.849	13.072
Return on Net Fixed Assets (percentage)	19.080	99.506	39.119	32.561	20.558	7.612	3.020	8.637
Cumulative Profitability	0.341	2.701	0.401	0.336	0.349	0.226	0.420	
Operating Profit Margin (percentage)	6.746	23.250	9.048	8.751	7.490	6.020	5.630	3.092
Pre-tax Profit Margin (percentage)	5.912	20.287	8.835	7.982	6.385	4.537	4.671	2.585
Net Profit Margin (percentage)	3.537	19.463	5.886	5.034	3.778	2.540	2.925	0.692
Turnover								
Turnover / Fixed Assets	6.409	11.062	6.496	6.179	6.020	5.930	2.741	7.197
Turnover / Net Current Assets	9.908	153.093	25.651	4.062	4.440	12.118	5.960	6.525
Stock Turnover	17.621	105.138	25.802	12.906	12.477	20.242	17.710	16.511
Debtors Turnover	7.431	12.803	7.590	6.983	7.491	7.305	7.392	7.871
Creditors Turnover	5.221	2.424	5.190	5.061	5.194	5.316	5.255	5.337

Table A3.1 - *Continued*

	Mean	St. Dev.	Annual Means					
	Levels		Levels					
	Full Sample 3,085 obs.		539 cases	539 cases	521 cases	505 cases	493 cases	488 cases
	1988-93		1988	1989	1990	1991	1992	1993
Financial Dimension								
Accounting Variable								
Gearing								
Capital Gearing (percentage)	33.221	99.393	25.174	36.902	31.771	37.460	31.269	37.252
Income Gearing (percentage)	9.239	922.089	16.703	18.192	57.520	-50.897	39.138	-28.376
Borrowing Ratio	0.614	5.110	0.504	0.937	0.702	0.356	0.547	0.624
Gross Cash-flow / Total Liabilities	0.098	0.684	0.171	0.101	0.090	0.070	0.093	0.054
Loan Capital / Equity and Reserves	0.336	4.052	0.224	0.596	0.346	0.216	0.324	0.297
Liquidity								
Working Capital Ratio	1.573	0.993	1.651	1.528	-0.080	1.548	1.621	1.585
Quick Assets Ratio	0.987	0.857	1.026	0.937	0.935	0.970	1.036	1.022
Other								
Market Value/Book Value	2.171	6.163	2.646	2.279	1.651	1.623	2.163	2.660
Payout Ratio	0.490	3.198	2.750	0.584	0.559	0.623	0.652	0.157
Assets Index (percentage)	1991.846	15673.119	1924.887	2018.541	1898.274	1997.071	2047.921	2078.299
Tax Ratio (percentage)	26.305	173.176	29.896	29.409	9.461	28.041	24.251	37.233

APPENDIX 4: VARIABLE DESCRIPTIVE STATISTICS FOR UK AND RUSSIAN CROSS-SECTIONS USED IN THE COMPARATIVE STUDY

Table A4.1 Means and t-statistics - Independent Variables for the Analysis of the Russian Data: the Estimation Sample for 1995, 20 Failed and 20 Non-failed Companies; and Pooled Estimation Sample for the Period 1995-96, 21 Failed and 28 Non-failed Companies, One Year Prior to Failure

Financial Dimension	Mean (n=40)			Mean (n=48)		
Accounting Variable	Failed	Non-failed	t-value	Failed	Non-failed	t-value
Size						
Log of Total Assets (total assets are measured in billions of roubles)	3.188	4.135	1.77*	3.251	4.327	1.88*
Profitability						
Return on Long-term Capital	-0.050	0.194	4.56***	-0.050	0.122	2.95***
Return on Net Fixed Assets	-0.065	0.415	2.94***	-0.066	0.319	3.03***
Pre-tax Profit Margin	-0.591	0.274	2.09**	-0.566	0.220	2.26**
Turnover						
Stock Turnover	3.515	5.614	1.56	3.515	5.187	1.47
Shareholders' Funds Turnover	0.648	1.931	2.18**	0.649	2.051	2.05**
Sales / Total Assets	0.375	0.761	3.14***	0.372	0.688	2.88***
Gearing						
Capital Gearing	0.067	0.042	0.85	0.065	0.042	0.80
Cover for Current Assets out of Shareholders' Funds	0.040	0.088	0.73	0.042	0.073	0.50
Total Liabilities / Total Assets	0.307	0.292	0.26	0.318	0.311	0.12
Assets Structure						
Debtors / Total Assets	0.033	0.021	0.73	0.036	0.590	0.80
Liquidity						
Quasi-Cash / Short-term Liabilities	0.120	0.141	0.27	0.115	0.105	0.14
Current Ratio	1.383	1.751	1.14	1.335	1.569	0.81

*** Significant at 0.01.
** Significant at 0.05.
* Significant at 0.10.

Table A4.2 Pairwise Correlations for the Estimation Sample of 40 Russian Companies, 1995 Sample Period, 20 Failed and 20 Non-failed Companies, One Year Prior to Failure

	Return on Long-term Capital	Return on Net Fixed Assets	Pre-tax Profit Margin	Stock Turn-over	Share-holders' Funds Turn-over	Sales/ Total Assets	Capital Gearing	Cover for Current Assets out of Share-holders' Funds	Total Liabi-lities/ Total Assets	Debtors/ Total Assets	Quasi-cash/ Short term Liabi-lities	Current Ratio
Log of Total Assets	0.160	0.214	0.111	0.393	-0.090	-0.058	-0.185	-0.103	-0.197	-0.022	0.165	-0.126
Return on Long-term Capital		0.460	0.280	0.134	0.515	0.652	-0.100	-0.028	0.189	-0.206	-0.084	0.107
Return on Net Fixed Assets			0.196	-0.016	0.146	0.341	-0.042	0.130	-0.076	-0.071	-0.096	0.090
Pre-tax Profit Margin				-0.043	0.321	0.317	0.048	0.029	0.033	0.072	0.029	0.166
Stock Turnover					0.008	0.289	-0.031	-0.170	-0.056	0.551	0.336	-0.113
Shareholders' Funds Turnover						0.568	0.077	0.033	0.480	-0.015	-0.165	0.021
Sales / Total Assets							0.287	0.043	0.474	0.150	-0.086	0.038
Capital Gearing								-0.077	0.328	0.057	-0.024	-0.191
Cover for Current Assets out of Shareholders' Funds									-0.162	-0.195	0.075	0.308
Total Liabilities / Total Assets										0.238	-0.369	-0.382
Debtors / Total Assets											-0.023	-0.133
Quasi-cash/Short-term Liabilities												0.150

Table A4.3 Pairwise Correlations for the Pooled Estimation Sample of 48 Russian Companies, 1995-96 Sample Period, 21 Failed and 27 Non-failed Companies, One Year Prior to Failure

	Return on Long-term Capital	Return on Net Fixed Assets	Pre-tax Profit Margin	Stock Turn-over	Share-holders' Funds Turn-over	Sales/ Total Assets	Capital Gearing	Cover for Current Assets out of Share-holders' Funds	Total Liabi-lities / Total Assets	Debtors/ Total Assets	Quasi-cash/ Short term Liabi-lities	Current Ratio
Log of Total Assets	0.346	0.141	0.108	0.268	-0.414	-0.105	-0.079	-0.120	-0.361	-0.331	0.078	-0.301
Return on Long-term Capital		0.409	0.225	0.106	-0.051	0.503	-0.023	-0.015	-0.130	-0.547	-0.013	0.005
Return on Net Fixed Assets			0.189	-0.008	0.092	0.334	-0.029	0.124	-0.080	-0.078	-0.070	0.109
Pre-tax Profit Margin				-0.048	0.232	0.290	0.043	0.027	0.028	0.050	0.015	0.137
Stock Turnover					0.042	0.347	0.041	-0.252	0.011	0.274	0.324	-0.074
Shareholders' Funds Turnover						0.453	0.015	-0.004	0.623	0.563	-0.148	0.171
Sales / Total Assets							0.310	-0.038	0.427	0.117	-0.059	0.089
Capital Gearing								-0.152	0.258	-0.012	-0.007	-0.174
Cover for Current Assets out of Shareholders' Funds									-0.187	-0.157	0.080	0.283
Total Liabilities / Total Assets										0.545	-0.334	-0.216
Debtors / Total Assets											-0.114	0.042
Quasi-cash/Short-term Liabilities												0.185

Table A4.4 Means and t-statistics - Independent Variables for the Analysis of the UK Data, The Estimation Sample for 1990-91, 20 Failed and 20 Non-failed Companies, One Year Prior to Failure

Financial Dimension / *Accounting Variable*	Mean (n=40)		
	Failed	Non-failed	t-value
Size			
Log of Total Sales (Net of Trade Discounts; £,m)	10.335	11.947	3.00***
Profitability			
Return on Shareholders' Equity (percentage)	34.760	14.501	1.13
Return on Net Fixed Assets (percentage)	-23.849	37.170	2.39**
Pre-tax Profit Margin (percentage)	-7.141	7.621	3.88***
Turnover			
Turnover / Fixed Assets	5.666	6.174	0.24
Stock Turnover	25.262	9.341	1.29
Debtors Turnover	6.356	21.969	1.52
Creditors Turnover	4.444	6.229	2.19**
Gearing			
Capital Gearing (percentage)	82.928	28.495	4.61***
Income Gearing (percentage)	-296.214	29.362	0.95
Liquidity			
Working Capital Ratio	0.824	1.738	4.01***
Quick Assets Ratio	0.506	1.145	2.68**
Stock and Work-in-Progress/ Current Liabilities	0.319	0.593	2.01*

*** Significant at 0.01.
** Significant at 0.05.
* Significant at 0.10.

Table A4.5 Pairwise Correlations for the Estimation Sample of 40 UK Companies, 1990-91 Sample Period, 20 Failed and 20 Non-failed Companies, One Year Prior to Failure

	Return on Share-holders' Equity	Return on Net Fixed Assets	Pre-tax Profit Margin	Turn-over/ Fixed Assets	Stock Turn-over	Debtors Turn-over	Creditors Turn-over	Capital Gearing	Income Gearing	Working Capital Ratio	Quick Assets Ratio	Stock& Work-in-Progress/ Current Liabi-Lities
Log of Total Sales	-0.043	0.195	0.347	0.197	-0.188	0.300	0.119	-0.175	0.086	-0.081	-0.189	0.189
Return on Shareholders' Equity		-0.153	-0.155	0.049	0.014	-0.006	-0.205	0.536	-0.131	-0.268	-0.108	-0.311
Return on Net Fixed Assets			0.601	0.601	-0.091	0.393	-0.065	-0.416	0.083	0.325	0.102	0.431
Pre-tax Profit Margin				0.185	-0.286	0.178	0.030	-0.521	0.082	0.469	0.482	0.014
Turnover / Fixed Assets					-0.164	0.271	-0.006	-0.027	0.069	0.196	-0.073	0.504
Stock Turnover						-0.047	-0.214	0.027	-0.006	-0.233	-0.087	-0.284
Debtors Turnover							0.243	-0.225	0.040	-0.043	-0.206	0.292
Creditors Turnover								-0.318	0.029	0.425	0.250	0.352
Capital Gearing									-0.289	-0.568	-0.458	-0.246
Income Gearing										0.097	0.053	0.089
Working Capital Ratio											0.855	0.344
Quick Assets Ratio												-0.192

APPENDIX 5: LISTS OF UK AND RUSSIAN COMPANIES

Table A5.1 Company Names and Years of Entering Insolvency Regime, of UK Failed Quoted Industrials Used in the Estimation Sample for the Cross-sectional Analysis

Allied Partnership Group	1992	Ketson	1990
Arley Holdings	1990	Lawtex	1991
Arnkliffe Holdings	1991	Lilley	1993
Astra Holdings	1992	Lyon & Lyon	1990
AT Trust	1990	Maxwell Comms. Corporation	1991
ATP Communications Group	1992	Miller (Stanley) Holdings	1990
Audit & General	1991	Oakwood Group	1990
Bestwood	1990	Parkfield Group	1990
C.H. Industrials	1991	Pavilion Leisure	1991
Chelsea Man	1991	Pavion International	1989
Chequers Group	1992	Peters (Michael) Group	1990
Clearmark Group	1991	Polly Peck International	1990
Colographic	1992	Reliant Group	1990
Coloroll	1990	Rockwood Holdings	1990
Conder Group	1992	Rush & Tomkins Group	1990
Crown Communications Group	1993	Sale Tilney	1992
Doctus	1991	Toothill (R.W.)	1991
Ferrari Holdings	1991	Trilion	1992
Fobel International	1991	Turriff Corporation	1991
Futura Holdings	1993	Video Store Group	1991
Gaynor Group	1991	Ward Group	1992
Goldberg (A.) & Sons	1990	West Industries	1992
Grovewood Securities	1991	Westerly	1991
Halls Homes & Gardens	1992	Willaire Group	1992
Hey & Croft Group	1992	Williams (John) Industries	1990
Huges Food Group	1991	Yellowhammer	1990
International Resort Holdings	1992		

Table A5.2 Company Names and Years of Entering Insolvency Regime of UK Failed Quoted Industrials Used in the Holdout Sample for the Cross-sectional Analysis

Automagic Holdings	1995	Ferranti International	1993
Beckenham Group	1994	Harland Simon Group	1992
Bimec Industries	1994	McLaughlin & Harvey	1993
Bullers	1995	Pentos	1995
Dunkeld	1993	Scottish Heritable Trust	1994

Table A5.3 Company Names of UK Non-failed Quoted Industrials Used in the Estimation Sample for the Cross-sectional Analysis

600 Group
Abbott Mead Vickers
Acatos & Hutcheson
Adwest Group
Aegis Group
African Lakes Corporation
AIM Group
Albion
Allied Leisure
Allied Textile Companies
Amec
Amersham
Andrews Sykes Group
Anglo United
API Group
Arabis
Arcolectric (Holdings)
Arlen
Ashtead Group
Associated British Foods
Associated British Ports
Astec (BSR)
Atlas Converting Equipment
Avon Rubber
Ayshire Metal
Bailey (Ben)
Bailey (C.H.)
Banks (Sidney C.)
Bardon Group
Barr & Wallace Arnold Trust
Barr (AG)
Barratt Developments
Baynes (Charles)
Beales Hunter
Bearing Power International
Beauford
Bellway
Bellwinch
Bemrose Corp.
Benson Group
Bentalls
Berisford
Bespak
Betterware
Bicc
Billam
Bilston & Battersea
Blue Circle Industries
Bogod Group
Boots
Brake Bros
Brammer
Bridport-Gundry
Brit. Building & Engineering Appliances
British Bloodstock Agency
British Dredging
Brit. Polytheline Industries
British Vita
Brooke Industrial Holdings
Brown (N.) Group
Bristol United Press
BTP
Bunzl
Burton Group
BWI
Cable and Wireless Comms.
Cadbury Schweppes
Cape
Capital Radio
Carlton Communications
Castle Mill International
Caverdale Group
Chamberlin & Hills
Charter
Chemring Group
Chloride Group
Christie's International
Chrysalis Group
City Centre Restaurants
Clyde Blowers
CML Microsystems
Coats Viyella
Cook (William)
Cookson Group

Table A5.3 - *Continued*

Cooper (Frederick))	Grampian Television
Corporate Services Group	Granada Group
Courts	Green (E.) & Partners Holdings
Coutts Consulting Group	Greenalls Group
Cradley Group Holdings	Gresham Computing
Craig & Rose	Gt. Unvl Stores
Crest Nicholson	Guinness
Cropper (James)	Halma
Davis Servide Group	Hampson Industries
De La Rue	Havelock Europa
Densitron International	Hawtal Whiting Holdings
Dewhurst	Hawtin
Dixons Group	Hay (Norman)
Druck Holdings	Heavitree Brewery
Drummond Group	Henlys Group
Dyson (J&J)	Heywood Williams
Eadie Holdings	Hicking Pentecost
Eclipse Blinds	Hickson International
EIS Group	Highland Distillers
Eldridge,Pope & Co	Home Counties Newspapers Holdings
Electronic Data Processing	Hollas Group
Etam	Holt (Joseph)
Feedback	Hopkinsons Group
Fife Indmar	Hornby
FII Group	How Group
First Choice Holidays	HTV Group
Firth Holdings	Hunting
Fisher (James) and Sons	HuntleighTechnology
FKI	Ibstock
Forminster	IMI
Fortnum & Mason	Imperial Chemical Industries
Garton Engineering	Intereurope Techn. Services
GBE International	Jacks (William)
GEI International	Jacobs Holdings
Gieves Group	Jarvis
GKN	Jerome Group
Glaxo Wellcome	Jeyes Group
Glenchewton	Johnson Matthey
Glenmorangie	Jones, Stroud (Holdings)
Glynwed International	Kalon Group
Goodwin	Kelsey Industries
Grampian Hoildings	Kingfisher

Table A5.3 - *Continued*

Kode International
Kwik Save Group
Kwik-Fit Holdings
Kynoch Group
Ladbroke Group
Lambert Howarth Group
Lamont Holdings
Laporte
Laser-Scan Holdings
Latham (James)
Leigh Interests
Lex Service
Liberty
Lilleshall
Linton Park
Lister & Co
Locker (Thomas)
Lopex
Lovell (Y.J.) Holdings
Law & Bonar
M-R Group
Mallett
Manders
Maunders
McCarthy & Stone (Holdings)
McKechnie
Menvier-Swain
Menzies (John)
Meristem
Metal Bulletin
Micro Focus Group
Microgen Holdings
Microvite
Mitie Group
ML Holdings
MMT Computing
Molins
Morgan Grucible Company
Morland
Morrison (WM)Supermarkets
Moss Bros Group
Mowlem (John) & Company
Nichols (J.N.) (Vimto)
Northern Foods
Osprey Communications
Oxford Instruments
Page (Michael) Group
Parity
Parkland Group
Pascoe's Group
Paterson Zochonis
Pegasus
Pen.&Ornt Steam Navigator Company
Perkins Foods
Perry Group
Persimmon
Photo-Me International
Pifco Holdings
Pittards
Plasmec
Porter Chadburn
Powerscreen
Premier Farnell
Psion
Quadrant Group
Radius
Rank Group
Real Time Control
Record Holdings
Reed Executive
Reed International
Reliance
Renold
Reurters Holdings
Rexam
Ricardo Group
Richardsons Westgarth
Ropner
Rubicon Group
Safeway
Sainsbury (J)
Saltire
Salvesen (Chris.)
Scapa Group
Scottish TV
Serif

Table A5.3 - *Continued*

Shani Group	Transtec
Sharpe & Fisher	Trinity International Holdings
Shilon	Triplex Lloyd
Signet Group	TT Group
Silenthight Holdings	Tunstall Group
Sinclair WM Holdings	Unigate
Sketchley	Upton & Southern
Slingsby (H.C.)	Usborne
Smith (WH) Group	Verity Group
Somic	Vibroplant
Soundtracs	Vickers
Sperati (C.A.) (The Special Agency)	Victoria Carpet
Springwood	Volex Group
Stakis	Waddington
Sterling Industries	Walker (Thomas)
Stirling Group	Wardle Storeys
Storehouse	Waterman Ptshp
Stylo	Watmoughs Holdings
Sutcliffe, Spkmn	Watts, Blake, Bearne & Company
Swan (John)	Weir Group
Syltone	Wembley Group
Tate & Lyle	Whessoe
Taylor Woodrow	Wickes
TDS Circuits	Widney
Telemetrix	Williams Holdings
Tesco	Wilson (Connolly)
Tex Holdings	WPP Group
Thorpe (FW)	Wyko
Tibbett & Britten	Yorkshire Group
Tomkins	Young (H) Holdings
Tomkinsons	Yule Catto

Table A5.4 Company Names of UK Non-failed Quoted Industrials Used in the Holdout Sample for the Cross-sectional Analysis

Abbot Group
ABI Leisure Group
Airspring Furniture
Alliance Unichem
Alphameri
Argos
Argo Wiggins Appleton
Armitage Brothers
Associated British Engineering
Austin Reed Group
Black (Peter)
Blick
Boosey & Hawkes
Bostrom
BPB
Breedon
Brunel Holdings
BTR
Capital Industries
Church & Co.
Claremont Garments
Clarke (T)
Cobham
Cordiant
Daily Mail
Derby Group
Delphi Group
Domino Printing
Eidos
Flare Group
Formal Group
Forward Technology Industries
Gaskell
Gibbs & Dandy
Gibbs Mew
Gleeson (MJ) Group
Haden Maclellan
Haggas (John)
Hartstone
Hi-Tec Sports
Highbury House Communications
Hodder Headline
Howden Group
INN Business
Intercare
Isotron
Leeds Group
Lonrho
Lookers
Macro 4
Marley
Marshalls
McLeod Russel
Medeva
Mirror Group
Mitie Group
P & P
Paramount
Pex
Phoenix Timber
Pifco Holdings
Prowting
QS Holdings
Quiligott
Radamec
RMC Group
Rotork
RTZ Corp.
Rugby Group
Savoy Hotels
Scottish & Newcastle
Sears
Senior Engr.
Seton Healthcare Group
Sidlaw Group
SIG
Smith (David S.)
Southnews
Spirax-Sarco
Thorntons
TSL
Ugland International Holdings
Ulster T.V
Wace Group
Walker Group
World of Leather

Table A5.5 Company Names and Years of Entering Insolvency Regime of UK Failed Quoted Industrials Used in the Panel Analysis

Allied Partnership Group	1992	Halls Homes & Gardens	1992
Arley Holdings	1990	Harland Simon Group	1992
Arnkliffe Holdings	1991	Hey & Croft Group	1992
Astra Holdings	1992	International Resort Holdings	1993
AT Trust	1990	Ketson	1991
ATP Communications Group	1992	Lawtex	1993
Audit & General	1991	Lilley	1990
Beckenham	1994	Maxwell Comms. Corporation	1991
Bimec Industries	1994	McLaughlin & Harvey	1995
Bullers	1995	Parkfield Group	1990
C.H. Industrials	1991	Pavilion Leisure	1990
Chelsea Man	1991	Pentos	1990
Chequers Group	1992	Peters (Michael) Group	1990
Clearmark Group	1991	Polly Peck International	1992
Colographic	1992	Reliant Group	1994
Coloroll	1990	Rush & Tomkins Group	1991
Conder Group	1992	Sale Tilney	1992
Crown Communications Group	1993	Scottish Heritable Trust	1991
Doctus	1991	Toothill (R.W.)	1991
Dunkeld Group	1993	Trilion	1992
EIT Group	1993	Turriff Corporation	1992
Ferranti International	1993	Video Store Group	1991
Ferrari Holdings	1991	Ward Group	1992
Fobel International	1991	West Industries	1990
Futura Holdings	1993	Westerly	1990
Gaynor Group	1991	Willaire Group	1992
Goldberg (A.) & Sons	1990	Williams (John) Industries	1990
Grovewood Securities	1991	Yellowhammer	1990

Table A5.6 Company Names of UK Non-failed Quoted Industrials Used in the Panel Study

600 Group
Abbot Group
Acal
Acorn Computer
Aegis Group
AIM Group
Airflow Streamlines
Albert Fisher
Albion
Alexanders Holdings
Alexandra Workware
Alexon Group
Allied Colloids
Allied Textile Companies
Alvis
Amber Industrial Holdings
Amec
Amersham International
Amstrad
Andrews Sykes Group
API Group
APV
Arabis
Arcolectric (Holdings)
Arlen
Armitage Brothers
Armour Trust
Asda Group
Ash & Lacy
Associated British Foods
Associated British Ports
Astec (BSR)
Austin Reed Group
Avon Rubber
Ayshire Metal
Baggeridge Brick
Baird (William)
Bandt
Banks (Sidney C.)
Bardon Group
Barr (A G)
Barratt Developments
Bass
B.A.T. Industries
Baynes (Charles)
BBA Group
Beales Hunter
Beattie (James)
Beauford
Bellway
Bemrose Corp.
Bensons Crisps
Bentalls
Berisford
Bespak
Bett Bros.
Beverley Group
Bibby (J)
Bicc
Billam
Birkdale Group
Black (A&C)
Black (Peter)
Black Arrow Group
Blagden Industries
Blockleys
Blue Circle Industries
BOC Group
Booker
Boosey & Hawkes
Boot (Henry)
Booth Industrials Group
Boots
Braime (Tf & JH)
Brammer
Brake Bros
Brasway
Brent International
Bridon
British Aerospace
Brit. Building & Engineering Appliances
British Mohair Holdings

Table A5.6 - *Continued*

British Polytheline Industries
British Vita
Brooke Industrial Holdings
Brown (N.) Group
Brunel Holdings
Bryant Group
BS Group
BSS Group
Bristol United Press
BTP
BTR
Budgens
Bullough
Bulmer (HP)
Bunzl
Burndene Investments
Barton Group
Burtonwood Breweries
Cable and Wireless Comms.
Cadbury Schweppes
Caffyns
Canning (W)
Carclo Engineering Group
Castings
Castle Mill International
Caverdale Group
Channel Holdings
Chamberlin & Hills
Charter
Chemring Group
Chloride Group
Christie's International
Chrysalis Group
Church & Co.
City Centre Restaurants
Clarke (T)
Clyde Blowers
CML Microsystems
Coats Viyella
Cobham
Cohen
Concentric
Cook (William)
Cookson Group
Cooper (Frederick))
Cordiant
Corporate Services Group
Costain Group
Countryside Propeties.
Courtaulds
Courts
Cowie Group
Cradley Group Holdings
Craig & Rose
Crest Nicholson
Croda International
Cropper (James)
CRT Group
Cussins Property Group
Dalgety
Davenport Knit.
Davis Servide Group
Dawson International
Deanes Holdings
De La Rue
Delta
Denmans Elect.
Dewhirst Group
Dickie (James)
Dinkie Heel
Diploma
Dixons Group
Dolphin Pack.
Dowding & Mills
Druck Holdings
Dyson (J&J)
EBC Group
Eclipse Blinds
EIS Group
Elbief
Eldridge,Pope & Co
Electrocomp.
Elliott (B)
Ellis & Everard
Emap
EMI Group

Table A5.6 - *Continued*

ERA Group
ERF Holdings
European Colour
Eurotherm
Expamet International
Feedback
Fenner
Ferguson International
Ferraris Group
Ferrum Holdings
Fife Indmar
FII Group
Fine Arts Developments
Finlay (James)
First Call Group
First Leisure
Firth Holdings
Fitch
FKI
Flare Group
Forminster
Fortnum & Mason
Forward Technology Industries
Foster (John)
French
French Connection
Friendly Hotels
Fuller Smith
Galliford
Garton Engineering
Gaskell
GBE International
General Electric Company
Gent (SR)
Gibbs & Dandy
Gibbs Mew
Gieves Group
GKN
Glaxo Wellcome
Gleeson (MJ)
Glynwed International
Goodwin
Grampian Hoildings
Grampian Television
Granada Group
Grand Metropolitan Hotels
Graseby
Greenalls Group
Greene King
Greggs
Great Universal Stores
Guinness
Hall Engineering
Halstead (James)
Hampson Industries
Hanson
Hardys & Hansons
Harris (Philip)
Harrisons & Cros.
Hawtal Whiting Holdings
Hay (Norman)
Hazelwood Foods
Henlys Group
Hepworth
Hewden-Stuart
Heywood Williams
Hicking Pentecost
Hickson International
Highland Distillers
Hill & Smith
Home Counties Newspapers Holdings
Hollas Group
Holt (Joseph)
Hopkinsons Group
Howard Holdings
Howden Group
HTV Group
Hunting
Ibstock
Iceland Group
IMI
Imperial Chemical Industries
Inchcape
Instem

Table A5.6 - *Continued*

Intelek
Intereurope Techn. Services
Jacks (William)
Jacobs Holdings
Jerome (S) & Sons
Johnson Cleaners
Johnson Matthey
Johnston Group
Jones & Shipman
Jones, Stroud (Holdings)
Jourdan (Thomas)
Kalamazoo Computing
Kalon Group
Kelsey Industries (keep)
Kingfisher
Kwik Save Group
Kwik-Fit Holdings
Kynoch Group
Ladbroke Group
Laing (John)
Laird Group
Lambert Howarth Group
Lamont Holdings
Laporte
Laser-Scan Holdings
Latham (James)
Leeds Group
Leigh Interests
Lex Service
Liberty
Lilleshall
Linton Park
Lionheart
Lister & Co
Loades
Locker (Thomas)
Logica
London International Group
Lookers
Lovell (Y.J.) Holdings
Lowe (Robert H.)
LPA Industries
Lyles (S.)
M Y Holdings
M-R Group
Macfarlane Group
Manders
Mansfield Brewery
Marley
Marshalls
Marston Thompson
Martin International
Matthew Clark
Matthews (Bernard)
Maunders (John)
Mayflower Corp.
McAlpine (Alfred)
McCarthy & Stone (Holdings)
McKechnie
McLeod Russel
Meggitt
Mentmore Abbey
Menzies (John)
Merrydown
Metalrax Group
Meyer International
Microgen Holdings
ML Holdings
MMT Computing
Molins
Morgan Sindall
Morland
Mosaic Investments
Moss Bros Group
Mowlem (John) & Company
Neepsend
Newman Tonks
Nichols (J.N.) (Vimto)
Norcros
Northern Foods
North Midland Construction
Ocean Group
OMI International
Owen & Robinson

Table A5.6 - *Continued*

Oxford Instruments
Parkland Group
Pascoe's Group
Paterson Zochonis
Pearson
Peek
Pegasus
Pen.&Ornt Steam Navigator Company
Perkins Foods
Phoenix Timber
Photo-Me International
Pifco Holdings
Pilkington
Plasmec
Plysu
Pochin's
Portsmouth and Sunderland Newspapers
Powerscreen
Premier Farnell
Premier Health Group
Quadrant Group
Queens Moat Houses
Quicks Group
Racal Electronic
Radiant Metal
Raine
Rank Group
Ransom (William)
Ransomes
Readicut International
Redland
Reed International
Regal Hotel Group
Relyon Group
Renishaw
Renold
Reurters Holdings
Rexam
Ricardo Group
Richardsons Westgarth
RMC Group
Rolfe & Nolan
Ropner
Ross Group
Rotork
Rubicon Group
Rugby Group
Safeway
Sainsbury (J)
Saltire
Savoy Hotel
Scapa Group
Scottish & Newcastle
Scottish TV
Seet
Senior Engr.
Sharpe & Fisher
Sheffield United
Shilon
Sidlaw Group
Siebe
Signet Group
Silenthight Holdings
Simon Engr.
Sinclair WM Holdings
Sirdar
Sketchley
Slingsby (HC)
Smith & Nephew
Smith (David S.)
Smith (WH) Group
Smith Industries
Spirax-Sarco
Spring Ram Corporation
Stakis
Sterling Industries
Stat-Plus Group
Staveley Industries
Sterling Industries
Stirling Group
Stoddard Sekers
Stylo
Sunleigh
Sutcliffe Speakman

Table A5.6 - *Continued*

Swan (John)
Swan Hill Group
Syltone
T & S Stores
Tarmac
Tate & Lyle
Taylor Woodrow
TDS Circuits
Telemetrix
Tex Holdings
Thorpe (FW)
TI Group
Time Products
Tomkins
Tomkinsons
Toye
Transport Dev
Transtec
Trinity International Holdings
TT Group
Tudor
TurnPyke
Ugland International Holdings
Unigate
Upton & Southern
United News & Media
Verity Group
Vickers
Victoria Carpet
Vitex Group
Volex Group
Wage Gruop
Waddington
Wagon Ind. Holdings
Walker (Thomas)
Walker Greenbank
Wassall
Watmoughs Holdings
Watson & Philip
Weir Group
Wellman
Wembley Group
WF Electrical
Whessoe
Whitbread
Whitecroft
Widney
Wiggins Group
Williams Holdings
Wilson (Connolly)
Wimpey (George)
Wolseley
Wolstenholme Rink.
Wolv. & Dudley
Wood (Arthur)
Worthington
WPP Group
WT Foods
Young & Co's Brewery
Yorklyde
Yorks. Group
Young (H) Holdings
Yule Catto

Table A5.7 Company Names and Years of Entering Insolvency Regime of UK Failed Quoted Industrials Used in the Estimation Sample for the Comparative Study

Allied Partnership Group	1992	International Resort Holdings	1992
Astra Holdings	1992	Lilley	1993
ATP Communications Group	1992	Sale Tilney	1992
Chelsea Man	1991	Toothill (R.W.)	1991
Chequers Group	1992	Trilion	1992
Doctus	1991	Video Store Group	1991
Gaynor Group	1991	Ward Group	1992
Grovewood Securities	1991	West Industries	1992
Halls Homes & Gardens	1992	Willaire Group	1992
Hey & Croft Group	1992	Williams (John) Industries	1990

Table A5.8 Company Names of UK Non-failed Quoted Industrials Used in the Estimation Sample for the Comparative Study

Bailey (C.H.)	Jones, Stroud (Holdings)
Benson Group	Kwik Save Group
Cadbury Schweppes	McCarthy & Stone (Holdings)
FII Group	Meristem
Fortnum & Mason	MMT Computing
Granada Group	Persimmon
Greenalls Group	Quadrant Group
Henlys Group	Smith (WH) Group
Holt (Joseph)	Tate & Lyle
Johnson Matthey	Transtec

Table A5.9 Names, Years of Insolvency, and Accounts Years of Failed Russian Industrial Companies (All Companies are Organised as Joint Stock Companies)

Failed Company Name	Insolvency Year	Financial Year
Astrakhanzhilstroy	1996	1995
Belgorodskii Mashinostroitelnii Zavod Progres	1996	1995
Egor'yevskii Derevobrabativayushchii Kombinat	1996	1995
Elektroinstrument	1997	1996
Elkon	1996	1995
Gorokhoveztkii Sudostroitelnii Zavod	1996	1995
Karpinskaya Khlopkopryadilnaya Fabrika	1996	1995
Kasimovskii Stroitelnii Kombinat	1996	1995
Keramik	1996	1995
Kostromaenergostroy	1996	1995
Mozhginskii Zavod Dubil'nikh Ekstraktov	1996	1995
Orlovskii Zavod Upravl'ayushchikh Vychislitelnich Mashin	1996	1995
Pishchekombinat Kyrovsky	1996	1995
Tekhnomash	1996	1995
Torgovii Dom	1996	1995
Tulaelektroprivod	1996	1995
Valamazskii Stekolnii Zavod	1996	1995
Vereshchagenskii Trikotazh	1996	1995
Viborgskii Priborostroitelnii Zavod	1996	1995
Viborgskii Tselulozno-Bumazhnii Kombinat	1996	1995
Yeletskii Zavod Elta	1996	1995

Table A5.10 Names and Accounts Years of Non-failed Russian Industrial Companies (All Companies are Organised as Joint Stock Companies)

Non-failed Company Name	Financial Year
Beskudnikovskii Kombinat Stroitelnich Materialov	1995
Cherkizovskii Myasopererabativauyshchii Zavod	1996
Electrosv'yaz	1995
Irbitskii Stekolnii Zavod	1995
Ivanovskii Zavod Tyazhelogo Stankostroyeniya	1996
Kalugastroyservis	1996
Karacharovsky Mekhanicheskii Zavod	1996
Kostromskoii Sudomechanicheskii Zavod	1995
Krasnii Treugolnik	1995
Krasnodarelektrostroykonstruktsi'ya	1995
Mashinostrioitelnii Zavod	1995
Moskovskii Chugunoliteynii Zavod Stankolit	1995
Moskovskii Pishchevoy Kombinat	1995
Omskii Elektromekhanicheskii Zavod	1995
Peterburgskaya Telefonnaya Set	1995
PO Khimprodukt	1995
Promtractor-CHLZ	1996
Serpuchovskaya Bumazhnaya Fabrika	1995
Severnaya Zarya	1995
Sukremlskii Chugunoliteynii Zavod	1996
Trekhgornaya Manufactura	1996
Trikotazh, town of Irkutsk	1995
Tumentelekom	1995
Uralskii Shchinii Zavod	1995
Uralsvyazinform	1995
Yargorgrazhdanstroy	1995
Yuzhnouralskii Farforovii Zavod	1995

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