A Dynamic Study of the Characteristics, Predictive Power and Profitable Opportunities Underlying Takeover Prediction Models: Evidence from the UK and the USA

Julian Perez Alzueta

A Thesis submitted for the degree of Doctor of Philosophy

School of Business and Social Sciences

Trinity College of Dublin University

October 2010

DECLARATION

I give permission for the Library to lend or copy this thesis upon request.

Signed:

Declaration Of Authorship

I, Julian Perez Alzueta, declare that the thesis entitled *A Dynamic Study of the Characteristics, Predictive Power and Profitable Opportunities Underlying Takeover Prediction Models: Evidence from the UK and the USA* and the work presented in the thesis are both my own, and have been generated by me as the result of my own original research. I confirm that:

- this work was done wholly or mainly while in candidature for a research degree at Trinity College, University of Dublin;
- where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
- where I have consulted the published work of others, this is always clearly attributed;
- where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
- I have acknowledged all main sources of help;
- where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;

Signed: ....

Date: 14/03/2011

Abstract

Takeover prediction models can be defined as a cross-sectional regression using a firms corporate accounting information in order to measure its likelihood of becoming an acquisition target. Given the theoretical and empirical evidence that these models are unstable both over time and across economies, the research objectives of this thesis are to (i) determine persistent takeover characteristics over a ten-year time span, (ii) analyze the model's predictive accuracy and (iii) investigate whether long-term abnormal returns can be earned by investing in realistic portfolios based on the model's predictions and whether the model's profitability is correlated with its predictive ability.

As shown in the second and third chapter, for the past four decades, researchers have provided mixed evidence on the usefulness of accounting data in order to predict takeover activity. Although the literature suggests that takeover prediction models are unstable across time and economies, there seems to be no work having studied the stability of the estimated coefficients, the predictive power, and the portfolio performance as captured by takeover prediction models. This thesis provides a unique attempt to unfold the dynamic characteristics underlying takeover forecasting models.

Chapters four and five present the methodology and the data employed in this thesis. Following recent works in takeover prediction and in the time series forecasting literature, the model's dynamic stability is here studied using one calendar year window rolling forecast estimations during the period 1998-2007. Forecasting performance is measured ex-ante by using holdout samples in the year following each estimation year. This method aims to replicate a scenario where a practitioner employs a takeover prediction model based on the most recent takeover activity in order to achieve long-term profitability. In addition, the study tests the influence of the results across two levels: country and model choice. The geographical variability is studied by considering two different economies characterized by the highest takeover activity: the United Kingdom and the United States. Furthermore, I control for the model's specification by using both Logistic Regression and Artificial Neural Networks (ANN) specifications which were deemed to

accurately represent the traditional frameworks in parametric and non-parametric modeling respectively.

Consistent with the literature, the estimation results, presented in chapter six, show that most variables are inconsistent over time. As suggested by previous work, both sign and significance of the estimated coefficients appear to behave erratically over the selected period. However, for a small number of variables, the estimated coefficients show moderate sign persistency and a relatively frequent significant discriminatory power therefore providing evidence that takeovers may exhibit consistent characteristics over long periods of time. These characteristics also appear to be context-specific thus suggesting that explanatory variables should be chosen in relation to the M&A environment under study.

The prediction results, presented in chapter six, show that the model's forecasting power is highly volatile over time for both the UK and the US. In the US context, judging by the low explanatory power and the relatively poor predictive performance achieved by the logistic-based models, ANN seem to provide a superior ability in capturing takeover activity. Probably due to the smaller size of the resulting validation samples, the evidence appears to be mixed in the UK context.

In the portfolio section analyzed in chapter seven, I show that, in the case of the UK, ANN offer a solid basis for an investment strategy based on takeover predictions. In the US context however, despite ANN-based model's significant ability to predict takeovers relative to a random selection, both models failed to provide significant abnormal returns when controlling for common market factors. Finally, average predictive power appears to be strongly correlated with the model's long-term profitability in the UK context whereas no such correlation was measured in the US, suggesting a more efficient pricing of takeover vulnerability within the US market.

Acknowledgements

I would like, first, to express my gratitude to my supervisor Professor Brian M. Lucey for his constant help, support, and guidance at every crucial step of my work. His enthusiasm and optimism have been a constant source of both motivation and inspiration. Working with him was and will always be a pleasure.

I am also grateful to Professor Maurice Peat who introduced me to the core subject of my PhD. Our discussions have always enlightened my research and helped me to debug and clarify my views on several concepts.

Professor Colm Kearney has been a constant source of motivation and I sincerely appreciate his generous and targeted suggestions. His passion for research is both contagious and inspirational.

Prof. Jean Philippe Bouchaud has guided me through my passage from Physics to Finance and I would like to warmly thank him for being part of this challenging and rewarding experience.

A special thank you is due to my family and friends for always feeding my ambitions and supporting every decision. I am deeply indebted to my mother and my father for their encouraging advice towards enjoying every step of the research process. I will never thank my sister enough for her unconditional good humor and the taste for life she gives me every time I think of her.

I am also deeply grateful to my girlfriend Sigita for her unbreakable moral support and for always believing in me even when I logically prove myself wrong.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Introduction to the topic and statement of research objectives

Mergers and Acquisitions (henceforth: M&A) define the complex process through which a company integrates the services of another firm in order to, in theory, achieve combinational efficiencies. As frequently mentioned in the literature, the complexity underlying the M&A process may, to some extent, be explained by the large number of approaches showing that an M&A transaction seems to be affected by general economic, financial and legal factors both at the global and firm-level. Additionally, the significant influence of the human factor combined with the relative low frequency of the event makes drawing general conclusions on M&A activity a particularly difficult task. Among all these documented factors, *time*, although contended to explain a large number of disagreements and controversies within the M&A literature, is often mentioned but rarely accounted for in cross-sectional empirical studies. While dynamic patterns of M&A activity have been extensively documented, the impact of the selected time period on their reported results has generally been neglected. Therefore, the general objective of this thesis is to investigate, in the particular case of takeover prediction models, the effect of time on the different characteristics exhibited by M&A-based models.

A takeover prediction model can be defined as a multivariate model whose principal objective is to investigate the predictive power of cross-sectional publicly available financial and non-financial information in relation to takeover activity. The motivations behind takeover prediction have been extensively mentioned in the literature. First, from a theoretical viewpoint, as mentioned by Powell (1997), these models offer the possibility for a better understanding in relation to the reasons underlying an acquisition attempt. Moreover, the model's specification can be employed as an empirical test of the several motivations that have been documented within the M&A literature. Secondly, from an economic perspective, it is well-known that target shareholders earn substantial abnormal return the day of the announcement. In a review of the existing empirical evidence at the time, Jensen and Ruback (1983) show that target shareholders earned an average of 20.2% following the deal's announcement.[1] Therefore, a model able to persistently predict targets with high level of accuracy may potentially become the basis of a profitable investment strategy. Finally, as stated by Espahbodi and Espahbodi (2003), takeover prediction techniques could potentially provide corporate management with a measure of their firm's takeover vulnerability thus offering the possibility of taking appropriate defense measures or of submitting an anticipated warning to the board of directors of such an event.

One of the main characteristics of the takeover literature is that, despite the assertion that models are seemingly unstable over time and across economies, studies have generally assumed both the model's estimations and performances to be stationary. However, there are two types of time instabilities that should be here considered. The first one, common to all prediction models, accounts for the unexplained random and fixed factors related to the studied event as well as for the inherent distributional data instability. Within the bankruptcy prediction literature, studies such as Mensah (1984) and, more recently, Pompe and Bilderbeek (2005) have studied the influence of the business cycle in the model's predictive ability by comparing the model's performances in two or more periods of time. In addition, this technique is frequently used in the time-series literature in order to measure forecasting uncertainty.[2] Stock (2004) offers an interesting discussion as well as a review of the evidence of the general structural dynamic instability characterizing macroeconomic models. The second type of dynamic instability relates to the event in itself and is specific to the study in question. As I shall subsequently argue, although recent research has focused on the dynamic instability of bankruptcy prediction models, M&As have additional underlying instabilities likely to affect the model's predictive ability. First, as argued by Barnes (1999), given the multifarious factors affecting a takeover

[1] The reader is referred to Gaughan (2005), Chapter 3 (p.130) for a comprehensive analysis of the historical and more recent evidence on the short and long-run gains available to target shareholders during the time period following the deal's announcement.

[2] The reader may refer to Tashman (2000) for a review. Chapter 4 will also provide a detailed review on rolling forecast estimation techniques.

decision, takeover prediction models are likely to be more unstable when compared to bankruptcy prediction models where the event does not significantly change over time (except in cases where, for example, regulatory changes affect the underlying definition of liquidation). Secondly, given the motivation of generating economic rewards present in the takeover prediction literature, an additional question arises concerning the dynamic instability of the generated portfolios and, to what extent, the predictive instabilities are translated into portfolio risk. The latter point is particularly interesting given the recent debate on the potential sources of gains underlying takeover prediction models: while some state that gains stem from the bid premium or the abnormal performance during the announcement (e.g. Barnes, 1999; Arnull-Almond, 2007), others believe that firms with higher takeover likelihood are likely to provide an attractive financial profile for an investment (e.g. Wansley et al., 1983; Cremers et al., 2009). Finally, Pompe and Bilderbeek (2005) note that the model's predictive ability is affected by the significant increase in the number of bankruptcies during recession periods. Throughout the literature, a large amount of work has attempted to describe the dynamic patterns generated by M&A activity (Golbe and White, 1987; Town, 1992) and also to explain the drivers underlying such patterns (Gort, 1969; Mitchell and Mulherin, 1996; Roll, 1986). This literature shows, overall, that M&A activity is generally triggered by structural economic shocks that lead to collective incentives for M&A plans. Consistent with the empirical evidence provided by this thesis, M&A activity varies over time and there are multiple factors expected to influence such changes. As a result, assuming that changes in the number of events influence the predictive ability of the models, such an effect is likely to be even more pronounced in an M&A environment relative to other dichotomous events.

Given the mixed evidence found within the takeover prediction literature, a dynamic analysis of both the predictive and portfolio performance of takeover prediction models is needed in order to describe and analyze the potential instabilities underlying such models. Unique to the takeover prediction literature, this research therefore studies the dynamic features of takeover prediction models in relation to (i) the characteristics of takeovers (ii) the model's predictability and (iii) the abnormal profitability of an investment based on the model's predictions. The dynamic analysis uses a rolling estimation window technique generating multiple out-of-sample forecasts and aiming to replicate a practitioner's yearly attempt to predict takeover activity and use the model's predictions as a basis of an investment strategy. The use of the rolling-forecast technique has been recently used by Cremers et al. (2009) and constitutes a well-adapted tool to analyze a cross-sectional model's stability. Two modeling frameworks, the Logistic Regression and Artificial Neural Networks, were selected because of their persistent support and their complimentary functional advantages. The results are reported for both the UK and the US in order to investigate the generalizability of our results within the two economies most studied in relation to M&A activity.

The remainder of the chapter is structured as follows. Section 1.2 provides detailed definitions of the terms that were found to appear as potentially ambiguous or frequently present in the discussions outlined and hence in need of clarification. Section 1.3 both describes the motivations and provides a statement of the three research questions underlying the present research. Section 1.4 lists the several contributions that the present thesis offers to the academic literature. Section 1.5 presents the main results and underlines some related implications. Section 1.6 describes the structure of the thesis by providing a brief summary of each remaining chapter. Section 1.7 presents the conferences/seminars where the methodology and the results of this research were presented. Finally, section 1.8 briefly summarizes the chapter.

1.2 Definitions

Given the ambiguous use of some terminologies within the M&A literature and given their frequent appearance in the analysis here reported, this paragraph aims to clarify their definition within the present literature.

Takeover: Following Bartley and Boardman (1990), a broad definition of takeover was considered. All announced and completed deals are included in the definition as well as hostile and friendly bids. In addition to mergers and acquisitions, the definition also includes other types of corporate controls and corporate restructurings such as minority stake purchases, leveraged buy-outs, and corporate alliances. A complete definition as well as descriptive statistics in the employed M&A data are provided in Chapter 5

Takeover vulnerability: The term defines a firm's exposure to a takeover attempt (see e.g. Cremers et al., 2009). In this thesis, the term will be used to distinguish a model's true predictive ability which measures its ability to correctly forecast takeover attempts from the model's ability to capture takeover risk which is generally measured as the firm's takeover likelihood.

Rolling window estimation/forecast: This method, generally used in time-series forecasting, generates multiple forecasts by re-estimating the model using a fixed estimation window length and translating the origin of the estimation period. A rolling origin forecast is different from a rolling window forecast in relation to the number of generated forecasts as the former calculates forecasts for several time-horizons while the latter uses a constant time-horizon for all its forecasts. The reader may refer to Tashman (2000) for a detailed description.

Financial and non-financial ratios: Financial ratios refer to the variables built using the accounting information provided in the balance sheet, income and cash-flow statements whereas non-financial variables represent other corporate characteristics such as those describing a firm's corporate governance.

1.3 Statement of research questions

1.3.1 First research question

On the basis of the substantial disagreement on the general features defining a takeover target, one of the objectives of this thesis is to investigate the persistence of target firm characteristics over an extended number of time periods. In addition, by considering two of the economies hosting the largest number of takeovers, I here also examine how these features change across different countries. The first research question can be therefore stated as follows:

First Research Question: Do the estimators of multivariate takeover predictive models exhibit persistent sign consistency and discriminatory power during the period 1998-2007 in the UK and/or the USA and, if so, do the two countries share any common features?

1.3.2 Second research question

It is perhaps surprising that given the contention of the literature suggesting that takeover predictive models are unstable over time, there seems to be no study attempting to characterize the predictive variations of such models. Our study therefore aims to measure the forecasting accuracy underlying takeover prediction models by analyzing the persistence of their ex-ante predictive performance over a ten-year period– namely 1999-2008. Additionally, given the suggested superiority of non-parametric techniques, the study uses both a Logistic and an Artificial Neural Network for the model's specification. The resulting second research question can be stated as follows:

Second Research Question What is the uncertainty of takeover predictive model's yearly predictive power over the selected period and how are these results influenced by the country choice and by the choice of the model's specification?

1.3.3 Third research question

The implied underlying dynamic instability coupled with the often contradictory reported results related to the performances achieved by takeover prediction models, cast doubt on their underlying ability to persistently generate a profitable investment. Although some effort has recently been made to incorporate dynamic features in the portfolio selection, the literature generally fails to inform the investor on the long-term risk of a portfolio based on takeover predictions. In addition, there does not seem to be a clear understanding of the potential sources of gain underlying takeover prediction models. The third research question can thus be formulated as follows:

Third Research Question: How profitable is a long-term investment strategy based on the predictions of a takeover prediction model and what is the link between the model's predictability and its ability to generate abnormal returns?

1.4 Contributions

This thesis provides several contributions to the existing literature. The first contribution is the production of a large and comprehensive database containing the accounting and financial information of all publicly quoted firms having been subjected to an M&A announcement bid during the recent period 1998-2008. By extending the database to firms traded over the counter and traded in secondary exchanges, a more realistic universe of firms was generated while increasing the number of companies used in previous studies. Details on the number, types and size of the M&A deals included in the database are given in Section 5.3. In addition, the information has been collected for the two most studied economies: the United Kingdom (hereafter: UK) and the United States of America (hereafter :US).

The next three contributions are related to the employed methodology. First, based on a multiple cross-sectional estimation, the present study extends previous efforts made by the extant literature to analyze the time dependence of takeover targets' characteristics. Previous works have compared only two periods of time and have used different approaches to analyze the time variation of the estimated coefficients (see the works of Harris et al., 1982 and Powell, 1997). In this thesis, the analysis is extended to a comparison between ten consecutive periods. In addition, both the sign, as in Harris et al. (1982), and the statistical significance, as in Powell (1997), of the estimated coefficients are combined to analyze the time dependence of M&A drivers. Secondly, as far as I was able to ascertain from the current literature, there has been no attempt to describe the inherent variability of either the predictability or the profitability of takeover prediction models. Based on point forecasts, most of the previous work assumed that the model's predictability is stationary therefore failing to inform on the model's predictive robustness. In this study, the inherent variability of takeover prediction models is described by calculating a point forecast for each estimation and therefore generating a time series of ten predictions. Finally, from a portfolio management perspective, it is unclear if takeover prediction models can provide a reliable investment tool. The study of Brar et al. (2009) generates portfolios using a monthly update of takeover probabilities in order to incorporate the most recent market information. The study offers an insightful view on both the usefulness of market related variables and the significant long-term profitability of a portfolio based on takeover prediction models. However, their study does not provide any information on the dynamic of the portfolio nor on the relation between predictability and portfolio returns. Adding some evidence to the long-term performance of takeover prediction models, this thesis attempts to explore the link between predictability and profitability and therefore contributes by offering a viable method to measure the extent to which the model's profitability is driven by its accuracy to predicting takeover or by its ability to capture non-trivial aspects of takeover vulnerability.

The last contribution relates to the cross-country comparison. As I shall carefully described in Chapters 2 and 3, the takeover prediction literature suggests that reported results may not be generalizable across different economies (Harris et al., 1982; Barnes, 1999; Arnull-Almond, 2007). To the best of my knowledge, no study has attempted to compare the performances of a takeover prediction model across different countries while controlling for the vast number of modeling factors. In order to fill such a gap, the present study offers a cross-country comparison between the UK and the USA and contributes to providing an insight into (i) the geographical variations of target characteristics when controlling for the period and the modeling framework, (ii) the influence of the chosen economy in the model's ability to capture takeover activity, and (iii) the usefulness of takeover prediction models in achieving abnormal performance in different but comparable markets.

1.5 Thesis structure

This thesis is structured as follows. Chapter 2 first introduces the reader to the influences of the extant bankruptcy prediction literature and the M&A theory literature which respectively helped building a consistent methodological and theoretical framework. Section 2.2 provides an introductory discussion to the assumptions and limitations inherent to any forecasting exercise. Section 2.3 introduces the main methodological advances as well as relevant results in relation to the bankruptcy prediction literature, thereby establishing a ground of comparison for the results that will be later shown for the takeover prediction literature. Secondly, the main motivational hypotheses found in the M&A literature are presented and discussed in section 2.4. Finally, section 2.5 provides a comprehensive chronological literature review along with an extensive revision of the relatively small amount of literature from the late 1960's to our current period.

Chapter 3 provides a critical review of Chapter 2 and offers an analytical comparison between the works previously described. The chapter is divided in three main sections each one describing and highlighting the gaps that were found in the literature. Section 3.2 provides evidence on the disagreement on the literature on takeover characteristics. Given the dynamic characteristics of merger activity, Section 3.3 attempts to emphasize the lack of reliability of point forecast estimates and therefore the need to analyze the predictive ability of takeover prediction models from a multiple forecast perspective. From a portfolio management perspective, Section 3.4 highlights a recent debate discussing two potential sources of profitability underlying takeover prediction models. The section also describes the recent efforts of Brar et al. (2009) and Cremers et al. (2009) to incorporate a time feature in their predicted portfolios and underlines the need for more evidence to describe more accurately the risks underlying an investment based on a takeover prediction strategy.

Chapter 4 describes the methodology employed in this study and is divided into four main sections. Section 4.2 introduces the reader to the general framework of binary choice models. The section also provides details on the selected modeling specifications such as the Logistic regression and the Artificial Neural Network. Section 4.3 describes the multiple out-of-sample forecasts methodology generally used in time-series linear regression models and shows how the latter can be applied to binary choice prediction models. Section 4.4 provides technical detail on the calculations underlying the different evaluation methods employed across this study to measure the yearly and long-term performance of the model's performances. Section 4.5 describes the abnormal return calculation. Abnormal returns are defined, and a description of the chosen benchmarks is provided.

Chapter 5 describes the data collection process together with the definition used for "takeover" and the method used to select the financial explanatory variables. Details on the data transformation and yearly univariate analysis are also provided. After a detailed definition of the term *takeover* employed in this thesis, section 5.2 provides the method of collection as well as descriptive statistics of the M&A data. Section 5.3 describes the sources, and the method of selection of the financial variables used for model building. Finally, section 5.4 describes two algorithms used to automatize the rolling estimation and the portfolio construction process therefore illustrating how algorithmic techniques can optimize the complex and time-consuming task of a multiple matching process.

Chapter 6 shows the results obtained during the estimation and the prediction stages. Section 6.2 discusses the time dependence of the coefficients by examining both their significance and the sign changes over the selected period. Section 6.3 analyzes the dynamics of the estimated model's predictability for both the Logistic and the ANN based models. All the results are shown for both the UK and the USA.

Chapter 7 shows the results obtained during the portfolio optimization stage. Section 7.2 reviews the investment strategy employed to assess a takeover prediction model's ability to outperform the selected benchmarks and comments on the limitations of such implementation. Section 7.3 shows the portfolio abnormal performance relative to a suitable market index benchmark aiming to show the real returns achieved during the investment period. Acknowledging the limitations of a market index reference, as suggested by Barber and Lyon (1997), abnormal returns are calculated using a single control firm portfolio-matching method as it was shown to eliminate several biases present in other commonly used benchmarks. The chapter ends by offering a synthesis of the results and offering a possible environment to build a profitable investment strategy based on takeover prediction models.

Finally, Chapter 8 concludes the thesis by providing a summary of this research's contributions as well as a thorough discussion of the implications and limitations of the obtained results. Section 8.1 first provides a summary of the results and underlines the contributions that were made to the current literature. Section 8.2 analyzes the practical implications of the obtained results. Section 8.3 provides a detailed listing of the limitations and potential biases following the choices and restrictions imposed on this study.

Section 8.4 mentions the possible future research paths that could extend and improve our results.

1.6 Main findings

By studying the time dependence of different features of takeover prediction models, a number of findings were obtained.

First, the analysis of the time dependence of the regressor over the ten-year period 1998-2007 shows that, although most of the variables have an inconsistent effect over time, some variables seem to have a moderate persistence suggesting that takeover targets have stable characteristics. Furthermore, the dissimilarities between the target profiles in the UK and the US show that these characteristics may be unstable across economies. These results provide motivation for using such a methodology to find stable predictors that could potentially make parametric models more stationary and therefore more reliable.

A second finding relates to the time variability of a takeover model's prediction over time. Independently of the chosen country and the model's specification, these predictions are generally highly volatile over time and suggest that a single prediction is not representative of the model's predictive ability. This result indicates the need of a forecasting methodology accounting for this type of instability.

A third finding of our work relates to the predictive outperformance of Artificial Neural Networks relative to the Logistic Regression in both the UK and the US. Artificial Neural Networks show a persistent ability to outperform a randomly selected sample whereas the Logistic Regression, although achieving extremely high predictability for some given years, performs poorly out-of-sample in most cases. In addition, using cross-validation techniques the generalizability of Artificial Neural Networks could be further improved. Supporting the small amount of evidence in the literature, the results indicate that ANN models are a well-suited tool to predict takeover activity within the two selected economies.

Similar to the results obtained during the prediction analysis, the portfolio optimization section shows that a single profitable outcome is not representative of the ability of a model to generate a sustainable long-term investment. The results show that high cut-off values (i.e. in the range 0.7-0.9) can generate high profits but frequently generate significant losses. The use of lower cut-off values (i.e. in the range 0.1-0.3) appears to be a safe choice for reducing the model's predictive volatility and its underlying long-term investment risk. This result applies for both models and for the two considered economies.

In relation to the cross-country comparison, I find that the UK seems to be a more suitable economy to apply takeover prediction models. As a first argument, although the prediction stage shows that ANN-based takeover prediction models achieve a better rate of predictions in the US than in the UK, the market performance of the predicted portfolios is significantly better in the UK than in the US. This result indicates that takeover activity is better anticipated and therefore more efficiently captured in the US market. In addition, in the UK, the average predictive power of the model is strongly correlated with the long-term market performance therefore suggesting that the long-run generated gains are being driven by the model's ability to accurately capture takeover vulnerability. Overall, ANN-based takeover prediction models seem to have a promising potential as a long-term investment strategy in the UK context.

Last but not least, the results outline the usefulness of a methodology based in multiple forecasts to analyze forecasting uncertainty in binary choice models. Such a method could also be used by practitioners in order to estimate the forecasting error underlying a binary model's prediction in the fields of credit rating, bankruptcy prediction, and auditor's opinion prediction. In addition, the method offers an heuristic method to select the cut-off threshold that statistically maximizes the model's performance.

1.7 Conference presentations based on this thesis

The methodological concept of this thesis based on a rolling window estimation of cross-sectional takeover prediction models was developed and discussed during the Annual Econophysic Fribourg Symposium (Fribourg, Switzerland, November 2007).

A first paper entitled *Study of a Takeover Prediction Model's Dynamic using Rolling-Forecats Estimations: Evidence from the UK and the USA* was presented at the 7^{th} INFINITI Conference on International Finance (Dublin, Ireland, June 2009) and at the Midwest Finance Association (M.F.A.) Annual Conference (Las Vegas, USA, February 2010). The paper was submitted to the Journal of Banking and Finance and is presently under review.

A second paper entitled *Dynamic performance of a Neural Network-based Takeover Prediction Model: an Empirical Study in the UK and the USA* was presented at the European Financial Management Association (E.F.M.A.) Annual Meeting (Aarhus, Denmark, June 2010). The paper was submitted to the Review of Quantitative Finance and Accounting and is presently under review.

An overview of the thesis will be presented at the E.M.R.B.I. Doctoral Colloquium on Mergers and Acquisition as well as at the 3^{rd} Annual Conference of EUROMED Academy of Business (Cyprus, Nicosia, November 2010).

1.8 Summary

The assumption of statistical stationarity, under which takeover prediction models are estimated, does not seem to be supported by the evidence regarding the inherent dynamic of both the levels of activity or the motivational drivers underlying the M&A process. Following the inspiring works of Harris et al. (1982) and Powell (1997), a multiple forecast methodology based on a rolling-window estimations is here employed to study the time variability of features underlying takeover prediction models.

This thesis contributes to the present literature from a number of standpoints. The work extends previous efforts existing in the literature aiming to analyze the dynamic of takeover characteristics by using a larger number of estimations. Furthermore, the study offers a unique analysis on the dynamic of both the predictability and the profitability of takeover prediction models. In addition, this study is the first to research the cross-country dependence on takeover prediction model's performance. The thesis also provides evidence of the relative superiority of an ANN framework relative to a Logistic regression in building a takeover prediction model able to persistently predict M&A activity better than chance selection. Finally, this study highlights the unreliable nature of a point forecast estimation to assess a takeover prediction model's performance and shows how such a drawback can be overcome by using a rolling forecast methodology.

Chapter 2

Takeover Prediction literature review: its influences and developments

2.1 Introduction and overview

Takeover prediction models are the fruit of a more general underlying literature using multivariate regression models based on both financial and non-financial variables in order to classify or predict a discrete outcome. Among all subjects, bankruptcy prediction has attracted particular interest and has therefore been a constant reference for methodological improvements. The first objective of this chapter is therefore to present the bankruptcy prediction literature and show some of the seminal works that guided the takeover prediction literature in the use of both econometric and sampling methods. As a main difference from other binary choice frameworks, the takeover literature has developed a theoretical framework based on a number of hypotheses likely to explain the reasons underlying a takeover attempt. These hypotheses have all been well documented and several interpretations have been advanced on their behalf. Therefore, a second objective is to present these frequently documented motivations of takeovers and describe their foundations as well as the support they have received. Finally, in order to provide a clear view of the methodological differences —namely target definitions, selected periods, specification choices, and abnormal profitability measures, just to name a few— this chapter reviews the relatively small number of results related to the implementation of takeover prediction models. Given the focus of this thesis on the impact of time on the related results, the literature is described chronologically in order to capture any consistent pattern among contemporary works.

The chapter is structured as follows. As a general introduction to a prediction oriented literature, section 2.2 presents the motivations, assumptions and limitations inherent to any forecasting exercise as well as the role they play in the present study. Section 2.3 introduces the framework of bankruptcy prediction models in order to place takeover prediction models in a broader framework and present a list of the most influential works in relation to the contributions to the takeover prediction literature. Section 2.4 introduces the reader to the main hypotheses documented in the takeover prediction literature and discusses different views and interpretations perhaps originated from the generally inconsistent support they have received. From a more methodological perspective, section 2.5 provides a comprehensive chronological review of the literature attempting to forecast takeover activity. Finally, section 2.6 summarizes and concludes the chapter.

2.2 An epistemological note regarding forecast-based studies

Models are generally built in order to achieve a better understanding of the laws governing the observed universe of economics and finance. Behind this gain in knowledge, often underlies the objective of achieving an improvement in the forecasting accuracy of important economic and financial measures helpful to the establishment of more suitable and effective economic policies or financial regulations.

General econometric methods are based on a parametric specification which conciliates the possibility of analyzing the significant factors responsible for the model's explanatory power with the ability of using the model for out-of-sample prediction purposes. The recent development of non-parametric methods has shown that more complex "black box" specifications offered the possibility of providing an improved data recognition where no trivial analysis of the effect of the variables is available. These techniques therefore raise the question of whether parametric models offer an accurate understanding of the analyzed series or just a simple way of interpreting the effect of the factors used for specification. From another side, "black box" models, although generating a more complex data fit and potentially achieving higher predictability, cannot be used either to test hypothesis or to understand the influence of exogenous factors on the generated results thereby severely limiting their potential as a theoretical tool. This represents an on-going debate as there is still no clear-cut evidence of the superiority of non-parametric models. In an effort to benefit from both techniques, as I shall describe in Chapter 4, this thesis considers both parametric and non-parametric models. This decision combines the opportunity of studying the time-varying aspects of takeover characteristics as captured by parametric models while providing a more complete analysis of the dynamics underlying a model's predictive and economic performance.

From a more conceptual perspective, every forecasting attempt carries the assumption that knowledge about past events provides some information on future events. This assumption appears to hold in Natural Sciences where experiment conditions and structural relationships tend to be stationary across long periods of time. However, for most applications in fields such as Economics and Finance, the latter assumption does not hold and should not be given for granted when building a forecasting model. As carefully described in McCauley (2009), the main reason of the ability of Natural Sciences to predict into the future is the existence of invariances mainly in the space dimension and over time. Although time invariance is often an assumption in Finance, it is, by definition, a system where players adapt themselves to new environmental rules (i.e. laws, regulations, business cycles, new technologies, etc.) therefore making the time dimension particularly influential in the obtained results. In addition, Roehner (2002) explains that the level of complexity characterizing the financial markets is comparable to the most complex systems in physics based on the type of interactions governing these systems. His analogy between financial mechanisms and meteorology provides a meaningful idea of the complexity of financial forecasting. Therefore, in addition to the lack of symmetries highlighted by McCauley (2009), the interactions governing financial systems are similar to the most complex systems in natural sciences.

In this thesis, acknowledging the limiting results of a point forecast estimate, a rolling forecast method is used to generate multiple forecast measures and therefore achieve a more accurate estimation of the true predictive ability of the models. As mentioned in Roehner (2002) (p.16): "by extending the cluster of similar events under investigation, it is possible to converge toward a reliable model" .

2.3 The bankruptcy prediction literature

2.3.1 Origin of the concept

The first works in bankruptcy prediction models remain a frequently mentioned source in recent works. The latter represent the cornerstone of an innovative framework with a large number of possible extensions to different research areas. Beaver (1966) was first to provide empirical evidence that financial differences existed between bankrupt and non-bankrupt firms using a univariate measure of relative solvency applied to a pair-matched design. Although univariate analysis may be useful to detect statistical differences between groups, it provides little information on the relative level of distress for individual firms. In response to a growing disbelief in financial ratio analysis, Altman (1968) first provided an ordinal ranking allowing to measure the relative likelihood of default by "combining several measures into a meaningful predictive model". The latter combination refers to the applied Multivariate Discriminant Analysis (MDA hereafter) which, through a linear combination of a firm's financial ratios, generates an output related to the firm's level of distress. With the resulting model achieving an overall classificatory power of 94%, Altman shows that multivariate analysis offers a practical and successful way to accurately identify distressed firms. Despite numerous subsequent contributions, his model, also known as the Z-score, remains among the most quoted references within modern works in bankruptcy prediction models as in many other fields, as in the case of takeover prediction models.

2.3.2 Methodological influences

Historically, works in bankruptcy prediction have often pioneered methodological advances relative to other binary prediction literatures. Given the importance of some of the latter advances within the takeover prediction literature, a review of the most influential and acknowledged methodological improvements is here provided. Three main methodological issues are addressed regarding (i) the sampling method, (ii) the choice of a functional model and (iii) the use of industry-relative ratios.

Similar to the problem faced when collecting takeover data, due to the low proportion of bankrupt firms in the population, many studies have employed a choice-based sampling method where the total number of bankrupt firms is matched to a random group of non-bankrupt firms. Acknowledging the potential biases inherent to such methods, other studies have chosen to include full available data in their estimation and holdout samples. Responding to this specification dichotomy, Zmijewski (1984) analyses the significance of both the over-fitting biases generated by choice-based-sample and the selection biases produced by samples using complete data. He concludes that both sampling methods generate a significant bias. However, none of these biases were found to significantly impact the classificatory and predictive ability of the model. As mentioned by the author, selection bias arises because bankrupt firms are less likely to have all available data compared to going concern firms. In the case of takeovers, selection biases are likely to be less significant given that targets are not less likely to have available information compared to other non-target companies.[1]

In order to avoid the strong distributional assumptions of MDA, Ohlson (1980) employs a Logistic (a.k.a. logit) regression to estimate the bankruptcy prediction model. His findings show that the model is able to generate stable and accurate predictions of corporate distress. Although the logit regression has generally been the reference for binary choice applications, other types of models based on data pattern recognition have recently increased in popularity. Early works by Frydman et al. (1985) and Coats and Fant (1993) respectively used recursive partitioning and Artificial Neural Networks (ANN) to predict financial distress. Both papers show that the new models' forecasting performance compared favorably to the usual parametric modeling frameworks (i.e Logit and MDA).

Finally, Platt and Platt (1990) used industry-relative ratios in order to improve the distributional stability of the estimated models. The adjustment was defined as the value of the financial ratio divided by its industrial mean and multiplied by one hundred. The results show that industry-adjusted models achieve higher out-of-sample predictions both overall and within groups suggesting that industry normalization improves the estimated model's stability over time.

[1]Except, of course, in the case of bankruptcy acquisitions accounting for a small proportion of the total number of takeovers.

2.4 Motivations and hypotheses related to an M&A takeover attempt

In this section, I introduce the reader to the main hypotheses that have been mentioned in the takeover prediction literature along with the relative support that they have received. Although not perfectly disjoint, the hypotheses have generally been classified into ten different topics related to M&A theories. The objective is to familiarize the reader with the documented motivations behind a takeover attempt and the financial variables that were generally used to proxy them. Finally, as some documented M&A motivations do not have suitable financial proxys based on the firm being taken over, the section presents an additional number of important takeover motivations that have not been accounted within the takeover prediction literature. The qualitative interpretation of the hypotheses is summarized in Table 2.1.

2.4.1 The Inefficient Management Hypotheses

2.4.1.1 The Market for Corporate Control Hypothesis

This hypothesis is often associated with the work of Manne (1965) on the Market for Corporate Control (MCC). Two different, but somewhat related, interpretations can be found on the MCC mechanisms leading firms into a merging process. Firstly, in the view of Manne (1965), by perceiving inefficiencies, acquirers can increase the firm's value by improving the target's operating efficiency. Additional support to this view was given by Marris (1964) who suggests that the separation between management and ownership leads the former to take self-interested actions. From another viewpoint, Jensen (1988) considers the MCC as having a disciplinary role that forces management to work in the best interest of the vast amount of non-controlling shareholders. Therefore, self-interested managers are likely to avoid self-interested actions given the threat of a takeover attempt. In both theories, acquisitions are meant to eliminate inefficient management, however the former considers efficiency as a motive whereas the latter suggests that efficiency is an aggregate consequence of the disciplinary role of takeovers. In terms of takeover characterization, these theories predict that firms with lower levels of profitability are more likely to be targeted by more efficiently managed acquiring firms. Arnull-Almond (2007), in the Australian context, supports this view as his results show a significantly negative relationship between profitability and the probability of being taken-over.

More generally, however, the literature appears to provide weak evidence on the relationship existing between profitability and takeover likelihood as most studies found an insignificant and inconsistent linkage between profitability and takeover likelihood (see e.g. Dietrich and Sorensen, 1984; Walter, 1994; Alcalde and Espitia, 2003). Perhaps due to the mixed results provided by profitability measures, takeover prediction studies have also considered the possibility that firms with higher profitability might also be attractive as acquisition targets. The often cited hypothesis is that the acquiring firm's management might consider a takeover as a cash flow generating investment. In this view, an acquirer, instead of wasting cash in potentially unprofitable investments, will seek to spend its excess cash in purchasing a firm whose value (and its corresponding bid premium) would be lower than the present value of its expected future cash flows. As a result, firms showing signs of profitability are more attractive as targets for acquisition. This view is supported by Stevens (1973) and Cremers et al. (2009) who found that higher profitability was significantly related to takeover likelihood. Overall, the literature does not seem to agree on the relationship to be expected between profitability and takeover likelihood. This disagreement is well summarized by the estimation results presented in Barnes (1999) where opposite and significant signs were found between the two selected profitability ratios.

To proxy this hypothesis, the takeover prediction literature has mainly used two types of variables: profitability ratios and stock market measures of performance. The most frequently employed profitability ratios are Return on Assets (Palepu, 1986; Walter, 1994) and Return on Equity (Barnes, 1990; Alcalde and Espitia, 2003). However, several other financial ratios were used such as Return on Capital Employed (Powell, 2004), Profit Margin (Dietrich and Sorensen, 1984), and similar ratios replacing Net Income by Earnings Before Interests and Taxes (E.B.I.T.). Stock market performance has also been accounted in several ways. Palepu (1986) and Ambrose and Megginson (1992) use the firm's average excess returns relative to a market model over a four year period. Similarly, Barnes (1998) has accounted for "anticipatory price changes" by considering the firm's abnormal returns relative to the market model two months before the bid. Brar et al. (2009) use momentum as a proxy of returns defined as the past returns divided by the stock's volatility. Recent evidence in the UK context provided by Cosh and Guest (2001) shows that hostile takeovers present an abnormally negative performance during the year prior to the takeover bid. The result therefore suggests that previous market performance may be an important determinant in explaining acquisition likelihood.

2.4.1.2 The Free-Cash Flow Hypothesis

Marris (1964) provides a clear picture of the underlying conflict of interests between managers and shareholders: given the associated compensation incentives, managers are likely to be more concerned with a firm's size growth rather than with the creation of firm value. As suggested by Jensen (1986), firms achieving high levels of free cash flow (FCF hereafter) are more exposed to managers being reluctant to deliver excess cash to shareholders as this equals a loss of control over potentially larger assets. The FCF Theory therefore predicts that managers from such firms will tend to misallocate the unused cash flow by getting involved in Negative Present Value projects such as, for example, unprofitable acquisitions. As shown in the paper, the theory provides a good explanation of the series of unprofitable acquisitions during the 1980's that was undertaken by firms having high FCF profile characteristic. Jensen (1986) also mentions that *agency costs*, defined as the expenses incurred by a firm in order to align managerial objectives with shareholder's benefits, are likely to be significant in firms generating high levels of FCF. Inefficiently managed firms with high amounts of excess cash will therefore tend to waste capital in agency costs in order to eliminate internal operational inefficiencies. As contended in the takeover prediction literature, the FCF Hypothesis seems to suggest that firms exhibiting high levels of FCF are more likely to be taken over as the free cash flow can be invested in positive net present value projects by firms with excess profitable opportunities. However, Jensen (1986) provides a less clear picture by concluding that:

> Targets will be of two kinds: firms with poor management that have done

poorly prior to the merger, and firms that have large FCF which they refuse to pay out to shareholders.

Although the latter target profile fits the previously mentioned characteristics, the former seems to fit the unprofitable profile depicted by the more general inefficient management hypothesis analyzed in the previous paragraph. Contrary to the prediction of the FCF Theory, firms with poor performance prior to the merger are likely to have lower levels of free cash flows. As a result, the first (second) case predicts a positive (negative) relationship between the firm's relative free-cash flow and takeover likelihood. Overall, although the FCF Theory predicts a positive relationship between a firm's generated cash flows and takeover likelihood, it is possible that the selected proxy measuring management inefficiency could make its interpretation problematic.

The most commonly used proxy for this hypothesis is the firm's Free-Cash Flow divided by the firm's Total Amount of Shares Outstanding in the year prior to the announcement (Belkaoui, 1978; Walter, 1994; Powell, 1997).

2.4.1.3 The Activity Hypothesis

Activity has frequently been considered in the literature more as a measure of efficiency rather than profitability. Although general profitability measures are based on the firm's Net Income, this hypothesis underlines the importance of a firm's ability to generate high levels of turnover relative to its assets. As suggested by the takeover prediction literature, a firm's level of activity may influence its exposure to a takeover attempt in different ways. First, Rege (1984) contends that high activity ratios may imply a high demand for the firm's generated product. An acquirer able to supply additional capital could therefore be able to increase the firm's production output and take advantage of potential profits by adjusting the output to the existing demand. In addition, in the same view as the Free-Cash Flow hypothesis, firms achieving high levels of free cash flow may decide to invest the excess capital in productive firms seemingly able to generate profitable opportunities.[2] Both arguments suggest that a firm's activity should be positively

[2]This interpretation is also closely related to the growth-resource mismatch hypothesis which will be later described in Section 2.4.4

related to a firm's takeover likelihood. The results of Stevens (1973) and Barnes (1999) support this view as takeovers were found to generate higher profits and revenues than their industrial peers relative to their size. From another perspective, firms with low activity ratios may appear as firms undertaking heavy investments without being able to generate a desirable output. Therefore, more in the view of the inefficient management hypothesis, an acquirer could provide operating efficiencies allowing to increase the overall output of such firms. This interpretation suggests that takeover likelihood should be negatively related to a firm's productivity. This relationship is supported by the results of Dietrich and Sorensen (1984) and Arnull-Almond (2007). As a general result, the literature does not seem to agree on the sign to be expected from the activity proxy during the parametric regression's estimation.

The most common proxy for the Activity Hypothesis is Total Asset Turnover, measured by a firm's Sales and Revenues divided by its Total assets. Overall, the literature does not seem to agree on the relationship between asset turnover and takeover likelihood.

2.4.2 The Undervaluation Hypothesis

2.4.2.1 The Market-to-book ratio Hypothesis

Also known as the Q-theory of mergers, this hypothesis states that firms showing signs of undervaluation (low Q-ratio) are likely to be taken over by firms showing signs of overvaluation (high Q-ratio). As shown in a recent study by Jovanovic and Rousseau (2002), the differences of Q-ratios between acquirers and targets may explain, to some extent, the changes in levels of merger activity over time thus suggesting that acquirers do take advantage of market misvaluations. Since takeover prediction models are unable to measure the acquirer's overvaluation, the literature has only considered the undervalued profile of the target firm. Hasbrouck (1985) was the first to account for a firm's undervaluation considering that, for a firm seeking to be involved in a new sector, it is strategically interesting to acquire an undervalued firm. In the same line of reasoning, from a purely valuation perspective, in a stock-offer, a bidder using overvalued stock as a method of payment for undervalued stock can expect an increase in the firm's value over the medium-long horizon. In the words of Morck et al. (1988), "if the market does not price the firms properly, firms having a better valuation of the firm might find cheaper to buy the company rather than buy the new goods". Overall, this view asserts that target firms are bought as a bargain just as investors would invest in an undervalued stock. More related to the inefficient market hypothesis, Walter (1994) states that undervalued firms might have been discounted by a large number of or influential shareholders due the management's inability to maximize the firm's value. All of the previously mentioned arguments supporting this hypothesis predict a negative relationship between a firm's overvaluation and its acquisition likelihood.

Two proxys have been considered for this hypothesis. Hasbrouck (1985) and Bartley and Boardman (1990) measured overvaluation using the Q-ratio, defined as the firm's market capitalization divided by the replacement cost of its assets. Most authors, however, have employed the market-to-book ratio as a valuation measure in order to avoid potential measurement errors induced by the several assumptions underlying the calculation of asset replacement costs (Palepu, 1986; Walter, 1994; Espahbodi and Espahbodi, 2003).

2.4.2.2 The Price-to-Earnings ratio Hypothesis

Conceptually similar to the market-to-book ratio, the price-to-earnings ratio (henceforth: P/E) has been often used in the financial literature as a proxy for undervaluation. Gort (1969) denominates the "bargain theory" the concept that acquirers may decide to acquire a firm whose stock appears to be undervalued relative to their industrial peers and to, in particular, to the acquirer itself. The latter is tested by calculating the correlation of the difference between the acquirer's and the target's P/E and the size of the deal's bid premium. Using similar arguments, Walter (1994) suggests that lower P/E ratios relative to industrial peers may be a sign of undervaluation. As argued in the previous paragraph, undervaluation might lead to an acquisition due to the expected long-term increase in the target's value.

As a main difference from the market-to-book ratio hypothesis, a certain number of studies provide additional interpretations to the P/E hypothesis in addition to the market mispricing attractiveness of the target. Two views were found to explicitly suggest the effect of the P/E ratio on a firm's acquisition likelihood. From one side, Palepu (1986) suggests that high P/E acquirers would seek to acquire low P/E firms since, by increasing the value of the acquired earnings, the acquisition should yield instant gains. The latter argument assumes that the market generally values the acquired shares at the P/E of the acquirer prior to the acquisition. Harris et al. (1982) further supports this view arguing that a lower P/E ratio represents a prospective growth in earnings per share for the acquiring firm. As a second viewpoint, Dietrich and Sorensen (1984) suggest that a high P/E ratio generally increases acquisition transaction costs. Common to all mentioned arguments, the literature appears to predict a negative relationship between a firm's P/E ratio and its probability of being subject to a takeover attempt.

The proxy of this hypothesis is the price-to-earnings ratio.

2.4.3 The Dividend Payout Hypothesis

During the early stages of growth, a firm has the choice of retaining its earnings and investing them on a potentially profitable investment or to pay dividends to shareholders. Exploring the link between the Free-Cash Flow Hypothesis and a firm's dividend payout, Espahbodi and Espahbodi (2003) suggest that low dividends may signal higher agency costs or that a firm is financially constrained. In the same line, Barnes (1999) claims that shareholders disappointed with the levels of dividends may find it more profitable to tender their shares in the case of a takeover attempt rather than wait for their compensation. In both cases, the potential conflict of interest between managers and shareholders generated by the lower dividend payout would tend to increase the likelihood of a takeover attempt. Using a different argument, Dietrich and Sorensen (1984) suggest that higher dividend payouts express the lack of investment opportunities and therefore reduce the profitability of a potential acquisition. Again, in this case, higher dividends decrease the likelihood of a firm being taken over. From another viewpoint, Espahbodi and Espahbodi (2003) also provide the argument that smaller dividends yields are frequently associated with higher growth potential. Shareholders from fast growing firms paying lower amounts of dividends would rather keep their shares hoping to obtain a higher gain by increasing firm value. The latter will therefore be reluctant to tender their shares given their substantial underlying long-term profits. In this case, contrary to the argument of Dietrich and Sorensen (1984), firms with higher dividend payouts would be easier to acquire since shareholders are more likely to accept the tender offer either due to the management's misuse of the generated earnings or because a bid premium appears as a better option to exit the investment on a firm with no prospects of higher growth. Although the literature provides arguments for both sign expectations, the literature generally contends that target firms pay lower dividends than their non-target counterpart.

Several proxies were used in the literature to measure dividend payout. The most common of these proxies is the ratio between total cash dividends paid and earnings. Other measures include the ratio between cash dividends and total assets (Harris et al., 1982) and between cash dividends and free cash flow (Belkaoui, 1978). Early studies have used the retention ratio as a proxy for dividend payout (see e.g. Kuehn, 1975). By definition, the retention ratio is expected to have the opposite relationship than the one expected to be found using the dividend payout ratio.

2.4.4 The Growth-Resource Mismatch Hypothesis

Takeover may happen due to structural deficiencies which could be advantageous to an acquirer able to use such imbalance to generate growth opportunities. In this view, a firm with few growth opportunities/large resources or high growth/little resources are likely to be targets for acquisitions. In the former case, an efficient acquirer could use their expertise to invest the excess of resources into profitable projects therefore increasing the value of the acquired firm. As mentioned by Alcalde and Espitia (2003), this view is in agreement with the Free-Cash Flow hypothesis which predicts that firms with higher resources and limited growth opportunities will misuse the excess capital therefore becoming potential targets of more efficiently managed companies. In the latter case, firms with good investment ideas but limited by their lack of resources represent a seemingly profitable investment to an acquirer as a mean of achieving higher growth on its excess of resources. As summarized by Barnes (1999), the existence of "cash starved" and "cash rich" firms may lead to takeover attempts.

As in the Q-theory of mergers, although the hypothesis is based on a combination of characteristics between the acquirer and the target firm, the takeover prediction literature only focuses on the imbalance regarding the target firm. With this in consideration, several measurements were adopted to proxy the hypothesis. Palepu (1986) found significant support for this hypothesis using a dummy variable assigning the value '1' for firms having high growth-low liquidity-high leverage or low growth-high liquidity-low leverage and assigning the value '0' in all other cases. Cudd and Duggal (2000) supported Palepu (1986)'s results whereas Ambrose and Megginson (1992) found that the variable provided insignificant discriminatory power.

Although providing a less accurate measure of the hypothesis, most authors have considered Growth, Leverage and Liquidity as separate variables. The advantage of such a method is that explanatory power is generally increased given that each variable independently contributes to the model's explanatory power. In addition, the type of imbalance can be inferred by examining the relationship between the signs of the estimated coefficients. The overall theoretical and empirical evidence does not seem to provide a clear picture on the relationship between these three variables and acquisition likelihood. In the case of leverage, Barnes (1999) suggests that high levels of leverage reduce the target's ability to "fight" against a hostile bid whereas Lewellen (1971) claims that low leverage could be due to unused debt capacities that could be better exploited by a more experimented acquirer. In the case of liquidity, Walter (1994) suggests that firms exhibiting high levels of liquidity may signal an inefficient allocation of resources or a lack of investment opportunities whereas, in the view of Rege (1984) more liquid firms are more likely to become takeovers as transactions costs are reduced. Similarly, Barnes (1999) suggests that firms with lower growth and activity are more likely to become takeover targets as this might suggest an inefficient capital allocation whereas higher growth might be attractive for a firm aiming to improve its productivity.

Commonly used proxys for growth, liquidity and leverage are one to three years Sales Growth, Current and Quick Ratios, and Long Term and Total Debt over Total Assets respectively. Particularly for leverage, several other measures can be found such as Long-Term and Total Debt over Total Capital (Powell, 2004) and Total Liabilities over Total Assets (Arnull-Almond, 2007).

2.4.5 The Inefficient Financial Structure Hypothesis

This hypothesis states that a firm could be targeted for an acquisition due to the lack of an efficient capital structure. It complements the inefficient management hypothesis by suggesting that there are structural weaknesses in the firm that might not be captured by common profitability measures. In the general M&A literature, this motivation is also known under the names of *operating/financial synergies* and argues that a merger could fix structural imbalances existing in both of the firms involved in an M&A deal. I here mention some specific ratios used by the general takeover prediction literature aiming to capture several specific structural imbalances.

Fixed assets might have a particular influence in the attractiveness of a firm in cases where operational efficiencies are expected from the acquisition process. Ambrose and Megginson (1992) suggest that fixed assets such as Property, Plant and Equipment relative to size could have an influence in a firm's takeover likelihood. Although apparently in contradiction with their previous investigation, the authors rectify their previous conclusion by suggesting that small (large) targets tend to have higher (lower) levels of fixed assets. For this hypothesis, although an opposite sign is expected between size and fixed assets, the hypothesis does not predict any relationship between fixed assets and takeover likelihood. The proxy used by Ambrose and Megginson (1992) is Fixed assets over Total Assets while Bartley and Boardman (1990) used Fixed Assets over Sales. Complementary to the measures based on fixed assets, authors have also included variables capturing a firm's proportion of short-term capital and its ability to generate sales through its everyday operations and non-current assets. Often considered as an additional liquidity measure, Harris et al. (1982) and Palepu (1986) used Working Capital over Total Assets and Belkaoui (1978) employed Working Capital over Net Sales which is similar to turnover measures.

In addition, a firm's interest coverage also can make a firm more exposed to a takeover as it reflects the margin that the company has for paying its debtholders. Two different views can be found in relation to the expected influence of the variable on takeover likelihood. Dietrich and Sorensen (1984) suggests that low interest coverage signals unused debt potential, and therefore a negative relationship is expected between a firm's interest coverage and its takeover likelihood. From another perspective, based on the concept of financial synergy, Arnull-Almond (2007) states that an acquirer may increase the value of equity of a target firm by improving the firm's credit rating and by reducing the volatility of the target's earnings per share which generally reduces the average EPS during recession periods. Therefore, an acquirer may be able to provide the cash resources that are unavailable for targets with higher than average interest coverage. This view predicts a positive relationship between interest coverage and takeover probability.

The financial literature has also studied the importance of tax in corporate decisions. As underlined by Modigliani and Miller (1963), taxes play a significant role when considering choices on a firm's capital structure. Within the M&A literature, some authors have suggested that some takeovers may be motivated by tax advantages. The argument is based on the fact that accumulated tax losses are deducted during the write-up of the contract when assets are valued at their fair market price. As a result, the takeover literature has accounted for the possibility of a takeover being motivated by the such tax gains. Walter (1994) uses Current Costs divided over Total Assets as a measure of inflationary tax loss carry forward. This variable was also considered in Harris et al. (1982) but was finally omitted due to the low number of companies having available data. Overall, the variable has not shown to provide significant explanatory power in relation to acquisition attempts.

Finally, a number of non-financial variables have been used in some studies as potential discriminators of takeover activity. Additionally to Palepu (1986)'s financial variables, Ambrose and Megginson (1992) employs variables capturing a firm's ownership structure to investigate if the presence of large blocks of insider and/or institutional shareholding affects the efficiency of a firm's management and also analyzes whether the use of different types of takeover defenses reduces a firm's acquisition exposure. He finds that Blank Checks Preferred-Stock Authorizations, Voting right restrictions and net changes in institutional shareholding in the quarter prior to acquisition have a strong influence in takeover likelihood. Similarly, Cremers et al. (2009) study the influence of the presence of institutional shareholder blocks and the level of shareholder's voting rights on a firm's takeover exposure. Their results show that both variables have significant discriminatory power on takeover likelihood. In addition, Espahbodi and Espahbodi (2003) also include proxies of takeover defense strategies as well as the level of antitrust law reinforcement in their set of explanatory variables. Their findings suggest that the presence of golden parachutes has a positive significant influence in takeover likelihood.

2.4.6 The Size Hypothesis

Size is a frequently considered variable that experienced significant support in relation to its ability to classify target and non-target firms. Its well established discriminatory power led some early authors to build their estimation samples by matching target and non-target firms by firm size (Belkaoui, 1978; Rege, 1984). Although such procedure is contended to generate biases due to the non-randomness of the non-target subsample, the method was recently applied by Weir and Laing (2003) claiming that matching by size allows for a more accurate test of the synergy hypothesis.

Most studies, however, have explicitly accounted for size as an explanatory variable and two different theories can be found in relation the size hypothesis. First, as described in Dietrich and Sorensen (1984), Palepu (1986) and Espahbodi and Espahbodi (2003) large firms are more difficult to absorb given the increased complexity of the acquisition process related to the relatively higher transaction costs, the larger number of steps of the integration process, and the higher probability of receiving antagonist reactions from a well-established firm culture. This view predicts a negative relationship between size and a firm's probability of being subject to a takeover bid. Most of the empirical evidence seems to support this view as targets were generally found to be significantly smaller than other non-target firms. With a different argument, Barnes (1999) claims that management may also be interested in acquiring larger firms as this is generally followed by compensation benefits. The management's decision will be thus oriented towards large target firms in order to achieve an observable increase on the firm's size. It should be noted that, recent evidence has supported this view as suggested by the works of Arnull-Almond (2007) and Ouzounis et al. (2008) where targets were found to be larger, on average, than the rest of the considered population. These findings would seem to suggest that large companies can be subject to a takeover attempt thus implying that larger companies might no longer be safe against corporate control actions.

The natural logarithm of total assets is the most common proxy for the size variable. Other measures include Total Market Capitalization (Barnes, 1999), natural logarithm of Shareholder's Equity (Bartley and Boardman, 1990) and natural logarithm of Net Sales (Wansley et al., 1983).

2.4.7 The Industry Disturbance Hypothesis

Economic shocks such as technological innovation, stock market discrepancies and regulatory changes appear to be important in explaining the levels of M&A activity both over time and across different industrial sectors. Gort (1969) states that these changes in the rate of mergers might be explained by differences in the valuation of expected cash flows between owners and non-owners. This implies that waves of acquisitions (i) are triggered when the future expected value of non-owners exceeds the one of the owners and (ii) end when the market sector incorporates the valuation of acquirers into the value of the potentially targeted firms. Mitchell and Mulherin (1996) provide empirical evidence that merger waves do cluster by sector and suggest that merger waves are triggered by industry shocks. Overall, these results therefore suggests that a firm's industry can influence its probability of becoming an acquisition target.

The takeover prediction literature has incorporated this hypothesis in two different ways. First, given the persistency of M&A activity across industries (i.e. evidence on merger waves), a number of studies considered a binary variable capturing the level of activity within a firm's industry in a period prior to the observation year. Palepu (1986) constructed the variable by assigning '1' if the firm's industry, as measure by the four-digit Standard Industry Code (SIC), experienced at least one acquisition during the year prior to the observation year and '0' otherwise. Accounting for Palepu (1986)'s suggestion that industry effects might be better captured using shorter time lags, Cudd and Duggal (2000) employed a similar variable except that industry activity was measured based on the industry activity during the 12 months preceding the month when the acquisition was announced. The results show that using shorter time lags improved the discriminatory accuracy of the industry variable therefore suggesting that "a more precise measure of the disturbance variable is necessary to accurately reflect the effect of such acquisition waves". Although the authors calculate the model's predictive accuracy, the authors fail to clarify how the industry variable is constructed in the prediction sample where the acquisition month of the firm is a priori unknown. The second method uses industry-relative ratios in order to eliminate aggregate industry effects among the selected financial ratios. As mentioned in Barnes (1999), normalizing the explanatory variables by industry is a method that can replace the use of the industry disturbance binary variable. This method, although not capturing the aggregate industry effect due to previous M&A activity, allows elimination of any constant industry factor equally affecting all financial variables within the industry. Finally, authors such as Cudd and Duggal (2000) and Arnull-Almond (2007) have employed both methods.

2.4.8 Other Hypotheses

There are several other hypotheses present in the M&A literature that are absent within the takeover literature. Reasons for not including these hypotheses are that (i) the acquirer's information is involved in the statement of the hypothesis or (ii) there are no observable data allowing to accurately proxy the hypothesis. By far the most documented one is the Synergy hypothesis which states that, due to increased efficiencies, the combination of the acquiring and the acquired companies exceeds the value of the two companies considered separately. In a recent case study, Larsson et al. (2004) analyzed the differences between the synergies produced by failed and successful mergers in order to identify the key factors of a successful merger. Their results show that best efficiencies are obtained through high strategic combination potential, high employee collaboration, high organizational integration and a fast-paced long-term orientation process. However, do these efficiencies generate enough profit to counterbalance the bid premium and the transaction costs? Roll (1986) answers this question by suggesting that confident managers tend to overstate the potential value of the target as well as the potential synergies between firms and, therefore, tend to overpay when offering a bid premium to target shareholders. This argument is known under the name of the Hubris hypothesis. As a discussion of all documented hypotheses is not relevant for the present study, the reader is referred to Trautwein (1990) for a review on different merger motives. Arguing that a large amount of insignificant evidence has been provided to efficiency hypothesis of M&As, the latter provides an interesting critic to the several tests provided by, among other research areas, the here analyzed takeover prediction literature.

2.5 A comprehensive review of the extant takeover prediction literature

This section provides a comprehensive review of the academic literature context related to the development of takeover prediction models. Our focus is mainly centered in methodological innovations and the resulting forecasting ability of the models. Additionally, an effort has been made both to provide detail of the articles having a distinctive influence or presence in our work and to briefly mention the works whose analyzes or contributions were not deemed relevant for the present study.

A chronological structure was chosen for the literature review here presented. Three main reasons support this choice. The first one is the relatively small and therefore manageable size of the academic work that has focused in the prediction of takeover events compared to bankruptcy events. Therefore, as a contribution to this literature, I shall here provide a comprehensive historical review of the works in takeover prediction with an emphasis on their methodological contributions. Secondly, the relevance and limitations of results are better identified in a chronological review as contemporaneous works often share the same methodological frameworks. Finally, as merger characteristics are believed to change over time, a separate review of the results based on neighbouring time-periods facilitates the analysis of consistencies in takeover characteristics.

2.5.1 Early works: birth of the concept

The first works in takeover prediction gave birth to a series of papers attempting to characterize and/or predict target firms. During this decade, the models are based on Multiple Discriminant Analysis (MDA hereafter) as the basis for multivariate regression models. The research is mainly exploratory as the authors do not consider any theoretical framework to support the choice of the variables underlying their models, however these first attempts of takeover prediction covered the main methodological issues on which the literature would place its focus during the following decade:

1. The potential misspecification of mixing different motivational trends by pooling targets firms from different time periods.
2. Extending the latter point, the underlying dynamical instability of takeover prediction models and the need to systematically update the reported estimations.
3. The need for an industry-specific ratio to normalize the distributional variations across industries.
4. The failure to measure the ex-ante predictive ability of the model by using validation samples from the same period as the estimation sample.
5. The need for a method allowing to calculate ex-ante the optimal cut-off threshold.

The work of Kuehn (1975), based on his Ph.D. dissertation, appears as the first study attempting to use multivariate statistical methods in order to describe takeover characteristics. The study uses UK data during the period 1957-1969. The author first underlines the importance of considering individual industries when attempting to characterize takeover activity thus recognizing that potential misleading results may be obtained when considering takeovers as an aggregate sector sample. From a dynamic viewpoint, he analyzes the variations of takeover activity across the period and suggests that time-varying factors such as the business cycle and the differences in valuation between targets and acquirers seem to be correlated with the levels of merger activity (see p. 14).[3] Furthermore, Kuehn builds a first theoretical framework (see Chapter 2) by setting several hypotheses based on the latter analysis and relating them to the theory of the firm. His results first show that industry-specific analyses do not improve the model's ability to capture takeover characteristics. Secondly, using a Probit regression and aggregate takeover data, he finds that the probit transformation provides a significant improvement relative

[3]This will later emerge as the undervaluation hypothesis or the Q-theory of mergers (described in Section 2.4.2.1).

to the linear regression models as indicated by the higher explanatory power. From a merger characterization perspective, UK takeovers appear to be undervalued firms with low performance during the pre-bid period as measured by a lower profitability ratio and a lower growth rate in sales.

In a new UK-based study, Singh (1971) attempts to characterize take-over companies in order to test the disciplinary role of the stock market in M&A activities. This is conducted by using both univariate and multivariate techniques based in 9 financial ratios. The initial estimation period 1955-1960 was split into two sub-periods (i.e. 1955-1958 and 1959-1960) and the models were estimated for each industry separately. The results show that, except for size, the variables show poor discriminatory power and the multivariate model, estimated with aggregated data, achieves a maximum classificatory power of 64.4%. As in Kuehn (1975), Singh earlier cautioned future research by addressing a double "pooling problem" to which the user is faced when collecting the model's input data – namely the potential misspecification of a sample resulting from pooling target firms across different time periods and the potential statistical bias generated by pooling firms' data across industries.

In the same year, Simkowitz and Monroe (1971) publishes the first academic paper using statistical techniques based on corporate financial information in the context of takeover prediction. Because of the large number of diversified acquisitions that took place during the second half of the 1960's, the sample was restricted to conglomerate targets acquired during the period April – December 1968. Using an MDA regression based on 24 financial variables, an estimation sample containing 23 targets and 35 non-target firms was considered. Using a backward stepwise method, only seven variables with high explanatory power were finally included in the model. The results show that acquired firms seem to be smaller in size, have lower price to earnings ratio, lower dividend payout and lower growth in equity. Using a validation sample of 23 firms, the model achieves a significant overall predictive accuracy of 77 % thus showing that accurately identifying takeovers was possible. However concern was raised in relation to the commonly employed methodology by suggesting the use both of out-of-samples tests to assess predictive ability and of industry-specific ratios to normalize the financial data.

In a later study, Stevens (1973) addresses the importance of eliminating multicollinearity in order to obtain stable estimated parameters. Using a factor analysis, the twenty initial variables were reduced to six independent components measuring (1) Profitability (2) Liquidity (3) Activity (4) Leverage (5) Dividend payout and (6) Stock valuation. The MDA model was estimated using a sample of 40 firms targeted during the year 1966 matched by size to 40 non-acquired companies. Although the model achieved a moderate overall classificatory accuracy of 70%, acquired firms were classified with an 85% accuracy. In addition, the split validation sample technique[4] shows a classificatory accuracy of 67.5% suggesting that the model is cross-sectionally stable. The estimated coefficients show that target firms appear to have higher liquidity, lower levels of leverage and higher sales turnover compared to non-target control firms. Finally, following the recommendations of Simkowitz and Monroe, the model's time stability is tested using two holdout samples, each containing 20 targets and 20 non-target firms from the years 1967 and 1968. For each year, an overall prediction accuracy of 70% was obtained suggesting that takeover prediction models are accurate and consistent over time.

Although more from a perspective of analyzing the pre-bid and post-bid share price patterns, Firth (1976) offers an interesting analysis of the characteristics of bidees and biders involved in an M&A deal within the UK context. His univariate results show that target characteristics do not seem to differ significantly from control firms with similar size and belonging to the same industry. Similar to the results obtained by Kuehn (1975) for the period 1957-1969, UK takeovers in the period 1973-1974 appear to show signs of lower profitability and lower growth when compared to their industrial peers. As a main difference, neither the valuation ratio nor the price-to-earnings ratio were found to be significantly different from the matched control firms.

In the first study applied outside the UK and the US, Fogelberg et al. (1978) apply the MDA analysis to predict takeover activity in New Zealand. Their study uses a state based sample matched by size and industry sector containing 86 companies. Supporting Singh

[4]This method splits the initial estimation sample into two halves. One half is used to re-estimate the model and the other is used to validate the estimated model. As both samples consider the same time period, the method aims to test the model's cross-sectional stability. It should be mentioned that this method was however incorrectly used for prediction tests in several works such as in Belkaoui (1978), Dietrich and Sorensen (1984) and in more recent papers such as Cheh and Weinberg (1999) and Brar et al. (2009).

(1971)'s results, they find that the model shows poor discriminatory ability and that no conclusions could be advanced since none of the employed variables were found to be significant. Possibly due to the poor results in the New Zealand context, for a period of more than twenty years, takeover prediction studies have avoided using data from small and underdeveloped economies.

In the canadian context, Belkaoui (1978), acknowledging the influence of the cut-off choice on the model's predictive performance, applies Altman (1968)'s optimal cut-off method to minimize misclassification errors. His MDA model used 16 potential predictors of takeover likelihood grouped by Non-liquid Assets, Liquid Assets to Total Assets, Liquid Assets to Current Debt and Liquid Asset Turnover. The model's classificatory (predictive) performance was tested in a state based sample of 50 (22) companies matched by size. His results show that the model achieves high overall classificatory (predictive) accuracy ranging from 72% to 84% (70% to 85%) depending on the year selected to measure the financial variables. As a conclusion, the author recommends the use of non-liquid ratios and suggests that the model's financial data should stand at two or three years before the bid date. Ignoring previous research, the author does not eliminate multicollinearity, nor does he test the predictive ability of the model in a different time period.

2.5.2 1980s: theoretical and methodological improvements

Previous results seem to show that forecasting takeovers is plausible. However, the presence of some systematic methodological flaws cast doubt on their optimistic results. In addition, no clear results have been achieved in relation to the characterization of target firms. During this following period, a consistent theoretical framework for takeover characterization is developed based on the different hypotheses described in the previous section 2.4. Moreover, several methodological improvements were achieved in both the specification of the models and the statistical validity of the reported results.

Levine and Aaronovitch (1981) performed the first "ground-clearing" attempt of defining a theoretical framework based on different theories of the firm. The following hypotheses were considered: (1) The Importance of Size, (2) Investor's Gain, (3) Mergers and Optimal Resource Allocation, and (4) Managerial Theories of Mergers. Twelve financial ratios were selected to conduct a multivariate analysis in order to investigate the differences between acquiring and acquired firms. The estimation sample contains a complete sample of companies involved in large UK deals (i.e. over 3 million pounds of transaction value) during the year 1972. Their findings show that, except for size, no variable seems to have significant discriminatory power. Although mentioning that the importance of size is a non-trivial result, Levine and Aaronovitch conclude that, given the large number of reasons behind the acquisition process, no general *theory of mergers* is likely to emerge from a multivariate analysis based on individual financial characteristics of acquired firms.

Supporting Singh's concern of pooling firms from different periods, Harris et al. (1982) provide evidence on the underlying dynamic instability of takeover characteristics. Both fixed and random probit regression are considered for the model's specification, and between five and seven variables are used as regressors. The time stability of takeover characteristics is investigated by estimating the models in two consecutive periods of two years. The two estimation periods are 1974-1975 and 1976-1977 containing 45 and 61 target firms respectively and approximatively 1200 non-target firms for each period. The results show that not only most of the financial variables provide little additional information but, most importantly, that the explanatory variables explain a very small proportion of the overall merger activity. By comparing the sign of the estimated coefficients between the two periods, he also concludes that takeover characteristics seem to change over time therefore providing indirect support to Levine and Aaronovitch (1981)'s contention that no consistent general theory of M&As can be drawn using multivariate models based on target accounting characteristics.

Given the profitable potential of takeover predictive models, Wansley et al. (1983) investigate the possibility of earning abnormal returns by investing in the samples predicted by a takeover prediction model[5]. As a main difference from previous studies, the authors chose to estimate their model using two linear classification functions to distin-

[5]The argument behind such an investment being that, as the evidence shows that takeovers earn abnormal returns the day of the announcement (see for instance Jensen and Ruback, 1983, for a comprehensive review), if a model can predict ex-ante with a high degree of accuracy then a portfolio based on the model's predictions can generate a profitable investment.

guish between targets and non-targets[6]. The data for the estimation (holdout) sample was collected in the period 1975-1976 (1977) resulting in 44 (39) takeovers which were pair-matched to a random group of non-acquired firms. The two estimated functions produce a classificatory power of 75% which was reduced to 69.9% in the holdout sample. Using a real population sample during the year 1977, two portfolios are constructed with 25 and 50 companies having the highest probabilities of being acquired. Although no target was present in the portfolios, the results show that both portfolios earned abnormal returns relative to the market benchmark suggesting that takeover predictive models can be used as the basis of an investment strategy. The poor predictive ability of the model is consistent with the previous findings of Levine and Aaronovitch (1981) and Harris et al. (1982). However, contrary to the present belief in the literature, Wansley et al. provide evidence that low predictive performance does not necessarily derive from low profitability therefore suggesting that firms with similar financial profiles to acquired firms offer, on average, a profitable source for an investment.

As mentioned by Singh (1971) and Harris et al. (1982), takeovers seem to show different characteristics in different periods, however no study seems to define the number of years that minimizes the "pooling" bias. Noticing that studies using a shorter period exhibit higher performances, Rege (1984) addresses the problem of the length of the estimation period as a possible source of misspecification. He further contributes by analyzing the differences between foreign and domestic canadian take-overs. An MDA analysis based on 5 financial ratios was used to specify the model. The study considers two estimation periods, 1962-1973 and 1968, containing sample sizes of 88 and 18 firms respectively and three models are tested aiming to differentiate (i) domestic targets from non-target firms (ii) foreign targets from non-target firms and (iii) foreign target from domestic target firms. Perhaps surprisingly, the findings show, first, that the estimation period's length does not influence the classificatory ability of the models and, secondly, that none of the models offer significant explanatory power therefore bringing further support to the contention that multivariate models are not able to differentiate between target and non-target firms. Although not mentioned by the author, given the sign changes of some of

[6]As mentioned by the authors, classification functions are mutually exclusive operators and differ from the discriminant analysis typically employed by previous research. In this case, the firm will be considered as a potential target (non-target) if the target (non-target) classification function has the highest output value.

the coefficients in both the domestic and the foreign target prediction models, the results seem to confirm that the target characteristics in 1968 do not match the overall characteristics of takeover activity during the decade 1962-1973.

The study of Dietrich and Sorensen (1984) discusses two methodological issues: the advantages of both the logistic regression to estimate takeover probabilities (relative to MDA) and the use of industry-relative ratios defined as the variable's value relative to its industrial average. Based on the firm's valuation principle as theoretical framework, the 10 considered variables were chosen only if they were likely to have an effect on the net present value of the firm's acquisition valuation method. Both within the period 1969-1973, a state-based sample of 24 target and 24 non-target firms and a holdout sample containing 16 non-target and 6 target firms were used to respectively measure the classificatory and predictive ability of the model. Firms with higher traded volume and lower dividend payout, turnover, size and leverage are found to have a higher probability of being targets. The final model achieves significant classificatory (predictive) power of 92.5% (91%) which represents the highest predictive ability reported on the takeover prediction literature. Contrary to the previous trend, Dietrich and Sorensen defend the potential use of takeover predictive models and conclude that the use of logistic-based models and industry-relative ratios are well-suited for binary choice problems.

Hasbrouck (1985) presents a more structured theoretical basis supported by six main hypotheses in order to study the motives for takeovers. Although the q-ratio is at the center of the analysis, financial leverage, liquidity, and size are also considered to capture the presence of tax-incentives and managerial inefficiency. The model is based in a logistic regression accounting for 7 financial variables. The study uses both industry-matched and size-matched estimation samples with 86 targets and 172 non-target firms. The results show that targets seem to be smaller companies characterized by a low q-ratio leading Hasbrouck to conclude that managerial incompetence seems to be the main reason behind a takeover attempt.

Often considered as the most influential work in takeover prediction literature, Palepu (1986) attempts to bring a solution to several methodological flaws present in the previous literature and develops a consistent methodological framework to be used by further research. His study is based on a logistic regression framework estimated using a 1:3 ratio containing all target firms and randomly selected non-target firms selected during the period 1971-1979. Along with Hasbrouck (1985), Palepu provides a structured target characterization based on a set of 10 financial variables used as proxys to test six takeover motivation hypotheses previously documented in the M&A literature. As a second part of his work, Palepu demonstrates that state-based samples generate efficient but inconsistent estimators and contends that they are likely to result in "erroneous inferences" in relation to the model's predictive ability. He further suggests that previously reported predictive accuracies are likely to be biased for using (i) holdout state-based sample therefore simplifying the problem of finding a small number of targets among a large number of non-target firms and/or (ii) sub-samples of the estimation period to measure predictive ability therefore failing to capture the model's true ability to classify targets in the future. Finally, he argues that most of the authors have arbitrarily chosen a default cut-off probability of 0.5 without noticing that the cut-off choice has a significant impact on the predictive accuracy of the model. His results show that, while being able to select a large number of targets, the model also predicted a large proportion of non-target firms. Probably due to the model's lack of specificity and the large number predicted firms, the resulting buy-and-hold strategy earned insignificantly negative excess returns relative to the market model. The conclusions of the paper are that previous work had important methodological flaws and, when correcting them, takeover predictive models do not show any ability to either predict potential targets or constitute the basis of a sound economic investment.

Rarely mentioned in the takeover literature, the work of Chapman and Junor (1987) in the Australian context provides an interesting and original perspective on some of the flaws and limitations present in previous works. Among these are included: (i) the absence of adjustment for inflation, (ii) the failure to include control-ownership type, (iii) the presence of subsidiaries and (iv) the variability of the sample. Adjusting for these potential misspecifications, the authors build a consistent data sample of 69 non-acquired and 29 acquired firms during the period 1978-1981. Their results show that target characteristics are consistent over time[7] and that the control-type variable is an important discriminator

[7]It should be noted that the analysis differs from the one reported by Harris et al. (1982) as the latter uses

of takeover activity. Overall, Australian takeovers appear to be small, unprofitable firms with low leverage, low liquidity and higher levels of management ownership when compared to their non-acquired counterparts.

Given the large debate questioning the public and private benefits of conglomerates and takeovers at the end of the 1980s, M&A research focused on the determinants guiding both synergistic and disciplinary acquisitions. As previous takeover research had considered target firms as an homogenous group, Morck et al. (1988) investigate the distinctive characteristics between hostile and friendly takeovers. The takeover data sample contains firms that were listed in the Fortune 500 in 1980 and having been subject to a bid during the period 1981-1985. The final sample contains 454 non-target firms, 42 friendly and 40 hostile targets. As in Harris et al. (1982), the multivariate analysis uses a probit regression and is based on the five (financial and non-financial) variables having the highest univariate discriminatory power. Although some disagreement exists between their univariate and multivariate analyses, their findings show that hostile targets are more likely to be smaller companies with lower growth and located in a low q industry than the average whereas friendly targets do not appear to show any distinctive feature. In other words, hostile (friendly) acquisitions seem to be guided by disciplinary (synergistic) motives and using an aggregate sample of targets could be misleading.

Bartley and Boardman (1990) tested the advantages of using inflation adjusted ratios in MDA-based takeover predictive models during the period 1979-1981. Their definition of takeover expands the notion to every attempt of control exceeding or equal to 5% of ownership acquisition. Using realistic proportions of target and non-targets (i.e 41 targets and 153 non-targets) in the estimation, they compare a current-cost model, a constant dollar model, an historical cost model, and a model using a combination of the previous ratios. While the combined model achieves the maximum classificatory ability of 79.9%, the historical data model achieves only 69.6% suggesting the superiority of inflation adjusted data relative to historical data in discriminating target from non-target firms. Given these results, the authors recommend to use a mix of current-cost, constant dollar and historical data when the purpose is to maximize predictive performance. Un-

---

two different samples of takeover in two different periods whereas, in this paper, the same sample of firms is analyzed at three different points in time (similar to a panel data regression).

fortunately, they do not test the predictive ability of their models which questions the generalizability of their results.

In the UK context, Barnes (1990) provides a discussion on the relative impact of Palepu's findings when the objective is to maximize target prediction performance. He also discusses how data instability, both over time and across industries, affects the estimation results of takeover prediction models. Using an MDA model estimated during the period is 1986-1987 and resulting in a pair-matched estimation (validation) sample of 55 (37) targets and non-target firms, he finds that the model is able to classify 68.8% of the firms correctly. Acknowledging the flaws of the predictive ability test, a sub-sample of targets and non-target firms from the estimation sample is used for validation resulting in the model classifying 74.3% of the firms correctly. It should be stressed that, although the stated objectives of the paper were to expand recent methodological advances, the paper does not consider any of the major methodological points raised by Palepu – namely the use of a more realistic unmatched estimation sample, the choice of prediction samples in subsequent periods, and the calculation of an optimum cut-off value – therefore casting some uncertainty on the reported results.

During this period, the literature was able to answer some of the points enumerated on the previous section. First, Dietrich and Sorensen (1984) showed clear evidence on the advantages of using industry-adjusted ratios. Secondly, Palepu (1986) clearly described the sources of misspecification present in previous prediction tests, and proved the need for realistic out-of-sample predictions to asses the predictive ability of the model. In addition, an ex-ante estimation method of the optimal cut-off is offered where the optimal cut-off is defined as the value minimizing the total errors. In relation to the last point and adding evidence to Singh's pooling problem, Harris et al. (1982) showed that some of the estimated coefficients change both quantitative and qualitatively over time which suggests that, due to the dynamical complexity underlying merger determinants, both classificatory and predictive ability are likely to be unstable over time.

2.5.3 1990s: a consistent analytical framework

The work of Palepu (1986) provided a solid theoretical core to characterize the motivations behind a takeover attempt based on six hypotheses present in the M&A literature. During this subsequent period, academic works have progressively incorporated the theoretical and methodological improvements achieved during the previous decade.

Ambrose and Megginson (1992) use a similar framework to the one used by Palepu and test the influence of different non-financial factors in takeover acquisition likelihood such as ownership concentration, insider and institutional shareholding, takeover defenses and measures of asset structure. The logistic regression was estimated during the period 1981-1986 which resulted in an estimation sample of 169 targets and 237 non-targets. Although insignificant when employing the financial variables, the model's discriminatory ability becomes significant when adding the structural variables suggesting the importance of their effect in takeover likelihood. Contrary to Barnes (1990), as the main objective is to determine the effect of purely structural variables in a firm's probability of being taken-over, the paper focuses on a purely explanatory point of view. In addition, a temporal matching scheme (such as the one used in the paper) cannot be used for predictive purposes since the value of the structural variables depend on the date when the takeover took place which is, by definition, unknown in the prediction sample.

Also accounting for Palepu's methodological improvements, Walter (1994) compares the performances in both predicting and earning abnormal when using historical cost and current cost models. The models are based on a logistic regression and are estimated using a realistic sample of 33 targets and 274 non-target firms relative to the period 1981-1984. In addition, the year 1985 containing 10 target and 81 non-target companies was used to test the model's predictive ability. The estimation sample contains all target firms and all non-target firms having all the available current-cost data information. The findings show that when comparing the current cost and the historical cost model, the latter is able to predict target firms with a higher degree of accuracy (i.e. 102% better than chance) while the former only achieves moderate predictive accuracy (i.e. 25% better than chance). However, when assessing the economic performance during a one-year buy and hold investment, the historical cost model generates negative and significant abnormal returns of -10.09% whereas the current cost model generates positive and insignificant returns of 0.46%. This apparent contradiction suggests that predictive accuracy may not be related to investment performance.

Similar to Morck et al. (1988)'s conceptual idea of characterizing different types of merger, Meador et al. (1996) use a logistic regression-based model to study the financial profiles of the firms involved in horizontal and vertical acquisitions. Their takeover sample accounts for 50 vertical and 50 horizontal mergers collected within the period 1981-1985. These companies are pair-matched to 100 non-acquired firms by industry and size. Based on six M&A hypotheses, twenty-four financial variables were selected to estimate the model. The model using the aggregate target sample shows that targets tend to have a significantly higher financial leverage than their non-target peers. Their specific-merger models show that horizontal targets have higher growth in sales and higher long-term financial leverage and vertical targets are smaller in size and have a higher dividend payout ratio than their matched peers. The opposite signs between the two measurements of financial leverage and asset/sales growth, suggest the existence of high levels of multicollinearity (in particular between the asset, market value and sales variables) and therefore questions the validity of the presented results. Although this fact is acknowledged in the conclusion, multicollinearity should have been eliminated if the purpose of the study was to analyze the estimated coefficients.

By studying the accuracy of takeover predictive models in the Greek context, Zanakis and Zopounidis (1997) describe several of the obstacles encountered by a practitioner when dealing with the data of a small economy. The study also compares logistic and MDA based models in order to investigate the most suitable basis for predicting takeovers. The models were estimated using state-based estimation sample containing 40 targets and 40 non-target firms matched by asset size, volume of sales and number of employees. A similar predicted sample was used containing 30 companies. The findings show that MDA compares favorably to logistic based models both in its classificatory and predictive ability. The study suffers however from several methodological drawbacks such as the use of non-random state-based sample, the use of a predicted sample with unrealistic proportions and the choice of a predictive period overlapping with the estimation period.

Mainly based on the work of Morck et al. (1988) and indirectly related to the work of Harris et al. (1982), Powell (1997) studies the differences between hostile and friendly takeovers and the stability of such characteristics over time. The author uses a methodology based on a multivariate logistic model based on eight financial ratios representing six main hypotheses of takeovers and adjusts for industrial factors by extracting the industrial average to each variable. The initial estimation sample covering the period 1984-1991 is split into two additional sub-periods of 4 years (i.e. 1984-1987 and 1988-1991) to measure the time sensitivity of the estimators. His results show that industry effects seem to play an important role and should be considered when assessing takeover prediction likelihood. Furthermore, he finds that friendly and hostile takeovers share different characteristics suggesting that the use of homogenous samples in the estimation leads to misspecified models. Finally, in order to analyze the changes in takeover characteristics, Powell looks at the changes in the estimator's significance from one period to another. He finds that these characteristics, for all friendly, hostile and aggregated bids, are inconsistent over time. These results support the suggestive views of Singh, Harris et al., and Rege that takeover prediction models are not stable over time.

In a seminal paper, Barnes (1999) analyzes general conceptual and methodological issues remaining in the literature and suggests some options for improvement. By observing the different takeover patterns across industries, the performance of a general model using industry-relative ratios is compared to the aggregate performance of industry-specific models. He also contributes by exploring the advantages of using a cut-off choice method based on the maximization of expected returns[8]. The general model was estimated using a sample containing both successful and unsuccessful bids in the UK during the year 1993 resulting in a sample of 82 targets and 82 randomly matched non-target companies[9]. The estimated coefficients show that firms with lower growth seem to be more exposed to a potential bid. A holdout sample from the year 1994 containing 16 (13) targets and 1064 (886) non-targets was used to test the predictive ability of the industry-specific (gen-

[8]This is an alternative to Palepu's cut-off estimation technique based on the minimization of total errors. As no targets were predicted by any of the models, the potential profitability underlying Barnes' method was not tested in the paper.

[9]The estimation period for the industry-specific models was extended to 1991-1993 in order to increase the population sample in each industry

eral) model. The results show that the models although achieving a high overall predictive accuracy, have poor ability in identifying targets suggesting that takeover predictive models are not useful either to predict targets or to earn abnormal returns. It should be noted that, whereas most of the academic research has excluded financial firms from their samples mainly because of the difference in their accounting standards, this paper considers an aggregate sample of all industry sectors which may have lead to a misspecified general model.

From a theoretical perspective, most of the works (with the exception of Zanakis and Zopounidis, 1997) have adopted a theoretical framework similar to the one suggested by Palepu. From a methodological perspective, logistic regression was adopted as the analytical reference and industry-relative ratios were accepted to improve the stability of the estimated parameters. Furthermore, the use of out-of-sample forecasts to assess predictive ability increased the confidence in the reported results. Despite all these advances, no consistent characterization of targets seems to appear in the reported results. Moreover, the well-specified prediction tests show a poor ability to accurately predict targets in the future suggesting that previous optimistic results had indeed overstated the true predictive ability of the models.

2.5.4 Current research: new models and economies

Recently published papers have generally attempted to innovate in the employed analytical framework or to estimate takeover predictive models in a new economy. Although the results seem to show that takeover prediction is possible, unfortunately many works employ flawed methodologies and some results are potentially overstated.

The work of Cheh and Weinberg (1999) is what appears to be the first application of data pattern recognition modeling into takeover prediction models. They use a feed forward Artificial Neural Network (ANN) and compare its performance to the MDA method. The paper selects one qualitative variable measuring industrial activity and eight other financial variables. As each financial variable was measured in each of the three years previous to the firms' assigned year, therefore the model effectively uses 25 variables which are likely to be highly correlated. The optimum ANN model was found to be a one hidden layer with eight hidden units and a momentum of 0.1. The selected estimation (holdout) period is 1985-1987 (1988-1992) resulting in a realistic sample of 1275 (1338) unacquired and 173 (186) acquired firms. The results show that the ANN model outperforms MDA in both the ability to accurately predict future targets and the profitability of the underlying buy-and-hold investment based on the predictive firms. The paper suggests that non-parametric techniques, such as Neural Networks, should be considered when the objective of the takeover model is to enhance predictive ability. The results remain however unclear in the extent to which the portfolio's profitability is related to the effectively predicted targets. Furthermore, daily abnormal returns are calculated using an arithmetic average and only compared to a market benchmark. As we will later see in chapter 4, there are potential biases and inconsistencies underlying these two approaches.

Acknowledging the motivational changes in the M&A environment, Sorensen (2000) investigates the characteristics of both targets and acquirers during the year 1996 and compares with published findings in previous periods. The estimation sample contains 286 targets, 232 acquirers and 217 non-merging firms. The author uses a logistic regression to separately analyze the differences between target and acquirers with non-merging firms. The results show that acquirers seem to be more profitable companies, however, no explanatory variables was found in the target prediction model which lead Sorensen to conclude that, as mergers during the 1990's were mostly friendly, targets' characteristics are very similar to the average financial profile. It is however surprising that the author did not include size as a potential discriminatory variable considering that is one of the most supported variables in the literature and that it was not used in the sample's matching procedure. Furthermore, similar to early studies, the author does not include any theoretical framework which limits the interpretation of the results. Overall, the results support once more the contention that takeover motives change over time.

Although the advantages of industry-relative ratios had been mentioned by prior research (see for instance Dietrich and Sorensen, 1984; Powell, 1997; Barnes, 1999), no consistent method of normalization had been used. Moreover, these previously used methods do not account for dispersion intra-industry. For example, Dietrich and Sorensen (1984) define the industry-adjusted ratio as the difference of the raw value and its industrial average divided by the latter, Barnes (1990) uses a ratio between the raw value and the industrial average of the variable, and finally Harris et al. (1982) uses the same method but defines a ratio's industrial average as the ratio of the variables' industrial average which is statistically different from the average of the ratio. The study of Cudd and Duggal (2000) therefore contributes with a well-specified industry-relative ratio based on an industry-specific gaussian normalization. His estimation sample covered the period 1987-1991 and contained 108 target firms and 235 of the available non-target firms. The holdout sample contains a more realistic proportion with 13 targets and 460 non-targets. The findings show that, from the six considered hypotheses, the raw (adjusted) model is consistent with one (three) of them suggesting that the use of industry-relative is important to the well-specification of the estimated models. The predictive results are however less clear, since the model using raw ratios achieves a higher overall predictive accuracy than the model using industry-specific model with prediction rates of 61.9% and 57.7% respectively.

Similar to the work of Wansley et al. (1983), Powell (2001) investigates the possibility of earning abnormal returns using takeover predictive models. He also compares the effect of industry-relative ratios in both the predictive and economic performance of the model. The estimation sample is based on 471 successful and unsuccessful targets and 471 randomly matched non-target firms during the 10-year period 1986-1995. A holdout sample of 29 targets and 971 non-targets was used to assess the predictive ability of the model in the year 1996. Abnormal returns are measured using a market-adjusted model (MAM) and a size-adjusted model (SAM). Predictive samples are built using two cut-off values P_{CR} andP_{ME} derived from target proportion maximization[10] and from Palepu's minimization of total errors method respectively. Supporting the results of previous research (e.g. Dietrich and Sorensen, 1984; Platt and Platt, 1990), the findings show that industry-relative ratios and economy-relative ratios improve the classificatory ability of the model. Furthermore, supporting Barnes (1999)'s discouraging results, he finds that takeover predictive models have a very poor predictive ability. Contrary to the results expected by the maximization of returns hypothesis, the economic performance of the predicted sample based in P_{ME} outperforms the one generated by the predicted sample

[10]Although Powell introduces the cut-off choice method based on the maximization of the targets' proportion in the predicted sample, Barnes (1999) had already established such contributions with additional theoretical support.

based in P_{CR}[11]

Espahbodi and Espahbodi (2003) compare the performance of four different binary choice models – namely probit, logit, MDA and recursive partitioning. They use a set of 14 commonly used financial variables and 4 non-financial variables. Accounting for Powell (1997)'s warnings on takeover motivational changes over time, a short period of six months (two months) was used to build the estimation (validation) sample. Takeover data was collected over the last six months of the year 1997 and each target was then matched to up to three non-target firms based on the fiscal year-end and the industry sector resulting in an estimation sample of 133 target and 385 non-target firms. Their validation period covers the first two months of 1998 resulting in 38 targets and 200 non-target firms. The results show that recursive partitioning achieves a classificatory and predictive accuracy of 89% and 66% while the rest of the models achieve a maximum of 63.2% and 55% respectively. Supporting the work of Cheh and Weinberg (1999), superior overall performance is achieved using a pattern recognition based model.

Using the sampling data and applying the multivariate logistic regression previously employed in Powell (2001) and Powell (1997) respectively, Powell (2004) studies different investment profiles generated by hostile and friendly takeover prediction models. The study is based on 8 financial variables and, as in his previous works, the model uses a combination of industry and economic relative financial ratios. From a predicted sample containing 29 targets from a total of 1000 firms, the combined normalized multinomial model (binomial logit model) predicts 8 (2) targets correctly from a total of 298 (42) predicted firms. His finding thus shows that, although multinomial takeover prediction models are able to identify a larger number of targets, due to the large number of miss-classifications, their predictive ability remains less accurate than the one achieved by the general binomial logistic model. The buy-and-hold strategy shows that only the investment based on hostile target predictions generates significant long-term abnormal returns with a maximum of 17% in 36 months. Although potentially "spurious", as categorized by Arnull-Almond (2007) given the insignificant target proportion in the predicted

[11]The predicted sample based in P_{CR} generates significant (insignificant) losses over a holding period of one year in the framework of the MAM (SAM) whereas the predicted sample based in P_{ME} generates insignificant positive returns (insignificant losses) using the MAM (SAM) benchmark.

sample, Powell's results support the view of Wansley et al. (1983) that firms predicted but not acquired are potentially interesting investments as they share a similar financial profile with actual targets used for the model's specification.

With a similar methodology, Arnull-Almond (2007) analyzes the differences both between successful and unsuccessful offers and between hostile and friendly takeovers in the Australian context. The study uses both nominal and multinomial logistic regression as basis for the models. After elimination of multicollinearity, 18 variables were selected based on the eight hypothesis considered by Palepu. For the general single adjusted binomial model the estimation (predictive) sample contained 62 (108) targets and 996 (946) non-target firms from the year (period) 2004 (2004-2005). In the same line as Bartley and Boardman (1990), both estimation and prediction samples use full complete data available. The estimation results show that targets tend to be profitable companies with poor abilities to generate revenues. In relation to their predictive accuracy, binomial models appear to be more accurate in predicting takeovers compared to multinomial models as the concentration ratio was found to be 22.45% and 14.57% respectively. Supporting Powell (2004)'s findings, the out-of-sample forecasts show that binomial models' predicted samples contain a higher target concentration thus making them a more adapted tool to earn abnormal returns. Finally, considering a two-year horizon buy-and-hold investment to evaluate the model's portfolio performance, the portfolio built as a combination of binomial models' predictions earned a significant and positive unadjusted abnormal return of 68.67%. Unfortunately, assuming that portfolio performance is correlated with the predicted portfolio's target concentration, the author does not provide the specific models' portfolio performance and therefore the comparative economic superiority of the binomial model was not empirically tested.

In one of the most recently published works, Brar et al. (2009) develop a general takeover predictive model using an aggregate sample of all domestic and cross-border european takeovers during the period 1992-2003. Additionally, they incorporate market variables[12] into takeover predictive models and build a dynamic investment strategy meant to cap-

[12] Although the authors failed to notice that Dietrich and Sorensen (1984) had already included a market variable in their model (i.e. traded volume), they contribute by adding other types of market variables such as price momentum and market sentiment.

ture the short-term signals given by the market. In order to validate the model, the initial sample is split into two sub-samples (similar to the split validation sample technique used by Stevens, 1973). Both the estimation and the validation sample preserve realistic proportions of targets and non-targets for each year within the selected period. The resulting estimation (validation) sample contains 262 (268) targets and 722 (712) non-target firms. The estimation results show that european targets are smaller, pay relatively higher dividends, have lower sales growth and are heavily traded. Robust checks, such as adding country specific variables and changing the matching procedure of the estimation sample, are provided and show that the results are not dependent on the chosen methodology. The model achieves an overall classificatory (predictive) performance of 72.56% (71.73%) accuracy and correctly classifies 42.42% (45%) of the firms predicted in the portfolio The paper finally offers a timing portfolio strategy which is based on a dynamic portfolio including, for each month, the 10% of the firms having the highest probability of becoming a target. The best performing portfolio earns 17.5% annual abnormal return with a significant information ratio of 1.03. Additional tests show that the latter performance cannot be explained by common risk factors such as size and market-to-book ratio therefore suggesting that the model allows to capture non-trivial characteristics of target firms. The results highlight the accurate predictive ability and the underlying profitability of takeover prediction models. Some methodological drawbacks should be however mentioned. First, the paper fails to test the true ex-ante predictive ability of the model since (i) it uses a split validation sample technique and generates a validation sample from the same period as the estimation sample and (ii) the selection of the variables is derived from an univariate analysis that includes the validation sample[13]. Finally, the portfolio construction spans a sub-period of the estimation and, most importantly, selects the firms from a sample including the firms used during the model's estimation. It is therefore highly probable that the firms having the highest likelihood of becoming targets are the actual targets included in the estimation sample.

Although not rigorously belonging to the takeover prediction literature, the recent work of Cremers et al. (2009) is recent application of takeover prediction models using an in-

[13]The stability test is therefore biased since the selection of the variables is partially dependent on the characteristics of the target firms included in the validation sample

novative rolling window estimation in order to measure the persistent impact of takeover likelihood on the cross-section of returns. Their study successfully shows that by considering institutional and corporate governance variables when measuring takeover likelihood, the resulting ex-ante probabilities appear to well-capture the risk related to a firm's corporate structure weaknesses that the authors call *takeover vulnerability*. To calculate takeover probabilities, a logistic regression is used based on the variables previously employed by Palepu (1986) and additional non-financial variables such as the presence of shareholder's block, ownership concentration. Fixed estimations were calculated using the estimation periods 1981-2004 and 1991-2004 whereas rolling estimations were calculated using a ten-year rolling estimation window during the period 1991-2004. The results show that firms with higher takeover vulnerability exhibit higher returns than firms with a lower takeover exposure. Although the size of the yearly portfolios is not reported, the smallest considered portfolio accounts for the 10% of the US listed firms which, on average, corresponds to portfolios exceeding 100 firms. As in Brar et al. (2009), the use of decile portfolios generates large and unrealistic portfolios and therefore their results, although providing strong evidence on the profitable potential underlying takeover prediction models, do not inform an investor on the risks and expected outcomes when employing a more realistic investment strategy.

Finally, several works have been recently undertaken with the objective of investigating takeover characteristics in an unexplored context. Two different groups can be distinguished. The first is defined by works aiming to test takeover predictive models in new and usually underdeveloped economies. Some examples are Misra (2009) and Barai and Mohanty (2009) in India, Tsagkanos et al. (2006) and Siriopoulos et al. (2006) in Greece[14], Dencic-Mihajov and Radovic (2006) in Serbia and Montenegro, and Alcalde and Espitia (2003) in Spain. The second group has focused on the takeover features within a particular industry sector. Some examples are given by Kim and Arbel (1998) and Gu and Yuh (2001) who use industry-specific models to characterize target companies in the pharmaceutical industry and the gaming industry respectively. In addition, as most of the authors have excluded financial firms, there are a certain number of papers aiming to

[14]These works contribute to the evidence provided by Zanakis and Zopounidis (1997) that takeover prediction models do not seem to capture takeover characteristics in the Greek context. However, the latter was not referenced in the here mentioned works thus limiting the extent of some of their claimed contributions.

characterize takeovers in the banking and, more generally, in the financial industry (e.g. Thomas, 2001; Pasiouras et al., 2005).

2.6 Summary

In this chapter, I have introduced the reader to the takeover prediction literature by:

1. First, introducing the inspirational results obtained within the bankruptcy prediction literature.
2. Secondly, describing the different hypotheses that have been constructed over the years and underlining the disagreement between the different interpretations.
3. Finally, by providing a chronological comprehensive review of the methodologies, assumptions and results reported by the works using multivariate regression in order to classify or predict takeover activity.

Among the large number of contributions provided by the bankruptcy prediction literature, I have focused on three major results that seem to be mentioned in several works in the takeover prediction literature. First, Altman (1968)'s Z-score model opened a vast area of research for all fields whose variable of interest corresponds to a possible dichotomous outcome. As a second point, the sample construction and therefore the use of matched samples vs. full data samples, has been long discussed and different viewpoints remain on the question. Finally, industry-relative ratios have been reported to provide a more stable data distribution for the considered explanatory variables and similar results were obtained in the framework of takeover prediction.

Influenced by these and other advances in bankruptcy prediction, takeover prediction models have structured a consistent methodological framework correcting for many specification problems addressed by the earlier literature. Surprisingly absent in other similar frameworks, the takeover prediction literature has also been able to build a theoretical framework based on several documented hypotheses within the M&A literature generally based on the theory of the firm and the efficiency of the Market for Corporate Control.

These hypotheses are summarized in Table 2.1. Perhaps due to the variety of reported results, as we can observe, the theory generally does not provide a clear-cut interpretation of the sign expected by the hypotheses. The disagreement generally stems from the fact that some authors describe the target as an inefficient firm likely to be replaced with more efficient management whereas another strand suggests that takeovers are decisions made by inefficient management investing in profitable firms in order to increase their asset control.

As we can see in the provided literature review, despite the advantages of having developed a consistent theoretical framework, the takeover literature does not seem to provide a clear a picture neither on the characteristics of takeovers, nor on the potential predictive or economic abilities of takeover prediction models. This general disagreement may possibly explain, to some extent, the confusion existing in the statement of the hypothesis mentioned in the previous paragraph. The general contention seems to be that takeover prediction models are unstable over time and both across economies and between industries. The next section gives a critical review of the results and examines the limitations of the methodologies in relation to the model's contended instabilities.

Table 2.1: *Summary of the qualitative relationship[a] predicted for each hypothesis by the takeover prediction literature*

Hypothesis	Positive relationship	Negative relationship
Market for Corporate Control Hypothesis[b]	Profitable firms may be a suitable investment for companies lacking of investment opportunities	Poorly performing and inefficiently managed firms are likely to be taken over by a more efficient management team able to better satisfy target shareholders' interests
Free-cash flow hypothesis	Higher levels of free-cash flow are susceptible to be followed by negative present value investments.	Idem
Activity hypothesis	Because a gap may exist between the production level and the product's demand, efficient firms may be an profitable capital investment.	Idem
Undervaluation Hypothesis[c]	No support	Undervalued firms are a good opportunity for an overvalued acquirer planning an acquisition.
Dividend Payout Hypothesis	Low dividend pay-outs are a sign of future growth and provide higher immunity to takeovers	Low dividend pay-out may signal that management does not distribute its due earnings to shareholders
Size	Asset growth is often the main objective of a firm's management	Lower firms provide fewer transaction costs and a simpler integration process
Growth-resource mismatch hypothesis	Firms with low (high) leverage, high (low) liquidity and low (high) growth are more likely to be taken over	No support
Growth	No support	Lower growth may signal a firm's inefficient resource management
Liquidity	Firms with higher liquidity reduce the transaction costs of the acquisition	Higher liquidity may also be seen as a sign of inefficient allocation of resources
Leverage	High levels of leverage reduces the ability of a firm to "fight" against a takeover attempt	Low leverage may indicate unused debt capacities
Inefficient Financial Structure Hypothesis[d]	No support	An inefficient financial structure increases the likelihood of a takeover attempt
Industry Disturbance	Firms belonging to industries with higher records of merger activity are more likely to be taken over	No support

[a] The relationship refers to the expected sign expected by the theory in relation to the frequently used proxies.
[b] As represented by profitability and market-based measures.
[c] As represented by valuation measures such as the market-to-book ratio and the price-to-earnings ratio.
[d] The sign refers to the measure of structure inefficiency and does not consider any particular variable. Depending on the variable used to proxy this hypothesis a negative or a positive sign will be an indicator of inefficient financial structure.

Chapter 3

A critical review on the extant takeover prediction literature

3.1 Introduction and overview

The previous chapter has provided both the evidence on recent research investigating the methodological contributions of bankruptcy prediction models and the state of the art on both the takeover prediction literature and the hypotheses that are contended to drive takeover activity. Within the reviewed literature, although frequently suggesting its need, no study has yet attempted to investigate the observed dynamical uncertainties present in the reported results. As I shall argue below, these potential uncertainties are numerous within the M&A context and are likely to explain, to some extent, the general disagreement and controversies of the takeover prediction literature. In addition, given the potential changes in the drivers behind a takeover attempt, the inherent instabilities are likely to be more pronounced in the takeover prediction context than in bankruptcy prediction. Based on these results, the objectives of this chapter are to:

1. Provide clear evidence of the underlying instabilities of both bankruptcy and takeover prediction models in characterizing the related event, achieving significant predictive power and generating substantial abnormal market performance. These results are to establish a ground of comparison for a later discussion on the dynamic instabilities underlying takeover prediction models.

2. Describe the main sources of variability underlying such instabilities and the need to control and test for the influence of methodologies and context choices in the reported results.

3. Highlight the need of dynamic analysis of the features underlying takeover prediction models and underline the meaningless results provided by point forecast estimations.

4. Discuss the impact of such dynamic forecasting instabilities on the model's economic performance and present the literature's contentions of the sources of gain underlying takeover predictive models.

The remainder of the chapter is organized as follows. Section 3.2 presents the main results on the dynamic stability of bankruptcy prediction models. Section 3.3 provides both a synthesis of the general disagreement about the main features characterizing takeover forecasting models and an analysis of the different potential causes of such heterogeneity. Based on the latter evidence, section 3.4 questions the reliability of single forecast estimations and highlights the need of a methodology measuring the forecasting uncertainty underlying the reported results. Section 3.5 examines the implications of the latter uncertainty on the investing proficiencies reported in previous studies and discusses a recent debate about different sources of profitability underlying takeover prediction models. Section 3.5 summarizes the chapter and concludes.

3.2 Stability of bankruptcy prediction models

Several works have warned researchers about the potential instabilities underlying bankruptcy prediction models. Among these we find the changes on the definition of "failing firm", the non-normality of data distribution, the non-stationarity of the estimates, and the influence of the sampling method (Balcaen and Ooghe, 2006, p.71).

In contrast to theoretical expectations, the empirical evidence seems to agree on some general characteristics of bankrupt firms and, most importantly, these characteristics seem to be stable both over time and across economies. The work of Zmijewski (1984) offers an example of a multiple estimation of the bankruptcy prediction model in seven different consecutive years. The results show the remarkable consistency and efficiency of the estimates across the seven years. For all variables except liquidity, the sign of the coefficient is constant and the significance is maintained at the 5% level for every year in the period. Furthermore, the low dispersion around the mean of the estimated values suggests the underlying efficiency of the estimators. In addition, the problematic role of the liquidity variable was reported in several other empirical works (see for instance Altman, 1968; Ohlson, 1980; Bilderbeek, 1979). In particular, Bilderbeek (1979) presented a model with moderate predictive accuracies which was significantly stable over the considered five-year period. He explains that the stability was obtained by eliminating the liquidity variable from the model's specification. Some other studies have attempted to improve the predictive accuracy by accounting for the inherent dynamic of the bankruptcy event. As an example, Shumway (2001) shows that the use of a hazard model eliminates some of the misspecifications present in single-period models and lead to an improvement of the model's predictive accuracy. His results show, however, that the hazard model does not predict better that the single period logistic model. These results suggest the presence of a weak dynamic effect on the estimates produced by general multivariate bankruptcy prediction models. To the best of my knowledge, three works have explicitly studied the non-stationary characteristics of distress prediction models. The work of Mensah (1984) provides a comprehensive analysis of the influence of economic conditions on the predictability of distress prediction models. The author finds that although the coefficients vary over time, the signs are consistent over the different examined periods. In the same line, a recent study by Sung et al. (1999) shows the predictive difference of distress prediction models in two extreme market conditions (i.e. normal and crisis environments). Their results suggest that market conditions can have a significant influence in both the estimated parameters and the predictive ability of the model. Thirdly, focusing the study on a period of economic decline, Pompe and Bilderbeek (2005) use a belgian dataset to study the influence of the year where financial ratios are measured and studies the influence of worsening market conditions on the model's predictive ability. The results are consistent with Mensah (1984) showing that recessionary periods tend to be identified with a lower predictive ability. As I shall argue in a subsequent paragraph, given the persistently reported inconsistencies, this thesis underlines the need to extend the study of stationarity to the takeover prediction literature.

Another source of time stability was found to be the number of years separating the estimation year and the year of bankruptcy. Studies such as Altman (1968) and Ohlson (1980) show that, although bankruptcy prediction models have a good performance when estimated a year prior to bankruptcy, their predictive ability falls sharply when increasing the lag between the estimation year and the bankruptcy event. This result is generally consistent in the bankruptcy prediction literature, except for the work of Pompe and Bilderbeek (2005) who find that the year prior to acquisition provides a lower performance compared to one achieved using more distant observation years.

An important, but often neglected, question related to the anticipatory capacity of the bankruptcy event remains whether these type of models are able to capture distress more efficiently than the stock market. In an early study, Altman (1969) contributes with a potential investment available to market makers willing to take the risk of investing in firms having filed for bankruptcy. Using a test based on a Stockholder Profitability Index to measure abnormal returns, he finds that, even when overestimating the expected return of risky investors, the potential profit is positive but insignificant. A second study by Morse and Shaw (1988) attempts to measure the impact of the 1980s Bankruptcy Act on the potential returns to be earned in distressed firms. Supporting Altman's result, no significant abnormal returns were found. The evidence suggests that investing in failing firms is a risky investment, and deeper knowledge and research needs to be undertaken before including such firms in a portfolio.

Overall, bankruptcy prediction models show a general consistency among the reported empirical results and also a common specification framework that facilitates the comparability of the models. In addition, from an economical perspective, bankrupt firms do not seem to be an attractive basis for investment. These two results indicate that, perhaps due to their distinctive financial profile, the market probably recognizes well in advance a firm's trend towards bankruptcy. With this result in mind, the focus is now turned to the evidence of stability in the takeover prediction literature.

3.3 Dynamic characteristics of takeover firms

I here provide a comprehensive analysis of the evidence related to the characterization of takeover targets. In the first part, we show that some of the commonly employed variables show some degree of consistency over time. The second part examines the theoretical explanations of the lack of consistency among the results and some of the warnings related to historical comparisons. Finally, we provide some detail on the works attempting to control for some of the specification-related variations.

3.3.1 Meta-analysis on the empirical evidence

Table 3.1 recapitulates the list of the most frequently employed variables and the respective support they received in the literature.

As it can be observed, *Size* has been a frequently used variable which additionally had a consistent support among researchers therefore indicating that targets are generally smaller firms compared to the overall population. As stated by Levine and Aaronovitch (1981), *size tells us all we need to know*. The result is consistent from the end of the 1950s until the end of the 1990s. However, recent works by Arnull-Almond (2007) and Ouzounis et al. (2008), accounting for the most recent periods, report a positive and significant sign for the size variable. I believe two possible factors may have lead to this result. Interestingly, these two works were the only studies having considered an estimation period post 90s which may indicate that, in recent periods, target firms are larger in size than the average population. Secondly, contrary to previous works, Arnull-Almond (2007) does not constrain the firms to have a large period of available accounting data which may have reduced the survivorship bias of previous samples. This argument, however, does not apply to the work of Ouzounis et al. (2008) who considered a five-year estimation period. Secondly, in addition to being specific to the period, the result could be a particular feature of the Australian and the UK economies which may not be consistent with the results reported in the US economy. Another variable showing consistent support is *Free cash flow per share* which suggests that target firms are more likely to be characterized by higher amounts of free cash flow available when compared to non-target firms thus providing a relatively consistent support for the Free-Cash flow theory of mergers.

In addition, three other variables seem to show a moderate sign persistency in at least two thirds of the considered cases. The first variable is *Sales growth* which was found to be negatively related to a firm's acquisition likelihood in six out of a total of eight cases. Furthermore, the latter was found to be significantly negative in three studies while no study found it to be positive and significant. Then, *Profitability* was found to be positively related to takeover acquisition likelihood in twelve of the sixteen cases where the variable was considered. In addition, the latter was found to positive and significant in three studies and only one found a significantly negative relationship. Finally, *Asset turnover* was found to reduce a firm's takeover probability in seven out of ten cases. The variable was found to be significantly negative in four cases and only one study reported a positive and significant sign. These results partially support the contention that targets are profitable firms having lower sales growth and presenting more difficulties to generate sales from their assets than the average population.

The rest of the considered variables do not appear to show any trivial pattern of either significance or sign stability. Although some characteristics are suggested by the presented analysis, the results do not give a clear picture of what the general features of takeovers are. As we will now see, the literature provides several arguments suggesting the potentially misleading results of such a meta-analysis.

3.3.2 Theoretical explanations of time instability

Different reasons have been put forward to explain the variability of the results in the takeover prediction literature. As summarized by Cheh and Weinberg (1999),

> Possible explanations for these inconsistent results include the constantly evolving motives and environment for acquisitions, different model specifications by different researchers and different time periods studies by different researchers.

Within the list of reasons mentioned by Cheh and Weinberg, we can identify two different groups of explanations. The first one, the common-factor type, groups all the reasons that are inherent to the M&A mechanism whereas the second one, the specification type, relates to different types of methodologies and user-related choices that affect the ability to capture those mechanisms.

The first type of arguments focus on the idea that the lack of consistency in the results is related to the complexity of the M&A process. The literature seems to show three distinctive dimensions to which merger motives seem to be sensitive to. The first one, and most frequently mentioned, is time. Consistent with Gort (1969)'s economic disturbance theory of mergers, merger trends seem to be triggered by macroeconomic shocks and are therefore likely to differ from one period to the other. The work of Andrade et al. (2001) provides further support with a recent review of the empirical work on different merger theories which lead them to conclude that these motives seem to explain only particular periods of merger activity. Secondly, there is evidence that merger motives vary across industries. Barnes (1999) provides a detailed discussion of the empirical and theoretical evidence on the subject. The third dimension of variability is related to the belief that merger drivers are country-specific. Possibly due to differences in regulations, corporation different countries have different incentives for acquisitions. Another characteristic of the M&A process worth mentioning is that it involves two companies: the target and the acquirer. Harris et al. (1982) and Powell (1997) pointed out that the main factors behind the lack of the model's explanatory power is probably related to the acquirer's particular preferences. In other words, the inputs considered in a valuation and the valuation method itself are likely to change from one corporation to another one. As represented by Harris et al. (1982), the subjective complexity of an acquisition is based on the fact that "beauty lies in the eye of the beholder". Other binary outcomes such as bankruptcy, bond rating or audit decisions, are less sensitive to this type of interdependence since they are the outcome of regulated decisions such as corporate laws or accounting standards. In their conclusions, both Harris et al. (1982) and Powell (1997) suggested that a model wiling to accurately predict target firms should incorporate the interactions between the target and the acquirer's corporate information. Although such models are an interesting path for future research, they lay outside the scope of this work in relation to the structure of takeover predictive models.

The second class of explanations is more related to the effect of the model's specification among different researchers. These type of variations are more likely to influence the inferences on the selected explanatory variables. The first potential bias stems from the different definitions of the observable variable (i.e. the takeover event). Used in e.g. Powell (1997), the most constrained definition considers only completed acquisitions of at least 50% of the firm's ownership whereas the broadest definition of the term was considered by Bartley and Boardman (1990) who accounted for all attempts of acquisition of more than 5% of ownership advocating that the purchase of small ownership portions is often a signal of a future acquisition plan. Other studies have considered a moderate definition that considers both successful and unsuccessful acquisition bids for at least 50%of the target's ownership. A second potential source of variation is the lack of a defined core of explanatory variables as the number, the type and the definition of variables generally change from one study to another. As a result, underspecification biases and estimates' dispersions are likely to vary significantly from one study to the other therefore making their comparison problematic. Furthermore, the use of inconsistent methods in the variable's treatments such as industry normalization, multicollinearity elimination, and the choice of period to collect the financial information are likely to amplify the differences between different types of estimation methods. Finally, accounting for the previously mentioned evidence that merger motives change over time, the length of the chosen estimation periods is also likely to influence the reported results. At the very early stage of takeover prediction, Singh (1971) made a distinction within his estimation sample between a financial trend, following the market boom in the 1950s, and a commercial trend which followed the abolition of differential tax profits in 1958. Other studies, such as Espahbodi and Espahbodi (2003) have used an estimation period as short as six months to avoid time-varying effects on merger motives. However, many studies have pooled the data across several years, the maximum being a twelve-year period used by Rege (1984) and Brar et al. (2009) . It should be mentioned that the studies also differ by the model's choice to specify the relationship between the explanatory variables and the explained variable. However such changes, although certainly having an influence in the magnitude of the estimated parameters, are not likely affect the qualitative consistency of the reported results (see Wooldridge, 2002, Chapter 15).

Although the first type of arguments are common to all studies, the second type suggests that a historical comparison of the result would not be a reliable approach to identify takeover characteristics as it bears the error generated by the methodological inconsistencies among researchers.

3.3.3 Empirical evidence on the instabilities underlying takeover prediction models

An early work aiming to capture takeover characteristics led Firth (1976, p. 174) to conclude that:

> The other main point [...] is that the financial characteristics and the make-ups of the bidee do change across smallish periods of time. [...] It also implies that the research results can only be used for decision purposes up to a couple of years ahead; thus the emphatic claims made by some earlier researchers should be treated cautiously beyond few years after the time period used in the study.

As most studies have not considered the effect of time in their estimations, in this paragraph, I present some of the empirical works having attempted to measure the time stability of takeover prediction models. During my research, I was only able to find two studies in the literature having attempted to control user-related biases, by estimating the same takeover prediction model in two different periods of time.

Harris et al. (1982) estimated the model in two consecutive periods of two years (i.e. 1976-1977 and 1978-1979). By looking at the signs of the regressors in these two periods, he concludes that the estimated coefficients are time-dependent. The only variables having both sign and significance persistency were size and price-to-earnings ratio suggesting their attractive potential as predictors of merger motives. Although the model offers significant explanatory power at 1% level of significance, the author highlights the poor discriminatory ability between groups and suggest that financial variables do not explain the largest proportion of mergers.

A similar work by Powell (1997) estimates the same model in two different periods of four years (i.e. 1984-1987 and 1988-1991). He also analyzes the influence of using industry relative variables. The main difference between Harris et al. (1982)'s and Powell (1997)'s work is that the former examines the sign consistency of the estimators whereas the latter focuses only on the changes in the regressor's significance. Given that significance was generally not persistent across the two periods, Powell concludes that takeover models (i) generate inconsistent estimates over time and (ii) are likely to generate poor performances both in their prediction and, a fortiori, in the derived investment strategy. By not looking at the sign stability of the estimates, Powell fails to recognize that the two industry-adjusted binomial models, with the exception of two variables, are telling similar stories. Moreover, the relative sign stability suggests that the model's predictive ability would have probably exceeded Powell's expectations.

By offering a comparison between two periods, these studies provide some evidence that while the effect of some factors seem to change over time, others seem to have a more coherent qualitative behavior therefore indicating a greater consistency in discriminating takeovers. However, with only two periods it is difficult to make any conclusions on the stability of any of the selected parameters. We need more estimations to draw more reliable conclusions. For example, the multiple estimation shown in Zmijewski (1984) was built by calculating a different estimation for each year over an eight-year period. His results clearly show not only the consistency of profitability and leverage but also the erratic behavior of the liquidity variable. Such an analysis is absent in the takeover prediction literature.

Other studies such as Brar et al. (2009) and Cremers et al. (2009) have accounted for time variability, by respectively updating the market variables and using rolling window estimations when estimating takeover likelihood. However, none of the studies provide any information on the dynamic patterns of either the estimated coefficients or the model's predictive power.

3.4 Implications for single forecast results

As shown in the previous paragraph, both theoretical and empirical evidence suggest that takeover predictive models are unstable both over time and across economies. As a general result for unstable models, such a contention has an important implication: one point is not representative of the model's performance. As reported in Table 3.2, the prediction rate seems to be highly unpredictable. Whereas most of the models have found some combination of characteristics defining takeovers, only a few of them reported a significant predictive ability. Furthermore, when predictive ability is reported, for most of the early works, they failed to assess the ex-ante predictive ability of the model.

Although the works of Harris et al. (1982) and Powell (1997) have shown that the estimated coefficients change both in its significance and its qualitative sign, no documented information was found on the impact of these changes on the predictive accuracy of the model. The inherent heterogeneity of a takeover sample, both cross-sectionally and dynamically, is consistent with the fact that the features captured by the estimates change over time. However, this does not (necessarily) imply that the model will exhibit a poor predictive performance. This could be explained by assuming, for example, that using the information from previous years may generate the values of a local maximum instead of the ones associated with the global maximum generated by the maximum likelihood method. In this case, the prediction will still be moderately high without being maximized. In other words, the estimates generated with the information from prior years may capture the information from a certain group of firms that are the majority in the estimation sample but not in the prediction sample. A closer look to the works of Harris et al. (1982) and Powell (1997) shows that the result are not as pessimistic as they were pictured in their works. From an explanatory viewpoint, there is certainly little to add to their analyze. However, when looking at the estimates of both works, we can see that, except for a few variables the signs are maintained in both periods. Although a parameter's significance is important from an explanatory perspective, it is less relevant when predictive accuracy is the main concern. Unfortunately, none of the authors attempted to measure the predictive ability of the model which would have provided information on the impact of the estimates' dynamical changes on the predictive ability of the models.

3.5 Investment risk of prediction-based portfolios

This section will focus on the absence of an investment risk measure within the takeover prediction literature. The first part explains the different ideas that support the concept of an investment based on the predictions of takeover prediction models. The second part examines the empirical evidence and the relative support for each one of the previous explanations. The last part, aims to highlight the need to investigate the underlying volatility of a long-term investment based on target prediction models.

3.5.1 The sources of profitability of takeover prediction models: a recent conceptual debate

Two views can be distinguished in the literature in relation to the profitable potential of takeover prediction models. Although they both conclude that takeover prediction models are potentially profitable, they disagree on the theoretical sources of the latter.

The first one, suggested by Wansley et al. (1983), states that average predicted companies are likely to perform better than the average as they share a similar attractive financial profile that lead to the bid of the actual takeover targets. The theory therefore assumes that profitability is not affected by the prediction accuracy of the model give that the predicted companies will perform well in the market whether they are free raiders or real targets. This explanations is supported by the results given that none of the two portfolios considered in the calculation of abnormal returns contained any real target. In addition, Powell (2004)'s work also provides indirect support since his sample of hostile takeovers was able to earn substantial abnormal returns with a low predictive accuracy.

The second theory states that the profitability of a portfolio based on takeover prediction is directly related to the predictive accuracy of the model as it is directly related to the bid premium offered by the acquirer or the price run-up generally experienced the day of the announcement. Arnull-Almond (2007) explicitly qualified as "spurious" Powell (2004)'s results given that abnormal returns are probably generated by random non-target firms.

3.5.2 Empirical evidence of takeover prediction models' profitability

It has been well-documented that target shareholders earn substantial abnormal returns on the day of the announcement of a takeover bid. Several authors provide detailed reviews of the evidence documenting the pre and post event characteristics of the price movements in relation to an M&A deal and the reader may refer to Jensen and Ruback (1983) for a review. In this paragraph, the focus of the analysis is turned to the evidence related to the potential profitability of takeover predictive models.

The last column of Table 3.2 shows that there seems to be no agreement on the question since seven out of thirteen reported results show that significant abnormal returns can be earned. However, several indices suggest that most recent studies seem to show that takeover models can be used to generate a profitable investment.

Do these results provide any evidence supporting one of the previously mentioned explanations? The short answer is no. From one side, the studies of Wansley et al. (1983) and Powell (2004) both support the first explanation since they both find that abnormal returns can be earned but their predicted sample contained a very low concentration of targets. From another perspective, Brar et al. (2009) supports the second explanation by applying several robustness checks to show that outperformance is related to the target firms included in the predicted sample and is not due to trivial market factors. They do however provide some support to the first theory by stating that the generated abnormal returns may also be related to "firms that benefit from merger speculation or rumours that may not necessarily end up in a takeover bid". By rejecting the first explanation, Powell (2001)'s results also provide support to the second theory by showing that the low target concentration in his portfolio causes significant losses compared to both a market and a size-adjusted benchmark. Similarly, Palepu (1986) suggests that no abnormal returns can be achieved due to the poor predictive accuracy of his model. However, his portfolio contained 625 firms of which 14 were actual targets, and such a large portfolio is thus likely to dilute, even with a higher predictive accuracy (i.e. a larger number of correctly predicted targets), any profit earned by either actual targets or firms with a target financial profile. The results reported by Arnull-Almond (2007) are also ambiguous since he shows that the profitability is related to the predicted target's performance only after adjusting the sample by eliminating a non-target firm due to its abnormally high returns. His results therefore support both explanations. Overall, it appears that none of the two theoretical explanations seems to be favored by the empirical evidence.

Again, it seems surprising that no article has attempted to measure the stability of a portfolio based on a sequence of predictions on different periods. From a risk management perspective, the literature does not provide a clear idea on the risk that an investor should expect when using takeover prediction models. The study of Brar et al. (2009) generates an investment with a timing feature where each predicted portfolio is updated every month by re-estimating the population's takeover likelihood and taking the first decile with the highest probability. They provide some information on the average annual volatility of the investment over a nine-year period but they do not provide any information on the characteristics of the portfolio in the intermediate steps. Although the study provides a first estimation of investment risk, we do not have any information on the dynamic stability of the portfolio (i.e. the distribution of yearly performances). Furthermore, a main drawback is that they do not consider ex-ante predicted samples and therefore their method is not replicable from a practitioner's perspective.

3.6 Summary

After several decades of takeover prediction, there is no clear picture neither on the general characteristics of takeovers nor of their ability to discriminate between targets and non-targets. Moreover, as the qualitative changes have been studied by comparing only two periods, the literature provides little knowledge on the parameters' instability over time. In addition, although the latter instability is clearly suggested both by the empirical works of Harris et al. (1982) and Powell (1997) and the theoretical analysis present in Barnes (1999), to the best of our knowledge, there has been no attempt to estimate its impact neither on the predictive ability nor on the profitability of the models.

In the next chapter, I shall describe the methodology employed in this thesis in order to study the influence of both time and economy choice on takeover prediction model's performances.

Table 3.1: *Review of documented takeover characteristics and reported significance[a] during the past four decades*

Authors	Code[b]	Period	I-norm[c]	PF[d]	FC[e]	MB[f]	PE[g]	DP[h]	GR[i]	LI[j]	LE[k]	AC[l]	SZ[m]
Panel A: Estimation periods covering the 1960s													
Singh (1971)	UK	1959-60	No										-
Stevens (1973)	US	1966	No	+			(-)	(+)		+	+	+	
Simkowitz and Monroe (1971)	US	1968	No				(-)	(-)		(-)			-
Rege (1984)	CA	1968	No	(+)				(+)		(-)	(+)	(+)	
Kuehn (1975)	UK	1957-69	No	-		(-)		(+)	-				
Rege (1984)	CA	1962-73	No	(-)				(+)		(-)	(+)	(-)	
Panel B: Estimation periods covering the 1970s													
Dietrich and Sorensen (1984)	US	1969-73	Yes	(+)			(+)	-		(+)	(-)	-	-
Palepu (1986)	US	1969-76	No	(+)		(+)	(+)		-	(-)	-		-
Levine and Aaronovitch (1981)	US	1972	No										-
Harris et al. (1982)	US	1974-75	No	(-)			-	(+)		+	(+)	(-)	(-)
Wansley et al. (1983)	US	1975-76	No				(-)		(+)		(-)		(-)
Harris et al. (1982)	US	1976-77	No	(+)			-	(-)		(-)	(-)	(-)	(-)
Panel C: Estimation periods covering the 1980s													
Walter (1994)	US	1981-84	Yes	(+)		-	(+)	(-)		(+)	(+)	-	-
Meador et al. (1996)	US	1981-85	Yes	(-)		(-)	(+)	(-)	(+)	(-)	(+)	-	(+)
Powell (1997)	US	1984-87	Yes	(+)	(+)	(-)			(-)	(-)	(-)		-
Barnes (1990)	UK	1986-87	Yes	(+)						(+)			
Powell (1997)	US	1988-91	Yes	(+)	(+)	(+)			(-)	(-)	(+)		-
Cudd and Duggal (2000)	US	1987-91	Yes	-		(-)	(+)		(-)		(-)		-
Panel D: Estimation periods covering the 1990s													
Barnes (1999)	UK	1993	Yes	+	+	(+)	(+)	(-)	-		(+)	(+)	(-)
Powell (2004)	US	1986-95	Yes	(+)						-	+		-
Espahbodi and Espahbodi (2003)	US	1997	Yes		+	(-)							
Brar et al. (2009)	EU	1992-03	Yes					+	-	(-)			-
Cremers et al. (2009)	US	1991-04	No	-	(+)	-					+		-
Panel E: Estimation periods covering the 2000s													
Arnull-Almond (2007)	AU	2004	Yes	+				-		+	-	-	+
Ouzounis et al. (2008)	UK	2001-05	Yes	(-)	(+)	-	(-)	(-)					+

[a] the sign is shown in parenthesis when it was reported as exhibiting insignificant discriminatory power.
[b] reports the context where the study was undertaken and the abbreviations AU, CA, EU, UK, and US represent Australia, Canada, Europe, the United Kingdom and the United States of America respectively.
[c] shows whether or not the authors used industry-relative ratios to normalize corporate financial data.
[d] shows the estimated coefficient sign for the aggregated profitability measures.
[e] shows the estimated coefficient sign for the aggregated free-cash flow ratios.
[f] shows the estimated coefficient sign for the aggregated undervaluation measures (generally reported as market-to-book ratio).
[g] shows the estimated coefficient sign for the price-to-earnings ratio.
[h] shows the estimated coefficient sign for the aggregated dividend payout measures.
[i] shows the estimated coefficient sign for the aggregated sales and revenue growth variables.
[j] shows the estimated coefficient sign for the aggregated liquidity ratios.
[k] shows the estimated coefficient sign for the aggregated leverage ratios.
[l] shows the estimated coefficient sign for the aggregated activity ratios (generally reported as asset turnover).
[m] shows the estimated coefficient sign for the aggregated size measures (generally reported as the natural logarithm of Total Assets).

Table 3.2: *Review of the reported takeovers prediction model's predictive and investment performances during the past four decades*

Authors	Country	Period	MODEL[a]	VAR[b]	CUTMET[c]	PRDAC[d]	ABNRET[e]
Panel A: Estimation periods covering the 1960s							
Stevens (1973)	US A	1966	MDA	5		67.5% oa	
Belkaoui (1978)	Canada	1960-68	MDA	16	ME[f]	84% oa	
Panel B: Estimation periods covering the 1970s							
Dietrich and Sorensen (1984)	US A	1969-73	Logit	10		205.6% btcs	
Palepu (1986)	US A	1969-76	Logit	10	ME	30.1% btcs	-1.62% (-0.77)
Wansley et al. (1983)	US A	1975-76	LDA	5	Quartile	0 ntp	28%(NA)
Panel C: Estimation periods covering the 1980s							
Walter (1994)	US A	1981-84	Logit	11	ME	102.5% btcs	-10.09%(NA)
Powell (2001)	US A	1984-87	Logit		MR/ME		-11%(-2.79)/-5%(-2.92)
Cheh and Weinberg (1999)	US A	1985-87	ANN	25		539% btcs	23.25% (3.31)
Cudd and Duggal (2000)	US A	1987-91	Logit	9	ME	76.1% oa	
Panel D: Estimation periods covering the 1990s							
Barnes (1999)	UK	1993	Logit	17	MR	0 ntp	
Powell (2004)	US A	1986-95	M-Logit	9	MR	-8.0 btcs	7%(1.85)
Powell (2004)	US A	1986-95	Logit	9	MR	64.1% btcs	-13% (-1.63)
Espahbodi and Espahbodi (2003)	US A	1997	Logit	17	ME	52.1% oa	
Espahbodi and Espahbodi (2003)	US A	1997	RP	17	ME	65.97% oa	
Brar et al. (2009)	Europe	1992-03	Logit	8	Decile	71.73% oa	17.5%
Cremers et al. (2009)	US	1991-04	Logit	10	Quintile		7.95%(2.74)
Cremers et al. (2009)	US	1991-04	Logit	10	Decile		13.54%(3.34)
Panel E: Estimation periods covering the 2000s							
Arnull-Almond (2007)	AU	2004	M-Logit	18	MR/ME	94.26% btcs	68.67%(9.17)
Ouzounis et al. (2008)	UK	2001-05	MDA	6	MR	66.20% oa	1.44%(13.70)
Ouzounis et al. (2008)	UK	2001-05	ANN	6		64.64%oa	1.17%(9.97)

[a] indicates the model's functional specification underlying the estimation. The acronyms ANN, Logit, M-Logit, RP represent Artificial Neural Networks, Logistic regression, Multinomial Logistic Regression, and Recursive Partitioning respectively.

[b] shows the number of variables included in the model's final specification.

[c] indicates the cut-off choice method employed to determine the predicted samples.

[d] reports the ex-ante predictive accuracy of the model. The abbreviations btcs, ntp and oa represent Better Than Chance Selection, Number of Targets Predicted and Overall Accuracy respectively.

[e] reports the abnormal profitability generated by the predicted portfolios. When provided, the test-statistic testing for the null-hypothesis that abnormal returns are not different from 0 is shown in parenthesis and the value NA is otherwise given.

[f] In this particular case, ME does not refer to the Minimization of Errors method used by Palepu (1986) but to the one used in Altman (1968).

Chapter 4

Methodological framework and evaluation methods

4.1 Introduction and overview

This chapter describes the general methodology that was employed to estimate the models and provides explicit detail on the different numerical calculations used to analyze the models' performances. As shown in the previous chapter, takeover prediction models are seemingly unstable over time and the uncertainty underlying the models' predictive ability casts doubt on the stationarity of the results reported by the previous academic research. As an additional source of variability, I also highlighted the problematic presence, within the literature, of a large variety of user-choices in relation to fundamental aspects such as the definition of takeover, the model's specification or the length of the time period used for the model's estimation. By controlling for several methodological choices and using a multiple forecasting method, this thesis provides a first attempt to develop a methodology allowing to investigate the time-varying characteristics and the long-term performances underlying takeover prediction models. In order to test the model's stability over time, this study uses a rolling window estimation methodology allowing to generate several predictions over a selected time-period. Controlling for the potential disadvantage of using a pre-specified functional form, I have selected both parametric and semi-parametric specifications as represented by the Logistic Regression and the Feedforward Backpropagating Artificial Neural Network (FBANN) respectively. Finally, given the profitable potential of takeover prediction models, two portfolio benchmarks were chosen in order to provide a complete characterization of the prediction's long-term abnormal profitability.

The chapter is structured as follows. Section 4.2 presents the general specification of binary choice models and subsequently describes the two models that were finally selected. The section also offers a comparative analysis of the advantages and limitations of both parametric and semi-parametric methods. Section 4.3 defines the multiple forecast methodology and provides details of its implementation. Section 4.4 provides details on the different evaluation methods used during the analysis. Section 4.5 presents the calculation of abnormal returns and describes the two selected benchmarks chosen for this study. Finally, section 4.6 provides a summary and a conclusion of the chapter.

4.2 Model specification

4.2.1 Binary choice models

The more general category of limited dependent variable model is broadly defined by a model whose dependent variable ranges across a restricted number of values. Included in the this category, binary choice models represent the particular case where the dependent variable can take only two values (Wooldridge, 2002). The latter have been extensively documented given the fact that many events in natural sciences, medicine, economics and finance can be modeled as a binary outcome. Within the financial literature, examples of these events are default versus on going concern firms, high grade rating versus high yield bonds, or, as in the present study, target versus non-target firms. The general specification of such models can be described as follows:

$$Y_i = \Phi(X_1^i, \ldots, X_N^i) + \epsilon_i \tag{4.1}$$

where Y_i is the binary dependent variable stating the class assigned to observation i, Φ defines the general specification of the regression, ϵ_i represents the idiosyncratic firm residual, and, for all k in [1,N], X_k^i is the cross-sectional selected independent variable for item i.

4.2.2 A comparison between parametric and semi-parametric methods

The difference between parametric and semi-parametric methods is the role played by the function Φ considered in equation 4.1 shown above. In a parametric framework, the structural relationship between the independent variables and the dependent variable is fully predetermined before the estimation and therefore the final function Φ does not depend on the data used during the model's optimization. In a non-parametric (or semi-parametric) regression, the model's functional form is optimized to provide an optimum fit and is therefore strongly dependent on the data underlying the model's estimation.

When choosing parametric models to specify Φ, several factors should be accounted. First, Y_i being a binary variable, the model should be adapted for the truncated distribution of the dependent variable. As described by Wooldridge (2002), estimation procedures such as Ordinary Least Squares (OLS) are not adapted for these situations as their output extends over the entire interval of real numbers. Parametric techniques such as probit, logistic and tobit regressions are better suited for this type of problems as their output can be interpreted as the probability of being classified in one of the two predefined categories. Secondly, as in the case of Multiple Discriminant Analysis (MDA hereafter), a number of distributional assumptions need to be verified by the data underlying the independent variables. Barnes (1982) shows that financial ratios are generally non-normally distributed and this can have substantial impact on both the efficiency and the consistency of the estimators.

Given the importance allocated to the model's interpretation and the possibility of extracting causal relationships relating the explanatory and explained variables, parametric methods have historically appeared more frequently than non-parametric ones. However, non-parametric techniques provide several advantages that should be considered when the user's objective is to maximize the model's predictive ability. First, given their mapping recognition abilities, these techniques provide both a greater goodness of fit during the estimation and, potentially, a higher out-of-sample generalizability. As a second point, given their ability of capturing flexible non-linear relationships, the distributional characteristics of the underlying data do not significant affect the estimation results.

In this thesis, I have estimated takeover likelihood using both a Logistic and an Artificial Neural Networks as the model's specifications. Although the characteristics of each particular method will be detailed in the following sections, I here provide some evidence of the complementary benefits of employing two different methods to estimated expected

Table 4.1: *Comparison between the advantages and disadvantages[a] of parametric and semi-parametric models.*

Topic	Logistic Regression	Artificial Neural Networks
Variable's Distribution	D: Weak distributional constraints: (i) extreme values may affect the estimation (ii) the variable's distribution should be symmetric (but not necessarily normal)	A: No distributional constraints
Optimization	A: Efficient and reliable estimation (i.e. Maximum Likelihood Estimator)	D: User dependent optimization. Time consuming and possibly subject to unobservable user-specific factors.
Regression function	D: Pre-specified	A: Function adapted to the processed data
Interpretation	A: *Ceteris-paribus* analysis of the parameters	D: Non-trivial interpretation of the estimated parameters (i.e. black-box system)

[a] For each of the selected methods, the letters A and D respectively indicate whether the described characteristic is generally considered an advantage or a disadvantage.

returns. As a first point, the use of different mapping procedures offers the possibility to investigate the influence of the chosen analytical framework on the reported results. Secondly, as our study focuses on the analysis of the drivers of a takeover attempt while also aiming to maximize the model's predictive potential, it was deemed necessary to employ a parametric method to analyze the effect of the selected variables and a semi-parametric method to test for possible improvements on the model's predictive power. Finally, as seen above, both methods have advantages and disadvantages that are difficult to weight against each other. Several studies in the general literature have compared the performances between Logistic and Neural Network models for different types of problems, but the evidence is not always clear and both seem to be supported. Table 4.1 shows a non-comprehensive list of the complimentary advantages and disadvantages of both methods. In the following two paragraphs, the focus is turned to the specific details of the Logistic Regression and Artificial Neural Networks respectively.

4.2.3 Logistic Regression

Within the financial literature, Ohlson (1980) appears to be the first author to introduce the advantages of the logistic regression technique when applied to multivariate dichotomous problems. However, given the frequent dichotomous characteristics of clinical experiments, the logistic model had been used before in medical research. Truett et al. (1967), for example, analyzed the performance of a logistic regression model in predicting heart diseases. In addition, well-specified models for binary problems such as probit had been previously used by Kuehn (1975) and Singh (1971).

As seen in chapter 2, early works in takeover prediction have generally used MDA for the model's specification. This method was used in studies such as Stevens (1973), Bartley and Boardman (1990), Barnes (1990), and Zanakis and Zopounidis (1997). In this thesis, I have chosen the logistic regression for several reasons. First, the model overcomes some of the unrealistic statistical assumptions on the explanatory variable's distributions under which operate some other commonly applied specifications such as MDA. Secondly, as outlined by Ohlson (1980) the MDA technique provides only an ordinal ranking therefore offering little room for interpretation and rendering the cut-off choice more difficult. Finally, recent studies have preferred the logistic regression over the MDA analysis. Moreover, most studies employing MDA as the main functional specification, with the exception of Stevens (1973), do not measure the ex-ante predictive ability of the models therefore failing to provide an estimation of the model's true out-of-sample discriminatory ability. Although recent studies comparing parametric and non-parametric model performance (Cheh and Weinberg, 1999; Ouzounis et al., 2008) have employed MDA as a parametric reference, their choice over the logistic regression is neither discussed nor justified.

The binomial logistic model is defined as follows (Wooldridge, 2002):

$$Z_i = log(\frac{p_i}{1-p_i}) = \beta_0 + \beta_1 \times X_1^i + \ldots + \beta_N \times X_N^i \tag{4.2}$$

$$p_i = \frac{1}{1+e^{-Z_i}} \tag{4.3}$$

where p_i is the probability of a company i of being taken over, β_0 is the intercept and for k in [1,N] β_k is the regressor corresponding to the financial variable X_k^i. The ratio $\omega = \frac{p_i}{1-p_i}$ defines the odds of a takeover outcome.

As given by the right hand side of the formula, equation 4.2 appears to be linear, however, in this case, the explained variable is a non-linear transformation of the dependent variable (i.e. the probability of a takeover event). To better see the non-linearities underlying a logistic regression, Equation 4.2 can be re-written as follows:

$$\omega = e^{Z_i} = e^{\beta_0} \times \underbrace{e^{\beta_1 \times X_1^i}}_{=\sum_{q=0}^{\infty} \frac{1}{q!}(\beta_1 \times X_1^i)^q} \times \ldots \times e^{\beta_N \times X_N^i} \tag{4.4}$$

As we can observe, the odds of a takeover event are a non-linear combination of the explanatory variables and the equation can only be considered linear as an approximation at the first degree of differentiation when the weighted sum of the variables tends to zero. By differentiating Equation 4.2 towards any explanatory variable X_k^i, we obtain:

$$\forall k \in [1, N], \; \frac{\partial p_i}{\partial X_k^i} = \beta_i \times p_i \times (1 - p_i) \tag{4.5}$$

As suggested by Arnull-Almond (2007), an additional advantage of the logistic regression is that the effect of an extreme value on a firm's takeover likelihood is attenuated by the factor $p_i \times (1 - p_i)$ which has a maximum at 0.5 and is worth 0 at the extremes 0 and 1. As a result, the impact of an extreme value will have an impact only if the probability of takeover likelihood is near 0.5. This can also be seen by plotting the logistic function, and noting that the highest variability, as measured by the absolute value of the slope, occurs at $p_i = 0.5$.

Because of the non-linear characteristics of a logit model, the least-squared estimation is not an appropriate method to measure the total residual error of the regression. As explained in Wooldridge (2002), the Maximum Likelihood Estimator (MLE) is a general approach which is well specified for occasions when residuals are no longer normally distributed. The MLE is defined as a the cumulative probability density function underlying the observed dependent variable. Asymptotically unbiased and consistent, the method allows to determine a unique set of coefficients maximizing the number of correct classifications. Based on such estimation, the literature offers different ways of measuring the model's goodness of fit: the log-likelihood ratio (LR) and the $\mathrm{R}^2(\mathrm{McFadden})$. The latter are defined as follows:

$$\text{LR} = 2 \times (\text{Log likelihood of the specified model - Log likelihood of the intercept}) \quad (4.6)$$

$$R^2(McFadden) = 1 - \frac{\text{Log likelihood of the specified model}}{\text{Log likelihood of the intercept}} \quad (4.7)$$

The higher the LR the better the goodness of fit. The $R^2(McFadden)$ offers a similar interpretation as the R^2 defined in the Ordinary Least Square Regression (OLS). However, it should be noted that the values generally reported for a $R^2(McFadden)$ are significantly smaller than the ones reported for OLS as a value of over 4% is considered providing significant discriminatory power.

4.2.4 Feedforward backpropagating Artificial Neural Networks

4.2.4.1 General framework of Artificial Neural Networks

Artificial Neural Networks is a subproduct of the research based on Artificial Intelligence (AI) in terms of attempting to replicate the functions of the human brain through the use of computer-based algorithms. An Artificial Neural Network (ANN hereafter) is a *semi-parametric* technique using a neural structure in order to capture complex relationships within the data. Although ANN has proven to be highly efficient as a regression tool, the term "intelligent" is misleading as it suggests that the technique provides other more advanced technicalities beyond data pattern recognition. As mentioned by Sarle (1994), ANNs techniques are not more "intelligent" than any other statistical method and the analogy with the human brain (and, more generally, with the entire nervous system) should therefore be considered as structural and not functional. The following paragraphs provide details on general ANN structures and the learning procedure needed to generate a map of the injected data.

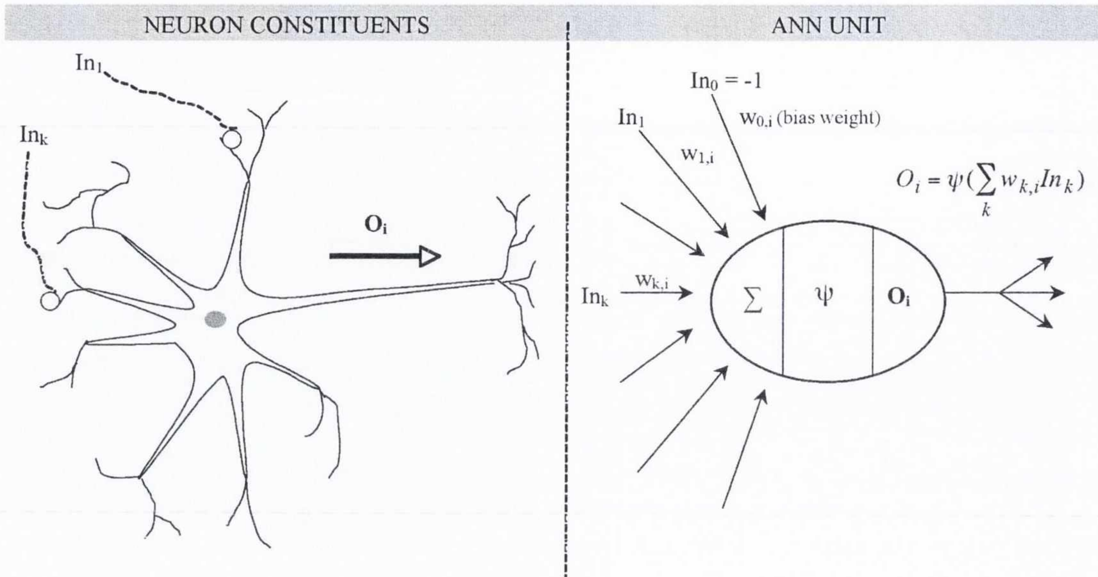


Figure 4.1: *Comparison between the structure of a biological neuron and the structure of a node in a Neural Network model. The symbol $\sum$ defines a weighted sum of the input values and the function Ψ defines the activation function. In_k are the node's input values and O_i the node's output.*

4.2.4.1.1 Description of an ANN unit

Neurons are the elementary unit of a nervous system whose principal function is the collection, transformation and dissemination of electric signals. Similarly, in ANN, a node represents a network junction being able to receive, transform and/or transmit data information. Figure 4.1 shows the analogy between a neuron and the node representation in ANN[1].

As shown in the above figure, a direct transfer of information between inputs and the node simplifies the complex function of the synapse whose role is to regenerate the action potential when transferring the information from one neuron to the other. The activation function Ψ represents the non-linear transformation applied to an input combination in order to re-scale the generated output into a consistent and comparable value across the considered nodes. Different classes of Neural Nets can be found depending on the type of function Ψ being employed. The Multi-Layer Perceptron (MLP) represents the most common class of Neural Networks where Ψ is a non-linear function applied to the weighted

[1]In a modified version, the figure combines the figures found in Russell and Norvig (2003) Chapter 1, Section 2 and Chapter 20, Section 5.

sum of the inputs from previous layers. Another frequently used class is the Radial Basis Function (RBF) where Ψ is a radial function defined as a weighted sum of the distance between the input value In_k and the vector weight $w_{k,i}$. In both cases, if the weighted sum of the inputs exceeds a certain threshold (here represented as the bias weight), the neuron "fires" the output O_i and does not generate any output otherwise.

4.2.4.1.2 ANN architectures

The previous paragraph presented a simple model of how neurons process input information. The simplicity of the unit process already suggests that ANN's ability to map complex data patterns strongly depends on the architecture through which these nodes are interconnected. Intuitively, a larger number of links should be able to generate a better map of the data.

There are two classes of neural networks, feed-forward and recurrent, defined by different levels of complexity in relation to the links between nodes within a given network structure. In a feed-forward network, the information received by a node depends only on the information generated by the previous layer. As a result, the output is a function of its own inputs. On the contrary, in a recurrent network there are loops feeding the information generated by a given node into the inputs of previous layers. As mentioned in Russell and Norvig (2003), the resulting feedback can produce oscillatory and chaotic time-series and is useful to study short-memory effects. In this thesis, I will focus on feed-forward neural networks as the advanced features of recurrent networks are not necessary in classificatory problems. Figure 4.2 shows two examples of commonly referenced feed-forward networks.

As shown in Bishop (1995), a simple perceptron network can be used to solve linearly separable problems. A special case of such networks is the logistic regression (described in the last section) which is obtained through a linear combination of the inputs and using a sigmoid activation function in the output node. Bishop (1995) also describes several documented limitations related to perceptron networks which led researchers to suggest a more flexible combination of inputs as the one offered by multi-layer neural networks.

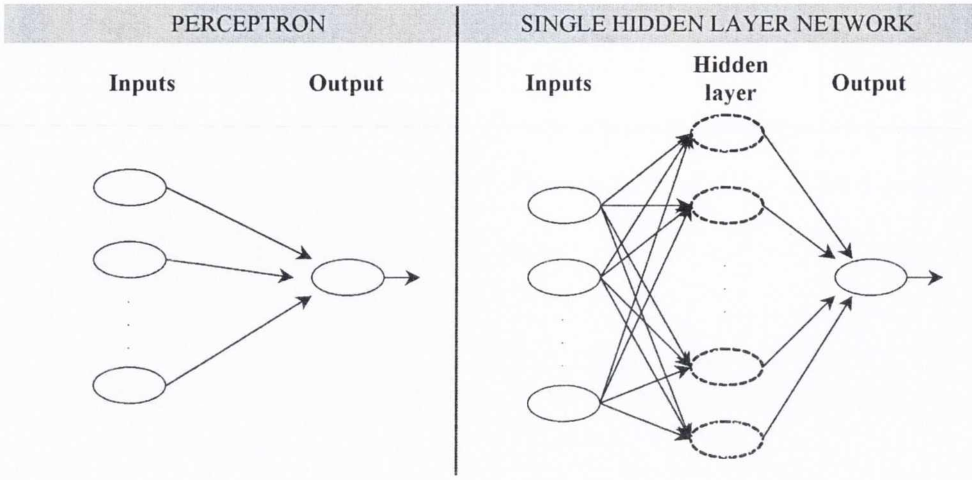


Figure 4.2: *The perceptron defines a function where an activation function is applied after transformation of the input data. The single hidden layer network defines a more complex structure where the input data is first processed through the hidden nodes and then received and transformed by the output node.*

The general equation to be estimated for a single-layer perceptron model is given by:

$$\hat{O}_s = g(\alpha_s + \sum_{p=1}^{P} w_{sp} X_p) \tag{4.8}$$

where O_s is the output of the single-layer network, X_p is taken as the input variables, w_{np} is the input weight of variable p connected to node n and w_{on} the output weight of node n connected to the output. α_n and β represent the intercepts of node n and the output respectively. In equation 4.8 we have up to P inputs and N hidden units and g(.) is the output's activation function.

Multi-layer neural networks offer the possibility of generating additional intermediate calculations by adding one or more layers, each one composed of several perceptrons. This results in more complex combinations between the input variables as the neural network now offers the possibility of estimating a model based on the response of several perceptrons. In other words, the model's output is a product of a combination of the outputs of several parametric regressions and not just one as in the case of the logistic regression. Moreover, as shown in Hornik et al. (1989), with one hidden layer, a neural net is capable of mapping any continuous function relating the input variables and the output variable. With two hidden layers any discontinuous function can be approximated.

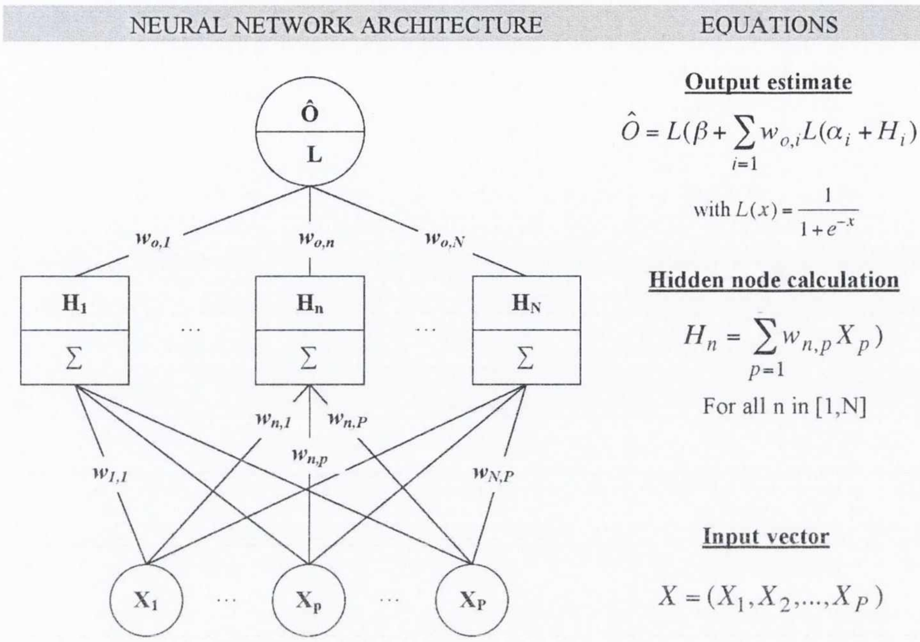


Figure 4.3: *Sequential calculation steps of a one hidden layered Neural Network*

Although some studies have exploited the advantages of using more than one hidden layer, a single hidden layer is generally sufficient for forecasting purposes (Zhang et al., 1998, p.44). In addition, Tortum et al. (2007) shows that the number of nodes in the second hidden layer is of secondary influence in the model's overall performance. Therefore, in this thesis, only single hidden layer networks are considered. Figure 4.3 shows the different stages in the Neural Network's input information process in order to generate the output.

The more general equation to be estimated for a feed-forward multi-layer perceptron model is therefore given by:

$$\hat{O}_m = h(\beta_m + \sum_{n=1}^{N} w_{mn} g(\alpha_n + \sum_{p=1}^{P} w_{np} X_p) \tag{4.9}$$

where O_m is the output of the multi-layer network, X_p represent the p^{th} input variable, w_{np} is the input weight of variable X_p connected to the n^{th} node and w_{on} the output weight of the n^{th} node connected to the output. α_n and β_m represent the intercepts of node n and the output resepctively. In equation 4.9 we have up to P inputs and N hidden units and g(.) and h(.) two activation functions corresponding to the hidden nodes and to the output respectively.

4.2.4.1.3 The learning process

Neural Networks learn by minimizing the classificatory error. Methods such as the maximum likelihood estimator cannot be applied to multi-layer neural networks since each weight cannot be identified to a single input variable. As mentioned by Bishop (1995), for a given input and output, it is not possible to determine which hidden node is responsible for the highest error contribution.

The error back-propagation technique is an efficient method of minimizing the errors generated by each hidden node which consists in propagating the error from layers higher up in the network towards the bottom layers and update the network weights using a gradient descending algorithm. The technique was made popular by Rumelhart et al. (1988) but similar concepts were used in previous academic works such as Werbos (1974) and Parker (1985). A mathematical explanation of the link between the delta rule and the minimization if the total error can be found in Russell and Norvig (2003, Chapter 20).

One of the main advantages of the gradient descending technique is its calculation efficiency. On the other side, the main disadvantage is that the optimization procedure can result in a local minima of the total error. The learning rate η and the momentum μ are parameters that can be optimized to improve the performance of the algorithm. However, even in optimal conditions, the possibility of the algorithm getting trapped in a local minima cannot be avoided. Other methods offer the possibility to improve the results of the gradient descending algorithm. The detail of such techniques is, however, out of the scope of this thesis and the reader is referred to Bishop (1995, Chapter 7) for an overview.

4.2.4.2 Optimization of the neural net's parameters

4.2.4.2.1 Description of the selected optimization method

Although, until now, a neural net's architecture structure was assumed to be fixed, the optimization of a multi-layered neural network requires the specification of a large number of parameters. These include the number of hidden layers, the number of nodes in each layer, the momentum, the learning rate and the choice of an activation function. As a result, the optimization of a Neural Network structure is, as stated in Zhang et al. (1998), "more an art than a science". This problem is closely related to the non-parametric characteristics of ANN since the optimum architecture will depend on the complexity of the input data. Bishop (1995) defines the optimum generalization point as a trade-off between bias and variance. More precisely, a low (high) order specification will generate high bias (variance) and therefore the model's greatest generalizing ability should be found in between these two extremes. However, achieving this point is not a trivial task. Since the architecture is sample dependent, there seems to be no general rule to estimate the parameters that optimize the ANN structure. Despite a vast number of applications of Neural Networks, the methods used to optimize the models remain often obscure and sometimes the network's defining parameters are not even reported (see Zhang et al., 1998, for a recent review on the topic). An effort was made by Tortum et al. (2007) who uses a general experimental procedure based on the experimental planning using a Taguchi Method in order to draw general conclusions on the influence of the above mentioned parameters. Following Tortum et al. (2007), the different steps executed during the optimization process of the ANN are the following:

A. <u>*Data transformation*</u>: We use three main industries (i.e. Industrials, Transportation and Utilities) which are defined by Datastream's Industry Numbers (code: INUM) 1, 2 and 3. Following Cudd and Duggal (2000), we transform the raw ratios as shown in equation 4.10:

$$X_{IY} = \frac{X - \overline{X_{IY}}}{\sigma_{IY}} \tag{4.10}$$

Where $\overline{X_{IY}}$ is the average and σ_{IY} the standard deviation of the variable X in the industry I on the year Y. X_{IY} is the resulting normalized variable for a variable X belonging to the industry I in the year Y.

B. _The percentage of trained data_: To control for overfitting, the estimation sample was split into training and validation samples. As in Cheh and Weinberg (1999) and Tortum et al. (2007), 80% of the estimation sample was used for training and 20% for validation.

C. _Number of hidden nodes in the first layer_: Tortum et al. (2007) tests a large and spread range of hidden nodes (i.e. 1, 20, 40 and 60) and shows that this parameter has the greatest influence on the model's performance. Using a higher sampling frequency but a smaller range, Zhang et al. (1999) finds that the net's performance can be sensitive even to a unity change in the number of nodes. Here, more in the view of Tortum et al. (2007) and as suggested by some of the common rules of thumb applied to select the number of hidden nodes[2], a larger number of nodes with higher space interval rather than a small number with a higher sampling frequency was chosen for the study. Eight different levels of hidden nodes such as 5, 10, 15, 20, 25, 30, 35, and 40 were tested. A 5 nodes interval was chosen between each test as it was the approximate number of nodes needed to perceive a significant difference in the net's performance.

D. _Number of hidden nodes in the second layer_: Following Tortum et al. (2007), we have considered only one hidden layer in the optimization process as the number of nodes in the second layer was found to be of "secondary" influence. Furthermore, Hornik et al. (1989) shows that one hidden layer is sufficient to map any pattern in the data.

E. _Activation function_: As previously shown in Figure 4.3, the log sigmoid was chosen as the activation function. It was also shown by Tortum et al. (2007) that this function achieves the greatest performance.

This method was applied for every yearly estimation sample during the period 1998-2007 in both the UK and the US.

[2]As described in Zhang et al. (1998, p. 24), these rules imply that the optimal number of hidden nodes is related to the number of input nodes n e.g. n/2, n, n+1, 2n+1

4.2.4.2.2 Underlying simplifications and limitations

Given the large number of initial tests that were here considered, some steps in the optimization process were simplified. I here describe and justify in detail the choices leading to a manageable experimentation plan and the potential limitations linked to the latter.

First, the literature suggests that each Neural Network Model should be validated using a cross-validation technique[3]. The technique consists in testing the model's performance by calculating an average predictability based on multiple training and test samples. Zhang et al. (1999) use this method to test the sample robustness of a bankruptcy predictive model using both ANN and logistic regression by dividing the sample into five sub-samples of which four were used for the model's training and one for the model's validation. They conclude that ANN models are robust given the small difference in the results between the considered test samples. In addition, with the exception of works such as the previously mentioned Zhang et al. (1999) and Hu et al. (1999), while failing to apply the rigorous cross-validation technique, the general literature still provides evidence of high predictive performances therefore suggesting that the generated bias induced by overfitting the validation sample may not have a significant impact on the model's predictability. As mentioned by Russell and Norvig (2003), the literature generally neglects this point as cross-validation techniques can be extremely time-consuming and therefore add to the complexity of a neural net's optimization procedure. In this thesis, given the suggested robustness of Neural Networks to the potentially small overfitting effect on the test sample, the validation of the model's performance was measured using single validation samples.

A second simplification relates to the ANN's learning parameters. Ideally, these parameters should be optimized for each considered network architecture and, the practitioner should carefully select the set of values optimizing the network's learning process by reducing the probability of getting trapped into a local minima and, at the same time, avoiding to rapidly overfit the training sample. Considering the parameters employed

[3]The cross-validation technique is qualitatively presented in Russell and Norvig (2003, Chapter 18) as a method to avoid *peeking* into the validation sample. The reader may also refer to Stone (1974) who provides a statistical proof on the advantages of a cross-validation technique relative the use of a single validation sample.

by Cheh and Weinberg (1999), a learning rate of 0.2 and a momentum of 0.1 were arbitrarily selected. These parameters were found to suit the vast majority of the samples that were used in this thesis. In order to minimize the chances of a procedure resulting in local minima estimators, the random seed was changed in cases where the optimization procedure was trapped over the first iterations.

4.3 Forecasting methodology

4.3.1 Review of forecasting methodologies

Early works in takeover prediction have generally used missleading methods to assess a model's predictive power. Using within period validation, authors such as Wansley et al. (1983); Rege (1984); Brar et al. (2009) employed in-sample tests to measure the predictive accuracy of the estimated models. Even less informative, some authors have used the goodness of fit as a sole indicator of the model's ability to predict future takeover events (Bartley and Boardman, 1990). As mentioned by Palepu (1986), these reported predictions overstate the model's predictive accuracy as they measure ex-post classificatory accuracy rather than ex-ante predictive accuracy. Furthermore, as suggested by Fildes and Makridakis (1995), statistical models tend to show poor generalizability as indicated by evidence that goodness of fit and predictability are often weakly related.

Most of the recent works have acknowledged this issue, and it has been accepted that predictions should be calculated in out-of-sample manner intervals. As a result, cross-sectional multivariate prediction models are generally tested using point forecast estimations[4].

By definition, a point forecast assumes that the model's predictive ability is stationary. This can be understood in settings such as the bankruptcy prediction literature where, as seen in section 3.2, the models seem to achieve comparable estimates and relatively consistent prediction power. However, as described in section 3.3.1, the disagreement

[4]A point forecast can be defined as a an out-of-sample test of the a model's ability to classify or predict an outcome in a sample different from the one used for the estimation.

within the takeover prediction literature on the model's predictive ability suggests that the forecasting error may be significant. Therefore, a point forecast estimate does not seem to reflect a takeover prediction model's predictive ability. As one of the objectives of this thesis is to implement a methodology allowing to measure the inherent variability of a takeover prediction model's performances this study employs a multiple forecast methodology. The following paragraphs provide a detailed description on the nature and advantages of such method.

4.3.2 Rolling forecast estimation concept

A rolling forecast methodology attempts to replicate statistical experiments in order to draw well-founded conclusions on the model's forecasting accuracy and therefore on its ability to persistently explain a given phenomena. Rolling forecast estimations are frequent when assessing the predictive accuracy of time series econometric models and the reader may report to Tashman (2000) for a recent review of such forecasting techniques. Although different specifications have been used, equation 4.11 offers a general specification for a multivariate framework covering a large number of the models found within this literature.

$$y_t = \alpha_0 + \sum_{j=1}^{J} \alpha_j y_{(t-j)} + \sum_{k=1}^{K} \sum_{j=1}^{J} \beta_{kj} x_{k,(t-j)} + \epsilon_t \tag{4.11}$$

where j is the lag length, t marks the time period, $y_(t-j)$ denotes the variable of interest measured at time $t-j$, and $x_{k,(t-j)}$ denotes the k^{th} independent variable measured at time $t-j$. α_j and β_{kj} represent the regression coefficients of $y_(t-j)$ and $x_{k,(t-j)}$ respectively.

Tashman (2000) presents two different forecasting methods: rolling window and fixed-origin. Fixed origin forecasts use a single estimation of the model and attempt to predict on a variable forecasting window whereas rolling window forecasts use fixed forecasting windows with rolling estimation origins (i.e. the estimation period depends on the period the user attempts to predict).

Based on a review of the empirical results, Tashman (2000) underlines the following recommendations in relation to the way rolling forecasts should be applied:

1. The need of using out-of -sample data when testing the model's predictive ability. As shown in the previous paragraph, this has often been incorporated in the takeover prediction literature.

2. The advantages of rolling origin forecasting techniques in removing the forecasting accuracy's dependence on the selected estimation origin.

3. The usefulness of increasing the number of periods considered in order to test the potential influence of the business cycle on the model's forecasting power. As suggested by Pompe and Bilderbeek (2005) within the bankruptcy prediction context, the selected economic period may have an influence on the model's predictive ability.

Points 2. and 3. summarize the critics established on the previous paragraphs, and the lack of reliability underlying a point forecast estimation.

4.3.3 Implementation of the rolling forecast technique within the takeover prediction framework

4.3.3.1 Parameters defining the employed rolling window forecast

Three choices need to be made in order to define a rolling window forecast process: (i) the number of years used to build the estimation sample, (ii) the size of the rolling window, and (iii) the total number of desired forecasts.

In relation to the first point, several authors have pooled takeover data over large periods of time (e.g. nine years in Belkaoui, 1978 and Palepu, 1986; ten years in Powell, 2001). However, Harris et al. (1982) and Powell (1997) show that takeover characteristics seem to change over the medium horizon suggesting that misspecified estimation samples are likely to be obtained when pooling targets across long periods of time. Accounting for this potential misspecification, some authors have recently reduced the considered estimation period (e.g. one year in Barnes, 1999; six months in Espahbodi and Espahbodi, 2003; one year in Weir and Laing, 2003 and two years in Arnull-Almond, 2007). Following this trend, for each estimated model, the rolling estimation window used to build the target sample was restricted to one calendar year.

Regarding the second point, the rolling window was defined as one calendar year as it is the general method employed in the literature consisting in estimating a model and predicting in the year following the estimation. This method assumes that takeover characteristics do not significantly change in two consecutive periods and therefore that the most recent M&A data contains the highest amount of information on future takeover activity. This argument is partially supported by the persistent characteristic of M&A activity over time.

Finally, as mentioned in the previous paragraph, forecasting efficiency and reliability may be improved by using multiple test periods. In this study, the period 1998-2007 was selected to estimate the ten one-year rolling window cross-sectional models and calculate ten yearly out-of-sample forecasts during the period 1999-2008. The period is deemed to cover different types of business cycles which shall be described in the next chapter. The choice of a large period covering several business cycles therefore prevents our results from being dependent on the chosen time period.

4.3.3.2 Characteristics of the one-year estimation and holdout samples

A method called *State-Based Sampling* (a.k.a. Choice-based Sampling), where a random number of non-target companies are matched with the total number of targets, has been frequently used by previous researchers (e.g. Walter, 1994; Powell, 2001; Brar et al., 2009) to build the estimation sample. As shown by Zmijewski (1984) in the context of bankruptcy prediction literature, this method generates significant overfitting bias and is thus likely to generate unreliable predictions.[5] Platt and Platt (2002) have recently confirmed these results with a more rigorous study applied to the automobile industry. Given the potential drawbacks of this method, our estimation sample was built using complete data (i.e. including all target and non-target companies having all available financial information).

Out-of-sample forecasts were calculated the year following the estimation year. Consis-

[5]Although Zmijewski (1984) points out that a selection bias exists when using complete data samples, the latter is related to the probability of missing accounting information in distressed firms. Such bias is thus likely to be less significant when considering target firms as there is no apparent reason suggesting that target firms would be less likely to enter the final sample relative to non-target firms.

tent with Palepu (1986), the holdout sample was built using complete data (as the estimation sample) except that all target firms used in the estimation sample (and still active during the prediction year) were excluded.

4.3.3.3 Cut-off choice methodology

To determine the sample of companies predicted to be taken-over the user needs to determine a cut-off probability, P_C, beyond which a company is considered as likely to be the subject of a target bid.

Two main cut-off choice methods have been discussed in the literature. The *minimization of error method*, first introduced by Palepu (1986), claims that the cut-off should be chosen as the probability that minimizes the sum of Type I and Type II errors whereas the *maximization of returns method* suggests that, if the aim is to build a portfolio strategy, the cut-off threshold should be chosen as the one maximizing the C-ratio (see e.g. Barnes, 1999; Powell, 2001). Within the bankruptcy prediction literature, Hopwood et al. (1994) uses an estimation of the optimal cut-off value based on the relative costs of misclassifications.

Although theoretically sound, there is no empirical evidence showing that any of these techniques consistently optimize the predictive ability of takeover prediction models. In order to avoid constraining our analysis of the models predictions to one single cut-off value, the results are here presented for a series of nine equally spaced cut-off values within the unit interval.

4.3.4 Methodological contributions and potential limitations

The idea of considering multiple cross-sectional estimations is not unfamiliar to the binary choice prediction literature. While attempting to measure the estimation bias generated by the use of complete data samples, Zmijewski (1984) employs a probit regression to estimate a bankruptcy prediction model in each year of the period 1972-1978. The author concludes that most of the coefficients are consistent over time therefore supporting the contention that bankrupt firms are characterized by a well-defined financial profile.

In the takeover prediction literature, two similar works have attempted to compare the regressed coefficients in two different periods. Harris et al. (1982) compares the coefficients of a probit-based takeover prediction model estimated in the periods between 1974-1975 and 1976-1977. He concludes that, with the exception of the Price-to-Earnings ratio, the estimated regressors are unstable over time. Similarly, Powell (1997) compares the estimation of a logit-based takeover prediction model in the periods 1984-1987 and 1988-1991. He also concludes that coefficients are inconsistent over time. The main difference between the two previously mentioned studies is that the former focuses the comparison on the sign of the coefficients while the latter refers only to the stability of the regressor's significance. In this thesis, I extend the aforementioned work, by considering a multiple cross-sectional estimation over the ten-year period 1999-2008 and the analysis of both the significance and sign stability over time are included in our results. This methodology attempts to answer the first research question of the present thesis.

From a target prediction perspective, although these previous studies underline the consistency (or inconsistency) of the model's specification over time, none of the studies has yet attempted to measure the impact of such inconsistencies on the model's predictive power. In relation to the second research questions, this thesis therefore contributes to the current literature by using a rolling forecast methodology in order to analyze the stability of the takeover forecasting accuracy over time.

From a portfolio perspective, Cremers et al. (2009) use a rolling estimation technique based on a logistic regression in order to capture the influence of takeover vulnerability in the cross-section of returns. They show that over a fourteen-year period the model is able to generate substantial abnormal return as measured by the Fama and French (1992) and Carhart (1997) four-factor model. Although their result provides a strong motivation for study, their samples are too large to be the basis of a portfolio investment. As a result, within the context of the third research question, this thesis further explores this achieved result by (i) providing the dynamic of the portfolios within the selected period, (ii) considering more realistic portfolios from an investment management perspective and (iii) using a yearly control portfolio benchmark resulting in an accurate measure of long-term average abnormal profitability.

It should be first noticed that the literature suggests several limitations when using multiple regression estimations. First, there might be random and fixed effects affecting the model's estimations. The changes in the coefficients could be then affected by exogenous factors linked to the political and/or economical factors and therefore the changes the sign and/or value of a coefficient would not be linked to a change in takeover characteristics but to a model's misspecification. Although this is a possibility, the study of Zmijewski (1984) shows that the estimation of bankruptcy prediction seems to show consistent results over time therefore suggesting that exogenous factors do not seem to have a significant effect within the bankruptcy prediction context. In addition, as I will show in section 5.3.4, the use of industry-relative ratios should increase the stability of the coefficients across different periods (Platt and Platt, 1990). A second issue is related to the heterogeneity of the coefficients and the correlation of the error terms both cross-sectionally (between firms) and across periods (firm specific time-varying error). This is certainly a potential limitation regarding the analysis on the coefficients' time stability that will be provided in chapter 6. Despite the influence of these potential biases on the re-estimated coefficients, the question remains whether more coefficients might have a stable relationship towards acquisition likelihood when accounting for these effects. However, the limitation is not likely to significantly alter the conclusions on the coefficients that are found stable over the selected period.

4.4 Evaluation methods

4.4.1 Dynamical stability of takeover characteristics

One of the objectives of this thesis is to capture stable takeover characteristics over the selected time period. As mentioned in the paragraph above, the takeover prediction literature offers two methods of investigating the stability of takeover characteristics. As both were applied to only two periods, their methodology needs to be adapted for the here considered ten year-period 1998-2007.

In Powell (1997)'s method, the coefficient's significance is given by both the mean value and standard error resulting from the regression. In this thesis, persistent discriminatory power was considered significant when a variable achieved significant classificatory power in more than three periods. As only few variables were significant more than three times, this method selects only the few variables having relatively persistent discriminatory power.

By considering the sign in two periods, the work of Harris et al. (1982)'s method does not offer a method allowing to determine sign stability over a longer period. In order to test the significance of a coefficient's sign stability, a parametric t-statistics was used based on the values of the coefficients over the ten-year period and testing whether the obtained values are significantly different from zero. The latter can be expressed as folows:

$$t_{coeff} = \frac{\overline{\beta}}{\sigma_t(\beta)/\sqrt{T}} \tag{4.12}$$

where $\overline{\beta}$ and $\sigma_t\beta$ respectively measure the time-series arithmetic average and the time-series standard deviation of the yearly estimated coefficient during the period 1998-2007 and T is the number of periods in the sample (equal to ten in the particular case of this study).

4.4.2 Measures of predictive performance

The predictive performance of the models is measured using the C-ratio (C_P) and the model's performance relative to chance (PRC) which are defined as follows:[6]

$$C_P = \frac{n_{TP}}{n_P} \tag{4.13}$$

$$PRC = \frac{C_P - D_T}{Min(C_P, D_T)} \tag{4.14}$$

where n_P is the total number of firms predicted to be targets, n_{TP} defines the number of firms correctly predicted as target and D_T represents the target density in the sample defined as the total number of targets divided by the total number of firms.

[6]The overall accuracy of the model, defined as the total number of correct predictions divided by the total number of firms, is also generally reported in the studies, however the measures C_P and PRC were selected given the focus of our study on the model's ability to accurately predict target firms rather than on its overall discriminatory power.

In addition, a two-samples parametric t-statistic was calculated in order to measure the difference between the series of yearly predictions and a series based on random predictions.

$$t_{pred} = \frac{\overline{C_P} - \overline{C_R}}{\sqrt{\sigma_t(C_P)^2 + \sigma_t(C_R)^2/\sqrt{T}}} \tag{4.15}$$

where $\overline{C_P}$ ($\overline{C_R}$) and $\sigma_t(C_P)$ ($\sigma_t(C_R)$) respectively are the time-series average and time-series standard deviation of the yearly concentration-ratio C_P (yearly total target density C_R) and T is the number of periods in the sample (equal to ten in the particular case of this study).

4.5 Calculation of abnormal returns

This section presents the investment strategy that was employed to assess the profitability underlying takeover prediction models. First, details on the evaluation of the calculations used to define the abnormal profitability of the samples is provided. Given the fundamental role played by the benchmark used to assess abnormal profitability, the section ends by describing the two benchmarks used in this study: the market index benchmark and the control firm portfolio recommended in Barber and Lyon (1997).

4.5.1 Definition of abnormal returns and measures of performance

The final step of this thesis will be to analyse the reward of an investment strategy based on the yearly predictions of both the Logistic and the ANN-based takeover prediction models. In order to test the portfolio performance, an equally weighted buy-and-hold portfolio strategy is built based on the sample of companies predicted to become targets. The investment is thus initialized at the beginning of the calendar year in which the forecast was realized and held for 12 months. Monthly buy-and-hold returns were first calculated using Datastream's Return Price Index (code:RI) for each firm included in the portfolio. The index is calculated by accounting for share price movements as well as for any type of shareholder compensation (share repurchase, dividend payment, etc.). Buy-and-hold abnormal returns (BHAR) were calculated following Barber and Lyon (1997). As in Loughran and Ritter (1995), if a company was delisted prior to its anniversary date, the return was truncated at the last traded month. The abnormal return earned by a firm i during the buy-and-hold investment can therefore be defined as:

$$BHAR_{iT} = \prod_{t=start}^{min(T,T_{delist})} [1 + R_{it}] - \prod_{t=start}^{min(T,T_{delist})} [1 + E(R_{it})] \tag{4.16}$$

where *start* and T are the first (January) and last (December) month of the given prediction year respectively, T_{delist} is, in case of delisting, the last month in which firm i was traded, and R_{it} and $E(R_{it})$ are the price return and the expected return of firm i at month t respectively. Two different ways were employed to estimate. First, a suitable market index was used to compare the portfolio performance to a standardized market benchmark.

Consistent with Barber and Lyon (1997), we test the null-hypothesis that abnormal returns are not significantly different from zero using the following parametric test statistic:

$$t_{BHAR} = \frac{\overline{BHAR_{\tau}}}{(\sigma_{\tau}/\sqrt{n})} \tag{4.17}$$

where $\overline{BHAR_{\tau}}$ is the sample arithmetic average and σ_{τ} is the cross-sectional standard deviation of abnormal returns for a sample of n firms. [7]

Using the ten-year portfolio performance, the significance of the average long-run investment performance was measured by the t-statistic based on the null hypothesis that abnormal returns are not different from zero and defined as follows:

$$t_{\overline{BHAR}} = \frac{\langle\overline{BHAR}\rangle}{\sigma_t(\overline{BHAR})/10^{0.5}} \tag{4.18}$$

where $\langle\overline{BHAR}\rangle$ and $\sigma_t(\overline{BHAR})$ measure the average and the time-series standard deviation of the long-term abnormal return generated by the yearly predicted portfolios over the ten-year period 1999-2008.

Finally, in order to assess the risk-return profile of the firms included in the portfolios,

[7] The formulas are given by: $\overline{BHAR_{\tau}} = \frac{1}{n}\sum_{i=1}^{n} BHAR_{i\tau}$ and $\sigma_{\tau} = [\frac{1}{n-1}\sum_{i=1}^{n}(BHAR_{i\tau} - \overline{BHAR_{\tau}})^2]^{\frac{1}{2}}$.

the yearly Information ratio (IR) was calculated as follows:

$$\text{Information Ratio} = \frac{\sum_{t=1}^{12} BHAR_t}{\sigma_t(BHAR_t) \times 12^{0.5}} \tag{4.19}$$

where the abbreviation $\sum BHAR_t$ measures the monthly abnormal return generated by the predicted portfolios over the twelve-month period of the selected year, $\sigma_t(BHAR_t)$ represents the monthly time series standard deviation and 12 is the number of months during the selected calendar year.

4.5.2 The market index benchmark approach

In order to provide a general assessment of the models' portfolio performance in the UK and the US, for each selected cut-off value, the predicted samples' profitability is calculated relative to a representative market index. The chosen benchmarks for the UK and the US were the FTSE All Shares Index (FASI) and the Dow Jones Total Stock Market Index (DJTM) respectively. These indices were chosen since, for both economies, the predicted firms did not display any aggregated feature at the size level (market capitalisation) nor at the industry level. In addition, accounting for smaller firms, these indexes generate, for most years, a greater performance than other commonly used indexes. The market benchmark is useful to assess the yearly raw profitability of the portfolios and also provides a meaningful long-term performance relative to a single benchmark over the entire period. Although not controlling for common market factors, these benchmarks provide information on the real investment outperformance underlying the models. Cheh and Weinberg (1999) and Brar et al. (2009) are some examples of works having used a market index benchmark to calculate abnormal returns by subtracting the return of an equally-weighted market index from the return of the stock.

4.5.3 The control firm portfolio

As shown in Barber and Lyon (1997), the single firm control portfolio benchmark method to calculate abnormal returns overcomes the several biases related to other methods such as the market index benchmark approach.[8] Following the authors' recommendations, the method was applied as a second benchmark method in order to test the influence of common market factors on a predicted portfolio's profitability.

For each firm included in the predicted portfolio, the selection process of the control firm follows two steps aiming to match the predicted firm by size and subsequently by its market-to-book ratio. First, all companies having a size between 70% and 130% of the predicted firms market capitalization are grouped into a common size group. Out of this group, the control firm is selected as the one having the closest value compared to the predicted firm's market-to-book value. Consistent with the calculation of return on the prediction portfolio, in case of delisting, we truncate the control firm's return at the last traded month. Although some authors have matched the control firms by industry (see for instance Chan et al., 2007), some others, such as Loughran and Ritter (1995), have advocated the use of random samples over the entire corporate landscape. In our study, consistent with the construction of the estimation sample wherein financial and infrequently traded firms were excluded, we have also excluded these firms when selecting control firms.

4.6 Summary

This chapter introduced the methodology employed in this thesis to estimate takeover likelihood as well as to evaluate and characterize the performance and the stability of the considered takeover prediction models.

Parametric and semi-parametric models both offer advantages that are important for properly addressing the problem of dynamic instability. From one side, a logistic regression provides a suitable specification for dichotomous dependent variable problems and has weaker statistical assumptions on the variables' distributions relative to other parametric techniques such as MDA. In addition, as a general characteristic of parametric specifications, a logit-based model offers a *ceteris paribus* interpretation of the esti-

[8] In their paper, Barber and Lyon (1997) show that most of the benchmarks used by previous research to calculate long-term abnormal returns are subject to three potential bias namely: (1) the new listing bias, (2) the rebalancing bias and (3) the skewness bias.

mated coefficients. The latter is needed to analyze the variables' influence in takeover likelihood over time. From another viewpoint, Artificial Neural Networks offer a specification based on more complex combination of the input variables which depends on the neural net's architecture but, most importantly, on the data that underlies the process. The flexibility of Neural Network-based models thus offers a promising method to maximize the model's predictive power. As the objective of the thesis is to analyze the models' persistent ability to predict takeover targets, semi-parametric techniques should be considered in order to ensure that our result does not depend on a weak functional representation between the variables and a firm's takeover likelihood.

To study the dynamical features of takeover prediction models, this study uses a one-year rolling estimation over the period 1998-2007 allowing to generate ten out-of-sample forecasts over the period 1999-2008. The one-year estimation window was chosen in order to isolate takeover motives as the evidence shows that merger drivers seem to change over time (Harris et al., 1982; Powell, 1997; Andrade et al., 2001). Although several studies use long periods of time during the estimation process, most of the recent works have chosen a short period of time (Espahbodi and Espahbodi, 2003; Weir and Laing, 2003; Arnull-Almond, 2007). The estimation samples use complete data as they generally overcome the potential biases of choice-based sampling (Platt and Platt, 2002). Holdout samples are constructed as in Palepu (1986), using complete data and excluding the target firms used during the model's estimation.

One of the main disadvantages of Neural Networks is the complexity of their optimization process. Following Tortum et al. (2007), this study implements several experiments in order to build an optimal architecture with good generalization properties. In order to minimize construction costs we have not used cross-validation techniques and therefore our results may be dependent on the validation samples that have been randomly chosen. However, the danger of "peaking" into the validation sample seems to be low when considering that studies employing a cross-validation technique report the similar performances in their validation samples (e.g. Zhang et al., 1999). A commonly adopted simplification relates to the arbitrary choice of the neural net's learning parameters. In our study, based on frequently reported values, a learning rate of 0.2 and a momentum of 0.1 were arbitrarily selected.

Buy-and-hold abnormal returns were calculated as in Barber and Lyon (1997) in order to account for cumulative to compounding. Two benchmarks were chosen to measure abnormal profitability. First, a market index benchmark was selected in order to provide a common base to assess the differences in overall performance between the different selected portfolios. Given the several potential flaws of using a market benchmark, as recommended by Barber and Lyon (1997), a control firm portfolio is used to assess the abnormal profitability of the portfolios by controlling for common market factors. Control firms are selected using a two step process. For each firm in the predicted sample, all firms in the range of 70% and 130% of the firm's market capitalization are selected. Within this group, the control firm is selected as the one having the closest book-to-market ratio.

Finally, given the multiple forecast framework of this thesis, other statistical methods were used to measure the significance of the model's long-term performance. In relation to the consistency of the estimated coefficients and based on two existing methods employed by Powell (1997) and Harris et al. (1982) respectively, this thesis uses an innovative technique allowing to capture both the sign stability and the frequent discriminatory power of the regressors over the selected period 1998-2007. Regarding forecasting performance, the C-ratio (target density in the predicted portfolio) and the Relative to Chance ratio (PRC) are used to measure yearly predictive performance. Long-run predictive performance is measured by the average C-ratio over the ten-year period and its significance is measured using a two sample test-statistics testing whether the average predicted C-ratio is different from a random sample selection. Regarding portfolio performance, the significance of the yearly achieved buy-and-hold abnormal returns was calculated as in Barber and Lyon (1997). In addition, long-term performance was measured as the ten-year average of the yearly achieved abnormal returns and its significance was measured using a test-statistics based on the null hypothesis that average abnormal returns are not different from zero.

Chapter 5

Data collection, data treatments and descriptive statistics

5.1 Introduction and overview

Due to the data-intensive characteristic of the multiple forecasting methodology employed in this thesis, a considerable amount of work was dedicated to the filtering, post-treatment, and organization of the data obtained from two different sources. This chapter's first objective is to describe the selected data sources from which both the M&A and the corporate public financial information were collected. As several decisions, such as the variable and the target selection process, were based on data characteristics, the chapter also provides detail on the data collection process and all the intermediate steps leading to building the estimation and holdout samples. Furthermore, the chapter provides descriptive statistics of both data sources in order to (i) examine the different types of M&A considered as well as the dynamic pattern of the level of M&A activity across the selected period, and (ii) provide information on the distributional characteristics of the financial ratios used for model development. Finally, to illustrate the automatization of the data I present two examples of the algorithmic methods used to generate the estimation/forecasting samples (see details in Section 4.3.4) and the matched control firm portfolio (see details in Section 4.5.3).

The chapter is structured as follows. Section 5.2 describes the collected M&A data and provides an analysis on the dynamic of takeover activity during the selected period for both the UK and the US. Section 5.3 describes the financial data information that was finally selected for the model's specification. The section describes the method for reducing the total number of variables included in the model, analyzes the selected data treatments and provides descriptive statistics on the resulting collected data. Section 5.4 presents the algorithmic techniques that were used to automatize two of the matching processes used during the study. The section also describes the assumptions that were considered during the matching process and analyzes the advantages and limitations of these choices. Finally, section 5.5 summarizes the chapter.

5.2 M&A data characteristics

5.2.1 Definition of takeover

A large number of definitions of the term *takeover* can be found in the literature. Three main points were found to be discussed around the definition. The first point relates to the status of the deal. Powell (1997) has only considered completed deals. As mentioned by several authors, the completion or the withdrawal of a deal is often related to factors other than the financial and non-financial characteristics of the target firm involved. In addition, by excluding deals that failed to be completed, the sample may fail to include firm characteristics that are seen as attractive by potential raiders. Secondly, different choices have been considered regarding the percentage of ownership defining a takeover bid. Although most authors have selected all deals involving a bid of at least 50% of the firm's ownership, authors such as Bartley and Boardman (1990) have included minority stake purchases as they often represent a sign of a forecoming takeover attempt. Finally, while some authors have limited their sample to domestic deals, others have included both cross-border and domestic deals. The work of Rege (1984) studies the different characteristics between foreign and domestic takeovers and their results show that there seems to be no characteristic able to differentiate these two types of mergers.

The former was used to extract publicly available information on deals announced during the selected period. Following Bartley and Boardman (1990), the definition of takeover adopted in this thesis covers data from all the different types of both announced and completed M&A deals (e.g. Leveraged Buy-outs, Minority Stake Purchases, Debt Restructuring, just to name a few) with the exception of rumours and buybacks. Rumours were excluded because they are more related with media speculation and market sentiment rather than with a formalized intention of corporate control. Buybacks were also excluded as they are defined as large stake purchases undertaken by an already existing owner and therefore represent an attempt of maintaining rather than gaining control of a firm's management. Additionally, based on Rege (1984)'s findings, both cross-border and domestic M&A deals were included in the sample. The next paragraph provides details on the source and the method of extraction of the M&A data in order for the latter to comply with the previously stated definition.

5.2.2 Source and filtering of the M&A data

Data for publicly announced M&A deals during the period 1995-2008 were extracted from Thomson One Banker database (TOBD). This database provides an extensive number of M&A deals listing all disclosed attempts of acquiring significant ownership control (i.e. a bid for more than 5% of the firm's market capitalization). The Advanced Research feature on TOBD provides multiple options to filter specific M&A data. However, these filters must be carefully chosen as they tend to shrink the data when selecting options having frequently unavailable data. For both the UK and the US, data was therefore downloaded in its most general form by selecting the following minimum filtering:

1. Targets firms belong to the specified economy.
2. The deal's announcement date falls between the 01/01/1995 and the 31/12/2008.
3. Target firms must be public.

For each deal, the following descriptive characteristics were selected:

1. Target Name.
2. Announcement date.
3. Target datastream code.
4. Transaction Value.
5. Deal's status.
6. Deal's Form.
7. Acquisition technique.

The data containing all deal characteristics was uploaded to an SQL database providing further control on the filtering applied to the data. As mentioned in the previous paragraph, rumoured deals and buybacks do not correspond to the definition of takeover considered in this thesis. Using the *deal's status* and the *deal's form* information, all deals classified as Buybacks, Rumors or Discarded Rumors were therefore excluded from the analysis.

5.2.3 Types of M&A deals considered

The previous paragraph focused on the deals that were excluded from the M&A data but no information was given on the type of deals that were effectively included in the sample. This paragraph therefore describes the different types of M&A deals included in the broad takeover definition here considered. The *acquisition technique* item provides a large list of deal's characteristics. However, the non-uniqueness of this classification as well as the frequent unavailability of the data are problematic for providing descriptive statistics as well as a consistent filtering process.[1] Although not overly informative, the item *deal form* overcomes the problem of data unavailability and was therefore used to generate the descriptive statistics. In this classification, the item "Merger" includes Leveraged Buyouts, Self-Tenders, Tender Offers, Mergers and I added Acquisition of Majority Interest; the item "Acquisition Minority Interest" includes Privately negotiated Minority Stakes Purchases as well as a certain number of Joint Ventures and Strategic Alliances; the item "Acquisition of Assets" includes Bankruptcy Acquisitions and Recapitalizations; the item "Acquisition (others)" includes Spin-offs, Divestitures and Debt Restructurings; finally, the item "Exchange Offer" includes a special form of transfer control consisting of the exchange of ownership from one firm to another. Panel A and Panel B in Table 5.1 show, at an aggregated level across the period of study, the proportion of different types of deals considered in the UK and in the US respectively. The data shows that the proportions of the different included deals are very similar in the UK and the US. For both economies, we can observe that "Mergers" is the main constituent among the considered deals. Acquisition of minority purchases (defined as stake purchases exceeding 5%) also represent

[1] As an example, the characteristics Leveraged Buyout, Going Private and Financial Acquiror are generally included in the same definition of acquisition technique.

a significant proportion of the considered deals. The latter is somewhat higher in the US with a number exceeding a third of the total deals. Although of insignificant proportion, a difference can be seen in the number of Exchange Offers which seems to be proportionately more common in the US than in the UK. Overall, deals involving Mergers and Acquisitions account for nearly two thirds of the considered deals in both the UK and in the US therefore providing a consistent basis to the employed takeover definition.

Table 5.1: *Data description of the types of M&A considered in the UK context during the period 1995-2008.*

Form of Deal[a]	Aggregate number	Percentage
Panel A: Aggregate distribution of considered M&A types in the UK		
Mergers	1643	63.3
Acquisition Minority Interest	781	30.1
Acquisition Remaining Interest	78	3.0
Acquisition of Assets	78	3.0
Acquisition (others)	13	0.5
Exchange Offer	1	0.04
TOTAL	2594	100.0
Panel B: Aggregate distribution of considered M&A types in the US		
Mergers	5471	55.3
Acquisition Minority Interest	3690	37.3
Acquisition Remaining Interest	320	3.2
Acquisition of Assets	301	3.0
Acquisition (others)	54	0.6
Exchange Offer	50	0.5
TOTAL	9886	100.0

[a] The form of deal corresponds to the M&A Deal's Specific Transaction Type classification provided by the Thomson One Banker database system. In this classification, the item "Merger" includes Leveraged Buyouts, Self-Tenders, Tender Offers, Mergers and I added Acquisition of Majority Interest; the item "Acquisition Minority Interest" includes Privately negotiated Minority Stakes Purchases as well as a certain number of Joint Ventures and Strategic Alliances; the item "Acquisition of Assets" includes Bankruptcy Acquisitions and Recapitalizations; the item "Acquisition (others)" includes Spin-offs, Divestitures and Debt Restructurings; finally, the item "Exchange Offer" includes a special form of transfer control consisting of the exchange of ownership from one firm to another.

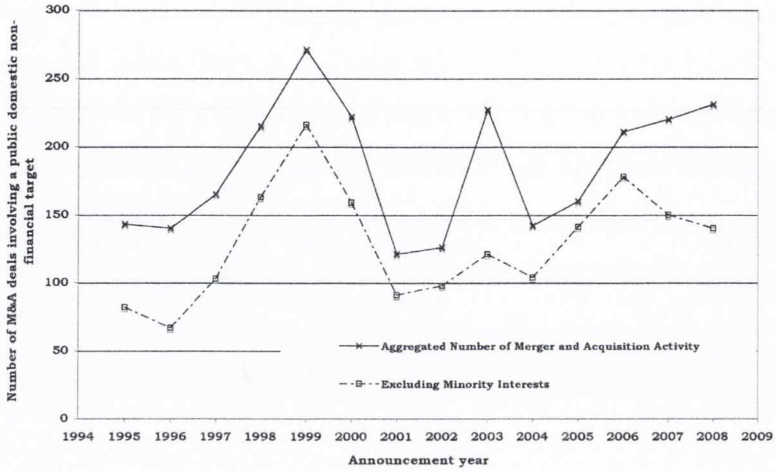
5.2.4 Levels of M&A across the selected period

The following paragraph examines the dynamical changes of the level of M&A activity characterizing the selected period. As shown by Singh (1971), the dynamic of M&As offers a possible measure of detecting different cycles or trends of M&A activity. Figure 5.1 and Figure 5.2 show the M&A activity during the period 1995-2008 as measured by the aggregated number of deals and the aggregated transaction value involving a public domestic non-financial target in the UK and the US respectively. As we can observe, there is a progressive increase in the number of M&As at the end of the dot-com bubble (i.e. period 1995-2000) followed by a significant reduction in both the number and the transaction values during the period 2001-2003. A similar pattern is shown in the following years where we can observe a significant increase in the M&A level during the recovery period 2004-2007 followed by a significant decrease during the beginning of the credit crisis in the year 2008. The M&A dynamic shows that the selected period offers a highly versatile M&A environment with significant changes in the levels of M&A activity and with possibly several merger motivations involved. These characteristics present both an advantage and a disadvantage. As discussed by Singh (1971) and Barnes (1999), when different acquisitions motives are present simultaneously, the selected targets result in a misspecified sample and a regression model unable to accurately identify takeover characteristics. From another viewpoint, the presence of different types of M&A environments ensures that the reported results are not likely to depend on either the business-cycle or a specific trend of M&A characterizing the selected period.

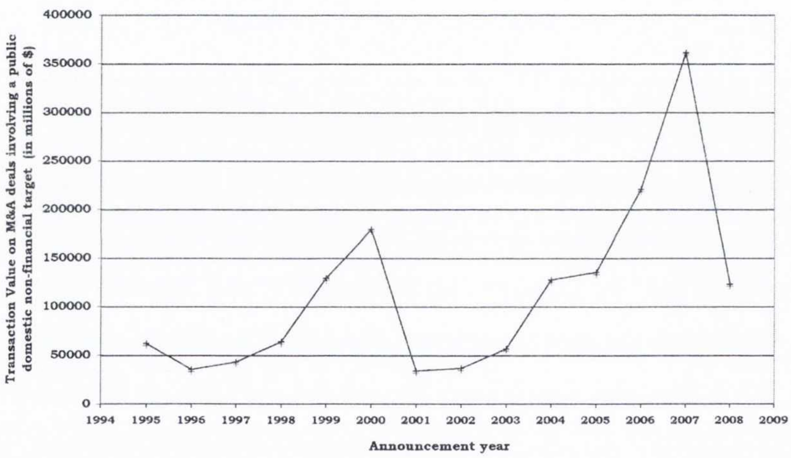
5.3 Data collection of corporate financial information

5.3.1 Source of financial data

For all public firms in the UK and the US, Worldscope-Datstream database was used to extract corporate financial accounting information for each year during the period 1997-2007. The constituent lists WSCOPEUK and WSUSX for $1 \leq X \leq 19$ were used to select the total number of public firms in the UK and the US respectively. Depending on the



(a)



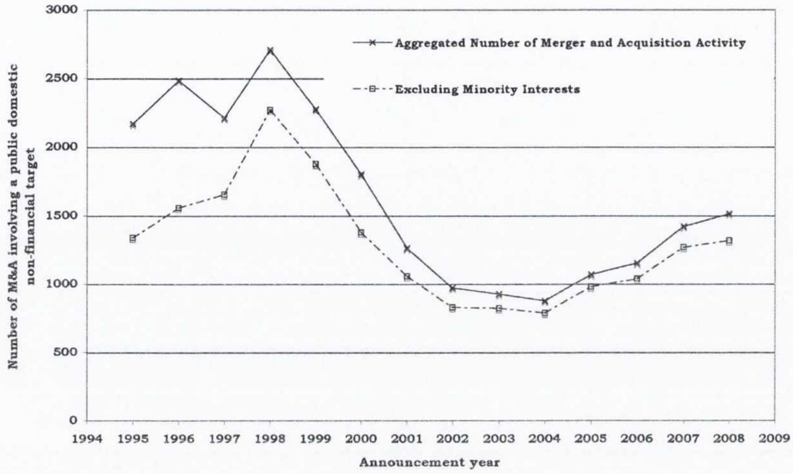
(b)

Figure 5.1: *Merger and acquisition dynamic characteristics as measured by the aggregated number of deals (subfigure 5.1a) and the aggregated transaction value (subfigure 5.1b) involving a public domestic non-financial target in the UK context during the period 1995-2008.*

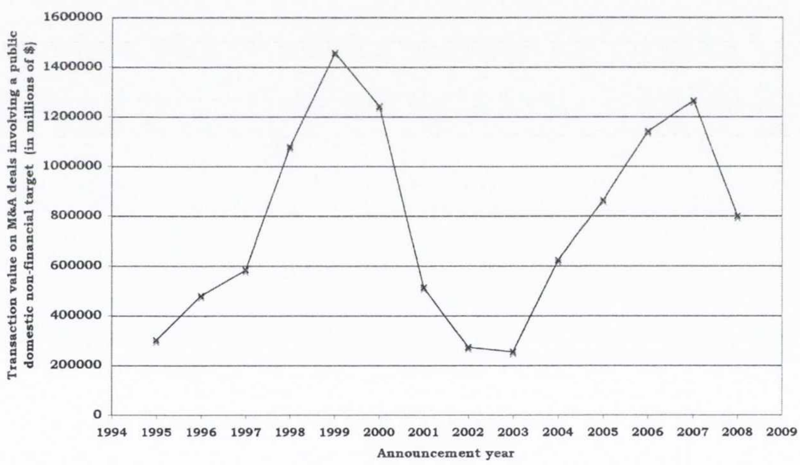
year selected for estimation, this amounted to a number of companies between 629 and 802 UK firms and between 1518 and 2128 US firms.

Building a realistic universe of firms for each year is a challenging task. Although Datastream records the date at which a company began to be publicly traded, it does not record the date at which the company was listed on a particular stock exchange.[2] As

[2]It should be noted that the Datastream code ENAME provides the name of the stock exchange in which firms are presently listed. The static nature of such classification does not allow the user to trace a firm's presence in a stock exchange during prior years.



(a)



(b)

Figure 5.2: *Merger and acquisition dynamic characteristics as measured by the aggregated number of deals (subfigure 5.2a) and the aggregated transaction value (subfigure 5.2b) involving a public domestic non-financial target in the US context during the period 1995-2008.*

discussed in Powell (2001) and Arnull-Almond (2007), many previous studies have cumulated company-level data across long periods of time while constraining the analysis to firms that were listed at the time of collection therefore generating survivorship bias. As a result, some authors have included firms traded over the counter (e.g. Wansley et al., 1983; Walter, 1994). Here, an effort was made to build a more realistic corporate landscape by considering, for each estimation year, all then active public firms. A firm was considered inactive if the estimation year followed the firm's inactive date (datacode IDATE) and if the firm's monthly price did not change during the year prior to the estimation year. The advantages of such a procedure are twofold. Firstly, by generating a more realistic universe of companies (listed and non-listed) survivorship bias is minimized. Secondly, the inclusion of all traded firms allows us to consider other investment opportunities in less traded and perhaps less efficient markets.

As in most of the studies dealing with corporate forecasting, financial companies have been excluded from our analysis for three main reasons: (i) their corporate variables have often different meaning (e.g. assets) (ii) some of the considered ratios are not available for these industries (iii) the distribution of their ratios is often different from the rest of the industries and are therefore likely to generate inconsistent estimators. Financial companies were eliminated using the Worldscope's General Industry Classification Number (code:WC06010) and by eliminating firms with code numbers greater than 3 corresponding to Bank/Savings and Loan, Insurance, and other financial companies. In addition, all companies for which the financial information was not reported were also excluded from our sample.

5.3.2 Selection method of the financial variables

Following Barnes (1999), the first selection of variables consisted in a large number of ratios previously employed in the M&A literature. Two types of literature were used to select these ratios. The first type corresponds to the literature related with takeover predictions models while the second concerns the literature describing the accounting methods employed to value a target firm in a Merger and Acquisition plan. The latter describes the variable used in practice to discriminate between a list of takeover candidates, and, therefore, they are likely to have an impact in the predictive power of our models. Gole and Morris (2007, Chapter 3, Appendix A), for example, provide several examples of the financial ratios that are frequently included in the financial analysis of targeted companies. In addition, Arzac (2008) gives an explicit way of estimating the targets value based on the firm's forecasted discounted Free Cash Flows. We added to the list of variables that were mentioned within this literature while missing in previous studies. As discussed in Chapter 2, the takeover prediction literature has defined nine main hypothesis for selecting the variables with potential explanatory power. The se-

Table 5.2: *Full list of variables initially considered as potential predictors of takeover likelihood*

Hypothesis	Proxy variables[a]	Expected sign
Inefficient Management		
Performance	CAPEX over TA, Operating Margin, Return on Assets, Return on Capital Employed, Return on Equity, EBIT over TA, EBIT over SE, Prior Market Performance	+/-
Free-cash flow hypothesis	FCF over Total Shares Outstanding, FCF over Total Net Worth	+/-
Activity hypothesis	SR over TA, Inventory Turnover	+/-
Undervaluation	Market-to-Book ratio, Price-to-Earnings ratio	-
Dividend Payout	CD over EBIT, CD over Net Income, CD over SE, CD over FFOP	+/-
Size	TA, Market Capitalization, SR, Total Shares Outstanding	-
Growth-resource mismatch		
Growth	One-year SG, Three-years SG, Five-years SG, EBIT growth	+/-
Liquidity	Current Assets over TA, Current ratio, Quick ratio, Working Capital over TA, Cash over Liabilities, Cash over Total Assets, Average Days Inventory held, Inventory Change	+/-
Leverage	Total Debt over TA, Total Debt over SE, Total Debt over Total Capital Employed, LTD over TA, LTD over SE, LTD over Total Capital Employed, Total Liabilities over SE	+/-
Inefficient Financial Structure	Current Assets over SR, Working Capital over SR, Fixed Assets over SR, Research and Development over SR	+/-
Industry Disturbance[b]	Two possibilities of dummy variables as constructed in Palepu (1986) and in Cudd and Duggal (2000)	+

[a] Provides the formula used to calculate the formulas. The abbreviations CAPEX, CD, EBIT, FCF, FFOP, LTD, SE, SG, SR and TA stand for Capital Expenditures, Common Dividends Paid, Earnings before Interest and Taxes, Free-Cash Flow, Funds from Operations, Long-Term Debt, Shareholder's Equity, Sales Growth, Total Sales/Revenues and Total Assets respectively.
[b] This variable was finally excluded as for all considered industries, except for the Transportation industry in the UK for the years 2002 and 2004, merger activity was recorded in the year prior to observation (see Table 5.4 in Section 5.3.4 below).

lected variables were considered as proxys for these hypotheses. As a result, forty-five variables were initially selected as potential predictors. These variables are shown in Table 5.2 below along with the expected relationship between the hypothesis and takeover likelihood. High correlation between variables is one factor that is well known to generate inconsistent estimators, and, as one of the objectives of this thesis is to analyse the dynamic of the coefficient's values over time, it is important to eliminate any potential source affecting the consistency of the estimators.

Trivial mutual correlations were first eliminated by examining similarly constructed vari-

Table 5.3: *Final selection of corporate financial variables*

Hypothesis - Variable	Calculation[a]	Symbol	Empirical support	Mnemonic code[b]
Inefficient Management Hypothesis				
Expenditures	CAPEX / Total Assets	CETA	Levine and Aaronovitch (1981)	WC08416
Market Returns	Year-End MP Adjusted for Special Dividends / Last Years Year-End MP - 1	TIRE	Brar et al. (2009)[c]	WC08801
Operating Profit Margin	Operating Income / SR	OPMA	Dietrich and Sorensen (1984)	WC08316
Return on Equity	Net Income after PD / Last years Common Equity	ROET	Arnull-Almond (2007)	WC08295
Dividends Payout	Common CD / Net Income after PD	DPEA	Dietrich and Sorensen (1984)	WC08256
Undervaluation	Year-End MP / Book Value per Share	PTBR	Palepu (1986)	WC09344
Activity Hypothesis				
Inventory Turnover	Costs of Goods Sold / Average of the Past Two Years Inventories	ITUR	Bartley and Boardman (1990)	WC08136
Asset Turnover	SR / Total Assets	TATU	Harris et al. (1982)	WC08401
Free Cash Flow	FFOP net of CAPEX and CD / Total amount of shares outstanding	FCFS	Powell (1997)	WC05507
P/E ratio	Year-End Market Price / Year-End EPS	PTER	Barnes (1990)	WC09104
Size	Natural Log (Total Assets)	LNTA	Powell (1997)	Ln(WC07230)
	SR	SREV	Meador et al. (1996)	WC07240
Growth-Resource Mismatch Hypothesis				
Growth	SR(Year-End) / SR(Prior Year End)-1	GSOY	Brar et al. (2009)	WC08631
Liquidity	Total Current Assets / Total Current Liabilities	CRAT	Barnes (1990)	WC08106
	Inventories (Days held)	IDHE	Arzac (2008)	WC08126
Leverage	Long Term Debt / Total CP	LDTC	Powell (2004)[e]	WC08216
Inefficient Financial Structure Hypothesis				
Interests Coverage	EPS Before Interest and Taxes / Interest Expenses	ICOV	Dietrich and Sorensen (1984)	WC08291
Fixed Assets Turnover	Net Sales / Fixed Assets	NSFA	Bartley and Boardman (1990)	WC08431
Working Capital Turnover	Net Sales / Working CP	NSWC	Belkaoui (1978)	WC08141

[a] Provides the formula used to calculate the formulas. The abbreviations CAPEX, CD, CP, EPS, FFOP, PD, MP and SR stand for Capital Expenditures, Common Dividends, Capital, Earnings per Share, Funds from Operations, Preferred Dividends, Market Price and Total Sales/Revenues respectively.
[b] Indicates the Worldscope-Datastream code used to extract the information from each corporate financial variable.
[c] The authors accounted for prior market returns (momentum) but divided the variable by the price volatility during the year before the announcement.
[d] The author used Total Debt over Total Capital Employed.

ables. Variables exhibiting a correlation factor greater than 0.8 were dropped. This filter first reduced the set of variables to twenty one. The mutual correlations between these twenty one variables are shown in Appendix A. As we can observe, remain below the 0.8 threshold for both the UK and the US. Second order multicollinearity, as measured by the Variance Inflation Factors (VIF hereafter), led to the elimination of two additional variables, EBIT over Shareholder's Equity and Total Debt over Common Equity which exhibited a VIF exceeding 5 in several of the considered years. Although the variable Price-to-Book ratio also shows a VIF frequently exceeding 5, this was no longer the case after the exclusion of the two previous variables. The yearly VIF tables are reported in Appendix A. Table 5.3, shown below, reports the final set of nineteen financial variables included for model specification.

5.3.3 Treatment of outliers

Given the potential influence of extreme values on the estimation generated by parametric methods, it is legitimate to consider their elimination before any normalization is applied to the data. As in this thesis, parametric methods and non-parametric methods are compared, the elimination of outliers is, for the least, questionable. Regression methods such as Multiple Discriminant Analysis make strong statistical assumptions of normality of the input data used to generate the estimations. The present study uses a Logistic regression which relaxes the previous statistical assumption of normality therefore being less sensible to the influence of extreme values compared to other similar parametric methods. As seen in the previous chapter, non-parametric and semi-parametric methods such as Artificial Neural Networks do not make any assumptions on the data underlying the estimation and therefore their result is not influenced by the presence of outliers. Consequently, in order to establish a fair comparison between the predictive power of the compared methods, outliers were not eliminated from the input data.

A problem arises however in the estimation section when the sign of the coefficients is studied over time. Given the potential misspecification of the estimators due to the presence of outliers, the compared results may be considered as misleading. Within the takeover prediction literature, rare are the attempts and no systematic method was found regarding the exclusion of extreme values. Walter (1994), for example, excluded extreme values for specific variables such as the Price-to-Earnings ratio, but no information is provided on the filtering method applied to other considered variables. I was able to find two works explicitly disclosing an outlier elimination procedure. First, Powell (1997) winsorizes all variables at three standard deviations from the mean. Secondly, Arnull-Almond (2007) eliminates all observations containing a variable whose value exceeds three standard deviations from the mean. The latter, as suggested by Powell (1997) has the disadvantage of resulting in the loss of a high number of observations. This thesis incorporates a more parsimonious procedure employed by Shumway (2001) where all extreme values are winsorized at a minimum (maximum) given by the value corresponding to the one (ninety-nine) percentile.

5.3.4 Industry-relative ratios

As mentioned by Platt and Platt (1990) and as suggested by most of the recently published literature (see for example Barnes, 1999 and Arnull-Almond, 2007, the use of industry-relative size ratios seems to improve the predictive ability of a model by partially eliminating the dynamic instabilities of the financial data as well as the distributions variation across industries. While many previous articles have normalized only by scaling the variable by the industry average, as mentioned by Arnull-Almond (2007), this method has two main drawbacks (i) it generates an opposite sign in the estimated coefficients if the variables average is negative (ii) since the average is not subtracted to the main value, the interpretation of the sign of the coefficients is difficult to interpret. Arnull-Almond (2007) corrected the previous scaling by substracting the industry mean and dividing by absolute value of the industry mean. However, such a normalisation is likely to generate variables with a large proportion of extreme values when the average of the variable is close to 0. Brar et al. (2009), based on the study of Cudd and Duggal (2000), use the following standard gaussian normalization in order to compensate the latter drawbacks:

$$X_{IY} = \frac{X - \overline{X_{IY}}}{\sigma_{IY}} \tag{5.1}$$

where $\overline{X_{IY}}$ is the average and σ_{IY} the standard deviation of the variable X in the industry I on the year Y. X_{IY} is the resulting normalized variable for a variable X belonging to the industry I in the year Y. This is the normalization method that was employed in our study.

In this study, the normalization was based on three main industries—namely Industrials, Telecommunication and Transportation. These three sectors correspond to the remaining industries represented by the Worldscope's General Industry Classification Number (code:WC06010) after excluding financial firms. Panel A and Panel B from Table 5.4 show the yearly distribution among the three industries for the period 1998-2007. The Industrial sector seems to be significantly more represented than the two other sectors. This is due to the large amount of manufacturing firms. An effort to reduce the overrepresentation of the Industrial sector was made by attempting to sub-divide it using the first two digits of the Standard Industrial Code (SIC). However some industries had a very small number of firms for some years and this method was therefore abandoned.

Table 5.4: *Distribution of the three selected industries in the sample population for the period 1998-2007*

Year	Group	Total	Industrials	Utilities	Transportation
Panel A: UK yearly industrial distribution					
1998	Non-Target	710	673	21	16
	Target	92	87	4	1
1999	Non-Target	686	649	16	21
	Target	99	93	3	3
2000	Non-Target	663	619	27	17
	Target	86	79	4	3
2001	Non-Target	657	616	25	16
	Target	41	34	6	1
2002	Non-Target	686	645	26	15
	Target	46	45	1	0
2003	Non-Target	582	547	22	13
	Target	92	89	2	1
2004	Non-Target	606	572	20	14
	Target	55	54	1	0
2005	Non-Target	567	536	19	12
	Target	62	55	6	1
2006	Non-Target	578	550	19	9
	Target	73	65	5	3
2007	Non-Target	618	583	22	13
	Target	78	71	5	2
Panel B: US yearly industrial distribution					
1998	Non-Target	1854	1676	127	51
	Target	216	188	21	7
1999	Non-Target	1818	1654	113	51
	Target	240	211	25	4
2000	Non-Target	1892	1725	117	50
	Target	241	223	11	7
2001	Non-Target	1803	1649	102	52
	Target	106	97	3	6
2002	Non-Target	1674	1532	95	47
	Target	73	70	2	1
2003	Non-Target	1450	1334	81	35
	Target	70	64	5	1
2004	Non-Target	1463	1345	79	39
	Target	89	84	3	2
2005	Non-Target	1489	1355	94	40
	Target	106	96	5	5
2006	Non-Target	1509	1382	84	43
	Target	122	112	6	4
2007	Non-Target	1460	1333	86	41
	Target	139	123	9	7

5.4 Computer-based algorithms processing input data

5.4.1 Algorithm matching M&A data and corporate financial data

Building the yearly estimation and forecasting samples requires the merging of the M&A data with the corporate financial data. As names assigned to firms are generally different in TOBD and WD, and since matching firms manually is not possible for all firms, an algorithm was build in order to match the names of firms subject to a takeover bid.

Details on the algorithm are provided in appendix D. The idea of the algorithm is to try to match the names assigned for each firm even if the name does not perfectly match. Therefore the algorithm attempts to match firms by name and when no name provides a match, the Datastream Codes are matched considering the possibility of a change on the firm's name. When a target company is matched a Worldscope ID code is assigned to the SQL table for that specific M&A deal. The algorithm works as follows:

1. If the target full firm's name in TOBD matches a full name in WD, then the company ID was linked.
2. If not, if the first word of the target firm's full name in TOBD matches a unique full name in WD, then the company ID was linked.
3. If the first word does not find a unique match and if the first two words of the target firm's full name in TOBD matches a unique full name in WD, then the company ID was linked.
4. If the first two words do not find a unique match and if the first two words of the target firm's full name in TOBD matches a unique full name in WD, then the company ID is linked.
5. The process stops when increasing one word in the matching process whether matches a unique firm or generates an empty match.
6. When the word matching fails, if available, Datastream Codes are matched.
7. If no matching was achieved, the companies remained unlinked and the target firm was not included in the estimation sample.

All firms matched by word were referenced by a matching number corresponding to the number of words needed to match the two firms.[3] Given the imperfect matching generated by the word matching procedure, the links were manually corrected when two different firms were incorrectly linked. As a final step, it was checked that companies linked by Datastream Code had changed their name. When the Datastream Code

[3]The maximum number of words needed to match a firm was found to be four, however this was not an arbitrary choice.

matched a subsidiary with its Parent Company, firms were unlinked as the financial variables of the Parent company were not deemed to accurately represent the financial profile of the subsidiary.

Yearly estimations samples were therefore built as follows. For each year, a table containing all the firm's corporate information corresponding to all variables included in the final set and belonging the non-financial sectors. Such a table thus contains all non-financial firms containing all available information in the year prior to acquisition. Secondly, the dependent variable was built by assigning the value '1' to all firms having been subject of a takeover bid announcement during the estimation year but also having a link between TOBD and WD. The rest of the firms were considered as non-targets and a value '0' was assigned to the dependent variable. As a result, the yearly estimation samples contain all non-financial firms having publicly available information in the year prior to the estimation year to which a value '1' is assigned if the firm was subject to a bid during the estimation year and '0' otherwise. As mentioned in the previous chapter, forecasting samples are similar to estimation samples except that targets used during the estimation are excluded.

5.4.2 Algorithm matching predicted firms with control firms

Assigning a control sample to the models' yearly predicted firms also requires a computer generated algorithm to ensure a systematic matching process. As described in the previous chapter, the method recommended in Barber and Lyon (1997) was adapted to extract control firms from a similar population sample from which prediction samples were generated. For each predicted firm i, the algorithm proceeds as follows:

1. All public companies having available size (measured by the predicted firm's market capitalization) and book-to-market ratio during the prediction year.
2. The sample was reduced by excluding financial firms as well as firms that were not traded the year prior to the prediction year.
3. From this sample, a size group was created containing all firms whose size falls between 70% and 130% of the predicted firm's market capitalization.

4. From this size group, the firm whose book-to-market ratio was the closest to the predicted firm was selected as a control firm for predicted firm *i*.
5. When the matching does not provide a unique firm, the control firm is randomly selected from the remaining group of firms.

The complete algorithm is shown in appendix D. One of the main constraints of this algorithm is that, given the power law distribution followed by the firm's size distribution, the reduced samples are larger for smaller firms than for larger firms. Therefore, the algorithm may find some problems when attempting to match a large sample of firms. In practice, this was shown to be the case when considering the lowest cut-off value 0.1 which generated on average samples exceeding 200 firms. As a result, the algorithm failed to build a matching control firm portfolio given that the sample of all firms in the 70% - 130% market capitalization was empty (i.e. all firms belonging to that size range had already been matched to other firms in the sample).

5.5 Summary

In this chapter, I described the different sources of data used to collect the information needed to follow the modeling framework described in the previous chapter. The first section recalled the definition of takeover that was considered in this study and presented the data collection process that was used to collect the M&A information associated with this definition. The corporate financial information section, presents the selection procedure of financial variables and describes the data collection process of these variables as well as the post-treatments that were applied. Finally, a last section provided two examples of the algorithms that were constructed in order to build the estimation and holdout samples as well as the one generating the sequential matching of control firm portfolios to each predicted sample.

The M&A data was collected from Thomson One Banker database (TOBD). Consistent with Bartley and Boardman (1990) a wide definition of takeover was adopted encompassing Tender Offers, Minority and Majority Stake Purchases, and Debt re-structurings excluding rumored deals. For each year, a realistic universe of firms was built using

Datastream's Worldscope Database (WS). All active and traded public firms having publicly available financial information in the year prior to the estimation year were included in the sample. Such choice is likely to minimize survivorship bias and to provide a more realistic universe of firms than the one represented by a single major stock exchange. The firm's financial information was obtained using the Datastream database. Industry-relative ratios were used for each year within the selected period as they are likely to generate more stable distributions over time (Platt and Platt, 1990).

Following Barnes (1999), the variables used to estimate the models were first selected from both the vast M&A literature and the takeover prediction literature. A first list of forty-five variables was obtained. In order to preserve the maximum amount of information while minimizing the impact of multiple correlations in the estimated coefficients, multicollinearity was eliminated by excluding the variables that had correlation factors greater than 0.8 and Variance Inflation Factors greater than 5. As a result, a final set of nineteen variables was obtained.

Two fundamental algorithms were presented in order to illustrate the automatized construction of different samples used in this study. The first one executed a multiple matching procedure aiming to generate a link between the firms listed in TOBD and in WS. This matching process determines a unique identifier linking the two databases therefore allowing to extract the corporate financial information (extracted from WS) of each target listed in TOBD. The second presented algorithm described the construction of the control firm portfolio based on a given predicted sample. The process implements the control matching procedure described in Barber and Lyon (1997).

Chapter 6

Estimation and predictive performance results

6.1 Introduction and overview

Following the analysis of the relevant literature and the description of the employed methodology, this chapter presents the estimation results of the takeover prediction models as well the assessment of their predictive ability. As presented in the previous chapter, the estimation of the models is based on one-year rolling window estimations generating one estimation for each year during the period 1998-2007. For each estimation, out-of-sample forecasts were calculated thereby generating ten forecasts over the period 1999-2008.

Although most studies base their interpretation in one parametric estimation to determine takeover characteristics, following the efforts of Powell (1997) and Harris et al. (1982), this chapter aims to analyze how these characteristics change over a longer time period. As mentioned by both authors, this is motivated by the contention that pooling data across long periods of time generates misspecified samples of target firms. In addition, by analyzing the persistency of the model's parameters over an extended period, the objective is to capture the variables offering a frequently significant classificatory power but also showing sign consistency therefore making them a strong predictor as well. In addition, a cross-country analysis of the finally selected variables will be used to examine the existence of global takeover characteristics. From a forecasting perspective, the ex-ante predictive power of the model tests the ability of capturing potential acquisition targets in the future. Perhaps surprisingly, while repeatedly suggesting the instability of the model's predictive ability both over time and across economies, the literature does not provide any attempt of measuring the predictive instability on any of these two levels. As most studies are based on point forecast estimates, a dynamic analysis of the model's robustness is crucial to understand the extent to which reported results are an accurate representation of the model's true predictive power. This chapter presents a unique empirical analysis of the predictive variability of takeover prediction models both over time and across two economies, the UK and the US.

The remainder of the chapter is organized as follows. Section 6.2 presents the estimations results encompassing (i) the univariate analysis of the selected financial variables, (ii) the dynamical analysis of the logistic regression's coefficients, and (iii) the empirical results from the neural net's optimization. Section 6.3 presents, the analysis of the models' predictability in the UK and the US over the period 1999-2008. The results are presented separately for the Logistic Regression and Artificial Neural Networks followed by a comparative analysis on the techniques' predictive performance. Finally, Section 6.4 summarizes and concludes the chapter.

6.2 Estimation results

6.2.1 Univariate analysis of the differences between targets and non-targets

Although an independent analysis of the employed independent variables is generally not relevant to determine the significant explanatory power of the variables, particularly for this present study, it has the advantage of informing about distributional changes as well as persistent differences over the selected period. This section therefore presents the univariate statistical differences between target and non-target firms during the period 1998-2007. For each variable, the yearly univariate distributional characteristics are shown in Appendix A. The relationship between the variables and takeover likelihood will be further analyzed using multivariate models in the following sections.

As we can observe, in the UK, most variables show a significant difference between targets and non-targets in at least one of the considered years. In the US, there are also several variables showing significant differences between targets and non-targets. These variables are CETA (Capital Expenditures over Total Assets), FCFS (Free-Cash Flow per Share), and TATU (Total asset Turnover) in the UK context and FCFS (Free-Cash Flow per Share), GSOY (One Year Sales Growth), ITUR (Inventory Turnover), and OPMA (Operating Margin) in the US context. A priori, this result suggests that variables are likely to have a similar discriminatory power in the UK and in the US. The results in the next section will show that this is not the case, and the UK-based model will show a much higher and robust explanatory power in a multivariate framework.

Furthermore, the yearly maximum and minimum values shows the existence of extreme distributional values that could affect the estimation of parametric models. This point justifies the outlier treatment undertaken in later section 6.2.2.4 where the impact of these extreme values is analyzed.

The following paragraphs describe the discriminatory power of the variables under a multivariate framework.

6.2.2 Logistic regression's estimation results

Among the two selected specification methods, the logistic regression is the only one offering the possibility of an analysis of the model's estimated parameters. As mentioned in the previous chapter, this advantage is coupled to a lack of flexibility of the model given the pre-specified functional form of the model.

Table B.1 and Table B.2, reported in Appendix B, show the results of the logistic regressions estimated in each year of the period 1998-2007 using complete data in the UK and the US respectively. In order to analyze the time dependence of these estimated coefficients, three different methods have been here considered. First, following Powell (1997), the study focuses on the variables' significance and examines their ability to repeatedly providing significant classificatory power. Then, as in Harris et al. (1982), the sign stability of the estimates is studied with the objective of capturing variables providing a consistent effect over time. Finally, unique to the takeover prediction literature, I provide an analysis accounting for both views thus capturing robust variables in relation to both sign and significance.

6.2.2.1 Stability of the coefficient's significance

As in Powell (1997), this section analyzes the variables' persistency classificatory power. Table 6.1 shows the variables frequently showing a significant discriminatory power over the period 1998-2007.

In the UK context, size (LNTA) seems to be a good predictor of takeover activity as it shows the highest significance persistency and a robust positive sign stability. Surprisingly, the sign contradicts several of the results found in the literature and therefore such finding deserves further discussion. Different sources were found to provide potential explanations. First, it is possible that some spurious correlation between the selected variables or data anomaly (e.g. outliers) may be driving this result. As I will later show in section 6.2.2.4, using a one and ninety-nine percentile winsorization, the elimination of extreme values generates insignificant changes and do not alter the previous conclusions. Another potential factor is the larger sample of firms contained in the Worldscope-Datastream database. As mentioned in Chapter 4, the latter contains a larger number of public firms as no listing in a major stock exchange is imposed. This suggests that a larger number of smaller firms (i.e. not satisfying the conditions for being listed in a major stock exchange) are included in our samples. As a result, although targets may be smaller firms relative to the average listed firm, this might not be the case when considering a more complete universe of firms. Finally, it is possible that our definition of takeover, including other strategies of corporate control such as leveraged buy-outs and corporate re-structurings, may generate a sample containing larger companies than when using the more strict definition. Although the sign is not consistent with the general literature, it seems to be supported by some of the recently reported results. In a similar analysis within the UK context, Ouzounis et al. (2008) find a positive sign in the size variable therefore providing strong support for our result. In addition, Arnull-Almond (2007), in the Australian context, found a significant positive sign in the size variable. Cremers et al. (2009) find an insignificant positive sign in the size variable even when considering only completed during the period 1991-2004, however, a significant negative sign is found when considering both announced and completed deals. Overall, although the sign is not consistent with the general literature, the latter result may suggest that larger mergers might well be a current characteristic of these economies. Momentum (TIRE) appears to have a negative effect on takeover likelihood. The result contradicts the recent result of Brar et al. (2009) who find that momentum has a significant positive effect on takeover probability and this is probably due to the fact that momentum is measured two months before the acquisition in order to capture the abnormal stock movements preceding the announcement. The result is however consistent with the M&A theory for two reasons. First, the bad stock performance of a target in the year preceding an acquisition is coherent with the inefficient management hypothesis. Indeed, following a repeated bad management performance, stockholders are likely to penalize the firm by selling their shares. As a second argument, following a bad stock performance, a firm is more exposed to be acquired given the bargain resulting in a possible stock offer. This result is in partial support of the undervaluation theory and supports the recent findings of Cosh and Guest (2001) in relation to the bad stock performance of hostile UK takeovers the year prior to acquisition. The positive sign on Leverage (LDTC) contradicts Lewellen (1971)'s interpretation and is in agreement with recent findings by Barnes (1999), Powell (2004) and Cremers et al. (2009). Price-to-book ratio seems to show a strong discriminatory power. However, its sign's inconsistency cast doubt on its ability to predict takeover activity. Finally, Interest coverage (ICOV) seems to be a moderately strong predictor showing a relatively stable negative sign and a frequent ability to discriminate target firms which is in agreement with Dietrich and Sorensen (1984). This provides further support to the relatively little evidence on the classificatory power of this variable.

In the US, the number of variables showing frequent significance is significantly larger. As we can see, several variables show no sign consistency over the period. The positive sign on Liquidity (CRAT) is consistent with the Growth-Resource Mismatch hypothesis. The negative sign in the dividend payout ratio (DPEA) is in agreement with the results of Dietrich and Sorensen (1984) and Arnull-Almond (2007). As mentioned by the latter, it is surprising that given the consistent support of this variable, a very small number of authors have included it in their models. As in the UK, leverage (LDTC) has a positive sign therefore providing greater support for the variable's consistency. Operating Margin (OPMA) has a positive and stable sign and is in agreement with Barnes (1999). The negative relationship between Return on Equity (ROET) and takeover likelihood is consistent with most works accounting for similar measures of performance such as Cudd and Duggal (2000), Brar et al. (2009), and Cremers et al. (2009). The positive sign in Total asset turnover (TATU) is relatively puzzling as it is in partial contradiction with the bad performing characteristics suggested by previous ratios. However, such a result was found in the literature by a number of authors such as Stevens (1973) and Weir and Laing (2003) who find a positive and significant relationship and Barnes (1999) who finds a positive but insignificant effect. Finally, I find a negative and relatively persistent effect between Sales and Revenues (SREV) and takeover likelihood. The sign is in contrast with the findings of Tsagkanos et al. (2006) but is in agreement with the sign found in Meador et al. (1996).

Common to both economies, no variable shows a significant discriminatory power during the entire period. The fact that several of the variables do not present a consistent sign over time makes it difficult to characterize the profile of takeovers during the selected period. Although significance is an important aspect of the model's ability to accurately select target firms, the sign persistence is also a crucial aspect as it determines the ability of a variable to generate consistent predictions. This aspect is analyzed in the following section.

Table 6.1: *Variables showing frequently significant discriminatory power[a] in the UK and the US during the period 1998-2007*

Variable	98	99	00	01	02	03	04	05	06	07
Panel A: UK - Logistic Regression Model										
GSOY	-0.903***	-0.895*	-0.960**							
ICOV	0.153**	-0.466*			-0.411***	-1.626**				
PTBR		0.274**		-0.760**	0.401***	-0.324**				
TIRE	-0.702*		-0.465***							-0.36***
LNTA		0.375***	0.430***		0.575**		0.787*	1.047*	0.355***	0.623*
Panel B: US - Logistic Regression Model										
CETA		-2.182*					-1.628**		3.350*	
CRAT							1.440**	6.508***	0.618**	
DPEA	-0.179**		-0.169**	-0.287*						
FCFS		-1.168***			44.09*		-12.46*			
GSOY				-0.531***			2.695*	-16.88*		
LDTC						9.049**	16.80*	2.440***		
OPMA	0.922***				0.3784*	21.528**	-12.38*			
PTER	0.159***	-0.452***								0.368***
ROET	-1.557***				-12.53*			-8.292**		
TATU							2.313**	1.394**	2.140**	
TIRE	-0.231***			-1.907*	1.878*		0.463***	0.151**		
SREV		-0.492*							-0.348***	-0.328***

[a] A variable was considered to exhibit frequently significant discriminatory power if it was found significant in at least three of the ten considered years.The discriminatory power's significance (given by the regression) is based on a t-test of the null-hypothesis that the estimated coefficient is not different from zero. The degrees of freedom of the test depend on the number of observations available in each estimation year. $*$, $**$, $***$ indicate significance using a two-tail t-test at the 1%, 5% and 10% respectively.

6.2.2.2 Sign stability

Unlike Harris et al. (1982)'s comparative study, Powell (1997) fails to notice that, for the majority of the firm-specific variables (except for leverage and tangible assets), signs remained unchanged suggesting that the estimated model may have achieved above average predictive power had it been tested in the consecutive period. Given its importance for both the model's consistency and its underlying predictive power, our focus will be now turned to the variables featuring sign stability over time.

Panel A in Table 6.2 lists the yearly values of the estimators having a moderate stability over time in the UK. As we can see, these variables (the average sign is shown between brackets) are: GSOY (-) except for the year 2007, LDTC (+) except for the year 2005, TATU (-) except for the year 2007, TIRE (-), LNTA (+) except for the year 1998, and SREV (-) except for the year 1998. In the UK, target firms seem to have lower growth, higher asset turnover, lower total investment return, bigger size and lower total amount of sales and revenues when compared to their respective industrial average. These results support the inefficient management, activity, growth-mismatch, and, as discussed in the previous section, they support recent results related to the size hypothesis. The inefficient management hypothesis is strongly supported given that TIRE is the only variable that does not suffer of any sign change over the entire period. Our finding that targets have lower growth supports the results of Palepu (1986) and Barnes (1999) who find a significant negative impact of growth on takeover likelihood. The results also show that leverage is positively related with the probability of a firm being taken-over in agreement with the works of Stevens (1973) and Cremers et al. (2009), just to cite a few. Furthermore, the positive sign on asset turnover is consistent with the findings of Rege (1984) and Barnes (1999) but contradicts the findings of Sorensen (2000) and Arnull-Almond (2007). The size hypothesis, although not supported in a consistent manner, is supported by stability of both the positive sign of LNTA and the negative sign of SREV.

In the US context, Panel B in Table 6.2 lists the different yearly value of the estimators having a moderate stability over time. These variables (the average sign is shown between brackets) are: ICOV (-) except for the year 2000, DPEA (-) except for the year 2006, NSFA (-) except for the year 2005, LDTC (+) except for the years 1999 and 2007, TATU (+) except for the years 2000 and 2001. In this case, target firms appear to be characterized by lower interest coverage, lower dividends over earnings, lower net sales over fixed assets, higher long term debt over total invested capital and higher total asset turnover than their industrial average. These results are supported by several of the previous findings among the takeover prediction literature. First, we find a negative relationship between the amount of dividends paid relative to earnings and the likelihood of takeover. Our finding is in agreement with the results of Dietrich and Sorensen (1984) and Arnull-Almond (2007). Secondly, the persistently negative coefficient of the variable NSFA supports the results of Ambrose and Megginson (1992) providing further evidence for the argument that targets are firms characterized by higher net fixed total assets compared to their industrial average. Finally, the negative relationship between the interest coverage and the firms acquisition probability is consistent with Bartley and Boardman (1990)'s findings as well as with the previous result showing that US target firms have higher levels of leverage and therefore a lower capacity for covering their liabilities.

By comparing the two panels in Table 6.2, we can observe that two variables, LDTC (Long Term Debt over Total Capital) and TATU (Total asset Turnover), show a persistent sign stability in both the UK and the US. Not only do I find that the latter present a stable relationship towards acquisition likelihood but, most importantly, the reported sign is the same in both economies therefore suggesting the variables' strong predictive power. The result also suggests that this variables should be included when building general takeover prediction models. The analysis seems to provide a clear takeover profile in the US context where target firms seem to be good performers with high levels of leverage that seem to result in excessive pressure from shareholders. In the UK context, however, the analysis does not seem to provide a consistent takeover profile as, for example, the positive sign of Total Asset Turnover seems to be in contradiction with the positive sign obtained for log(Assets) combined with the negative sign of Sales.

Table 6.2: *Variables showing sign stability[a] in the UK and the US for the estimation period 1998-2007*

Variable	Average (t-test)[b]	98	99	00	01	02	03	04	05	06	07
Panel A: UK - Logistic Regression Model											
CRAT	-0.807 (-1.457)	-2.00	-0.34	-0.87	-0.16	-4.27	-0.46	1.68	-2.18	1.55	-1.83
GSOY	-0.727** (-3.08)	-0.90	-0.90	-0.96	-0.89	-0.62	-0.41	-0.16	-0.26	-2.49	0.32
LDTC	0.400** (2.67)	0.44	0.28	0.49	0.75	0.36	0.45	0.31	-0.44	0.14	1.41
TATU	0.154** (2.60)	0.01	0.04	0.05	0.05	0.24	0.35	0.55	0.19	0.01	-0.11
TIRE	-0.284** (-3.095)	-0.70	-0.10	-0.47	-0.82	-0.04	-0.02	-0.17	0.10	-0.08	-0.36
LNTA	0.439* (4.10)	-0.13	0.38	0.43	0.13	0.58	0.20	0.79	1.05	0.36	0.62
SREV	-1.11* (-4.287)	0.02	-0.77	-0.39	-2.82	-1.14	-0.99	-1.51	-1.61	-0.35	-1.54
Panel B: US - Logistic Regression Model											
DPEA	-0.131* (-4.82)	-0.18	-0.11	-0.17	-0.29	-0.10	-0.08	-0.13	-0.18	0.05	-0.12
ICOV	-0.663** (-2.98)	-0.86	-0.12	0.07	-0.25	-2.19	-1.06	-0.39	-0.48	-1.31	-0.03
NSFA	-0.29* (-3.51)	-0.41	-0.03	-0.05	-0.35	-0.52	-0.10	-0.49	0.003	-0.16	-0.78
LDTC	3.22*** (1.856)	0.44	0.09	0.49	1.36	1.12	9.05	16.80	2.44	0.69	0.65
TATU	0.843** (2.606)	0.19	0.22	-0.26	-0.53	1.10	0.40	2.31	1.39	2.14	-0.11

[a] A variable was considered to show moderate sign stability if the same sign was found in at least 8 of the ten considered years.
[b] The t-test examines the null-hypothesis that the average of the coefficient is not different from zero. $*$, $**$, $* * *$ indicate significance using a two-tail t-test with 9 degrees of freedom at the 1%, 5% and 10% respectively.

6.2.2.3 Comparative study between the two approaches and cross-country comparison

As a combination of Harris et al. (1982) and Powell (1997)'s analytical frameworks, this paragraph offers an innovative method aiming to identify variables achieving both frequent discriminatory power and significant sign stability over the selected period. The results are shown in Table 6.3. For each economy, three variables appear to define robust features characterizing takeover targets during the period 1998-2007.

In the UK, firms seem to be bigger in size and having both lower productivity and lower market performance compared to their industrial average. The resulting picture seems to provide strong support to the inefficient management hypothesis. UK targets seem to be companies that have become larger than average altogether with disappointing sales growth which seems to be followed by shareholder's discontent and a subsequent takeover.

In the US, target firms appear to incur higher levels of leverage and be able to efficiently transform the capital in profitable investments. The low dividend payout combined with the high profitability and above average levels of leverage suggests that these are young firms at the earlier stages of growth using abnormally high levels of leverage. We can therefore see that, although some variables overlap in the previous analyzes, none of the variables seems to apply for both economies when considering both aspects. The features described are even in stalking contrast with the characteristics shown by UK targets. US targets can be seen as productive firms struggling to find the capital needed to evolve into subsequent stages of growth.

Finally, some variables appear as irrelevant since they display neither significance nor sign stability during the considered period. Their persistently low explanatory power combined with an erratic sign over time suggests their inability to discriminate between target and non-target companies. These variables are: CETA (Capital Expenditures over Total Assets) for the UK and ITUR (Inventory Turnover) for the US.

Table 6.3: *Variables showing both frequently significant discriminatory power[a] and sign stability[b] in the UK and the US for the estimation period 1998-2007*

Variable	Average (t-test)[c]	98	99	00	01	02	03	04	05	06	07
Panel A: UK - Logistic Regression Model											
GSOY	-0.727** (-3.08)	-0.90***	-0.895*	-0.96**	-0.89	-0.62	-0.41	-0.16	-0.26	-2.49	0.32
TIRE	-0.284** (-3.095)	-0.702*	-0.10	-0.47***	-0.82	-0.04	-0.02	-0.17	0.10	-0.08	-0.36***
LNTA	0.439* (4.10)	-0.13	0.38***	0.43***	0.13	0.575**	0.20	0.787*	1.05*	0.36***	0.62*
Panel B: US - Logistic Regression Model											
DPEA	-0.131* (-4.82)	-0.18**	-0.11	-0.17**	-0.29*	-0.10	-0.08	-0.13	-0.18	0.05	-0.12
LDTC	3.22*** (1.856)	0.44	0.09	0.49	1.36	1.12	9.049**	16.80*	2.44***	0.69	0.65
TATU	0.843** (2.606)	0.19	0.22	-0.26	-0.53	1.10	0.40	2.31**	1.39**	2.14**	-0.11

[a] A variable was considered to exhibit frequently significant discriminatory power if it was found significant in at least three of the ten considered years.The discriminatory power's significance (given by the regression) is based on a t-test of the null-hypothesis that the estimated coefficient is not different from zero. The degrees of freedom of the test depend on the number of observations available in each estimation year. $*, **, ***$ indicate significance using a two-tail t-test at the 1%, 5% and 10% respectively.

[b] A variable was considered to show moderate sign stability if the same sign was found in at least 8 of the ten considered years.

[c] The t-test examines the null-hypothesis that the average of the coefficient is not different from zero. $*, **, ***$ indicate significance using a two-tail t-test with 9 degrees of freedom at the 1%, 5% and 10% respectively.

As a general conclusion of this section, and as an answer to our first research question, the results suggest the existence of takeover characteristics achieving frequently significant discriminatory power and showing robust sign stability over long periods of time. In addition, contrary to the two previous analysis, the procedure provides a consistent set of characteristics defining the profile of target firms during the period 1998-2007 in both the UK and the US context. It should be underlined, however, that these variables are not stable across economies therefore suggesting that variables should be selectively chosen depending on the context takeover activity is being considered. The result provides support to the contention in the literature that takeover characteristics are inconsistent across-economies.

6.2.2.4 Influence of outliers

As mentioned in the previous chapter, in order to ensure that the present results are not driven by outliers, the estimations of the models was calculated using truncated data. Table B.3 and Table B.4, reported in Appendix B, show the details on the regressions estimated during the period 1998-2007 using the Shumway (2001)'s winsorization procedure in the UK and the US respectively.

The exclusion of extreme values seems to have a small effect on the results using untruncated data. Table 6.4 shows, as in the previous section, the estimated coefficients (based on winsorized data) showing both frequent significant discriminatory power and moderate sign stability over time. The general results are consistent with the previous analysis. However, for both the UK and the US, a new variable entered the selection.

In the UK, Sales and Revenues seems to have a consistent negative and significant effect on takeover likelihood. The result is consistent with the low performing profile of UK target firms found in the previous analysis shown in Panel A of Table 6.3.

In the US, prior market performance (TIRE) shows a persistently negative sign over the considered period. However, the variable is significantly positive in 2004, therefore resulting in an insignificant average over the ten-year period. The result suggests that the variable may not offer a consistent explanation of takeover activity and is consistent with the conflicting results in the literature examining thelong-run pre-announcement performance of target firms in the US. As recently shown by Agrawal and Jaffe (2003), US targets do not show any particular stock return performance in the pre-announcement period.

Table 6.4: *Winsorized variables showing both frequently significant discriminatory power[a] and sign stability[b] in the UK and the US for the estimation period 1998-2007*

Variable	Average (t-test)[c]	98	99	00	01	02	03	04	05	06	07
Panel A: UK - Logistic Regression Model using winsorized data											
GSOY	-0.287** (-3.09)	-0.16	-0.69*	-0.44***	-0.51**	-0.14	-0.09	-0.70	0.10	-0.35	0.10
TIRE	-0.291** (-3.150)	-0.68*	-0.11	-0.42***	-0.89*	-0.23	-0.02	-0.18	-0.01	-0.09	-0.30**
LNTA	0.566* (5.045)	-0.18	0.32	0.70*	0.60	0.82**	0.32	0.82**	1.12*	0.53**	0.61*
SREV	-0.604* (-2.376)	0.071	-0.39***	-0.496**	-2.84	-0.45***	-0.386	-0.51***	-0.409**	-0.31***	-0.32***
Panel B: US - Logistic Regression Model using winsorized data											
DPEA	-0.135* (-5.365)	-0.173**	-0.11***	-0.18*	-0.28	-0.11	-0.10	-0.10	-0.19	0.03	-0.14
LDTC	0.282** (2.595)	0.18	-0.001	0.07	0.26	0.10	0.50***	1.05*	0.16	0.61**	-0.10
TATU	0.08*** (2.226)	-0.10	0.08	-0.11	0.08	0.13	0.14	0.15***	0.23***	0.19**	0.02
TIRE	-0.067 (-0.437)	-0.20***	-0.104	-0.404	-0.297**	0.044	-0.175	1.236**	-0.115	-0.471**	-0.179

[a] A variable was considered to exhibit frequently significant discriminatory power if it was found significant in at least three of the ten considered years.The discriminatory power's significance (given by the regression) is based on a t-test of the null-hypothesis that the estimated coefficient is not different from zero. The degrees of freedom of the test depend on the number of observations employed on each estimation year. $*, **, ***$ indicate significance using a two-tail t-test at the 1%, 5% and 10% respectively.

[b] A variable was considered to show moderate sign stability if the same sign was found in at least 8 of the ten considered years.

[c] The t-test examines the null-hypothesis that the average of the coefficient is not different from zero. $*, **, ***$ indicate significance using a two-tail t-test with 9 degrees of freedom at the 1%, 5% and 10% respectively.

6.2.3 Neural net optimization results

Following the optimization procedure described in Chapter 4 Section 4.2.4.2, I here provide the results on the different architectures that were considered during the neural net's optimization process.

As previously mentioned, we have tested eight different numbers of nodes equally spaced between five and forty. For each year, each estimation sample was divided in a training sample and a validation sample accounting for 80% and 20% of the total sample respectively. The estimation of the model was executed using the training sample and the validation sample was used to assess the model's out-of sample performance. The latter was calculated for five different numbers of epochs such as 5000, 10000, 20000, 50000, and 100000. The same randomizing seed was used for every number of nodes, however its value was changed if the model was trapped in a local minima during the first cycles. A cut-off value of 0.5 was chosen to calculate the predictive performance of the model in order to minimize the selection bias towards lower or higher cut-offs[1]. Most of the previous works have chosen to measure predictive performance on the validation sample by using the total number of correctly classified firms divided by the total number of firms (i.e. overall predictive accuracy) (see e.g. Maher and Sen, 1997; Zhang et al., 1999). Here, predictive performance is defined by the C-ratio, defined in chapter 4 equation 4.13, and the optimal number of nodes was therefore chosen as the one maximizing the proportion of targets in the validation sample. The reason behind this choice is that, because of the small proportion of targets in the population, the highest overall performance is frequently achieved by a model unable to predict any targets and such measure is not therefore desirable when the objective is to maximize the proportion of targets in the predicted portfolio.

After selecting the optimal number of nodes, optimization of the number of cycles was executed. Table 6.5 summarizes the characteristics of the Neural Network optimization process in both the UK and the US and for each of the estimation years considered during the period 1998-2007.

Table 6.5: *Details on the Neural Net's optimization procedure for the UK and the US during the estimation period 1998-2007*

Estimation year	UK validation test			US validation test		
	Opt. HN[a]	*Opt. epochs*[b]	*Target density*[c]	*Opt. HN*[a]	*Opt. epochs*[b]	*Target density*[c]
1998	25	5000	0.25	25	7000	0.273
1999	30	12000	0.667	15	2000	0.5
2000	35	9000	0.429	10	4000	1
2001	5	4000	0.095	10	19000	0.114
2002	10	17000	0.4	10	2000	0.25
2003	10	10000	0.375	5	20000	0.111
2004	5	8000	1	20	9000	0.4
2005	10	10000	0.125	5	45000	0.167
2006	40	3000	0.333	5	3000	0.333
2007	5	5000	0.5	5	35000	0.5

[a] The column *Opt. HN* shows the optimal number of hidden nodes selected for the given estimation year. .
[b] The column *Opt. epochs* shows the optimal number of cycles maximizing the proportion of correctly predicted targets in the validation sample given the selected number of hidden nodes.
[c] The column *Target density* reports the proportion of correctly predicted target proportion using the validation sample.

After selecting the optimal number of nodes, the optimal number of epochs was selected as the one achieving the highest C-ratio in the validation sample. The latter was sampled every 1000 epochs for a given number of epochs usually between 2000 and 20000.

[1]For some years, a very low number of predicted targets arose from a 0.5 cut-off value as most of the models failed to predict any targets. As a result, a 0.1 cut-off value was used for the estimation years 2002, 2003, 2004 for the UK and 2002, 2003 for the US.

As a general feature of ANN, predictive performance increases during the first series of cycles and then starts decreasing showing signs of overfitting. However, for some of the estimation years, the patterns were found to be erratic and some decisions had to be taken in these unusual cases. First, if the same validation performance was found for two different number of epochs, then the performance was calculated for a different cut-off value (0.1 or 0.5 depending on the cut-off value chosen in the estimation year). Secondly, for one estimation year in the US context, the validation performance did not decrease when the number of epochs were increased. In that case, the process was stopped at the lowest number of cycles after which the same performance in the validation sample was observed.

6.3 Dynamic analysis of the predictive power of takeover forecasting models

6.3.1 Logistic regression model

This section presents the prediction results based on the logistic regression as the model's specification. Table 6.6 and Table 6.7 show, for all considered cut-off values, the yearly proportions of firms predicted to be targets relative to the number of correctly predicted targets and the associated PRC in the UK and the US respectively for the period 1999-2008.

In the UK, Table 6.6 shows that the cut-off choice plays an important role in relation to the model's predictability. High cut-off values generate unstable predictions where relatively infrequent high performances are interspersed by frequent poor performances failing to include any target within the predicted sample. The result is consistent with the results reported by Barnes (1999) who, choosing a high cut-off value in order to maximize the target density in the predicted portfolios, did not manage to predict any targets correctly. Lower cut-off values, on the contrary, achieve a greater predictive stability as they fail to predict in only one or two years compared to six to eight years in the previous case. However, in some years, the increase in stability is generally followed by a decrease in the predictive performance. Therefore, the question to be now answered is: when lowering the cut-off value, does the stability improvement offset the decrease in predictive performance? Looking at the average rate of prediction and the respective t-test statistics, Table 6.6 shows that the predictive ability is clearly improved. Although the reported t-statistics do not allow us to reject at the 10% significance level the null hypothesis that the model does not predict better than chance over the selected period, a cut-off value of 0.2 appears to achieve the best predictive performance over the selected time frame of study.

In the US, Table 6.6 shows that there does not seem to be a strong effect between the choice of the cut-off value and the model's predictive performance. Although less pronounced than in the UK, higher cut-off values generate a certain degree of predictive instability as the model fails to predict any targets in three of the ten selected years. However, in the US, the instability does not significantly improve when lowering the cut-off value. As we can see, for high cut-off values the models do not predict any targets in three to four years compared to two years for low cut-off values (excluding the cut-off value 0.1). Overall, the small increase in stability partially offset the higher predictive power shown by higher cut-off values resulting in middle cut-off values achieving the highest predictive performance (as shown by the average C-ratio and the corresponding test-statistics).

For both economies, none of the selected cut-offs allows us to reject the hypothesis that the logistic-based model predicts better than chance selection. The results, however, suggest that high cut-off values generate unstable predictive performances. In addition, consistent with the low explanatory power of the models, the prediction results seem to slightly outperform chance selection. Finally, both models show, even for lower cut-off values, an unstable predictive behavior suggesting that a point forecast estimate is generally not representative of the true ex-ante predictive ability of takeover prediction models. The implications of such results will be analyzed in the comparative analysis established in Section 6.3.3.

Table 6.6: *Dynamic of the Logistic Model's Yearly Predictive Power in the UK during the period 1999-2008*

Prediction year	Targets / Firms[a] — Total —	PREDICTED TARGETS / TOTAL NUMBER OF PREDICTED FIRMS [PRC][b]								
		Cut-off probability (P_C)								
		0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
1999	96 / 755	0 / 0 [NA]	0 / 1 [NA]	0 / 3 [NA]	0 / 5 [NA]	0 / 8 [NA]	0 / 13 [NA]	2 / 23 [-46.2]	9 / 106 [-49.8]	57 / 414 [-8.3]
2000	81 / 720	0 / 2 [NA]	0 / 4 [NA]	0 / 5 [NA]	1 / 10 [-12.5]	1 / 14 [-57.5]	2 / 20 [-12.5]	5 / 41 [8.4]	15 / 90 [48.2]	63 / 423 [32.4]
2001	36 / 671	0 / 2 [NA]	0 / 2 [NA]	0 / 3 [NA]	0 / 5 [NA]	0 / 5 [NA]	0 / 7 [NA]	1 / 22 [-18.0]	3 / 76 [-35.9]	16 / 366 [-22.7]
2002	42 / 717	0 / 5 [NA]	0 / 5 [NA]	0 / 7 [NA]	0 / 7 [NA]	0 / 7 [NA]	0 / 11 [NA]	0 / 15 [NA]	1 / 24 [-40.6]	12 / 121 [69.3]
2003	88 / 656	4 / 19 [56.9]	4 / 20 [49.1]	4 / 22 [35.5]	4 / 24 [24.2]	4 / 24 [24.2]	4 / 24 [24.2]	4 / 25 [19.3]	4 / 26 [14.7]	4 / 30 [-0.6]
2004	44 / 617	0 / 2 [NA]	0 / 2 [NA]	0 / 3 [NA]	0 / 3 [NA]	0 / 4 [NA]	0 / 7 [NA]	1 / 13 [7.9]	6 / 46 [82.9]	36 / 506 [-0.2]
2005	57 / 605	0 / 1 [NA]	0 / 2 [NA]	0 / 3 [NA]	0 / 4 [NA]	0 / 4 [NA]	0 / 5 [NA]	0 / 6 [NA]	1 / 10 [6.1]	31 / 202 [62.9]
2006	72 / 625	0 / 4 [NA]	0 / 4 [NA]	0 / 4 [NA]	1 / 6 [44.7]	1 / 9 [-3.7]	2 / 14 [24.0]	4 / 21 [65.3]	7 / 40 [51.9]	22 / 238 [-24.6]
2007	72 / 658	0 / 2 [NA]	0 / 2 [NA]	0 / 2 [NA]	0 / 2 [NA]	0 / 3 [NA]	1 / 5 [82.8]	1 / 6 [52.3]	2 / 12 [52.3]	19 / 159 [9.2]
2008	71 / 667	1 / 3 [213.2]	1 / 3 [213.2]	2 / 7 [168.4]	2 / 7 [168.4]	3 / 9 [213.2]	4 / 17 [121.0]	5 / 28 [67.8]	11 / 76 [36.0]	35/ 318 [3.4]
$\overline{C}$[c]		**5.44**	**5.33**	**4.68**	**7.19**	**6.83**	**8.45**	**10.27**	**12.03**	**11.09**
t_C[d]		**-1.204**	**-1.246**	**-1.634**	**-0.860**	**-0.897**	**-0.500**	**0.222**	**1.493**	**1.062**

[a] The column provides the total number of targets / the total number of firms included in the holdout sample.

[b] PRC refers to the prediction accuracy measure relative to chance selection shown in equation 4.14. The value NA is assigned when the model failed to correctly predict any target firm.

[c] Provides the average predicted C-ratio,C_P (defined in equation 4.13), during the period 1999-2008.

[d] The t-test examines the null-hypothesis that the average of the coefficient is not different from zero. $*$, $**$, $***$ indicate significance using a two-tail t-test with 9 degrees of freedom at the 1%, 5% and 10% respectively.

6.3.2 Artificial Neural Network model

Table 6.8 and Table 6.9 show, for all considered cut-off values, the yearly proportions of firms predicted to be targets relative to the number of correctly predicted targets and the yearly associated PRC in the case of the UK and the US respectively for the period 1999-2008.

In the UK, as shown by Table 6.8, the cut-off value does not appear to have a strong influence on the model's predictive power. It can be noticed that, for cut-off values higher than 0.2, the model fails to predict any targets in several years therefore suggesting that lower cut-off values generate a more stable predictive accuracy. This increase in stability is, however offset by the greater predictive performance generated by higher cut-offs in most of the other years. As a result, the ANN-based models' predictive performance seems to be independent from the choice of the cut-off value in the UK context.

In the US, the results show a much clearer picture. As shown by Table 6.9, the ANN-

Table 6.7: *Dynamic of the Logistic Model's Yearly Predictive Power in the US during the period 1999-2008*

Prediction year	Targets / Firms[a] — Total —	TARGETS PREDICTED / TOTAL NUMBER OF PREDICTED FIRMS [PRC][b]								
		Cut-off probability (P_C)								
		0.9	*0.8*	*0.7*	*0.6*	*0.5*	*0.4*	*0.3*	*0.2*	*0.1*
1999	230 / 1966	0 / 1 [NA]	0 / 3 [NA]	1 / 6 [42.5]	1 / 8 [6.9]	1 / 10 [-17.0]	2 / 15 [-14.0]	2 / 18 [-5.3]	8 / 45 [52.0]	100 / 783 [9.2]
2000	226 / 2043	0 / 1 [NA]	0 / 1 [NA]	0 / 1 [NA]	0 / 1 [NA]	0 / 1 [NA]	0 / 1 [NA]	0 / 9 [NA]	0 / 14 [NA]	165 / 1418 [5.2]
2001	96 / 1836	1 / 3 [537.5]	1 / 3 [537.5]	1 / 3 [537.5]	1 / 3 [537.5]	1 / 3 [537.5]	1 / 3 [537.5]	1 / 6 [218.8]	1 / 11 [73.9]	661 / 1120 [12.7]
2002	73 / 1714	0 / 1 [NA]	0 / 3 [NA]	0 / 3 [NA]	0 / 3 [NA]	0 / 3 [NA]	0 / 4 [NA]	0 / 7 [NA]	0 / 7 [NA]	0 / 26 [NA]
2003	69 / 1492	1 / 23 [-6.4]	1 / 24 [-11.0]	1 / 27 [-24.9]	1 / 30 [-38.7]	2 / 32 [35.2]	2 / 33 [31.1]	2 / 36 [20.1]	2 / 40 [8.1]	3 / 65 [-0.2]
2004	86 / 1520	1 / 7 [152.5]	2 / 12 [194.6]	2 / 15 [135.7]	2 / 16 [120.9]	2 / 18 [96.4]	2 / 23 [53.7]	2 / 30 [17.8]	2 / 35 [1.0]	8 / 72 [96.4]
2005	103 / 1562	2 / 8 [279.1]	2 / 9 [237.0]	2 / 9 [237.0]	2 / 10 [203.3]	2 / 12 [152.8]	2 / 15 [102.2]	2 / 16 [89.6]	3 / 23 [97.8]	18 / 184 [48.4]
2006	117 / 1595	1 / 14 [-2.7]	1 / 18 [-32.0]	2 / 28 [-2.7]	3 / 36 [13.6]	4 / 49 [11.3]	5 / 56 [21.7]	5 / 69 [-1.2]	6 / 81 [1.0]	6 / 105 [-28.4]
2007	132 / 1555	2 / 21 [12.2]	2 / 28 [-18.8]	2 / 34 [-44.3]	3 / 42 [-15.9]	5 / 60 [-1.8]	6 / 84 [-15.9]	10 / 115 [2.4]	16 / 194 [-2.9]	43 / 541 [-6.8]
2008	85 / 1477	0 / 5 [NA]	0 / 7 [NA]	0 / 7 [NA]	1 / 8 [117.2]	1 / 8 [117.2]	1 / 11 [58.0]	1 / 14 [24.1]	2 / 23 [51.11]	45 / 647 [20.9]
$\overline{C}$[c]		**9.36**	**8.91**	**10.23**	**10.96**	**10.64**	**9.99**	**7.56**	**7.50**	**7.64**
t_C[d]		**0.557**	**0.451**	**0.844**	**1.105**	**1.045**	**0.885**	**0.241**	**0.233**	**0.492**

[a] The column provides the total number of targets / the total number of firms included in the holdout sample.

[b] PRC refers to the prediction accuracy measure relative to chance selection shown in equation 4.14. The value NA is assigned when the model failed to correctly predict any target firm.

[c] Provides the average predicted C-ratio,C_P (defined in equation 4.13), during the period 1999-2008.

[d] The t-test examines the null-hypothesis that the average of the coefficient is not different from zero. $*$, $**$, $***$ indicate significance using a two-tail t-test with 9 degrees of freedom at the 1%, 5% and 10% respectively.

based model's predictive accuracy is highly unstable for higher cut-off values showing frequently low predictive rates with bursts of high predictive performance as in years 2001 and 2008. For lower cut-offs, the model gains stability achieving a persistent and moderate predictive accuracy. By calculating the average C-ratio over the ten-year period, the maximum average prediction seems to be located on the 0.2 - 0.3 cut-off range. The result suggests that, in the US, more stable and greater average prediction performance can be achieved by using lower cut-off values.

Overall, ANN-based models seem to offer an attractive tool to predict takeover activity. Although the result is mixed for high cut-off values, in both the UK and the US, the model achieves positive and high predictive power relative to chance selection within the low cut-off range. The next section provides a comparison between the performances achieved by the Logistic and ANN-based models.

Table 6.8: *Dynamic of the ANN Model's Yearly Predictive Power in the UK during the period 1999-2008*

Prediction year	Targets / Firms[a] — Total —	PREDICTED TARGETS / TOTAL NUMBER OF PREDICTED FIRMS [PRC][b]								
		Cut-off probability (P_C)								
		0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
1999	96 / 755	5 / 29 [35.60]	5 / 37 [6.28]	5 / 47 [-19.52]	5 / 53 [-34.78]	5 / 56 [-42.4]	7 / 64 [-16.25]	8 / 69 [-9.67]	9 / 76 [-7.37]	9 / 90 [-27.15]
2000	81 / 720	10 / 86 [3.36]	18 / 110 [45.46]	21 / 129 [44.7]	21 / 143 [30.54]	25 / 159 [39.76]	26 / 178 [29.84]	27 / 200 [20]	31 / 219 [25.83]	37 / 264 [24.58]
2001	36 / 671	1 / 37 [-98.51]	1 / 41 [-120.0]	1 / 45 [-141.4]	1 / 52 [-179.0]	3 / 61 [-9.09]	4 / 71 [5.01]	4 / 71 [5.01]	9 / 97 [72.94]	9 / 113 [48.45]
2002	42 / 717	2 / 38 [-11.30]	4 / 49 [39.36]	6 / 60 [70.71]	7 / 71 [68.31]	7 / 76 [57.24]	7 / 82 [45.73]	7 / 96 [24.47]	9 / 111 [38.42]	16 / 161 [69.65]
2003	88 / 656	6 / 29 [54.23]	6 / 32 [39.78]	6 / 34 [31.55]	6 / 35 [27.79]	6 / 37 [57.24]	6 / 38 [17.7]	6 / 40 [11.82]	6 / 41 [9.09]	7 / 45 [15.96]
2004	44 / 617	2 / 16 [75.28]	2 / 18 [55.81]	3 / 24 [75.28]	3 / 27 [55.81]	4 / 37 [20.89]	5 / 48 [46.07]	7 / 70 [40.23]	8 / 98 [14.47]	12 / 168 [0.16]
2005	57 / 605	4 / 21 [102.17]	5 / 25 [112.28]	6 / 26 [150.7]	6 / 27 [135.9]	6 / 28 [51.6]	6 / 29 [119.6]	6 / 31 [105.43]	6 / 34 [87.31]	6 / 39 [63.29]
2006	72 / 625	2 / 24 [-38.24]	2 / 25 [-44.0]	2 / 30 [-72.8]	3 / 33 [-26.7]	3 / 37 [-42.1]	3 / 39 [-49.76]	3 / 42 [-61.28]	3 / 48 [-84.32]	5 / 56 [-29.02]
2007	72 / 658	0 / 1 [NA]	0 / 1 [NA]	0 / 2 [NA]	0 / 3 [NA]	0 / 9 [NA]	0 / 14 [NA]	0 / 19 [NA]	9 / 55 [49.55]	28 / 230 [11.27]
2008	71 / 667	1 / 14 [-49.03]	2 / 21 [-11.77]	2 / 23 [-22.41]	2 / 27 [-43.7]	2 / 34 [-80.96]	3 / 43 [-52.57]	5 / 53 [-12.83]	6 / 73 [-29.51]	15 / 148 [-5.03]
$\overline{C}$[c]		**10.45**	**10.79**	**10.77**	**10.29**	**10.12**	**10.13**	**9.90**	**11.47**	**11.12**
t_C[d]		**0.294**	**0.460**	**0.402**	**0.207**	**0.135**	**0.146**	**0.036**	**1.081**	**1.035**

[a] The column provides the total number of targets / the total number of firms included in the holdout sample.

[b] PRC refers to the prediction accuracy measure relative to chance selection shown in equation 4.14. The value NA is assigned when the model failed to correctly predict any target firm.

[c] Provides the average predicted C-ratio,C_P (defined in equation 4.13), during the period 1999-2008.

[d] The t-test examines the null-hypothesis that the average of the coefficient is not different from zero. $*, **, ***$ indicate significance using a two-tail t-test with 9 degrees of freedom at the 1%, 5% and 10% respectively.

6.3.3 Comparative analysis and literature support

Following the analysis of each specification separately, this paragraph aims to compare their yearly performances.

For the UK, the models seem to have a similar predictive power and no model seems to be superior to the other one over the selected period. Some differences can be noticed as the logistic regression seems to perform better than ANN for low cut-off values and the opposite relationship is found when the cut-off value is increased. However, the difference is small and, in any of these cases, the hypothesis that the predictive power of the model is not different than the one generated by a random sample can be rejected. The result supports the work of Ouzounis et al. (2008) who find that ANN and Multiple Discriminant Analysis (MDA) have similar predictive abilities.

Contrary to the previous results, in the US context, ANN-models perform better for lower cut-off values whereas Logit-based models appear to perform better for higher cut-off

Table 6.9: *Dynamic of the ANN Model's Yearly Predictive Power in the US during the period 1999-2008*

Prediction year	Targets / Firms[a] — Total —	TARGETS PREDICTED / TOTAL NUMBER OF PREDICTED FIRMS [PRC][b]								
		Cut-off probability (P_C)								
		0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
1999	230 / 1966	1 / 15 [-75.48]	4 / 26 [31.5]	6 / 32 [60.27]	6 / 34 [50.84]	7 / 39 [53.42]	9 / 46 [67.24]	9 / 51 [50.84]	13 / 90 [23.47]	86 / 683 [7.63]
2000	226 / 2043	0 / 5 [NA]	0 / 5 [NA]	0 / 6 [NA]	0 / 8 [NA]	2 / 10 [80.8]	2 / 12 [50.66]	2 / 21 [-16.15]	4 / 52 [-43.81]	123 / 1040 [6.91]
2001	96 / 1836	1 / 5 [282.5]	1 / 6 [218.75]	1 / 7 [173.2]	1 / 9 [112.5]	1 / 10 [91.25]	1 / 11 [73.86]	3 / 18 [218.75]	5 / 31 [208.47]	51 / 829 [17.66]
2002	73 / 1714	0 / 5 [NA]	0 / 7 [NA]	0 / 9 [NA]	0 / 10 [NA]	0 / 12 [NA]	1 / 13 [80.61]	1 / 14 [67.71]	1 / 20 [17.4]	2 / 36 [30.44]
2003	69 / 1492	0 / 0 [NA]	0 / 0 [NA]	0 / 0 [NA]	0 / 2 [NA]	0 / 6 [NA]	0 / 10 [NA]	0 / 15 [NA]	1 / 21 [2.97]	3 / 40 [62.17]
2004	86 / 1520	0 / 9 [NA]	0 / 9 [NA]	0 / 9 [NA]	1 /19 [-7.5]	1 / 24 [-26.36]	1 / 29 [-39.05]	2 / 51 [-44.28]	14 / 196 [26.25]	12 / 168 [35.67]
2005	103 / 1562	2 / 24 [26.38]	2 / 25 [21.32]	2 / 28 [8.32]	3 / 30 [51.65]	4 / 34 [78.41]	5 / 40 [89.56]	7 / 54 [96.58]	10 / 84 [80.54]	20 / 203 [49.41]
2006	117 / 1595	1 / 22 [-61.38]	1 / 22 [-61.38]	1 / 22 [-61.38]	1 / 22 [-61.38]	1 / 22 [-61.38]	1 / 22 [-61.38]	1 / 22 [-61.38]	1 / 22 [-61.38]	1 / 22 [-61.38]
2007	132 / 1555	0 / 6 [NA]	0 / 7 [NA]	0 / 7 [NA]	0 / 8 [NA]	0 / 10 [NA]	0 / 11 [NA]	2 / 14 [68.29]	4 / 23 [104.88]	33 / 319 [21.87]
2008	85 / 1477	2 / 11 [215.94]	2 / 11 [215.94]	2 / 13 [167.33]	2 / 13 [167.33]	2 / 13 [167.33]	2 / 14 [148.24]	2 / 14 [148.24]	2 / 15 [131.69]	5 / 61 [42.43]
$\overline{C}$[c]		**5.77**	**6.28**	**6.01**	**6.40**	**8.38**	**8.78**	**10.10**	**10.23**	**8.42**
t_C[d]		**-0.459**	**-0.300**	**-0.429**	**-0.295**	**0.602**	**0.848**	**1.593**	**1.814*****	**1.382**

[a] The column provides the total number of targets / the total number of firms included in the holdout sample.
[b] PRC refers to the prediction accuracy measure relative to chance selection shown in equation 4.14. The value NA is assigned when the model failed to correctly predict any target firm.
[c] Provides the average predicted C-ratio, C_P (defined in equation 4.13), during the period 1999-2008.
[d] The t-test examines the null-hypothesis that the average of the coefficient is not different from zero. $*$, $**$, $***$ indicate significance using a two-tail t-test with 9 degrees of freedom at the 1%, 5% and 10% respectively.

values. For a cut-off value of 0.2 the ANN-based model seem to be able to reject at the 10% level of confidence that the predictive power of the model is significantly better than chance. It therefore appears that ANN-based target prediction models are a more suitable tool for capturing takeover activity in the US. The result is in agreement with the findings of Cheh and Weinberg (1999) who provided evidence of the superiority of ANN relative to MDA as a regression tool to predict takeover activity.

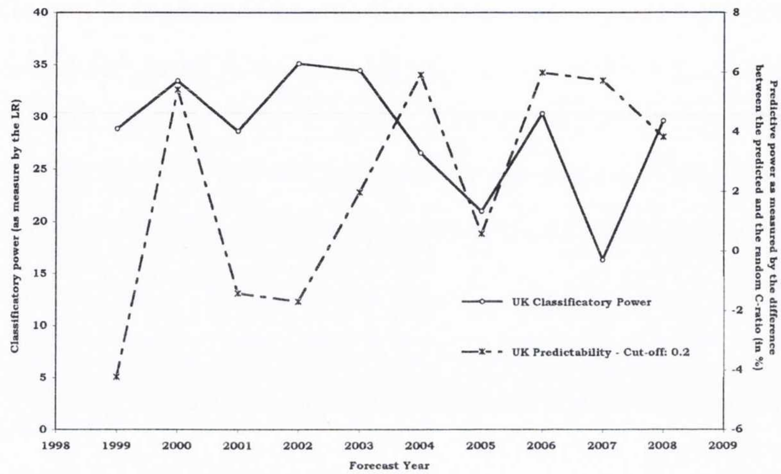
Our findings confirm recently reported results in the literature. First, as a general observation, for both the UK and the US, the models show a higher predictive instability when high cut-off values are selected. As a result, using higher cut-off choices do not seem to be an effective method to maximize the expected C-ratio which could explain, to some extent, the poor results achieved by Barnes (1999) and Powell (2001) when attempting to maximize the target proportion in their predicted portfolio. In addition, the results support the works of Cheh and Weinberg (1999) and Ouzounis et al. (2008) as Artificial Neural Networks seem to be a well-adapted tool to predict takeover activity in the US context whereas their performance in the UK context is comparable to other parametric techniques. Finally, our results emphasize the unreliable information of a point forecast estimation and show the advantage of a rolling forecast strategy to measure a model's predictive performance. As a result, the inherent predictive instability of the models explains, at least to some extent, the lack of consensus among the works within the takeover prediction literature.

6.3.4 Comparison between classificatory and predictive power

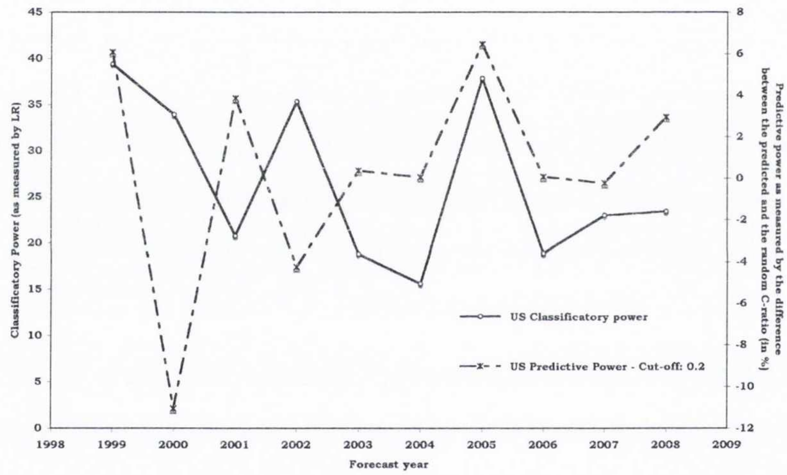
Given the low classificatory power exhibited by the logistic-based model in some of the considered years (in particular in the US context), it is important to analyze whether the latter is related to the model's poor predictive power. Following Fildes and Makridakis (1995)'s contention and given the variability of the predictive power, this section attempts to analyze the extent to which the model's predictive variability is driven by the achieved classificatory power. Figure 6.1 simultaneously shows the likelihood ratio (LR) obtained during the model's estimation and the predictive power generated using the estimated specification in the year following the estimation year in both the UK and the US contexts.

As shown in Figure 6.1a, in the UK context, no correlation seems to exist between the classificatory and the predictive performance of the models. In the US context, as shown by Figure 6.1b, we can observe a certain degree of correlation during the second half of the selected period. However, considering the entire period, no correlation seems to exist between the model's goodness of fit and its predictive power therefore suggesting that the observed predictive volatility is not due to the poor explanatory power achieve in some of the years.

In relation to the employed methodology, this result suggests that methods consisting in pooling M&A data across different periods, while certainly increasing the model's explanatory power, do not guarantee an increase in the model's predictive power. Perhaps of greater importance, in agreement with the estimation results, this finding underlines the importance of improving the sign and significance stability of the estimated regressors in order to build models with greater predictive robustness over time. Further research should focus on investigating takeover characteristics that are significantly stable



(a)



(b)

Figure 6.1: *Relationship between the logistic-based model's classificatory and predictive power in the UK (6.1a) and the US (6.1b) during the period 1999-2008. The classificatory power (straight line) is measured by the Log-likelihood ratio defined in equation 4.6 while the predictive power (dashed line) is represented by the yearly difference between the predicted and the random concentration ratio for a cut-off value of 0.2.*

over the medium and long-term horizon.

6.4 Summary

This chapter has presented both the estimation results and the prediction performance of takeover prediction models specified using both Logistic regressions and Artificial Neural Networks.

Under the methodology described in chapter 4, a one-year rolling estimation window was used to study the dynamic of the effects captured by the logistic regression translating into takeover characteristics. Combining the analytic methods of Harris et al. (1982) and Powell (1997), for each economy, three variables were detected characterized by a consistent sign and relatively frequent significance during the ten-year period 1998-2007. In the UK, targets seem to be larger companies, with lower growth in sales and poorer market performance compared to their industrial peers. In the US, target firms seem to pay lower dividends and have higher levels of leverage combined with higher levels of asset turnover. A comparative analysis shows that US targets seems to be more efficient in the management of resources compared to UK targets.

For each of the previously mentioned estimations, an out-of-sample forecast was calculated to study the inherent time-dependence of the takeover prediction model's predictive power. For all models, higher cut-offs generate more volatile predictions and, with the exception of the ANN-model within the UK context, fail to predict any targets in several occasions. Lower cut-offs seem to offer a more stable predictive environment and, with the exception of the US-based logistic model, generally offer a higher average predictive power over the selected period. Finally, although ANN-models show an improvement in the predictive power achieved in the US context, the evidence for the UK is mixed. The results seem to suggest that US target characteristics are not as trivially captured as in the UK context.

Chapter 7

Long-term investment risk and portfolio performance of predicted firms

7.1 Introduction and overview

From an investor's perspective, two main reasons can be found to use takeover prediction models as basis of an investment strategy. From one side, by accurately capturing target firms, abnormal returns may potentially be earned given the significant bid premium offered to target shareholders the day of the deal's announcement. In the words of Barnes (1990), if we compare the market for corporate control to a casino, the player able to systematically detect acquisition targets would certainly break the bank. The empirical evidence seems to confirm this idea as shown in Jensen and Ruback (1983) where a review of the documented acquisition gains are provided and where bid premiums as high as 40% are reported. From another viewpoint, by selecting firms with similar profiles as previously targeted firms, the models may potentially capture the set of characteristics making target firms attractive for acquirers and for the market as a whole. This contention is supported by the results of Wansley et al. (1983) who was able to generate significant abnormal returns by selecting samples that did not contain any target. In practice, the literature has provided mixed evidence on the model's ability to persistently outperform the market and the extent to which the portfolio's profitability is related to model's predictive ability. The objective of this chapter is to first investigate whether abnormal returns can persistently be earned using takeover prediction models during the period 1999-2008 as well as the risk characteristic of the predicted portfolios in order to measure the "price to pay" for such profitability. Secondly, similar to the correlation analysis between classificatory and predictive power, it is also meaningful to analyze the relationship between predictability and profitability in order to capture the extent to which profitability appears to be driven by the model's predictive ability. This relationship will help us to further understand the sources of gains underlying takeover prediction models.

The chapter is organized as follows. Section 7.2 presents the concept of the investment strategy that was used to assess the profitability of the selected predicted portfolios. Section 7.3 presents a first set of results using a market index benchmark allowing to measure the performance of the portfolios relative to a benchmark independent of the generated portfolios. Section 7.4 calculates the portfolios' abnormal profitability using a more accurate benchmark approach controlling for common market factors. Section 7.5 studies the relationship between the portfolios performance and the model's predictability. Finally, Section 7.6 summarizes and concludes the chapter.

7.2 Investment strategy

Following the literature, a buy-and-hold strategy based on an equally-weighted portfolio was built based on the models' yearly predicted firms as potential acquisition targets. For each prediction year and each considered cut-off value, abnormal returns were calculated using the investment procedure described in Chapter 4 Section 4.5.

It should be clarified that the objective of such a strategy is not to mimic an optimal trading strategy but to measure the potential abnormal profitability of firms selected by a takeover prediction model. As mentioned by Arnull-Almond (2007), a more realistic trading strategy would be to write call options on the firms most likely (and put options for the less likely in the case of Cremers et al. (2009)'s investment strategy) to be taken-over. Such a strategy would therefore put a heavier weight on the gains triggered by takeover bid premiums, stock market run-ups, and more generally good performing firms.

The assessment of abnormal performance requires the choice of an appropriate benchmark. As a first choice, a market index benchmark was chosen in order to provide a clear picture of the long-run abnormal returns generated by the predicted portfolios when compared relative to a conventional reference. Acknowledging the several flaws inherent to the market benchmark, a more exhaustive analysis is then conducted using a single control firm matching procedure in order to account for the common market risk factors potentially driving the portfolio's profitability.

7.3 Market index benchmark approach

7.3.1 Logistic regression

The results of the yearly Buy-and-Hold Abnormal Returns (henceforth BHAR) relative to the market index benchmark are shown in Table 7.1 and Table 7.2 for the UK and the US respectively.

In both the UK and the US, higher cut-off values show a more volatile portfolio performance compared to the low cut-off values. This can be observed in the low significance of the t-tstatistics t_M achieved in the higher cut-off range. Additionally, lower cut-off values seem to generate both significantly profitable and stable portfolios. Given the greater number of firms included in lower cut-off portfolios, the improved stability was to be expected.

In the US, the high portfolio performance achieved for a 0.9 cut-off deserves further discussion. As shown in Table 7.2, the 0.9 cut-off value seems to be an exception to the lower performance achieved by higher cut-off values as it generates an annual average abnormal performance of 32.27% over the ten-year period. Although offering seemingly substantial long-term profitability, when looking at the yearly performances, the average result is clearly driven by the abnormal performance of 410.5% achieved in 1999. Were the investment to be started in the year 2000, the portfolio would generate a total loss of 80.8% equivalent to a loss of 9.76% per annum during the nine-year period. Overall, the 0.9 cut-off value does not seem to provide a reliable long-term investment.

As we can observe, the market benchmark clearly fails to capture the substantial gain reported by the 0.9 cut-off in 1999 thus suggesting that the latter might not be an appropriate reference to measure abnormal profitability. This potential flaw is referred in Barber and Lyon (1997) as *skewness bias* which underlines the limit of a market benchmark to control for the right skewness of the return's distribution. Paraphrasing the authors, it is common to observe a sample firm with an annual return exceeding 100%, but uncommon to observe a return on the market index in excess of 100%. In the next section, a control firm portfolio is used in order to account for the potential market factors driving the returns in each of the considered portfolios.

Table 7.1: *Market index-based abnormal returns[a] (in %) generated by the logistic model's predictions in the UK during the period 1999-2008*

Prediction year	Market returns[b]	BUY AND HOLD ABNORMAL RETURNS (BHAR) OF THE PREDICTED PORTFOLIO (Significance)[c]								
		Cut-off probability (P_C)								
		0.9	*0.8*	*0.7*	*0.6*	*0.5*	*0.4*	*0.3*	*0.2*	*0.1*
1999	21.3	-21.3 (NA)	-31.8 (NA)	**-57.3**** (0.030)	-19.5 (0.515)	21.4 (0.695)	31.7 (0.390)	5.8 (0.795)	**49.9** (0.015)	**35.9*** (0.000)
2000	-8.0	32.7 (0.642)	23.5 (0.490)	9.7 (0.739)	6.2 (0.704)	0.6 (0.960)	3.3 (0.696)	4.5 (0.483)	**9.7**** (0.021)	**10.4*** (0.000)
2001	-15.4	23.2 (0.645)	23.2 (0.645)	23.1 (0.423)	11.2 (0.507)	11.2 (0.507)	8.5 (0.479)	**14.0***** (0.059)	**16.6*** (0.002)	**21.8*** (0.000)
2002	-25.0	-17.4 (0.104)	-17.4 (0.104)	**-20.9**** (0.018)	**-20.9**** (0.018)	**-20.9**** (0.018)	14.1 (0.699)	11.0 (0.683)	16.6 (0.396)	**10.3***** (0.096)
2003	16.6	26.4 (0.166)	19.6 (0.306)	23.5 (0.248)	19.2 (0.307)	19.2 (0.307)	19.2 (0.307)	18.9 (0.293)	17.1 (0.325)	18.1 (0.242)
2004	9.2	-7.6 (0.815)	-7.6 (0.815)	-3.1 (0.870)	-3.1 (0.870)	-8.8 (0.545)	-11.4 (0.302)	2.4 (0.809)	12.2 (0.270)	**10.7*** (0.000)
2005	18.1	-24.5 (NA)	-13.0 (0.376)	-11.3 (0.197)	**-14.2***** (0.066)	**-14.2***** (0.066)	**-20.7**** (0.046)	**-19.3**** (0.026)	0.1 (0.994)	**7.2*** (0.001)
2006	13.2	-42.0 (0.126)	-42.0 (0.126)	-41.9 (0.126)	-22.7 (0.267)	-22.7 (0.267)	-14.8 (0.296)	-2.4 (0.816)	3.1 (0.711)	**14.7*** (0.000)
2007	2.0	30.4 (0.268)	30.4 (0.268)	30.4 (0.268)	30.4 (0.268)	17.0 (0.410)	7.2 (0.749)	8.9 (0.626)	0.9 (0.929)	-0.1 (0.757)
2008	-31.5	-28.0 (0.121)	**-28.0** (0.051)	**-24.4**** (0.084)	**-24.4**** (0.032)	**-12.9** (0.038)	**-15.6**** (0.060)	**-17.0***** (0.010)	**-15.5*** (0.000)	**-11.8*** (0.000)
$\langle \overline{BHAR_M} \rangle$[d]		**-2.79**	**-4.29**	**-7.21**	**-3.72**	**-0.23**	**3.52**	**3.23**	**11.57*****	**11.63****
t_M[e]		**-0.31**	**-0.51**	**-0.78**	**-0.61**	**-0.05**	**0.68**	**0.82**	**2.17**	**2.87**

[a] Market index-based abnormal profitability is measured by calculating the buy-and-hold abnormal returns relative to the Market return benchmark. The investment is initiated the first month (January) and is terminated in the last month (December) of the calendar prediction year.

[b] The column *Market returns* shows the raw rate of returns achieved by a buy-and-hold investment in a general market index for the selected calendar prediction year. In the UK context, the FTSE All Share Index was chosen as the market index.

[c] The yearly abnormal return's significance is calculated using the t-test t_{BHAR} (shown in equation 4.17) based on the null-hypothesis that the yearly abnormal returns are not different from zero. The degrees of freedom of each test depend on the number of firms included in the predicted sample. $*$, $**$, $***$ indicate significance using a two-tail t-test at the 1%, 5% and 10% respectively.

[d] Calculates the annualized average abnormal return generated by the yearly predicted firms over the ten-year period 1999-2008.

[e] Shows the result of the t-test t_M (shown in equation 4.18) examining the null-hypothesis that the average long-term abnormal returns are not different from zero. $*$, $**$, $***$ indicate significance using a two-tail t-test with 9 degrees of freedom at the 1%, 5% and 10% respectively.

7.3.2 Artificial Neural Networks

Tables 7.3 and 7.4 show the Buy-and-Hold Abnormal Returns (BHAR) relative to a market index benchmark generated by the yearly predicted firms during the period 1999-2008 in the UK and the US respectively.

As shown in Table 7.3, in the UK context, for every selected cut-off value, the model seems to offer substantial total BHAR relative to the FTSE All Shares Index (FASI) with average long-term abnormal returns between a minimum of 14.92% at the 0.5 cut-off to a

Table 7.2: *Market index-based abnormal returns[a] (in %) generated by the logistic model's predictions in the US during the period 1999-2008*

Prediction year	Market returns[b]	BUY AND HOLD ABNORMAL RETURNS (BHAR) OF THE PREDICTED PORTFOLIO (in %) (Significance)[c] Cut-off probability (P_C)								
		0.9	*0.8*	*0.7*	*0.6*	*0.5*	*0.4*	*0.3*	*0.2*	*0.1*
1999	21.1	410.5 (NA)	89.0 (0.638)	59.6 (0.514)	51.2 (0.420)	39.8 (0.428)	15.1 (0.658)	28.2 (0.362)	30.6 (0.165)	**22.8*** (0.001)
2000	-11.2	-64.8 (NA)	-64.8 (NA)	-64.8 (NA)	-64.8 (NA)	-64.8 (NA)	-64.8 (NA)	25.5 (0.118)	11.8 (0.337)	**17.1*** (0.000)
2001	-12.1	-13.6 (0.420)	-13.6 (0.420)	-13.6 (0.420)	-13.6 (0.420)	-13.6 (0.420)	-13.6 (0.420)	0.2 (0.990)	4.7 (0.778)	**46.1*** (0.000)
2002	-22.1	-36.3 (NA)	5.4 (0.823)	5.4 (0.823)	5.4 (0.823)	5.4 (0.823)	-10.8 (0.823)	-5.0 (0.823)	-7.7 (0.823)	-4.2 (0.785)
2003	29.4	-36.3 (NA)	11.3 (0.383)	10.4 (0.402)	7.7 (0.461)	6.5 (0.521)	6.3 (0.524)	4.2 (0.659)	28.4 (0.230)	**13.6** (0.358)
2004	9.8	**33.6***** (0.094)	**35.2***** (0.056)	**31.3**** (0.034)	**30.9**** (0.025)	**32.0**** (0.011)	**24.7**** (0.014)	**21.0*** (0.008)	**17.7*** (0.010)	**13.2*** (0.005)
2005	5.6	-6.4 (0.729)	-0.8 (0.966)	-0.8 (0.966)	-7.9 (0.646)	-12.2 (0.405)	-6.9 (0.568)	9.1 (0.430)	-9.2 (0.322)	**20.8***** (0.077)
2006	13.9	-4.7 (0.526)	-7.1 (0.238)	-1.2 (0.793)	0.9 (0.813)	2.2 (0.524)	3.3 (0.300)	4.3 (0.155)	6.6 (0.025)	3.8 (0.156)
2007	3.9	0.5 (0.967)	-0.7 (0.933)	-2.2 (0.787)	-4.3 (0.511)	-1.6 (0.771)	-0.7 (0.897)	-1.7 (0.733)	3.7 (0.318)	**4.5**** (0.017)
2008	-38.7	-7.3 (0.591)	-9.9 (0.325)	-9.9 (0.325)	-15.5 (0.154)	-15.5 (0.154)	-11.6 (0.253)	-14.5 (0.108)	-9.4 (0.171)	**-2.7*** (0.000)
$\langle \overline{BHAR_M} \rangle$[d]		**32.27**	**4.30**	**5.45**	**-1.00**	**-2.19**	**5.91**	**5.30**	**7.72**	**13.50****
t_M[e]		**0.75**	**0.35**	**0.87**	**-0.10**	**-0.24**	**-0.77**	**1.14**	**1.68**	**2.89**

[a] Market index-based abnormal profitability is measured by calculating the buy-and-hold abnormal returns relative to the Market return benchmark. The investment is initiated the first month (January) and is terminated in the last month (December) of the calendar prediction year.

[b] The column *Market returns* shows the raw rate of returns achieved by a buy-and-hold investment in a general market index for the selected calendar prediction year. In the US context, the Dow Jones Total Stock Market Index (DJSM) was chosen as the market index.

[c] The yearly abnormal return's significance is calculated using the t-test t_{BHAR} (shown in equation 4.17) based on the null-hypothesis that the yearly abnormal returns are not different from zero. The degrees of freedom of each test depend on the number of firms included in the predicted sample. $*, **, ***$ indicate significance using a two-tail t-test at the 1%, 5% and 10% respectively.

[d] Calculates the annualized average abnormal return generated by the yearly predicted firms over the ten-year period 1999-2008.

[e] Shows the result of the t-test t_M (shown in equation 4.18) examining the null-hypothesis that the average long-term abnormal returns are not different from zero. $*, **, ***$ indicate significance using a two-tail t-test with 9 degrees of freedom at the 1%, 5% and 10% respectively.

maximum of 23.00% at the 0.9 cut-off. After adjusting for risk, the obtained test-statistic t_M varied between a minimum of 1.55 at the 0.3 cut-off value to a maximum of 2.0 at the 0.8 cut-off value suggesting that the stability of the portfolio does not seem to be significantly affected by an increase/decrease of the cut-off value.

In the US, the model offers a moderate positive total BHAR for low cut-off values with a maximum average of 10.19% at the 0.1 cut-off level and negative long-term average BHAR for high cut-off values such as 0.9 and 0.8. When considering the risk-adjusted performance, the cut-off value of 0.1 also generates the portfolio with the highest information ratio. In this case, the t-statistics t_M values vary over a much larger range between -0.67 and 2.19 corresponding to the cut-off values 0.9 and 0.1 respectively.

Table 7.3: *Market index-based abnormal returns[a] (in %) generated by the ANN model's predictions in the UK during the period 1999-2008*

Prediction year	Market returns[b]	BUY AND HOLD ABNORMAL RETURNS (BHAR) OF THE PREDICTED PORTFOLIO (in %) (Significance)[c]								
		Cut-off probability (P_C)								
		0.9	*0.8*	*0.7*	*0.6*	*0.5*	*0.4*	*0.3*	*0.2*	*0.1*
1999	21.3	124.7 (0.176)	109.2 (0.131)	107.7*** (0.065)	95.0*** (0.068)	91.9*** (0.060)	105.9** (0.027)	104.2** (0.020)	98.8** (0.015)	84.4** (0.023)
2000	-8.0	2.8 (0.502)	7.3** (0.049)	8.6* (0.010)	6.8** (0.029)	5.8** (0.043)	5.8** (0.027)	5.6** (0.023)	6.5* (0.006)	11.4* (0.000)
2001	-15.4	15.9*** (0.051)	17.9** (0.025)	15.1** (0.047)	19.3** (0.011)	20.2* (0.004)	21.1* (0.001)	24.3* (0.000)	22.8* (0.000.)	24.0* (0.000)
2002	-25.0	6.7 (0.557)	8.9 (0.473)	4.2 (0.685)	-0.7 (0.936)	2.8 (0.737)	1.1 (0.885)	3.1 (0.770)	4.6 (0.469)	-0.3 (0.953)
2003	16.6	28.7 (0.187)	28.7 (0.151)	25.3 (0.182)	25.8 (0.161)	24.2 (0.164)	25.1 (0.140)	26.3 (0.104)	25.7 (0.104)	24.0*** (0.100)
2004	9.2	-8.6 (0.496)	-7.9 (0.487)	-4.4 (0.626)	-4.8 (0.554)	-4.9 (0.437)	-2.5 (0.643)	-6.4 (0.165)	-3.5 (0.343)	6.7 (0.216)
2005	18.1	15.7 (0.479)	14.1 (0.449)	13.9 (0.437)	13.9 (0.420)	12.3 (0.461)	15.5 (0.344)	14.8 (0.336)	13.3 (0.344)	11.3 (0.382)
2006	13.2	9.3 (0.360)	9.7 (0.320)	10.3 (0.210)	10.1 (0.186)	11.4 (0.101)	12.2*** (0.068)	12.8** (0.045)	13.5** (0.022)	12.4** (0.016)
2007	2.0	50.5 (NA)	50.5 (NA)	28.7 (0.319)	14.6 (0.498)	-0.02 (0.998)	2.5 (0.836)	-11.9 (0.293)	-2.1 (0.726)	-2.8 (0.305)
2008	-31.5	-13.2 (0.225)	-14.3*** (0.051)	-12.8*** (0.084)	-14.6** (0.032)	-12.0** (0.038)	-9.9 (0.101)	-8.3 (0.113)	-6.2 (0.151)	-10.0* (0.003)
$\langle \overline{BHAR_M} \rangle$[d]		23.00	22.12***	19.41***	16.52	14.92	17.44	16.22	17.33	15.85***
t_M[e]		1.83	2.00	1.86	1.77	1.65	1.70	1.55	1.79	1.93

[a] Market index-based abnormal profitability is measured by calculating the buy-and-hold abnormal returns relative to the Market return benchmark. The investment is initiated the first month (January) and is terminated in the last month (December) of the calendar prediction year.

[b] The column *Market returns* shows the raw rate of returns achieved by a buy-and-hold investment in a general market index for the selected calendar prediction year. In the UK context, the FTSE All Share Index was chosen as the market index.

[c] The yearly abnormal return's significance is calculated using the t-test t_{BHAR} (shown in equation 4.17) based on the null-hypothesis that the yearly abnormal returns are not different from zero. The degrees of freedom of each test depend on the number of firms included in the predicted sample. $*, **, ***$ indicate significance using a two-tail t-test at the 1%, 5% and 10% respectively.

[d] Calculates the annualized average abnormal return generated by the yearly predicted firms over the ten-year period 1999-2008.

[e] Shows the result of the t-test t_M (shown in equation 4.18) examining the null-hypothesis that the average long-term abnormal returns are not different from zero. $*, **, ***$ indicate significance using a two-tail t-test with 9 degrees of freedom at the 1%, 5% and 10% respectively.

7.4 Control firm portfolio approach

As previously stated, a market index benchmark although providing a clear picture of the ability of outperforming a common market reference, does not account for common market factors that may be driving the portfolio results. In addition, as mentioned in Barber and Lyon (1997), testing for abnormal profitability using a market index benchmark suffers from three main potential biases namely (i) new listing bias (ii) rebalancing bias and (iii) skewness bias. Following the work of Barber and Lyon (1997), the control benchmark seems to be the more accurate benchmark in capturing random market factors relative to the market index benchmark, size and market-to-book portfolios, and the Fama and French (1992) three-factor model. For each cut-off value and for each year, the control firm approach was applied to the predicted samples as described in Chapter 4 Section 4.5.3.

Table 7.4: *Market index-based abnormal returns[a] (in %) generated by the ANN model's predictions in the US during the period 1999-2008*

Prediction year	Market returns[b]	BUY AND HOLD ABNORMAL RETURNS (BHAR) OF THE PREDICTED PORTFOLIO (in %) (Significance)[c]								
		Cut-off probability (P_C)								
		0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
1999	21.3	**-30.6*** (0.007)	**-21.9*** (0.006)	-8.2 (0.596)	-9.0 (0.540)	-12.4 (0.337)	-1.6 (0.919)	-1.6 (0.888)	-6.8 (0.345)	0.9 (0.895)
2000	-8.0	37.3 (0.447)	37.3 (0.447)	70.3 (0.206)	**80.9**** (0.063)	**89.2*** (0.002)	**82.1**** (0.011)	**47.0**** (0.026)	**36.4*** (0.001)	**17.5*** (0.000)
2001	-15.4	**-35.3**** (0.046)	-21.0 (0.286)	-18.8 (0.260)	-8.0 (0.579)	-3.8 (0.777)	2.9 (0.834)	-0.3 (0.969)	7.4 (0.302)	**41.7*** (0.000)
2002	-25.0	**-48.3**** (0.012)	-22.1 (0.142)	-16.6 (0.227)	-16.9 (0.171)	-16.4 (0.155)	-16.0 (0.132)	-15.9 (0.106)	**-13.9***** (0.079)	-5.1 (0.388)
2003	16.6	XXX (NA)	XXX (NA)	XXX (NA)	**-24.9***** (0.076)	-7.4 (0.384)	-5.1 (0.562)	-12.6 (0.310)	6.1 (0.698)	19.7 (0.136)
2004	9.2	**23.8**** (0.033)	**23.8**** (0.033)	**23.8**** (0.033)	**27.0**** (0.011)	**25.5*** (0.003)	**21.1*** (0.005)	**20.2*** (0.000)	**20.0*** (0.000)	17.6 (0.000)
2005	18.1	-3.2 (0.727)	-0.7 (0.941)	-0.3 (0.974)	-1.6 (0.839)	0.9 (0.897)	-2.6 (0.697)	3.8 (0.648)	22.1 (0.231)	**13.4***** (0.094)
2006	13.2	-6.7 (0.223)	-6.7 (0.223)	-6.7 (0.223)	-6.7 (0.223)	-6.7 (0.223)	-6.7 (0.223)	-6.7 (0.223)	-6.7 (0.223)	-6.7 (0.223)
2007	2.0	27.0 (0.384)	26.6 (0.310)	26.6 (0.310)	21.6 (0.347)	10.1 (0.998)	22.7 (0.326)	19.4 (0.299)	12.1 (0.308)	2.9 (0.389)
2008	-31.5	**-29.5*** (0.005)	**-29.5*** (0.005)	**-31.0*** (0.001)	**-31.0*** (0.001)	**-31.0*** (0.001)	**-31.0*** (0.000)	**-31.0*** (0.000)	**-28.6*** (0.001)	0.34 (0.944)
$\langle\overline{BHAR_M}\rangle$[d]		**-6.56**	**-1.43**	**3.92**	**3.13**	**4.80**	**6.58**	**2.22**	**4.56**	**10.19*****
t_M[e]		**-0.67**	**-0.18**	**0.40**	**0.30**	**0.46**	**0.67**	**0.32**	**0.79**	**2.19**

[a] Market-index based abnormal profitability is measured by calculating the buy-and-hold abnormal returns relative to the Market return benchmark. The investment is initiated the first month (January) and is terminated in the last month (December) of the calendar prediction year.

[b] The column *Market returns* shows the raw rate of returns achieved by a buy-and-hold investment in a general market index for the selected calendar prediction year. In the US context, the Dow Jones Total Stock Market Index (DJSM) was chosen as the market benchmark.

[c] The yearly abnormal return's significance is calculated using the t-test t_{BHAR} (shown in equation 4.17) based on the null-hypothesis that the yearly abnormal returns are not different from zero. The degrees of freedom of each test depend on the number of firms included in the predicted sample. $*, **, ***$ indicate significance using a two-tail t-test at the 1%, 5% and 10% respectively.

[d] Calculates the annualized average abnormal return generated by the yearly predicted firms over the ten-year period 1999-2008.

[e] Shows the result of the t-test t_M (shown in equation 4.18) examining the null-hypothesis that the average long-term abnormal returns are not different from zero. $*, **, ***$ indicate significance using a two-tail t-test with 9 degrees of freedom at the 1%, 5% and 10% respectively.

The cut-off value of 0.1 was excluded from the analysis as the large number of firms impeded to build in most cases a control firm portfolio (see Chapter 5 Section 5.4 for more detail on this issue). Although partially restricting our analysis, the extremely large size of the portfolios generated by the a 0.1 cut-off value are not realistic from an investment perspective and do not therefore represent a significant concern in the analysis of the model's potential economic benefits.

7.4.1 Logistic regression

This paragraph presents the results of the logit-model's profitability relative to a control firm portfolio. Table 7.5 shows the results for the best performing portfolios. For the sake of clarity, the best performing portfolios were chosen on the basis of total maximum amount and highest significance. As a result, Table 7.5 only includes the portfolios generated by a cut-off value of 0.2 in the UK (Panel A) and the portfolios generated by cut-off values 0.2 (Panel B) and 0.9 (Panel C) in the US. The complete results for all cut-off values are reported in Appendix C.

For both economies, the results show that a large portion of the abnormal profitability can be explained by the common market factors captured by the matched control firms. This is true in particular for the 0.9 cut-off value in the UK context where, for most, years, the control firm and the predicted portfolio show a similar profitability (i.e. a $BHAR_C$ close to 0). Contrary to the market benchmark, the control firm portfolio is able to capture the highly volatile abnormal performance generated by the 0.9 cut-off value. Although there are extreme deviations in the years 1999 and 2000, their opposite sign and relatively similar magnitude suggest that, in the long-run, a control firm portfolio is an unbiased measure of abnormal profitability. In agreement with Barber and Lyon (1997), the results confirm the efficiency of a control firm portfolio in capturing the firm's abnormal profitability using two common market factors such as size and book-to-market ratio.

As a general observation, logistic-based takeover prediction models do not seem to generate long-term abnormal returns. Although significant returns are achieved for some specific years, the relatively unfrequent out-performance is not sufficient to generate significant long-run profitability. Once more, the result underlines the importance of using a rolling estimation method in order to account for the underlying instability of the models. Furthermore, our result suggests that, takeover prediction models' profitability should be assessed by using multiple estimation rather than based on a single scenario. Cremers et al. (2009) use a rolling estimation window to calculate out-of-sample takeover probabilities and find that abnormal returns can be generated over the fourteen-year period 1991-2004. The difference with their results deserves a discussion. As a main difference with our model, Cremers et al. (2009) use corporate governance related variables and therefore include non-financial variables that are likely to have an important role within their concept of takeover vulnerability and therefore in the abnormal profitability of their selected predicted portfolios. If this is true, the result implies that logistic-based takeover prediction models using only accounting financial ratios have little hope in becoming successful investment tools within the US market. Another possible explanation is that, as their portfolios are based in decile/quintiles (i.e. 10% or 20% of the US population), the proportion of firms considered in their portfolios is larger than the portfolios generated by the cut-off range 0.2–0.9 here considered. Hence, as observed in Table 7.1, in the US, the 0.1 cut-off value generates larger portfolios and provides higher total and risk-adjusted returns which is consistent with Cremers et al. (2009)' results. This result would suggest that although takeover vulnerability accounts for a firm's expected return, the market seems to efficiently incorporate the takeover vulnerability into the stock price of firms with the highest takeover likelihood. Finally, by yearly matching the control firm portfolios and therefore accounting for the yearly variation of the predicted firm's financial profile, it is possible that the present work provides a more accurate measure of the long-run abnormal profitability of the predicted portfolios.

7.4.2 Artificial Neural Networks

Table 7.6 shows the portfolio performance results of the control firm approach in the Uk and the US. As in the previous paragraph, the results are shown for the predicted portfolios maximizing either the total value or the significance of the generated long-term abnormal relative to the market index benchmark. For the US, the cut-off value 0.2 (Panel C) is included as it generates the maximum abnormal returns while achieving the highest significance. In addition, the rest of the cut-off values generate significant losses in the long-run. In the UK, although the 0.8 (Panel B) cut-off value achieves both the highest total cumulated return along with the highest significance, the cut-off value 0.2 (Panel A) is also included in order to examine whether the previously reported stability of the UK portfolio performance across the cut-off interval is maintained when using a control firm portfolio approach. In addition, as I shall discuss in a later section, as the 0.2 cut-off value achieves the highest predictive ability, the robustness of the associated portfolios will be used to analyze the relationship between predictability and profitability. The complete results for all cut-off values are reported in Appendix C.

As we can observe, in the UK, the predicted sample generates an average annual return of 11.97% (26.21%) for a cut-off value of 0.2 (0.8) with an Information Ratio of 1.64 (1.92).

Table 7.5: *Control firm portfolio-based abnormal returns[a] generated by the logistic model's predictions[b] during the period 1999-2008 in the UK and the US*

Portfolio characteristics[c]	**99**	**00**	**01**	**02**	**03**	**04**	**05**	**06**	**07**	**08**
Panel A: UK- Logit Model using a 0.2 cut-off value										
Size	106	90	76	24	26	46	10	40	12	76
C-ratio (in %	8.49	16.67	3.95	4.17	15.39	13.04	10.00	17.5	16.67	14.47
PRC (in%)	-49.8	48.2	-35.9	-40.6	14.7	82.9	6.1	51.9	52.3	36.0
$\overline{BHAR_C}$ (in %)	-20.6	**10.4*****	**10.8*****	32.5	16.9	-3.5	-19.7	2.7	-3.6	0.2
p-value[d]	(0.511)	(0.096)	(0.984)	(0.129)	(0.448)	(0.841)	(0.223)	(0.799)	(0.831)	(0.970)
Information ratio	-0.51	0.43	1.14	1.59	0.63	-0.27	-0.82	0.52	-0.11	0.02
$\langle \overline{BHAR_C} \rangle$[e] (in %)	2.61									
t_C[f]	0.512									
Panel B: US- Logit Model using a 0.2 cut-off value										
Size	45	14	11	7	40	35	23	81	194	23
C-ratio (in %)	17.78	0.00	9.09	0.00	5.00	5.71	13.04	7.41	8.25	8.70
PRC (in%)	52.0	NA	73.9	NA	8.1	1.00	97.8	0.98	-2.93	51.1
$\overline{BHAR_C}$ (in %)	40.1	3.4	-26.4	-8.4	-0.3	**24.2****	-2.4	3.4	**8.2*****	-9.4
p-value[d]	(0.136)	(0.882)	(0.208)	(0.754)	(0.994)	(0.014)	(0.897)	(0.575)	(0.091)	(0.171)
Information ratio	0.69	0.06	-0.44	-0.36	-0.02	0.74	-0.13	0.19	0.71	-0.53
$\langle \overline{BHAR_C} \rangle$[e](in%)	3.25									
t_C[f]	0.560									
Panel C: US- Logit Model using a 0.9 cut-off value										
Size	1	1	3	1	23	7	8	14	21	5
C-ratio (in %)	0.00	0.00	33.33	0.00	4.35	14.29	25.00	7.14	9.52	0.00
PRC (in%)	NA	NA	537.5	NA	-6.4	152.5	279.1	-2.7	12.2	NA
$\overline{BHAR_C}$ (in%)	333.8	-207.5	-14.0	-74.0	-2.2	2.6	11.1	-2.2	-0.7	-18.9
p-value[d]	(NA)	(NA)	(0.719)	(NA)	(0.910)	(0.896)	(0.663)	(0.858)	(0.967)	(0.449)
Information Ratio	1.03	-0.87	-0.28	-0.48	-0.07	-0.27	-0.81	0.52	-0.05	-0.50
$\langle \overline{BHAR_C} \rangle$[e](in%)	2.79									
t_C[f]	0.066									

[a] Control firms portfolio-based abnormal profitability was measured by calculating the buy-and-hold abnormal returns relative to a control firm portfolio matched as in Barber and Lyon (1997). Details on the selection procedure of the control firms are provided in chapter 4 section 4.5.3. The buy-and-hold investment is initiated the first month (January) and is terminated in the last month (December) of the calendar prediction year.

[b] The table only shows the control firm approach for the cut-off values achieving the highest total amount and/or significance of abnormal profitability relative to the market benchmark.

[c] Size, C-ratio and PRC provide the sample size, the concentration ratio (as defined in equation 4.13), and the prediction performance relative to a random portfolio (defined in equation 4.14. $\overline{BHAR_C}$ denotes the yearly buy-and-hold abnormal returns generated by the predicted portfolio over the control firm portfolio.

[d] The yearly abnormal return's p-value is calculated using the t-test t_{BHAR} (shown in equation 4.17) based on the null-hypothesis that the yearly abnormal returns are not different from zero. The degrees of freedom of each test depend on the number of firms included in the predicted sample. $*, **, ***$ indicate significance using a two-tail t-test at the 1%, 5% and 10% respectively.

[e] Calculates the annualized average abnormal return generated by the yearly predicted firms over the ten-year period 1999-2008.

[f] Shows the result of the t-test t_C (shown in equation 4.18) examining the null-hypothesis that the average long-term abnormal returns are not different from zero. $*, **, ***$ indicate significance using a two-tail t-test with 9 degrees of freedom at the 1%, 5% and 10% respectively.

Thus, in the UK case, the market benchmark results (previously reported on Table 6.8) do not seem to be driven by common market effects such as the firms' size and market-to-book ratio characteristics. On the contrary, in the US context, the relatively low returns given by the 0.2 cut-off value relative to the market benchmark (previously reported on Table 7.4) seem to be significantly reduced when using control firm portfolios resulting in an average annual return of 1.37% and an information ratio of 0.25. Therefore, no abnormal returns seem to be available in the US when employing this type of takeover prediction model.

In looking at the risk-return profile of the yearly predicted portfolios in order to investigate if the higher returns achieved in the UK stem from the selection of high risk companies. As shown in Table 7.6, for the two considered cut-offs, UK yearly predicted portfolios present Information Ratios higher than 0.5 for at least half of the period and lower than -0.5 in only one year. The US shows a much riskier environment with Information Ratios higher than 0.5 in only three years and lower than -0.5 in also three years. The latter result suggests that UK predicted portfolios offer a more rewarding but also a more reliable risk-return profile.

Overall, for both economies, although the sign and significance of the reported abnormal returns are different, the conclusions confirm the market benchmark approach. As a summary, the UK context seems to be a more suitable context to use ANN-based takeover prediction models as an investment strategy. The evidence is also in agreement with Ouzounis et al. (2008) where ANN-based takeover prediction model strategies earn significant abnormal return over between a 12-months to a 21-months buy-and-hold period. Overall, the result provides further evidence for the use of ANN-based models in the US context and shows that, using size and market-to-book ratio matched control firms, no abnormal profitability seems to be achieved by the predicted portfolios over the long-term horizon relative to firms having similar size and market-to-book ratio characteristics. This result is in contradiction with the results reported by Cheh and Weinberg (1999), however, as they considered random benchmark portfolios to match their predicted portfolios, it is possible that common market factors were not properly accounted for. It is also possible that, by including three different lags for each explanatory variable, their model may anticipate more accurately acquisition factors that had not yet been discounted by the market. As I shall discuss in the next chapter, the influence of lagged variables remains an interesting subject for further research.

Table 7.6: *Control firm portfolio-based abnormal returns[a] generated by the ANN model's predictions[b] during the period 1999-2008 in the UK and the US*

Portfolio characteristics[c]	**99**	**00**	**01**	**02**	**03**	**04**	**05**	**06**	**07**	**08**
Panel A: UK- ANN Model using a 0.2 cut-off value										
Size	76	219	97	111	41	98	34	48	55	73
C-ratio (in %)	11.84	14.16	9.28	8.11	14.63	8.16	17.65	6.25	16.36	8.22
PRC (in%)	-7.37	25.83	72.94	38.42	9.10	14.47	87.30	-84.32	49.55	-29.51
$\overline{BHAR_C}$ (in %)	**72.05*** **	-3.12	**16.64***	1.0	14.97	-8.8	18.2	-4.24	2.9	**10.1*** **
p-value[d]	0.067	0.410	0.007	0.905	0.432	0.253	0.289	0.661	0.708	0.072
Information Ratio	1.12	-0.24	1.08	0.07	0.67	-0.69	0.57	-0.41	0.24	0.64
$\langle\overline{BHAR_C}\rangle$[e](in%)	11.97									
t_C[f]	1.64									
Panel B: UK- ANN Model using a 0.8 cut-off value										
Size	37	110	41	49	32	18	25	25	1	21
C-ratio (in %)	13.51	16.36	2.44	8.16	18.75	11.11	20.0	8.0	0.0	9.52
PRC (in%)	6.28	45.46	-119.97	39.36	39.77	55.8	112.28	-44.0	NA	-11.77
$\overline{BHAR_C}$ (in%)	98.28	3.23	**15.75*** **	18.5	11.49	-10.8	19.7	-13.01	114.43	8.4
p-value[d]	0.147	0.534	0.090	0.174	0.629	0.627	0.415	0.398	NA	0.462
Information Ratio	1.25	0.18	0.80	0.74	0.61	-0.24	0.49	-0.64	1.43	0.34
$\langle\overline{BHAR_C}\rangle$[e](in%)	26.59									
t_C[f]	1.92									
Panel C: US- ANN Model using a 0.2 cut-off value										
Size	90	52	31	20	21	196	84	22	23	15
C-ratio (in %)	14.44	7.69	16.13	5.00	4.76	7.14	11.91	4.55	17.39	13.33
PRC (in%)	23.47	-43.80	208.47	17.40	2.97	26.25	80.54	-61.38	104.88	131.69
$\overline{BHAR_C}$ (in %)	-9.7	19.4	-14.7	-18.3	-4.8	**13.0***	13.5	-1.0	**32.7****	**-16.3*** **
p-value[d]	0.497	0.160	0.133	0.204	0.822	0.006	0.499	0.917	0.023	0.052
Information Ratio	-0.77	0.47	-0.62	-0.62	-0.17	0.67	1.12	-0.07	0.65	-0.40
$\langle\overline{BHAR_C}\rangle$[e](in%)	1.37									
t_C[f]	0.25									

[a] Control firms portfolio-based abnormal profitability was measured by calculating the buy-and-hold abnormal returns relative to a control firm portfolio matched as in Barber and Lyon (1997). Details on the selection procedure of the control firms are provided in chapter 4 section 4.5.3. The buy-and-hold investment is initiated the first month (January) and is terminated in the last month (December) of the calendar prediction year.

[b] The table only shows the control firm approach for the cut-off values achieving the highest total amount and/or significance of abnormal profitability relative to the market benchmark.

[c] Size, C-ratio, PRC and Information Ratio measure the sample size, the concentration ratio (as defined in equation 4.13), and the prediction performance relative to a random portfolio (defined in equation 4.14) and the yearly information ratio(defined in equation 4.19 characterizing the yearly predicted portfolios. $\overline{BHAR_C}$ and Information Ratio denote the yearly buy-and-hold abnormal returns and the yearly information ratio(defined in equation 4.19 generated by the predicted portfolio over the control firm portfolio.

[d] The yearly abnormal return's p-value is calculated using the t-test t_{BHAR} (shown in equation 4.17) based on the null-hypothesis that the yearly abnormal returns are not different from zero. The degrees of freedom of each test depend on the number of firms included in the predicted sample. $*$, $**$, $***$ indicate significance using a two-tail t-test at the 1%, 5% and 10% respectively.

[e] Calculates the annualized average abnormal return generated by the yearly predicted firms over the ten-year period 1999-2008.

[f] Shows the result of the t-test t_C (shown in equation 4.18) examining the null-hypothesis that the average long-term abnormal returns are not different from zero. $*$, $**$, $***$ indicate significance using a two-tail t-test with 9 degrees of freedom at the 1%, 5% and 10% respectively.

7.5 The relationship between predictability and portfolio performance

7.5.1 Logistic regression

This section attempts to provide further insight on the link between the predictive power of logistic-based takeover prediction models and their ability to generate abnormal returns. Figure 7.1 shows, for each considered cut-off value, the significance of the model's average predictability and the significance of the long-run average performance relative to the market benchmark for both the UK (7.1a) and the US (7.1b).

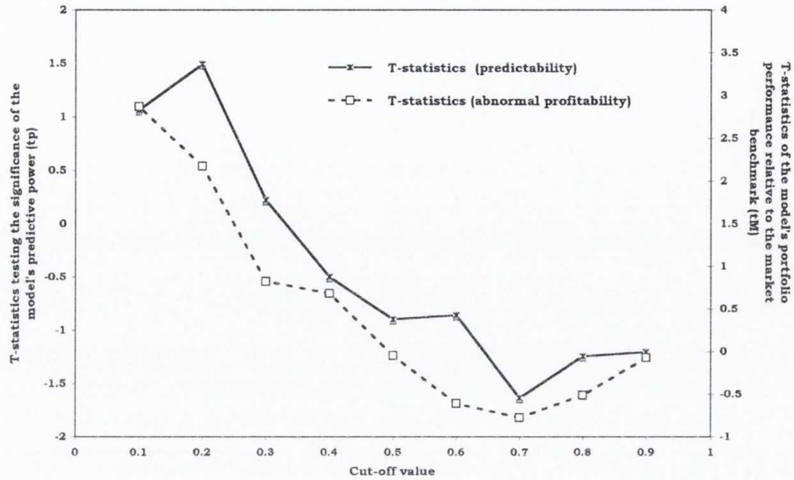
In the UK context, average portfolio returns seem to be strongly linked with the average predictive ability exhibited by the models. As seen in chapter 6, the logit model showed a poor and unstable predictive performance for higher cut-off values whereas a more stable and higher predictive ability was achieved at low cut-off values. Similarly, as shown in Table 7.1, the model generates a negative average performance for high cut-off values whereas it provides a long-run positive abnormal profitability for cut-off values lower than 0.4. However, high yearly predictions do not seem to be correlated with high yearly portfolio performance. The result implies that the profitability underlying takeover prediction models is less triggered by the bid premium or a takeover announcement run-ups but than by good performing aspects related to takeover targets including takeover vulnerability.

Interestingly, in the US context, the cut-off values maximizing the predictive ability are the ones that perform worse in the long-run. This weak relationship between predictability and portfolio performance may suggest that the US market is more efficient in anticipating takeover vulnerability and incorporating it into a firm's valuation.

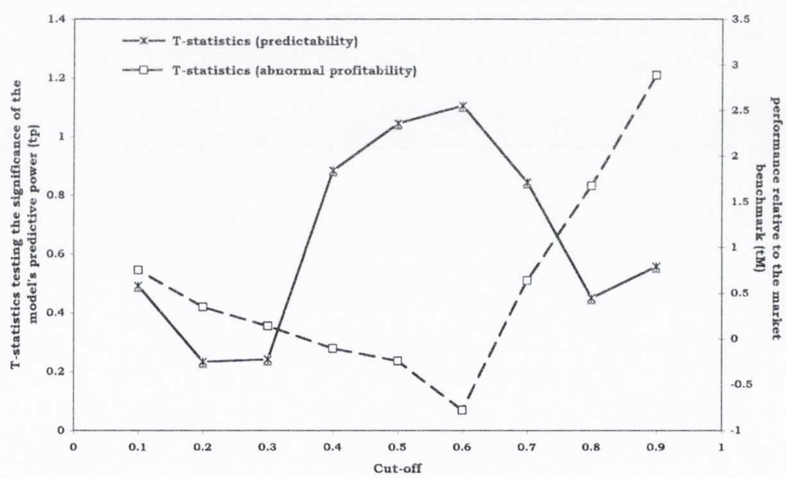
7.5.2 Artificial Neural Networks

This section compares the predictive power of the ANN-based takeover prediction model and their ability to generate abnormal returns. Figure 7.2 shows, for each considered cut-off value, the significance of the model's average predictability and the significance of the long-run average performance relative to the market benchmark for both the UK (7.2a) and the US (7.2b).

In the UK, when examining the hypothesis linking predictive ability and portfolio performance, average predictability appears to drive a portion of the average portfolio performance. However, the yearly predictive ability is generally not an accurate predictor of the yearly generated profits, as shown by the high portfolio performances in 1999 and



(a)



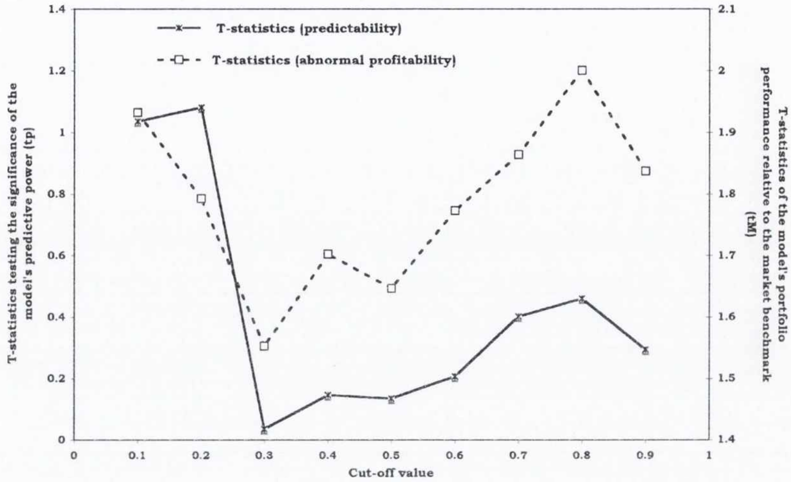
(b)

Figure 7.1: *The relationship between the significances of predictability relative to random selection and profitability relative to the market index benchmark using an logistic takeover prediction model for both the UK (subfigure 7.1a) and the US (subfigure 7.1b) during the period 1999-2008.*

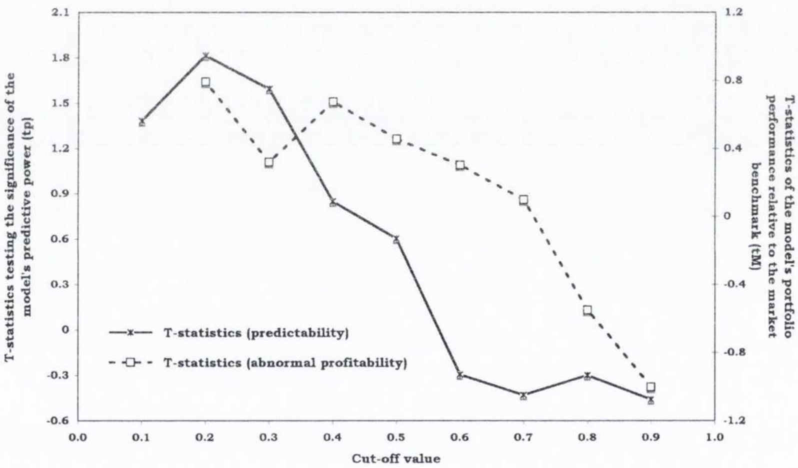
2007, two years where the model achieves a low predictive accuracy compared to random selection (reported on Table 6.8). Therefore, although the relationship holds when considering average performance, the results do not seem to be verified when considering the yearly performances. This result is in agreement with the hypothesis that takeover prediction models are potentially able to generate abnormal returns by selecting firms having the same attractive financial profiles as the one encountered in target firms (Wansley et al., 1983). As suggested by Brar et al. (2009), part of the predicted firm's attractive profile could be explained by stock market run-ups driven by rumors of takeover. In addition, more in the view of Cremers et al. (2009), the results further show that ANN-based takeover prediction models may be a more suitable method to measure takeover vulnerability in the UK relative to logistic-based models.

In the US context, Figure 7.2b suggests a relatively stronger relationship between the model's average predictive ability and the risk-adjusted portfolio performance. However, similar to the UK results, the relationship does not seems to be valid for every year as observed in the years 1999, 2002 and 2003 (2000) where the predicted portfolio achieves a positive (negative) PRC while earning negative (positive) abnormal returns. Therefore, in the US, the relationship between predictability and the predicted portfolios' performance seems to exist when considering average performances over the selected ten-year period.

Of greater interest, the significant predictive power achieved in the US is not translated into the possibility of earning significant long-term abnormal returns. Several reasons could explain this result. First, the US market being more active market than in the UK, it is possible that the potential outperformance of the model's predicted firms are anticipated with a greater long-run accuracy in the US. The latter point therefore implies that, in the US, the model is not able to "beat" the market's expectations sufficiently in advance. A second point could be that US target firms' general characteristics are not well captured by the present model. As reported by Ambrose and Megginson (1992), Espahbodi and Espahbodi (2003) and Walter (1994), several non-financial characteristics are likely to influence the selection of US target firms such as the importance of anti-takeover defenses such as blank-check preferred stocks, the different anti-takeover tax laws existing among different states, and the tax savings incentives respectively. Finally, it is possible that the common target characteristics are different in the two selected economies resulting in a model capturing more profitable financial profiles in the UK context.



(a)



(b)

Figure 7.2: *The relationship between the significances of predictability relative to random selection and profitability relative to the market index benchmark using an ANN takeover prediction model for both the UK (subfigure 7.2a) and the US (subfigure 7.2b) during the period 1999-2008.*

7.6 Optimal conditions to use takeover prediction models as an investment strategy

The market index benchmark approach previously showed that, for lower cut-off values (and sometimes for higher cut-off values), the models could potentially generate positive long-term abnormal return. As we have shown in this section, the use of a more accurate benchmark accounting for common market factors such as the control firm portfolio had a significant impact on the conclusions regarding the profitability of the logit-based takeover predictive model. The result therefore suggests that the latter selects takeover profiles that are easily captured by common profitability factors. However, in the case of the ANN-based model, the control firm portfolio approach only intensifies the conclusions established with the market benchmark approach. When applied to the UK, the ANN-model seems to capture non-trivial takeover characteristics that do not seem to be incorporated in the firm's price.

The UK context seems to be a more suitable context to use takeover prediction models as an investment strategy. This evidence is in agreement with Ouzounis et al. (2008) where ANN-based takeover prediction model strategies earn significant abnormal return over between a 12-month to a 21-month buy-and-hold period.

7.7 Summary

This chapter presented the long-run portfolio performance of takeover prediction models using an equally-weighted buy-and-hold strategy consisting of investing in portfolios built on the yearly predicted firms over the period 1999-2008.

First using a market index benchmark, for low cut-off values, takeover prediction models seems to provide higher returns in the UK than in the US. Higher cut-off values seem to generate a highly volatile investment. The logistic regression results shows a good picture of the level of risk underlying a high cut-off value choice. In the UK, a 0.9 cut-off value, despite the substantial gains in years 2000 and 2007, generates average losses on the long-run whereas, in the US, given the substantial performance in 1999, the portfolio offers a substantial abnormal return over the ten-year period. Overall, except for the UK-based ANN model, a higher cut-off value seems to generate a more risky investment portfolio. Our results therefore seem to relativize the results of Cremers et al. (2009), given that large portfolios (as captured by lower cut-off values) seem to provide long-run abnormal returns, however a portfolio built with firms with the highest takeover vulnerability does not seem to perform as well. The result suggests that market makers may incorporate takeover vulnerability in firms showing the highest takeover likelihood.

When using a control firm portfolios as a benchmark, we find that, whether using a logit or an ANN model, takeover prediction models do not seem to be an appropriate tool to generate long-term returns in the US. In the UK-based logit model, the generated returns seem to be explained by the common market factors captured by control firms. However, the UK-based ANN model seems to be able to generate stable long-term returns which seem to be relatively unaffected by common market factors. Overall, the UK context seems to be a more suitable context for using takeover prediction models as an investment tool and Artificial Neural Network seems to be the optimal specification to capture non-trivial target financial characteristics.

Finally, when comparing the portfolio performance with the prediction results shown in chapter 6, the predictive ability of the models seems to be weakly correlated with the portfolio performance. As suggested by Wansley et al. (1983), the predicted portfolios' returns are driven by the good performing profile of firms having similar characteristics to takeover targets. Another explanation is that, as more generally suggested by Cremers et al. (2009), firms with higher takeover vulnerability outperform firms less likely to be taken-over.

Chapter 8

Summary and conclusion

8.1 Discussion of findings

Given a lack of evidence on the impact of time on M&A forecasting, this dissertation has investigated the time-varying features of takeover prediction models and has contributed to the present academic literature by providing:

1. an extensive database containing the accounting financial information of all public domestic M&A deals during the period 1998-2008 in both the UK and the US (Chapter 4 – 5).
2. insight into the influence of the selected economy and the chosen specification on the models' general characteristics (Chapters 6 – 7).
3. a analysis of the time robustness of financial variables in explaining takeover attempts (Chapter 6).
4. a description of the dynamic characterizing a takeover prediction model's yearly predictive power (Chapter 6).
5. evidence on the relative suitability of takeover prediction models to build realistic portfolios generating long-term abnormal returns (Chapter 7).
6. an examination of the relationship between predictability and profitability allowing to unfold the underlying sources of gain in relation to an investment strategy based on takeover predictions (Chapter 7).

The models were estimated using a one-year rolling estimation window during the period 1998-2007. These estimations were used to calculate ten yearly out-of-sample forecasts allowing one to examine the dynamic of the models' predictive power as well as their ability to persistently outperform market expectations. In order to test the influence of the user's model-choice, the study considered both Logistic regression and Artificial Neural Networks in the models' specification. Finally, data from both the UK and the USA were examined to investigate the economic-specific nature of the models' performance.

The findings of this study are listed in the following six paragraphs which consecutively provide detail on the contributions enumerated above.

M&A deals' database in the UK and the US

As a general feature, the databases encountered in the takeover prediction literature have used a large estimation samples in order to increase the sample target proportion and a one-year holdout sample in order to test the model's ex-ante predictive ability.

In this thesis, data on M&A deals and firm's accounting financial data were collected for the period 1997-2007 in both the UK and the US. This database constitutes the largest database in the UK context and is comparable to recent databases created in the US for takeover prediction. Cremers et al. (2009) use a larger database in the US context to examine the impact of ex-ante takeover probabilities in the cross-section of returns, however, they do not provide details on either the classificatory or the predictive ability of the estimated takeover prediction models and, for that reason, I do not include their work within the takeover prediction literature.

Influence of country and model choice

A considerable contribution of this thesis is the possibility of exploring several directions of potential methodological instabilities. From one side, the influence of the country-choice on the reported takeover characteristics as well as on the models' performances is examined by considering data from both the UK and the US. By considering two culturally and structurally similar economies, the influence of institutional factors is minimized. In addition, these two economies have been most frequently reported in the literature as they are among the countries exhibiting the highest takeover activity. Although the literature acknowledges the existence of cross-country variations, existing studies are generally based on one single economy data. This thesis provides the first study attempting to measure differences in takeover prediction model's performances when applying the same methodology to two different economies.

Furthermore, two methodologies have been selected to estimate the models: the Logistic Regression and Artificial Neural Networks. Several recent studies such as Cheh and Weinberg (1999) and Ouzounis et al. (2008) have compared the performance between parametric and non-parametric techniques. Combined with the cross-country analysis, given that the relationship between the explanatory variables and takeover likelihood may be context-dependent, this thesis examines whether the predictive power of the considered techniques depends on the takeover context in which they are applied.

Time robustness of financial variables in explaining takeover activity

The disagreement within the extant literature as to what are the variables explaining takeover activity shows that an analysis based on single cross-sectional estimations might not be a consistent method for testing the considered hypotheses. Harris et al. (1982) and Powell (1997) provide supporting evidence showing that, for most of the variables employed, both sign and significance are not consistent between two consecutive periods.

Accounting for these two analyses independently and using a rolling window estimation technique, this thesis extends the work of these authors to a ten-year period thus providing a more suitable framework to describe the robustness of the estimated coefficients over time.

Finally, unique to the literature, this study integrates both viewpoints in order to select the variables that show both frequent explanatory power and a consistent relationship with takeover likelihood. In the UK, these variables were: One year sales growth (-), Total Investment return (-), Log[Total assets] (+). In the USA, the selected variables were: Dividend Payout (-), Long-Term debt over Total Capital (+), Total asset turnover (+). In the UK, takeovers thus appear to involve larger companies, with the lower growth and poor market performance prior to acquisition therefore consistent with the inefficient management and the size hypothesis. As a stark contrast, in the US, target firms appear to be efficient and highly productive firms as they pay lower dividends, while being highly leveraged and achieving a higher total asset turnover relative to their industrial peers. In the US, the target profile appears consistent with the activity and the dividend-payout hypothesis.

Dynamic of the models' predictability

In the UK, the Logistic regression exhibits a better predictive performance for the lowest cut-off values whereas the ANN-based model performs with a stable average predictive accuracy over the cut-off interval as the model predicts better than chance selection for all cut-offs. However, none of the models' predictions seems to be significant over the considered period.

In the US, the Logistic regression model shows both a low explanatory power for most of the years which also translates into a poor predictive power over time. On the contrary, the ANN-model shows a high predictive ability and, in the 0.2-0.1 cut-off range, the model's predictability is significantly different from a chance selection during the selected period. The evidence therefore suggests that ANN offer a more suitable framework to capture takeover activity in the US on the basis of accounting ratios.

Although ANN-models seem to achieve high predictive accuracy in both considered contexts, when comparing the predictability rate relative to the logistic regression, the evidence is not conclusive. Using ANN to specify takeover models denotes a clear superiority in the US context, but the results seem to be mixed for the UK. To some extent, this could be due to the inappropriateness of the optimization process in the UK context and to the greater risk of overfitting a validation sample when using smaller sample sizes. This point will be further analyzed in Section 8.3.

The suitability of takeover prediction models as investment strategies

Prior literature has drawn conclusions on takeover prediction model's profitability based on a single set of forecasted firms. The two recent exceptions are the works of Brar et al. (2009) and Cremers et al. (2009). The former, using a static specification, rebalances the predicted portfolios by monthly updating the market variables during the investment period 1995-2003 whereas the latter, similar to the methodology employed in this thesis, uses rolling window estimations to calculate out-of sample portfolios.

This thesis provides an analysis on the yearly portfolio performance generated by takeover predictions and provides evidence that, in most cases, portfolio returns are being driven by common market factors. Unique to the takeover prediction literature, the present study employs a single control firm approach in order to capture these market factors as recommended by Barber and Lyon (1997). Although Powell (2001, 2004); Brar et al. (2009) refer to the work of Barber and Lyon (1997) when building their benchmark, they use the portfolio benchmark approach which is shown to provide a misspecified measure of abnormal profitability. The results show that the control firm approach seems to be well suited to capture abnormal profitability in the takeover prediction context.

The findings suggest that, only within the UK context, ANN models seem to have a strong potential of providing a solid and robust basis for a financial investment strategy generating substantial long-run abnormal returns. In addition, the choice of a benchmark should be carefully examined as the results seem to be very sensitive to such a choice.

The relationship between predictability and profitability

The analysis of the relationship between average predictability and average profitability over the cut-off interval provided several interesting findings. As a first result, the UK presents a strong relationship between average predictability and average profitability during the period 1999-2008. Although this relationship does not hold when considering the yearly predictions, on average, long-term predictive power seems to be an accurate measure of profitability potential in this context. As suggested by the superior portfolio performance using ANN models, these characteristics need to be non-trivial in order to ensure that the selected firms have not incorporated their takeover vulnerability in their stock price. As a second point, in the US context, only in the case of ANN-based models (and probably due to the low explanatory power of the Logistic regression), a relationship was found between long-term average predictability and long-term average profitability. As in the UK, this relationship does not hold when considering yearly variations.

From one side, given the weak relationship between yearly predictability and profitability in both economies, the results show that, as suggested by Cremers et al. (2009), the portfolio gains do not seem to be driven by the model's ability to predict targets accurately. On another side, the strong relationship between long-term predictive power and profitability suggests that average long-term predictability is an accurate proxy of takeover vulnerability. These results are consistent with Wansley et al. (1983)'s contention that a model's profitable potential depends on its ability to capture the non-trivial attractive profile of prior target firms.

8.2 Implications

As a first implication, the findings, previously shown in the estimation section, have confirmed the literature's belief that takeover characteristics, as captured by parametric takeover prediction models, are generally inconsistent both over time and across economies. Consistent with Powell (1997)'s conclusions, this thesis provides evidence that a sample constructed by pooling M&A data across several years is likely to generate misleading results.

Regarding the second point, by combining the analytical frameworks of Harris et al. (1982) and Powell (1997), it was possible to select some distinctive variables with both high discriminatory power and significant sign stability. Although dynamically robust, the selected financial variables vary across different economies therefore suggesting that takeover characteristics should be analyzed in their specific context and not as general takeover characteristics. In the future, the literature should make a greater effort in selecting, for each economy, the variables efficiently proxying the several motivational hypotheses for M&As. Of greater interest, when only persistently significant and consistent characteristics are considered, the variables appear to give a clear picture of the general characteristics of takeover targets in both the UK and the USA in relation to some of the M&A hypotheses described in Chapter 2. Such a method appears to provide a solid basis for detecting robust takeover characteristics in an extended time period.

Thirdly, as evidenced in the literature, both of the takeover prediction models here considered seem to achieve unstable performances over time. As reported results are based on point forecast estimations, the existence of a recurrent disagreement on the predictive performance of takeover prediction models is therefore not surprising. The present thesis underlines the need to consider a method such as the rolling estimation forecast technique employed in this study in order to measure more accurately a model's ability to predict in the future. It is hoped that such an implementation will bring more consistency not only to the takeover prediction literature but to the binary prediction literature as a whole.

Fourthly, from an investor perspective, this thesis stresses the importance of repeatedly calculating the portfolio performance over time in order to obtain a better approximation of the long-run profitability of the model's predictions. Although some given years can yield significant abnormal returns, in most cases, the frequent losses generally nullify the few significant gains therefore achieving an insignificant and, frequently, negative average long-term abnormal profitability. The results show that, within the UK context only, an Artificial Neural Networks model provides the basis of significantly profitable and dynamically stable investment. In addition, the results are verified for all cut-off values in the range 0.2-0.9.

Finally, in relation to Cremers et al. (2009)'s work, the results suggest that takeover vulnerability in the US seems to be better captured using Artificial Neural Networks. Therefore, an ANN framework would appear to be better suited to capture takeover vulnerability and consequently to explain the cross-section of returns in the US context. As a main difference, the results here presented suggest that takeover prediction models are not a suitable as an investment tool. The disagreement may be due to different reasons. First, the inclusion of non-financial variables into the model's specification may be crucial to capture better performing firms. Secondly, the use of a different portfolio benchmarks may also influence the final result. In this thesis, the control firm portfolio seems to accurately capture the long-term profitability of the predicted portfolios. Additionally, this study measures yearly abnormal profitability whereas Cremers et al. (2009) calculate the excess return as measured by the intercept of a Fama and French (1992) and Carhart (1997) four factor model regressed over the period 1991-2004. As a last possible factor, the use of single control firm-matched portfolios as benchmark proved to be an accurate reference to calculate the abnormal profitability generated by the predicted samples. This method has the advantage of yearly updating the different size and market-to-book characteristics of the predicted portfolios. As mentioned in Barber and Lyon (1997), the main disadvantage of a Fama and French (1992) and Carhart (1997) four factor model is that it considers the portfolio characteristics as stationary over the considered period. A superior portfolio benchmark might therefore explain the less optimistic results achieved in the US context.

8.3 Limitations

Our study suffers from a number of possible limitations that should be considered when analyzing the reported results. These limitations are both the fruit of my analysis, the comments received during conference presentation, as well as the review provided by the journals where my work was submitted.

Model's specification choice

The present study considers an estimation window limited to one calendar year. A potential limitation arises from two main points. First, the year prior to the acquisition attempt might not be the best choice for predicting takeover activity. Belkaoui (1978) documents that the third year prior to the acquisition provides the best both classificatory and predictive accuracy. The explanation seems to be that, as takeover decisions are made several years prior to the announcement, the information prior to the bid might not be as relevant. Similar studies have been conducted in the bankruptcy literature. Recently, Pompe and Bilderbeek (2005) suggested that studies should not use models using prior year information as they generate a lower predictive accuracy. [1] This is a point that should be analyzed by future research and no solid evidence exists on the subject. As the takeover literature generally uses one-year prior information, this was deemed the best choice for our models.

As a second point, one calendar year might be considered as providing insufficient information on the companies involved in takeover activity. Although this can be true for some years such as 2001 and 2002 for both the UK and the USA, there are studies having used similar (and even smaller) proportions such as Harris et al. (1982) who uses to complete data samples containing 61 and 45 firms respectively over a total of 1200 firms. In addition, the advantages of using one calendar year are numerous. First, pooling across different time periods is avoided which is likely to generate better specified target samples. Secondly, using firms' data from different periods generates distributional heterogeneity and is likely to result in a overstatement of the model's true classificatory ability. Finally, the technique is structurally consistent as the one-year calendar used to build the estimation sample matches the one-year time frame usually selected to build the holdout sample.

Neural net's optimization method

This study assumes an important simplification during the net's optimization procedure related to the absence of cross-validation when specifying the architecture of the Neural Network. In the USA context, the ANN-model 's significant predictive accuracy suggests that little prediction power is lost due to the overfitting of the validation sample. However, the low performance in the UK for some given years (e.g. 2006 and 2008) may suggest possible improvements of the model's predictive ability by the use of a cross-validation technique. *A posteriori* however, this possible limitation is weakened given the significant abnormal profitability generated by the ANN-model suggesting its accuracy to capture takeover vulnerability.

[1] The authors, however, acknowledge that their result contradicts most findings in the literature and they attribute such disagreement to the inclusion of medium and small sized firms.

Firm's illiquidity

By considering other firms than the ones listed in the major Stock Exchanges, there is a risk that, given the potential illiquidity of some firms predicted to be targets, a large bid-ask spread would not allow an investor to take a position at exactly the price assumed in the strategy. More importantly, the investor might not be able to take any position at all as for some of the firms there would be no shares being sold. Although this might be possible for some firms, it is unlikely that the companies included in our sample are characterized by such levels of illiquidity given the number of variables that are reported. In relation to the first point, a one-year buy-and-hold strategy is considered and therefore the bid-ask spread should not have an impact unlike investment strategies involving transactions at higher frequencies. [2] In addition, by selecting firms having a minimum of trading activity during the year prior to acquisition, we ensure that the risk of complete illiquidity is minimized.

Control firm portfolio benchmark

While the results reported in Barber and Lyon (1997) recommend the use of a control firm portfolio, the authors acknowledge in their conclusion that:

> Matching on firm size and book-to-market ratio works well in random samples and samples with size-based or book-to-market based sampling biases. However, as future research in financial economics discovers additional variables that explain the cross-sectional variation in common stock returns, it will also be important to consider these additional variables when matching sample firms to control firms.

Following the work of Carhart (1997), the literature has provided increasing evidence that price momentum is a factor having a significant impact in the cross-section of returns. One of the limitations of the control firm portfolio is that it does not account for this

[2] See for example Jegadeesh and Titman (1993) and Bettman et al. (2009) for momentum based strategies accounting for the size of the bid-ask spread in daily transactions.

factor. However, implementing the incorporation of price momentum into the control firm portfolio requires, first, a change the window length of the size and book-to-market filters and, secondly, a study confirming that the resulting control firm benchmark indeed provides well-specified t-statistics in relation to the measurement of abnormal returns. In addition to the complex computational task of implementing such a procedure, the results of the control firm portfolio show that they are able to capture the common market factors present in the yearly predicted portfolios. However, the possibility that price momentum drives a fraction of the abnormal returns achieved by the ANN-model in the UK context cannot be excluded.

8.4 Future areas of research

This work can be extended to several areas for future research. I here suggest some ideas that could be used to provide stronger evidence for the herein reported results as well as to improve the underlying specification of takeover prediction models.

As a first point, given the evidence of predictive instability, an effort should be made in building takeover prediction models achieving a more stable predictive performance over time. The bankruptcy prediction literature seems to be more advanced in model development and several models have still not been applied to takeover prediction. As an example, Shumway (2001)'s hazard model offers an exciting model incorporating the time-dynamic of accountability ratios. In addition there are several models not yet tested in the takeover prediction literature which have demonstrated enhanced classificatory and predictive performances within the accounting and bankruptcy prediction literature. As reported in Barniv and McDonald (1999), the modeling framework of exponential generalized beta of the second kind shows a significant improvement in four key performing areas relative to more traditional techniques such as logit and probit models. Similarly, rolling-logit models (see e.g. Lin, 2007, for a recent application) could also provide a method of increasing a model's predictive robustness by including a firm's vulnerability to takeover during prior periods into the model's specification.

A second improvement can be achieved in relation to the reliability of the reported results. The rolling estimation technique here presented and also used in Cremers et al. (2009) represents a useful method to analyze the underlying variability of a selected model. In addition, this technique may allow future research to investigate the specific factors having a strong impact on the model's prediction and to build new methods attenuating these effects. Although, as mentioned by Mensah (1984) and Pompe and Bilderbeek (2005), business cycles can have a strong effect on the model's predictive ability, this does not seem to be the case in takeover prediction. Overall, these techniques should be used both to improve the quality of the reported results and to identify and control for the factors that have a strong influence on the model's stability.

Finally, a greater effort needs to be made in the selection of the benchmark used to measure abnormal profitability. As shown in Barber and Lyon (1997), the Fama and French (1992) three-factor benchmark is well-suited for studies cumulating returns across long investment periods such as Cremers et al. (2009), but it is not applicable to buy-and-hold portfolios and generates negatively biased t-statistics in more realistic investment periods (i.e. inferior to three years). Although Barber and Lyon (1997) recommend the use of control firms to measure abnormal profitability, their results have generally been misrepresented within the takeover prediction literature. As an example, although reference portfolios based on size and book-to-market ratio are shown to generate negatively biased test-statistics, they were persistently used within the takeover prediction literature (see e.g. Powell, 2001, 2004; Brar et al., 2009). This thesis provides evidence that a control firm portfolio is, on average, an appropriate method to capture general market factors. Future research in takeover prediction should consider new different factors affecting the cross-section of returns such as momentum to match the control firms when assessing a predicted portfolio's abnormal profitability.

Bibliography

Agrawal, A. and J. F. Jaffe (2003). Do takeover targets underperform? evidence from operating and stock returns. *The Journal of Financial and Quantitative Analysis 38*, 721–746.

Alcalde, N. and M. Espitia (2003). The characteristics of takeover targets: The spanish experience 1991-1997. *Journal of Management and Governance 7*, 1–26.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance 23*, 589–609.

Altman, E. I. (1969). Bankrupt firm's equity securities as an investment alternative. *Financial Analyst Journal 25*(4), 129–133.

Ambrose, B. W. and W. L. Megginson (1992). The role of asset structure, ownership structure, and takeover defenses in determining acquisition likelihood. *The Journal of Financial and Quantitative Analysis 27*(4), 575–589.

Andrade, G., M. Mitchell, and E. Stafford (2001). New evidence and perspectives on mergers. *Journal of Economic Perspectives 15*(2), 103–120.

Arnull-Almond, B. (2007). *The Prediction of Australian Takeover Targets: A Binomial and Multinomial Logit Analysis*. Ph. D. thesis, University of Sydney.

Arzac, E. R. (2008). *Valuation for Mergers, Buyouts and Restructuring*. Chichester: John Wiley and Sons Inc.

Balcaen, S. and H. Ooghe (2006). 35 years of studies on business failure: an overview of the classic statistical methodologies and their related problems. *The British Accounting Review 38*, 63–93.

Barai, P. and P. Mohanty (2009). Predicting acquisitions in india. Working Paper.

Barber, B. M. and J. D. Lyon (1997). Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. *Journal of Financial Economics 43*, 341- 372.

Barnes, P. (1982). Methodological implications of non-normally distributed financial ratios. *Journal of Business Finance and Accounting 9*(1), 51–62.

Barnes, P. (1990). The prediction of takeover targets in the uk by means of multiple discriminant analysis. *Journal of Business Finance and Accounting 17*, 73–84.

Barnes, P. (1998). Can takeover targets be identified by statistical techniques?: Some uk evidence. *The Statistician 47*(4), 573–591.

Barnes, P. (1999). Predicting uk takeover targets: Some methodological issues and empirical study. *Review of Quantitative Finance and Accounting 12*, 283–301.

Barniv, R. and J. B. McDonald (1999). Review of categorical models for classification issues in accounting and finance. *Review of Quantitative Finance and Accounting 13*, 39–62.

Bartley, J. W. and C. M. Boardman (1990). The relevance of inflation adjusted accounting data to the prediction of corporate takeovers. *Journal of Business Finance and Accounting 17*, 53–72.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research 4*, 71–111.

Belkaoui, A. (1978). Financial ratios as predictors of canadian takeovers. *Journal of Business Finance and Accounting 5*, 93–108.

Bettman, J. L., T. R. B. Maher, and S. J. Sault (2009). Momentum profits in the australian equity market: A matched firm approach. *Pacific-Basin Finance Journal 17*, 565–579.

Bilderbeek, J. (1979). An empirical study of the predictive ability of financial ratios in the netherlands. *Zeitschrift Fr Betriebswirtschaft 5*, 388–407.

Bishop, C. M. (1995). *Neural Networks for Pattern Recognition*. New York, US: Oxford University Press.

Brar, G., D. Giamouridis, and M. Liodakis (2009). Predicting european takeover targets. *European Financial Management 15*(2), 430–450.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance 52*(1), 57– 82.

Chan, P. T., F. Moshirian, D. Ng, and E. Wu (2007). The underperformance of the growth enterprise market in hong kong. *Research in International Business and Finance 21*, 428–446.

Chapman, D. R. and C. W. Junor (1987). Inflation, firm control-type and vulnerability to takeover. *Oxford Economic Papers, New Series 39*(3), 500–515.

Cheh, J. J. and R. S. Weinberg (1999). An application of an artificial neural network investment system to predict takeover targets. *The Journal of Applied Business Research 15*(4), 33–45.

Coats, P. K. and L. F. Fant (1993). Recognizing financial distress patterns using a neural network tool. *Financial Mangement 22*(3), 142–155.

Cosh, A. and P. Guest (2001). The long-run performance of hostile takeovers: Uk evidence. ESRC, Center of Business Research, University of Cambridge, Working paper.

Cremers, K. J. M., V. B. Nair, and K. John (2009). Takeovers and the cross-section of returns. *The Review of Financial Studies 22*(4), 1409– 1445.

Cudd, M. and R. Duggal (2000). Industry distributional characteristics of financial ratios: An acquisition theory application. *The Financial Review 35*(1), 105–119.

Dencic-Mihajov, K. and O. Radovic (2006). Problems ate predicting target firms at the undeveloped capital markets. *Facta Universitatis, Series: Economics and Organization 3*, 59–68.

Dietrich, K. J. and E. Sorensen (1984). An application of logit analysis to prediction of merger targets. *Journal of Business Research 12*, 393–402.

Espahbodi, H. and P. Espahbodi (2003). Binary choices and corporate takeover. *Journal of Banking and Finance 27*, 549–574.

Fama, E. F. and K. R. French (1992). The cross-section of expected stock returns. *The Journal of Finance 47*(2), 427– 465.

Fildes, R. and S. Makridakis (1995). The impact of empirical accuracy studies on time series analysis and forecasting. *International Statistical Review 63*(3), 289–308.

Firth, M. (1976). *Share Prices and Mergers: A Study of Stock Market Efficiency*. Westmead, Farnborough, Hants, England: Saxon House, D .C. Health Ltd.

Fogelberg, G., C. R. Laurent, and D. G. McCorkindale (1978). The usefulness of published financial data for assessing takeover vulnerability of companies in new zealand. *New Zealand Economic Papers 12*, 184–206.

Frydman, H., E. I. Altman, and D.-L. Kao (1985). Introducing recursive partitioning for financial classification: The case of financial distress. *The Journal of Finance 40*(1), 269–291.

Gaughan, P. A. (2005). *What Can Go Wrong and How to Prevent It*. Hoboken, New Jersey, US: John Wiley and Sons, Inc.

Golbe, D. L. and L. J. White (1987). *A Time-Series Analysis of Mergers and Acquisitions in the U.S. Economy* (A. Auerbach ed.). Chicago: University of Chicago Press.

Gole, W. J. and J. M. Morris (2007). *Mergers and Acquisitions: Business Strategies for Accountants*. Chichester: John Wiley and Sons Inc.

Gort, M. (1969). An economic disturbance theory of mergers. *The Quarterly Journal of Economics 83*(4), 624–642.

Gu, Z. and S. J. Yuh (2001). A logistic analysis of the financial features of takeovers in the gaming industry. *International Journal of Hospitality and Tourism Administration 2*, 1–20.

Harris, R. S., J. F. Stewart, D. K. Guilkey, and W. T. Carleton (1982). Characteristics of acquired firms: Fixed and random coefficients probit analyses. *Southern Economic Journal 49*(1), 164–184.

Hasbrouck, J. (1985). The characteristics of takeover targets: q and other measures. *Journal of Banking and Finance 9*, 351–362.

Hopwood, W., J. C. McKeown, and J. F. Mutchler (1994). A reexamination of auditor versus model accuracy within the context of the going-concern opinion decision. *Contemporary Accounting Research 10*(2), 409–431.

Hornik, K., M. Stinchcombe, and H. White (1989). Multilayer feedforward networks are universal approximators. *Neural Networks 2*(5), 359–366.

Hu, M. Y., G. Zhang, C. X. Jiang, and E. B. Patuwo (1999). A cross-validation analysis of neural networks out-of-sample performance in exchange rate forecasting. *Decision Sciences 30*(1), 197–216.

Jegadeesh, N. and S. Titman (1993). Returns to buying winners and selling loosers: Implications for stock market efficiency. *The Journal of Finance 48*, 65–91.

Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *American Economic Review 76*, 323–329.

Jensen, M. C. (1988). Takeovers: Their causes and consequences. *Journal of Economic Perspectives 2*(1), 21–48.

Jensen, M. C. and R. S. Ruback (1983). The market for corporate control: The scientific evidence. *Journal of Financial Economics 11*, 5–50.

Jovanovic, B. and P. L. Rousseau (2002). The q-theory of mergers. *American Economic Review 92*(2), 198–204.

Kim, W. G. and A. Arbel (1998). Predicting merger targets of hospitality firms (a logit model). *Hospitality Management 17*, 303–318.

Kuehn, D. (1975). *Takeover and the Theory of the Firm: An Empirical Analysis for the United Kingdom 1957-1969.* London and Basingstoke: The Macmillan Press Ltd.

Larsson, R., K. R. Brousseau, M. J. Driver, and P. L. Sweet (2004). *The Secrets of Merger and Acquisition Success: A Co-competence and Motivational Approach to Synergy Realization* (Pablo, Amy. L. and Mansour Javidan ed.). MA: Blackwell Publishing Ltd.

Levine, P. and S. Aaronovitch (1981). Characteristics of firms and theories of merger activity. *The Journal of Industrial Economics 30*, 149–172.

Lewellen, W. G. (1971). A pure financial rationale for the conglomerate merger. *The Journal of Finance* 26(2), 521–537.

Lin, C.-L. (2007). *Validation of a Rolling-Logit Model to Predict TSE Corporate Bankruptcy.* Ph. D. thesis, Lynn University.

Loughran, T. and J. R. Ritter (1995). The new issues puzzle. *The Journal of Finance 50,* 23–51.

Maher, J. J. and T. K. Sen (1997). Predicting bond rating using neural networks: A comparison with logistic regression. *Intelligent Systems in Accounting, Finance and Management 6,* 59–72.

Manne, H. G. (1965). Mergers and the market for corporate control. *Journal of Political Economy 73,* 110–120.

Marris, R. (1964). *The Economic Theory of 'Managerial' Capitalism.* London: McMillan and Company Ltd.

McCauley, J. L. (2009). *Dynamics of markets: The New Financial Economics* (Second Ed. ed.). The Edinburgh Building, Cambridge CB2 2RU, UK: Cambridge University Press.

Meador, A. L., P. H. Church, and G. L. Rayburn (1996). Development of prediction models for horizontal and vertical mergers. *Journal of Financial and Strategic Decisions* 9(1), 11–23.

Mensah, Y. M. (1984). An examination of the stationarity of multivariate bankruptcy prediction models: A methodological study. *Journal of Accounting Research* 22(1), 380–395.

Misra, D. S. (2009). Determinants of target firms in a takeover. *International Research Journal of Finance and Economics 29,* 172–178.

Mitchell, M. L. and J. H. Mulherin (1996). The impact of industry shocks on takeover and restructuring activity. *Journal of Financial Economics 41*(2), 193–229.

Modigliani, F. and M. Miller (1963). Corporate income taxes and the cost of capital: A correction. *American Economic Review 53,* 433–443.

Morck, R., A. Shleifer, and R. W. Vishny (1988). *Characteristic of Targets of Hostile and Friendly Takeovers* (A.J. Auerbach ed.). University of Chicago Press.

Morse, D. and W. Shaw (1988). Investing in bankrupt firms. *The Journal of Finance 43*(5), 1193–1206.

Ohlson, J. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research 18*, 109–131.

Ouzounis, G., C. Gaganis, and C. Zopounidis (2008). Prediction of acquisitions and portfolio return. Working paper.

Palepu, K. G. (1986). Predicting takeover targets: A methodological and empirical analysis. *Journal of Accounting and Economics 8*, 3–35.

Parker, D. B. (1985). Learning logic. Technical Report TR-47, MIT Center for Research in Computational Economics and Management Science, Cambridge MA.

Pasiouras, F., S. Tanna, and C. Zopounidis (2005). *Application of Quantitative Techniques for the Prediction of Bank Acquisition Targets.* World Scientific Publishing.

Platt, H. D. and M. D. Platt (1990). Development of a class of stable predictive variables: The case of bankruptcy prediction. *Journal of Business Finance and Accounting 17*, 31–51.

Platt, H. D. and M. D. Platt (2002). Predicting corporate financial distress: Reflections on choice-based sample bias. *Journal of Economics and Finance 26*(2), 184–199.

Pompe, P. P. M. and J. Bilderbeek (2005). Bankruptcy prediction: the influence of the year prior to failure selected for model building and the effects of a period of economic decline. *Intelligent Systems in Accounting, Finance, and Management 13*(2), 95–113.

Powell, R. G. (1997). Modelling takeover likelihood. *Journal of Business Finance and Accounting 24*, 1009–1030.

Powell, R. G. (2001). Takeover prediction and portfolio performance. *Journal of Business Finance and Accounting 28*, 993–1011.

Powell, R. G. (2004). Takeover prediction models and portfolio strategies: A multinomial approach. *Multinational Finance Journal 8*, 35–72.

Rege, U. P. (1984). Accounting ratios to locate takeover targets. *Journal of Business Finance and Accounting 11*, 301–311.

Roehner, B. M. (2002). *Patterns of Speculation: A Study in Observational Econophysics*. The Edinburgh Building, Cambridge CB2 2RU, UK: Cambridge University Press.

Roll, R. (1986). The hubris hypothesis of corporate takeovers. *The Journal of Business 59*(2), 197–216.

Rumelhart, D. E., G. E. Hinton, and R. J. Williams (1988). *Learning Internal Representations by Error Propagation* (Rumelhart, D. E. , McClelland J. L., and the PDP Resaerch Group ed.). MA: MIT Press.

Russell, S. and P. Norvig (2003). *Artificial Intelligence: a Modern Approach* (Second Edition ed.). Upper Saddle River, New Jersey 07458, US: Pearson Education, Inc.

Sarle, W. S. (1994, April). Neural networks and statistical models. Proceedings of the Nineteenth Annual SAS User Group International Confernece.

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *Journal of Business 74*(1), 101–124.

Simkowitz, M. A. and R. J. Monroe (1971). A discriminant function for conglomerate targets. *Southern Journal of Business 38*, 1–16.

Singh, A. (1971). *Take-overs: Their Relevance to the Stock Market and the Theory of the Firm*. University Press: Cambridge.

Siriopoulos, C., A. Georgopoulos, and A. Tsagkanos (2006). Does the 'market for corporate control' hypothesis explain takeover targets? *Applied Economics Letters 13*, 557–561.

Sorensen, D. E. (2000). Characteristics of merging firms. *Journal of Economics and Business 52*, 423–433.

Stevens, D. L. (1973). Financial characteristics of merged firms: A multivariate analysis. *Journal of Financial and Quantitative Analysis 8*, 149–158.

Stock, J. H. (2004). Structural stability and models of the business cycle. *De Economist 152*(2), 197–209.

Stone, M. (1974). Cross-validatory choice and assessment of statistical predictions. *Journal of the Royal Statistical Society 36*(2), 111–147.

Sung, T. K., N. Chang, and G. Lee (1999). Dynamics of modelling in data mining: Interpretive approach to bankruptcy prediction. *Journal of Management Information Systems 16*(1), 63–85.

Tashman, L. J. (2000). Out-of-sample tests of forecasting accuracy: An analysis and review. *International Journal of Forecasting 16*, 437–450.

Thomas, J. (2001). Identifying targets and acquirers in bank mergers. Master's thesis, East Carolina University.

Tortum, A., N. Yayla, C. Celik, and M. Godag (2007). The investigation of model selection criteria in artificial neural networks by the taguchi method. *Physica A 386*(1), 446–468.

Town, R. J. (1992). Merger waves and the structure of merger and acquisition time-series. *Journal of Applied Econometrics 7*, S83–S100.

Trautwein, F. (1990). Merger motives and merger prescriptions. *strategic Management Journal 11*(4), 283–295.

Truett, J., J. Cornfield, and W. Kannel (1967). A multivariate analysis of the risk of coronary heart disease in framingham. *Journal of Chronic Disease 20*(7), 511–524.

Tsagkanos, A., A. Georgopoulos, and C. Siriopoulos (2006). Predicting takeover targets: New evidence from a small open economy. *International Research Journal of Finance and Economics 4*, 183–194.

Walter, R. M. (1994). The usefulness of current cost information for identifying takeover targets and earning above-average stock returns. *Journal of Accounting, Auditing, and Finance 9*, 349–377.

Wansley, J. W., R. Roenfeldt, and P. Cooley (1983). Abnormal returns from merger profiles. *The Journal of Financial and Quantitative Analysis 18*(2), 149–162.

Weir, C. and D. Laing (2003). The selection of friendly take-over targets in the uk: Some empirical evidence. *Management Decisions 41*(6), 550–557.

Werbos, P. J. (1974). *Beyond Regression: New Tools for Prediction and Analysis in the Behavioral Sciences*. Ph. D. thesis, Harvard University, Boston, MA.

Wooldridge, J. M. (2002). *Econometric Analysis of Cross-Section and Panel Data*. Cambridge, Massachusetts, London, England: The MIT Press.

Zanakis, S. H. and C. Zopounidis (1997). Prediction of greek company takeovers via multivariate analysis of financial ratios. , *Journal of the Operational Research Society 48*, 678–687.

Zhang, G., M. Y. Hu, B. E. Patuwo, and D. C. Indro (1999). Artificial neural networks in bankruptcy prediction: General framework and cross-validation analysis. *European Journal of Operational Research 116*(1), 16–32.

Zhang, G., B. E. Patuwo, and M. Y. Hu (1998). Forecasting with artificial neural networks: The state of the art. *International Journal of Forecasting 14*(1), 35–62.

Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research 22*, 59–82.

Appendix A

Data characteristics

A.1 Correlation tables

Table A.1: *UK Correlation Matrix – Year: 1998*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	-0.12	-0.08	0.04	-0.22	0.13	0.02	-0.21	0.09	0.08	-0.21	0.06	-0.15	0.06	-0.02	0.07	-0.09	0.03	0.08	-0.02	0.01
CRAT		1.00	-0.06	-0.11	0.06	0.00	0.01	0.27	-0.07	-0.15	0.09	0.02	-0.18	-0.05	0.23	-0.04	-0.16	-0.08	-0.04	-0.15	-0.06
DPEA			1.00	0.13	0.06	-0.08	0.02	-0.02	-0.07	-0.07	-0.02	0.03	0.07	-0.05	0.22	0.17	0.10	0.00	-0.16	0.29	0.11
EBSE				1.00	0.06	0.00	0.01	-0.08	-0.01	0.01	0.05	0.01	0.10	0.07	0.08	0.26	0.11	0.22	0.01	0.08	0.04
FCFS					1.00	0.01	0.03	-0.01	-0.10	-0.08	0.03	-0.01	0.25	0.00	0.42	0.07	0.08	-0.01	0.07	0.03	0.00
GSOY						1.00	0.04	-0.04	0.01	0.00	0.00	-0.02	-0.01	0.03	-0.24	0.01	-0.04	-0.01	0.05	-0.01	-0.02
ICOV							1.00	-0.03	-0.01	-0.11	-0.01	0.04	-0.01	0.00	0.01	0.04	0.04	-0.03	0.04	-0.06	-0.02
IDHE								1.00	-0.17	-0.06	0.24	-0.01	0.05	-0.04	-0.04	-0.02	-0.25	-0.03	-0.03	-0.03	-0.05
ITUR									1.00	0.23	0.01	-0.02	-0.23	0.07	0.04	-0.02	0.04	0.11	-0.01	-0.01	-0.02
LDTC										1.00	-0.03	-0.01	-0.12	0.12	-0.02	-0.07	-0.07	0.20	-0.07	0.13	0.02
NSFA											1.00	0.01	-0.02	0.00	-0.01	0.03	0.32	0.00	0.06	-0.03	-0.05
NSWC												1.00	-0.04	-0.01	0.00	-0.01	0.06	0.05	0.00	-0.02	-0.01
OPMA													1.00	-0.06	0.14	0.05	-0.05	-0.02	0.06	0.04	-0.01
PTBR														1.00	-0.01	-0.08	0.01	0.56	0.07	0.03	0.02
PTER															1.00	0.11	-0.02	0.03	0.06	0.12	0.04
ROET																1.00	0.07	-0.06	0.13	0.12	0.02
TATU																	1.00	-0.02	0.08	-0.14	-0.02
TDCE																		1.00	-0.06	0.10	0.02
TIRE																			1.00	-0.02	0.04
LNTA																				1.00	0.45
SREV																					1.00

Table A.2: *UK Correlation Matrix – Year: 1999*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	-0.03	-0.02	0.04	-0.14	0.02	-0.02	-0.11	0.00	0.24	-0.05	0.10	-0.12	0.08	-0.05	-0.01	-0.03	0.05	0.02	-0.02	0.01
CRAT		1.00	-0.09	0.00	-0.03	0.04	0.06	0.23	-0.04	-0.10	0.06	0.01	-0.13	-0.03	-0.13	-0.02	-0.15	-0.02	0.04	-0.16	-0.08
DPEA			1.00	0.01	0.06	-0.13	0.03	-0.07	0.02	-0.02	-0.05	-0.02	0.11	-0.05	0.18	0.16	0.08	-0.04	-0.06	0.32	0.12
EBSE				1.00	0.02	0.02	-0.02	-0.04	0.00	0.01	-0.01	-0.01	0.02	0.42	0.03	0.53	0.04	0.72	0.01	0.11	0.04
FCFS					1.00	-0.02	0.04	0.06	-0.05	-0.16	0.01	-0.03	0.03	0.01	0.07	0.09	0.08	-0.02	0.04	0.03	-0.03
GSOY						1.00	0.00	0.05	0.04	0.07	0.09	0.02	-0.03	0.02	0.04	0.03	0.00	0.00	0.10	-0.11	-0.04
ICOV							1.00	0.01	0.03	-0.05	-0.01	-0.01	0.02	0.08	0.07	0.11	0.04	-0.02	0.11	-0.03	-0.03
IDHE								1.00	-0.11	-0.02	0.06	-0.08	-0.21	0.00	-0.02	-0.05	-0.17	0.00	-0.04	-0.05	-0.05
ITUR									1.00	0.08	0.02	0.03	-0.01	0.02	0.04	0.00	0.05	0.01	0.08	-0.03	-0.02
LDTC										1.00	-0.05	0.06	-0.06	0.01	-0.02	0.02	-0.06	0.06	0.05	0.13	0.05
NSFA											1.00	0.01	0.01	0.00	0.00	0.00	0.25	0.00	0.00	-0.02	-0.02
NSWC												1.00	-0.12	-0.01	0.01	0.00	0.11	0.00	0.03	-0.02	0.01
OPMA													1.00	0.00	0.07	0.05	0.03	-0.01	0.08	0.10	0.02
PTBR														1.00	0.06	0.30	0.06	0.77	0.08	0.06	0.06
PTER															1.00	0.13	0.03	0.00	0.23	0.11	0.09
ROET																1.00	0.02	0.35	0.16	0.25	0.06
TATU																	1.00	0.02	0.03	-0.13	0.00
TDCE																		1.00	-0.04	0.07	0.03
TIRE																			1.00	0.09	0.08
LNTA																				1.00	0.50
SREV																					1.00

Table A.3: *UK Correlation Matrix – Year: 2000*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	-0.10	-0.09	0.01	-0.06	0.30	0.00	0.01	0.00	0.03	-0.09	-0.03	-0.02	0.02	-0.05	-0.01	-0.14	0.01	0.04	0.00	-0.02
CRAT		1.00	-0.09	-0.03	-0.10	0.02	0.13	0.09	0.04	-0.11	0.00	0.01	-0.08	-0.13	-0.14	-0.06	-0.12	-0.05	0.15	-0.14	-0.08
DPEA			1.00	0.05	0.01	-0.16	0.03	0.03	-0.02	-0.05	0.00	-0.01	0.06	-0.03	0.22	0.01	0.16	0.03	-0.11	0.32	0.16
EBSE				1.00	0.02	0.02	0.00	-0.05	0.00	0.04	-0.02	-0.06	0.00	0.26	0.03	0.07	-0.02	0.79	0.00	0.05	0.01
FCFS					1.00	0.01	-0.02	0.07	-0.03	-0.10	-0.02	0.00	0.01	0.06	0.05	0.05	0.06	-0.01	-0.18	-0.07	-0.03
GSOY						1.00	-0.03	-0.05	0.02	0.02	0.17	-0.03	0.01	0.08	-0.06	-0.01	-0.10	0.02	0.02	-0.09	-0.03
ICOV							1.00	-0.08	0.47	-0.24	0.11	0.01	-0.02	-0.03	0.03	0.01	0.08	-0.04	0.02	-0.09	-0.04
IDHE								1.00	-0.07	-0.25	-0.07	0.05	0.02	-0.03	0.02	-0.05	-0.02	-0.02	-0.07	0.00	-0.02
ITUR									1.00	0.02	0.01	0.00	-0.02	0.01	0.01	-0.01	0.06	0.00	0.01	-0.04	-0.01
LDTC										1.00	-0.20	-0.03	0.05	0.31	0.00	0.10	-0.05	0.11	0.03	0.21	0.05
NSFA											1.00	-0.02	-0.04	0.05	-0.03	-0.02	0.21	0.00	0.00	-0.06	-0.03
NSWC												1.00	0.00	-0.01	-0.01	-0.01	0.01	-0.05	0.00	-0.01	-0.02
OPMA													1.00	-0.01	0.03	0.02	0.06	0.01	-0.01	0.11	0.01
PTBR														1.00	0.03	0.16	0.06	0.33	0.17	0.01	0.01
PTER															1.00	0.04	0.00	0.01	0.00	0.15	0.07
ROET																1.00	0.00	0.27	-0.02	0.10	0.01
TATU																	1.00	-0.02	-0.07	-0.12	-0.02
TDCE																		1.00	0.00	0.08	0.01
TIRE																			1.00	-0.05	-0.01
LNTA																				1.00	0.44
SREV																					1.00

Table A.4: *UK Correlation Matrix – Year: 2001*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	0.04	0.05	0.17	-0.02	-0.01	0.04	-0.03	-0.01	-0.06	0.00	-0.09	-0.15	-0.07	0.02	0.04	0.02	-0.08	0.05	-0.04	-0.01
CRAT		1.00	-0.08	-0.11	0.00	0.02	-0.02	0.07	-0.03	0.00	0.01	0.01	-0.49	0.11	-0.08	-0.04	-0.02	-0.05	0.11	-0.04	-0.03
DPEA			1.00	0.13	0.09	-0.10	0.07	-0.11	0.05	0.10	-0.05	0.02	0.10	-0.09	0.21	0.13	0.20	0.00	-0.15	0.34	0.10
EBSE				1.00	0.00	-0.11	0.09	-0.09	0.02	-0.05	0.00	-0.01	0.29	-0.17	0.08	0.22	0.05	-0.24	0.00	0.13	0.05
FCFS					1.00	-0.03	0.04	0.01	0.00	0.05	0.01	0.00	0.01	0.02	0.02	0.02	0.08	0.03	0.04	0.01	0.02
GSOY						1.00	-0.05	-0.02	0.00	-0.03	0.00	0.00	-0.06	0.07	-0.02	-0.04	-0.07	0.00	0.01	-0.05	-0.01
ICOV							1.00	-0.02	0.04	-0.17	0.03	0.00	0.08	0.01	0.11	0.06	0.11	-0.09	0.00	-0.06	-0.02
IDHE								1.00	-0.02	-0.07	-0.01	-0.01	-0.08	0.06	-0.05	-0.02	-0.13	-0.03	0.12	-0.10	-0.02
ITUR									1.00	-0.03	0.01	0.00	0.03	0.02	0.03	0.01	0.08	-0.02	-0.01	-0.03	0.00
LDTC										1.00	-0.08	0.04	0.12	-0.05	-0.02	0.01	-0.11	0.57	-0.15	0.27	0.01
NSFA											1.00	0.02	-0.02	0.02	0.00	0.01	0.19	-0.03	0.02	0.00	-0.01
NSWC												1.00	0.01	0.01	0.03	0.00	0.03	0.01	0.00	-0.03	-0.01
OPMA													1.00	-0.40	0.06	0.12	-0.03	-0.01	-0.11	0.14	0.02
PTBR														1.00	0.02	0.02	0.04	0.27	0.20	-0.09	-0.01
PTER															1.00	0.09	0.01	0.00	-0.04	0.16	0.04
ROET																1.00	0.02	0.06	-0.02	0.15	0.03
TATU																	1.00	-0.05	-0.05	-0.07	0.01
TDCE																		1.00	-0.12	0.10	-0.01
TIRE																			1.00	-0.13	-0.04
LNTA																				1.00	0.39
SREV																					1.00

Table A.5: *UK Correlation Matrix – Year: 2002*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	0.02	-0.08	0.00	-0.01	0.16	0.00	-0.05	0.19	-0.01	-0.11	-0.03	0.05	0.09	-0.04	-0.06	-0.07	-0.01	0.01	-0.06	-0.02
CRAT		1.00	-0.09	-0.01	0.01	0.01	-0.17	0.04	-0.02	-0.06	0.07	0.03	0.01	-0.06	-0.04	-0.01	-0.11	-0.10	-0.13	-0.10	-0.03
DPEA			1.00	0.10	0.05	-0.10	0.12	-0.02	-0.05	0.09	-0.04	-0.05	-0.01	0.05	0.22	0.15	0.17	0.05	0.27	0.40	0.18
EBSE				1.00	0.15	-0.01	0.05	-0.02	-0.05	0.09	-0.01	-0.01	0.12	-0.06	0.04	-0.27	0.07	-0.33	0.12	0.09	0.02
FCFS					1.00	0.04	0.03	0.01	0.00	0.01	0.00	0.00	0.07	0.04	0.02	0.03	0.04	0.02	0.09	0.01	0.01
GSOY						1.00	-0.02	-0.02	0.14	-0.03	0.06	0.05	0.05	0.03	-0.05	-0.05	0.03	-0.08	-0.08	-0.07	-0.02
ICOV							1.00	-0.02	-0.10	0.05	-0.10	-0.01	0.02	0.05	0.09	0.04	0.02	0.00	0.12	0.08	0.02
IDHE								1.00	-0.07	-0.01	0.00	-0.01	-0.01	-0.01	-0.06	-0.01	-0.07	0.01	-0.02	-0.03	-0.01
ITUR									1.00	-0.01	0.12	0.02	-0.07	0.03	-0.02	-0.05	0.08	-0.07	-0.08	-0.05	0.00
LDTC										1.00	-0.12	-0.05	0.14	-0.02	0.01	0.51	-0.09	-0.09	0.06	0.19	0.01
NSFA											1.00	0.09	-0.01	0.08	0.03	0.01	0.33	0.01	0.01	-0.04	-0.02
NSWC												1.00	0.01	-0.02	-0.01	0.00	0.15	-0.04	0.05	-0.02	-0.01
OPMA													1.00	0.09	-0.05	0.01	-0.04	0.06	0.03	-0.01	-0.03
PTBR														1.00	0.09	0.20	0.10	0.46	0.09	0.09	0.06
PTER															1.00	0.07	0.04	0.01	0.12	0.14	0.04
ROET																1.00	0.04	0.15	0.16	0.14	0.03
TATU																	1.00	-0.01	0.21	-0.07	0.02
TDCE																		1.00	0.03	0.08	0.02
TIRE																			1.00	0.23	0.05
LNTA																				1.00	0.39
SREV																					1.00

Table A.6: *UK Correlation Matrix – Year: 2003*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	-0.17	0.02	0.10	-0.05	-0.02	0.07	-0.10	-0.02	0.01	-0.09	-0.03	0.00	0.03	-0.04	0.01	-0.05	-0.01	0.04	0.04	0.01
CRAT		1.00	-0.02	-0.04	0.00	0.01	-0.07	0.18	-0.04	-0.14	0.01	0.02	-0.38	0.01	-0.01	-0.01	-0.08	-0.03	0.00	-0.08	-0.02
DPEA			1.00	0.13	0.09	-0.03	0.14	-0.08	-0.06	0.07	-0.06	0.02	0.10	0.07	0.31	0.16	0.09	0.00	0.26	0.48	0.19
EBSE				1.00	0.03	0.00	0.05	-0.10	0.04	0.07	-0.03	-0.02	0.07	-0.32	0.09	0.01	0.02	-0.31	0.14	0.09	0.00
FCFS					1.00	0.01	0.02	0.01	0.01	-0.07	0.02	-0.01	0.01	0.03	0.06	0.06	0.09	0.02	0.12	0.08	0.02
GSOY						1.00	0.00	-0.01	0.02	0.01	0.10	0.01	0.00	0.01	0.01	0.00	-0.05	-0.01	0.10	-0.05	-0.01
ICOV							1.00	-0.04	0.01	0.06	-0.01	-0.01	0.10	0.00	0.09	0.04	0.07	0.01	0.13	0.14	0.02
IDHE								1.00	-0.06	-0.03	0.00	0.02	-0.12	-0.01	-0.06	-0.05	-0.18	-0.01	-0.05	-0.08	-0.03
ITUR									1.00	-0.07	0.03	0.00	-0.01	-0.01	-0.01	0.00	0.06	-0.01	-0.05	-0.06	-0.01
LDTC										1.00	-0.09	0.02	0.17	-0.07	0.02	-0.20	-0.14	0.00	-0.03	0.16	0.03
NSFA											1.00	-0.03	-0.04	0.01	-0.02	0.00	0.16	0.04	-0.01	-0.06	-0.02
NSWC												1.00	0.02	-0.01	0.00	-0.01	0.01	0.00	0.02	-0.02	-0.01
OPMA													1.00	0.00	0.08	0.03	-0.02	0.01	0.10	0.16	0.02
PTBR														1.00	0.05	0.12	0.09	0.39	0.06	-0.01	0.00
PTER															1.00	0.09	0.04	0.02	0.17	0.23	0.06
ROET																1.00	0.05	0.06	0.13	0.14	0.03
TATU																	1.00	-0.01	0.18	-0.06	0.02
TDCE																		1.00	-0.04	0.03	-0.03
TIRE																			1.00	0.16	-0.01
LNTA																				1.00	0.38
SREV																					1.00

Table A.7: *UK Correlation Matrix – Year: 2004*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	-0.13	-0.01	-0.07	-0.07	0.09	0.04	-0.02	-0.03	-0.10	-0.06	-0.02	-0.09	0.07	-0.02	0.13	-0.08	-0.01	-0.04	0.02	0.01
CRAT		1.00	-0.04	0.08	-0.02	-0.05	0.02	0.17	-0.02	0.04	0.00	0.02	-0.05	-0.32	-0.06	-0.12	-0.06	-0.08	0.06	0.00	-0.03
DPEA			1.00	0.09	0.04	-0.05	0.12	-0.10	0.00	0.02	-0.05	0.05	0.13	0.09	0.39	0.16	0.11	-0.01	-0.07	0.41	0.13
EBSE				1.00	-0.02	-0.06	-0.17	0.26	0.01	0.32	0.00	0.01	-0.40	-0.48	0.06	-0.32	-0.02	-0.38	0.04	0.08	0.02
FCFS					1.00	-0.02	0.04	-0.01	0.01	-0.21	0.01	0.00	0.02	0.05	0.04	0.23	0.04	0.04	0.05	0.03	0.01
GSOY						1.00	0.05	-0.07	0.02	-0.08	-0.01	-0.01	0.05	0.09	-0.01	0.08	-0.04	0.03	0.00	-0.01	0.00
ICOV							1.00	-0.11	0.01	-0.27	0.01	0.00	0.48	0.38	0.18	0.36	0.12	0.03	0.11	0.04	0.00
IDHE								1.00	-0.08	0.24	0.01	-0.01	-0.50	-0.52	-0.09	-0.47	-0.16	-0.12	-0.09	-0.08	-0.05
ITUR									1.00	0.02	0.04	-0.01	0.01	0.04	0.02	0.03	0.26	-0.01	0.06	0.02	0.02
LDTC										1.00	-0.04	-0.03	-0.18	-0.50	-0.04	-0.34	-0.12	0.10	-0.10	0.11	0.03
NSFA											1.00	0.00	0.00	0.00	-0.02	-0.01	0.24	-0.02	0.01	-0.06	-0.01
NSWC												1.00	0.00	0.00	0.04	0.01	0.09	-0.02	-0.02	0.04	0.01
OPMA													1.00	0.63	0.15	0.64	0.02	0.16	0.08	0.13	0.02
PTBR														1.00	0.07	0.71	0.07	0.12	0.09	0.08	0.02
PTER															1.00	0.17	0.03	0.01	0.10	0.23	0.06
ROET																1.00	0.05	0.16	0.15	0.19	0.07
TATU																	1.00	-0.04	0.03	-0.03	0.03
TDCE																		1.00	-0.07	0.06	0.02
TIRE																			1.00	0.00	-0.03
LNTA																				1.00	0.37
SREV																					1.00

Table A.8: *UK Correlation Matrix – Year: 2005*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	-0.14	-0.03	-0.03	-0.24	0.07	-0.03	0.03	-0.02	0.03	-0.06	-0.02	-0.19	-0.02	-0.12	-0.01	-0.06	-0.03	0.27	-0.05	-0.01
CRAT		1.00	-0.06	0.03	0.11	0.03	0.10	0.10	0.03	-0.16	0.06	0.01	-0.01	-0.04	-0.07	-0.01	-0.02	0.00	0.04	-0.04	-0.05
DPEA			1.00	0.14	-0.02	-0.07	0.05	-0.01	-0.01	0.05	-0.05	-0.08	0.08	0.00	0.40	0.13	0.14	-0.02	-0.11	0.40	0.10
EBSE				1.00	-0.01	0.00	0.04	-0.02	0.00	0.11	0.03	0.01	0.00	-0.50	0.09	0.16	0.10	-0.36	0.00	0.20	0.05
FCFS					1.00	-0.05	0.02	0.03	0.00	-0.10	0.00	0.01	-0.24	-0.01	0.03	0.00	0.03	-0.01	0.05	-0.05	0.00
GSOY						1.00	0.06	0.00	0.00	-0.07	0.03	0.00	-0.04	-0.01	-0.05	0.01	-0.01	0.00	0.00	-0.06	-0.02
ICOV							1.00	-0.23	0.02	-0.28	0.09	0.02	0.02	0.20	0.14	0.06	0.15	-0.05	0.02	-0.03	-0.01
IDHE								1.00	-0.04	-0.04	0.04	-0.01	0.07	-0.01	-0.01	-0.02	-0.14	0.01	-0.03	-0.05	-0.03
ITUR									1.00	0.03	0.09	0.00	-0.02	0.04	-0.07	0.01	0.30	0.02	0.00	0.04	0.02
LDTC										1.00	-0.09	-0.05	0.18	0.11	-0.04	-0.06	-0.13	0.39	-0.11	0.19	0.04
NSFA											1.00	0.01	-0.03	0.01	0.01	0.03	0.22	-0.03	0.00	0.05	-0.02
NSWC												1.00	0.01	0.01	0.00	0.00	-0.01	-0.01	0.00	-0.05	0.02
OPMA													1.00	-0.01	0.09	-0.03	-0.17	0.05	-0.22	0.10	0.00
PTBR														1.00	-0.01	0.02	0.03	0.60	0.05	-0.08	0.01
PTER															1.00	0.11	0.05	-0.05	0.02	0.23	0.03
ROET																1.00	0.02	-0.05	0.08	0.13	0.03
TATU																	1.00	-0.09	0.01	-0.01	0.05
TDCE																		1.00	-0.08	0.01	0.00
TIRE																			1.00	-0.03	-0.02
LNTA																				1.00	0.37
SREV																					1.00

Table A.9: *UK Correlation Matrix – Year: 2006*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	-0.26	-0.04	0.01	-0.24	0.04	0.02	-0.05	-0.01	-0.07	-0.06	0.00	0.00	0.08	0.03	-0.03	0.01	-0.08	0.16	-0.03	-0.03
CRAT		1.00	-0.04	-0.14	-0.16	0.01	-0.06	0.20	-0.02	-0.03	0.12	0.07	-0.03	-0.21	0.01	-0.01	-0.08	-0.04	-0.02	-0.05	-0.04
DPEA			1.00	0.09	-0.05	-0.05	0.05	-0.08	0.03	0.12	-0.02	0.00	0.07	0.03	0.23	0.16	0.14	0.01	0.05	0.40	0.09
EBSE				1.00	-0.05	0.00	0.06	-0.04	0.03	0.04	0.01	-0.01	-0.01	0.24	0.02	0.04	0.17	0.27	0.10	0.04	0.01
FCFS					1.00	0.00	-0.01	0.01	0.01	0.07	0.01	-0.07	-0.03	0.21	0.00	-0.03	0.00	0.07	0.00	0.04	0.07
GSOY						1.00	0.00	0.03	0.00	-0.03	-0.01	0.01	0.00	0.00	0.01	0.00	0.02	0.00	0.00	-0.06	-0.01
ICOV							1.00	0.00	-0.01	0.01	0.02	0.00	0.01	0.01	0.02	0.02	0.06	0.00	0.03	0.05	0.00
IDHE								1.00	-0.03	-0.01	0.01	0.02	-0.72	-0.01	-0.03	-0.02	-0.14	0.00	-0.05	-0.05	-0.02
ITUR									1.00	0.04	0.10	-0.02	0.01	0.05	-0.01	0.01	0.31	0.02	-0.03	0.04	0.02
LDTC										1.00	-0.09	-0.03	0.06	0.00	0.10	0.07	-0.11	0.22	0.01	0.32	0.05
NSFA											1.00	0.01	0.01	0.00	-0.03	0.00	0.16	-0.01	-0.01	-0.03	-0.02
NSWC												1.00	0.00	0.01	0.08	0.01	0.02	-0.02	0.08	0.01	0.00
OPMA													1.00	-0.03	0.04	0.01	0.03	-0.01	0.10	0.08	0.02
PTBR														1.00	0.02	-0.01	-0.05	0.31	0.03	0.03	0.00
PTER															1.00	0.07	0.01	0.01	0.18	0.24	0.01
ROET																1.00	0.01	0.10	0.07	0.18	0.02
TATU																	1.00	-0.06	0.03	-0.09	0.01
TDCE																		1.00	-0.04	0.05	0.01
TIRE																			1.00	0.19	0.02
LNTA																				1.00	0.36
SREV																					1.00

Table A.10: *UK Correlation Matrix – Year: 2007*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	-0.05	-0.06	0.01	-0.17	0.21	0.02	-0.04	-0.03	-0.02	-0.16	0.01	0.02	0.00	-0.02	0.01	-0.07	0.00	0.06	-0.02	-0.02
CRAT		1.00	-0.14	-0.01	0.00	0.01	-0.11	0.17	-0.06	-0.10	0.15	0.04	-0.02	0.00	-0.13	-0.04	-0.18	-0.05	-0.05	-0.11	-0.08
DPEA			1.00	0.07	0.07	-0.09	0.09	-0.09	-0.05	0.12	-0.05	-0.03	0.06	0.03	0.33	0.26	0.14	0.07	0.13	0.46	0.19
EBSE				1.00	0.04	-0.01	0.05	-0.06	0.00	0.05	-0.03	-0.01	0.00	-0.87	0.04	0.18	0.03	-0.46	0.07	0.08	0.03
FCFS					1.00	-0.05	0.05	0.07	-0.03	0.05	0.12	-0.02	0.02	0.03	0.08	0.16	0.04	0.02	0.12	0.30	0.23
GSOY						1.00	-0.02	0.00	-0.01	-0.04	-0.01	0.01	-0.01	0.00	-0.07	-0.05	-0.08	-0.01	0.00	-0.01	-0.03
ICOV							1.00	0.01	-0.02	0.06	-0.06	0.00	0.05	0.01	0.07	0.12	0.06	0.02	0.06	0.05	0.02
IDHE								1.00	-0.14	0.00	0.10	0.04	0.00	0.01	-0.07	-0.06	-0.25	0.09	-0.04	-0.02	-0.03
ITUR									1.00	0.00	0.01	-0.01	-0.01	0.03	-0.04	-0.02	0.08	0.00	-0.04	-0.07	-0.04
LDTC										1.00	-0.10	0.01	0.04	0.05	0.03	0.08	-0.07	0.31	0.12	0.19	0.08
NSFA											1.00	-0.01	0.00	0.00	-0.03	0.01	0.17	0.06	0.02	-0.03	-0.05
NSWC												1.00	-0.01	-0.01	-0.01	-0.05	-0.09	0.01	0.00	-0.08	-0.25
OPMA													1.00	0.02	0.04	0.03	0.03	0.02	0.10	0.06	0.02
PTBR														1.00	0.03	0.05	0.02	0.60	0.04	0.04	0.02
PTER															1.00	0.20	0.05	0.02	0.20	0.24	0.05
ROET																1.00	-0.02	0.07	0.24	0.38	0.12
TATU																	1.00	-0.05	-0.01	-0.09	0.01
TDCE																		1.00	-0.01	0.08	0.02
TIRE																			1.00	0.26	0.03
LNTA																				1.00	0.57
SREV																					1.00

Table A.11: *US Correlation Matrix – Year: 1998*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	0.07	-0.12	0.05	-0.37	0.44	0.00	-0.09	0.05	0.00	-0.02	-0.03	-0.02	0.03	0.04	-0.05	0.00	0.04	0.04	-0.05	-0.01
CRAT		1.00	-0.17	0.02	0.03	0.24	0.11	0.06	-0.05	-0.20	0.09	-0.02	0.11	0.03	0.04	0.01	-0.02	0.02	-0.01	-0.27	-0.14
DPEA			1.00	-0.01	0.02	-0.08	-0.02	0.01	-0.07	0.06	-0.15	0.02	0.06	-0.01	-0.10	0.09	-0.05	-0.02	0.04	0.38	0.20
EBSE				1.00	0.01	-0.01	0.01	0.07	0.00	0.21	-0.01	0.00	0.02	0.73	0.00	-0.02	-0.01	0.75	-0.01	-0.01	0.00
FCFS					1.00	-0.22	0.05	-0.01	0.03	-0.03	0.01	0.00	0.03	0.06	-0.03	0.12	0.02	0.03	0.00	0.01	0.02
GSOY						1.00	0.02	0.00	0.00	0.02	0.01	-0.04	0.12	0.02	0.00	0.04	-0.06	0.00	0.04	-0.01	-0.01
ICOV							1.00	-0.04	-0.01	-0.12	0.00	-0.01	0.07	0.03	-0.01	0.08	0.01	0.00	0.02	-0.06	-0.02
IDHE								1.00	-0.23	0.01	0.01	0.16	0.16	0.11	-0.03	-0.07	-0.25	0.11	-0.01	0.02	-0.02
ITUR									1.00	-0.04	0.03	-0.03	-0.18	-0.03	0.01	-0.03	0.19	-0.02	0.05	-0.04	-0.02
LDTC										1.00	-0.11	-0.01	0.00	0.16	0.01	-0.03	-0.26	0.20	0.00	0.23	0.07
NSFA											1.00	0.00	-0.01	0.00	-0.03	-0.01	0.26	0.00	0.05	-0.12	-0.03
NSWC												1.00	0.07	-0.01	0.00	-0.02	-0.04	0.00	0.02	0.04	0.04
OPMA													1.00	0.13	-0.06	0.27	-0.28	0.06	-0.01	0.07	0.01
PTBR														1.00	0.05	0.35	-0.05	0.74	-0.03	0.01	0.00
PTER															1.00	-0.06	-0.02	0.02	-0.08	-0.03	-0.03
ROET																1.00	0.00	0.12	0.14	0.02	0.02
TATU																	1.00	-0.04	0.01	-0.13	0.00
TDCE																		1.00	-0.02	0.00	0.00
TIRE																			1.00	0.05	0.04
LNTA																				1.00	0.49
SREV																					1.00

Table A.12: *US Correlation Matrix – Year: 1999*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	0.18	-0.08	0.03	-0.08	0.22	0.06	-0.14	-0.06	-0.07	-0.02	0.14	0.07	0.01	0.01	0.18	0.00	-0.07	0.06	-0.04	-0.02
CRAT		1.00	-0.07	0.01	-0.01	0.09	0.05	0.19	-0.02	-0.14	-0.01	-0.03	0.20	-0.01	0.00	0.03	-0.05	-0.04	0.06	-0.17	-0.09
DPEA			1.00	0.02	0.01	-0.04	0.01	-0.02	-0.05	0.07	-0.10	-0.01	-0.01	0.05	-0.06	0.08	-0.03	-0.01	0.01	0.34	0.20
EBSE				1.00	0.01	0.01	0.02	-0.10	0.05	0.11	-0.01	-0.01	0.09	0.01	-0.03	0.15	-0.07	0.78	0.32	0.05	0.02
FCFS					1.00	-0.03	0.00	-0.01	0.01	0.03	0.01	-0.06	0.02	0.01	0.00	0.05	0.01	0.00	0.02	0.01	0.01
GSOY						1.00	-0.03	0.14	-0.07	0.03	-0.02	0.01	0.07	-0.01	-0.03	0.05	-0.11	0.01	-0.03	-0.03	-0.02
ICOV							1.00	-0.01	-0.01	-0.13	0.01	-0.01	0.08	0.04	-0.01	0.10	0.01	-0.03	0.08	-0.04	-0.02
IDHE								1.00	-0.22	-0.06	-0.02	0.04	0.09	-0.04	-0.02	-0.07	-0.24	-0.04	-0.09	-0.08	-0.05
ITUR									1.00	-0.02	0.07	-0.04	-0.12	0.01	0.03	-0.06	0.31	-0.03	0.06	-0.02	-0.02
LDTC										1.00	-0.03	-0.02	-0.06	0.17	0.03	0.19	-0.08	0.20	-0.03	0.27	0.08
NSFA											1.00	0.00	-0.06	-0.01	-0.01	-0.02	0.13	0.01	0.01	-0.07	-0.01
NSWC												1.00	-0.02	-0.01	-0.01	-0.02	-0.04	0.00	0.00	0.00	0.00
OPMA													1.00	0.07	-0.06	0.34	-0.36	-0.07	0.08	0.01	-0.01
PTBR														1.00	0.02	-0.01	0.11	0.21	-0.01	0.02	0.04
PTER															1.00	-0.06	0.02	-0.01	0.01	-0.03	-0.01
ROET																1.00	-0.03	-0.17	0.10	0.10	0.05
TATU																	1.00	-0.09	-0.07	-0.07	0.03
TDCE																		1.00	0.22	0.02	0.00
TIRE																			1.00	0.13	0.14
LNTA																				1.00	0.49
SREV																					1.00

Table A.13: *US Correlation Matrix – Year: 2000*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	0.02	-0.08	0.05	-0.01	-0.03	-0.01	-0.21	0.09	0.00	-0.02	-0.02	0.13	0.04	-0.01	0.01	0.00	0.01	-0.07	-0.06	-0.02
CRAT		1.00	-0.14	-0.14	0.00	-0.05	0.14	0.14	-0.06	-0.27	0.02	0.02	0.07	0.01	0.04	0.00	-0.10	0.01	0.06	-0.20	-0.10
DPEA			1.00	0.04	-0.02	-0.01	-0.02	-0.02	-0.06	0.07	-0.11	-0.01	-0.03	-0.01	-0.02	0.00	-0.05	0.01	-0.05	0.36	0.20
EBSE				1.00	-0.01	0.01	0.00	-0.01	-0.01	0.11	0.00	0.00	0.08	0.00	-0.04	0.03	-0.04	0.00	0.10	-0.03	0.01
FCFS					1.00	-0.01	0.00	0.00	-0.01	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00	-0.03	-0.01
GSOY						1.00	0.03	-0.26	0.03	0.06	0.07	0.03	-0.09	0.00	0.03	0.00	0.05	0.01	0.03	0.05	0.01
ICOV							1.00	-0.01	-0.01	-0.13	0.00	0.00	0.06	0.00	0.01	0.00	-0.01	0.00	0.04	-0.03	-0.02
IDHE								1.00	-0.14	-0.05	-0.02	-0.03	0.06	-0.01	0.04	-0.01	-0.17	0.00	-0.06	-0.05	-0.02
ITUR									1.00	0.04	0.23	0.03	-0.03	0.00	-0.01	0.00	0.12	0.01	-0.01	-0.04	-0.02
LDTC										1.00	0.03	0.02	-0.01	0.02	0.00	0.05	-0.13	0.01	-0.09	0.21	0.06
NSFA											1.00	0.03	-0.02	0.00	-0.01	-0.01	0.42	0.00	-0.01	-0.05	-0.01
NSWC												1.00	0.01	0.00	0.00	0.00	-0.01	0.00	-0.03	-0.02	-0.01
OPMA													1.00	0.04	-0.02	0.01	-0.24	0.00	0.20	0.00	-0.01
PTBR														1.00	0.00	0.01	0.01	0.13	-0.01	0.01	0.00
PTER															1.00	-0.01	-0.02	0.00	0.01	0.06	0.05
ROET																1.00	-0.01	0.01	0.01	-0.05	0.00
TATU																	1.00	-0.03	0.01	-0.13	0.03
TDCE																		1.00	0.00	0.05	0.01
TIRE																			1.00	-0.02	0.00
LNTA																				1.00	0.45
SREV																					1.00

Table A.14: *US Correlation Matrix – Year: 2001*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	-0.04	-0.04	-0.06	0.00	0.03	-0.03	-0.14	0.02	-0.09	-0.09	0.00	-0.04	-0.07	0.57	0.03	-0.07	-0.10	-0.05	-0.01	-0.01
CRAT		1.00	-0.10	-0.09	0.01	-0.03	0.08	0.09	-0.02	-0.18	0.21	0.02	-0.28	-0.03	0.00	0.05	0.00	-0.04	-0.19	-0.10	-0.08
DPEA			1.00	-0.01	0.01	-0.05	0.00	-0.02	-0.05	0.06	-0.09	0.04	0.05	-0.02	-0.03	0.05	-0.04	-0.01	0.09	0.33	0.19
EBSE				1.00	0.01	0.01	0.01	0.24	-0.02	0.16	0.08	0.00	0.08	0.56	-0.02	-0.16	0.19	0.56	-0.08	-0.06	0.00
FCFS					1.00	0.00	0.00	0.00	-0.01	0.01	0.00	-0.03	0.01	0.00	0.00	0.01	0.01	0.00	0.02	0.04	0.01
GSOY						1.00	0.04	-0.10	-0.01	0.19	0.06	0.00	0.04	-0.04	-0.06	0.05	-0.01	-0.05	0.00	-0.01	-0.01
ICOV							1.00	-0.04	0.00	-0.19	0.12	0.00	0.03	-0.02	-0.02	0.07	0.04	-0.03	0.05	0.01	-0.01
IDHE								1.00	-0.12	0.19	0.03	0.01	-0.05	0.43	-0.01	-0.15	-0.16	0.43	-0.04	-0.03	-0.02
ITUR									1.00	-0.05	0.05	0.00	-0.03	-0.02	-0.01	0.01	0.07	-0.02	-0.02	-0.02	-0.01
LDTC										1.00	-0.03	0.00	-0.06	0.27	0.00	-0.09	-0.19	0.30	0.07	0.16	0.04
NSFA											1.00	-0.05	-0.32	-0.04	-0.07	0.01	0.51	-0.04	-0.04	-0.03	0.02
NSWC												1.00	-0.02	0.00	0.00	0.01	-0.09	0.00	-0.05	0.03	0.01
OPMA													1.00	-0.02	0.00	0.06	-0.04	-0.03	0.34	-0.10	0.00
PTBR														1.00	-0.01	-0.40	-0.04	1.00	-0.04	-0.03	-0.01
PTER															1.00	0.00	-0.11	-0.03	-0.02	0.03	0.00
ROET																1.00	0.00	-0.37	0.05	0.12	0.03
TATU																	1.00	-0.04	0.10	-0.10	0.06
TDCE																		1.00	-0.03	-0.02	-0.01
TIRE																			1.00	0.08	0.05
LNTA																				1.00	0.45
SREV																					1.00

Table A.15: *US Correlation Matrix – Year: 2002*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	-0.01	-0.02	-0.16	0.05	0.16	0.00	-0.07	0.10	-0.13	-0.01	0.13	-0.01	-0.08	0.01	-0.04	0.07	-0.05	-0.25	0.05	0.01
CRAT		1.00	-0.09	-0.02	0.02	0.02	0.10	0.13	-0.05	-0.25	0.02	0.04	-0.05	0.15	0.08	-0.01	0.11	-0.08	0.01	-0.14	-0.09
DPEA			1.00	0.11	0.01	-0.01	0.01	0.00	-0.04	0.08	-0.08	0.01	0.01	-0.01	-0.04	0.08	-0.04	0.04	0.01	0.34	0.20
EBSE				1.00	-0.08	-0.31	0.08	-0.18	0.01	0.11	-0.01	0.01	0.04	0.19	-0.03	0.41	-0.15	0.26	0.34	0.03	0.03
FCFS					1.00	0.09	-0.01	0.06	-0.02	0.10	0.04	0.03	-0.01	-0.12	0.04	0.11	0.11	-0.01	-0.08	0.03	0.01
GSOY						1.00	0.07	0.10	0.05	-0.17	0.04	-0.02	-0.03	-0.08	0.04	-0.37	0.17	-0.20	-0.35	0.10	0.01
ICOV							1.00	-0.05	-0.01	-0.16	0.00	0.01	0.00	0.19	0.02	0.03	0.05	-0.01	-0.05	-0.04	-0.02
IDHE								1.00	-0.25	0.10	0.02	0.08	-0.01	-0.09	0.02	-0.09	-0.12	-0.04	-0.21	0.02	0.01
ITUR									1.00	-0.11	0.01	-0.02	0.00	0.00	-0.02	-0.07	0.18	-0.04	0.06	-0.05	0.00
LDTC										1.00	-0.03	-0.10	0.01	-0.25	-0.01	0.41	-0.14	0.34	0.00	0.09	0.03
NSFA											1.00	0.01	0.00	-0.03	-0.02	0.03	0.05	-0.04	-0.04	-0.04	-0.01
NSWC												1.00	0.00	0.07	0.00	0.05	-0.07	-0.03	0.04	0.03	0.02
OPMA													1.00	0.02	0.00	0.03	-0.02	0.02	0.03	0.01	0.01
PTBR														1.00	0.07	0.01	-0.06	0.11	-0.06	-0.03	0.00
PTER															1.00	0.00	0.00	0.04	-0.04	0.01	-0.01
ROET																1.00	0.01	0.24	0.24	-0.06	0.01
TATU																	1.00	-0.07	-0.04	-0.05	-0.02
TDCE																		1.00	0.12	0.02	0.01
TIRE																			1.00	-0.18	-0.06
LNTA																				1.00	0.43
SREV																					1.00

Table A.16: *US Correlation Matrix – Year: 2003*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	0.00	-0.02	0.05	-0.05	0.02	0.02	0.02	0.00	-0.18	-0.04	0.06	0.04	-0.08	0.01	0.01	-0.03	-0.06	0.06	-0.03	-0.01
CRAT		1.00	-0.11	-0.02	-0.02	0.00	0.16	0.02	-0.02	-0.04	0.00	0.00	-0.01	0.02	0.04	0.02	0.01	-0.08	-0.02	-0.16	-0.11
DPEA			1.00	0.08	-0.01	-0.05	-0.01	0.00	-0.02	0.04	-0.08	0.00	0.03	-0.05	-0.05	0.04	-0.04	0.05	-0.01	0.30	0.19
EBSE				1.00	0.21	-0.45	0.01	-0.16	-0.02	0.29	-0.05	-0.07	0.65	-0.73	-0.05	0.19	-0.35	-0.14	0.18	-0.05	0.00
FCFS					1.00	-0.09	-0.01	-0.04	0.00	0.08	-0.01	-0.02	0.21	-0.20	0.00	0.04	-0.08	-0.06	0.10	-0.05	-0.01
GSOY						1.00	0.03	0.01	0.02	-0.12	0.04	0.07	-0.23	0.46	0.03	-0.07	0.21	0.13	-0.02	0.09	0.02
ICOV							1.00	-0.01	0.00	-0.05	0.00	0.00	0.05	0.01	-0.03	0.03	0.04	-0.06	-0.02	-0.02	-0.02
IDHE								1.00	-0.02	-0.03	-0.01	0.07	-0.07	0.10	-0.02	-0.02	-0.03	0.03	-0.12	0.03	0.01
ITUR									1.00	-0.01	0.01	0.00	-0.02	0.02	0.00	-0.01	0.02	0.00	0.01	-0.05	-0.01
LDTC										1.00	-0.07	-0.01	0.34	-0.28	-0.02	0.04	-0.26	0.01	0.08	0.08	0.02
NSFA											1.00	-0.02	-0.06	0.05	-0.01	-0.03	0.04	0.02	-0.01	-0.02	0.02
NSWC												1.00	-0.01	0.08	0.01	-0.01	-0.12	0.02	-0.01	0.01	-0.02
OPMA													1.00	-0.64	-0.06	0.14	-0.64	-0.17	0.27	-0.04	-0.01
PTBR														1.00	0.06	-0.12	0.43	0.23	-0.34	0.12	0.03
PTER															1.00	-0.02	0.06	-0.01	0.00	0.03	0.02
ROET																1.00	-0.07	0.14	0.05	0.03	0.01
TATU																	1.00	0.07	-0.08	-0.05	0.00
TDCE																		1.00	-0.06	0.16	0.15
TIRE																			1.00	-0.05	-0.01
LNTA																				1.00	0.43
SREV																					1.00

Table A.17: *US Correlation Matrix – Year: 2004*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	0.25	-0.04	0.01	-0.14	0.42	-0.03	-0.05	0.07	-0.13	-0.05	0.00	0.30	0.00	0.08	0.01	-0.04	-0.08	-0.07	-0.03	-0.02
CRAT		1.00	-0.08	0.04	-0.04	-0.03	0.24	0.00	0.16	-0.51	0.05	0.02	0.11	0.06	0.01	-0.01	0.16	-0.12	0.06	-0.17	-0.07
DPEA			1.00	0.05	0.02	0.02	-0.01	-0.04	-0.05	0.08	-0.08	-0.02	0.03	0.01	-0.07	0.00	-0.07	0.02	-0.02	0.31	0.15
EBSE				1.00	-0.13	-0.07	0.02	0.01	0.04	-0.33	-0.03	-0.01	0.00	0.91	0.02	-0.69	-0.05	0.43	0.01	0.06	0.02
FCFS					1.00	0.00	0.00	0.01	0.00	0.12	0.03	0.00	-0.09	-0.13	-0.01	0.11	0.02	-0.03	-0.01	0.04	0.01
GSOY						1.00	-0.02	-0.05	0.11	0.19	0.03	0.00	-0.19	-0.02	0.09	-0.04	0.14	0.01	-0.03	0.07	0.00
ICOV							1.00	-0.01	0.10	-0.17	0.01	0.00	0.05	0.01	-0.01	0.00	0.01	-0.03	-0.01	-0.04	-0.02
IDHE								1.00	-0.14	0.00	0.00	0.01	-0.02	0.01	0.00	0.07	0.04	0.00	0.00	-0.08	-0.02
ITUR									1.00	-0.13	0.05	-0.01	-0.20	0.09	0.05	-0.10	0.07	0.02	-0.07	-0.02	-0.02
LDTC										1.00	-0.02	0.00	-0.14	-0.36	0.00	0.20	-0.15	0.17	-0.24	0.21	0.06
NSFA											1.00	0.02	-0.12	-0.01	-0.03	-0.01	0.22	0.01	0.06	-0.05	0.01
NSWC												1.00	0.00	0.00	0.01	0.01	0.03	0.01	0.00	-0.04	-0.02
OPMA													1.00	-0.13	-0.09	0.21	-0.30	-0.11	-0.04	-0.07	-0.02
PTBR														1.00	0.05	-0.80	0.00	0.48	-0.01	0.02	0.01
PTER															1.00	-0.05	-0.02	0.00	-0.06	0.04	-0.02
ROET																1.00	0.18	-0.57	-0.01	-0.07	-0.01
TATU																	1.00	-0.08	0.03	-0.15	0.00
TDCE																		1.00	-0.03	0.10	0.06
TIRE																			1.00	-0.05	-0.01
LNTA																				1.00	0.44
SREV																					1.00

Table A.18: *US Correlation Matrix – Year: 2005*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	0.08	-0.05	-0.52	-0.12	0.12	0.06	-0.09	0.02	-0.07	0.03	0.03	-0.16	-0.09	0.03	-0.37	0.14	-0.52	0.01	-0.02	-0.01
CRAT		1.00	-0.07	-0.11	-0.02	0.20	0.00	0.01	0.02	-0.12	0.08	-0.01	-0.31	-0.03	0.03	-0.19	0.18	0.04	0.01	0.02	0.00
DPEA			1.00	0.05	-0.02	-0.02	-0.02	-0.01	-0.03	0.02	-0.10	-0.01	0.02	0.05	-0.05	0.01	-0.10	-0.01	-0.02	0.31	0.15
EBSE				1.00	0.03	-0.18	0.02	0.09	-0.02	-0.04	-0.04	0.01	0.24	-0.31	-0.02	0.74	-0.06	0.00	-0.01	0.02	0.01
FCFS					1.00	-0.06	-0.02	-0.03	0.00	0.14	-0.01	-0.01	-0.02	-0.11	0.00	0.06	-0.01	0.01	0.00	-0.02	-0.01
GSOY						1.00	-0.02	0.05	0.02	-0.04	0.13	0.01	-0.14	0.25	0.02	-0.30	0.16	-0.04	0.01	0.04	0.01
ICOV							1.00	-0.02	0.00	-0.20	-0.01	0.00	0.01	0.01	0.00	0.02	0.04	-0.01	0.00	-0.05	-0.02
IDHE								1.00	-0.04	0.02	0.02	-0.06	-0.07	0.02	0.01	0.02	-0.05	0.00	0.00	0.03	-0.01
ITUR									1.00	-0.02	0.02	0.00	-0.01	0.01	0.00	-0.02	0.02	0.00	0.00	-0.02	-0.01
LDTC										1.00	-0.04	0.03	0.04	0.00	-0.01	0.01	-0.35	0.03	-0.01	0.11	0.02
NSFA											1.00	0.01	-0.08	0.07	-0.02	-0.07	0.32	0.00	0.01	-0.02	0.02
NSWC												1.00	-0.01	-0.01	0.00	0.00	0.05	0.00	0.00	-0.03	0.00
OPMA													1.00	-0.19	-0.03	0.37	-0.33	-0.02	-0.01	-0.04	-0.02
PTBR														1.00	0.01	-0.48	0.15	0.38	0.00	0.04	0.02
PTER															1.00	-0.04	-0.02	0.00	0.00	0.02	-0.01
ROET																1.00	-0.09	-0.07	-0.02	-0.07	-0.01
TATU																	1.00	0.05	0.12	-0.15	0.02
TDCE																		1.00	0.00	0.01	0.00
TIRE																			1.00	-0.05	-0.01
LNTA																				1.00	0.45
SREV																					1.00

Table A.19: *US Correlation Matrix – Year: 2006*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	-0.18	-0.04	-0.05	-0.11	0.06	0.06	-0.20	-0.02	-0.04	-0.02	0.00	-0.18	0.01	0.02	-0.01	0.00	0.00	0.04	-0.02	-0.02
CRAT		1.00	0.02	-0.05	0.07	-0.08	0.18	0.16	-0.02	-0.25	0.00	-0.01	0.34	0.01	-0.02	0.01	-0.09	-0.10	-0.10	-0.10	-0.05
DPEA			1.00	0.06	-0.02	-0.03	-0.01	0.01	-0.04	0.04	-0.10	0.06	0.01	0.01	-0.06	0.01	-0.03	0.06	0.01	0.31	0.14
EBSE				1.00	0.03	0.28	0.00	-0.01	0.05	0.14	0.02	0.00	-0.25	0.26	-0.04	0.27	0.19	0.25	0.37	0.15	0.06
FCFS					1.00	-0.11	0.03	0.01	0.02	0.02	0.01	-0.01	0.18	0.07	-0.01	0.00	0.01	-0.03	-0.13	0.04	0.08
GSOY						1.00	-0.07	-0.02	0.04	-0.12	0.05	0.01	-0.52	0.36	0.02	0.17	0.20	0.25	0.65	0.16	0.03
ICOV							1.00	-0.10	0.08	-0.25	0.01	-0.01	0.11	0.25	0.01	0.00	0.15	-0.11	-0.11	-0.07	-0.03
IDHE								1.00	-0.15	0.01	-0.01	-0.01	0.06	-0.11	0.01	-0.01	-0.19	-0.01	-0.03	-0.03	-0.02
ITUR									1.00	-0.10	0.09	0.01	-0.01	0.04	-0.01	0.03	0.17	0.00	0.03	-0.05	-0.01
LDTC										1.00	-0.02	0.01	0.00	-0.16	-0.01	-0.06	-0.27	0.27	0.00	0.10	0.01
NSFA											1.00	0.01	-0.10	0.07	-0.03	0.03	0.10	0.03	0.10	-0.06	0.01
NSWC												1.00	-0.02	0.01	-0.01	0.01	0.02	0.03	0.03	-0.02	0.01
OPMA													1.00	-0.44	-0.03	-0.09	-0.50	-0.30	-0.74	-0.09	-0.02
PTBR														1.00	0.00	0.13	0.52	0.17	0.46	0.07	0.03
PTER															1.00	-0.01	-0.04	-0.02	0.00	-0.05	-0.03
ROET																1.00	0.08	0.28	0.16	0.04	0.02
TATU																	1.00	0.03	0.15	-0.08	0.00
TDCE																		1.00	0.36	0.11	0.05
TIRE																			1.00	0.17	0.04
LNTA																				1.00	0.44
SREV																					1.00

Table A.20: *US Correlation Matrix – Year: 2007*

X	CETA	CRAT	DPEA	EBSE	FCFS	GSOY	ICOV	IDHE	ITUR	LDTC	NSFA	NSWC	OPMA	PTBR	PTER	ROET	TATU	TDCE	TIRE	LNTA	SREV
CETA	1.00	0.01	-0.03	-0.11	-0.01	0.11	0.07	-0.15	0.02	-0.10	-0.03	-0.03	-0.18	0.06	0.09	-0.02	-0.08	0.02	0.10	0.00	-0.01
CRAT		1.00	-0.01	0.04	0.01	0.12	0.02	0.19	0.01	-0.29	0.06	0.00	0.03	0.05	-0.01	0.17	0.01	-0.01	0.17	-0.09	-0.05
DPEA			1.00	0.10	-0.01	-0.02	0.03	0.03	-0.03	0.02	-0.06	-0.02	0.03	0.02	-0.10	-0.02	-0.03	0.03	0.00	0.29	0.13
EBSE				1.00	0.01	0.01	0.06	-0.04	0.00	0.07	0.03	-0.01	-0.03	0.12	-0.07	0.33	0.07	0.52	0.17	0.10	0.03
FCFS					1.00	-0.02	0.00	0.00	0.00	-0.02	0.00	0.00	0.03	0.07	0.00	0.01	-0.01	-0.01	-0.01	0.07	0.13
GSOY						1.00	-0.01	0.03	0.01	0.03	0.10	-0.01	-0.52	-0.02	0.12	-0.30	0.09	0.08	0.30	0.09	0.01
ICOV							1.00	-0.02	0.00	-0.05	0.00	0.00	0.02	0.08	0.01	0.02	0.01	-0.06	0.01	-0.01	-0.01
IDHE								1.00	-0.04	-0.05	0.00	-0.01	0.02	-0.12	-0.01	0.00	-0.13	-0.01	-0.03	-0.01	-0.01
ITUR									1.00	-0.03	0.03	0.00	-0.05	0.02	-0.01	0.00	0.06	0.02	0.01	-0.02	-0.01
LDTC										1.00	-0.06	-0.02	0.10	-0.18	0.01	-0.04	-0.25	0.06	0.01	0.08	-0.01
NSFA											1.00	0.00	-0.12	0.03	0.01	0.01	0.33	0.02	0.06	-0.05	0.01
NSWC												1.00	-0.02	-0.07	0.00	0.02	0.00	-0.02	-0.02	0.03	0.01
OPMA													1.00	0.01	-0.06	0.10	-0.33	-0.09	-0.33	-0.09	-0.03
PTBR														1.00	0.10	-0.03	0.27	0.03	-0.10	-0.04	0.00
PTER															1.00	-0.10	-0.03	0.01	-0.03	-0.03	-0.02
ROET																1.00	0.10	0.01	0.04	0.02	0.01
TATU																	1.00	0.01	0.07	-0.17	0.03
TDCE																		1.00	0.05	0.03	0.00
TIRE																			1.00	0.10	0.01
LNTA																				1.00	0.44
SREV																					1.00

A.2 Variance Inflation Factors

Table A.21: *Yearly Variance Inflation Factors (VIF) in the UK*

	Estimation year									
Variable	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
CETA	1.25	1.14	1.17	1.12	1.12	1.09	1.17	1.31	1.26	1.12
CRAT	1.40	1.16	1.17	1.38	1.09	1.27	1.30	1.11	1.30	1.14
DPEA	1.28	1.24	1.26	1.30	1.37	1.49	1.44	1.47	1.32	1.47
EBSE	1.19	3.02	**7.50**	1.32	1.44	1.26	1.73	1.68	1.21	**5.49**
FCFS	1.40	1.07	1.10	1.02	1.05	1.04	1.22	1.20	1.22	1.19
GSOY	1.13	1.06	1.21	1.03	1.07	1.04	1.03	1.02	1.01	1.06
ICOV	1.02	1.05	1.48	1.08	1.08	1.06	1.52	1.39	1.02	1.05
IDHE	1.37	1.19	1.16	1.06	1.02	1.10	1.64	1.14	2.28	1.15
ITUR	1.17	1.04	1.33	1.01	1.12	1.03	1.09	1.13	1.14	1.04
LDTC	1.17	1.16	1.50	1.81	1.66	1.16	1.79	1.63	1.22	1.24
NSFA	1.32	1.11	1.21	1.06	1.21	1.06	1.08	1.10	1.06	1.16
NSWC	1.02	1.05	1.01	1.02	1.04	1.01	1.02	1.01	1.03	1.09
OPMA	1.26	1.12	1.03	1.85	1.07	1.25	2.79	1.28	2.18	1.02
PTBR	1.05	1.26	1.35	1.31	1.13	1.17	3.95	1.66	1.19	**5.23**
PTER	1.61	1.14	1.09	1.09	1.08	1.14	1.27	1.29	1.13	1.18
ROET	1.16	1.66	1.38	1.11	1.82	1.11	2.96	1.09	1.06	1.45
TATU	1.44	1.24	1.18	1.17	1.34	1.19	1.26	1.33	1.31	1.27
TDCE	1.63	**5.23**	**8.25**	1.90	1.54	1.25	1.30	1.99	1.26	1.89
TIRE	1.12	1.18	1.13	1.14	1.22	1.20	1.09	1.20	1.14	1.19
LNTA	1.52	1.71	1.57	1.54	1.53	1.61	1.48	1.54	1.68	2.36
SREV	1.27	1.38	1.26	1.20	1.20	1.19	1.18	1.18	1.18	1.68

Table A.22: *Yearly Variance Inflation Factors (VIF) in the US*

	Estimation year									
Variable	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
CETA	1.43	1.24	1.12	1.76	1.19	1.07	1.70	2.44	1.19	1.17
CRAT	1.23	1.18	1.21	1.24	1.17	1.07	1.56	1.22	1.40	1.32
DPEA	1.24	1.17	1.19	1.15	1.16	1.14	1.13	1.14	1.14	1.13
EBSE	**5.34**	**5.18**	1.06	1.67	1.52	2.86	**6.32**	2.90	1.38	1.83
FCFS	1.20	1.01	1.00	1.00	1.07	1.07	1.05	1.07	1.09	1.03
GSOY	1.36	1.11	1.10	1.13	1.38	1.42	1.57	1.21	1.88	1.70
ICOV	1.04	1.05	1.04	1.09	1.08	1.05	1.09	1.06	1.25	1.03
IDHE	1.22	1.23	1.22	1.37	1.23	1.06	1.06	1.04	1.16	1.12
ITUR	1.11	1.19	1.09	1.02	1.12	1.01	1.16	1.00	1.10	1.01
LDTC	1.26	1.38	1.18	1.54	1.76	1.23	2.39	1.26	1.48	1.26
NSFA	1.12	1.03	1.33	1.70	1.02	1.02	1.07	1.14	1.04	1.15
NSWC	1.04	1.04	1.01	1.01	1.07	1.05	1.00	1.01	1.01	1.01
OPMA	1.27	1.49	1.17	1.50	1.01	3.16	1.74	1.41	**5.04**	1.78
PTBR	**6.13**	1.10	1.01	2.04	1.25	2.91	**9.73**	1.66	2.01	1.22
PTER	1.05	1.02	1.01	1.53	1.02	1.02	1.04	1.01	1.02	1.06
ROET	2.26	1.78	1.01	1.46	1.74	1.08	4.01	3.08	1.18	1.44
TATU	1.39	1.45	1.46	1.68	1.17	1.94	1.51	1.62	2.90	1.64
TDCE	**72.37**	**5.55**	1.02	**171.29**	1.26	1.15	1.87	1.82	1.38	1.49
TIRE	1.08	1.19	1.09	1.25	1.46	1.23	1.15	1.02	4.92	1.28
LNTA	1.65	1.60	1.53	1.50	1.44	1.40	1.46	1.44	1.46	1.48
SREV	1.33	1.34	1.28	1.28	1.24	1.25	1.25	1.27	1.25	1.28

A.3 Univariate analysis

Table A.23: *Univariate analysis of variable CETA in both economies during the period 1997-2007*

Year	Group	N[a]	Mean	Std. Dev.	Minimum	Maximum	t-stat difference[b]
Panel A: UK univariate analysis							
1997	Non-Target	710	-0.06119	0.45035	-1.265	3.6427	
	Target	92	-0.07429	0.36316	-0.6482	1.366	-0.316
1998	Non-Target	686	-0.03414	0.17651	-1.1653	2.7966	
	Target	99	-0.01036	0.16605	-0.0698	1.6329	1.321
1999	Non-Target	663	0.02438	0.97587	-1.3537	11.2933	
	Target	86	0.03561	0.87647	-0.6872	5.0818	0.110
2000	Non-Target	657	-0.0289	0.15466	-1.4573	2.9019	
	Target	41	-0.04361	0.0505	-0.1612	0.1042	-1.481
2001	Non-Target	686	-0.03417	0.27026	-1.2557	1.9219	
	Target	46	-0.0604	0.19749	-0.4342	0.7731	-0.849
2002	Non-Target	582	-0.03117	0.34617	-0.8696	4.3084	
	Target	92	-0.062	0.22181	-0.6281	1.0368	-1.133
2003	Non-Target	606	-0.02475	0.37099	-0.7721	5.6366	
	Target	55	-0.00863	0.21384	-0.3922	1.0239	0.495
2004	Non-Target	567	-0.04594	0.21111	-0.8319	4.0225	
	Target	62	-0.03511	0.19043	-0.4068	1.3127	0.42
2005	Non-Target	578	-0.05653	0.17194	-0.9537	3.1499	
	Target	73	-0.07654	0.12271	-0.7326	0.4371	-1.247
2006	Non-Target	618	-0.02593	0.31614	-0.9727	6.753	
	Target	78	-0.05629	0.13657	-0.9167	0.2045	-1.516
2007	Non-Target	624	-0.03417	0.31535	-0.4685	4.0813	
	Target	80	-0.04618	0.23426	-0.3865	1.0842	-0.413
Panel B: US univariate analysis							
1997	Non-Target	1854	-0.04805	0.24583	-1.1115	5.0854	
	Target	216	-0.04538	0.18675	-0.954	1.6847	0.192
1998	Non-Target	1818	-0.02759	0.17688	-1.0197	2.7821	
	Target	240	-0.04846	0.07228	-0.5127	0.1731	-3.343*
1999	Non-Target	1892	-0.00956	0.15821	-0.7862	2.9569	
	Target	241	-0.00325	0.14275	-0.2158	1.4219	0.638
2000	Non-Target	1803	-0.01872	0.17433	-0.5996	6.7012	
	Target	106	-0.01661	0.14463	-0.7015	1.1558	0.144
2001	Non-Target	1674	-0.03163	0.04553	-0.3926	1.9372	
	Target	73	-0.0351	0.0458	-0.4159	0.0157	-0.634
2002	Non-Target	1450	-0.02082	0.09621	-0.5902	1.9779	
	Target	70	-0.01813	0.12738	-0.2942	0.9792	0.174
2003	Non-Target	1463	-0.01498	0.15978	-0.5836	4.2481	
	Target	89	0.01326	0.41232	-0.6633	3.8284	0.643
2004	Non-Target	1489	-0.01752	0.0388	-0.1812	1.0813	
	Target	106	-0.01675	0.03117	-0.1384	0.2187	0.241
2005	Non-Target	1509	-0.03326	0.06523	-0.5301	1.0161	
	Target	122	-0.02634	0.08071	-0.5103	0.4918	0.923
2006	Non-Target	1460	-0.03011	0.11138	-0.616	1.1491	
	Target	139	-0.01866	0.14935	-0.4812	1.3062	0.881
2007	Non-Target	1428	-0.02908	0.03519	-0.2164	1.0718	
	Target	89	-0.02916	0.01957	-0.1553	-0.0103	-0.035

[a] The column provides the number of firms present in the target and the non-target group.
[b] This column provides a two sample test-statistics for the null hypothesis that there is no significant difference between the yearly means of the target and the non-target group. $*, **, ***$ indicate significance using a two-sample two-tail t-test at the 1%, 5% and 10% respectively.

Table A.24: *Univariate analysis of variable CRAT in both economies during the period 1997-2007*

Year	Group	N[a]	Mean	Std. Dev.	Minimum	Maximum	t-stat difference[b]
Panel A: UK univariate analysis							
1997	Non-Target	710	-0.07595	0.22124	-1.0261	2.3847	
	Target	92	-0.10251	0.15789	-0.7979	0.5529	-1.441
1998	Non-Target	686	-0.08125	0.62366	-1.4876	8.9025	
	Target	99	-0.16859	0.34052	-0.8056	0.9788	-2.095**
1999	Non-Target	663	-0.10162	0.25345	-0.7798	3.4662	
	Target	86	-0.14148	0.15221	-0.5649	0.488	-2.083**
2000	Non-Target	657	-0.04372	0.09971	-0.7073	1.178	
	Target	41	0.02278	0.78561	-0.7624	4.8449	0.542
2001	Non-Target	686	-0.09498	0.22609	-1.0389	2.3446	
	Target	46	-0.12541	0.13217	-0.9299	0.0852	-1.428
2002	Non-Target	582	-0.02994	0.24366	-1.0017	4.3618	
	Target	92	-0.03694	0.1094	-1.0566	0.1946	-0.459
2003	Non-Target	606	-0.03623	0.11195	-1.2563	1.512	
	Target	55	-0.02884	0.01458	-0.1354	-0.0208	1.492
2004	Non-Target	567	-0.06277	0.09201	-1.1143	0.4468	
	Target	62	-0.0751	0.14577	-1.0424	0.259	-0.652
2005	Non-Target	578	-0.07424	0.10606	-1.0266	1.1559	
	Target	73	-0.07275	0.08382	-0.4928	0.4336	0.139
2006	Non-Target	618	-0.17947	0.15213	-0.9357	1.7075	
	Target	78	-0.194	0.0799	-0.2857	0.3082	-1.33
2007	Non-Target	624	-0.16382	0.20706	-1.4861	1.6616	
	Target	80	-0.09749	0.37481	-0.278	2.1617	1.553
Panel B: US univariate analysis							
1997	Non-Target	1854	-0.08981	0.23198	-1.3287	2.4853	
	Target	216	-0.08111	0.34489	-0.7328	4.0918	0.361
1998	Non-Target	1818	-0.05811	0.19029	-1.2473	3.5065	
	Target	240	-0.05979	0.16424	-0.6221	1.6545	-0.146
1999	Non-Target	1892	-0.08006	0.08877	-0.3594	0.9558	
	Target	241	-0.0825	0.07464	-0.3215	0.2829	-0.467
2000	Non-Target	1803	-0.06079	0.11299	-0.6074	1.7847	
	Target	106	-0.06923	0.08658	-0.4637	0.2097	-0.957
2001	Non-Target	1674	-0.04911	0.16013	-0.6731	2.5302	
	Target	73	-0.03595	0.10065	-0.308	0.4207	1.06
2002	Non-Target	1450	-0.04415	0.25474	-0.3136	3.2016	
	Target	70	-0.08441	0.16426	-0.2839	0.8719	-1.941***
2003	Non-Target	1463	-0.03723	0.22692	-1.0409	4.6727	
	Target	89	-0.0321	0.26013	-0.3993	2.3003	0.182
2004	Non-Target	1489	-0.02794	0.03977	-0.2964	0.3142	
	Target	106	-0.02255	0.03682	-0.2061	0.1768	1.448
2005	Non-Target	1509	-0.05684	0.10359	-0.8673	2.0699	
	Target	122	-0.00509	0.67169	-0.4972	7.3025	0.85
2006	Non-Target	1460	-0.04836	0.08485	-0.5496	1.4365	
	Target	139	-0.05653	0.08913	-0.4286	0.4453	-1.037
2007	Non-Target	1428	-0.05981	0.07994	-0.4534	1.4054	
	Target	89	-0.05122	0.09724	-0.3448	0.7295	0.816

[a] The column provides the number of firms present in the target and the non-target group.

[b] This column provides a two sample test-statistics for the null hypothesis that there is no significant difference between the yearly means of the target and the non-target group. $*, **, ***$ indicate significance using a two-sample two-tail t-test at the 1%, 5% and 10% respectively.

Table A.25: *Univariate analysis of variable DPEA in both economies during the period 1997-2007*

Year	Group	N[a]	Mean	Std. Dev.	Minimum	Maximum	t-stat difference[b]
Panel A: UK univariate analysis							
1997	Non-Target	710	0.36215	0.89576	-1.2284	2.9643	
	Target	92	0.48351	0.98019	-1.169	2.9328	1.128
1998	Non-Target	686	0.23518	0.96243	-1.4529	3.144	
	Target	99	0.40397	0.92974	-1.0924	2.9393	1.681***
1999	Non-Target	663	0.20623	0.96777	-1.6917	3.3402	
	Target	86	0.47981	1.01911	-0.9629	2.8997	2.356**
2000	Non-Target	657	0.32875	1.01698	-1.3326	3.1982	
	Target	41	0.07731	1.00828	-1.0493	2.5354	-1.548
2001	Non-Target	686	0.31825	1.05474	-1.1973	3.2442	
	Target	46	-0.1978	0.79549	-0.7792	2.1501	-4.161*
2002	Non-Target	582	0.36205	1.0953	-1.0812	3.5144	
	Target	92	0.12603	1.06973	-1.0812	3.4571	-1.960***
2003	Non-Target	606	0.39028	1.1182	-1.0579	3.6041	
	Target	55	0.43625	1.12095	-0.6352	3.5047	0.291
2004	Non-Target	567	0.49609	1.15132	-0.9195	3.7357	
	Target	62	0.5233	1.02158	-0.6751	3.2932	0.197
2005	Non-Target	578	0.47079	1.10621	-0.8778	3.7907	
	Target	73	0.49433	1.02626	-0.8778	3.0547	0.183
2006	Non-Target	618	0.39878	1.10605	-0.7777	4.1802	
	Target	78	0.58228	1.23416	-0.7777	3.8881	1.251
2007	Non-Target	624	0.38251	1.12536	-1.0298	4.1634	
	Target	80	0.27067	1.08482	-0.7421	3.3913	-0.864
Panel B: US univariate analysis							
1997	Non-Target	1854	0.30289	1.13218	-0.8861	5.6454	
	Target	216	0.11236	1.00753	-0.8861	4.4913	-2.595*
1998	Non-Target	1818	0.4081	1.27634	-0.8517	6.5262	
	Target	240	0.28962	1.19549	-0.8517	6.1585	-1.431
1999	Non-Target	1892	0.40915	1.32933	-0.7941	6.6974	
	Target	241	0.17967	1.07386	-0.7941	6.7215	-3.034*
2000	Non-Target	1803	0.3908	1.29711	-0.786	6.8591	
	Target	106	0.05979	0.80288	-0.4258	2.8726	-3.952*
2001	Non-Target	1674	0.37464	1.33865	-0.7186	6.5723	
	Target	73	0.11681	1.18907	-0.4272	5.9833	-1.803***
2002	Non-Target	1450	0.39145	1.29849	-0.7294	6.5117	
	Target	70	0.25835	1.38709	-0.7294	5.7331	-0.786
2003	Non-Target	1463	0.40583	1.28913	-0.748	6.5151	
	Target	89	0.13657	1.05795	-0.748	4.0443	-2.299**
2004	Non-Target	1489	0.38084	1.19339	-0.8575	6.1885	
	Target	106	0.16414	1.05219	-0.8575	4.7676	-2.03**
2005	Non-Target	1509	0.35524	1.16658	-0.8995	5.9089	
	Target	122	0.45906	1.45083	-0.8995	6.1987	0.771
2006	Non-Target	1460	0.33781	1.16389	-0.9241	6.0797	
	Target	139	0.21786	1.07618	-0.9241	4.3961	-1.247
2007	Non-Target	1428	0.29145	1.11865	-1.019	5.8656	
	Target	89	0.25049	1.3014	-1.019	5.5351	-0.29

[a] The column provides the number of firms present in the target and the non-target group.

[b] This column provides a two sample test-statistics for the null hypothesis that there is no significant difference between the yearly means of the target and the non-target group. $*, **, ***$ indicate significance using a two-sample two-tail t-test at the 1%, 5% and 10% respectively.

Table A.26: *Univariate analysis of variable FCFS in both economies during the period 1997-2007*

Year	Group	N[a]	Mean	Std. Dev.	Minimum	Maximum	t-stat difference[b]
Panel A: UK univariate analysis							
1997	Non-Target	710	0.03561	0.59399	-14.9835	3.5783	
	Target	92	-0.03276	0.61498	-5.3572	0.3955	-1.007
1998	Non-Target	686	0.03169	0.74658	-15.4244	1.7878	
	Target	99	0.04936	0.29594	-2.8019	0.5303	0.429
1999	Non-Target	663	-0.03029	0.34647	-6.7247	0.7752	
	Target	86	-0.03709	0.29354	-1.9042	1.1583	-0.198
2000	Non-Target	657	0.02012	0.69797	-13.5003	0.8699	
	Target	41	0.06583	0.18285	-0.8343	0.4968	1.158
2001	Non-Target	686	0.03592	0.28785	-5.1489	1.0872	
	Target	46	0.02585	0.08814	-0.4889	0.0637	-0.592
2002	Non-Target	582	-0.02883	0.32828	-6.5933	0.411	
	Target	92	-0.02072	0.17528	-1.6326	0.2797	0.356
2003	Non-Target	606	0.00838	0.92767	-18.456	3.5684	
	Target	55	0.09104	0.29044	0.0322	2.2208	1.521
2004	Non-Target	567	0.03411	0.2953	-2.5961	5.0341	
	Target	62	0.0301	0.03787	-0.1728	0.1376	-0.301
2005	Non-Target	578	0.03164	0.13906	-1.8361	1.5447	
	Target	73	0.02805	0.41551	-2.6091	2.3837	-0.073
2006	Non-Target	618	0.03687	0.11697	-1.1586	1.5698	
	Target	78	0.03999	0.05072	-0.0631	0.3443	0.42
2007	Non-Target	624	-0.00791	0.25357	-2.2139	3.1949	
	Target	80	-0.01159	0.21281	-0.7476	1.5086	-0.142
Panel B: US univariate analysis							
1997	Non-Target	1854	0.00551	0.15314	-3.4506	2.4487	
	Target	216	0.00107	0.10238	-0.9674	0.5122	-0.568
1998	Non-Target	1818	0.01777	0.0825	-2.162	1.1315	
	Target	240	0.0191	0.03261	-0.0906	0.3845	0.465
1999	Non-Target	1892	0.03144	0.01281	-0.0761	0.2412	
	Target	241	0.03044	0.01232	-0.076	0.1227	-1.181
2000	Non-Target	1803	0.03016	0.02124	-0.7824	0.0776	
	Target	106	0.03141	0.01158	0.028	0.0771	1.015
2001	Non-Target	1674	0.02844	0.01895	-0.0814	0.07	
	Target	73	0.02941	0.01318	-0.0787	0.0509	0.602
2002	Non-Target	1450	0.02243	0.02413	-0.0612	0.2725	
	Target	70	0.02209	0.02045	0.0164	0.1668	-0.135
2003	Non-Target	1463	0.02153	0.03427	-0.4371	0.8649	
	Target	89	0.01615	0.05357	-0.4688	0.073	-0.936
2004	Non-Target	1489	0.02128	0.1254	-0.1678	5.0374	
	Target	106	0.01045	0.02861	-0.1963	0.0826	-1.265
2005	Non-Target	1509	0.01864	0.04455	-1.4785	0.4638	
	Target	122	0.01958	0.01974	0.0149	0.1885	0.443
2006	Non-Target	1460	-0.00199	0.03467	-0.0229	0.7364	
	Target	139	-0.0354	0.40864	-4.8218	0.1577	-0.964
2007	Non-Target	1428	0.01568	0.11639	-3.2217	0.8678	
	Target	89	-0.0035	0.1631	-1.5096	0.2511	-1.092

[a] The column provides the number of firms present in the target and the non-target group.
[b] This column provides a two sample test-statistics for the null hypothesis that there is no significant difference between the yearly means of the target and the non-target group. $*, **, ***$ indicate significance using a two-sample two-tail t-test at the 1%, 5% and 10% respectively.

Table A.27: *Univariate analysis of variable GSOY in both economies during the period 1997-2007*

Year	Group	N[a]	Mean	Std. Dev.	Minimum	Maximum	t-stat difference[b]
Panel A: UK univariate analysis							
1997	Non-Target	710	0.01001	1.22045	-0.9666	15.7533	
	Target	92	-0.07796	0.05279	-0.3042	0.186	-1.907***
1998	Non-Target	686	-0.05216	0.7488	-1.0516	12.6356	
	Target	99	-0.16672	0.15293	-0.7038	0.2417	-3.529*
1999	Non-Target	663	-0.04632	0.50792	-0.7623	6.8237	
	Target	86	-0.10979	0.14519	-0.5282	0.4941	-2.52**
2000	Non-Target	657	-0.01974	0.7626	-0.8615	13.9261	
	Target	41	-0.08319	0.06727	-0.3487	0.0859	-2.011**
2001	Non-Target	686	-0.02628	0.27207	-1.4119	3.3404	
	Target	46	-0.03997	0.06765	-0.4768	0.0828	-0.951
2002	Non-Target	582	-0.02442	0.58963	-0.5522	13.4461	
	Target	92	-0.06138	0.16809	-1.2095	0.9519	-1.229
2003	Non-Target	606	-0.00542	0.93236	-2.2555	14.9114	
	Target	55	-0.06978	0.03098	-0.252	-0.0068	-1.689***
2004	Non-Target	567	-0.04998	0.48177	-0.7718	10.5408	
	Target	62	-0.08563	0.21183	-0.9354	0.8974	-1.059
2005	Non-Target	578	0.02005	1.55943	-0.9877	17.2141	
	Target	73	-0.07158	0.09981	-0.7028	0.2191	-1.39
2006	Non-Target	618	-0.01186	0.37479	-0.2951	7.0322	
	Target	78	-0.01148	0.39154	-0.7555	3.311	0.008
2007	Non-Target	624	-0.00778	1.02546	-0.4583	15.7513	
	Target	80	0.01843	0.76509	-0.3298	6.7663	0.276
Panel B: US univariate analysis							
1997	Non-Target	1854	-0.02552	0.08949	-1.0831	1.6825	
	Target	216	-0.01886	0.14747	-0.5102	1.4348	0.65
1998	Non-Target	1818	-0.02618	0.18039	-1.5174	5.4186	
	Target	240	-0.02973	0.07819	-0.5489	1.017	-0.539
1999	Non-Target	1892	-0.066	0.0259	-0.1782	0.5574	
	Target	241	-0.06657	0.01908	-0.1142	0.1321	-0.417
2000	Non-Target	1803	-0.02603	0.1588	-1.7522	5.5578	
	Target	106	-0.03529	0.05412	-0.3865	0.0448	-1.435
2001	Non-Target	1674	-0.0288	0.03757	-0.2872	0.783	
	Target	73	-0.02788	0.02976	-0.217	-0.0195	0.255
2002	Non-Target	1450	-0.03029	0.05289	-0.6188	0.4543	
	Target	70	-0.03217	0.04815	-0.3813	0.0	-0.318
2003	Non-Target	1463	-0.02363	0.0582	-0.6734	0.7523	
	Target	89	-0.00784	0.18605	-0.6846	1.5982	0.798
2004	Non-Target	1489	-0.03093	0.02833	-0.1298	0.9214	
	Target	106	-0.03356	0.02116	-0.1943	-0.0238	-1.205
2005	Non-Target	1509	-0.02132	0.03926	-0.245	0.5286	
	Target	122	-0.02448	0.04435	-0.2284	0.0109	-0.763
2006	Non-Target	1460	-0.02168	0.02558	-0.3108	0.3215	
	Target	139	-0.02256	0.0237	-0.1862	0.0604	-0.415
2007	Non-Target	1428	-0.02844	0.08737	-1.8982	0.7956	
	Target	89	-0.02878	0.06523	-0.4698	-0.0131	-0.047

[a] The column provides the number of firms present in the target and the non-target group.

[b] This column provides a two sample test-statistics for the null hypothesis that there is no significant difference between the yearly means of the target and the non-target group. $*, **, ***$ indicate significance using a two-sample two-tail t-test at the 1%, 5% and 10% respectively.

Table A.28: *Univariate analysis of variable ICOV in both economies during the period 1997-2007*

Year	Group	N[a]	Mean	Std. Dev.	Minimum	Maximum	t-stat difference[b]
Panel A: UK univariate analysis							
1997	Non-Target	710	0.04824	0.67121	-3.7121	11.6574	
	Target	92	0.1644	1.77162	-0.3953	17.0513	0.623
1998	Non-Target	686	0.06868	0.91195	-5.8911	13.5011	
	Target	99	-0.04122	0.07125	-0.2724	0.3312	-3.092*
1999	Non-Target	663	0.02807	0.45364	-1.7917	5.8396	
	Target	86	0.09307	0.58089	-0.0703	4.5364	0.999
2000	Non-Target	657	0.16626	0.72184	-2.1652	9.1823	
	Target	41	0.08529	0.41371	-0.9254	2.4183	-1.149
2001	Non-Target	686	0.06848	0.57861	-9.0096	7.8294	
	Target	46	0.11285	0.24918	-0.4177	1.6752	1.035
2002	Non-Target	582	0.10657	0.22322	-2.7501	2.106	
	Target	92	0.03077	0.74857	-6.5578	0.8935	-0.964
2003	Non-Target	606	0.03391	0.09787	-1.3753	0.9451	
	Target	55	0.01153	0.26091	-1.8983	0.203	-0.632
2004	Non-Target	567	0.0564	0.27631	-2.0343	4.4298	
	Target	62	0.03893	0.05695	-0.2005	0.1861	-1.278
2005	Non-Target	578	-0.00759	0.68387	-15.7312	3.265	
	Target	73	0.01784	0.1031	-0.1141	0.857	0.823
2006	Non-Target	618	0.04516	0.2807	-4.956	2.428	
	Target	78	0.05483	0.04659	-0.1567	0.2059	0.776
2007	Non-Target	624	0.0292	0.52495	-11.6667	4.4562	
	Target	80	0.04648	0.11353	-0.2967	0.9333	0.704
Panel B: US univariate analysis							
1997	Non-Target	1854	0.02378	0.33552	-1.2393	7.966	
	Target	216	-0.00643	0.05331	-0.3064	0.2729	-3.515*
1998	Non-Target	1818	0.04508	0.35509	-0.9392	11.1772	
	Target	240	0.03392	0.35193	-3.3242	4.1372	-0.461
1999	Non-Target	1892	0.07264	0.27329	-0.5401	5.6786	
	Target	241	0.07263	0.25434	-0.2105	3.6374	-0.001
2000	Non-Target	1803	0.02309	0.14439	-0.213	5.2267	
	Target	106	0.01378	0.04997	-0.1728	0.3408	-1.571
2001	Non-Target	1674	0.06123	0.48671	-0.4782	13.1192	
	Target	73	0.02938	0.02005	-0.0755	0.1139	-2.627*
2002	Non-Target	1450	0.08899	0.19593	-1.0875	4.9459	
	Target	70	0.07265	0.03146	0.0054	0.2548	-2.564**
2003	Non-Target	1463	0.06466	0.35797	-2.7407	10.8034	
	Target	89	0.03471	0.06041	-0.278	0.4118	-2.641*
2004	Non-Target	1489	0.07744	0.39461	-0.2721	9.8837	
	Target	106	0.04851	0.13077	-0.1461	1.2738	-1.774***
2005	Non-Target	1509	0.03084	0.19106	-0.4015	5.1899	
	Target	122	0.01582	0.0645	-0.123	0.6495	-1.967**
2006	Non-Target	1460	0.07649	0.96272	-28.7532	11.0198	
	Target	139	0.04693	0.05175	-0.0972	0.2718	-1.156
2007	Non-Target	1428	0.07674	0.87762	-11.2172	14.7023	
	Target	89	0.03447	0.07469	-0.3037	0.5552	-1.723***

[a] The column provides the number of firms present in the target and the non-target group.
[b] This column provides a two sample test-statistics for the null hypothesis that there is no significant difference between the yearly means of the target and the non-target group. $*, **, ***$ indicate significance using a two-sample two-tail t-test at the 1%, 5% and 10% respectively.

Table A.29: *Univariate analysis of variable IDHE in both economies during the period 1997-2007*

Year	Group	N[a]	Mean	Std. Dev.	Minimum	Maximum	t-stat difference[b]
Panel A: UK univariate analysis							
1997	Non-Target	710	-0.02846	0.43154	-0.5003	4.5466	
	Target	92	0.00605	0.5067	-0.5652	3.3363	0.625
1998	Non-Target	686	-0.03719	0.33748	-0.7588	3.9835	
	Target	99	-0.07674	0.17509	-0.8672	0.8672	-1.813***
1999	Non-Target	663	-0.02942	0.26577	-0.8712	3.3615	
	Target	86	-0.07473	0.15995	-0.8982	0.0143	-2.254**
2000	Non-Target	657	-0.0075	1.09653	-0.5814	15.7134	
	Target	41	-0.01347	0.33748	-0.3216	1.3611	-0.187
2001	Non-Target	686	-0.04364	0.86301	-20.0572	6.4311	
	Target	46	0.10616	0.77964	-0.2067	3.7398	1.253
2002	Non-Target	582	-0.07343	0.33273	-0.59	3.9832	
	Target	92	-0.04475	0.52447	-0.5245	4.4474	0.509
2003	Non-Target	606	-0.064	0.27094	-0.8578	3.3395	
	Target	55	-0.08764	0.09731	-0.3237	0.4988	-1.38
2004	Non-Target	567	-0.03833	0.31965	-0.6406	5.0253	
	Target	62	-0.07413	0.13151	-0.5853	0.3288	-1.671***
2005	Non-Target	578	-0.04367	0.60841	-0.9006	10.7921	
	Target	73	-0.07565	0.36245	-0.8116	2.4349	-0.647
2006	Non-Target	618	-0.0758	0.33386	-0.8477	2.3694	
	Target	78	0.0512	1.16898	-0.8123	9.6679	0.955
2007	Non-Target	624	-0.04458	0.66694	-0.8163	11.4587	
	Target	80	-0.02544	0.47626	-0.7189	2.7845	0.321
Panel B: US univariate analysis							
1997	Non-Target	1854	-0.02669	0.12739	-0.5344	2.5076	
	Target	216	-0.04553	0.13466	-0.5166	0.9792	-1.957***
1998	Non-Target	1818	-0.04652	0.25851	-0.872	5.016	
	Target	240	-0.07337	0.15974	-0.7786	0.4735	-2.245**
1999	Non-Target	1892	-0.06131	0.18358	-0.8843	3.2832	
	Target	241	-0.06545	0.14801	-0.8316	1.2258	-0.397
2000	Non-Target	1803	-0.06798	0.15134	-0.7303	2.6234	
	Target	106	-0.02953	0.42205	-0.6933	3.2651	0.934
2001	Non-Target	1674	-0.04395	0.12944	-0.8175	2.687	
	Target	73	-0.04627	0.08756	-0.6909	0.1947	-0.216
2002	Non-Target	1450	-0.03472	0.1321	-0.6434	2.0302	
	Target	70	-0.03476	0.07042	-0.4007	0.2559	-0.004
2003	Non-Target	1463	-0.07312	0.38072	-0.5717	12.3559	
	Target	89	-0.02593	0.35026	-0.1589	2.9195	1.228
2004	Non-Target	1489	-0.04465	0.10333	-0.5352	1.2756	
	Target	106	-0.04154	0.07463	-0.2928	0.4629	0.402
2005	Non-Target	1509	-0.06083	0.18913	-0.7417	4.7036	
	Target	122	-0.04558	0.30026	-0.6964	3.0522	0.552
2006	Non-Target	1460	-0.02604	0.20438	-0.7453	5.4142	
	Target	139	-0.05072	0.12856	-0.7453	0.7163	-2.032**
2007	Non-Target	1428	-0.06265	0.19654	-0.7212	4.3759	
	Target	89	-0.06006	0.12552	-0.411	0.6484	0.181

[a] The column provides the number of firms present in the target and the non-target group.

[b] This column provides a two sample test-statistics for the null hypothesis that there is no significant difference between the yearly means of the target and the non-target group. $*, **, ***$ indicate significance using a two-sample two-tail t-test at the 1%, 5% and 10% respectively.

Table A.30: *Univariate analysis of variable ITUR in both economies during the period 1997-2007*

Year	Group	N[a]	Mean	Std. Dev.	Minimum	Maximum	t-stat difference[b]
Panel A: UK univariate analysis							
1997	Non-Target	710	-0.07976	0.26021	-0.4692	3.6169	
	Target	92	-0.03269	0.62032	-0.2418	5.8254	0.72
1998	Non-Target	686	-0.06138	0.68842	-0.3914	7.4309	
	Target	99	-0.05607	0.60288	-0.3199	5.7837	0.08
1999	Non-Target	663	0.00157	1.28129	-0.5192	17.3963	
	Target	86	0.09043	0.76061	-0.3004	5.6904	0.926
2000	Non-Target	657	0.02175	1.28023	-0.9151	17.2568	
	Target	41	-0.12551	0.20224	-0.8618	-0.0109	-2.492**
2001	Non-Target	686	-0.04304	0.28378	-1.0423	3.5694	
	Target	46	-0.05232	0.15111	-0.6185	0.6011	-0.375
2002	Non-Target	582	-0.01033	0.89656	-0.6974	12.3325	
	Target	92	-0.06956	0.22548	-0.3691	1.9302	-1.347
2003	Non-Target	606	-0.01638	1.18477	-0.7016	15.5274	
	Target	55	-0.05144	0.2128	-0.4117	1.1024	-0.626
2004	Non-Target	567	0.03007	1.36072	-0.7584	15.9656	
	Target	62	-0.06673	0.2214	-0.6002	0.7572	-1.52
2005	Non-Target	578	0.00765	1.16788	-1.0923	14.7226	
	Target	73	0.04931	0.81448	-0.5766	6.2589	0.389
2006	Non-Target	618	-0.02515	0.76483	-0.5771	10.375	
	Target	78	0.05369	0.83809	-0.5189	5.4368	0.79
2007	Non-Target	624	-0.04674	0.76183	-0.6509	10.8401	
	Target	80	0.08516	1.6253	-0.5913	14.4202	0.716
Panel B: US univariate analysis							
1997	Non-Target	1854	-0.03863	0.3489	-0.5864	7.6751	
	Target	216	-0.01957	0.27959	-0.5045	1.6297	0.922
1998	Non-Target	1818	-0.04102	0.28861	-0.4001	9.3821	
	Target	240	-0.05125	0.10953	-0.3452	0.7513	-1.045
1999	Non-Target	1892	-0.0202	0.67643	-0.611	19.3972	
	Target	241	0.00645	1.03253	-0.5738	15.5549	0.39
2000	Non-Target	1803	-0.03405	0.47061	-0.4642	18.0708	
	Target	106	-0.02145	0.23096	-0.469	1.3689	0.504
2001	Non-Target	1674	-0.02173	0.27889	-0.458	8.3201	
	Target	73	-0.01193	0.0821	-0.1138	0.4283	0.832
2002	Non-Target	1450	-0.0213	0.76472	-0.3664	20.7319	
	Target	70	0.00849	0.30777	-0.2529	1.7665	0.623
2003	Non-Target	1463	-0.03843	0.10601	-0.5171	1.809	
	Target	89	-0.04762	0.0741	-0.477	0.1463	-1.103
2004	Non-Target	1489	-0.0292	0.66897	-0.4755	19.8941	
	Target	106	0.07016	1.36836	-0.4159	13.9907	0.737
2005	Non-Target	1509	-0.03398	0.3193	-0.4488	7.7424	
	Target	122	-0.01707	0.18292	-0.3931	1.0124	0.915
2006	Non-Target	1460	-0.0432	0.50226	-0.2822	17.4641	
	Target	139	-0.05039	0.09865	-0.2602	0.6263	-0.461
2007	Non-Target	1428	-0.03957	0.14479	-0.2687	4.388	
	Target	89	-0.0377	0.06374	-0.2421	0.2289	0.241

[a] The column provides the number of firms present in the target and the non-target group.
[b] This column provides a two sample test-statistics for the null hypothesis that there is no significant difference between the yearly means of the target and the non-target group. $*, **, ***$ indicate significance using a two-sample two-tail t-test at the 1%, 5% and 10% respectively.

Table A.31: *Univariate analysis of variable LDTC in both economies during the period 1997-2007*

Year	Group	N[a]	Mean	Std. Dev.	Minimum	Maximum	t-stat difference[b]
Panel A: UK univariate analysis							
1997	Non-Target	710	0.01717	0.16662	-1.2885	2.2489	
	Target	92	0.03334	0.22527	-0.6055	1.8215	0.665
1998	Non-Target	686	-0.01489	0.22774	-1.2738	2.6051	
	Target	99	0.00937	0.17407	-0.2583	1.6389	1.242
1999	Non-Target	663	0.02277	0.21777	-1.4955	1.6286	
	Target	86	0.05885	0.33416	-1.2128	2.2068	0.975
2000	Non-Target	657	-0.00485	0.20725	-1.0396	1.6658	
	Target	41	0.00149	0.36039	-1.0076	0.9745	0.111
2001	Non-Target	686	-0.0162	0.36233	-6.9254	2.8118	
	Target	46	0.05673	0.34201	-0.1679	1.9365	1.395
2002	Non-Target	582	-0.0228	0.0967	-0.2932	1.5968	
	Target	92	0.02333	0.67938	-0.526	6.4364	0.650
2003	Non-Target	606	-0.03814	0.17757	-0.9936	2.2405	
	Target	55	-0.03776	0.16975	-0.599	0.9353	0.016
2004	Non-Target	567	0.04695	1.08488	-1.1957	12.4848	
	Target	62	0.00292	0.12995	-0.5614	0.3365	-0.909
2005	Non-Target	578	0.0178	0.22953	-1.519	3.3172	
	Target	73	0.05414	0.18019	-0.3132	0.8241	1.57
2006	Non-Target	618	0.02295	0.17864	-2.351	1.4515	
	Target	78	0.04264	0.17586	-0.3503	1.4713	0.930
2007	Non-Target	624	0.03241	0.26261	-0.9101	3.0318	
	Target	80	-0.0166	0.20047	-0.9101	0.4022	-1.980**
Panel B: US univariate analysis							
1997	Non-Target	1854	0.01713	0.15734	-1.1101	1.3042	
	Target	216	0.03844	0.212	-0.7071	1.5398	1.432
1998	Non-Target	1818	0.00993	0.17016	-3.3814	0.8503	
	Target	240	0.01578	0.15533	-0.6316	0.3864	0.542
1999	Non-Target	1892	0.03723	0.10115	-0.6824	0.9001	
	Target	241	0.04395	0.1113	-0.2706	0.7102	0.892
2000	Non-Target	1803	0.02379	0.08874	-0.8265	0.7534	
	Target	106	0.043	0.13886	-0.5844	1.1498	1.408
2001	Non-Target	1674	0.01801	0.06636	-0.6028	0.479	
	Target	73	0.01248	0.0601	-0.3981	0.2756	-0.766
2002	Non-Target	1450	-0.00906	0.03213	-0.4119	0.3128	
	Target	70	0.00092	0.05887	-0.0164	0.3801	1.408
2003	Non-Target	1463	-0.01227	0.06083	-0.6111	0.7706	
	Target	89	0.00042	0.04058	-0.2534	0.1216	2.767*
2004	Non-Target	1489	-0.00578	0.04717	-0.4277	0.6453	
	Target	106	-0.00252	0.05181	-0.1805	0.341	0.63
2005	Non-Target	1509	0.02551	0.11714	-0.8677	1.0494	
	Target	122	0.02697	0.10052	-0.5396	0.5602	0.152
2006	Non-Target	1460	0.00734	0.11324	-0.8926	0.9375	
	Target	139	0.01248	0.17565	-0.8054	0.9347	0.338
2007	Non-Target	1428	0.0017	0.12496	-0.948	1.1914	
	Target	89	-0.00342	0.09848	-0.8457	0.1821	-0.468

[a] The column provides the number of firms present in the target and the non-target group.
[b] This column provides a two sample test-statistics for the null hypothesis that there is no significant difference between the yearly means of the target and the non-target group. $*, **, ***$ indicate significance using a two-sample two-tail t-test at the 1%, 5% and 10% respectively.

Table A.32: *Univariate analysis of variable NSFA in both economies during the period 1997-2007*

Year	Group	N[a]	Mean	Std. Dev.	Minimum	Maximum	t-stat difference[b]
Panel A: UK univariate analysis							
1997	Non-Target	710	-0.07247	0.68857	-0.499	8.9782	
	Target	92	-0.04751	0.53183	-0.49	2.5295	0.408
1998	Non-Target	686	0.00473	1.13802	-0.4039	15.1359	
	Target	99	-0.12817	0.33796	-0.3916	1.3212	-2.41**
1999	Non-Target	663	-0.04522	0.15588	-0.4795	2.7715	
	Target	86	-0.02189	0.34174	-0.4066	3.0395	0.625
2000	Non-Target	657	0.00633	1.36843	-0.608	17.7398	
	Target	41	-0.10782	0.26738	-0.3784	1.051	-1.684***
2001	Non-Target	686	-0.03747	0.50746	-0.5659	8.0844	
	Target	46	-0.0687	0.19592	-0.4738	0.636	-0.898
2002	Non-Target	582	0.01747	1.42325	-0.6418	19.4518	
	Target	92	-0.01402	0.5725	-0.6205	4.585	-0.375
2003	Non-Target	606	0.00835	1.38323	-0.4008	16.6359	
	Target	55	-0.15314	0.24299	-0.3187	1.328	-2.483**
2004	Non-Target	567	-0.10711	0.67049	-0.4736	8.8606	
	Target	62	-0.12014	0.94364	-0.4271	6.8178	-0.106
2005	Non-Target	578	-0.07454	0.70176	-0.711	10.4775	
	Target	73	-0.11058	0.58421	-0.6698	4.0419	-0.485
2006	Non-Target	618	-0.04221	0.99987	-0.7535	11.4013	
	Target	78	0.08224	0.95781	-0.3973	5.4055	1.076
2007	Non-Target	624	-0.04802	0.43414	-0.8564	6.6291	
	Target	80	-0.06757	0.32476	-0.3419	2.1189	-0.486
Panel B: US univariate analysis							
1997	Non-Target	1854	-0.05395	0.65219	-0.4208	9.6206	
	Target	216	-0.13139	0.31527	-0.4192	1.5783	-2.949*
1998	Non-Target	1818	-0.03629	0.38064	-0.329	12.1185	
	Target	240	-0.04162	0.19457	-0.3276	1.4016	-0.346
1999	Non-Target	1892	-0.0145	0.61524	-0.2832	16.2667	
	Target	241	-0.03076	0.40694	-0.278	3.1555	-0.546
2000	Non-Target	1803	-0.02168	0.08354	-0.3103	1.4952	
	Target	106	-0.02738	0.08147	-0.2986	0.3991	-0.699
2001	Non-Target	1674	-0.02445	0.1995	-0.1414	5.6707	
	Target	73	-0.03056	0.11018	-0.1258	0.6034	-0.443
2002	Non-Target	1450	-0.03459	0.27834	-0.1279	7.7796	
	Target	70	-0.04173	0.17179	-0.1241	1.1733	-0.328
2003	Non-Target	1463	-0.03104	0.31	-0.366	6.6579	
	Target	89	-0.04889	0.17251	-0.3602	1.2145	-0.892
2004	Non-Target	1489	-0.03886	0.13396	-0.1521	3.1694	
	Target	106	-0.02834	0.12551	-0.1484	0.6841	0.83
2005	Non-Target	1509	-0.03198	0.2858	-0.2897	6.3446	
	Target	122	-0.04579	0.18974	-0.282	1.101	-0.739
2006	Non-Target	1460	-0.03697	0.24393	-0.2706	4.2307	
	Target	139	-0.06283	0.11538	-0.2699	0.7195	-2.213**
2007	Non-Target	1428	-0.05585	0.19341	-0.2723	3.8274	
	Target	89	-0.06795	0.13631	-0.2634	0.9274	-0.789

[a] The column provides the number of firms present in the target and the non-target group.
[b] This column provides a two sample test-statistics for the null hypothesis that there is no significant difference between the yearly means of the target and the non-target group. $*, **, ***$ indicate significance using a two-sample two-tail t-test at the 1%, 5% and 10% respectively.

Table A.33: *Univariate analysis of variable NSWC in both economies during the period 1997-2007*

Year	Group	N[a]	Mean	Std. Dev.	Minimum	Maximum	t-stat difference[b]
Panel A: UK univariate analysis							
1997	Non-Target	710	-0.01923	0.29252	-3.3485	3.9686	
	Target	92	-0.02863	0.08866	-0.5235	0.3048	-0.655
1998	Non-Target	686	0.02346	0.36463	-3.5647	6.285	
	Target	99	0.01107	0.10797	-0.4775	0.6833	-0.702
1999	Non-Target	663	0.05204	1.21537	-13.3032	14.2271	
	Target	86	-0.01139	0.76581	-4.0158	3.5512	-0.667
2000	Non-Target	657	0.01402	1.06638	-12.6962	12.5332	
	Target	41	0.22071	1.61634	-0.9169	10.1946	0.808
2001	Non-Target	686	0.00764	1.30753	-12.1886	15.6993	
	Target	46	-0.03572	0.18546	-0.5621	0.5541	-0.762
2002	Non-Target	582	-0.05364	0.7337	-15.3458	0.5496	
	Target	92	-0.00509	0.08028	-0.2724	0.4811	1.539
2003	Non-Target	606	0.08911	1.48572	-5.5759	17.1767	
	Target	55	-0.01853	0.23136	-1.1433	0.8958	-1.584
2004	Non-Target	567	-0.05784	1.65052	-20.1443	4.6204	
	Target	62	0.01871	0.26256	-1.2623	0.9182	0.995
2005	Non-Target	578	0.05466	0.80385	-6.3864	12.9852	
	Target	73	-0.17541	0.95244	-7.3635	0.7251	-1.977**
2006	Non-Target	618	-0.07216	1.65773	-21.4766	2.6624	
	Target	78	0.03571	0.09687	-0.3449	0.4783	1.596
2007	Non-Target	624	-0.02952	0.44919	-4.0853	4.2346	
	Target	80	0.24737	2.14922	-2.1083	15.0789	1.027
Panel B: US univariate analysis							
1997	Non-Target	1854	0.02059	0.58641	-10.4739	15.5195	
	Target	216	0.01111	0.31433	-0.9193	4.1289	-0.374
1998	Non-Target	1818	0.01742	0.28589	-3.1728	9.1104	
	Target	240	-0.04877	0.99385	-15.2145	1.0544	-1.026
1999	Non-Target	1892	-0.01642	0.55036	-18.7983	8.8897	
	Target	241	0.03872	0.50791	-0.9398	7.5413	1.572
2000	Non-Target	1803	0.02377	0.58558	-3.5081	17.5591	
	Target	106	-0.10787	1.07455	-10.8546	0.9497	-1.25
2001	Non-Target	1674	-0.0087	0.4132	-11.9854	8.9866	
	Target	73	0.00329	0.06582	-0.1874	0.4764	0.944
2002	Non-Target	1450	-0.01895	0.29205	-8.9571	1.9091	
	Target	70	-0.00873	0.03892	-0.1272	0.1885	1.139
2003	Non-Target	1463	-0.04991	1.93389	-19.9282	15.2056	
	Target	89	0.08509	0.44711	-1.2876	3.7859	1.948***
2004	Non-Target	1489	0.02568	1.30818	-22.9778	20.4066	
	Target	106	0.05739	0.25217	-0.5376	1.6557	0.758
2005	Non-Target	1509	0.03398	0.84805	-7.7517	18.8949	
	Target	122	0.19263	1.6018	-0.9915	11.6158	1.082
2006	Non-Target	1460	0.01198	0.93452	-13.8309	20.5892	
	Target	139	0.0015	0.75307	-7.003	5.0021	-0.153
2007	Non-Target	1428	0.05505	1.72851	-18.0773	28.2275	
	Target	89	0.01322	0.26568	-0.8349	1.8164	-0.779

[a] The column provides the number of firms present in the target and the non-target group.

[b] This column provides a two sample test-statistics for the null hypothesis that there is no significant difference between the yearly means of the target and the non-target group. $*, **, ***$ indicate significance using a two-sample two-tail t-test at the 1%, 5% and 10% respectively.

Table A.34: *Univariate analysis of variable OPMA in both economies during the period 1997-2007*

Year	Group	N[a]	Mean	Std. Dev.	Minimum	Maximum	t-stat difference[b]
Panel A: UK univariate analysis							
1997	Non-Target	710	0.05611	0.20405	-2.55	3.3031	
	Target	92	0.04089	0.21771	-1.5448	1.3151	-0.635
1998	Non-Target	686	0.08075	0.13359	-2.4035	1.6992	
	Target	99	0.07602	0.04444	-0.3141	0.2404	-0.698
1999	Non-Target	663	0.05857	0.70366	-17.3883	2.2173	
	Target	86	0.06851	0.15631	-0.9925	0.1389	0.31
2000	Non-Target	657	0.06514	0.2489	-3.7471	3.1383	
	Target	41	-0.0189	0.47603	-2.7801	0.7009	-1.121
2001	Non-Target	686	0.03668	0.03336	-0.0574	0.2752	
	Target	46	0.03057	0.0172	0.0061	0.1434	-2.153**
2002	Non-Target	582	0.09024	0.30888	-4.4699	2.778	
	Target	92	0.02325	0.35434	-2.342	0.3124	-1.713***
2003	Non-Target	606	0.03559	0.31281	-5.4775	1.8238	
	Target	55	0.03272	0.11137	-0.7856	0.0507	-0.146
2004	Non-Target	567	0.0745	0.22115	-1.2971	2.6276	
	Target	62	0.07319	0.14476	-0.3051	0.8109	-0.064
2005	Non-Target	578	0.05766	0.70988	-16.2432	2.0551	
	Target	73	0.10799	0.26303	-1.1142	1.8903	1.180
2006	Non-Target	618	0.03957	0.05819	-0.3996	0.7634	
	Target	78	0.04032	0.04653	0.0271	0.3413	0.130
2007	Non-Target	624	0.07239	0.12245	-1.3864	1.3723	
	Target	80	0.07407	0.03007	-0.0378	0.1996	0.283
Panel B: US univariate analysis							
1997	Non-Target	1854	0.06585	0.10345	-0.8999	2.5411	
	Target	216	0.06994	0.21736	-1.1099	2.2498	0.273
1998	Non-Target	1818	0.06518	0.07272	-0.4114	1.4753	
	Target	240	0.06705	0.08751	-0.4236	0.9553	0.317
1999	Non-Target	1892	0.06125	0.06886	-0.3767	1.3238	
	Target	241	0.05998	0.08646	-0.5229	1.2406	-0.219
2000	Non-Target	1803	0.01979	0.02123	-0.0029	0.1865	
	Target	106	0.021	0.02851	0.0137	0.2002	0.430
2001	Non-Target	1674	0.03403	0.19433	-7.9053	0.0783	
	Target	73	0.03713	0.00711	0.0258	0.0767	0.643
2002	Non-Target	1450	0.06944	0.0135	-0.009	0.2457	
	Target	70	0.07035	0.01205	0.0631	0.143	0.614
2003	Non-Target	1463	0.07628	0.02116	-0.1239	0.2338	
	Target	89	0.07421	0.02876	-0.0315	0.3081	-0.668
2004	Non-Target	1489	0.07471	0.01482	-0.0146	0.4251	
	Target	106	0.07279	0.0418	-0.2265	0.3758	-0.471
2005	Non-Target	1509	0.04813	0.01819	-0.0023	0.3717	
	Target	122	0.04983	0.02783	0.0438	0.312	0.663
2006	Non-Target	1460	0.04771	0.02256	-0.1001	0.3809	
	Target	139	0.04897	0.02257	0.0411	0.1977	0.629
2007	Non-Target	1428	0.04154	0.02899	0.0107	0.6759	
	Target	89	0.03939	0.02798	-0.0512	0.2845	-0.702

[a] The column provides the number of firms present in the target and the non-target group.
[b] This column provides a two sample test-statistics for the null hypothesis that there is no significant difference between the yearly means of the target and the non-target group. $*, **, ***$ indicate significance using a two-sample two-tail t-test at the 1%, 5% and 10% respectively.

Table A.35: *Univariate analysis of variable PTBR in both economies during the period 1997-2007*

Year	Group	N[a]	Mean	Std. Dev.	Minimum	Maximum	t-stat difference[b]
Panel A: UK univariate analysis							
1997	Non-Target	710	-0.01754	0.35671	-2.1186	5.4715	
	Target	92	-0.0612	0.51393	-4.2692	2.3482	-0.791
1998	Non-Target	686	-0.01037	0.52647	-6.0352	7.1076	
	Target	99	0.09165	0.97918	-0.3667	9.5223	1.016
1999	Non-Target	663	0.03061	0.80662	-9.6069	15.0436	
	Target	86	0.08195	0.46626	-0.207	2.439	0.867
2000	Non-Target	657	0.01432	0.41242	-3.276	4.2655	
	Target	41	-0.08156	0.1828	-0.3985	0.6168	-2.926*
2001	Non-Target	686	-0.01392	0.44648	-6.7977	1.7465	
	Target	46	0.11283	1.08	-0.196	7.2676	0.791
2002	Non-Target	582	0.01132	0.45414	-5.224	5.115	
	Target	92	-0.17233	1.48856	-14.0233	1.247	-1.175
2003	Non-Target	606	0.00922	0.28603	-3.297	5.1428	
	Target	55	0.00898	0.17821	-0.0762	1.2737	-0.009
2004	Non-Target	567	0.00535	0.35871	-2.1657	6.7394	
	Target	62	-0.03612	0.11718	-0.8917	0.1247	-1.958***
2005	Non-Target	578	-0.02279	0.61845	-11.9567	5.2585	
	Target	73	-0.03229	0.06211	-0.4098	0.1242	-0.355
2006	Non-Target	618	-0.0129	0.47415	-8.3358	3.1696	
	Target	78	0.0082	0.11696	-0.3084	0.7748	0.909
2007	Non-Target	624	-0.00204	0.62713	-1.2485	15.119	
	Target	80	0.00247	0.32236	-0.2573	2.6635	0.103
Panel B: US univariate analysis							
1997	Non-Target	1854	-0.02912	0.10424	-2.2147	1.8893	
	Target	216	0.00305	1.36144	-10.2742	17.1446	0.347
1998	Non-Target	1818	-0.00361	0.15441	-0.4951	4.8186	
	Target	240	-0.0104	0.09084	-0.1614	0.9737	-0.985
1999	Non-Target	1892	0.00086	0.03743	-1.3034	0.3626	
	Target	241	0.04306	0.64341	-0.0501	10.0049	1.018
2000	Non-Target	1803	0.01124	0.02577	-0.1531	0.6047	
	Target	106	0.11793	1.10614	-0.1205	11.4508	0.993
2001	Non-Target	1674	0.01672	0.03685	-0.098	1.0337	
	Target	73	0.01255	0.00896	-0.0578	0.0331	-3.017*
2002	Non-Target	1450	0.00653	0.01391	-0.0851	0.1521	
	Target	70	0.00698	0.01099	-0.0497	0.01	0.330
2003	Non-Target	1463	0.00417	0.19967	-7.6002	0.317	
	Target	89	0.01205	0.03812	-0.0689	0.3585	1.194
2004	Non-Target	1489	0.01574	0.01475	-0.0792	0.3006	
	Target	106	0.0141	0.01701	-0.0724	0.0436	-0.967
2005	Non-Target	1509	0.00713	0.01859	-0.17	0.2795	
	Target	122	0.00539	0.01807	-0.1127	0.0107	-1.021
2006	Non-Target	1460	0.01069	0.02195	-0.1607	0.4402	
	Target	139	0.00994	0.02443	-0.1774	0.1281	-0.349
2007	Non-Target	1428	0.00068	0.04619	-0.1685	1.4132	
	Target	89	-0.00331	0.01475	-0.0788	0.0439	-2.010**

[a] The column provides the number of firms present in the target and the non-target group.

[b] This column provides a two sample test-statistics for the null hypothesis that there is no significant difference between the yearly means of the target and the non-target group. $*, **, ***$ indicate significance using a two-sample two-tail t-test at the 1%, 5% and 10% respectively.

Table A.36: *Univariate analysis of variable PTER in both economies during the period 1997-2007*

Year	Group	N[a]	Mean	Std. Dev.	Minimum	Maximum	t-stat difference[b]
Panel A: UK univariate analysis							
1997	Non-Target	710	0.05343	0.89867	-10.1681	16.823	
	Target	92	0.01505	0.37624	-1.4579	1.47	-0.742
1998	Non-Target	686	-0.02695	0.54777	-7.8938	7.6098	
	Target	99	-0.0075	0.21789	-0.545	1.3217	0.642
1999	Non-Target	663	0.00242	0.322	-2.8866	5.3285	
	Target	86	0.02367	0.14001	-0.3357	0.7063	1.084
2000	Non-Target	657	0.0667	0.5342	-2.0522	9.2369	
	Target	41	-0.01699	0.2682	-0.4895	1.4366	-1.789***
2001	Non-Target	686	0.11511	0.80082	-8.9131	10.1271	
	Target	46	-0.094	0.39797	-1.8298	0.8906	-3.160*
2002	Non-Target	582	0.0836	0.51815	-5.3916	5.4289	
	Target	92	0.17398	1.05959	-0.9568	9.0926	0.803
2003	Non-Target	606	0.05243	0.50711	-3.7464	4.2065	
	Target	55	0.07312	0.49649	-0.8214	2.6062	0.295
2004	Non-Target	567	0.08367	0.5252	-4.9523	2.1311	
	Target	62	0.22348	0.63069	-1.5326	3.071	1.683***
2005	Non-Target	578	0.06988	0.70552	-6.8129	8.1945	
	Target	73	0.12669	0.46048	-1.2307	1.6115	0.926
2006	Non-Target	618	0.13405	0.78537	-4.2521	15.0204	
	Target	78	0.17181	0.61991	-3.5788	2.0116	0.491
2007	Non-Target	624	0.10524	1.17941	-5.7465	20.6194	
	Target	80	0.09945	0.56637	-2.3483	1.8761	-0.073
Panel B: US univariate analysis							
1997	Non-Target	1854	-0.07184	0.40204	-0.8086	4.6971	
	Target	216	0.02711	1.14183	-0.7881	15.4234	1.265
1998	Non-Target	1818	-0.03688	0.58698	-0.3366	17.7402	
	Target	240	-0.08161	0.12699	-0.2539	1.0173	-2.792*
1999	Non-Target	1892	-0.03426	0.45275	-0.3923	14.065	
	Target	241	-0.04787	0.16295	-0.2784	1.9986	-0.921
2000	Non-Target	1803	-0.04345	0.3545	-0.4549	10.1542	
	Target	106	-0.02834	0.39385	-0.4016	3.4916	0.386
2001	Non-Target	1674	-0.04562	0.40336	-0.7799	13.0039	
	Target	73	-0.04318	0.16831	-0.1431	1.0979	0.111
2002	Non-Target	1450	-0.02515	0.24279	-0.7011	5.5325	
	Target	70	-0.02015	0.1709	-0.0894	1.3095	0.234
2003	Non-Target	1463	-0.04332	0.27302	-0.7276	4.5955	
	Target	89	-0.01196	0.30485	-0.1951	1.6896	0.948
2004	Non-Target	1489	-0.01744	0.45376	-0.639	13.9119	
	Target	106	-0.04784	0.27873	-0.6937	2.5883	-1.030
2005	Non-Target	1509	-0.04164	0.594	-0.7241	18.8751	
	Target	122	-0.07667	0.21234	-0.6547	1.1794	-1.426
2006	Non-Target	1460	-0.06221	0.27656	-0.7478	3.671	
	Target	139	-0.01878	0.50421	-0.5995	4.2246	1.001
2007	Non-Target	1428	-0.05203	0.55431	-0.5475	13.972	
	Target	89	-0.03698	0.32071	-0.5666	1.9015	0.406

[a] The column provides the number of firms present in the target and the non-target group.
[b] This column provides a two sample test-statistics for the null hypothesis that there is no significant difference between the yearly means of the target and the non-target group. $*, **, ***$ indicate significance using a two-sample two-tail t-test at the 1%, 5% and 10% respectively.

Table A.37: *Univariate analysis of variable ROET in both economies during the period 1997-2007*

Year	Group	N[a]	Mean	Std. Dev.	Minimum	Maximum	t-stat difference[b]
Panel A: UK univariate analysis							
1997	Non-Target	710	-0.02129	1.52791	-25.2928	1.3882	
	Target	92	0.03215	0.26927	-1.9701	1.6132	0.837
1998	Non-Target	686	0.02833	0.33978	-5.3131	2.3861	
	Target	99	-0.08559	0.72246	-4.9866	0.4354	-1.544
1999	Non-Target	663	0.02975	0.39032	-6.8912	3.255	
	Target	86	0.03322	0.23646	-1.0444	0.8785	0.117
2000	Non-Target	657	0.04789	0.23108	-3.4497	1.7788	
	Target	41	-0.04991	0.37244	-1.9586	0.2724	-1.662***
2001	Non-Target	686	0.02135	0.39819	-6.6406	0.8196	
	Target	46	-0.00401	0.24875	-1.4739	0.2651	-0.639
2002	Non-Target	582	0.04746	0.27456	-5.6534	0.4691	
	Target	92	0.01502	0.38281	-3.4399	0.6345	-0.782
2003	Non-Target	606	0.02226	0.10917	-2.4389	0.3217	
	Target	55	0.02345	0.02199	0.0183	0.185	0.223
2004	Non-Target	567	-0.01245	0.06366	-0.8973	0.5436	
	Target	62	-0.02743	0.15637	-1.1517	0.2127	-0.748
2005	Non-Target	578	0.02824	0.37701	-8.5381	0.6412	
	Target	73	0.04031	0.12687	-0.8812	0.2299	0.559
2006	Non-Target	618	0.03599	0.15295	-2.3269	0.9771	
	Target	78	0.0534	0.10849	-0.5107	0.6967	1.267
2007	Non-Target	624	0.02217	0.09801	-1.616	0.3139	
	Target	80	0.03055	0.03402	-0.1311	0.1266	1.534
Panel B: US univariate analysis							
1997	Non-Target	1854	0.03738	0.04464	-0.6976	0.4892	
	Target	216	0.02748	0.18976	-2.5676	0.5296	-0.764
1998	Non-Target	1818	0.10148	0.14989	-3.5422	1.8157	
	Target	240	0.10586	0.13022	-0.6423	1.1271	0.481
1999	Non-Target	1892	0.06368	0.5696	-0.7451	15.761	
	Target	241	0.0501	0.03086	-0.0814	0.2057	-1.025
2000	Non-Target	1803	0.05237	0.15627	-5.398	0.534	
	Target	106	0.03565	0.25273	-2.5234	0.1909	-0.674
2001	Non-Target	1674	0.03432	0.04055	-0.2607	0.6295	
	Target	73	0.03061	0.02434	-0.0078	0.1767	-1.230
2002	Non-Target	1450	0.06812	0.11765	-2.2928	2.3677	
	Target	70	0.0663	0.05654	-0.2226	0.3796	-0.245
2003	Non-Target	1463	0.0434	0.1682	-1.85	5.189	
	Target	89	0.03186	0.03106	-0.0355	0.2316	-2.101**
2004	Non-Target	1489	0.03252	0.02715	-0.4383	0.5097	
	Target	106	0.03245	0.01887	0.0078	0.151	-0.036
2005	Non-Target	1509	0.08781	0.10751	-1.391	3.2636	
	Target	122	0.08906	0.03379	-0.0177	0.32	0.303
2006	Non-Target	1460	0.02356	0.03341	-0.3926	0.7116	
	Target	139	0.02516	0.03205	-0.0462	0.3509	0.560
2007	Non-Target	1428	0.11103	0.25384	-1.7945	6.6743	
	Target	89	0.08761	0.10633	-0.6076	0.1881	-1.785***

[a] The column provides the number of firms present in the target and the non-target group.
[b] This column provides a two sample test-statistics for the null hypothesis that there is no significant difference between the yearly means of the target and the non-target group. $*, **, ***$ indicate significance using a two-sample two-tail t-test at the 1%, 5% and 10% respectively.

Table A.38: *Univariate analysis of variable TATU in both economies during the period 1997-2007*

Year	Group	N[a]	Mean	Std. Dev.	Minimum	Maximum	t-stat difference[b]
Panel A: UK univariate analysis							
1997	Non-Target	710	-0.0109	0.78443	-1.5402	4.0036	
	Target	92	0.05226	0.82352	-1.3757	2.8842	0.696
1998	Non-Target	686	0.03349	0.86228	-1.4367	5.3621	
	Target	99	0.01263	0.81735	-1.3103	3.4858	-0.236
1999	Non-Target	663	0.01762	0.77788	-1.2	5.4493	
	Target	86	0.06056	0.76893	-1.0978	2.4961	0.487
2000	Non-Target	657	0.08583	0.80892	-1.2926	4.2287	
	Target	41	0.04013	0.83394	-1.1279	2.2464	-0.341
2001	Non-Target	686	0.0542	1.08087	-1.2813	14.1229	
	Target	46	0.08892	0.64526	-0.6874	1.4508	0.335
2002	Non-Target	582	0.03269	0.58988	-1.2201	2.758	
	Target	92	0.09066	0.64843	-0.8146	2.1361	0.806
2003	Non-Target	606	0.02091	0.66336	-1.1559	5.1305	
	Target	55	0.06215	0.63168	-0.8117	1.8926	0.462
2004	Non-Target	567	0.01277	0.56042	-1.2881	4.7795	
	Target	62	-0.02484	0.49834	-0.8064	1.5226	-0.557
2005	Non-Target	578	0.07821	0.54163	-1.2465	3.8881	
	Target	73	0.05996	0.63817	-1.1368	3.5522	-0.234
2006	Non-Target	618	0.08878	0.54211	-1.2033	3.1498	
	Target	78	0.03067	0.53696	-0.6716	2.2534	-0.900
2007	Non-Target	624	0.00548	0.29173	-1.3671	2.7842	
	Target	80	-0.03632	0.26749	-0.9467	0.8704	-1.302
Panel B: US univariate analysis							
1997	Non-Target	1854	0.00501	0.21004	-1.0374	3.0242	
	Target	216	0.00115	0.20438	-0.7192	2.0697	-0.262
1998	Non-Target	1818	-0.00728	0.15994	-0.9476	2.3693	
	Target	240	-0.00409	0.24287	-0.8958	3.1181	0.198
1999	Non-Target	1892	0.06141	0.28168	-0.9402	3.7246	
	Target	241	0.04854	0.22679	-0.874	1.1497	-0.805
2000	Non-Target	1803	0.00279	0.21897	-0.9595	3.4585	
	Target	106	-0.01292	0.25671	-0.904	2.0076	-0.617
2001	Non-Target	1674	-0.02027	0.08431	-0.8615	0.9323	
	Target	73	-0.01133	0.02941	-0.0522	0.2334	2.228**
2002	Non-Target	1450	-0.02596	0.11945	-0.9088	1.6899	
	Target	70	-0.03478	0.08317	-0.3514	0.0231	-0.846
2003	Non-Target	1463	-0.02529	0.10828	-0.6445	1.8229	
	Target	89	-0.00912	0.18544	-0.3651	1.6367	0.814
2004	Non-Target	1489	-0.01251	0.15778	-0.8742	1.8263	
	Target	106	0.01462	0.16038	-0.665	0.708	1.685***
2005	Non-Target	1509	-0.02127	0.12043	-0.8656	1.3484	
	Target	122	-0.02778	0.09076	-0.711	0.0623	-0.741
2006	Non-Target	1460	0.00216	0.18719	-0.9556	2.4668	
	Target	139	0.00326	0.26957	-0.8709	2.3652	0.047
2007	Non-Target	1428	-0.00704	0.15045	-0.9407	1.171	
	Target	89	-0.011	0.20064	-0.7168	1.2269	-0.183

[a] The column provides the number of firms present in the target and the non-target group.
[b] This column provides a two sample test-statistics for the null hypothesis that there is no significant difference between the yearly means of the target and the non-target group. $*, **, ***$ indicate significance using a two-sample two-tail t-test at the 1%, 5% and 10% respectively.

Table A.39: *Univariate analysis of variable TIRE in both economies during the period 1997-2007*

Year	Group	N[a]	Mean	Std. Dev.	Minimum	Maximum	t-stat difference[b]
Panel A: UK univariate analysis							
1997	Non-Target	710	0.03365	0.87677	-2.4355	9.4328	
	Target	92	-0.30195	0.71957	-1.8932	2.3689	-4.097*
1998	Non-Target	686	0.07068	0.88307	-1.7506	4.8357	
	Target	99	-0.03353	0.66967	-1.2187	2.5545	-1.384
1999	Non-Target	663	-0.0317	0.68454	-1.0162	10.0343	
	Target	86	-0.13772	0.28817	-0.6987	1.0216	-2.593*
2000	Non-Target	657	-0.02395	0.78546	-1.4523	8.0367	
	Target	41	-0.17074	0.65213	-0.7481	2.8942	-1.380
2001	Non-Target	686	0.20164	0.95312	-1.563	7.0127	
	Target	46	-0.03858	1.47277	-1.5551	7.8903	-1.091
2002	Non-Target	582	0.22602	1.00926	-1.8307	7.0694	
	Target	92	0.18535	1.12621	-1.8858	5.584	-0.326
2003	Non-Target	606	0.02428	0.84355	-1.8528	5.1286	
	Target	55	-0.05952	0.64185	-1.1381	2.994	-0.900
2004	Non-Target	567	-0.03412	0.45171	-1.707	2.9218	
	Target	62	-0.00824	0.40834	-0.6108	2.4645	0.469
2005	Non-Target	578	0.10537	0.76882	-1.6951	5.9383	
	Target	73	0.10053	0.67286	-1.2862	2.6986	-0.057
2006	Non-Target	618	0.06051	0.73218	-1.6841	4.1148	
	Target	78	0.01866	0.56296	-1.8768	1.4625	-0.596
2007	Non-Target	624	0.06427	0.82356	-1.7665	5.0766	
	Target	80	0.01841	0.83822	-1.4489	3.0774	-0.462
Panel B: US univariate analysis							
1997	Non-Target	1854	0.09462	0.7454	-1.9405	6.1509	
	Target	216	-0.05586	0.74322	-1.3729	3.993	-2.815*
1998	Non-Target	1818	-0.00458	0.37482	-1.2214	4.7734	
	Target	240	-0.03893	0.3222	-1.3701	1.4687	-1.521
1999	Non-Target	1892	-0.0756	0.17087	-1.1171	5.5244	
	Target	241	-0.08688	0.08697	-0.7445	0.563	-1.649
2000	Non-Target	1803	0.03024	0.2522	-1.2292	5.2108	
	Target	106	-0.02118	0.17479	-0.5429	1.3752	-2.859*
2001	Non-Target	1674	-0.00224	0.13171	-1.0195	1.461	
	Target	73	0.04157	0.43663	-0.0561	3.6873	0.856
2002	Non-Target	1450	-0.01908	0.12268	-0.9404	2.3854	
	Target	70	-0.03758	0.08062	-0.6918	0.0395	-1.821***
2003	Non-Target	1463	-0.02539	0.28099	-0.1616	8.689	
	Target	89	-0.03174	0.01946	-0.1869	-0.0129	-0.832
2004	Non-Target	1489	-0.01043	0.82681	-0.2184	21.8772	
	Target	106	-0.03336	0.03316	-0.3017	0.0834	-1.058
2005	Non-Target	1509	-0.02658	0.0142	-0.1345	-0.0004	
	Target	122	-0.02629	0.01259	-0.1032	-0.0209	0.242
2006	Non-Target	1460	-0.02473	0.04425	-0.3701	0.3389	
	Target	139	-0.02774	0.06173	-0.3528	0.4085	-0.561
2007	Non-Target	1428	-0.02415	0.0515	-0.6477	0.8991	
	Target	89	-0.02667	0.07594	-0.6974	0.2039	-0.309

[a] The column provides the number of firms present in the target and the non-target group.

[b] This column provides a two sample test-statistics for the null hypothesis that there is no significant difference between the yearly means of the target and the non-target group. $*, **, ***$ indicate significance using a two-sample two-tail t-test at the 1%, 5% and 10% respectively.

Table A.40: *Univariate analysis of variable LNTA in both economies during the period 1997-2007*

Year	Group	N[a]	Mean	Std. Dev.	Minimum	Maximum	t-stat difference[b]
Panel A: UK univariate analysis							
1997	Non-Target	710	0.3797	0.84243	-1.9898	3.6887	
	Target	92	0.30933	0.74246	-1.2216	2.6159	-0.842
1998	Non-Target	686	0.23659	0.89063	-3.082	3.5399	
	Target	99	0.38268	0.74455	-0.94	2.3978	1.777***
1999	Non-Target	663	0.26041	0.85814	-1.8984	3.4409	
	Target	86	0.47387	0.71233	-1.7951	2.3606	2.549**
2000	Non-Target	657	0.34788	0.87562	-1.8991	3.6358	
	Target	41	0.12105	0.56902	-1.1331	1.4117	-2.383*
2001	Non-Target	686	0.3366	0.85455	-3.2888	3.511	
	Target	46	0.32994	0.69049	-0.9868	2.0495	-0.062
2002	Non-Target	582	0.39333	0.85531	-1.8616	3.38	
	Target	92	0.28697	0.71168	-1.8011	2.0803	-1.293
2003	Non-Target	606	0.43323	0.82322	-2.4751	3.2659	
	Target	55	0.60007	0.60327	-0.8394	2.1768	1.897***
2004	Non-Target	567	0.49008	0.8522	-1.5909	3.358	
	Target	62	0.79898	0.68425	-1.1962	2.0799	3.287*
2005	Non-Target	578	0.53263	0.9185	-1.4925	3.5452	
	Target	73	0.67584	0.69739	-0.6358	2.3785	1.589
2006	Non-Target	618	0.4316	0.94588	-1.9935	3.5839	
	Target	78	0.64219	0.83045	-1.4811	2.7656	2.076**
2007	Non-Target	624	0.37752	0.95295	-1.6587	3.6126	
	Target	80	0.66856	0.91248	-0.9852	3.188	2.672*
Panel B: US univariate analysis							
1997	Non-Target	1854	0.37798	0.74299	-2.1491	3.2635	
	Target	216	0.33505	0.7108	-1.2809	2.6013	-0.836
1998	Non-Target	1818	0.56979	0.64537	-1.5922	3.1405	
	Target	240	0.55113	0.56492	-0.7791	1.9073	-0.473
1999	Non-Target	1892	0.48933	0.68079	-1.3918	3.0063	
	Target	241	0.46048	0.61418	-0.84	2.8551	-0.678
2000	Non-Target	1803	0.50047	0.67852	-1.5912	2.9168	
	Target	106	0.48182	0.62193	-1.2115	2.2007	-0.298
2001	Non-Target	1674	0.51176	0.65347	-1.5521	2.8392	
	Target	73	0.36149	0.56789	-0.9185	1.8824	-2.198**
2002	Non-Target	1450	0.55322	0.62621	-1.7324	2.7908	
	Target	70	0.49239	0.61702	-0.9028	2.6326	-0.805
2003	Non-Target	1463	0.58721	0.6186	-1.3078	2.7457	
	Target	89	0.44038	0.65273	-1.5822	2.0065	-2.066**
2004	Non-Target	1489	0.61038	0.61676	-1.2432	2.7502	
	Target	106	0.58979	0.59572	-1.3354	2.6114	-0.343
2005	Non-Target	1509	0.62854	0.61354	-1.3796	2.4525	
	Target	122	0.65097	0.54827	-1.1302	1.8178	0.431
2006	Non-Target	1460	0.61137	0.62388	-1.3959	2.7109	
	Target	139	0.6646	0.56774	-0.9432	1.9717	1.047
2007	Non-Target	1428	0.57784	0.62077	-1.4357	2.6974	
	Target	89	0.72529	0.55773	-0.4135	2.2047	2.403*

[a] The column provides the number of firms present in the target and the non-target group.

[b] This column provides a two sample test-statistics for the null hypothesis that there is no significant difference between the yearly means of the target and the non-target group. $*, **, ***$ indicate significance using a two-sample two-tail t-test at the 1%, 5% and 10% respectively.

Table A.41: *Univariate analysis of variable SREV in both economies during the period 1997-2007*

Year	Group	N[a]	Mean	Std. Dev.	Minimum	Maximum	t-stat difference[b]
Panel A: UK univariate analysis							
1997	Non-Target	710	0.08026	1.36998	-0.524	28.2783	
	Target	92	0.03412	0.66584	-0.4295	4.5642	-0.534
1998	Non-Target	686	0.04169	1.00085	-0.5338	17.6557	
	Target	99	-0.0413	0.4236	-0.5007	3.1277	-1.451
1999	Non-Target	663	0.05317	1.29933	-0.6374	23.6804	
	Target	86	0.01743	0.6717	-0.3646	5.1884	-0.405
2000	Non-Target	657	0.07518	1.40068	-0.5795	24.0164	
	Target	41	-0.1378	0.17837	-0.4931	0.6583	-3.472*
2001	Non-Target	686	0.07321	1.43381	-0.6119	27.6969	
	Target	46	-0.05685	0.17318	-0.1707	0.91	-2.153**
2002	Non-Target	582	0.11028	1.57941	-0.6703	25.4401	
	Target	92	-0.06615	0.21162	-0.6356	1.5098	-2.554**
2003	Non-Target	606	0.1166	1.59301	-0.7086	28.0625	
	Target	55	-0.02054	0.23246	-0.1126	1.3114	-1.907***
2004	Non-Target	567	0.14443	1.67535	-0.6516	27.7948	
	Target	62	0.01778	0.29499	-0.664	1.495	-1.589
2005	Non-Target	578	0.16193	1.71519	-0.627	30.3885	
	Target	73	0.06261	0.55817	-0.6349	3.7176	-1.027
2006	Non-Target	618	0.13497	1.65384	-0.6176	29.9597	
	Target	78	-0.01876	0.30043	-0.6095	2.0137	-2.057**
2007	Non-Target	624	0.12127	1.58	-0.6489	29.0059	
	Target	80	0.04386	0.47533	-0.3503	2.6855	-0.937
Panel B: US univariate analysis							
1997	Non-Target	1854	0.07754	1.20342	-0.508	25.0365	
	Target	216	0.0767	1.05749	-0.4741	8.6704	-0.011
1998	Non-Target	1818	0.16627	1.43198	-0.4912	27.2455	
	Target	240	-0.00435	0.38906	-0.4497	2.6853	-4.069*
1999	Non-Target	1892	0.14938	1.3783	-0.504	25.6779	
	Target	241	0.11226	1.85762	-0.4741	27.4873	-0.300
2000	Non-Target	1803	0.16483	1.48605	-0.4907	27.2692	
	Target	106	0.14837	1.18222	-0.4884	10.0432	-0.137
2001	Non-Target	1674	0.12567	1.29373	-0.5143	27.9653	
	Target	73	-0.04984	0.38536	-0.494	2.3227	-3.186*
2002	Non-Target	1450	0.13763	1.31446	-0.5269	29.6931	
	Target	70	0.28997	2.70205	-0.41	22.5638	0.469
2003	Non-Target	1463	0.16912	1.40667	-0.5325	28.0179	
	Target	89	-0.04292	0.38117	-0.5337	2.8006	-3.881*
2004	Non-Target	1489	0.18189	1.41697	-0.5313	26.7114	
	Target	106	0.19342	1.79069	-0.501	18.0678	0.065
2005	Non-Target	1509	0.17598	1.40466	-0.5237	27.4842	
	Target	122	0.0406	0.50102	-0.5058	2.6078	-2.334**
2006	Non-Target	1460	0.16747	1.37367	-0.5416	26.3496	
	Target	139	0.04814	0.531	-0.5201	3.1207	-2.071**
2007	Non-Target	1428	0.12597	1.25042	-0.56	25.4541	
	Target	89	0.22051	1.56466	-0.4196	13.7797	0.559

[a] The column provides the number of firms present in the target and the non-target group.

[b] This column provides a two sample test-statistics for the null hypothesis that there is no significant difference between the yearly means of the target and the non-target group. $*, **, ***$ indicate significance using a two-sample two-tail t-test at the 1%, 5% and 10% respectively.

Appendix B

Estimation results of the logistic regression-based takeover prediction model

B.1 Estimation results with normalized variables

Yearly estimated coefficients of the UK-based Logistic model for the period 1998-2007 using complete data

Variable	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Intercept	-2.328*	-2.253*	-2.602*	-3.397*	-2.592*	-1.938*	-2.927*	-3.08*	-2.392*	-2.934*
	(-13.29)	(-14.85)	(-13.59)	(-12.04)	(-9.85)	(-12.73)	(-11.31)	(-10.79)	(-10.47)	(-8.14)
CETA	-0.054	0.586	0.108	-0.108	-0.812	-0.222	0.195	0.444	-1.168	-1.246
	(-0.205)	(1.31)	(0.682)	(-0.253)	(-0.838)	(-0.795)	(0.687)	(0.774)	(-0.998)	(-0.873)
CRAT	-1.20	-0.336	-0.867	-0.161	-4.273**	-0.464	1.68***	-2.175	1.551	-1.827
	(-1.607)	(-1.304)	(-1.217)	(-0.275)	(-2.22)	(-1.188)	(1.802)	(-1.288)	(1.424)	(-1.339)
DPEA	0.05	0.148	0.224***	-0.176	-0.760*	-0.223	-0.132	-0.218	-0.112	0.05
	(0.366)	(1.186)	(1.738)	(-0.865)	(-2.613)	(-1.474)	(-0.723)	(-1.575)	(-0.856)	(0.392)
FCFS	-0.039	0.171	0.012	0.634	0.246	0.072	1.005**	0.079	-0.178	-0.256
	(-0.256)	(0.903)	(0.025)	(1.363)	(1.056)	(0.220)	(2.052)	(0.301)	(-0.194)	(-0.225)
GSOY	-0.903***	-0.895*	-0.960**	-0.894	-0.616	-0.411	-0.156	-0.257	-2.492	0.318
	(-1.74)	(-2.714)	(-2.243)	(-1.596)	(-0.984)	(-0.745)	(-1.170)	(-0.360)	(-1.511)	(0.598)
ICOV	0.153**	-0.466*	0.274	-0.064	0.154	-0.411***	-1.626**	-0.793	0.113	0.323
	(2.025)	(-2.825)	(1.048)	(-0.259)	(0.771)	(-1.93)	(-2.019)	(-1.124)	(0.593)	(1.291)
IDHE	0.362	-0.350	-1.429	-0.344	0.318	0.128	-0.502	-0.904	-0.037	0.343**
	(1.437)	(-0.937)	(-1.642)	(-0.584)	(1.176)	(0.405)	(-0.978)	(-1.161)	(-0.094)	(2.293)
ITUR	0.203	-0.057	-1.5e-03	-2.621**	-0.810	-0.361	0.021	-0.234	0.026	0.189
	(1.009)	(-0.568)	(-0.023)	(-2.071)	(-1.258)	(-1.117)	(-0.313)	(-0.586)	(0.377)	(1.283)
LDTC	0.435	0.281	0.492	0.746	0.361	0.448	0.122	-0.440	0.141	1.41**
	(0.728)	(0.648)	(1.053)	(0.837)	(1.023)	(1.398)	(0.139)	(-0.648)	(0.242)	(2.044)
NSFA	0.055	-0.205	1.020**	-0.079	-0.278	-0.101	-1.067	-0.039	-0.141	0.116
	(0.363)	(-0.956)	(2.506)	(-0.598)	(-0.671)	(-0.860)	(-1.230)	(-0.154)	(-0.445)	(1.252)
NSWC	-0.166	-0.203	-0.035	0.135	-0.068	0.211	-0.136	0.073	-0.409**	0.556
	(-0.832)	(-0.878)	(-0.399)	(1.127)	(-1.162)	(1.419)	(-1.275)	(1.241)	(-2.555)	(0.994)
OPMA	-0.197	-0.832	-2.6e-03	-0.979	-30.67*	-0.572	0.052	0.236	0.353	1.048
	(-0.496)	(-1.283)	(-0.030)	(-1.572)	(-2.978)	(-1.425)	(0.158)	(0.434)	(0.825)	(0.350)
PTBR	-0.363	0.274**	0.081	-0.760**	0.401***	-0.324**	0.020	-0.861	-0.091	0.074
	(-1.181)	(2.126)	(0.817)	(-1.977)	(1.873)	(-2.490)	(0.042)	(-1.547)	(-1.018)	(0.368)
PTER	0.076	0.199	0.097	-0.233	-0.194	0.301**	0.176	0.508***	0.082	-0.024
	(0.419)	(1.202)	(0.353)	(-0.337)	(-1.528)	(2.10)	(0.489)	(1.913)	(0.558)	(-0.218)
ROET	0.556	-0.492**	-0.312***	-0.606	0.478	0.310	-0.089	-2.336	3.3e-03	1.303
	(1.216)	(-2.059)	(-1.742)	(-1.165)	(0.539)	(0.741)	(-0.138)	(-1.612)	(0.015)	(0.834)
TATU	0.096	0.037	0.048	0.053	0.243	0.347***	0.550***	0.187	0.096	-0.114
	(0.591)	(0.245)	(0.30)	(0.190)	(1.054)	(1.757)	(1.830)	(0.615)	(0.328)	(-0.426)
TIRE	-0.702*	-0.102	-0.465***	-0.820	-0.040	-0.015	-0.165	-0.097	-0.076	-0.36***
	(-2.943)	(-0.786)	(-1.83)	(-1.396)	(-0.170)	(-0.121)	(-0.870)	(-0.365)	(-0.387)	(-1.85)
LNTA	-0.128	0.375***	0.430***	0.126	0.575**	0.200	0.787*	1.047*	0.355***	0.623*
	(-0.828)	(1.955)	(1.877)	(0.386)	(2.026)	(0.905)	(2.663)	(4.170)	(1.856)	(2.722)
SREV	0.020	-0.767	-0.391	-2.823	-1.137	-0.989	-1.514***	-1.613**	-0.352	-1.535
	(0.346)	(-1.567)	(-0.838)	(-1.367)	(-1.470)	(-1.556)	(-1.92)	(-2.314)	(-1.032)	(-1.630)
Pseudo-R^2	0.0363	0.0433	0.0389	0.0523	0.0485	0.0398	0.0322	0.0489	0.0253	0.0435
Lilkelihood										
Ratio	28.88***	33.47**	28.66***	35.10**	34.43**	26.58	20.97	30.31**	16.29	29.61***
p-value	0.0679	0.0212	0.0716	0.0136	0.0164	0.1148	0.3383	0.0479	0.6381	0.0570
Obs	802	779	743	693	730	671	659	629	648	687

$*, **, ***$ indicate significance of a two-tailed t-test at the 1%, 5% and 10 % respectively.

Yearly estimated coefficients of the US-based Logistic model for the period 1998-2007 using complete data

Variable	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Intercept	-2.231*	-2.357*	-1.972*	-3.156*	-3.626*	-4.101*	-1.278*	-2.805*	-1.838*	-3.082*
	(-20.31)	(-17.23)	(-6.66)	(-16.30)	(-12.69)	(-6.01)	(-2.91)	(-4.58)	(-2.50)	(-5.83)
CETA	-0.432	-2.218*	-0.242	0.110	-1.631	0.177	-1.628**	-0.236	3.350*	0.182
	(-1.284)	(-2.789)	(-0.578)	(0.155)	(-0.451)	(0.103)	(-2.265)	(-0.142)	(2.653)	(0.287)
CRAT	0.041	0.170	-0.620	-0.475	0.546	-1.096	1.440**	6.508***	0.618**	-0.815
	(0.156)	(0.455)	(-0.719)	(-0.692)	(1.230)	(-1.279)	(2.279)	(1.946)	(2.315)	(-0.559)
DPEA	-0.179**	-0.109	-0.169**	-0.287*	-0.104	-0.079	-0.130	-0.179	0.047	-0.118
	(-2.115)	(-1.560)	(-2.52)	(-2.806)	(-0.812)	(-0.631)	(-1.194)	(-1.536)	(0.527)	(-1.225)
FCFS	-0.241	-1.618***	-8.941	0.309	44.09*	-13.462	-12.456*	-0.445	2.015	-2.978
	(-0.713)	(-1.79)	(-1.158)	(0.146)	(4.645)	(-1.492)	(-2.634)	(-1.044)	(0.441)	(-0.440)
GSOY	0.596	0.133	-1.493	-0.531***	0.757	-0.245	2.695*	-16.882*	-8.516	2.990
	(0.890)	(0.489)	(-0.514)	(-1.87)	(0.331)	(-0.157)	(2.877)	(-2.609)	(-1.428)	(0.780)
ICOV	-0.862**	-0.115	0.065	-0.248	-2.19***	-1.062***	-0.393	-0.478	-1.312	-0.034
	(-2.123)	(-0.309)	(0.295)	(-0.469)	(-1.95)	(-1.75)	(-1.457)	(-0.882)	(-0.717)	(-0.919)
IDHE	-2.094**	-0.894**	-0.104	0.257	0.069	0.277	0.140	1.154	0.493	-1.594
	(-1.993)	(-2.568)	(-0.306)	(0.502)	(0.053)	(0.493)	(1.107)	(1.309)	(0.857)	(-1.120)
ITUR	0.037	-0.546	0.031	0.049	0.058	8.7e-03	-1.150	0.062	0.150	-0.056
	(0.215)	(-1.472)	(0.320)	(0.616)	(0.372)	(0.293)	(-0.993)	(0.997)	(1.068)	(-0.626)
LDTC	0.440	-0.089	0.494	1.357	1.123	9.049**	16.804*	2.440***	0.689	-0.122
	(0.859)	(-0.183)	(0.620)	(1.039)	(0.487)	(2.285)	(4.492)	(1.742)	(0.771)	(-0.146)
NSFA	-0.410**	-0.029	-0.054	-0.354	-0.523	-0.101	-0.490	3.4e-03	-0.162	-0.780
	(-2.265)	(-0.221)	(-0.444)	(-0.226)	(-0.511)	(-0.248)	(-1.293)	(6.4e-03)	(-0.453)	(-1.241)
NSWC	-0.018	-0.256*	0.252	-0.796*	0.123	0.118	0.074	0.015	0.095	-0.043
	(-0.177)	(-2.743)	(1.578)	(-4.323)	(1.187)	(0.677)	(0.989)	(0.466)	(1.349)	(-0.367)
OPMA	0.922***	-0.017	-0.123	0.905	0.378*	21.528**	-12.38*	2.360	11.562	6.971
	(1.771)	(-0.018)	(-0.072)	(0.187)	(2.661)	(2.135)	(-2.584)	(0.282)	(1.122)	(0.797)
PTBR	0.179***	-0.348	1.279	1.029***	-20.747	9.993	0.292	-6.575	-14.403	-1.016
	(1.727)	(-0.582)	(0.516)	(1.751)	(-1.201)	(1.196)	(0.289)	(-0.891)	(-1.119)	(-0.351)
PTER	0.159***	-0.452***	-0.111	-0.048	-0.049	0.176	0.106	-0.420	-0.175	0.368***
	(1.864)	(-1.77)	(-0.760)	(-0.108)	(-0.281)	(0.651)	(0.481)	(-0.443)	(-0.660)	(1.762)
ROET	-1.557***	0.508	-0.142	2.688	-12.533*	0.0375	-0.314	-8.292**	0.086	1.689
	(-1.89)	(0.776)	(-1.130)	(1.102)	(-2.935)	(0.090)	(-0.475)	(-1.990)	(0.242)	(0.639)
TATU	0.192	0.216	-0.258	-0.526	1.096	0.403	2.313**	1.394**	2.140**	0.647
	(0.592)	(0.453)	(-0.892)	(-0.992)	(1.029)	(0.441)	(2.410)	(2.367)	(2.020)	(1.016)
TIRE	-0.231***	-0.258	-0.869	-1.907*	1.878*	-0.974	0.463***	-0.151**	53.426	-0.632
	(-1.91)	(-1.293)	(-0.998)	(-3.669)	(4.239)	(-0.824)	(1.727)	(-1.961)	(1.449)	(-0.207)
LNTA	-0.023	0.324**	-0.018	0.139	-0.184	-0.282	-0.240	0.148	0.331	0.517**
	(-0.200)	(2.039)	(-0.153)	(0.816)	(-0.875)	(-1.363)	(-0.972)	(0.801)	(1.579)	(2.502)
SREV	0.039	-0.492*	0.011	-0.047	-0.159	0.082	-0.34	1.9e-03	-0.348***	-0.328***
	(0.813)	(-2.912)	(0.162)	(-0.617)	(-0.680)	(1.231)	(-0.986)	(0.021)	(-1.80)	(-1.828)
Pseudo- R^2	0.01915	0.0166	0.0098	0.0188	0.0109	0.0104	0.0248	0.0119	0.0142	0.0147
Likelihood										
Ratio	39.40*	33.92**	20.77	35.36**	18.83	15.62	37.82*	18.87	22.97	23.41
p-value	0.0039	0.0188	0.3499	0.0126	0.4680	0.6790	0.0062	0.4652	0.2387	0.2200
Obs	2067	2055	2128	1906	1744	1518	1551	1594	1630	1597

$*, **, ***$ indicate significance of a two-tailed t-test at the 1%, 5% and 10 % respectively.

B.2 Estimation results using winsorized variables

Yearly estimated coefficients of the UK-based Logistic model for the period 1998-2007 using winsorized data at the one and ninety-nine percentiles

Variable	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Intercept	-2.213*	-2.282*	-2.651*	-4.023*	-3.278*	-2.089*	-3.027*	-2.923*	-2.436*	-2.497*
	(-13.50)	(-14.46)	(-11.74)	(-6.58)	(-11.03)	(-12.49)	(-11.29)	(-10.75)	(-12.77)	(-11.06)
CETA	-0.063	0.032	0.089	0.336	-0.136	-0.085	0.25	-0.086	-0.246	0.148
	(-0.351)	(0.215)	(0.471)	(1.637)	(-0.521)	(-0.584)	(1.272)	(-0.323)	(-0.988)	(0.904)
CRAT	-0.437	-0.149	-0.469	-0.389	-0.832	-0.948**	-0.283	-0.695	0.141	-0.389
	(-1.466)	(-0.729)	(-1.111)	(-0.497)	(-1.62)	(-2.554)	(-0.648)	(-0.916)	(0.509)	(-0.848)
DPEA	0.022	0.156	0.201	-0.26	-0.65**	-0.246	-0.167	-0.238***	-0.098	0.065
	(0.154)	(1.227)	(1.492)	(-1.291)	(-2.483)	(-1.528)	(-0.895)	(-1.663)	(-0.771)	(0.502)
FCFS	-0.135	0.42	0.472	0.782**	-0.159	0.025	0.317**	-0.207**	-0.097	-0.118
	(-0.93)	(1.278)	(0.836)	(2.24)	(-1.474)	(0.183)	(2.092)	(-2.025)	(-0.807)	(-1.027)
GSOY	-0.162	-0.685*	-0.441***	-0.511**	-0.14	-0.089	-0.695	0.102	-0.345	0.095
	(-0.983)	(-3.408)	(-1.762)	(-2.116)	(-1.013)	(-0.517)	(-1.412)	(0.617)	(-1.261)	(0.761)
ICOV	0.002	-0.373**	0.091	-0.051	0.529	-0.29**	-0.011	-0.086	0.056	0.271
	(0.015)	(-2.528)	(0.967)	(-0.153)	(1.263)	(-2.009)	(-0.06)	(-0.431)	(0.482)	(1.367)
IDHE	0.217	-0.298	0.106	-0.136	0.298**	-0.046	-0.063	-0.002	0.036	0.159
	(1.432)	(-1.518)	(0.587)	(-0.476)	(2.341)	(-0.282)	(-0.205)	(-0.001)	(0.172)	(0.839)
ITUR	0.072	-0.152	0.17***	-1.712	-0.051	-0.162	0.157	0.044	0.179***	0.204**
	(0.564)	(-0.900)	(1.650)	(-1.469)	(-0.392)	(-1.07)	(1.274)	(0.387)	(1.871)	(2.06)
LDTC	-0.118	0.394**	0.178	0.004	0.146	-0.126	-0.006	-0.096	0.165	0.018
	(-0.766)	(2.387)	(1.018)	(0.014)	(1.031)	(-0.674)	(-0.012)	(-0.382)	(0.865)	(0.137)
NSFA	0.028	-0.049	-0.177	0.022	-0.152	-0.038	-0.453	-0.094	-0.111	0.241**
	(0.202)	(-0.314)	(-0.957)	(0.114)	(-0.824)	(-0.269)	(-1.221)	(-0.36)	(-0.434)	(2.351)
NSWC	-0.072	-0.159	-0.074	0.046	-0.08	-0.052	-0.045	0.003	-0.211**	-0.033
	(-0.769)	(-1.291)	(-0.519)	(0.251)	(-0.755)	(-0.53)	(-0.35)	(0.029)	(-2.579)	(-0.376)
OPMA	0.001	-0.235	-0.219	-1.056**	-0.363***	-0.591**	0.007	-0.437	0.239	-0.081
	(0.005)	(-0.947)	(-1.51)	(-2.455)	(-1.752)	(-2.413)	(0.035)	(-0.871)	(0.658)	(-0.154)
PTBR	-0.098	0.161	0.228***	-0.826**	-0.047	-0.191	0.036	-0.361**	-0.316**	0.141
	(-0.615)	(1.293)	(1.786)	(-1.987)	(-0.243)	(-1.22)	(0.156)	(-2.174)	(-2.07)	(1.262)
PTER	-0.024	0.194	0.12	0.044	-0.289***	0.26	0.064	0.341	0.155	0.231
	(-0.119)	(0.92)	(0.56)	(0.091)	(-1.719)	(1.325)	(0.212)	(1.482)	(0.822)	(1.076)
ROET	0.216	-0.213**	-0.246***	-0.137	0.01	0.018	-0.019	0.308***	0.018	-0.021
	(1.285)	(-2.18)	(-1.785)	(-0.828)	(0.066)	(0.128)	(-0.103)	(1.743)	(0.089)	(-0.088)
TATU	0.098	0.02	0.193	0.147	0.553*	0.196	0.318	0.143	0.046	-0.101
	(0.542)	(0.137)	(1.159)	(0.459)	(2.876)	(1.195)	(1.202)	(0.731)	(0.249)	(-0.539)
TIRE	-0.675*	-0.106	-0.416***	-0.893**	-0.232	-0.024	-0.179	-0.008	-0.086	-0.296***
	(-3.042)	(-0.788)	(-1.711)	(-2.204)	(-1.132)	(-0.199)	(-0.979)	(-0.057)	(-0.454)	(-1.939)
LNTA	-0.176	0.316	0.700*	0.603	0.815**	0.316	0.821**	1.12*	0.534**	0.609*
	(-0.887)	(1.628)	(3.123)	(1.233)	(2.48)	(1.261)	(2.428)	(3.644)	(2.466)	(2.594)
SREV	0.071	-0.391***	-0.496**	-2.843	-0.447***	-0.386	-0.513***	-0.409**	-0.305***	-0.32***
	(0.461)	(-1.725)	(-2.034)	(-1.336)	(-1.898)	(-1.408)	(-1.701)	(-2.347)	(-1.836)	(-1.753)
Pseudo-R^2	0.0339	0.0500	0.0505	0.0655	0.0540	0.0400	0.0345	0.0466	0.0364	0.0399
Lilkelihood										
Ratio	27.06	38.66*	37.14*	43.56*	38.24*	26.71	22.46	28.96**	23.40	27.16
p-value	0.1030	0.0049	0.0076	0.0011	0.0055	0.1115	0.2622	0.0666	0.2201	0.1011
Obs	802	779	743	693	730	671	659	629	648	687

$*, **, ***$ indicate significance of a two-tailed t-test at the 1%, 5% and 10 % respectively.

Yearly estimated coefficients of the US-based Logistic model for the period 1998-2007 using winsorized data at the one and ninety-nine percentiles

Variable	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Intercept	-2.205*	-2.394*	-2.151*	-2.931*	-3.765*	-4.142*	-3.052*	-1.744*	-3.965*	-2.762*
	(-13.31)	(-9.71)	(-5.92)	(-4.72)	(-8.47)	(-7.67)	(-6.84)	(-3.22)	(-3.66)	(-10.84)
CETA	-0.088	-0.418**	0.07	-0.078	0.124	-0.087	0.276	0.01	0.815*	-0.237
	(-0.827)	(-2.391)	(0.315)	(-0.287)	(0.666)	(-0.306)	(1.145)	(0.025)	(3.051)	(-0.805)
CRAT	0.063	-0.26	-0.323	-0.02	0.086	-0.157	0.005	0.333	0.198	-0.253
	(0.421)	(-1.12)	(-1.145)	(-0.088)	(0.582)	(-0.553)	(0.02)	(1.494)	(0.661)	(-0.964)
DPEA	-0.173**	-0.112***	-0.175*	-0.278*	-0.114	-0.103	-0.103	-0.185	0.033	-0.142
	(-2.09)	(-1.657)	(-2.706)	(-2.682)	(-0.881)	(-0.817)	(-0.966)	(-1.597)	(0.376)	(-1.439)
FCFS	0.132	0.238	-0.017	2.966	3.484	-0.151	0.111	-0.15	0.317	-0.131
	(0.858)	(0.891)	(-0.074)	(0.967)	(1.288)	(-0.989)	(0.465)	(-0.424)	(1.191)	(-0.94)
GSOY	-0.089	-0.336	-0.142	-0.348	1.274	0.479	0.502	-1.54***	-0.983	-0.69
	(-0.446)	(-1.215)	(-0.379)	(-0.566)	(1.392)	(1.053)	(0.998)	(-1.898)	(-1.329)	(-0.94)
ICOV	-0.125	0.006	0.087	-0.079	-0.127	-0.047	-0.06	-0.209	-0.083	-0.054
	(-1.349)	(0.054)	(0.618)	(-0.469)	(-1.065)	(-0.145)	(-0.387)	(-1.072)	(-0.602)	(-0.788)
IDHE	-0.06	-0.332**	-0.002	0.016	0.31***	-0.129	0.386*	0.062	0.209	-0.63***
	(-0.51)	(-2.234)	(-0.014)	(0.097)	(1.699)	(-0.485)	(2.684)	(0.258)	(1.303)	(-1.945)
ITUR	0.061	-0.063	-0.069	0.169***	0.222**	0.23**	-0.095	0.116	0.188**	-0.03
	(0.725)	(-0.735)	(-0.77)	(1.755)	(2.236)	(2.117)	(-0.576)	(0.884)	(2.263)	(-0.296)
LDTC	0.18	-0.001	0.067	0.255	0.104	0.501***	1.047*	0.16	0.611**	-0.096
	(1.523)	(-0.01)	(0.437)	(1.409)	(0.423)	(1.659)	(4.138)	(0.6)	(2.515)	(-0.351)
NSFA	-0.192***	0.017	0.01	-0.059	-0.098	-0.067	-0.05	0.079	-0.02	-0.118
	(-1.685)	(0.184)	(0.117)	(-0.462)	(-0.552)	(-0.457)	(-0.371)	(0.638)	(-0.136)	(-0.809)
NSWC	-0.12	-0.035	0.145**	-0.04	0.012	-0.052	0.125	0.067	0.118	-0.063
	(-1.405)	(-0.514)	(2.311)	(-0.438)	(0.112)	(-0.632)	(1.02)	(0.88)	(1.317)	(-0.838)
OPMA	0.57	0.631	-0.521	-2.276	0.048	5.774**	1.402	-6.124***	5.293	-1.477
	(0.949)	(0.635)	(-0.328)	(-0.789)	(0.276)	(2.534)	(0.752)	(-1.713)	(0.903)	(-1.647)
PTBR	-0.134	-0.028	-0.057	0.226	-0.312	0.03	-0.368**	0.333	-0.194	-0.499
	(-0.983)	(-0.197)	(-0.256)	(1.631)	(-1.291)	(0.078)	(-2.014)	(1.099)	(-1.384)	(-1.53)
PTER	0.099	-0.145***	0.014	0.088	0.101	0.082	0.089	-0.091	0.012	0.098
	(1.261)	(-1.961)	(0.186)	(0.699)	(0.883)	(0.695)	(0.797)	(-0.609)	(0.113)	(1.004)
ROET	-0.138	-0.165	0.122	0.241	0.229	0.016	-0.600**	-0.211	0.658	0.912***
	(-0.824)	(-0.574)	(0.791)	(0.783)	(0.425)	(0.124)	(-2.44)	(-0.393)	(1.102)	(1.842)
TATU	-0.097	0.082	-0.113	0.083	0.127	0.135	0.152***	0.228***	0.191**	0.015
	(-0.842)	(0.714)	(-1.056)	(0.571)	(0.615)	(0.546)	(1.757)	(1.713)	(2.33)	(0.087)
TIRE	-0.201***	-0.104	-0.404	-0.297**	0.044	-0.175	1.236**	-0.115	-0.471**	-0.179
	(-1.838)	(-1.06)	(-1.501)	(-1.99)	(0.244)	(-0.731)	(1.997)	(-0.377)	(-2.283)	(-0.947)
LNTA	-0.127	0.233	0.057	0.033	-0.121	-0.154	-0.356	0.323	0.171	0.477**
	(-0.908)	(1.406)	(0.385)	(0.168)	(-0.526)	(-0.552)	(-1.336)	(1.387)	(0.713)	(2.084)
SREV	0.112	-0.224**	-0.108	0.054	-0.171	-0.074	-0.194	-0.105	-0.16	-0.215***
	(1.244)	(-2.488)	(-1.159)	(0.528)	(-0.952)	(-0.504)	(-0.933)	(-1.016)	(-1.426)	(-1.868)
Pseudo- R^2	0.0171	0.0146	0.0113	0.0122	0.0102	0.0141	0.0304	0.0138	0.0215	0.0150
Likelihood Ratio	35.11**	29.89***	24.05	23.05	17.61	21.20	46.18*	21.91	34.70**	23.84
p-value	0.0135	0.0533	0.1942	0.2353	0.5488	0.3258	0.0005	0.2889	0.0152	0.2025
Obs	2067	2055	2128	1906	1744	1518	1551	1594	1630	1597

$*, **, ***$ indicate significance of a two-tailed t-test at the 1%, 5% and 10 % respectively.

Appendix C

Control Firm Portfolio Performance Results

C.1 Logistic regression

Table C.1: *Control firm portfolio based abnormal returns[a] using an Logistic-based model in the UK during the period 1999-2008*

Prediction year	BUY AND HOLD ABNORMAL RETURNS (BHAR) OF THE PREDICTED PORTFOLIO (in %) (Significance)[b]							
	Cut-off probability (P_C)							
	0.9	*0.8*	*0.7*	*0.6*	*0.5*	*0.4*	*0.3*	*0.2*
1999	NA (NA)	-17.0 (NA)	-195.2 (0.309)	-115.6 (0.270)	-39.8 (0.599)	-1.2 (0.981)	-41.4 (0.315)	-20.6 (0.511)
2000	60.8 (0.556)	59.5 (0.250)	37.1 (0.406)	24.0 (0.313)	12.0 (0.514)	-7.6 (0.649)	0.7 (0.952)	**10.4***** (0.097)
2001	51.1 (0.418)	51.1 (0.418)	18.4 (0.721)	16.2 (0.601)	16.2 (0.601)	19.5 (0.363)	8.3 (0.440)	**10.8***** (0.084)
2002	**-20.9***** (0.056)	**-20.9***** (0.056)	**-16.8**** (0.029)	**-16.8**** (0.029)	**-16.8**** (0.029)	32.9 (0.424)	26.0 (0.384)	32.5 (0.129)
2003	26.8 (0.316)	20.0 (0.447)	19.7 (0.487)	21.3 (0.385)	5.3 (0.865)	6.8 (0.832)	16.6 (0.497)	16.8 (0.448)
2004	24.9 (0.778)	24.9 (0.778)	4.0 (0.934)	4.0 (0.934)	-21.5 (0.636)	-10.9 (0.634)	3.2 (0.880)	-3.5 (0.841)
2005	-130.1 (NA)	-90.1 (0.357)	-78.4 (0.132)	**-67.1***** (0.074)	**-67.1***** (0.074)	**-62.8**** (0.031)	**-56.7**** (0.019)	-19.7 (0.223)
2006	-53.6 (0.414)	-53.6 (0.414)	-53.6 (0.414)	-4.9 (0.903)	-11.1 (0.710)	7.0 (0.767)	13.5 (0.443)	2.7 (0.799)
2007	52.9 (0.652)	52.9 (0.652)	52.9 (0.652)	52.9 (0.652)	31.3 (0.601)	18.8 (0.595)	11.5 (0.690)	-3.6 (0.831)
2008	23.1 (0.360)	23.1 (0.360)	**25.4***** (0.094)	**25.4***** (0.094)	18.7 (0.117)	**18.6**** (0.020)	10.0 (0.183)	0.2 (0.970)
$\langle \overline{BHAR_C} \rangle$[c]	**3.50**	**4.98**	**-18.65**	**-6.06**	**-7.27**	**2.10**	**-0.82**	**2.61**
t_C[d]	**0.18**	**0.32**	**-0.80**	**-0.38**	**-0.76**	**0.25**	**-0.10**	**0.51**

[a] Control firm based abnormal profitability is measured by calculating the buy-and-hold abnormal returns relative to a matched control firm portfolio benchmark (details on the control portfolio are given in section 4.5.3). The investment is initiated the first month (January) and is terminated in the last month (December) of the calendar prediction year.

[b] The yearly abnormal return's significance is calculated using the t-test t_{BHAR} (shown in equation 4.17) based on the null-hypothesis that the yearly abnormal returns are not different from zero. The degrees of freedom of each test depend on the number of firms included in the predicted sample. $*, **, ***$ indicate significance using a two-tail t-test at the 1%, 5% and 10% respectively.

[c] Calculates the annualized average abnormal return generated by the yearly predicted firms over the ten-year period 1999-2008.

[d] Shows the result of the t-test t_C (shown in equation 4.18) examining the null-hypothesis that the average long-term abnormal returns are not different from zero. $*, **, ***$ indicate significance using a two-tail t-test with 9 degrees of freedom at the 1%, 5% and 10% respectively.

Table C.2: *Control firm portfolio based abnormal returns[a] using a Logistic-based model in the USA during the period 1999-2008*

Prediction year	BUY AND HOLD ABNORMAL RETURNS (BHAR) OF THE PREDICTED PORTFOLIO (in %) (Significance)[b]							
	Cut-off probability (P_C)							
	0.9	*0.8*	*0.7*	*0.6*	*0.5*	*0.4*	*0.3*	*0.2*
1999	333.8	15.0	48.1	45.3	46.7	-24.7	25.8	40.1
	(NA)	(0.949)	(0.638)	(0.544)	(0.422)	(0.668)	(0.553)	(0.136)
2000	-207.5	-207.5	-207.5	-207.5	-207.5	-207.5	11.3	3.4
	(NA)	(NA)	(NA)	(NA)	(NA)	(NA)	(0.743)	(0.882)
2001	-14.0	-14.0	-14.0	-14.0	-14.0	-14.0	-1.2	-26.3
	(0.719)	(0.719)	(0.719)	(0.719)	(0.719)	(0.719)	(0.960)	(0.208)
2002	-74.0	-0.8	-0.8	-0.8	-0.8	-15.4	-10.4	-8.4
	(NA)	(0.992)	(0.992)	(0.992)	(0.992)	(0.772)	(0.740)	(0.754)
2003	-2.1	-11.8	-44.4	-30.1	-15.4	-36.3	**-51.8****	-0.3
	(0.910)	(0.505)	(0.145)	(0.208)	(0.487)	(0.153)	(0.031)	(0.994)
2004	2.6	28.5	**28.7*****	4.9	**26.8*****	**21.7*****	12.1	**24.2****
	(0.896)	(0.170)	(0.094)	(0.876)	(0.065)	(0.070)	(0.185)	(0.014)
2005	11.1	18.6	17.0	-9.7	-3.6	-7.3	8.9	-2.4
	(0.663)	(0.391)	(0.454)	(0.814)	(0.838)	(0.794)	(0.570)	(0.897)
2006	-2.2	-5.3	0.5	-3.3	-2.2	6.8	3.7	3.4
	(0.858)	(0.606)	(0.961)	(0.732)	(0.769)	(0.304)	(0.536)	(0.575)
2007	-0.7	-11.5	-9.0	-5.3	-9.0	1.3	-3.7	**8.2*****
	(0.967)	(0.386)	(0.412)	(0.573)	(0.274)	(0.869)	(0.626)	(0.091)
2008	-18.9	-11.3	-9.0	-20.1	-20.1	**-9.0**	**-26.0****	-9.4
	(0.449)	(0.352)	(0.543)	(0.259)	(0.259)	(0.487)	(0.033)	(0.171)
$\langle\overline{BHAR_C}\rangle$[c]	**2.79**	**-20.01**	**-19.05**	**-23.39**	**-19.91**	**-28.43**	**-3.13**	**3.25**
t_C[d]	**-0.07**	**-0.94**	**-0.85**	**-1.09**	**-0.91**	**-1.38**	**-0.45**	**0.56**

[a] Control firm based abnormal profitability is measured by calculating the buy-and-hold abnormal returns relative to a matched control firm portfolio benchmark (details on the control portfolio are given in section 4.5.3). The investment is initiated the first month (January) and is terminated in the last month (December) of the calendar prediction year.

[b] The yearly abnormal return's significance is calculated using the t-test t_{BHAR} (shown in equation 4.17) based on the null-hypothesis that the yearly abnormal returns are not different from zero. The degrees of freedom of each test depend on the number of firms included in the predicted sample. $*, **, ***$ indicate significance using a two-tail t-test at the 1%, 5% and 10% respectively.

[c] Calculates the annualized average abnormal return generated by the yearly predicted firms over the ten-year period 1999-2008.

[d] Shows the result of the t-test t_C (shown in equation 4.18) examining the null-hypothesis that the average long-term abnormal returns are not different from zero. $*, **, ***$ indicate significance using a two-tail t-test with 9 degrees of freedom at the 1%, 5% and 10% respectively.

C.2 Artificial Neural Networks

Table C.3: *Control firm portfolio based abnormal returns[a] using an ANN-based model in the UK during the period 1999-2008*

Prediction year	BUY AND HOLD ABNORMAL RETURNS (BHAR) OF THE PREDICTED PORTFOLIO (in %) (Significance)[b]							
	Cut-off probability (P_C)							
	0.9	*0.8*	*0.7*	*0.6*	*0.5*	*0.4*	*0.3*	*0.2*
1999	104.1	98.3	**98.5*** **	**80.8*** **	70.9	**86.2*** **	**84.0** **	**72.1*** **
	(0.230)	(0.149)	(0.073)	(0.099)	(0.128)	(0.057)	(0.047)	(0.069)
2000	-3.2	3.2	2.3	-1.2	-5.1	-4.3	-5.0	-3.1
	(0.626)	(0.534)	(0.656)	(0.799)	(0.262)	(0.300)	(0.219)	(0.410)
2001	14.5	**15.8*** **	12.2	13.4	**13.5*** **	**14.2*** **	**19.1* **	**16.6* **
	(0.137)	(0.090)	(0.174)	(0.117)	(0.092)	(0.051)	(0.005)	(0.007)
2002	14.0	18.5	12.2	6.1	5.9	5.4	-2.4	1.0
	(0.251)	(0.174)	(0.292)	(0.552)	(0.540)	(0.541)	(0.787)	(0.905)
2003	0.1	11.5	10.3	-3.8	12.1	1.8	4.7	15.0
	(0.999)	(0.629)	(0.647)	(0.883)	(0.555)	(0.939)	(0.836)	(0.432)
2004	-3.6	-10.8	-2.5	-4.0	-13.9	-11.5	-12.3	-8.8
	(0.882)	(0.627)	(0.885)	(0.791)	(0.274)	(0.294)	(0.117)	(0.253)
2005	17.6	19.7	15.7	20.9	16.2	21.1	20.9	18.2
	(0.537)	(0.415)	(0.490)	(0.337)	(0.448)	(0.305)	(0.273)	(0.289)
2006	-21.9	-13.0	-11.9	-10.3	-10.4	-4.3	-7.5	-4.2
	(0.200)	(0.398)	(0.388)	(0.396)	(0.339)	(0.679)	(0.424)	(0.661)
2007	114.4	114.4	39.0	15.3	-13.4	-3.2	-13.6	2.9
	(NA)	(NA)	(0.777)	(0.825)	(0.487)	(0.856)	(0.336)	(0.708)
2008	9.2	8.4	14.0	10.9	6.2	5.7	8.4	**10.1*** **
	(0.576)	(0.462)	(0.144)	(0.210)	(0.455)	(0.457)	(0.207)	(0.072)
$\langle \overline{BHAR_C} \rangle$[c]	**24.52**	**26.59*** **	**18.98*** **	**12.80**	**8.20**	**11.12**	**9.63**	**11.97**
t_C[d]	**1.68**	**1.93**	**1.93**	**1.56**	**1.05**	**1.25**	**1.05**	**1.64**

[a] Control firm based abnormal profitability is measured by calculating the buy-and-hold abnormal returns relative to a matched control firm portfolio benchmark (details on the control portfolio are given in section 4.5.3). The investment is initiated the first month (January) and is terminated in the last month (December) of the calendar prediction year.

[b] The yearly abnormal return's significance is calculated using the t-test t_{BHAR} (shown in equation 4.17) based on the null-hypothesis that the yearly abnormal returns are not different from zero. The degrees of freedom of each test depend on the number of firms included in the predicted sample. $*, **, ***$ indicate significance using a two-tail t-test at the 1%, 5% and 10% respectively.

[c] Calculates the annualized average abnormal return generated by the yearly predicted firms over the ten-year period 1999-2008.

[d] Shows the result of the t-test t_C (shown in equation 4.18) examining the null-hypothesis that the average long-term abnormal returns are not different from zero. $*, **, ***$ indicate significance using a two-tail t-test with 9 degrees of freedom at the 1%, 5% and 10% respectively.

Table C.4: *Control firm portfolio based abnormal returns[a] using an ANN-based model in the USA during the period 1999-2008*

Prediction year	BUY AND HOLD ABNORMAL RETURNS (BHAR) OF THE PREDICTED PORTFOLIO (in %) (Significance)[b]							
	Cut-off probability (P_C)							
	0.9	*0.8*	*0.7*	*0.6*	*0.5*	*0.4*	*0.3*	*0.2*
1999	-62.9 (0.227)	-13.6 (0.276)	-6.4 (0.745)	-26.5 (0.364)	4.4 (0.757)	-7.0 (0.752)	3.0 (0.860)	-9.7 (0.497)
2000	-35.1 (0.775)	14.3 (0.849)	-26.8 (0.815)	-0.3 (0.997)	76.3 (0.107)	28.9 (0.531)	12.1 (0.702)	19.4 (0.160)
2001	-62.0 (0.117)	-25.8 (0.358)	-19.5 (0.484)	-16.4 (0.430)	-13.0 (0.511)	-9.6 (0.673)	-11.5 (0.423)	-14.7 (0.133)
2002	**-43.9***** (0.084)	-38.7 (0.242)	-26.8 (0.309)	-26.0 (0.279)	-23.8 (0.230)	-21.9 (0.230)	-25.8 (0.128)	-18.3 (0.204)
2003	NA (NA)	NA (NA)	NA (NA)	-50.3 (0.744)	-59.8 (0.180)	-24.3 (0.337)	6.0 (0.735)	-4.8 (0.822)
2004	23.7 (0.128)	**30.3***** (0.067)	24.4 (0.111)	**27.1**** (0.035)	**27.2**** (0.013)	**18.5***** (0.069)	**14.8***** (0.061)	**13.0*** (0.006)
2005	-32.4 (0.235)	-29.9 (0.257)	-27.5 (0.240)	-27.4 (0.217)	-19.8 (0.322)	-20.3 (0.240)	-10.2 (0.497)	13.5 (0.499)
2006	-11.8 (0.237)	2.7 (0.770)	-4.0 (0.698)	1.9 (0.839)	-0.6 (0.927)	-4.4 (0.586)	-3.4 (0.659)	-1.0 (0.917)
2007	31.3 (0.360)	30.0 (0.198)	30.3 (0.250)	48.3 (0.126)	23.5 (0.189)	**43.6***** (0.074)	28.8 (0.152)	**32.7**** (0.023)
2008	**-32.1**** (0.041)	**-32.3*** (0.001)	**-30.1*** (0.001)	**-18.7***** (0.061)	**-21.1**** (0.043)	**-33.3*** (0.001)	**-35.2*** (0.003)	**-16.3***** (0.052)
$\langle \overline{BHAR_C} \rangle$[c]	**-22.52*****	**-6.32**	**-8.64**	**-8.93**	**-0.67**	**-2.98**	**-2.14**	**1.37**
t_C[d]	**-2.17**	**-0.74**	**-1.19**	**-0.97**	**-0.06**	**-0.37**	**-0.35**	**0.25**

[a] Control firm based abnormal profitability is measured by calculating the buy-and-hold abnormal returns relative to a matched control firm portfolio benchmark (details on the control portfolio are given in section 4.5.3). The investment is initiated the first month (January) and is terminated in the last month (December) of the calendar prediction year.

[b] The yearly abnormal return's significance is calculated using the t-test t_{BHAR} (shown in equation 4.17) based on the null-hypothesis that the yearly abnormal returns are not different from zero. The degrees of freedom of each test depend on the number of firms included in the predicted sample. $*, **, ***$ indicate significance using a two-tail t-test at the 1%, 5% and 10% respectively.

[c] Calculates the annualized average abnormal return generated by the yearly predicted firms over the ten-year period 1999-2008.

[d] Shows the result of the t-test t_C (shown in equation 4.18) examining the null-hypothesis that the average long-term abnormal returns are not different from zero. $*, **, ***$ indicate significance using a two-tail t-test with 9 degrees of freedom at the 1%, 5% and 10% respectively.

Appendix D

Algorithmic based sample constructions

Code Listing D.1: *Algorithm used to build the matched M&A database*

```
#! /usr/bin/python
# created: 03/2008 trial

##################### AIM OF THE PROGRAM ########################
# THIS PROGRAM EXTARCTS THE INFO FROM THE FILE dir_info+filename AND
    CREATES:
# AND CREATES A TABLE table_title in the DB db_user

# - 1RST COLUMN: TARGET_NAME
# - 2ND COLUMN : TARGET_NATION
# - 3RD COLUMN : TARGET_IND
# - 4TH COLUMN : DATE_ANNOUNCED
# - 5TH COLUMN : DATE_EFF_UNC
# - 6TH COLUMN : DATE_EFF
# - 7TH COLUMN : DS_WITHD
# - 8TH COLUMN : ACQUIROR_NAME
# - 9TH COLUMN : ACQUIROR_NATION
# - 10TH COLUMN : ACQUIROR_IND
# - 11TH COLUMN : DS_ACQ
# - 12TH COLUMN : ACQ_P_STATUS
# - 13TH COLUMN : TRANS_VALUE
# - 14TH COLUMN : DEF_TRANS_VALUE
# - 15TH COLUMN : YEAR
# - 16TH COLUMN : QUARTER
# - 17TH COLUMN : STATUS
# - 18TH COLUMN : CONS_STRUCT
# - 19TH COLUMN : ATTITUDE
# - 20TH COLUMN : FLAG_CHANGE
# - 21ST COLUMN : PCT_CASH
# - 22ND COLUMN : PCT_OTHER
# - 23RD COLUMN : PCT_STOCK
# - 24TH COLUMN : PCT_ACQ_PM
# - 25TH COLUMN : PCT_TAR_PM
# - 26TH COLUMN : EV_ANNOUCEMENT
# - 27TH COLUMN : FORM_DEAL
# - 28TH COLUMN : ACQ_TECH1
# - 29TH COLUMN : ACQ_TECH2
# - 30TH COLUMN : ACQ_TECH3
# - 31ST COLUMN : ACQ_TECH4
# - 32ND COLUMN : ACQ_TECH5
# - 33RD COLUMN : TAR_WSCP_ID
```

```
# - 34TH COLUMN : MATCH_NUM

####################################################################
# Prog_query is a personal file containing the classes Connecting(),
    Executing(), Exiting(), and Finding().
import sys
import MySQLdb
from Prog_query import *

###################### GLOBAL VARIABLES #########################

country_code='UK'

dir_default='/Users/julianperezalzueta/'
dir_info=dir_default+'Desktop/PhD_Analysis_Data/Data_collection/
    MnA_data/TS_Target_TOB/%s_Target_yearly/'%country_code

db_user='predictive_db'#%country_code.lower()

yy_start=1995
yy_end=2008

table_title='%s_P_TARGET_%s_%s_FULL'%(country_code,str(yy_start),str
    (yy_end))#
table_wscp='WSCP_ID_%s'%country_code#refernce table containing the
    WSCP_ID and the names of the companies worldwide
table_filtered=table_title+'_FILTERED'#extracted rumors from "
    table_title"

filename='%s_P_Target_95_08_full_deal_form_gf.txt'%country_code#
    common name of the files containing MnA info, details on the deal
     form and having the good format
f_def='US_WPI.txt'#name of the file containing deflated index

#Each item is ordered following the column distribution of the file
    containing the MnA info
table_cols=['TARGET_NAME','TARGET_NATION','TARGET_IND','DS_TAR','
    DATE_ANNOUNCE','DATE_EFF_UNC','DATE_EFF','DATE_WITHD','
    ACQUIROR_NAME','ACQUIROR_NATION','ACQUIROR_IND','DS_ACQ','
    ACQ_P_ST','DEF_TRANS_VALUE','TRANS_VALUE','YEAR','QUARTER','
    STATUS','DEAL_STRUCTURE','ATTITUDE','ATT_CHANGE','PCT_CASH','
    PCT_OTHER','PCT_STOCK','PCT_SOUGHT_OFFER','PCT_SHARES_ACQ','
    PCT_OWNED_ACQ_PM','PCT_OWNED_TAR_PM','EV_ANNOUCEMENT','DEAL_FORM'
    ,'TAR_WSCP_ID','MATCH_NUM']
table_chars=['varchar(90)','varchar(2)','varchar(10)','varchar(6)',
    'date', 'date','date','date', 'varchar(90)','varchar(2)','varchar
    (10)','varchar(6)','varchar(10)','double(16,3)','double(14,3)','
    smallint(4)','smallint(1)','varchar(20)','varchar(10)','varchar(
    10)','varchar(1)','double(7,3)','double(7,3)','double(7,3)','
    double(7,3)','double(7,3)','double(7,3)','double(7,3)','double(16
    ,4)','varchar(20)','varchar(9)','smallint(1)']#each col 'i' gives
     the (max) number of digit of the 'i'st item from the list "
    table_cols"
```

```
num_files=1
line_start=4# number of the line where info starts (line after the
    titles)
col_stop=27# number of the last column that is going to be uploaded
col_date=5
col_tv=14# number of the column where the transaction value is given
col_acq_name=8

############ PRE PROC : FUNCTION DEFINITION #####################

#tt=table name, tt_wscp=table containing the woprldscope permanent
    IDs from the firms existing in Datastream,
#tn=name of the target firm,cc=country code
def matching_DS_firm(connection,tt,tt_wscp,tn,ds_tar,cc):
  #match_num indicates what type of matching has been used to match
     the companies.9=NO MATCH 0=NORMAL_MATCH 1=1rst WORD MATCH 2=2
     FIRST WORDS MATCH
  match_num='9'
  wsi='0'
  #"res_out" should contain, after the matching process, the wscp_id
     (1st item) and the match_num( 2nd item)
  res_out=[]

  name_match=tn.split('(')[0].split('{')[0].split(',')[0]

  #Matching with the full name.
  req="""select worldscope_id, company_name from %s where
     country_code="%s" and (COMPANY_NAME="%s" or COMPANY_NAME="%s");
     """%(tt_wscp,cc,name_match,name_match.replace("Co","COMPANY").
     replace("Cos","COMPANIES").replace("Ltd","LIMITED").replace(" &
     "," AND"))

  result=Executing().exec_fetch(connection,req)

  if len(result)==1:
    wsi=result[0][0]
    match_num=0
    print 'OK'
  else:
    print "Company name: %s"%name_match

    #Matching with the first word.
    cn=name_match.split()
    req="""select worldscope_id, company_name from %s where
       country_code="%s" and COMPANY_NAME>="%s" and COMPANY_NAME<="%
       sZ";"""%(tt_wscp,cc,cn[0],cn[0])
    result=Executing().exec_fetch(connection,req)

    if len(result)==1 and len(cn)<=3 and len(cn[0])>1:
      wsi=result[0][0]
      match_num=1
      print 'OK'
    elif len(result)==0:
```

```
    wsi='0'

  elif len(cn)>1:
    #Matching with the first two words.
    req="""select worldscope_id, company_name from %s where
        country_code="%s" and COMPANY_NAME>="%s" and COMPANY_NAME
        <="%sZ";"""%(tt_wscp,cc,cn[0]+' '+cn[1],cn[0]+' '+cn[1])
    result=Executing().exec_fetch(connection,req)

    if len(result)==0:
      wsi='0'
    elif len(result)==1:
      wsi=result[0][0]
      match_num=2
      print 'OK'
    elif len(cn)>2:
      req="""select worldscope_id, company_name from %s where
          country_code="%s" and COMPANY_NAME>="%s" and COMPANY_NAME
          <="%sZ";"""%(tt_wscp,cc,cn[0]+' '+cn[1]+' '+cn[2],cn[0]+'
           '+cn[1]+' '+cn[2])

      # Matching with the first three words.
      result=Executing().exec_fetch(connection,req)

      if len(result)!=1:
        wsi='0'
      else:
        wsi=result[0][0]
        match_num=3
        print 'OK'
    else:
      print 'Not enough information to decide from the list of
          suggested companies '
      wsi='0'
  else:
    print 'Not enough information to decide from the list of
        suggested companies '
    wsi='0'

if wsi=='0':
  #Matching by Datastream ID.
  req_ds="""select WORLDSCOPE_ID from %s where SECTOR_TYPE="%s";
      """%(tt_wscp,ds_tar)
  result=Executing().exec_fetch(connection,req_ds)

  if len(result)==1:
    wsi=result[0][0]
    match_num='4'
    print 'OK'
  elif len(result)==0:
    print 'No Datastream id matches'
    wsi='0'
  else:
```

```
      print 'ERROR: Datastream code %s is not unique. Check the
          corporate references.'%ds_tar
      Exiting().exit_connection(connection)

  res_out.append(wsi)
  res_out.append(match_num)
  return res_out

#########################  MAIN ##################################

### Database connection
conn=Connecting().db_conn(db_user)

answer=Finding().look_up_table(conn,table_title)
if answer=='y':
  ### Creation of the table with the same name of the file
  if len(table_cols)==len(table_chars):
    req_create="""create table %s(%s %s"""%(table_title,table_cols[0
        ],table_chars[0])
    for ii in range(1,len(table_cols)):
      req_create+=','+table_cols[ii]+' '+table_chars[ii]
    req_create+=");"
  else:
    print "ERROR: the variables and the variables's type tables have
        not the same size. The request has been cancelled"
    Exiting().exit_connection(conn)
  Executing().exec_only(conn,req_create)

# Attemp to deflate dollar values if necessary
try:
  txt_def=open(dir_info+f_def,'r')
  def_list=txt_def.readlines()
except Exception, why:
  print "------- ERROR --------:%s"%why
  Exiting().exit_connection(conn)

# Open "filename" containing the MnA information downloaded from
   Thomson One Banker
try:
  txt_file=open(dir_info+filename,'r')
  txt_list=txt_file.readlines()
  print '%s line(s) has/have been extracted from the file %s'%(len(
      txt_list)-1,filename)
except Exception, why:
  print "The file %s could not be found"%filename
  Exiting().exit_connection(conn)

# Generates a single country code for the US
if len(country_code)>2:
  ccg=country_code[0]+country_code[1]# All the files finishig USn (0
      <n<19) will have the same country_code 'US'
else:
  ccg=country_code
```

```
### Multi column insertion into database
i=0
len_db=len(txt_list)-line_start+1
for nn in range(line_start-1,len(txt_list)):
        line=txt_list[nn].split('\r')[0]
  db_list=line.split('\t')
  if db_list[0]!='COMPANY NAME':
    tar_name=db_list[0]
    target_ds_id=db_list[3].replace('-','0')
    # The "wscp_match_list" provides the worldscope ID as the first
       item and the matching number as the second one.
    wscp_match_list=matching_DS_firm(conn,table_title,table_wscp,
       tar_name,target_ds_id,country_code)
    wscp_id=wscp_match_list[0]
    matching_number=wscp_match_list[1]

    req="""insert into %s values("%s" """%(table_title,tar_name)
          for ll in range(1,col_stop):
      #Inserting a date in Col number 'col_date' 'col_date+1' and '
         col_date+2'
      if ll==(col_date-1):
        req+=','+'str_to_date("%s","%%m/%%d/%%Y")'%db_list[ll].
           replace('#N/A','00/00/0000').replace('-','00/00/0000')

      elif ll==col_date:
        req+=','+'str_to_date("%s","%%m/%%d/%%Y")'%db_list[ll].
           replace('#N/A','00/00/0000').replace('-','00/00/0000')

      elif ll==(col_date+1):
        req+=','+'str_to_date("%s","%%m/%%d/%%Y")'%db_list[ll].
           replace('#N/A','00/00/0000').replace('-','00/00/0000')

      elif ll==(col_date+2):
        req+=','+'str_to_date("%s","%%m/%%d/%%Y")'%db_list[ll].
           replace('#N/A','00/00/0000').replace('-','00/00/0000')

      elif ll==col_tv-1:

        dd=db_list[col_date-1]
        #print "selected date: %s"%dd

        date_list=dd.split('/')

        d2=date_list[2]#d2=two last numbers of the year

        if len(d2)==2:
          if int(d2)<=30:
                                    yy='20'+str(d2)
                                  else:
                                    yy='19'+str(d2)
        elif len(d2)==4:
            yy=str(d2)
```

```
        else:
          print "The date %s does not have the addecuate format"%str
              (d2)
          print "Exiting..."
          Exiting().exit_connection(connection)

        d1=int(date_list[1])#d1=month number

        if d1<=3:
          qtr=1

        elif d1>=4 and d1<=6:
          qtr=2

        elif d1>=7 and d1<=9:
          qtr=3

        elif d1>=10:
          qtr=4

        ll_def=4*(int(yy)-1980)+qtr
        #print "number of line: %s"%str(ll_def)
        def_index=float(def_list[ll_def].split('\r')[0].split('\t')[
            1])
        non_def_val=float(db_list[ll].replace('-','0').replace(',','
            .').replace(' ',''))#Standard number notation
        req+=','+str(non_def_val/def_index)+','+str(non_def_val)+','
            +yy+','+str(qtr)

      else:
        if ll==col_acq_name:
          req+=','+'"%s"'%db_list[ll].replace('#N/A','0')

        else:
                            req+=','+'"%s"'%db_list[ll].replace('#N/
                                A','0').replace('-','0')

    req+=',"%s","%s");'%(wscp_id,matching_number)

    try:
      Executing().exec_only(conn,req)
      i+=1
    except Exception,why:
      print "Could not execute the request %s: %s"%(req,why)
      print "Exiting..."
      Exiting().exit_connection(conn)

print '%d lines of %d has been uploaded'%(i,len_db)


print '\n%s TARGETS TABLE UPLOADED\n'%country_code
```

```
print 'FILTERING DEALS WHERE STATUS IS RUMORS OR DISCARDED RUMORS...
    '
req_filter="""create table %s (select * from %s where TAR_WSCP_ID
    !='0' and STATUS!='Dis Rumor' and STATUS!='Rumor');"""%(
    table_filtered,table_title)
Executing().exec_only(conn,req_filter)

print 'OK'

### Close db connection
print 'UPLOAD COMPLETED'
Exiting().exit_connection(conn)
```

Code Listing D.2: *Algorithm used to build the matched M&A database*

```
#! /usr/bin/python
#
# created: 07/2008 trial

#################### AIM OF THE PROGRAM ###########################

# General: This program matches, for each predicted firm, a control
    firm similar in size and book-to-market ratio.
# The program proceeds as follows
# - Selects a firm predicted in year "yy"
# - Selects all firms showing trading activity in the previous year
    and belonging to the three considered industries.
# - from the latter group we select the firms having an MCAP between
     70% and 130% of the predicted firm's size.
# - from the latter group the control firm is selected as the firm
    having the closest market-to-book ratio to the one of the
    predicted firm.

####################################################################

import sys
import MySQLdb
from Prog_query import *

###################### GLOBAL VARIABLES ###########################

cc='US'
db_user='%s_db'%cc.lower()#the db where the table containing
    information lies

dir_default='/Users/julianperezalzueta/'
dir_filestore=dir_default+'Desktop/PhD_Analysis_Data/%s_LR/
    Portfolios_returns_TS/%s/%s/%i_lags/RI_CC_OTC_%s/co%s/'%(cc,
    dir_suff,type_var,num_lags,mbv,str(cutoff).replace('.',''))

num_lags=1
cutoff=0.7

filter_suff='no_EBSE_TDCE_listed_no_rep'
type_var='full'
dir_suff='AV_%s'%filter_suff
suff_txt='full_noET_ltd_OTC_traded_nonf'
suff='%s_%s'%(type_var,filter_suff)

table_name='%s_PROBA_PREDICTED_%sLAGS_%s'%(cc,num_lags,suff.upper())
price_traded_table='%s_RETURN_MTLY_LP_DEC_97_08_TRADED'%cc
price_table='%s_RI_MTLY_LP_DEC_97_09'%cc
table_dead_firms='%s_DEAD_LIST_97_08'%cc
mcv='MCAP'
mbv='PTBR'
cfr="MONTH_NUM"
```

```
ys=1999
ye=2008

tint='test' #name of the intermediate table used in the filtering of
     control firms
opt_list=['prd']

##################### PRE_PROC: FUNCTION DEF ######################
#option='ths'-> targets in the hole sample
#option='prd'-> all companies in predicted sample
#option='tps' -> targets in the predictive sample
def extract_WSCP_list(connection,tbl_avoid,tbl_dead,tn,option,year,
    nl,co):
  tres='test_pred'
  ans=Finding().look_up_table(connection,tres)
  if option=='ths' and ans=='y':
    req="""create table %s(select WORLDSCOPE_ID from %s where
        FORECAST_YEAR='%s' and REAL_TAR='1');"""%(tres,tn,year)
  elif option=='prd' and ans=='y':
    req="""create table %s(select WORLDSCOPE_ID from %s where
        FORECAST_YEAR='%s' and PRED_PROB>='%s');"""%(tres,tn,year,co)
  elif option=='tps' and ans=='y':
    req="""create table %s(select WORLDSCOPE_ID from %s where
        FORECAST_YEAR='%s' and PRED_PROB>='%s' and REAL_TAR='1');"""%
        (tres,tn,year,co)
  else:
    print 'None of the option for selecting a sample has been
        selected. Check the option s spelling.'
    sys.exit(0)

  Executing().exec_only(connection,req)

  req="""select * from %s;"""%tres
  result=Executing().exec_fetch(connection,req)

  wscp_list=[]
  for ww in result:
    wscp_list.append(ww[0])
  ans=Finding().look_up_table(connection,tbl_avoid)
  if ans=='y':
    req_avoid="""create table %s(select * from (select WORLDSCOPE_ID
         from %s UNION DISTINCT select WORLDSCOPE_ID from %s where
        YEAR='%s') t1);drop table %s;"""%(tbl_avoid,tres,tbl_dead,
        year,tres)
    Executing().exec_only(connection,req_avoid)
  return(wscp_list)

# Assumption: table cc_var contains variable 'var'
def extract_CONTROL_ID(connection,wid,mcap_var,mtbv_var,avoid_table,
    nl,year_pred,country_code,traded_table=price_traded_table):

  year=str(int(year_pred)-1)
```

```
print "**** FINDING A CONTROL FIRM FOR COMPANY: %s      YEAR: %s
    ****"%(wid,year)

mcap_table='%s_%s'%(country_code,mcap_var)
mtbv_table='%s_%s'%(country_code,mtbv_var)

req="""select %s from %s where YEAR='%s' and WORLDSCOPE_ID='%s';
    """%(mcap_var,mcap_table,year,wid)
mcap_wid=Executing().exec_fetch(connection,req)[0][0]

req="""select %s from %s where YEAR='%s' and WORLDSCOPE_ID='%s';
    """%(mtbv_var,mtbv_table,year,wid)
mtbv_wid=Executing().exec_fetch(connection,req)[0][0]

print "%s: %s"%(mcap_var,mcap_wid)
print "%s: %s"%(mtbv_var,mtbv_wid)

mcap_low=0.7*float(mcap_wid)
mcap_high=1.3*float(mcap_wid)
print "Searching for companies with %s in the window:[%s - %s]"%(
    mcap_var,mcap_low,mcap_high)

ti='test_mcap'
ans=Finding().look_up_table(connection,ti)
if ans=='y':
  ti2='test_mcap_int'
  ans_int=Finding().look_up_table(connection,ti2)
  if ans_int=='y':
    req="""create table %s(select WORLDSCOPE_ID from %s where YEAR
        ='%s' and %s>='%s' and %s<='%s' and WORLDSCOPE_ID not in (
        select * from %s));"""%(ti2,mcap_table,year,mcap_var,
        mcap_low,mcap_var,mcap_high,avoid_table)
    Executing().exec_only(connection,req)

print "Filtring non-traded companies..."
req_trade="""create table %s(select * from %s where WORLDSCOPE_ID
    in (select distinct WORLDSCOPE_ID from %s where YEAR='%s'));
    drop table %s;"""%(ti,ti2,traded_table,year_pred,ti2)
Executing().exec_only(connection,req_trade)
print "OK."
req_len="""select count(*) from %s"""%ti
len_mcap_list=Executing().exec_fetch(connection,req_len)[0][0]
if len_mcap_list==0:
  print 'Error: there is no commpany to match %s by %s'%(wid,
      mcap_var)
  Exiting().exit_conection(connection)
else:
  print "%s companies found."%len_mcap_list
  req="""select %s, count(*) from %s where YEAR='%s' and IND_NUM!=
      4 and IND_NUM!=5 and IND_NUM!=6 and WORLDSCOPE_ID in (select
      * from %s) GROUP BY %s ORDER BY abs(%s-%s);"""%(mtbv_var,
      mtbv_table,year,ti,mtbv_var,mtbv_var,mtbv_wid)
  result=Executing().exec_fetch(connection,req)
```

```
    len_list=result[0][1]
    print "Closest %s value: %s"%(mtbv_var,result[0][0])
    print "%s companies having an %s= %s"%(len_list,mtbv_var,result[
        0][0])

    req="""select WORLDSCOPE_ID from %s where YEAR='%s' and IND_NUM
        !=4 and IND_NUM!=5 and IND_NUM!=6 and WORLDSCOPE_ID in (
        select * from %s) ORDER BY abs(%s-%s), rand() LIMIT %s;"""%(
        mtbv_table,year,ti,mtbv_var,mtbv_wid,len_list)

    result=Executing().exec_fetch(connection,req)
    print result
    wid_cont=result[0][0]

    print "Control company selected: %s"%wid_cont

    req_insert="""insert into %s values("%s"); drop table %s;"""%(
        avoid_table,wid_cont,ti)
    Executing().exec_only(connection,req_insert)

    return(wid_cont)

# tn=Table containing the firms' market price - wscp_id=Worldscope
    identifier of the company selected to extract its returns
def extract_returns(connection,tn,wscp_id,year,col_freq="MONTH_NUM",
    col_val="PRICE_RETURN"):

  wi=wscp_id
  req_len="""select count(*) from (select distinct %s from %s where
      YEAR='%s') t1;"""%(col_freq,tn,year)
  result=Executing().exec_fetch(connection,req_len)
  we_total=result[0][0]

  req="""select COMPANY_NAME from %s where WORLDSCOPE_ID='%s' and
      YEAR='%s' and %s='1';"""%(tn,wi,year,col_freq)
  cn=Executing().exec_fetch(connection,req)[0][0]

  ROI_list=[]
  ROI_list.append(cn)
  tr=1#tr= total returns= product of the yields of the company
      having a wscp_id='wi'
  print cn
  for ii in range(we_total):
    wn=ii+1#week number
    N=0#N counts the total number of companies of which price
        information is available

    req="""select %s from %s where WORLDSCOPE_ID='%s' and YEAR='%s'
        and %s='%s';"""%(col_val,tn,wi,year,col_freq,wn)
    pp1=Executing().exec_fetch(connection,req)

    if pp1[0][0]!='-999':
      rr=1+float(pp1[0][0])
```

```
      print 'return in month %s = %s'%(wn,rr)
      #txt_save.write(str(rr)+'\t')
      N+=1
      tr*=rr
    else:
      tr=0

    if N==1:
      ROI_list.append(str(tr))
      #txt_save.write(str(tr/float(N))+'\n')
    else:
      print 'ERROR: There number %s exceeds 1. Upload company %s
          failed.'%(N,wi)
      ROI_list.append('0')
      #txt_save.write(str(tr/float(N))+'\n')
      #print 'Exit'
      #connection.close()
      #sys.exit(0)

  if N==1:
    print 'An average yearly return of %s%% for company %s in %s'%(
        str(tr),cn,year)
  else:
    print 'An average yearly return of 0%% for company %s in %s'%(cn
        ,year)

  #txt_save.close()
  return(ROI_list)

###############################  MAIN ###############################

### Database connection
conn=Connecting().db_conn(db_user)

for yy in range(ys,ye+1):

  #fn='ROI_%s_targets_%s_%slags_co%s_%s.txt'%(cc,str(yy),num_lags,
     str(cutoff).replace('.',''),suff)
  for opt in opt_list:

    ROI_all_sets=[]
    if nn==1:
      fn='%s_ANN_CC_ROI_%s_%s_%sl_co%s_%s.txt'%(cc,opt.upper(),str(
          yy),num_lags,str(cutoff).replace('.',''),suff_txt)
    else:
      fn='%s_CC_ROI_%s_%s_%sl_co%s_%s.txt'%(cc,opt.upper(),str(yy),
          num_lags,str(cutoff).replace('.',''),suff_txt)
    wl=extract_WSCP_list(conn,tint,table_dead_firms,table_name,opt,
        str(yy),num_lags,cutoff)
    print wl
    print "The prediction-based portfolio contains: %s companies"%
        len(wl)
    for wscp_id in wl:
```

```
    control_wid=extract_CONTROL_ID(conn,wscp_id,mcv,mbv,tint,
        num_lags,str(yy),cc)
    ROI_all_sets.append(extract_returns(conn, price_table,
        control_wid,str(yy)))

  txt_save=open(dir_filestore+fn,'w')
  txt_save.write(cfr+'\t')
  for cn in ROI_all_sets:
    txt_save.write(cn[0]+'\t')
  txt_save.write('\n')
  if len(wl)>=2:

    we_num=len(ROI_all_sets[0])
    #check that all weeks have been taken in account in the three
        sets
    if we_num!=len(ROI_all_sets[1]):
      print 'The samples do not have the same length'
      Exiting().exit_connection(conn)
  else:
    we_num=13

  for ii in range(1,we_num):
    txt_save.write(str(ii)+'\t')
    for roi in ROI_all_sets:
      txt_save.write(roi[ii]+'\t')
    txt_save.write('\n')
  txt_save.close()
  req_drop="""drop table %s;"""%tint
  Executing().exec_only(conn,req_drop)

### Close db connection
print 'CONTROL FIRM SELECTION COMPLETED'
Exiting().exit_connection(conn)
```