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Development of bank acquisition targets prediction models

Pasiouras, Fotios

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Development of bank acquisition targets prediction models

By

Fotios Pasiouras

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Advisory Committee:

Dr. Sailesh Tanna (Coventry University)
Prof. Constantin Zopounidis (Technical University of Crete)
Prof. Angelos Tsaklanganos (Aristotle University of Thessaloniki)
Dr. Deb Ghosh (Coventry University)

Coventry University

in collaboration with

Technical University of Crete (Greece)

ABSTRACT

This thesis develops a range of prediction models for the purpose of predicting the acquisition of commercial banks in the European Union using publicly available data. Over the last thirty years, there have been approximately 30 studies that have attempted to identify potential acquisition targets, all of them focusing on non-bank sectors. We consider that prediction models developed specifically for the banking industry are essential due to the unusual structure of banks' financial statements, differences in the environment in which banks operate and other specific characteristics of banks that in general distinguish them from non-financial firms. We focus specifically on the EU banking sector, where M&As activity has been considerable in recent years, yet academic research relating to the EU has been rather limited compared to the case of the US.

The methodology for developing prediction models involves identifying past cases of acquired banks and combining these with non-acquired banks in order to evaluate the prediction accuracy of various quantitative classification techniques. In this study, we construct a base sample of commercial banks covering 15 EU countries, and financial variables measuring capital strength, profit and cost efficiency, liquidity, growth, size and market power, with data in both raw and country-adjusted (i.e. raw variables divided by the average of the banking sector for the corresponding country) form. In order to allow for a proper comparative evaluation of classification methods, we select common subsets of the base sample and variables with high discriminatory power, dividing the sample period (1998-2002) into training sub-sample for model development (1998-2000), and holdout sub-sample for model evaluation (2001-2002). Although the results tend to support the findings of studies on non-financial firms, highlighting the difficulties in predicting acquisition targets, the prediction models we develop show classification accuracies generally higher than chance assignment based on prior probabilities. We also consider the use of equal and unequal matched holdout samples for evaluation, and find that overall classification accuracy tends to increase in the unequal matched samples, implying that equal matched samples do not necessarily overstate the prediction ability of models.

The main goal of this study has been to compare and evaluate a variety of classification methods including statistical, econometric, machine learning and operational research techniques, as well as integrated techniques combining the predictions of individual classification methods. We found that some methods achieved very high accuracies in classifying non-acquired banks, but at the cost of relatively poor accuracy performance in classifying acquired banks. This suggests a trade-off in achieving high classification accuracy, although some methods (e.g. Discriminant) performed reasonably well in terms of achieving balanced overall classification accuracies of above chance predictions. Integrated prediction models offer the advantage of counterbalancing relatively poor performance of some classification methods with good performance of others, but in doing so could not out-perform all individual classification methods considered. In general, we found that the outcome of which method performed best depended largely on the group classification accuracy considered, as well as to some extent on the choice of the discriminatory variables. Concerning the use of raw or country-adjusted data, we found no clear effect on the prediction ability of the classification methods.

DEDICATION

I dedicate this Thesis to my parents and my sister for all their love, support and encouragement.

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Writing the acknowledgements for a PhD thesis is one of the happiest moments for two reasons. Firstly, it means that you have come to the end of an effort that requires at least three years of your life and is considered the highest academic qualification. Secondly, it offers you an opportunity to express your appreciation to all those that have contributed to the completion of the thesis.

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ACRONYMS

ANN	Artificial Neural Networks
AT	Austria
BE	Belgium
BSC	Banking Supervision Committee
CAMEL	Capital, Asset quality, Management, Earnings, Liquidity
CART	Classification And Regression Trees
CC	Current Cost
CD	Constant Dollar
CRA	Community Reinvestment Act
DA	Discriminant Analysis
DE	Germany
D/E	Debt/Equity
DEA	Data Envelopment Analysis
DH	Domestic Hypothesis
DFA	Distribution Free Approach
DK	Denmark
ECB	European Central Bank
EFA	Econometric Frontier Approach
ES	Spain
EU	European Union
FDIC	Federal Deposit Insurance Corporation
FH	Foreign Hypothesis
FI	Finland
FR	France
G10	Group of Ten
GR	Greece
HC	Historical Cost
IE	Ireland
IT	Italy
k-NN	k-Nearest Neighbours
K-S	Kolmogorov-Smirnov test
LA	Logit Analysis
LDA	Linear Discriminant Analysis
LU	Luxembourg
MAM	Market Adjusted Model
MCDA	MultiCriteria Decision Aid
M&As	Mergers and Acquisitions
MHDIS	Multi-group Hierarchical DIScrimination
MDA	Multiple Discriminant Analysis
NL	Netherlands
NPM	Net Profit Margin
NPV	Net Present Value
OLS	Ordinary Least Squares
OP	Operating Performance

PABAK	Prevalence-Adjusted-Bias-Adjusted Kappa
PNN	Probabilistic Neural Networks
PT	Portugal
QR	Quick Ratio
OSH	Optimal Separating Hyperplane
RH	Relative Hypothesis
ROA	Return On Assets
ROAA	Return on Average Assets
ROAE	Return on Average Equity
ROC	Receiver Operating Characteristics
ROE	Return On Equity
S/A	Sales/Assets
SAM	Size Adjusted Model
SDC	Securities Data Company
SE	Sweden
SIC	Standard Industrial Classification
SRM	Structural Risk Minimization
SVMs	Support Vector Machines
TFA	Thick Frontier Approach
UK	United Kingdom
US	United States
UTADIS	Utilités Additives DIScriminantes

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Chapter 1
Introduction

1.1 Overview

Over the last two decades, a number of significant changes occurred in the banking industry, such as deregulation, globalisation, financial innovations, improvements in communication and computing technology, increased competition from within the sector and from non-bank financial intermediaries, to name a few. In response to these changes, banks have attempted to adopt strategies to improve efficiency, increase output and expand the range of services offered (Goddard et al., 2001). The trend towards mergers and acquisitions (M&As) can be interpreted as the outcome of moves to achieve these goals (Berger et al., 1999; Beitel and Schiereck, 2001).

M&As of financial institutions as a trend began in the United States in the 1980s and quickly increased worldwide in the 1990s, becoming a global phenomenon. Data provided by Amel et al. (2004) indicate that most of the M&A activity in the financial sector between 1990 and 2001 involved banking firms, accounting for nearly 53% of all mergers in the financial sector (with 8,144 bank acquisitions among a total of 15,502 financial mergers), representing a value of $1,835 billion, approximately 68% of the total value of financial M&As[1] ($2,693.9 billions). Thus, it is not surprising, as Sobek (2000) claims that during the second half of the 1990s the most frequent words used in reports on banking were "merger" and "acquisition".

The last few years have also shown an increase in the number and value of large M&A deals, including "megamergers" (i.e. M&As between institutions with assets over 1$ billion). As Rhoades (2000) points out, in the US far more banks with assets greater than 1$ billion were acquired in the 1990s than over the 1980s. The report of the Group of Ten (2001) indicates that in the 13 countries studied over the 1990s, this trend was more evident towards the end of the decade. Of the 246 mega-deals that took place over the period 1990-1999, 197 (over 80%) occurred during the second half of this period (1995-1999). In Europe, a number of mega-deals occurred between 1999 and 2002 that resulted in the creation of five of the largest European banking groups (BNP Paribas in France, IntesaBsci in Italy, Banco Santander Central

[1] The data were obtained from Thomson Financial and SDC Platinum and refer to majority interests.

Hispano and Banco Bilbao Vizcaya Argentaria in Spain, and Natwest-Royal Bank of Scotland in the UK). Some M&As also reached the scale of "supermegamergers" (i.e. M&As between institutions with assets over $100 billion each). Based on market values, nine of the ten largest M&As in the US history took place in 1998 and four of these (Citicorp-Travelers, BankAmerica-NationsBank, Bank One – First Chicago and Norwest-Wells Fargo) occurred in banking (Moore and Siems, 1998).

Given the scale of such activity, it is not surprising that the academic literature on the topic of M&As in the banking industry has proliferated, and numerous empirical studies have been conducted to address different aspects of bank M&As. Beitel and Schiereck (2001) provide an overview of many recent event studies that examined the stock price performance of banks involved in M&As, and document a significant increase in the share price of acquired banks around the announcement day. It is therefore reasonable to assume that the ability to predict acquired banks in advance of the announcement date could form the basis for a successful investment strategy that entails holding the shares of acquired banks in the expectation of high returns. Similar results in event studies that examined non-financial firms have motivated researchers and practitioners to develop prediction models for identifying potential acquisition targets.

The major goal of this study is to compare and evaluate a variety of classification techniques for the purpose of predicting acquisition targets for the EU Banking industry. Prediction is of course based on identifying past cases of acquired firms, and combining these with a sample of non-acquired firms in order to evaluate the predictive accuracy of various classification techniques. In the light of recent changes and the growing trend of M&As in the EU banking industry (see Section 1.2 below), this study specifically aims to:

1. survey the wider literature on the reasons and motives for M&As in banking, with the objective of identifying the nature of underlying factors (or variables), whether internal or external to the industry, and assessing the evidence on acquiring or merged banks' operating performance.

2. examine the broader literature and the methodology for the development of prediction models applied to M&As, covering established statistical and econometric methods, as well more recently developed non-parametric methods

originating in the field of computing and operational research, that have also led to new ways of combining classification methods for developing integrated models of prediction.

3. develop prediction models for identifying cases of acquisitions in the EU banking industry, over the period 1998-2002, in order to compare and evaluate seven alternative classification methods, these being Discriminant analysis (DA), Logit (LA), Utilités Additives DIScriminantes (UTADIS), Multi-group Hierarchical DIScrimination (MHDIS), Classification And Regression Trees (CART), k-Nearest Neighbours (k-NN), and Support Vector Machines (SVMs)[2]. Of these, k-NN and SVMs have not been applied to the development of prediction models for acquisition targets, despite their promising results in other classification problems in finance (e.g. bankruptcy prediction, credit risk assessment, etc.).

4. review the methodology for combining classification methods into an integrated (multi-classifier) prediction model for the purpose of investigating the possibility of achieving higher prediction accuracy over individual classification methods. In this connection, we develop integrated prediction models for evaluating the relative efficiency of two multi-classifier techniques, namely majority voting and stacked generalization, and investigate whether integrated models actually lead to better classification accuracy.

The remainder of this chapter provides a step-by-step introduction to explain the purpose for undertaking this study, and in doing so we also highlight the practical importance of the study in relation to the broader literature. Thus, in Section 1.2, we present the main M&As trends in the EU banking industry over the last few years in order to provide an empirical focus for our study. Then, in Section 1.3, we emphasise the importance of the present study and its application to the EU banking industry. In section 1.4, we discuss the main objectives, while in section 1.5 we highlight the main contributions of the study. Finally, section 1.6 presents an outline of the thesis.

[2] For a discussion on these methodologies see chapter 4.

1.2 M&As trends in the European Union

Mergers and acquisitions within the European financial sector have significantly transformed the European banking market in the last decade. For example, the number of European banking institutions felt from 12,378 in 1990 to 8,395 in 1999 (European Central Bank - ECB, 2000) while 18 of the 30 largest European banks emerged as a result of recent M&As (Belaisch et al., 2001). Over the period 1995 to the first half of 2000, ECB (2000) records 2,153 M&As of credit institutions in the EU. Data from Table 1.1 provide a clear picture of the types of these M&As.

Table 1.1 - Number of Total bank M&As (domestic and international) in the EU

	1995	1996	1997	1998	1999	First half 2000	Total
Total bank M&As	326	343	319	434	497	234	2153
- of which domestic	275	293	270	383	414	172	1807 (84%)
- of which within EEA	20	7	12	18	27	23	107 (5%)
- of which with third country	31	43	37	33	56	39	239 (11%)

Source: ECB (2000)

Out of the total of 2,153 M&As, 84% were between banks from the same country, 5% occurred within European Economic Area (EEA) and 11% with banks from a third country. It is therefore clear that over the above period domestic M&As were far more common than cross-border ones. Nevertheless, cross-border M&As of acquiring European banks, and in particular of large ones, increased strongly in 2000. Beitel and Schiereck (2001) report that the share of cross-border M&A transactions in 2000 reached 50% and approximately 70% as a percentage of number and volume respectively. Another interesting observation is that M&As with institutions located in third countries, have outnumbered M&As within the EEA during all years, and where more than double on an aggregate basis for the entire period. Most European banks have chosen to expand into Latin America (e.g. banks from Netherlands, Spain, Portugal and Italy), South-East Asia (e.g. banks from Netherlands) and Central and Eastern Europe (e.g. banks from Netherlands and Ireland) probably in the search for markets offering higher margins or due to historical connections (ECB, 2000). Nevertheless, in some cases they have also expanded into developed markets such as the US (e.g. banks from Germany).

Table 1.2 presents the geographical distribution of the M&As. It is worthwhile to mention that around 80% of total M&As have involved credit institutions from Germany, Italy, France and Austria.

Table 1.2 – Total number of M&As of credit institutions (domestic and cross-border) in the EU

	1995	1996	1997	1998	1999	1st half 2000	Average 1995-99
Austria	14	24	29	37	24	8	26
Belgium	6	9	9	7	11	3	8
Germany	122	134	118	202	269	101	169
Denmark	2	2	2	1	2	2	2
Spain	13	11	19	15	17	29	15
Finland	9	6	5	7	2	5	6
France	61	61	47	53	55	25	55
Greece	0	1	3	9	8	1	4
Ireland	3	4	3	3	2	0	3
Italy	73	59	45	55	66	30	60
Luxembourg	3	2	3	12	10	8	6
Netherlands	7	11	8	3	3	5	6
Portugal	6	6	2	5	2	9	4
Sweden	1	2	5	1	7	2	3
UK	6	11	21	24	19	6	16
Total	326	343	319	434	497	234	

Source: ECB (2000)

Focusing on domestic bank M&As, 1999 was a peak year with 414 deals, a 50.55% increase from the 275 deals that occurred in 1995. With respect of the size of M&As (distinguishing between large M&As in which at least one of the involved institutions had assets above 1 billion euro and small M&As) it is clear that domestic M&As mainly occur between smaller institutions (Figure 1.1). A potential explanation is that the small institutions operating in the EU are by far much more than the large institutions. Nevertheless, since 1996, there has been a slight trend towards larger M&As. The number of large domestic M&As as a percentage of total domestic M&As reached 22.09% in the first half of 2000 compared to 9.56% in 1995.

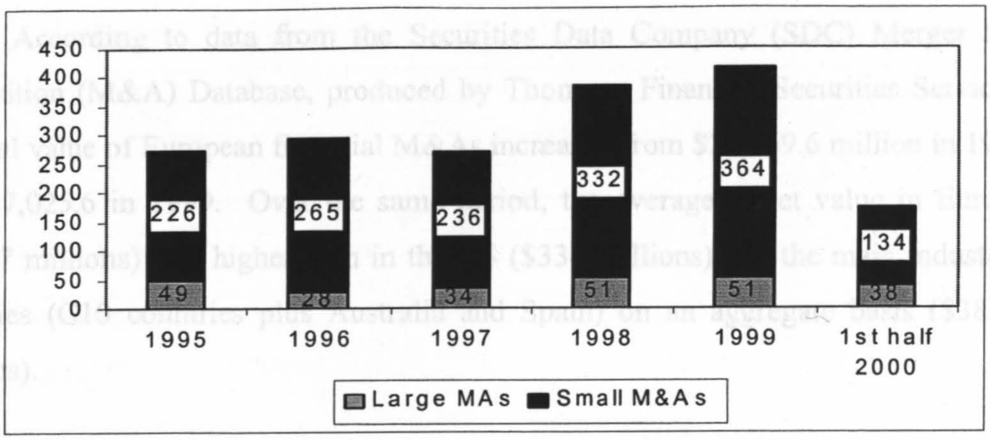

Figure 1.1 – Breakdown of domestic M&As in the EU by size

(Source: ECB, 2000)

Turning to the value of M&As (Tables 1.3 & 1.4), two general conclusions can be drawn. First, larger domestic M&As tended to be involved during the period 1995-1998. Second, large differences occurred among EU countries, both at the level of banking assets involved in M&As and in the trends either upwards or downwards. For example, increases in the values have been observed in Austria, Belgium, Germany, France, Italy and Luxembourg with assets ranging from less than 5% of banking assets involved in Germany to more than 50% in France in 1999, while decreases in relation to values (and numbers) have occurred in Portugal and Sweden.

Table 1.3 - Value of domestic mergers of credit institutions[1]

	1995	1996	1997	1998	1999	1st half 2000
Austria	5.42	3.01	13.37	13.68	1.16	0.31
Belgium	8.49	14.71	12.48	20.09	0.12	0.00
Germany	0.34	0.78	0.39	4.57	2.40	4.00
Denmark	0.40	7.70	0.10	15.50	0.00	0.10
Spain	0.50	7.70	0.00	1.40	20.12	18.44
Finland	45.59	3.36	0.21	29.43	0.00	3.18
France	2.90	12.10	19.00	10.80	57.50	10.28
Greece	0.00	0.00	9.94	32.78	9.01	0.00
Ireland	n.a.	n.a.	n.a.	1.40	0.00	0.00
Italy	1.30	0.17	0.10	1.07	0.04	0.00
Luxembourg	1.54	0.00	2.59	12.22	7.40	4.45
Netherlands	0.00	0.00	n.a.	0.00	0.00	0.17
Portugal	0.00	0.00	0.00	0.10	0.00	5.40
Sweden	0.00	0.07	18.00	0.00	0.00	0.00
UK	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.

[1] Value: Banking assets involved in mergers as a % of total domestic banking assets
Source: ECB (2000)

According to data from the Securities Data Company (SDC) Merger and Acquisition (M&A) Database, produced by Thomson Financial Securities Services, the total value of European financial M&As increased from $22,769.6 million in 1990 to $147,025.6 in 1999. Over the same period, the average target value in Europe ($467.7 millions) was higher than in the US ($334 millions) and the main industrial countries (G10 countries plus Australia and Spain) on an aggregate basis ($383.2 millions).

Table 1.4- Value of domestic acquisitions of credit institutions [1]

	Full Acquisitions						Majority Acquisitions					
	1995	**1996**	**1997**	**1998**	**1999**	**1st half 2000**	**1995**	**1996**	**1997**	**1998**	**1999**	**1st half 2000**
AT	0.00	0.00	34.84	2.38	0.00	0.06	n.a.	0.00	0.00	0.16	0.15	0.00
BE	0.39	1.03	2.81	0.18	0.23	0.00	0.00	0.00	0.00	0.00	0.11	0.00
DE	0.77	0.46	0.09	0.01	0.02	1.50	0.07	0.01	0.07	0.00	0.00	0.00
DK	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
ES	0.00	0.01	0.00	0.11	0.24	0.00	4.64	0.28	0.00	0.11	0.00	0.00
FI	0.77	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
FR	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	19.40	38.00	16.70	12.00	43.89	0.17
GR	0.00	0.00	0.21	0.12	0.90	0.00	0.00	0.00	0.00	3.67	4.36	0.00
IE	0.13	0.20	n.a.	0.10	0.10	0.00	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
IT	0.34	0.30	0.71	1.33	0.35	0.06	4.57	1.08	3.42	9.54	14.35	2.27
LU	0.00	0.21	0.00	1.82	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NL	n.a.	n.a.	n.a.	0.00	0.01	0.02	0.00	n.a.	n.a.	0.00	0.00	0.00
PT	13.30	1.90	0.00	0.00	0.00	5.29	11.50	5.90	0.30	0.00	0.00	0.01
SE	0.20	11.20	23.00	0.30	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00
UK	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.

[1] Value: Banking assets involved in acquisitions as a % of total domestic banking assets

AT: Austria; BE: Belgium; DE: Germany; DK: Denmark; ES: Spain; FI: Finland; FR: France; GR: Greece; IE: Ireland; IT: Italy; LU: Luxembourg; NL: Netherlands; PT: Portugal; SE: Sweden; UK: United Kingdom.

Source: ECB (2000)

Table 1.5 shows that in Europe, over the 1990s the average target value in within-industry deals ($562.1 millions) was almost double than in cross-industry ones ($289.0 millions). Furthermore, during the same period both total and average value of domestic mergers was by far higher than those of cross-border deals. Finally, with respect of the market segments, the average value of targets in banking ($630.7 millions) and insurance industry ($ 629.7 millions) was much higher than the average target value of security and other financial firms ($152.0 millions).

Table 1.5 – Values of M&As in European countries 1990-1999[1]

Deal Type	Value ($ millions)	1990-1999
Within- Border	Total Value	414,421.9
	Average Value	520.6
Cross-Border	Total Value	89,893.4
	Average Value	343.1
Within- Industry	Total Value	408,651.1
	Average Value	562.1
Cross-Industry	Total Value	95,664.2
	Average Value	289.0
Banking	Total Value	326,079.9
	Average Value	630.7
Insurance	Total Value	126,565.8
	Average Value	629.7
Securities/other	Total Value	51,669.8
	Average Value	152.0

[1]Deals classified by country and sector of target firm
Source: Group of Ten (2001)

1.3 The importance of the study

Now that we have briefly discussed the aims of the study and highlighted the main trends on M&As in the EU Banking industry, we are in position to emphasise why the study focuses on banks, why it examines the EU and to whom the results would be of particular interest.

1.3.1. Why study banks?

The large number of M&As in the banking industry motivated researchers to conduct numerous empirical studies examining various aspects of banks M&As. Most of the studies in banks M&As investigate the characteristics of the banks involved in M&As, the determinants of the premium paid for the target, the consequences of M&As on operating performance, the merged banks' stock performance around the M&A announcement date, and the consequences of banks M&As on other firms (see Berger et al., 1998). However, no empirical study can be found to have developed classification models for predicting banks' acquisition targets, although various techniques have been employed to develop such models in the literature on non-financial firms.

In this latter kind of research, motivated by the studies that have investigated the ability of publicly available data to predict corporate failure, a number of studies have attempted to construct classification models to predict acquisition targets. The development of such models can be of particular interest to the managers of acquirers, the managers of potential acquired firms, regulators, investors, and researchers[3].

However, these studies have focused on the prediction of acquisition targets from non-financial sectors (i.e. manufacturing, retail, hospitality, etc.) and excluded banks from the analysis because of the unusual structure of their financial statements, differences in the environment in which banks operate and other specific characteristics of banks that generally distinguish them from most non-financial firms. For example, the most obvious difference in the financial statements between non-financial firms and banks is that while loans constitute a liability item for non-financial firms, in the case of banks, it is an asset item. The opposite holds for deposits, which are part of the assets for non-financial firms, and part of the liabilities for banks.

Furthermore, there are various bank specific characteristics that distinguish banks from other corporations. Bauer and Ryser (2004) summarize some of these as follows:

- Banks have illiquid or even nontradeable long-term assets because of the transformation services they provide.
- Part of the illiquidity of banks' assets can be explained by their information sensitivity; banks can have comparative information advantages such as bankruptcy probabilities and recovery rates in their credit portfolio due to their roles as delegated monitors.
- In contrast to other firms, banks' liabilities are not only a source of financing but rather an essential part of their operation: depositors may implicit or explicit fees for deposit-related services. Therefore, the leverage in bank's balance sheets is many times higher.
- Bank deposits can be withdrawn at any time that can lead to a bank run situation, creating an inherent instability for banks' business.

In addition to the above, other distinguishing characteristics of banks, as outlined by the International Federation of Accountants (2000) are:

- Banks have custody of large volumes of monetary items whose physical security has to be assured.

[3] See section 1.3.3. for a discussion of these issues.

- Banks have assets that can rapidly change in value and whose value is often difficult to determine.
- Banks often derive a significant amount of their funding from short-term deposits.
- Banks engage in a large volume and variety of transactions both in terms of number and value.

Consequently, a prediction model specifically developed for the banking industry is obviously useful for at least two reasons. First, many empirical proxies typically included in the classification models for the prediction of acquisition targets from non-financial industries, such as current or quick ratio, are not meaningful for banks, and these models cannot be applied in the banking industry. Second, banks' managers may be driven towards M&As by different factors than the managers of non-financial firms (Hannan and Rhoades, 1987).

To take these issues into account, most of the variables considered for the development of the models in the present study are unique to the banking industry and originate from the CAMEL model[4]. Therefore, the present study builds upon both the literatures on banks' M&As and prediction of acquisition targets of non-financial firms by filling the gap between the two and by examining a number of issues relevant to the development of prediction models.

1.3.2 Why study the EU?

There are three main reasons for studying the EU banking sector. First, as noted in Section 1.2, M&As activity has been quite phenomenal in the 1990s, particularly in the latter half of the decade. These M&As have not only significantly transformed the European banking market but they also provided an opportunity for collecting a sample of data (on an adequate number of cases: acquired versus non-acquired banks), thus making an appropriate empirical basis for our study.

Second, most of the previous studies on bank M&As have focussed on the US market. Consequently, the literature on bank M&As in the EU is quite limited, with

[4] CAMEL is the acronym for an approach that is commonly used by regulators, analysts and researchers, since the 1970s, to access bank's financial condition. It refers to the analysis of the five key elements of banks performance: Capital adequacy, Asset quality, Management quality, Earnings, and Liquidity.

only a few recent studies that examine the operating performance of banks, (Vander Vennet, 1996; Huizinga et al., 2001; Diaz et al., 2004), the impact of merger announcement on the share prices of banks involved in M&As (Tourani Rad and Van Beek, 1999; Cybo-Ottone and Murgia, 2000; Beitel and Schiereck, 2001; Beitel et al., 2002; Lepetit et al., 2004), and the takeover premium paid (Dunis and Klein, 2005). This follows the lead of M&A activity in the US market and is also partly due to the methodological difficulties in studying the more fragmented European banking market (Leonard et al., 1992; Huizinga et al., 2001). As numerous authors have pointed out, the European banking situation differs from the US in many respects. Tourani Rad and Van Beek (1999) argue that the most important difference is that the EU banking industry is much more heterogeneous due to cultural, legal, and economic differences between the EU member states. Thus, owing to different environments in which EU banks operate, their operational characteristics need to be adjusted to the circumstances in each country. In addition, in the US, there have traditionally been restrictions on both geographic and product expansion, as opposed to the EU where the universal banking structure offers the opportunity for a wider range of products (Cybo-Ottone and Murgia, 2000; Diaz et al., 2004). Thus, most EU banks offer services related to insurance business, investment banking in addition to traditional commercial banking services. Another aspect in which EU differs from the US is the social environment (Tourani Rad and Van Beek, 1999). European labor unions are very powerful and European laws offer more protection to employees making almost impossible the lay off employees immediately after the completion of merger, which delays potential const savings. These differences between the EU and the US make it difficult to extrapolate any conclusions obtained from studies on US banks to EU ones (Cybo-Ottone and Murgia, 2000; Huizinga et al., 2001; Diaz et al., 2004).

Third, until now the majority of studies on the prediction of acquisition targets have examined the US and UK. The present study is the first that attempts the development of prediction models using a sample of banks drawn from over 15 EU countries, hence focussing on the EU banking sector as a whole.

1.3.3. Importance of study

Tartari et al. (2003) point out that the prediction of acquisitions is of major interest to stockholders, investors, and creditors and generally to anyone who has established a relation with the acquired firm. Obviously the managers of the banks are also among those that have increased interest in the development of prediction models. The results of this study would be of particular interest to academics and researchers who work on the prediction of acquisitions, bankruptcy and other classification problems in finance. We address below the potential benefits of developing classification models for the prediction of banks acquisition targets to: (a) Managers of acquirers, (b) Managers of potential targets, (c) Academics and researchers, and (d) Investors.

a. Managers of acquirers

Mergers have been characterised as an investment alternative similar to other large capital budgeting decisions that compete for limited funds (Stevens, 1973). Of course, acquiring or merging with another company is far more complex than simply buying a machine or constructing a new building and so the decision to acquire or merge with another company is of course extremely important. Therefore, even in cases where growth through acquisition or merger is a good idea, identifying the right candidate is a difficult step. As a result, most successful acquirers may evaluate numerous potential acquisition targets for every one they finally acquire. Consequently, from a managerial perspective, a prediction model of acquisition targets can be useful to managers who are interested in a decision tool that could allow them to identify potential candidates among a large set of banks and proceed to a more detailed examination of the ones that are closer to the typical profile of an acquired bank.

b. Managers of potential targets

We have seen above why the managers of acquirers may be interested in an acquisition targets prediction model. In addition, such a model could be of special interest to managers that would like to know whether their bank is developing a profile similar to the typical target, so that they can take the appropriate steps to avoid a potential hostile takeover attempt. For example, the bank may sell a large part of its stock at a low price to friendly parties, make all of its debt immediately payable if its management change, and/or provide huge retirement bonuses (golden parachutes), thus making it less attractive to the bidding bank.

c. Academics and researchers

From an academic perspective a study on the prediction of banks acquisition targets, can be useful in determining whether banks' acquisition can be accurately predicted. In addition, of particular interest to academics and researchers that employ classification methods will be (i) the performance of the relatively new method that is employed in the present study (e.g. SVMs), (ii) the comparison of numerous classification methods based on the same dataset that will allow one to draw conclusions on whether one method outperforms another, and (iii) the integration of different methods into combined models that could potentially lead to improved prediction ability, an issue that has recently received particular attention.

d. Investors

Several empirical studies demonstrate that the shareholders of acquired firms, financial or non-financial, earn large abnormal returns during the announcement date. Examples of such studies in the EU banking industry are those of Tourani Rad and Van Beek (1999) and Cybo-Ottone and Murgia (2000). Thus if one could develop a model to identify acquisition targets in advance, then holding a portfolio of predicted targets could result in the generation of abnormal returns.

1.4 Empirical Objectives

Having discussed the importance of this study and highlighted the main aims (in Section 1.1) we are now in a position to discuss in greater detail the empirical objectives of this study. It should be noted that the object of empirical studies that deal with the prediction of acquisition targets is not to explain why takeovers occur or to determine what factors contribute to the acquisition likelihood. Instead, the focus is rather restricted to whether individual takeovers can be predicted, and hence the prediction accuracy of the models is more important than the empirical validity of any particular acquisition theory (Barnes, 1990; Bartley and Boardman, 1990). With this in mind, we now discuss the main objectives and the contributions this study makes to the existing literature.

a. The first objective is to investigate the possibility of predicting (with a better than chance accuracy) the acquisition of commercial banks in the EU using publicly available data. As previously pointed out, although the literature on the prediction of acquisition targets in non-financial sectors has been developing for some time, this has not been the case for financial intermediaries and, to the best of our knowledge, no academic study has been published with a focus on the prediction of acquisition targets in the EU banking industry, the topic of the present thesis. As Barnes (2000) mentions, the assumption that acquisition targets can be predicted from publicly available data seems reasonable considering that, despite the many reasons for acquisitions, targets are not selected arbitrary but arise from a desire by a bidding company to reap benefits from the acquisition. After all, as Stevens (1973) argues, "*merger is an investment alternative similar to other larger capital budgeting decision which compete for limited funds. Therefore the decision to acquire a firm should be consistent with shareholder wealth maximization criteria, and financial characteristics have a role in the total decision*" (p. 149). Based on data availability, this study selects 19 financial variables most of which are unique to the banking industry, measuring capital strength, profit and cost efficiency, liquidity, growth, size and market power are initially considered. Both raw and country-adjusted data for a range of financial variables are examined. To avoid overfitting and multicollinearity problems, as well as to increase the applicability of the model on a daily basis we then select a subset of these variables that demonstrate high discriminatory power on the basis of univariate tests and low correlation with other variables. Then, we develop classification models using data from the period 1998-2000 and examine their prediction ability using data from a future time period (i.e. 2001-2002), thus considering a holdout sample of banks not used during the development of the models. We then evaluate these models by comparing their classification accuracies relative to each other as well as to the ones that could be obtained by chance assignment of banks in the two groups (i.e. acquired or non-acquired).

b. The second objective is to compare the relative efficiency of seven different classification techniques and examine, on the basis of a common set of samples, whether the choice of technique has an impact on classification accuracy. The question of which modeling method produces the best performing bankruptcy prediction models has already been raised in several papers (see Balcaen and Ooghe, 2004). However, as Espahbodi and Espahbodi (2003) have pointed out, not many studies have attempted to compare the ability of various classification procedures in predicting corporate takeovers. Thus our knowledge regarding whether some classification methods may be more effective, in terms of classification accuracy, than others is quite limited. The present study attempts a comparative analysis of 7 classification techniques, almost double in number than those compared in previous studies. In this context, we introduce two relatively new classification techniques, namely Support Vector Machines (SVMs) and k-Nearest Neighbours (k-NN), not previously applied in the prediction of acquisition targets. SVMs have emerged in recent years as a very successful pattern recognition method with several successful applications in classification and regression problems such as handwritten digit recognition, text categorization, spam categorization and 3D object recognition. Although a few financial applications of SVMs have been reported mainly for the forecasting of time series (Tay and Cao, 2001, 2002; Kim, 2003; Huang et al., 2005), bankruptcy (Shin et al., 2004) and credit (Huang et al., 2004), they have not been applied in the prediction of acquisition targets yet. Similarly, k-NN is another non-parametric method which has been applied in other problems in finance such credit risk assessment (e.g. Henley and Hand, 1996; West, 2000; Doumpos and Pasiouras, 2004), bankruptcy prediction (e.g. Tam and Kiang, 1992) and interest rate movements (Nowman and Saltoglu, 2003) but not in the prediction of acquisition targets.

c. The third objective is to develop prediction models using an integrated (multi-classifier) technique that combines the output of individual classification methods, in order to investigate the possibility of achieving higher prediction ability. The recent introduction of model combination methods promises to provide more accurate prediction, and reduces the burden of model selection, by combining existing algorithms (Breiman, 1996; Freund and Shapire, 1997). In the present study, two well-known integration techniques, namely majority voting rule and stacked generalization are employed. The approach to stacked generalization actually depends on which of the seven individual classification methods is used to stack the output of each model, and so by considering two sets of data, raw and country-adjusted for each model, we end up developing a total of 16 integrated models, providing a rich enough set of prediction models for investigating the relative efficiency of the multi-classifier approach.

1.5 Contributions of the study

This thesis makes a number of empirical contributions to the literature:

(i) First, it is the first study that is based on a set of variables most of which are unique to the banking industry and we develop numerous prediction models specifically designed for the banking sector. Although the results support the finding of studies on non-financial firms, highlighting the difficulties in predicting acquisition targets, the prediction models we develop are capable of performing better than chance.

(ii) Second, it is the first study that provides a comparative analysis of 7 classification techniques, that is almost double in number than those compared in previous studies, using a common set of samples and variables. Thus, although we find that the selection of the "best" model is a difficult task, we are able to evaluate the relative efficiency of each method. In this context, we find that Discriminant analysis, Logit analysis, UTADIS, CART and SVMs achieve higher rankings although this largely depends on the evaluation measure used.

(iii) Third, it is the first study that applies the techniques k-Nearest Neighbours (k-NN) and Support Vector Machines (SVMs) in acquisition targets prediction, and evaluates their performance in relation to others. In this context, we find that the predictive performance of k-NN is not satisfactory compared to others, although SVMs does relatively well and achieves better than chance accuracy.

(iv) Fourth, the study investigates whether the combination of individual models into multi-classifiers (i.e. integrated models) could lead to improved prediction ability, using two integration techniques, namely majority voting rule and stacked generalization. The majority voting rule is applied for the first time for the prediction of acquisition targets in the present study. While stacked generalization has also been applied in the study of Tartari et al. (2003), the application of this technique is considerably extended in the present study. The results could be summarized as follows. First, the majority voting model performs relatively well and outperforms some of the individual models from which it was developed but not all of them. A similar conclusion is drawn from the comparison of the stacked models with the individual ones. The comparison between the two integration techniques provides mixed results and the outcome depends on whether we use raw or country-adjusted financial data. However, considering that the majority rule can be far more easily implemented it provides a simpler and suitable technique for anyone interested in models integration.

1.6 Outline of the thesis

The remainder of this thesis is organized as follows.

Chapter 2 reviews the theoretical literature covering the main motives for acquisition in the banking industry; and also reviews selected studies in banks M&As. Acquisition theories such as synergy, hubris and agency are discussed along with practitioners' views on the reasons for recent banks M&As, as outlined in the reports of the European Central Bank (2000) and the Group of Ten (2001). In this chapter, we also review the main results of studies on banks M&As, directly or indirectly related to the motives behind banks M&As.

Chapter 3 provides an extensive study-by-study review of the empirical literature on acquisition targets prediction. The studies are classified in three categories based on the employed technique (a) statistical, (b) econometric and (c) non-parametric or various techniques.

Chapter 4 offers an exhaustive coverage of the methodological framework for the development of prediction models, dealing extensively with issues such as sampling (e.g. definition of acquisition, proportion of acquired and non-acquired firms in training and testing sample, use of holdout sample as opposed to re-sampling techniques), variables selection techniques (i.e. human judgment, factor analysis, test of group mean differences), available classification methods (i.e. parametric, non-parametric), and measures of models' performance. Although this chapter focuses mainly on the prediction of acquisitions, the majority of the issues discussed are also relevant to other problems in finance, such as bankruptcy prediction and credit risk assessment.

The empirical analysis beings with Chapter 5 providing a discussion of the data sources and issues relating to sample selection, the set of variables, and the criteria for selecting the final set of input variables for model development.

In Chapter 6, classification methods are used to develop prediction models with raw and country-adjusted ratios, as well as equal and double matched samples, drawn from the period 1998-2000. Finally, the models are tested in equal an unequal holdout samples using banks not used for model development and from a future period (2001-2002).

Chapter 7 deals with the integration of prediction models, describing and employing the procedures for two integration methods of classification, majority voting and stacked generalization, in an attempt to investigate their performance for improved classification accuracy relative to the individual classification models developed in chapter 6.

Finally, in chapter 8, we conclude the study by focusing on the main findings, and suggest some areas for further research.

Chapter 2
Reasons and Motives for Banks M&As

2.1 Introduction

As emphasized in Chapter 1, the focus of this study is to develop prediction models for banks M&As, and not to determine the factors that contribute to the acquisition likelihood in the European banking industry. Nevertheless, discussion of the underlying motives for M&As help to inform the selection of variables for inclusion in the prediction models. Therefore, in this chapter, we cover the theoretical background on the reasons and motives for M&As and discuss the evidence on banks M&As.

Often there is not one single reason but a number of reasons that lead management to the decision to merge with or acquire another firm. This chapter considers three issues. The first points to the main firm level motives and external factors for banks M&As (section 2.2). The second focuses on practitioner's views on reasons for banks M&As, as discussed in the reports of the European Central Bank (2000) and the Group of Ten (2001) (section 2.3). Finally, we discuss the main findings of empirical studies on bank M&As that are directly on indirectly related to bank M&As motives (section 2.4). All these issues could inform the selection of variables that could potentially be candidates for inclusion in the prediction models.

However, in common with the majority of previous studies on the prediction of M&As, the empirical part of the thesis (Chapters 5, 6 & 7) will consider only financial variables, reflecting capital strength, asset quality, liquidity and profit and cost efficiency. One reason for using only financial variables is that external economic factors (e.g. inflation, interest rates, etc) as well as internal firm specific characteristics (e.g. management quality, sector, ownership, etc) are implicitly reflected in banks' financial statements. Another reason is that it is in general difficult to collect non-financial data reflecting management quality, acquisition takeover defences, concentration of firm ownership, or agency and hubris motives. Thus, while we restrict our empirical focus to financial variables only, the scope of this chapter is somewhat broader in that it also covers issues of non-financial reasons that are of importance to M&As.

2.2 Firm level motives and external factors of M&As

In the neoclassical perspective, all firm decisions including acquisitions are made with the objective of maximizing the wealth of the shareholders of the firm. Nevertheless, agency conflicts between shareholders and managers could also lead to M&As that are motivated by managers' self interest. In addition to the firm level motives, decisions for M&As are also influenced by external factors (i.e regulations & laws, globalisation, technological progress, economic conditions, etc). In line with Berkovitch and Narayanan (1993) and Ali-Yrkko (2002) among others, the analysis that follows classifies the firm level motives in: synergy (or economic) motives, agency (or managerial) motives and hubris motives. With respect of the value maximization and non-value maximization distinction, the first set of motives that refers to synergy, are considered as value maximization, while the other two (i.e agency and hubris) are non-value maximization motives.

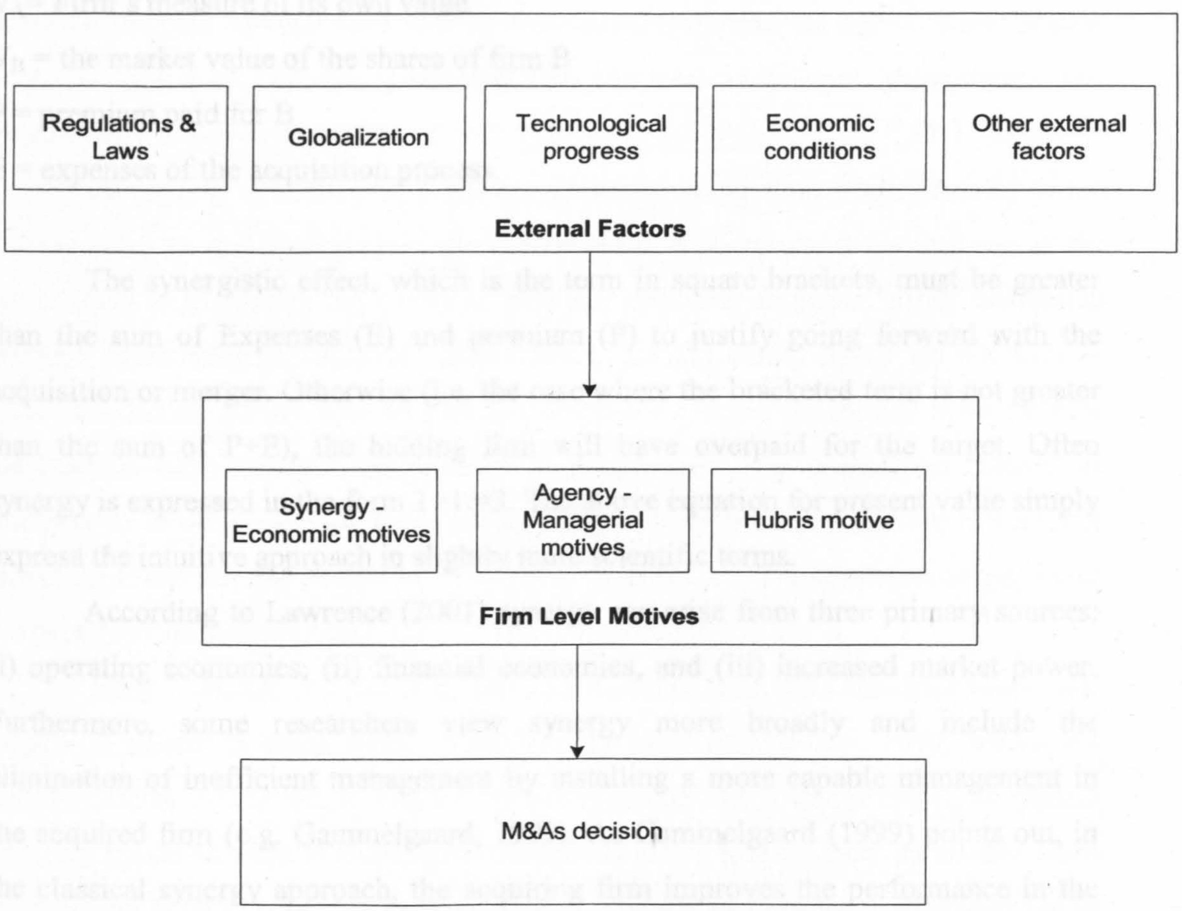

Figure 2.1 – Motives and Factors for M&As

2.2.1 Firm level motives

2.2.1.1 Synergy

Synergy, which is the name given to the concept that the combined entity will have a value greater than the sum of its parts, is one of the most often cited motives for M&As. The expected existence of synergistic benefits allows firms to incur the expenses of the acquisition process and still be able to afford to give target shareholders a premium for their shares. Synergy may allow the combined firm to appear to have a positive net present value:

$$NAV = V_{AB} - [V_A+V_B] - P - E = [V_{AB} - (V_A + V_B)] - (P+E)$$

Where,

V_{AB} = the combined value of the two firms

V_A= Firm's measure of its own value

V_B = the market value of the shares of firm B

P = premium paid for B

E = expenses of the acquisition process

The synergistic effect, which is the term in square brackets, must be greater than the sum of Expenses (E) and premium (P) to justify going forward with the acquisition or merger. Otherwise (i.e. the case where the bracketed term is not greater than the sum of P+E), the bidding firm will have overpaid for the target. Often synergy is expressed in the form 1+1 =3. The above equation for present value simply express the intuitive approach in slightly more scientific terms.

According to Lawrence (2001) synergy can arise from three primary sources: (i) operating economies, (ii) financial economies, and (iii) increased market power. Furthermore, some researchers view synergy more broadly and include the elimination of inefficient management by installing a more capable management in the acquired firm (e.g. Gammelgaard, 1999). As Gammelgaard (1999) points out, in the classical synergy approach, the acquiring firm improves the performance in the acquired firm by transferring resources and knowledge to the new subsidiary. Most common is the transfer of managerial resources. The main approach here is the differential efficiency theory where the purpose is to improve the management in the acquired firm by bringing it up to the same level as in the acquiring firm (Weston et al., 1990).

Economies of Scale

This theory assumes that economies of scale do exist in the industry and that prior to the merger, the firms are operating at levels of activity lower than those required to achieve the potential of economies of scale. The merger of two firms is thus an opportunity to produce lower average costs by spreading fixed costs across a larger volume of output. Achieving economies of scale has been suggested to be the natural goal of horizontal mergers. Many different types of economies of scale exist, such as those associated with marketing, production, distribution, finance and management sharing. The banking industry is one of the most well known examples. In the 1970s, there were many small banks in the United States. Many of them have grown by systematically buying up smaller banks and streamlining their operations. Most of the cost savings have come from closing redundant branches, consolidating systems and back offices, processing checks and credit-card transactions and payments (Brealey et al., 2001).

According to Dettmer (1963), the merger or acquisition leads naturally to the access of extra and sometimes unused production facilities, and the purpose of the investment is to reduce the overhead cost per unit. For example, many businesses possess assets such as buildings, machinery or people skills, which are not used to their full limits. In the case of banks, potential for scale economies arise because neither the buildings nor the services of employees in a branch are utilised as intensively as they could be. Thus, once a merger is completed, a number of branches are closed, leaving one or two in a particular location, with consequent savings made on property and labour costs.

Early research, especially in the United States, indicated that scale economies appeared mainly in small banks rather than in large ones (Short, 1979; Miller and Noulas, 1996). According to Clark (1988) and Hunter and Timme (1989), economies of scale appear to exist in banking institutions at assets levels below $5 billion, while Hunter and Wall (1989) state that costs of production in financial institutions appear to be relatively constant for asset sizes up to $25 billion. Most recent studies, both in the US (Berger and Mester, 1997) and in Europe (Molyneux et al, 1996, Vander Vennet, 2002) find unexploited scale economies even for fairly large bank sizes due to economic development and market liberalization. Vander Vennet (1998), however, found evidence of economies of scale only for the smallest banks with assets under ECU 10 billion in the EU, with constant returns thereafter and diseconomies of scale for the largest banks exceeding ECU 100 billions. A recent study by Pasiouras and Kosmidou (2005) has found a negative relation between size and bank's performance for both domestic and foreign banks operating in the EU over the period 1995 to 2001. The authors interpret this negative coefficient in their regressions as an indication of either economies of scale (and scope) for smaller banks or diseconomies for larger financial institutions. In general, research on the existence of scale economies in retail commercial banking finds a relatively flat U-shaped average cost curve, with a minimum somewhere below $10 billion of assets, depending on the sample, country and time period analysed (Amel et al., 2004). Hughes et al. (2001) argue that most research finds no economies of scale because it ignores differences in banks' capital structure and risk taking and demonstrate that scale economies exist but are elusive. They show that estimated scale economies depend critically on the way banks' capital structure and risk-taking are modelled. More specifically when they include equity capital, in addition to debt, in the production model and cost is computed from the value-maximizing expansion path rather than the cost-minimizing path, banks are found to have large-scale economies that increase with size.

Economies of Scope

As pointed out by Amel et al. (2004), exploitation of economies of scope is probably the second most quoted reason for M&As in the financial sector. Economies of scope can be cost based or revenue based. Costs based are those achieved by offering a broad range of products or services to a customer base and can originate from fixed costs incurred in gathering an information database or computer equipment. Revenue based is related to the ability of the firm to utilise one set of inputs to offer a broader range of products and services through cross selling to an existing customer base.

A common example in financial institutions M&As is the case of sharing inputs and offering a wider range of services through units such as the department of economic research. Smaller banks might not be able to afford the cost of creating these departments, while inputs such as computers systems can be shared to process a wide variety of loans and deposit accounts. Another example often quoted is the case of banking and insurance products offered from the combined entity after the merger of a bank and an insurance firm.

Increased Market Power

Another reason for M&As is the increase of market power. Gaughan (1996) argues that there are three sources of market power: product differentiation, barriers to entry and market share. Banking markets in the EU can be characterized as a system of national oligopolies (Vander Vennet, 1996). Therefore there is a potential for increased market power, defined as the ability of the firm to set and maintain price above competitive levels, and associated market gains are likely to occur as a result of the combined power of two firms within the same industry. Nevertheless, Gaughan (1996) argues that an increase in market share without product differentiation or barriers to entry could prevent a firm from raising the price above marginal cost, as this may only attract new competitors who will drive price down towards marginal cost.

Many studies have attempted to test the view that the consolidation trend in the banking industry has been motivated by a desire to gain market power and extract monopolistic profits. Vander Vennet (1994a,b) has shown for a large sample of EC credit institutions that when barriers to entry exist, the incumbent banks may be able to exploit the possibility of quasi-monopoly profits. Moore (1996) argues that bank's market share could influence the probability of being acquired through several channels. First of all, in a banking market where only banks with substantial market share can compete effectively, a bank with small share is likely to be acquired, by an in-market bank, since the assets of the small bank would become more valuable after the merger with the large bank. A problem that arises in this context, particularly applicable to horizontal mergers, is the legislative obstacle caused by the regulators concerned about the potential anticompetitive practices of the combined firms. This has the effect of reducing the probability of an in-market merger between two or more banks with a significant market share. Another reason for M&A is associated with the inefficient management hypothesis, which argues that the bank's small share could reflect a lack of success in the market, giving the potential acquirer the incentive to take over the firm in order to improve its market share and efficiency. Gilbert (1984), in a review of 45 studies employing the Structure-Conduct-Performance paradigm (SCP), according to which banks in highly concentrated markets tend to collude and therefore earn monopoly profits, found that only 27 provided evidence in support of this hypothesis, while Berger (1995) points out that the relationship between bank concentration and performance in the US depends critically on what other factors are held constant.

The market for bank control - Inefficient Management replacement

Academics have discussed the inefficient management hypothesis for many years. The inefficient management hypothesis, due to Manne (1965), argues that if the managers of a firm fail to maximize its market value, then the firm is likely to be an acquisition target and inefficient managers will be replaced. Thus, these takeovers are motivated by a belief that the acquiring firm's management can manage better the target's resources.

This view is supported by two specific arguments. First, the firm might be poorly run by its current management, partly because their own objectives are at variance from those of the shareholders. In this case, the takeover threat can serve as a control mechanism limiting the degree of variance between management's pursuits for growth from shareholders desire for wealth maximization. A merger may not be the only way to improve management, but if disappointed shareholders cannot accomplish a change in management that will increase the value of their investment within the firm, either because it is too costly or too slow, then a merger may be the more simpler and practical way of achieving their desired goals.

Second, the acquirer may simply have better management experience than the target. There are always firms with unexploited opportunities to cut costs and increase sales and earnings, and that makes them natural candidates for acquisition by other firms with better management (Arnold, 1998). Therefore, if the management of the acquirer is more efficient than the management of the target bank, a gain could result with a merger if the management of the target is replaced.

Grossman and Hart (1980) have challenged the view that companies not run in shareholder's interests will be taken over. The reason is that in every bid there are two groups of shareholders involved, those of the acquired and of the acquirer, with often conflicting, economic objectives. The acquirer will make an effort to offer a price that will allow realising a profit on the deal to compensate itself for the cost of making the bid, and the shareholders of the target have to be willing to sell their shares to the bidding company at that price. However, each individual shareholder, facing the option to keep or sell the shares and under the belief that the new management will succeed to improve the firm's performance, will probably hold on the shares in expectation of a rise in the price in the future. Thus, shareholders will be willing to sell their shares only if they will be offered a price that will reflect these future gains, which should therefore be higher than the one that could compensate the acquirer for the real resource cost involved in undertaking the bid. Consequently, the incentive small shareholders have to freeride, prevents the bid from occurring in the first place, and hence the market for corporate control cannot operate effectively.

The results from the existing empirical work are somewhat mixed. While some authors (Singh, 1971, 1975; Meeks, 1977; Levine and Aaronovitch, 1981; Cosh et al., 1984) indeed suggest that acquired companies are more likely to be less profitable, others (Dodd and Ruback, 1977; Hannan & Rhoades, 1987) failed to provide support for the inefficient management hypothesis.

<u>*Risk Diversification*</u>

Another primary reason, often advanced for M&As, is risk diversification. The main argument is that the integration of two firms can lower bank risk and reduce the probability of failure risk, if the firms' cash flow streams are not perfectly correlated. The two most common forms of diversification are geographic and product diversification. The former offers a reduction of risk, because the return on loans and other financial instruments issued in different locations may have relatively low or negative correlation. In a similar manner, the latter may reduce risk because the returns across different financial services industries may have relatively low or negative correlation. For example, Berger et al. (2000) found that correlations of bank earnings across international borders are often very low or negative, thereby supporting the possibility of diversification benefits from cross-border consolidation of banking organizations. In addition, Neely and Wheelock (1997) found that US banks' earnings are strongly influenced by the economic growth of the states where they are located.

The assumption behind diversification as a motive for M&As is that firm-based diversification is more efficient than diversification purchased on the market, such as credit derivatives and loan sales (Froot and Stein, 1998). However, Winton (1999) argues that diversification may not always reduce the risk of bank failure, pointing to the benefits and costs of monitoring loans and the possibility that diversification may lead banks into new sectors in which they might have less expertise.

Craig and Santos (1997) confirm the reduction of risk (as measured by the z-score statistic of default probability and by stock return volatility) and relate it to benefits from diversification. Benston et al. (1995) argue on the basis of pre-merger earnings volatility and target-acquirer correlation that the motivation for mergers in the first half of the 1980s must have been risk reduction through diversification, rather than the exploitation of the put option on deposit insurance funds. Akhavein et al. (1997) and Demsetz and Strahan (1997) find that bank mergers serve to diversify banks, allowing them to take on more investment risk for a given level of firm risk. Finally, in a more recent study, Laderman (2000) examined the potential diversification and failure reduction benefits of bank expansion into non-banking activities, based on a sample of Bank Holding Companies (BHCs) and especially of large BHCs during the periods 1979-1986 and 1987-97. Her results showed that relatively substantial levels of investment in life insurance underwriting were optimal for reducing the standard deviation of BHC return on assets (ROA). Appreciable levels of investment in life insurance underwriting, casualty insurance underwriting, and securities brokerage were found to be optimal, for reducing the probability of bankruptcy of the BHC.

Capital Strength

The importance of decisions relative to the amount of capital becomes obvious by the fact that financial regulators require commercial banks to sustain a minimum capital adequacy ratio. Although provisions and cumulative loan loss reserves provide early lines of defence against bad loans, bank's capital is the ultimate line of defence against the risk of bank's technical insolvency. This becomes apparent when considering that if the bank will face a serious asset quality problem then loan loss reserves will not be sufficient to allow all bad loans to be written off against the bank and consequently the excess will have to be written off against shareholders' equity.

Thus, since low capital to asset ratios may indicate financial weakness, an acquirer may strengthen the acquired bank's financial position. Wheelock and Wilson (2000) found that the less well capitalized a bank is, the greater the probability that it will be acquired, suggesting support for the acquisition of some banks just before they become insolvent. In addition, well-capitalized banks face lower risk of going bankrupt which increases their creditworthiness and consequently reduces the cost of funding. Therefore, in contrast to the above, banks with insufficient amounts of capital may acquire banks with relatively high capital to assets ratios. That could allow them to gain better access to financial markets and enjoy lower costs of raising capital, as the combined entity will be considered to be less risky and would probably be able to issue bonds offering a lower interest rate than before.

2.2.1.2 Agency Motives (Managerial Motives)

The agency theory extends the previous work by Manne (1965), who analysed the market for corporate control and viewed mergers as a threat of takeover if a firm's management lacked performance either because of inefficiency or because of agency problems. Jensen and Meckling (1976) formulated the implications of agency problems, which typically arise when management owns only a small proportion of share capital. It is well known that the modern corporate economy, characterised by large corporations with widespread distribution of ownership, is separated from management, in which case there is a potential for managers to pursue their own aims such as enhance their salary and prestige, diversify personal risk or secure their job through empire-building, rather than maximize profits, at the expense of shareholders. For example, although shareholders of acquired banks experience large increases in the value of their shares, top executives of acquired banks may often lose their autonomy and accept diminished job responsibilities or may even be forced to terminate their employment. Thus, during the bank merger negotiations, managers may be forced to choose between shareholders' best interest by accepting a value maximizing the takeover offer or their own best interest by maintaining their bank's independence (Hadlock et al., 1999).

The wage explanation implicit in the above argument is considered to be one of the most important managerial motives for M&As. Managers may want to increase the size of their firm as in most cases their wage is a function of firm size (Mueller, 1969). Thus having responsibility for a larger firm means that the managers have to be paid a lot of remuneration. In addition, most large firms set compensation by looking at the compensation of peer group executives, and size is the main determinant of which firms are in a peer group. Murphy (1999) provides a review of the compensation literature and observes that many studies report a strong link between firm size and managerial rewards (see e.g Roberts, 1956; Ciscel and Carroll, 1980; Agarwal, 1981). Bliss and Rosen (2001) examined the relationship between bank mergers and CEO compensation during 1986-1995 and found that acquisitions significantly increased CEO compensation even after accounting for the typical announcement data stock price decline. They argue that, although the decline in existing wealth partially offsets some of the subsequent salary gains, the vast majority of mergers increase the overall wealth of CEO, often at the expense of shareholders. Nevertheless, Anderson et al. (2004) examined bank CEO compensation changes associated with mergers among large banks in the 1990s and found no evidence of empire-building motives on the part of banks CEOs who engage in mergers. They found that changes in CEO compensation after mergers are positively related to anticipated gains from mergers measured at that announcement date.

Ravenscraft and Scherer (1987) argue that being in charge of a larger business and receiving a higher salary also brings increased status and power, and mergers constitute a rapid way of increasing balance sheet totals that attracts media attention when rankings are published. In addition, managers may also attempt to reduce insolvency risk through M&As by diversifying banks' portfolio below the level that is in shareholders' interest in order to increase their job security.

Finally, managers may also engage in empire building for job security reasons rather than compensation or prestige. It has been claimed by both financial analysts and researchers that, on average, acquisitions tend to occur between a large acquirer and a small target. Thus, the belief is that large banking organisations are less likely to be targets of hostile takeovers and hence it is less likely that the current management will be out of a job. Therefore firms may merge in order to become large themselves for the survival of the management team and not primarily for the benefit of the shareholders. An alternative hypothesis states that some mergers may have been motivated by managers' concerns, but by increasing the chances of becoming the target of friendly takeovers rather than hostile takeovers.

The numerous empirical event studies that found negative wealth effects for bidding banks' shareholders (e.g. Hawawini & Swary, 1990; Baradwaj et al., 1992; Houston & Ryngaert, 1994; Madura & Wiant, 1994; Siems, 1996) potentially provide support to the above arguments, namely that many M&As are motivated by managers own motives rather maximisation of shareholders' value.

2.2.1.3 Hubris Motives

An interesting hypothesis, proposed by Roll (1986), suggests that managers commit errors of over-optimism in evaluating M&As opportunities due to excessive prediction or faith on their own abilities. Consequently they engage in M&As even when there is no synergy. More specifically, the pride of bidders' management allows them to believe that their own valuation of the target is correct, even if objective information shows that target's true economic value, as reflected in its market valuation, is lower. Because of this arrogance (hubris) acquirers end up overpaying target firms, virtually transferring all gains from the transaction to the target shareholders.

As Gaughan (1996) points out, Roll did not intend the hubris hypothesis to explain all takeovers, but rather to reveal that an important human element enters takeovers when individuals are interacting and negotiating the purchase of a company. Thus, although hypothetically management's acquisition of a target should be motivated purely by a desire to maximize shareholder wealth, this is not necessarily the case, and the extent to which such motives play a role will vary from one M&A to another. Arnold (1998) suggests that hubris may also help explain why mergers tend to occur in greatest numbers when the economy and companies generally have had a few good years of growth arguing that during such periods managers are feeling rather pleased with themselves.

2.2.2 External Factors

The Group of Ten report (2001) highlights three major external forces that are creating pressures for change in the financial services industry and may help explain the recent pace of M&A activity: deregulation; technological advances; and globalisation of the market place. In addition, shareholder pressures and the introduction of euro are also stated as additional forces. Finally, macroeconomic conditions may have either direct on indirect effects on banks decisions to be involved in M&As. All these issues are considered in turn below.

Deregulation and Laws

Over the last twenty years or so, following changes in the legal and regulatory framework in which financial institutions operate, many barriers to consolidation have been relaxed. There are, however, five main ways through which governments can influence the restructuring process (Group of Ten, 2001). These are:

1. Through effects on market competition and entry conditions (e.g. placing limits on or prohibiting cross-border mergers or mergers between banks and other types of service providers in the interests of preserving competition).
2. Through approval / disapproval decisions for individual merger transactions.
3. Through limits on the range of permissible activities for service providers.
4. Through public ownership of institutions.
5. Through effects to minimise the social costs of failures.

The liberalisation of geographic restrictions on U.S. banking institutions beginning in the late 1970s has often been cited as one of the main reasons of the rapid consolidation of the U.S. banking industry. Berger et al. (1999) argue that the prior geographic restrictions on competition may have allowed some inefficient banks to survive, and the removal of these constraints allowed some previously prohibited M&As to occur, which may have forced inefficient banks to become more efficient by acquiring other institutions, by being acquired, or by improving management practices internally. In addition, removal of in-state branching restrictions also increased consolidation in the US, as Banks Holding Companies often merger their subsidiary banks into branching systems.

Europe has also been undergoing deregulation over the last 50 years. Dermine (2002) mentions that the actions taken by the European Commission and the Council of Ministers can be divided into five main periods: the removal of entry barriers into domestic markets (1957-1973), the harmonisation of banking regulations (1973-1983), the completion of the internal market (1983-1992), the creation of economic and monetary union leading to the single currency (1999), and the financial services action plan (1999-2005). Tourani-Rad and Van Beek (1999) argue that the merger wave in the European banking industry observed in the late 1980s as well as the late 1990s appear to be largely related to the Second Banking Directive. Under this directive, issued in 1989 and implemented in 1992, all credit institutions authorised in an EU country were able to establish branches or supply cross-border financial services in other countries within the EU without further authorisation, provided the bank was already authorised to provide such services in the home state. In other words, the EU banking directive permitted competition in the European marketplace through home country authorisation of entry, although banks had to operate under host country conduct of rules. This universal banking model adopted by the EU permitted banks to undertake investment banking activities, while leaving it to national regulators to control financial conglomerates, the ownership structure of the banks and their relationship with the industry.

Regulators (both national and European) often prevent M&As if the increases in concentration are expected to result in excessive increases in market power. For example, The Competition Commission in Britain blocked Lloyds TSB's 18.2 GBP billion hostile bid for Abbey National in July 2001, because the new bank would have dominated the segment of current accounts, with a 27% market share, and would have increased to 77% the market share of the top four British banks. Also in 2001, the European Commission opened an investigation into the announcement of 7.9 billion euro merger between Skandinaviska Enskilda Banken (SEB) and Foreningsparbanken (Swedbank) which would have resulted in the largest bank in Sweden that would probably have attained a dominant position in the domestic retail-banking sector. The two banks finally called of their plans to merge, blaming the European Commission's insistence that they should make large-scale divestitures in the retail banking segment for the deal to be approved, which would have undermined the logic of the deal.

It should be noted that while regulatory authorities have served to protect the public's interest in preserving competition in the market place, the national governments have also provided financial assistance or otherwise aid to troubled financial institutions in periods of financial crises. For instance, in the US, the Federal Deposit Insurance Corporation (FDIC) provided financial assistance to allow healthy banks to purchase over 1000 insolvent US banks between 1984 and 1991 (Berger et al., 1999), while a new 1991 rule allows the FDIC to takeover a financial institution whose capital falls below 2% of its risk adjusted assets, without waiting for further depletion of its capital base (Zanakis and Walter, 1994).

Technological developments

Technology, apart from deregulation, has been considered a catalyst for the recent wave of bank M&As. As Goddard et al. (2001) point out technological advances are currently having a dramatic impact on the structure, operations and economies of European banking markets. It is obvious that the same applies for banking markets around the world. Overall, banks are involved in introducing new technologies in the following four main areas: customer-facing technologies, business management technologies, core processing technologies, support and integration technologies (Goddard et al., 2001).

Technological changes may affect the restructuring of financial services in three direct ways (Group of Ten, 2001). First, through increases in the feasible scale of production of certain products and services (e.g. credit cards and asset management). Second, through scaled advantages in the production of risk management such as derivative contracts and other off-balance sheet guarantees that may be more efficiently produced by larger institutions. Third, through economies of scale in the provision of services such as custody, cash management, bank office operations and research.

Goddard et al. (2001) review six studies that examined the impact of technological changes on bank costs in the US (Hunter and Timme, 1991; Humphrey, 1993), Japan (McKillop et al., 1996), Spain (Maudos et al., 1996), Germany (Lang and Welzel, 1996) and the EU in total (Altunbas et al., 1999)). Three conclusions are drawn from these studies: (1) Reductions in costs up to 3.6% were found; (2) The impact of technological change on costs seems to have accelerated during the 1990s; (3) Larger banks benefit more than smaller ones.

In general, technological developments, apart from deregulatory changes, have helped to alter the competitive conditions of the financial sector, at both the production and the distribution level, and have created greater incentives for new output efficiency (Group of Ten, 2001).

Globalisation

Globalisation has been characterised as a by-product of technology and deregulation (Group of Ten, 2001). On the one hand, technological developments have decreased computing costs and telecommunications, while expanding capacity, thus making a global reach economically more feasible. On the other hand, deregulation has relaxed the restrictions in activities undertaken by foreign firms in both developed and developing countries around the world that has allowed entry into many markets.

As Berger et al. (1999) point out, the transfers of securities, goods, and services in international markets creates demands for currency, deposit, loan and other services by international financial institutions, thus the globalisation of markets has likely contributed to cross-border M&As and the globalisation of financial services firms. Many financial products are now offered internationally by efficient global competitors, through direct or targeted distribution channels (Group of Ten, 2001).

The globalisation also contributes to the shift from a bank-centred system to a market-based one, while a further influence is observed in the area of corporate governance (Group of Ten, 2001). With respect of the latter, as firms have crossed international boundaries, their shares begun to be held by a wider investor clientele, which demand more uniform standard or corporate governance.

Furthermore, as a result of the globalisation trend, the number of foreign banks has increased in every banking market leading to intensified competition and reduced profit margins in many European national banking sectors (Goddard et al., 2001). It is obvious that in such a competitive environment only the most efficient institutions will be able to survive in the long term.

Shareholder pressures

The increased importance attributed to the "shareholder value" concept, has led naturally to a focus on the return on assets and return on equity as benchmarks for performance, especially by large well-informed investors. Thus, in a sense, managers are under pressure to increase profits in an environment of intense competition, and this can only be accomplished through the creation of new sources of earnings, generation of fee income, reduction of cost-to-income ratios, optimal use of excess capital, or for some institutions, recapitalisation after a major crisis (Group of Ten, 2001). Obviously, these goals can be achieved through business gains, enhancement or more effective balance sheet management. Another way, that is perceived to be an easier strategy for many institutions, is through M&As.

Introduction of the euro

The introduction of the euro is considered to have an impact on the competitive environment in which financial institutions operate and consequently on the consolidation activity especially in the European arena. The Group of Ten (2001) emphasises a number of ways through which the introduction of euro can motivate M&As. In summary, these are: the integration of money market, the impact of the euro on the treasury activities of the corporate sector, the integration of the capital markets and the government bond markets. Opportunities for cost savings or revenue enhancement arising from these changes are therefore potential motives for bank consolidation.

Macroeconomic conditions

Macroeconomic conditions are considered to be another factor that could directly influence the decision of firms to merge with or acquire other firms. For example, merger waves seem to coincide with economic booms (Mueller, 1989). By definition, during booms the economy enjoys a rapid growth rate. Moreover, at the same time the stock market surge. Nelson (1959) reports that M&As are positively correlated with stock market prices. Furthermore, in some cases, macroeconomic changes lead to excess capacity and ultimately downsizing and exit (Ali-Yrkkö, 2002).

Macroeconomic conditions may also have an indirect effect on the decisions of banks to merge through their impact on banks' profitability. As banks do not operate in a vacuum, their performance is subject to the country's economy. For example, the growth of GDP is expected to have an impact on banks' performance, according to the well-documented literature on the association between economic growth and financial sector performance (e.g. King and Levine, 1993; Levine, 1997, 1998; Rajan and Zingales, 1998). Inflation may also affect both the costs and revenues of any organisation including banks. Perry (1992) points out that the effect of inflation on bank performance depends on whether the inflation is anticipated or unanticipated. A number of studies (e.g. Molyneux and Thorton, 1992; Abreu and Mendes, 2001; Staikouras and Wood, 2003; Pasiouras and Kosmidou, 2005) have empirically examined the determinants of EU banks profitability and reported the existence of a significant relationship between profits and various macroeconomic factors, such as GDP, inflation, unemployment and interest rates.

2.3 Practitioners' views on reasons for banks M&As

At this point, apart from the reasons that have been proposed by academic scholars and researchers, using either theoretical formulations or empirical evidence, it is essential to mention the views of practitioners (i.e. bankers and financial industry professionals). The following two sub-sections offer a summary of the findings of two main reports, conducted on behalf of the European Central Bank (ECB) and the Group of Ten respectively, that among others examined the issue of the causes of M&As in the financial sector.

2.3.1 The European Central Bank Report (2000)

In order to reveal the motives for M&As from an industry perspective in the EU banking sector, the European Central Bank (ECB) examined the views of bankers through a process of interviews and consultation of the views of bank supervisors. The report was prepared by the Banking Supervision Committee (BSC) and covered the period 1995 to 2000. The main reasons that were identified in the analysis of the rationale for M&As are presented in Table 2.1, and summarized below.

With respect of the domestic bank M&As, economies of scale was found to be the main rationale for small bank M&As, which sought to obtain critical mass to explore synergies arising from size and diversification. In addition, M&As were also intended to avoid takeovers. As for the large banks, M&As often reflected a repositioning of the institutions involved. The increase in size reflected a need to become big enough to compete in the domestic market. Larger banks aimed at increased market power and a larger capital base, with a greater focus on increasing revenue, in contrast to smaller banks, which sought to explore synergies and avoid threat of takeover. With regard of the international bank M&As, the need to be big enough for the regional or global markets, indicates that size is the main motive, although for international conglomerates economies of scale and scope are also important.

As for domestic conglomerates, economies of scope were also indicated as the main motive. These financial institutions aimed at achieving economies through cross-selling of different financial products to the larger customer base of the combined entity, utilizing new distribution channels to make more efficient use of the fixed costs associated with the banks' branches. Specifically, the amalgamation of banks and insurance firms occurred to achieve risk and income diversification and consequently to reduce sensitivity to economic cycles. With regard to international conglomeration, the two major reasons, as noted above, were economies of scope and size, aimed principally at increasing revenue through cross-selling and strong brands that is attractive to large international clients.

Table 2.1 - Main motives and possible rationalisations for the four types of Bank M&As

	Within one country	**In different countries**
	Domestic bank M&As	*International bank M&As*
Between credit institutions	- Economies of scale linked to costs are the main motive - Cutting distribution networks and administrative functions (rationalisation), including information technology and risk management areas	- Size, i.e the need to be big enough in the market, is the main motive -Matching the size of clients and following clients - Possible rationalisation within administrative functions
	Domestic conglomeration	*International conglomeration*
Across different sectors	- Economies of scope through cross selling is the motive - Risk and revenue diversification - Optimum usage of complementary distribution networks - Possible rationalisations within administrative functions may lead to economies of scale linked to costs	- Economies of scope through cross-selling together with size are the two main motives - Risk and revenue diversification - The M&A offers few rationalisations because institutions are in different countries and subject to different regulation and practices

Source: ECB (2000)

2.3.2 The Group of Ten Report (2001)

In a similar manner the Group of Ten conducted interviews with 45 selected financial sector participants and industry experts from the G10 countries[5]. The interviewees were asked for their opinions on the basis of a common interview guide, which listed a number of factors led to M&A activity. Table 2.2 details the factors that formed the basis for the interviews.

Table 2.2 - The interview guide used in the Group of Ten (2001) report

List of Factors		
Motives for consolidation	**Forces encouraging consolidation**	**Forces discouraging consolidation**
Cost savings attributable to: - Increased size (economies of scale) - Product diversification (economies of scope)	Technology: - Information and communications - Financial innovation - Electronic commerce	Market inefficiencies
Revenue enhancement due to: - Increased size (ability to serve larger customers) - Product diversification (ability to provide "one-shop shopping")	Globalisation: - expansion of domestic and international capital markets - trade in non-financial products - Institutionalisation of savings - creation of euro	Legal and regulatory constraints
Risk reduction due to product diversification	Deregulation	Cultural constraints (cross-firm and cross-segment)
Change in organisational focus	Privatisation	Deconstruction (breaking up of institutions into more specialized units)
Increased market power	Bailouts or financial conditions of firms	Outsourcing
Managerial empire building and retrenchment	Climate of capital markets	Internet

[5] The G10 comprises the following set of countries: Belgium, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, United Kingdom, and United States. Note there are eleven countries in the G10. The "ten" refers to the members of the Group who constitute the members of the International Monetary Fund. Switzerland, which joined the Group in 1984, is the eleventh member. Also added in the report were surveys for Australia and Spain.

Table 2.3 summarizes the main findings for the US and a selection of the EU countries that were considered in the report, outlining the particular firm-level motives as well as the external factors for M&As. In general, irrespective of the county of origin, the main reasons concerning firm-level motives can be summarised as follows.

With respect to within-country, within-segment mergers, the single strongest motivation factor has been the desire to achieve economies of scale. Other important motivating factors were revenue enhancement due to increased size and increased market power. It is important to mention at this point that most interviewees interpreted market power to mean market share, rather than the ability to influence price. Risk reduction due to product diversification and change in organisational focus were considered largely irrelevant for this type of consolidation, while economies of scope, revenue enhancement due to product diversification, and managerial empire building and entrenchment were considered to be more important.

Turning to within-country, across-segment mergers, the most important motive appears to be revenue enhancement due to product diversification, or the ability to offer customers "one-stop shopping". The desire to achieve economies of scope was perceived by interviewees to be the second most important motive. Economies of scale, revenue enhancement due to increased size, risk reduction due to product diversification, change in organizational focus, market power and managerial empire building and entrenchment were all considered to be slightly less important factors.

With regard to within-segment, cross-border consolidation, the strongest motives were the desire to achieve increased market power and revenue enhancement through both size and product diversification. Finally, with regard to cross-segment, cross-border consolidation, revenue enhancement was considered to be a strong motivator, but increased market power was viewed as only slightly important.

Turning to external forces encouraging consolidation, technological advances were considered to be the most important force, especially with regard to within-country, within-segment combinations. Among them, improvements in information and communications technology were ranked as the most important, followed by financial innovation, while electronic commerce was viewed as less important. Over half of the respondents also indicated that deregulation was equally important as a factor encouraging consolidation for domestic, within-segment institutions (with over one third ranking it as a very important factor). The responses regarding other types of consolidation were more or less the same. Globalisation of the non-financial sector did not rate as an important factor encouraging financial consolidation, while the institutionalization of savings was considered to be somewhere between "moderately important" to "very important" factor encouraging consolidation (by 50% to 60% of respondents for each type of consolidation considered). Finally, with respect to the influence of euro, the responses were mixed with the views varying among locations. Interviewees from euro area countries tended to rank this factor much higher than those outside the euro area. Nevertheless, some respondents indicated that the euro was likely to become a more significant force in the future than it has been to date.

Table 2.3 - Recent Causes of M&As in US and selected EU countries (Group of Ten report)

Country	Firm level motives	External factors
US	Cost savings due to economies of scale: moderately or very important as a driver of within-segment, within-country mergers and slightly important or not a factor in the case of cross segment mergers and cross-border mergers. Revenue enhancement due to product diversification: moderately to very important in motivating cross-segment mergers, both within and across borders. Change in organisational focus: mostly unimportant Market Power and Managerial empire building: various views.	Domestic consolidations- Most important: improvements in information and communications, technology, deregulation (especially interstate banking), bailouts (particularly in the last 1980s and early 1990s) and the climate of capital markets. Cross-border consolidation: Expansion of domestic and international capital markets.
France	Cost cutting (dominant motive), Revenue enhancement (less important)	Information technology, deregulation and privatisation.
Germany	Consolidation within segments at the domestic level: Cost savings and revenue enhancements attributable to size (primary motives), increased market power (second most cited motive). Consolidation across segments at the domestic level: Economies of scope (cost savings and revenue enhancement due to product diversification) and improvement in risk management (consolidation of banks with insurance companies), expertise in securities activities (consolidation of investment and commercial banks). Not fundamentally different motives in the case of cross-border consolidation.	Consolidation within segments at the domestic level: Technology was underlined by all interviewees, expansion of domestic and international capital markets was mentioned by all participants, euro was often cited as an important factor as well. Consolidation across segments at the domestic level: far lesser role of technology due to technological discrepancies and euro also loses much of its significance. Cross-border consolidation: euro was widely cited as an essential encouraging factor, deregulation is important as well, role to technology decreased.
Italy	Consolidation within segments at the domestic level: Cost savings attributable to increased size (main motive), revenue enhancement due to product diversification and to a lesser extent to increased size, as well as need of banks to increase their market share were mentioned as other relevant motives. Geographical diversification was also mentioned as an important factor for risk diversification and increased market share. Consolidation across segments at the domestic level: Product diversification (main motive). Cross-border operations: Revenue enhancement due to increased size tends to become more important, whereas the cost saving argument loses some of its relevance.	Information technology (primary factor), euro (second important factor) were the most important external factors. Deregulation has also played an important role over the last years, though it has in current times exhausted its effect. Privatisation was regarded as an additional important factor. Across segments: institutionalisation of savings tends to become more important Cross-border operations: Globalisation was more important compared to other less important such as privatisation and resolution of crises.
UK	Consolidation within sectors: Cost savings attributed to increased size (most important), increased market power and managerial empire building. Across sectors: Revenue enhancement due to size and due to product diversification were most important; managerial empire building continued to rate as an important motive costs savings due to size dropped to slightly important. Cross-border: revenue enhancement due to increased size and managerial empire building.	Within segments and across segments: Information & Communication technology and e-commerce were ranked highest, while deregulation and privatisation and the creation of euro were insignificant. Across borders: the creation of euro and institutionalisation of savings were ranked highest, followed by e-commerce, deregulation and privatisation.
Belgium	The leading motive was a combination of cost savings and revenue enhancement. Risk reduction and managerial empire building were not found to be very relevant.	Introduction of euro and globalisation and favourable climate of capital markets. The development in information technology and disintermediation were also identified as factors.
Nethe-rlands	Cost savings and revenue enhancement were the main motives, product diversification was also important particularly for consolidation across segments, though it last was connected to revenue enhancement rather than economies of scope or risk reduction. Psychological motives have been moderately important, particularly the fear of becoming a takeover target, as was the shareholders pressures to create value.	The development of technology was identified as one of the main factors. Deregulation was also commonly mentioned. Of the factors related to globalisation, the introduction of the euro and the process of European integration in general were mentioned. One interviewee highlighted the high stock prices.
Spain	The most important factor has been cost savings due to economies of scale. Attainment of critical mass for three main reasons: face the upcoming European consolidation, increase market share, defend against possible hostile acquisitions. Cross-border: revenue enhancement was the main motive, cost savings (economies of scope) was also important. Mixed opinions regarding risk reduction.	Bailouts, deregulation and the creation of euro, were the main forces. Expansion of domestic and international capital markets was also cited, as was the climate of capital markets. Mixed opinions regarding technology issues. Cross-border consolidation: deregulation, privatisation and bailouts were mentioned as the most important forces. Regarding technology issues, the opinions were mixed.
Sweden	Economies of scale was one of the main motives for consolidation. Shareholder pressures and the shift to offering retail customers more comprehensive service and integrated asset and liability management were additional motives. Empire building and psychological factors were also cited as potential main motives. Cross-border consolidation: mention was made of revenue enhancement due to geographic expansion.	Globalisation was thought to be a minor factor, while deregulation and privatisation were not regarded as important forces in 1990s.

Source: Group of Ten (2001)

2.4 Banks' M&As studies

This section provides a brief survey of the empirical studies that have examined banks' M&As. According to Berger et al. (1998), the majority of these studies can be classified into the following five categories: (1) studies that examine the characteristics of the banks involved in M&As, (2) studies that examine the determinants of the premium paid for the target, (3) studies that examine the consequences of M&As on operating performance, (4) event studies of the merged banks' stock performance around the M&A announcement date, (5) the consequences of banks M&As on other firms.

As our main objective is the development of prediction models for M&As, and much of the empirical evidence relating to M&As is somewhat tangential to this line of enquiry, we discuss in this section what on balance appears to be the main conclusions of the set of studies categorised above[6], rather than provide a detailed survey of the empirical evidence[7]. Furthermore, in the last sub-section (i.e. 2.4.5) we discuss separately a few studies that have focused on the EU banking sector.

2.4.1 Characteristics of Banks involved in M&As

Studies that fall within this category are those of Hannan and Rhoades (1987), Moore (1996), Hadlock et al. (1999) and Wheelock and Wilson (2000, 2004).

Hannan and Rhoades (1987) examined the relationship between banks performance and the likelihood that a bank will be acquired. They also examined the influence of additional bank and market characteristics on the likelihood of acquisition. Their sample consisted of 201 acquired banks (in Texas between 1970 and 1982) and 845 non-acquired banks, and they employed multinomial logit analysis to account for the fact that any bank could experience the following three events: (a) acquired by a bank operating within its market, (b) acquired by a bank operating outside its market, (c) not be acquired. Their results can be summarized as follows: (1) no evidence was found to support the argument that poorly managed banks were more likely to be acquired than well managed banks, (2) market concentration was found to reduce the likelihood of being acquired from within the target bank's market,

[6] We discuss the four of the five categories as the last one examines the impact of banks M&As on other firms (e.g. customers) and not on banks themselves.
[7] Chapter 3 provides a literature review of the empirical studies more relevant to the present study.

but not from outside the market, (3) high capital asset ratios were found to reduce a bank's attractiveness as an acquisition target, (4) larger market share and operation in urban areas increased a bank's attractiveness as a target, to banks not operating in the same market.

Moore (1996) also employed multinomial logit analysis to examine the characteristics of US banks acquired between June 1993 and June 1996. His results showed that the probability of being acquired tended to be higher for banks with low profitability, slow asset growth, low market share, low capital to asset ratio, and low ratio of non-small business loans to total loans. Small business loans per se and bank size, on the other hand, were not found to have a significant influence on the probability of being acquired.

Hadlock et al. (1999) examined a sample of 84 US banks that were successfully acquired between 1982 and 1992 and compared them to a matched sample of 84 banks that were not acquired. The authors analysed the effect of variables related to management incentives, corporate governance and performance on the likelihood of a bank's acquisition. Both univariate and multivariate methods were employed. They examined the mean and median values of the variables to identify any systematic differences between the two sample groups. They also estimated, in addition, four logit models using different explanatory variables and subsamples. They found that banks with higher levels of management ownership are likely to be acquired, especially in acquisitions where the managers of the acquired banks leave their job following the acquisition. They also found little evidence for other incentive, governance or performance variables to support the probability of a bank's acquisition.

Wheelock and Wilson (2000) attempted to identify the characteristics that increased the probability for a US bank to disappear either by being acquired or by failing, focusing especially on how managerial efficiency affected the likelihood of either outcome. Unlike the previous studies that used logit modes, they used proportional hazard models with time-varying covariates to examine a large dataset of US banks with assets over $50 million. They found that banks which were more close to failing were those that: (1) were less well capitalized, (2) had high ratios of loans to assets, (3) had poor-quality loan portfolios, (4) had low earnings, (5) were not located in states where branching was permitted, (6) had inefficient management as reflected in measures of cost or technical efficiency. As for the probability of acquisition, they found it to be higher for banks that: (1) had lower capitalization, (2) had lower return on assets, (3) were characterised by cost efficiency, (4) were located in states permitting state-wide branching.

In a latter study, Wheelock and Wilson (2004) used a two-part hurdle model, to investigate the determinants of the expected number of mergers and volume of deposits a bank absorbs through a merger within a fixed interval of time. The sample consisted of all U.S commercial banks with available data that were involved in over 3,000 mergers, which occurred between the second quarter of 1987 and the first quarter of 1999, while numerous explanatory variables were used as proxies of regulatory process, market characteristics, capital adequacy, asset quality, management, and earnings. The authors concluded that: (1) regulatory approval process served as a constraint on bank merger activity, (2) the quality of a bank's management, as reflected in the CAMEL component rating for management was positively related to the expected number of mergers while downgrade in CAMEL and Community Reinvestment Act (CRA) ratings reduced the expected number of mergers a bank will engage in, (3) the expected number of mergers fell with an increase in the concentration in the market that a bank is headquartered, (4) location in an urban market greatly increased the expected number of mergers a bank will engage over time, (5) a bank's size strongly influenced the expected number of mergers a bank will engage in, and (6) an increase in core deposits, and increases in some indicators of asset risk, raised the expected number of mergers.

2.4.2 Premium on Bank M&As

Several studies have examined the size of the merger premium paid in the bank M&As literature. These studies have used purchase price-to-book value or similar ratios of the target bank and other key characteristics of the banks to investigate the determinants of the magnitude of premiums paid.

Early studies are those of Beatty et al. (1987), Cheng et al. (1989), Rhoades (1987), Fraser and Kolari (1987), Rogowski and Simoson (1987), and Hunter and Wall (1989). Beatty et al (1987) examined the purchase price-to-book ratio of bank takeovers in 1984 and 1985. Cheng et al. (1989) investigated 135 mergers in the Southeast US that occurred between 1981 and 1986 and related the merger premiums to the characteristics of both acquirers and targets. Rhoades (1987) examined 1,835 bank mergers for the period 1973 to 1983. Fraser and Kolari (1987) examined the impact on pricing of 217 mergers in 1985 while Rogowski and Simonson (1987) studied pricing in 264 bank mergers between the beginning of 1984 and the third quarter of 1985. Hunter and Wall (1989) differentiated their study by using cluster analysis, examining a sample of 559 bank mergers that occurred during the period 1981-86 to reveal the financial characteristics that were highly valued by acquiring banks and systematically associated with attractive purchase prices. They found that the most valued characteristics in target banks included above-average profitability, faster deposit and asset growth, a higher ratio of loans to earning assets and judicious use of financial leverage.

Table 2.4 summarises the findings of 10 more recent studies that have examined the determinants of bank merger pricing, these being conducted mainly over the period covering the last two decades. The majority of these studies suggest that acquirers are willing to pay more for targets that operate with lower overhead expenses and generate higher returns. Furthermore, variables such as bank growth, market growth, method of accounting (purchase or pooling), type of deal (intrastate or interstate), market concentration were found to be significant in explaining the magnitude of acquisition premiums.

Table 2.4 - Summary of studies on premium paid in bank M&As conducted over the last decade

Author(s)	No of bank mergers	Period studied	Main Results
Adkisson & Fraser (1990)	174	1985-86	Capital ratio, deal term (percent of acquisition price paid in cash), target bank's ROA and change in population in the target market area were significant at the 10% level.
Frieder & Petty (1991)	164	1984-86	Profitability (measured by ROE) and growth (measured by market characteristics – state deposit growth and expected future population) were significant positive determinants of premiums paid in mergers. Charge-offs to total loans had a negative impact on the premiums and was significant at the 1% level.
Palia (1993)	137	1984-87	Merger premium was related to the characteristics of both acquirer and target banks and the regulatory environments in both acquirer and target bank states. The separation of ownership and control in acquirer and target banks had also a significant effect on merger premiums.
Shawky et al. (1996)	320	1982-90	Higher merger premiums were paid for (i) smaller size targets (ii) targets with higher return on common equity (iii) targets with higher leverage (iv) targets in a different sate than the bidder (v) transactions carried out through exchange of stock as opposed to cash purchase.
Hakes et al. (1997)	868	1982-94	The presence of state deposit caps reduced the premium paid. The impact of deposit caps was not constant across different sized banks. The premium paid to moderate size targets (assets between $77 million and $204) was greatly reduced while that paid for small and large banks was reduced less consistently.
Gart & Al-Jafari (1999)	159	1989-97	Higher premiums were paid to target banks that were managed efficiently and profitably, maintained strong quality and had smaller asset size. The accounting method used had also an effect. Larger banks were found to pay larger premiums when the pooling of interest method of accounting was used.
Jackson & Gart (1999)	200	1990-96	Target core deposits, target leverage, target ROA, accounting method, and a factor representing the target's state deposit cap restrictions were found statistically significant at the 1% level. Furthermore, target's non-performing assets, an intra-state variable and a combined factor of intra-state variable and relative size were significant at the 5% level.
Scarborough (1999)	243	1989-96, 1997-98 and 1989-98	Four variables were significant for all three periods. These were: accounting method, deal size, target's equity to total asset ratio, target's bank ROAA. Three more variables (target's size, percent of non-performing assets, whether the merger was intra-state or inter-state) were found to be statistically significant for at least one period.
Jitpraphai (2000)	214	1989-98	Five variables were statistically significant in explaining merger premiums (i) target bank's ROA, (ii) capital asset ratio, (iii) type of deal (interstate or intrastate merger), (iv) accounting method (purchase or pooling), (v) time trend variable

2.4.3 Evidence on Banks' Operating Performance

These studies have typically examined changes in accounting data, before and after the mergers to determine if there have been any significant changes in the merged banks' operating performance (OP). In these studies, statistically significant improvements in profitability, increases in operating efficiency, rapidly growing interest revenues, reduction in costs, more efficient asset management and decreased risk in the post-merger institutions are assumed to be indicators of successful mergers and potential reasons for the M&As themselves. Rhoades (1994) provides a review of 19 operating performance studies that were conducted between 1980 and 1993, while Berger et al. (1999) provide a review of more recent ones. These studies can be distinguished between those that use univariate t-tests and those that estimate efficiency usually measured by the best-practice cost or profit efficiency frontier.

Univariate t-test

The studies in this category employ univariate t-tests to compare profitability ratios such as return on assets (ROA) and return on equity (ROE) and cost ratios such as costs per employee or assets before and after M&As (e.g. Spindt & Tarhan, 1992; Rhoades, 1986, 1990; Rose, 1987; Srinivasan, 1992; Srinivasan & Wall, 1992; Cornett & Tehranian, 1992; Linder and Crane, 1993; Peristiani, 1993; Vander Vennet, 1996). Some of these studies have found improved ratios associated with M&A although others have found little or no improvement in these performance ratios. For example, Rose (1987) examined 106 bank mergers between 1970 and 1985 and found that profitability did not increase for the acquiring banks post-merger. Similar results were obtained by Linder and Crane (1993), who examined 47 M&As that occurred between 1982 and 1987 and found no improvement in either ROA or growth in operating income. By contrast, Cornett and Tehranian (1992) found improvements in return on equity as well as operating cash flow owing to increases in employee productivity, asset growth, loans and deposits. Spindt and Tarhan (1992) examined 79 small mergers and 75 medium-to-large mergers and found improvements in ROE, margin and employee cost or sizes of mergers compared to a control sample. Peristiani (1993) found some improvement in ROE for the combined entities following merger but no improvement in cost ratios.

A problem with drawing conclusions from these studies is that simple ratios (either profit or cost) incorporate both changes in market power and changes in efficiency, which cannot be disentangled without controlling for efficiency. In addition, the use of costs ratios does not account for the fact that some product mixes cost more to produce than others (Berger et al., 1999).

Efficiency studies

In an attempt to overcome the problems associated with the use of simple ratios. A number of studies have examined the effect of M&As on banks performance using an efficiency frontier function methodology, such as the econometric frontier approach (EFA), the thick frontier approach (TFA), the distribution free approach (DFA), and the data envelopment analysis (DEA).

The cost-efficiency studies employ cost functions to control for input prices, product mix and other factors. Berger et al. (1999) argue that cost-efficiency studies are superior to the cost ratios studies, in that by controlling for prices, they are able to disentangle efficiency changes from changes in market power, which may be incorporated into prices. Nevertheless, despite the differences in methodology from the univariate cost ratio studies, the results of most cost-efficiency studies have been quite similar. As Berger et al. (1999) point out, the studies of US banking generally show very little or no cost-efficiency on average from the M&As on the 1980s (e.g. Berger & Humphrey, 1992; Rhoades, 1993; DeYoung, 1997, Peristiani, 1997) while the studies that use data from the early 1990s provide mixed results (e.g Rhoades, 1998; Berger, 1998). Probably the potential gains from consolidating branches, computer operations etc, may have been offset by managerial inefficiencies or problems in integrating systems (Huizinga et al., 2001).

The studies on profit efficiency consequences of M&As are related to the scale scope, product mix and efficiency effects for both costs and revenues and might also include at least some of the diversification effects. The theoretical appeal of working with the profit function is that it accounts for the revenue effects as well as the cost effects of operating at incorrect levels or mixes of inputs and outputs (Akhavein et al., 1997). Akhavein et al. (1997) analysed a sample of megamergers (involving banks with assets exceeding $1 billion) that occurred in the 1980s and found that on average, mergers helped to improve profitability especially when both banks were relatively inefficient prior to the merger. The improvement in profit efficiency was mainly caused by risk diversification following a change in the output mix in favour of more loans and fewer securities holdings. Nevertheless, their measure of profit didn't account for changes in risk that could result from such a portfolio switch, assuming that equity markets would recognise and account for any such change. Berger (1998) found similar results in a study that included all US bank mergers, both large and small, from 1990 to 1995.

Overall Assessment of operating performance studies

As Houston et al. (2001) mention the mixed results of the literature that examines changes in the operating performance (OP) of merged banks are not surprising given the numerous empirical difficulties associated with these studies. The time period considered is one of the problems. Rhoades (1994) points out that the OP studies typically analyse operating performance for a period of one to six years after a merger occurs and during these years, many factors unique to the merged firm, other than the merger itself, may affect the firm's efficiency or general performance. Similarly, even if mergers improve performance, accounting based studies can fail to detect it because the flags between the completion of mergers and the realisation of operating improvements can be long and varied (Houston et al., 2001). In their study, Linder and Crane (1993) found that merging banks did not improve their operating profit margins significantly during the first 2 years following the merger, while improvements began to occur after 3 years. A selection bias problem also exists with respect to the industry benchmark since it is difficult to construct benchmarks of non-merged banks in a rapidly consolidating industry (Houston et al., 2001). Finally, the potential inaccuracies of accounting information in measuring economic value and accounting rules governing valuation of assets may also affect the observed results (Went, 2003). Nevertheless, despite these shortcomings, as Rhoades (1994) argues, the OP studies have the advantage of focusing on actual observed operating results of a merger rather than the expectations around the announcement date as event studies do.

2.4.4 Evidence on stock market performance

Event studies typically examine the impact of merger announcement on share prices of the acquiring banks and/or the target banks and/or the combined entities around the announcement period. Changes in share prices, adjusted using a marked model for changes in the overall stock, provide an estimate of the anticipated effect of M&As on the future profits of the consolidate institutions. Positive abnormal returns reflect a positive view of the event, while negative abnormal returns reflect the opposite. Although the underlying procedures for estimating the performance effects are more standardised in event studies than in operating performance studies, the former exhibit a great deal of variation with respect to sample size, number of merger announcements studied, period of time over which the market model is estimated, period of time over which abnormal returns are calculated and so on (Rhoades, 1994). The results for the US are mixed, and the outcome basically depends on whether it examines the share price of target bank, acquirer bank or the combined entity (on an aggregate basis).

Rhoades (1994) provides a comprehensive summary of 39 US bank M&As performance studies published during 1980-39, 21 of which used event study methodology. The author concludes that the main findings of these event studies are not consistent. For target banks, only one study found no abnormal returns while eight studies found significant positive abnormal returns. For acquiring banks, seven studies found that a merger announcement had a significant negative influence on the returns to shareholders, while seven others found no significant effect on the acquiring bank's stock return, three studies found positive returns, while four found mixed results.

More recent studies have examined not only the returns of targets or acquirers but also the net wealth changes in stock prices by incorporating both stock returns of the acquiring and the target bank during the event period as well. This net wealth effect is usually calculated as some type of market value weighted sum of the acquirer and the target. Table 2.5, taken from Beitel and Schiereck (2001), presents the findings of 30 event studies conducted between 1990 and 2000[8]. In general, these studies confirm the findings of earlier studies as it concerns the returns to bidders' and targets' shareholders. Furthermore, a large part of the recent empirical research also aims at explaining empirically the observed results. Among others such studies are those of Hawawini and Swary (1990), Houston and Ryngaert (1994), Madura and Wiant (1994), Becher (2000), DeLong (2001), Zolo and Leshchinkskii (2000), and Banerjee and Cooperman (1998).

[8] Some of the studies have been published after 2000. The dates of publication have been updated in Table 2.5 and may therefore not match exactly the ones in the study of Beitel & Schiereck (2001).

Table 2.5 - Findings of 30 recent event studies on banks M&As

(Source: Beitel & Schiereck, 2001)

Authors (year)	Country	Period	Sample	Event window (days)	CAR[a] Bidder	CAR Target	CAR combined entity
Hawawini & Swary (1990)	USA	'72-87	123	[0, +5]	-1.7%	+11.5%	+3.1%
Baradwaj et al. (1990)	USA	'80-87	53	[-60, +60]	n.s.	25.9 – 30.3%	N.A
Allen & Cebenoyan (1991)	USA	79-86	138	[-5,+5]	n.s.	N.A	N.A
Cornett & De (1991)	USA	82-86	152	[-15, +15]	n.s.	+9.7%	N.A
Baradwaj et al. (1992)	USA	81-87	108	[-5, +5]	-2.6%	N.A	N.A
Houston & Ryngaert (1994)	USA	85-91	153	[-4L; +1A]	-2.3%	+14.8%	+0.5%
Madura & Wiant (1994)	USA	83-87	152	[0, 36M]	-27.1%	N.A	N.A
Palia (1994)	USA	84-87	48	[-5, +5]	-1.5%	N.A	N.A
Seidel (1995)	USA	89-91	123	[-20, +20]	-1.8%	N.A	N.A
Zhang (1995)	USA	80-90	107	[-5, +5]	n.s.	+6.9%	+7.3%
Hudgins & Seifert (1996)	USA	70-89	160	[-1, +1]	n.s.	+7.8%	N/A
Siems (1996)	USA	1995	19	[-1, +1]	-2%	+13%	N/A
Pilloff (1996)	USA	82-91	48	[-10, 0]	N/A	N/A	+1.4%
Houston & Ryngaert (1997)	USA	85-92	209	[-4L, +1A]	-2.4%	+20.4%	N.A
Subrahmanyam et al. (1997)	USA	82-87	263	[-1, +1]	-0.9%	N.A	N.A
Banerjee & Cooperman (1998)	USA	90-95	92	[-1, 0]	-1.3%	+13.1%	N.A
Toyne & Tripo (1998)	USA	91-95	68	[-1, 0]	-2.2%	+10.9%	-0.7%
Cyree & DeGannaro (1999)	USA	89-95	132	[-1, 0]	n.s.	N.A	N.A
Kwan & Eisenbeis (1999)	USA	89-96	3844	[-1, 0]	N.A	N.A	+0.8%
DeLong (2001)	USA	88-95	280	[-10, 1]	-1.7%	+16.6%	n.s.
Tourani Rad & Van Beek (1999)	Europe	89-96	17targ. & 56 bid.	[-40, +40]	n.s	+5.7%	N.A
Cornett et al. (2003)	USA	88-95	423	[-1, +1]	-0.78%	N.A	N.A
Cybo-Ottone & Murgia (2000)	Europe	87-98	46	[-10, 0]	n.s.	+16.1%	+4.0%
Becher (2000)	USA	80-97	558	[-30, +5]	-0.1%	+22.6%	+3.0%
Brewer et al. (2000)	USA	90-98	327	{0, +1]	N.A	+8.3% – 14%	N.A
Houston et al. (2001)	USA	85-96	64	[-4L, A]	N.A	N.A	+3.1%
Kane (2000)	USA	91-98	110	[0]	-1.5%	+11.4%	N.A
Karceski et al. (2004)	Norway	83-96	39	[-7, 0]	n.s	+8.4%	N.A
Schiereck & Strauss (2000)	USA /Germ	98-99	1	[-20, +20]	n.s	+30.1%	N.A
Zollo & Leshchinskskii (2000)	USA	77-98	579	[10, +10]	N.A	N.A	N.A

[a] CAR = cumulated abnormal returns; n.s. = not significant, N.A= not research in the study' [b] Combined entity of the target and the bidder' [c] The authors study hostile (25.9%) and friendly (30.3%) takeovers' [d] The authors only study different sub-samples without representing results for the entire sample' [e] 4 days prior to the leakage date to 1 day after the announcement [f] No tests for significance' [g] Completed deals.

Hawawini and Swary (1990) examined 123 US bank M&As that occurred between 1972 and 1987 and found M&As to be more favorable for bidders when the targets were small relative to bidders. Hawawini and Swary (1990) also found that mergers between the two banks located in the same state create more value than mergers between banks located in different states, as did Madura and Wiant (1994). Becher (2000) examined the impact of the method of payment on M&As success and found that bank M&As create more shareholder wealth for bidder's shareholders in cash transactions as compared to stock transactions. DeLong (2001) examined 280 US bank M&As over the period 1988 to 1995 and found that increased product/activity focus had a significantly positive effect on M&As success of US banks. Zolo and Leshchinkskii (2000) studied 579 US bank M&As from the period 1977-88 and found that the size of the bidder had a significant negative impact on the acquirer's M&A success. Banerjee and Cooperman (1998) examined a sample of 20 acquirers and 62 targets that were involved in M&As in the US between 1990 and 1995 and found acquirers to be more successful if they were more profitable than their targets, thus providing support to the earlier studies of Hawawini and Swary (1990) and Houston and Ryngaert (1994) that had reached at the same conclusion.

Overall, the empirical evidence from event studies on bank M&As indicates that bank mergers do not create a statistically significant net increase in stock market value. Whereas the shareholders of targets earn positive cumulative abnormal returns the shareholders of the acquirers earn zero or negative cumulative abnormal returns suggesting a wealth transfer from the acquirer to the target shareholders in bank mergers. Due to the fact that acquirers often pay rather high premiums, these results are not surprising. Furthermore, the negative announcement return of bidding firms can reflect disappointment that the bidding banks is less likely to be acquired in the future (Houston et al., 2001).

Overall Assessment of Event studies

As Dunis and Klein (2005) mention, event studies are widely used to measure the effect of M&As announcements. Possible reasons are that stock price data are easily available, the calculations are straightforward and these studies do not rely on potentially misleading accounting data. Nevertheless, Rhoades (1994), Berger et al. (1999), Houston et al. (2001) and Dunis and Klein (2005) point out a number of problems that are associated with event studies. These can be summarized as follows:

(1) Information may have leaked prior to the M&A announcement or markets may anticipate M&As prior to their announcements. These problems may be particularly severe during "merger waves"; (2) The period around the announcement event day for which abnormal returns are analysed varies greatly from study to study, and the results often appear to be sensitive to the time period chosen; (3) It is difficult to select a reasonable benchmark in a rapidly consolidating industry; (4) The analysis assumes efficient markets that immediately incorporate new information and relies on the assumption that the market expectations are a good prediction of the long-term effects of an event; (5) The samples are usually small as this method is limited to publicly traded banks. Nevertheless, many merging banks are of course not publicly traded, thus results based on publicly traded stocks are not necessarily representative of all bank mergers; (6) It is impossible to differentiate between the specific value of consolidation and other wealth transfer effects associated with the transaction and to separate the effect of the merger from the company specific events. This is especially true in the case of multiple acquisitions or where new shares are issued to finance the acquisition. It is also difficult to distinguish if gains come from efficiency gains or market power.

2.4.5 Evidence on European banks M&As

Vander Vennet (1996)

Vander Vennet (1996) used a sample of 422 domestic and 70 cross border acquisitions of EC credit institutions that occurred over the period 1988-1993 to examine the performance effects of M&As. The analysis consisted of a univariate comparison of the pre-and post-merger performance of merging banks and covered a period starting three years before and ending tree years after a takeover. The results of the study can be summarized as follows: First, domestic mergers among equal-sized partners significantly increased the performance of the merged banks. Second improvement of cost efficiency was also found in cross-border acquisitions. Third, domestic takeovers were found to be influenced predominantly by defensive and managerial motives such as size maximization.

Tourani Rad and Van Beek (1999)

Tourani Rad and Van Beek examined a sample of 17 target and 56 bidding European financial institutions (i.e banks, investment funds, building societies, and insurance companies) that merged between 1989 and 1996. Using event study methodology with daily data and the market model, the authors found that target's shareholders experienced significant positive abnormal returns while abnormal returns to biddings' shareholders were not significant. Furthermore, the results suggested that returns to bidders were more positive when the bidder was larger and more efficient. They also found that cross-border mergers did not outperform domestic ones. Finally, there was no significant difference between mergers before the implementation of the EU-second banking directive and those that took place after the implementation.

Cybo-Ottone and Murgia (2000)

Cybo-Ottone and Murgia also employed an event study methodology to examine a sample of 54 very large deals (above $100mn), covering 13 European banking markets of the EU plus the Swiss market, that occurred between 1988 and 1997. It should be noted that the sample is not limited to bank mergers but also contains 18 cross-product deals in which banks expand into insurance or investment banking. The authors found a positive and significant increase in value for the average merger at the time of the deal's announcement. However, the results were mainly driven by the significant positive abnormal returns associated with the announcement of domestic deals between two banks and by product diversification of banks into insurance. Deals that occurred between banks and securities firms and between domestic and foreign institutions did not gain a positive market's expectation.

Huizinga, Nelissen and Vander Vennet (2001)

Huizinga et al. (2001) examined the performance effects of European bank M&As using a sample of 52 bank mergers over the period 1994-1998. The authors first investigated the existence of economies of scale in European banking. They also estimated the level of operational and profit efficiency for the European banking sector and for the banks involved in M&As. In addition, they used the efficiency analysis to reveal information about the ex ante conditions that predict whether a particular merger was likely to yield significant gains. Finally, they investigated whether or not merging banks were able to reap benefits from an increased use of market power on the deposit market. The authors found evidence of substantial unexploited scale economies and large X-inefficiencies in European banking. Comparing merging banks with their non-merging peers, they found that large merging banks exhibited a lower degree of profit efficiency than average, while small merging banks exhibited a higher level of profit efficiency than their peer group. The dynamic merger analysis indicated that the cost efficiency of merging banks was positively affected by the merger, while the relative degree of profit efficiency improved only marginally. Finally, they found that deposit rates tended to increase following a merger, suggesting that the merging banks were unable to exercise greater market power.

Beitel and Schiereck (2001)

In a recent study, Beitel and Schiereck examined the value implications of 98 large M&As of publicly traded European banks that occurred between 1985 and 2000. The perspectives of the shareholders of the targets, the acquirers and the combined, aggregate entity of the target and the bidder were considered. In addition to the entire sample, the authors also examined a number of sub-samples in an attempt to reveal the impact of geographic diversification, product/activity diversification, geographic and product/activity diversification, size, and time period on the abnormal returns. Furthermore, they also examined the deals between 1998 and 2000 using ordinary least square (OLS) regression analysis.

The authors report that for the entire sample the shareholders of targets earned significant positive cumulated abnormal returns in all intervals studied, while the shareholders of the bidding banks did not earn significant cumulated abnormal returns. From a combined view of the target and the bidder, European bank M&As were found to significantly create value on a net basis. Beitel and Schiereck argue that given the insignificant results for the bidding European banks the manager-utility-maximization hypothesis and the hubris-hypothesis cannot be supported in the case of Europe. They mention structural differences between Europe and the US such as the legal frameworks and the corporate governance structure of banks as the potential reasons of these differences between EU and US. Nevertheless, while examining the most recent deals that occurred between 1998 and 2000, they found significant negative cumulated abnormal returns and argue that it could be explained as a shift in these "European results". The results of the sub-sample analysis can be summarised as follows: (1) Cross-border bank-bank transactions with a European focus significantly destroy value; (2) M&As leading to "national champions" that aim at maintaining the existing market power in known markets and thus with a narrow geographic focus are valued higher by the capital markets than growth oriented international transactions that contribute to a single European market; (3) The product/activity diversifying M&As from a target and an aggregate point of view have more favourable value implications than transactions between banks; (4) Deals with targets of a manageable size seem to have a significant positive impact on value.

Beitel, Schiereck, Wahrenburg (2002)

The study of Beitel et al. (2002) builds on and extends the study of Beitel and Schiereck (2001), by examining the same data set but with a different objective. The authors analysed the impact of 13 factors that include relative size, profitability, stock efficiency, market-to-book ratio, prior target stock performance, stock correlation, M&A-experience of bidders and the method of payment on M&A-success of European bank mergers and acquisitions, in an attempt to identify those factors that lead to abnormal returns to target shareholders, bidders shareholders, and the combined entity of the bidder and the target around the announcement date of M&A. To accomplish this task they used dichotomisation analysis with mean-difference tests and multivariate cross-sectional regression analysis.

Their results showed that many of these factors have significant explanatory power, leading the authors to the conclusion that the stock market reaction to M&A-announcements can be at least partly forecasted. More important, the returns to targets' shareholders are higher when the target: (i) is small compared to the bidder; (ii) has a good cost to asset ratio relative to the bidder, and (iii) has a poor past stock performance track record. The abnormal returns to bidders' shareholders are higher when a transaction is more focused and involves targets: (i) with higher growth rates; (ii) with a high market to book ratio, and (iii) less profitable than bidders. Finally, the returns for the combined entity were high for non-diversifying transactions, when the bidder was engaged in relatively few M&A transactions, and when the target exhibited: (i) a high market to book ratio and (ii) a poor past stock performance.

Diaz, Olalla, Azofra (2004)

Diaz et al. (2004) examined the bank performance derived from both the acquisition of another bank and the acquisition of non-banking financial entities in the European Union. The sample consisted of 1,629 banks, where 181 acquisitions were noted over the period 1993-2000. Using a panel data methodology, Diaz et al. (2004) found that the acquirer obtains some efficiency gain in bank mergers. They also found some evidence on the impact of the takeover on the acquirer when acquiring non-bank firms and when the sample was split by type of acquirer (i.e. commercial banks, savings banks, cooperative banks). In particular the results reveal that the acquisitions of financial entities by European banks can increase their profitability. However, a lag of at least two years between the acquisition and the increase in performance was observed. The acquisition of other banks had an effect on acquirers' ROA as was revealed by the increase in the long-term profitability.

Lepetit, Patry, Rous (2004)

Lepetit et al. (2004) examined stock market reactions in terms of changes in expected returns to bank M&As that were announced between 1991 and 2001 in 13 European countries, by distinguishing between different types of M&As. More specifically, M&As were classified into several groups depending upon activity and geographic specialisation or diversification. To overcome some of the limitations of previous event studies they employed a Bivariate GARCH methodology that allows for some beta movements. The results showed that there was, on average, a positive and significant increase in value of target banks, as well as, that the market distinguishes among the different types of M&As. A probit estimation that was used to further explore the sample by crossing the criteria of M&As classification revealed that the combination of activity diversification and geographic specialisation decreased the probability of having a negative abnormal return.

Dunis and Klein (2005)

The underlying approach in the study of Dunis and Klein (2005) was to consider an acquisition as an option of potential benefits. Hence, assuming semi-efficient capital markets, the market capitalisation reflects the market participant's view on the value of those benefits once the merger is announced. In this case, the share price, equivalent to the option, is the cumulated market value of target and acquirer prior to the announcement of the deal terms, while the exercise price is the hypothetical future market value of both companies without the merger. Therefore, the option premium gives the value of this option and should be equivalent to the takeover premium. This call option is in the money if the market value of the merged entity exceeds the expected future market value of the two separate companies. The authors applied this real option pricing theory model to a sample of 15 European bank mergers announced between 1995 and 2000 to examine if these were possibly overpaid. The results showed that the option premium exceeded the actual takeover premium suggesting that, those acquisitions were not on average overpaid. Further analysis, assuming the option premium equalled the takeover premium, showed that either the implicitly assumed volatility was too low, the assumed time to maturity was very short and/or the assumed subsequent market performance was too optimistic.

Chapter 3
Literature Review on the prediction of acquisition targets

3.1 Introduction

This thesis is concerned with the prediction of acquisition targets in the banking sector However, to the author's best knowledge no previous studies have developed prediction models solely for banks, and so the literature reviewed in this chapter deals with the prediction of acquisition targets from the non-financial sector. Over the last thirty years several studies have attempted to develop classification models using publicly available information to predict acquisition targets (Tzoannos and Samuels, 1972; Palepu, 1986; Barnes, 1990, 2000; Zanakis and Zopounidis, 1997; Powell, 2001; Espahbodi and Espahbodi, 2003; Doumpos et al., 2004). Several methods for developing prediction models have been proposed, although multivariate statistical and econometric techniques such as discriminant and logit analyses have dominated the field; and only more recently with the advances in technology and the development of new techniques in other fields such as operations research and artificial intelligence, have researchers begun to develop new prediction models using alternative discrimination approaches. For the purpose of this chapter, we attempt to classify three groups of studies, related to the method employed. The first group includes studies that have employed the statistical technique of discriminant analysis. The second group of studies incorporates econometric models that employ logit analysis. The third group includes recent studies that have utilised non-parametric approaches, and also studies that have developed and compared models using various classification methods, or combined them in an integration model.

3.2 Studies on the prediction of acquisition targets

3.2.1 Statistical Techniques

Simkowitz and Monroe (1971)

Following the pioneering study of Altman (1968) in bankruptcy prediction, Simkowitz and Monroe (1971) were the first to use multiple discriminant analysis (MDA) to address the following questions: (1) What was the financial profile of firms absorbed by conglomerate firms during the period April - December 1968, and (2) Does financial characteristics of the absorbed firms provide a useful criterion for identifying those firms with a high probability of subsequently being acquired by a conglomerate?

Four groups of US firms were used in this study. The first two, considered as part of the analysis sample, consisted of 25 randomly chosen non-acquired firms and 23 firms that were acquired during 1968. This sample was used to develop the discriminant function that separated the acquired firms from the non-acquired firms. The other two groups of firms were used as a holdout sample, in order to test the classification accuracy of the discriminant function. The firms in the holdout sample were chosen with financial characteristics observed over the same time period of study and consisted of 65 non-acquired and 23 acquired firms.

The authors used an iterative process of selecting a set of financial variables to discriminate between groups. Twenty-four variables were initially chosen to provide quantitative measurements covering the following aspects of a firm's financial condition: (1) growth, (2) size, (3) profitability, (4) leverage, (5) dividend policy, (6) liquidity, and (7) stock market variables. Using stepwise discriminant analysis based on a maximisation principle with F-test values as a selection criterion, they reduced their initial choice of 24 to a set of 7 variables that achieved the best discrimination between the acquired and the non-acquired firms in the analysis sample. These seven variables were: (1) Market turnover of equity shares, (2) Price-earnings ratio, (3) Sales volume, (4) Three year average dividend payout, (5) Three year average percentage change in common equity, (6) Dummy variable for negative earnings, and (7) Three year average common dividend divided by common equity from the most recent year.

Their discriminant model classified correctly 77 percent of the firms in the analysis sample. This high classification accuracy is not unusual since the classification is based on the discriminant function derived from the same sample. A more appropriate test of the prediction model is how well it performs in the holdout sample. In this case, their model achieved a classification accuracy of 63.2 percent.

The above analysis assumes that (during the period of investigation) there are specific financial characteristics that permit the discrimination between acquired and non-acquired firms. Simkowitz and Monroe concluded that the following four financial ratios were the most important (based on the standardised coefficients of the discriminant function): (1) price-earning ratios, (2) dividend payout rates, (3) growth rates in equity, and (4) sales volume. In their study, the acquired firms (relative to the non-acquired) were smaller in size, and had lower price-earnings ratios, dividend payout and growth in common-equity.

One can find three limitations in the study of Simkowitz and Monroe. Firstly, their study was limited to conglomerate mergers. Secondly, the developed model was not tested in a holdout sample that relates to a different period rather than the same period used for the development of the prediction model. A different period holdout sample is more appropriate in order to examine the stability of the prediction model over time. Thirdly, it was not tested whether the normalisation of data by industry would add to the discrimination ability of the model.

Tzoannos and Samuels (1972)

Tzoannos and Samuels (1972) also used discriminant analysis to predict corporate acquisitions in the UK. Using a sample of 36 mergers that occurred between July 1967 and March 1968, and 32 companies that were not subject of takeover bids, they attempted to identify the financial characteristics of the type of company that became involved in merger and takeover activity. They used 11 variables as quantitative measurements of various aspects of a firms financial condition and found that the characteristics of the companies taken over (differentiated-from the non-taken-over) were a higher absolute level of capital, a higher rate of increase in the capital gearing, a slower increase in profits, a lower price earnings ratios, a slower rate of increase in dividends and a great variation over time in the rate of dividends. Acquirers were characterised by an above average downward trend in capital gearing, a higher than average increase in profits to capital employed, a higher than average increase in the trend of dividends and a lower absolute level of capital gearing.

From the 30 firms in the bidding sample, 21 were given a probability greater than 0.5, while from the 36 firms in the taken-over sample only 17 were given a probability greater than 0.5. This led the authors to conclude that the bidding firms were predicted with a higher degree of certainty compared to taken-over firms.

The major limitation of their study is that the same set of companies was used for both the estimation and testing of the model, resulting in a potential upward bias in the prediction of the bidding firms. It is obvious that in order to have a more meaningful indication of the models' ability to predict mergers and acquisitions it should be tested on a holdout sample of firms.

Stevens (1973)

In another study of US firms, Stevens (1973) corrected two of the limitations discussed above in Simkowitz and Monroe (1971) study. First, his study was not limited to conglomerate mergers, and second his holdout sample was taken from a different time period than the one used to develop the model. Stevens analysed a group of 40 firms acquired (during 1966) and a group of 40 non-acquired firms, thus making a total of 80 firms for the analysis sample. Unlike Simkowitz and Monroe (1971) who selected their sample of non-acquired firms randomly, Stevens matched the acquired firms to the non-acquired by size.

Stevens initially chose 20 variables to measure firm's liquidity, profitability, leverage, activity, price-earnings and dividend policy to develop a model that discriminated the acquired group from the non-acquired, using multiple discriminant analysis. To overcome potential multicollinearity problems encountered in previous studies that used discriminant analysis (Altman, 1968; Simkowitz and Monroe, 1971), he used factor analysis to reduce the dimensionality of 20 factors to 6 factors that accounted for 82.5 percent of the total variance. Thus, six of the original ratios, one from each factor were used as an input to the model. Finally, the discriminant function was derived based on the following four ratios: Earnings before interest and taxes divided by sales (x_1), Net Working Capital to Assets (x_2), Sales to Assets (x_3), Long Term Liabilities to Assets (x_4), suggesting the following form of the model:

$$Z = 0.108\, x_1 - 0.033\, x_2 + 0.987\, x_3 + 0.111\, x_4$$

The model achieved a total correct classification accuracy of 70% when applied in the same firms that were used for its development. When a split sample validation technique was employed (with half of the original sample used to develop the model and the other half used to test its classification ability) the total accuracy fell to 67.5%. Stevens also attempted a second type of validation to examine the stability of the model over time. He calculated the same ratios for two new samples of 20 firms each, taken from the acquisition years 1967 and 1968, and found that the model achieved 70 percent accuracy, which indicated the model's potential ability to predict over time.

Based on the findings, Stevens argued that financial characteristics alone provided a means by which acquired firms can be separated from others and therefore, no matter whatever the stated motive for merger, financial characteristics were either explicit decision variables or were directly reflected in non-financial decisions for acquisitions. However, it should be noted, as Stevens points out, that the financial ratios that were found to be important in his study were not the same as those found in the Simkowitz and Monroe (1973) study.

Belkaoui (1978)

Belkaoui (1978) was the first to examine the prediction of acquisitions in Canada. His sample consisted of 25 firms acquired between 1960 and 1968 compared with 25 non-acquired industrial firms that were still in existence in 1973. Thus, like Stevens (1973), Belkaoui matched acquired and non-acquired firms by size. Sixteen predictor ratios were calculated for each of the 50 firms and a discriminant function was derived for each of the five years prior to the acquisition. These ratios were: cash flow divided by net worth (x_1), cash flow divided by total assets (x_2), net income divided by net worth (x_3), net income divided by net assets (x_4), long-term debt (plus preferred stock) divided by total assets (x_5), current assets divided by total assets (x_6), cash divided by total assets (x_7), working capital divided by total assets (x_8), quick assets divided by total assets (x_9), current assets divided by current liabilities (x_{10}), quick assets divided by current liabilities (x_{11}), cash divided by current liabilities (x_{12}), current assets divided by sales (x_{13}), quick assets divided by sales (x_{14}), working capital sales (x_{15}), and cash sales (x_{16}).

The correct classification rates for the model were 72%, 80%, 84%,78% and 80%, respectively for the five years prior to the acquisition. To examine the prediction ability of the model, Belkaoui used a holdout sample of 11 acquired and 11 non-acquired firms (chosen from the same time period). The model achieved the following classification rates for years one through five: 70%, 76%, 85%, 76%, 75%, indicating on average slightly lower classification accuracy as expected.

Wansley and Lane (1983)

Wansley and Lane also used discriminant analysis to identify the financial profile of merged firms and predict acquisition targets in the late 1970s. They studied a sample of 44 U.S. acquired firms during the period 1975-1976, and an equal number of randomly selected non-acquired firms. In addition, a holdout sample of 39 merged firms in 1977 was used to test for the predictive power of the model in identifying acquisition candidates.

They considered 20 variables initially, to reelect the following aspects of a firm's financial profile: (1) profitability, (2) liquidity, (3) leverage, (4) size, (5) price-earnings, (6) stock market characteristics, (7) market valuation, (8) growth, (9) activity, and (10) dividend policy. The existence of multicollinearity among the variables led them to investigate the relative importance of individual variables using various approaches examined by Eisenbeis et al. (1973), Karson and Martell (1980) and Mosteller and Wallace (1963) to rank the variables such as the univariate F-test, the scaled coefficients, the Mosteller-Wallace approach of variables selection, and the forward stepwise method. This led to 5 variables finally entered in the discriminant function: natural log of net sales (x_1), market value of share to book value (x_2), three years average growth in net sales (x_3), Long-term debt to total assets (x_4), Price-earnings ratio (x_5), giving the following function

$$Z = 0.0953\ x_1 + 0.2080\ x_2 - 0.8158\ x_3 + 0.5315\ x_4 + 0.0047\ x_5$$

Their model suggests that acquisition targets relative to non-targets were smaller in size, were growing more rapidly, had smaller market value and smaller price-earning ratios, and used less debt. Their classification accuracy was 75% in the analysis sample and 69.2% on the holdout sample.

Rege (1984)

Rege (1984) examined a sample of 165 firms in Canada, consisting of three groups of 55 firms each, the first comprising domestic taken-over firms, the second foreign taken-over firms, and the third non-taken-over firms matched by industry classification, the year of the take-over and asset size. Rege used both univariate and multiple discriminant analyses to test three hypotheses: the *Domestic Hypothesis (DH)*, according to which a foreign taken-over firm can be distinguished from a non-taken-over firm on the basis of liquidation, leverage, payout, activity and profitability; the *Foreign Hypothesis (HD)*, which states that a foreign taken-over firm can be distinguished from a non-taken-over firm on a similar basis-; the *Relative Hypothesis (RH)*, according to which a foreign taken-over firm can be distinguished from a domestic taken-over firm, also on the same basis as the other two hypotheses. Table 3.1 presents Rege's results of the discriminant analysis for all three hypotheses, with two sets of data, from 1962-73 and from 1968.

Table 3.1 – Rege (1984) study-Coefficients of Discriminant Variables

Hypothesis	Liquidity	Leverage	Payout	Activity	Profitability
I 1962-73 Sample					
DH	-0.17	0.38	0.40	-0.54	-0.15
FH	-0.33	0.07	0.56	0.53	-0.02
RH	-0.50	-0.43	0.15	0.14	-0.07
II 1968 Sample					
DH	-0.37	0.41	0.85	0.44	0.10
FH	0.43	-0.06	0.67	0.64	-0.32
RH	1.04	-0.25	-0.00	-0.13	-0.11

The results indicated that the financial characteristics of the firm were not sufficiently significant to discriminate between the three hypotheses, i.e. between either domestic and non-taken-over, foreign and non-taken-over, or foreign and domestic firms. Rege suggested further examination as to whether characteristics based on forecasted data would be more powerful than those based on historical data in locating take-over targets.

Bartley and Boardman (1986)

Bartley and Boardman have used multivariate discriminant analysis to test the hypothesis that the valuation ratio, defined as the market value of the firm divided by the net current value of its individual assets and liabilities, is the main determinant of whether a firm will be an acquisition target or not.

Thirty-three acquired firms were matched with 33 non-acquired firms in 1978 by industry and size of total assets. Seven variables, including the valuation ratio, were selected to measure five financial aspects: performance, leverage, liquidity, profitability and valuation using both replacement cost and historical cost data for their computation. Two variables were measured at two different rates. Price to earnings and valuation ratios were calculated using each acquired firm's stock price eight and twelve months prior to the announcement of acquisition. Five models were developed in the analysis: two using historical cost measures, differing only with respect to the dates for which the price-earnings and valuation ratios were calculated; and two using replacement cost measures of leverage, liquidity, profitability and the valuation ratio for the same two dates. The fifth model was developed using a stepwise procedure. Using both historical and replacement cost measures meant a total of 14 independent variables all together, but only three were finally included in the discriminant function that gave the model the highest classification accuracy, thereby offering a direct comparison of historical costs and replacement cost measures.

The fifth model had the following form:

Z = 0.63 Valuation + 0.48 Historical Cost Leverage – 0.61 Replacement Cost Leverage

where:

Valuation = Total market value of Common Stock / Stockholders' Equity plus Total Replacement cost adjustment

Historical Cost Leverage = Total debt / Stockholders' equity

Replacement Cost Leverage = Total debt / Stockholders' equity plus Total Replacement cost adjustment.

The classification accuracy of the model was tested using a one-at-a-time holdout procedure described by Lanchenbruch (1967, 1975). This approach can be described as follows: One observation is omitted at a time, while the remaining are used for estimating the discriminant model. Then the omitted observation is classified using the previously developed model. The above steps were repeated until 66 models were estimated. After all replications were performed, an unbiased estimate of the true classification rate was obtained as the average accuracy of all discriminant models estimated. The classification accuracy of the fifth model was 64%.

Bartley and Boardman (1990)

In a latter study Bartley and Boardman (1990) also used multivariate discriminant analysis to determine whether current and historical cost data combined with real (constant dollar) financial accounting data had the potential to improve the predictive ability of models classifying firms as takeover targets. In addition, the authors introduced three innovations. First, unlike most of the previous studies, they used financial data from one year (1979) to classify companies based on takeover attempts during a period of three years suggesting that "*most of prior studies have identified companies that were takeover targets during a single year and then obtained financial data from the financial statements immediately preceding the date of the takeover*"…" *By examining a period as short as one year, some companies are included in the nontarget group even though they have the characteristics of a target company and actually become targets shortly after the classification period*". Second, while most prior studies (with the exception of Hasbrouck (1985) and Bartley and Boardman (1986)) were based on whether a takeover was successful or not in order to classify the company as a target or nontarget, Bartley and Boardman (1990) studied takeovers irrespective of their ultimate outcome. The authors argued that there are other exogenous factors affecting whether a takeover attempt will be successful or not, such as managerial resistance, size of the bid premium etc. Furthermore, investors can earn abnormal returns from predictions of takeovers attempts regardless of their success, as the abnormal returns is observed around the announcement date and not the completion date of the deal. Thirdly, based on evidence that positive abnormal returns were produced by investment attempts for as little as 5% of a company's outstanding stock (Bradley et al, 1983; Harris and Risk, 1983), the authors decided to include all companies that were subject to investment attempts exceeding 5% of ownership in the target group, unlike prior studies which included only investments of more than 50% in their target group.

The authors examined a sample of 41 targets, which were subject of a takeover bid during the period 1979 to 1981, combined with 153 nontargets, in the US. Several variables representing performance, earning power, long-term solvency, short-term solvency and other characteristics were used to develop three models, based on Historical Cost (HC), Current Cost (CC) and Constant Dollar (CD) data respectively, as well as a fourth model that combined these measures. Because of the large number of variables that could potentially enter a model, they used a stepwise MDA method to reduce the number finally entering each model. Thus, of the 26 variables, only 12,11,10 represented the HC, CC and CD models respectively, while 18 entered the combination model. Interest coverage, growth rate of sales and total market value were important discriminating factors, and target companies were found to have lower interest coverage, higher growth rates and smaller size, compared to non-targets.

The classification ability of the models was tested using the Lachenbruch method. They obtained classification accuracies between 69.9% (HC model) and 79.9% (combination model) using equal prior probabilities. They argued that "*because the target and nontarget groups are greatly unequal in number, the use of actual prior probabilities would result in a large percentage of the sample companies being classified as nontargets irrespective of the statistical fit of the model. The high prior probability of a company being a nontarget could overwhelm subtle difference in the accuracy of the alternative sets of accounting data. The solution to this problem is to compare classificatory accuracy using equal prior probabilities*". Nevertheless, the authors also tested their model using actual priors for a preliminary sample of 233 companies in which 24% were targets and 76% were no-targets. Almost all models (with the exception of the HC models) were found to be more accurate than a benchmark proportional chance model based on actual priors that classified correctly 65% of the firms in the sample. In the case of the combination model, the total classification accuracy was as high as 82.5%.

Barnes (1990)

Barnes used a sample of 92 targets, subject of successful takeover bids of UK quoted companies in 19 industries over the period 1986-87, and 92 nontargets matched by industrial sector and market capitalization prior to the merger period, in an attempt to develop a model that would predict acquisition targets in the UK.

Nine financial ratios were obtained for each company for two years prior to the merger. For each of these 9 ratios, the "*industry-relative ratio*", defined as "*the ratio between it and the relevant sector average*" was used to avoid the stability problem across industries. Furthermore, factor analysis was used to reduce the effects of multicollinearity and overlapping of the 9 ratios and five factors where found to explain 91.48% of the variance in the original data matrix. The following five ratios were chosen to represent the five factors and used as inputs in the multiple discriminant model: Quick Assets divided by Current Liabilities (x_1), Current Assets divided by Current Liabilities (x_2), Pre-tax Profit Margin (x_3), Net Profit Margin (x_4), and Return on Shareholder's Equity (x_5).

Barnes (1990) discriminant model had the following form:

$$D = -1.91218 + -1.61605\, X_1 + 4.99448\, X_2 + 1.11363\, X_3 - 0.70484\, X_4 - 0.11345\, X_5$$

The classification accuracy of the model was 68.48% when tested on the analysis sample, but this increased to 74.3% in a holdout sample of 37 acquired and 37 matched, non-acquired companies. The holdout sample, however, was from the same period as the one used for the development of the model. Barnes argued that the reason for not using a holdout from a subsequent period was that it coincided with the collapse of the stock markets that brought an immediate halt to the merger activity that could potentially lead to a misleading evaluation of the model.

Kira and Morin (1993)

Following up earlier studies of Canada (Belkaoui, 1978; Rege, 1984), Kira and Morin (1993) selected a sample of 34 public Canadian firms acquired during 1990 and matched them with 34 non-acquired firms by industry and market capitalization.

Ten financial ratios were selected, calculated for the year prior to the takeover for each company. As in Barnes (1990), data were normalised prior to the analysis using the industry-relative technique employed by Platt and Platt (1990). Then, factor analysis was performed to extract 5 factors explaining 88.1% of the variation in the data set. The following five industry-relative ratios were finally used in the discriminant analysis: Quick Ratio (QR), Net Profit Margin (NPM), Return on Equity (ROE), Debt/Equity (D/E), Sales / Assets (S/A).

Their discriminant function has the following form:

$$D = -0.52445\, QR + 1.84699\, NPM + 1.58662\, ROE + 1.30537\, D/E$$

with the S/A ratio not being statistically significant and therefore not included in the function. By contrast, the D/E and QR ratios were the most significant discriminating variables (high D2), the former having the higher sensitivity of the two (i.e. largest absolute standardised coefficients).

The classification accuracy was 79.4% and 82.4% for the targets and non-targets respectively, with an overall accuracy of 80.77%. The jackknife method was then used to test the validity of the model; the classification accuracy achieved using this method was reduced to 64.7% and 67.6% for the targets and non-targets accordingly, with an overall accuracy of 66.17%. The authors concluded that despite some limitations of their study, takeover targets were predictable one year prior to the takeover using historical financial data with some degree of accuracy.

3.2.2 Econometric Techniques

Harris, Stewart, Carleton (1982)

Harris et al. (1982) were the first to introduce probit analysis to study the financial characteristics of acquired firms and to predict future corporate acquisitions in the US. Instead of using equal-sized samples of acquired and non-acquired firms, they used data reflecting the percentage of acquired and non-acquired firms in the population.

The sample used in their study consisted of manufacturing firms, of which 45 were acquired during the period 1974-1975, 61 were acquired during 1976-1977, and approximately 1,200 non-acquired firms traded as of May 1979. The data for all these firms were included in the COMPUSTAT database. Seventeen variables measuring aspects of firm liquidity, indebtedness, profitability, activity, internal versus external financing, dividend policy, price-earnings ratio, size, valuation plus two "additional variables", normalised by industry averages, were used to estimate various specifications of the probit model.

Despite estimating probit specifications with significant explanatory power, suggesting measurable characteristics that could affect the probability of acquisition, none were satisfactorily capable of providing substantive discriminatory power. The models for the years 1976-1977 reported extremely low probabilities of acquisition assigned to acquired firms. More specifically, the probit model predicted that, on average, 6.62% of the firms with the characteristics of the mean acquired firm would be acquired. Similarly, the model covering the period 1974-1975 predicted that, on average, 4.43% of firms with the characteristics of the mean acquired firms would be acquired. Based on these results, Harris et al. did not explore further the prediction ability of their model, arguing that "*Given our results, however, there does not appear to be a sound basis for out-of-sample attempts at predicting mergers based on the variables studied here*" (p. 239).

It could be argued that the small discrimination ability of their model is partly due to the sample they employed in their study. A sample comprising roughly the same ratio of acquired to non-acquired as in the population may be appropriate for testing the predictive ability of the model, however, as Palepu (1986) argues, the "information content of such a sample for model estimation is quite small, leading to relatively imprecise parameter estimates".

Dietrich and Sorensen (1984)

Dietrich and Sorensen (1984) were the first who applied logit estimation to predict the probability that a given firm will be a merger target. They selected a total of 106 firms from four industries: food and beverages, chemicals, electronics, and transportation. However, after eliminating 17 firms due to missing data, the sample used in their study comprised 30 firms acquired in the years 1969 to 1973, and 59 randomly selected non-acquired firms matched by industry and year. Their selection criterion was to ensure that firms in the non-merged sample were not mergers targets for a two-year period immediately after the 1969 to 1973 period. Thus, 24 of the acquired firms and 43 of the non-acquired, randomly selected firms were finally used in estimating the logit model. The remaining firms were used as a holdout sample for prediction testing.

Apart from their choice of logit estimation, Dietrich and Sorensen emphasized the selection of financial variables with regard to their potential impact on a net present value (NPV) basis. The use of this principle suggests that factors (or variables) tending to increase the NPV of cash flows of a potential target were expected to increase the attractiveness of a particular merger candidate, while factors increasing the cash outflows associated with a merger were expected to reduce its attractiveness. All variables relating to the non-merged firm's characteristics over the five-year period were calculated as a five-year average departure from the mean value for all non-merged firms in the sample (from the same industry over the same period). The variables reflecting the characteristics of merged firms were expressed as percent departures from the average performance for the industry in the last year for which data for the merged firm were available.

Table 3.2 presents their estimated results. Model 1 shows the estimates of all the variables, including those that are individually insignificant although overall the model is statistically significant at the 0.01 level and capable of predicting correctly 92.54% of the firms in the holdout sample.

Table 3.2 - Dietrich and Sorensen (1984) study -Logit Estimation Results

Variables	Coefficients – Model 1	Coefficients - Model 2
Price Earnings	0.43	-
Profit Margin	0.35	-
LT debt / Total Assets	-3.37[d]	-1.33[d]
EBIT / Interest Payments	-1.38	-
Dividends / Earnings	-0.81[b]	-0.74[a]
Capital Expenditure / Total Assets	-0.24	-
Sales / Total Assets	-14.80[a]	-11.64[a]
Current Ratio	2.24	-
Market Value of Equity	-7.24[b]	-5.74[a]
Trading volume in the year of acquisition	4.15[c]	2.55[c]
Constant	-14.36[b]	-10.84[a]

[a] Variables statistically significant at the 0.01 level, [b] Variables statistically significant at the 0.05 level
[c] Variables statistically significant at the 0.10 level, [d] Variables statistically significant at the 0.20 level

The authors tested further the sensitivity of the model by re-estimating it to exclude all the variables not found to be significant in the first model. The prediction ability of Model 2 using a holdout sample of 22 firms showed that it correctly classified approximately 91% of the target and non-target firms in the sample. These findings imply that the probability of a firm being acquired increased as dividend payout, turnover, size and leverage decreased, and activity increased.

Palepu (1986)

The study of Palepu (1986) is well known for providing a critique of the procedures followed by earlier studies. Palepu identified three methodological flaws that made previously reported prediction accuracies unreliable: (1) the use of non-random equal size target and nontarget samples for estimation leads to biased or inconsistent estimates of the acquisition probabilities, unless appropriate modification is made to the estimators, (2) the use of equal-size samples in prediction tests leads to error rate estimates, which fail to represent the model's predictive ability in the population, and (3) the use of arbitrary cut-off probabilities in prediction tests make the computed error rates difficult to interpret.

The author attempted to correct the above methodological problems by (1) applying the appropriate estimation procedure that accounted for the sampling scheme employed, (2) conducting prediction tests on a group of firms, which approximated the population over which the model would be used in a realistic forecasting application, and (3) testing the predictive ability of the model in the context of a specific forecasting application, using the relevant payoff function and prior probabilities to determine the optional cutoff probability in the prediction tests.

Palepu used a sample of 163 firms acquired between 1971-1979 and 256 non-acquired firms (as of 1979) from mining and manufacturing industries to estimate four different logit models with various independent variables (see Table 3.3). The independent variables were chosen on the basis of the following six hypothesis suggested in the literature, as likely reasons for companies to become acquisitions targets: (1) inefficient management hypothesis (i.e. firms with inefficient management are likely acquisition targets), (2) growth-resources imbalance hypothesis (i.e. firms with a mismatch between their growth and the financial resources at their disposal are likely acquisition targets), (3) industry disturbance hypothesis (i.e. firms in an industry that is subjected to economic shocks are likely acquisition targets), (4) size hypothesis (i.e. the likelihood of acquisition decreases with the size of the firm), (5) market to book hypothesis (i.e. firms whose market values are low compared to their book values are likely to be acquisition targets), and (6) price-earnings hypothesis (i.e. firms with low price earnings ratios are likely acquisition targets).

Table 3. 3 - Estimates of Palepu's (1986) logit acquisition likelihood models

Variables	Model 1	Model 2	Model 3	Model 4
Average Excess Return	-1.332 ^{a}	-1.338 ^{a}		
Return on Equity			0.003	0.005
Growth-Resource dummy	0.5467 ^{a}	0.4432 ^{b}	0.4616 ^{a}	0.4024 ^{b}
Annual rate of Change in the firm's net sales		- 0.0245 ^{a}		-0.0261
Net Liquid assets/ Total assets		-0.005		-0.008
Long Term Debt / Equity		-0.0035 ^{a}		-0.0034 ^{a}
Industry dummy	-0.7067 ^{a}	-0.6900 ^{a}	-0.5802 ^{a}	-0.5608 ^{a}
Total net book value of a firm's assets	-0.0005 ^{a}	-0.0005 ^{a}	-.00004 ^{a}	-0.0004 ^{a}
Market value of the common equity / Book equity	-0.0044	0.0117	-0.0051	0.0126
Price-earnings ratio	0.0065	0.0099	0.0031	0.0041
Constant	-2.1048 ^{a}	-2.1096 ^{a}	-2.1533 ^{a}	-2.1898 ^{a}

^{a}Significant at the 0.05 level, two tailed-test, ^{b}Significant at the 0.10 level, two tailed-test.

Table 3.3 shows the parameter estimates of the four different versions of the model. Model 1 is estimated with six variables, corresponding to the six hypotheses listed above. Model 3 differs from model 1 only by the use of return on equity instead of average excess return. Models 2 and 4, are simply re-estimates of models 1 and 3, respectively, with the inclusion of three additional variables measuring growth, liquidity and leverage. Although all models are statistically significant their explanatory power is small. Model 2 has the largest explanatory power and was used for further analysis. The predictive ability of the model was tested on a holdout group of firms consisting of 30 targets and 1087 non-targets. The model correctly identified a high percentage of actual targets, since from the 30 firms in the group that were actually targets, 24 (or 80%) were accurately predicted. But the model also erroneously predicted a large number of non-targets as targets, since from the 1087 non-targets only 486 (45%) were correctly predicted. Palepu also examined the possibility of earning abnormal returns from investing in the stocks of predicted targets. Unsurprisingly, the large number of firms erroneously classified as targets significantly reduced the overall economic usefulness of the model's prediction. On this basis, the author concluded that the model did not predict non-targets accurately and that the estimated model's ability to predict targets was not superior to that of the stock market.

However, there are possible explanations for the poor results of Palepu's study. First of all, the set of independent variables used is not exhaustive, there being only six variables based on six hypotheses supposed to affect the acquisition likelihood. The literature is inconclusive as to what are the main determinants of mergers and acquisitions (Ali-Yrkko, 2002). Second, Palepu defined as observation year (in the case of target firms) the year in which they were acquired while he defined 1979 as the observation year for all non-acquired firms. By following such a procedure, the author did not consider the problem of the potential instability of financial ratios over time and assumed that the value for a given variable remained constant across years (1971-1979). It should be obvious that a value for a variable in year 1979 need not necessarily be the same as for the year 1971 when an acquirer makes the decision to acquire firm X instead of firm Y. As Barnes (1990) correctly points out, it is unreasonable to expect the distributional cross-sectional parameters of financial ratios to be stable over time due to inflationary effects, technological and numerous other reasons, such as changing accounting policies. It is therefore important to ascertain as far as possible that the years of observation be the same for acquired and non-acquired firms.

Ambrose and Megginson (1992)

Ambrose and Megginson (1992) extended the logit model model of Palepu (1986) using a larger sample of target and non-targets firms, over the period 1981-1986. Despite having a broader coverage compared to the mining and manufacturing firms used by Palepu (1986), their sample selection criteria, however, excluded public utilities and financial firms. They found that the explanatory power of the Palepu model was much reduced when re-estimated over their sample, reporting that "*none of the variables in the Palepu update were significant and the overall model had negligible explanatory power and was not significant*". They extended Palepu's models by adding more variables, such as insider and institutional shareholdings, the importance of tangible assets in a firm's production process and the presence of formal takeover defences. The results of their estimations are presented in Table 3.4.

Table 3.4- Estimated coefficient values of Ambrose & Megginson (1992) models

Variables*	Model 1	Model 2	Model 3
Intercept	-1.058	-1.109	-1.096
Average Excess Return	-22.007	-13.215	-3.796
Growth-resource dummy	-0.072	-0.048	-0.098
Growth	-0.540	-0.516	-0.585
Liquidity	0.050	0.111	0.098
Market-to-Book ratio	0.020	0.025	0.026
Price-Earnings ratio	-0.0017	-0.0012	-0.0015
Size	-0.0001	-0.0001	-0.0001
Tangible (Fixed) Assets to Total Assets	0.914	0.999	1.022
% of Institutional Investor Shareholdings	0.0030	0.034	0.466
Change in Institutional Shareholdings	-6.7488	-3.815	-6.103
% of officer and director shareholdings	0.3273	0.330	0.195
Poison Pill	-	-0.226	-0.268
Anti-takeover Charter Amendments	-	-0.120	-
Classified Boards	-	-	0.238
Fair-Price Requirements		-	-0.695
Voting Rights	-	-	2.246
Supermajority requirements	-	-	0.515
Black-Check Preferred-Stock Authorizations	-	-	-1.053
Dual-Class Recapitalisations		-	-0.068
No of Observations (no of targets in parentheses)	331 (117)	327 (115)	327 (115)

* For details on the calculations of the variables the reader is referred to the original article, Table 2, page 579

The only model that is statistically significant is model 3 (with a chi-square value of 33.22 (p-value = 0.016), and a high explanatory power, given by a likelihood ratio index of 0.078). The results of this study shows that the probability of receiving a takeover bid is positively related to tangible assets, and negatively related to firm size and the net change in institutional holdings. Blank-check preferred stock authorisations are the only common takeover defence, being significantly (negatively) correlated with acquisition likelihood. The authors did not provide information regarding the classification accuracy of their model.

Walter (1994)

The study of Walter (1994) is one of the few that have tested the ability of the model to earn abnormal returns and hence is useful for an investment strategy that aims to "beat the market" and earn abnormal returns. Walter estimated two logit models, one with current cost (CC) data and another with historical cost (HC) data. In both cases, data were averaged over a two-year period and standardised by industry average. A total of 11 independent variables were constructed, including nine quantitative financial ratios and two categorical variables. Each one was associated with a different characteristic hypothesised to be related to acquisition likelihood. The models were estimated using a sample of 33 firms acquired over the period 1981 to 1984 and 274 non-acquired firms, using a backward stepwise technique. The models were then tested in a holdout sample of 10 companies acquired during 1985 and 81 non-acquired companies. The HC model classified correctly 60% of acquired firms and 74.1% of non-acquired while corresponding accuracies for the CC model were 40% and 69.1%. The predictions were then used to form two portfolios, for which the 250-day portfolio cumulative abnormal returns were calculated. The historical cost portfolio under-performed both the current cost portfolio and the entire prediction sample. The current cost portfolio on the other hand earned a statistically significant abnormal return compared to the prediction sample consisting of 9.2% of the population of firms that disclosed current cost data, but the model could only barely outperform the entire population of firms in the database irrespective of whether they disclosed current cost data or not.

Walter's study is interesting for three reasons. First, he used industry relative ratios, in an attempt to enhance comparability and the stability of the model. Second, he compared historical with current cost data, adding to the limited studies that had examined this issue. Third, he actually tested the ability of the model to earn abnormal returns, this being another issue that had received little attention in the literature. The only drawback of his study is the small sample size that was used for the acquired firms both in the estimation (33 firms) and the testing sample (10 firms). As Walter points out, this limits the generalisability of the findings (Walter, p. 375).

Meador, Church and Rayburn (1996)

Meador et al. (1996) also used logit analysis to examine the US case. The innovation in their study was the development of models to examine separately horizontal and vertical mergers. The authors collected data for 100 acquired firms, 50 horizontal and 50 vertical mergers, completed between 1981 and 1985 that were matched (using asset-size and industry) by an equal sample of 100 non-acquired firms. After removing firms with missing data and their matching counterparts, the final sample used for estimation consisted of 160 firms.

Drawing upon previous studies, variables representing liquidity, profitability, size, leverage, activity, growth, price-earnings, stock market characteristics, market valuation and dividend policy, were chosen. Stepwise Binary Logit regression was then used to for the whole sample as well as for the horizontal and vertical sub-samples of merged companies. Table 3.5 shows the results.

For the combined sample the prediction accuracy was 63.75% and the overall model was significant at the 1% confidence level. However, only the variables Long Term Debt to Total Assets and Long Term Debt to Market Value were significant (at the 5% and 10% level respectively).

Table 3.5 – The logit models of Meador et al. (1996)

Variable	Coefficients		
	Total	Horizontal	Vertical
MT[1]	0.060	-	-
Cash available + marketable securities (CA)	0.011	0.044	0.000
Current Ratio (CR)	-0.066	-0.321	0.354
Net Working Capital / Total Assets (WTCA)	1.472	4.594	1.833
Net Working Capital / Sales (WCS)	-0.627	-5.062	-2.843
Earnings Before Interest and Taxes (EBITS)	4.593	7.458	-1.113
Net Income / Total Stockholders Equity (ROE)	-6.950	-9.868	-10.424
Net Income / Total Assets (NIA)	0.670	5.036	8.160
Net Sales (NS)	-0.000	-0.003	0.000
Total Assets (TA)	0.000	0.003	-0.002
Long Term Debt / Total Assets (LDTA)	9.857*	20.367*	4.760
Long Term Debt / Net Stockholders Equity (LDSE)	-0.461	-1.116	-0.416
Total Liabilities / Total Assets (TLTA)	-3.933	-7.523	0.602
Long Term Debt / Market Value of Equity (LDMV)	-0.928**	-1.711*	-0.402
Sales / Total Assets (STA)	0.454	0.178	-0.378
Costs of Goods Sold / Inventory (CGSI)	0.049	0.046	0.055
2 Year Growth in Sales (SGR)	0.000	0.013**	0.003
2 Year Growth in Assets (AGR)	-0.002	-0.027**	0.006
2 Year Growth in EPS (EPSGR)	0.155	0.054	0.232
Market Price / EPS common (PE)	0.001	0.010	0.000
Common Shares traded / Common Shares Outstanding (CTSO)	0.462	1.547	0.454
Market Price per share / Book Value per share (MVBV)	-0.453	-1.122*	-0.143
2 Year percentage change in share price (SPGR)	-0.001	0.001	-0.000
Cash Dividends common / Earnings Available to common shareholders (DPCS)	-0.150	-0.634	1.784**
Intercept	0.287	2.119	-1.188
Prediction (Percent Correct)	63.75	78.21	67.07

[1]The authors do not provide any information about this variable but is presumed to be a dummy distinguishing the two types of mergers
*Significant at 95%, ** Significant at 90%

The model for vertical acquisitions showed a higher predictive ability (67.07% overall) and was significant at the 1% level, but with only one variable, dividend policy to common shareholders, significant at the 10% confidence level. Finally, the model for horizontal acquisitions showed the highest predictive ability (78.21% overall). This model also has more significance, with Long Term Debt to Total Assets, Long Term Debt to Market Value of Equity and Market Value to Book Value per share all significant at the 5% confidence level, and furthermore, Asset Growth and Sales Growth, also found to be significant at the 10% confidence level. The classification accuracy of this model was also tested using a holdout sample consisting of 10 firms merged in 1986, 12 firms merged in 1987 and 10 non-merged firms. Although the model correctly predicted 19 of the 22 merged firms (86.36%), it classified correctly only 3 of the 10 non-merged firms (30%). Based on the finding that the model predicted better horizontal rather than vertical M&As, the authors concluded that future studies should consider these types of business combinations as well as the role of qualitative variables on the acquisition decision.

Powell (1997)

Powell's study had three specific purposes. First, to explore the potentially separate roles for the characteristics of the firm and those of the industry to which that firm belongs to in understanding the takeover likelihood of a firm. Second, to investigate whether the various models of takeover likelihood developed were robust over time. Third, and probably most interesting, to investigate whether segregating targets into those subject to hostile bids and those subject to friendly bids improved models of takeover likelihood.

Powell used a sample of 411 targets and 532 non-targets over the period 1984-1991 and employed a multivariate logit probability model for estimation. In contrast to studies that initially chose a large set of variables that were consequently reduced using factor or stepwise procedures (e.g. Wansley and Lane, 1983; Barnes, 1990), Powell based his selection of variables on takeover theories, hence following the approach of Palepu (1986), Ambrose and Megginson (1992) and others. Eight variables were selected corresponding to six takeover theories noted earlier (i.e. replacement of inefficient management, firm undervaluation, free cash flow, firm size, real property, growth-resource mismatch). These variables were: accounting rate of return (x_1), market to book ratio (x_2), operating cash flow divided by total assets (x_3), log of total assets (x_4), tangible fixed assets divided by total assets (x_5), average sales growth (x_6), cash and marketable securities divided by total assets (x_7), and debt divided by the sum of total share capital and reserves (x_8).

Powell estimated four logit models to achieve the three specific purposes highlighted above. Most notable, the specifications and samples used sought to distinguish between the models as to whether they aggregated targets into a single group or treat hostile and friendly targets as separate, and whether raw or industry relative variables were used. The estimation sample, for example, consisted of a pooled sample of targets and non-targets drawn from the period 1984-1991, which was then sub-divided into two sub-samples: one drawn from the period 1984-1987 and another drawn from the period 1988-1991. A noteworthy aspect related to the sample of data is that Powell reconstructed as near as possible the true historical populations of firms, thus addressing the criticisms of previous studies that suffered from survivorship bias.

There are four main contributions of Powell's study, according to Thomas (1997). First, it confirmed, for the UK, some of the findings of Morck et al. (1988) that examined the US case. Second, it also confirmed that, as in the US, the characteristics relating to the takeover likelihood of firms in the UK are not robust over time. Third, the study revealed that the industry characteristics of a firm that is taken over could play a separate role (from the characteristics of the firm itself) in explaining the takeover likelihood of that firm. Fourth, and most interesting, the results provided evidence that hostile and friendly targets are viewed differently. Thus, the study provided a new insight that treating friendly and hostile takeovers as belonging to a single homogenous group of takeovers can produce misleading inferences about the effect of firm and industry characteristics on takeover likelihood.

Unfortunately, Powell does not provide any indication of the predictive ability of the developed models, using either the holdout sample or the estimation sample. In addition, Thomas (1997) highlighted the need for a statistical test before one could be confident that there is any temporal variation in the characteristics of those firms that are taken over. He also raised the issue of distinguishing between takeover bids and completed takeovers that were used interchangeably in the study of Powell.

Barnes (1998)

Another interesting study by Barnes (1998) examines several issues using a sample of UK firms: First, the author develops and compares industry-relative models and industry-specific models. Second, he examines whether the inclusion of anticipated share price changes as an input in regression would improve the predictive accuracy of the models developed using accounting data alone. Third, Barnes examines the following three alternative methods to determine the cut-off points when using a logit model: (1) a weighted cut-off point based on historical experience, (2) a cut-off based on the minimisation of errors estimated form the period used for models' estimation and (3) a cut-off based on the maximisation of returns.

Forty-two variables corresponding to three hypotheses of takeover likelihood (inefficient management, growth-resource mismatch, and size) were initially considered. Of these, the following 17 were finally selected taking account of possible multicollinearity problems (variables with correlations above 0.65 were dropped) while retaining full representation of the hypotheses: profit before tax divided by sales (x_1), profit before tax divided by shareholder's equity (x_2), growth of profit before tax over last 3 years (x_3), price (2 months before) divided by earnings (x_4), average divided for last 3 years divided by shareholders' equity (x_5), dividend growth over last 3 years (x_6), market capitalization divided by shareholders' equity (x_7), sales divided by total assets (x_8), total remuneration divided by sales (x_9), sales growth over last 2 years (x_{10}), sales growth over last 3 years (x_{11}), current assets divided by current liabilities (x_{12}), (current assets less current liabilities) divided by total assets (x_{13}), long-term debt divided by total assets (x_{14}), (profits before tax plus interest paid) divided by interest paid (x_{15}), long-term debt divided by shareholders' equity (x_{16}), market capitalization 2 months before the bid (x_{17}).

Four models were estimated in total. The first model, referred as the non-share price model was estimated across all industrial classifications based on industry relative ratios using the full set of 17 variables above. The second model included the effect of anticipatory share price changes (x_{18}) in addition to the 17 variables of the first model. The third and fourth models are simply the first two models re-estimated for each of the two industrial sectors (determined according to the first two digits of the SIC).

The estimation sample consisted of a group of firms that were the subject of both successful and unsuccessful bids during 1991-1993. As the population of some sectors was small the industry-specific models were estimated over the period 1991-1993 using a sample size of 323 bids in total. The general model was estimated using data from 82 targets that were the subject of a bid during 1993 matched with 82 non-targets. A holdout sample of 1185 UK quoted companies (as at January 1st 1994 of which 16 experienced a takeover bid during 1994) was used to test the predictive ability of the general models. In the case of the industry specific models the holdout sample was reduced to 874 non-targets and 13 targets.

The results of this study can be summarised as follows: First, in the first two models (i.e. both the general non-share price and the share price models), four variables (x_1, x_2, x_9, x_{10}) were significant, indicating that profitability, sales growth and shareholders' equity were the important discriminatory factors. Second, the difference between the likelihood values of these two models was negligible, implying that that the addition of the anticipated share price did not improve the goodness of fit (i.e. the effect of adding the latter variable (x18) in the second model was not significant and the predictive accuracy was only minutely improved). Third, the general model performed better than the industry-specific models in terms of overall classification (both targets and non-targets). However, none of the models was successfully in identifying targets. Fourth, predictions could not be significantly improved by the choice of cut-off point, as they were not sensitive to it, especially as it concerns the number of successful target predictions that is necessary to generate the excess returns.

Kim and Arbel (1998)

Kim and Arbel (1998) also used logit analysis but differentiated their study by focusing on the hospitality industry. A sample of 38 hospitality firms that were merger targets during the period 1980-1992, were combined with a sample of 78 firms that were not merger targets as of 1992, to develop their models.

They identified nine independent variables (see Table 3.6) as proxies for the following nine hypotheses suggested by the literature as reasons for M&As: (1) The firm size hypothesis, (2) The inefficient management hypothesis, (3), The financial leverage hypothesis, (4) The liquidity hypothesis, (5) The growth-resources imbalance hypothesis, (6) The relative capital expenditure hypothesis, (7) The dividend payout hypothesis, (8) The stock market trading volume hypothesis, and (9) The asset undervaluation hypothesis.

Among several models they estimated the best one predicted correctly 76% of the firms. Table 3.6 shows the variables used and the coefficient estimates of this model. Four variables, price-to-book ratio, growth-resource imbalance dummy, firm size and capital expenditure ratio were found to be significant in predicting which hospitality company is likely to become a merger target. With the exception of size, the remaining three variables were significant at the 5% level or better.

Table 3.6 - Kim and Arbel (1998) Logit Model

Variable	Coefficient Estimate
Size (log of sales)	0.34*
Asset Turnover	-0.39
% Average trading volume to shares outstanding	-0.01
Dividend Payout ratio	0.005
Price-to-Book ratio	-0.48***
Leverage (Long-term debt / equity)	-0.05
Growth-resource imbalance (dummy variable)	1.47**
Liquidity (current ratio)	-0.16
Capital Expenditure	5.20**

*Significant at 10% level, **Significant at the 5% level, ***Significant at the 1% level

The predictive ability of the model was also tested in a holdout sample of 14 targets and 31 non-targets. From the 14 targets, 11 firms (79%) were predicted correctly; while from the 31 non-targets 23 (74%) were correctly classified as non-targets. The authors compared their results with the model of Palepu (1986), which had significantly lower predictive ability (around 46%). However, despite their high classification accuracy the authors concluded that because of the low likelihood ratio (the pseudo R^2 which was 0.28), the model could be used only as a supplementary decision-supporting tool and suggested the use of additional information and judgment. The main reason for this was probably the fact that other characteristics not reflected in the nine financial characteristics used in their study, play important roles in mergers.

Cudd and Duggal (2000)

Cudd and Duggal replicated the study of Palepu (1986) for a latter period in order to re-investigate (1) the usefulness of the six acquisition hypotheses in predicting takeover targets, and (2) the importance of using industry-specific distributional characteristics in determining classification accuracies.

A sample of firms acquired between 1988-1991 and a random sample of firms not acquired as of 1991 were used for the estimation of the acquisition model. After randomly selecting a group of non-acquired firms and screening for data availability, their final sample consisted of 108 acquired and 235 non-acquired mining and manufacturing firms listed either on the American Stock Exchange or the New York Stock Exchange. A holdout sample consisted of 13 firms acquired in 1992 and 460 non-acquired firms.

The authors used the same variables as in Palepu (1986) to generate three models, with coefficient estimates shown in Table 3.7. The first model (Model 1) applied Palepu's financial variables unaltered as defined in Palepu's study. The second model (Model 2) applied an adjustment factor to the financial variables to capture the distributional effects unique to each firm's industry. Previous studies in acquisition prediction that used industry relatives calculated the adjusted ratios by simply dividing the value of the ratio with the corresponding average value of the industry. Cudd and Duggal followed a different procedure by calculating the adjusted ratios as follows: $D_i = (R_{ij} - N_j)/\sigma_j$ where: R_{ij} is the value of the financial ratio of firm i in industry j, N_j is the industry average financial ratio value of industry j, σ_j is the standard deviation of R_{ij} values within industry j, and D_i is the adjusted financial ratio deviation from the industry norm for firm i. The third model (Model 3) was identical to Model 2 but with the disturbance variable redefined to reflect acquisition activity occurring during the 12 months immediately preceding the month of acquisition (as opposed to on a calendar year basis).

The results (Table 3.7) show that, without adjustment for industry-specific distributional characteristics (Model 1), the findings are consistent only with the size hypothesis. However, after adjusting for distributional properties (Model 2), the findings are consistent, in addition with the inefficient management and growth-resources-mismatch hypotheses. Finally, Model 3 results also show the significance of the industry disturbance hypothesis.

Table 3.7 – Logit Models of Cudd and Duggal (2000)

Variable	Model 1	Model 2	Model 3
ROE	0.0066**	-0.3740**	-0.3826**
Growth-Resource-mismatch dummy	0.5630**	0.6534**	0.6950**
Growth	-0.204**	-0.1236	-0.1499
Liquidity	-1.3123**	0.0501	-0.1132
Leverage	-0.0009*	-0.0316	-0.0258
Industry disturbance dummy	0.0384	0.1269	1.2505**
Size	-0.0001**	-0.3209**	-0.3039**
Market-to-book	-0.0331	-0.0766	-0.0661
Price-earnings	0.0001	0.0209	0.02042
Constant	-1.1934**	-0.8065**	-1.1468**

**Indicates statistical significance at the 1% level; *Indicates statistical significance at the 5% level.

Based on these results and a t-test to access the differences in prediction accuracies between the models the authors concluded that the adjusted model produced classification accuracy significantly higher than chance, and significantly greater than that observed for the unadjusted model. However, it should be noted that although Model 3 achieved the highest overall classification accuracy, it also achieved the lowest correct classification of acquired firms (7.69% compared to 61.53% achieved by Model 1).

Powell (2001)

In line with the studies of Palepu (1986) and Cheh et al. (1999), Powell (2001) examines whether it possible to "beat the market" and earn abnormal returns by investing in the stocks of the predicted targets. The author argued that Palepu (1986) applied a classification rule, which resulted in his portfolio comprising a large number of non-target firms incorrectly predicted as targets. Palepu included in his portfolio all firms with positive expected abnormal returns, no matter how small. Nevertheless, investing in such a large portfolio is unlikely to yield abnormal returns since the abnormal returns to the small number of actual targets in the portfolio are diluted by the near zero abnormal returns to the large number of firms not taken over. Similar procedure with the one of Palepu (1986) was also followed in the study of Cheh et al. (1999).

Thus, in his attempt to "beat the market", Powell (2001) followed another procedure to construct the portfolios. He examined the concentration of target firms within portfolios constructed from the estimation sample of target and non-target firms. Ten portfolios were constructed by sorting each firm in the estimation sample in descending order by its probability of takeover. The classification rule (cut-off point) was derived from the portfolio that had the highest concentration of targets firms (G-ratio). Applying this classification rule to the population of firms results in smaller portfolios with higher average takeover probabilities.

The estimation sample consisted of a pooled sample of non-financial firms (targets and non-targets) listed on the London Stock Exchange, drawn from the true population of firms for the period 1986 to 1995. As in Powell (1997), the author again reconstructed the considered sample to reflect, as near as possible, to the "true population of firms". A total of 471 targets met data requirements and were included in the sample, while an equal number of non-targets were randomly selected from the same period. After removing outliers, the estimation sample comprised of 444 targets and 422 non-targets.

Two logit models, distinguished on the basis of the independent variables used, were estimated. The first model used only firm values for characteristics examined as independent variables. The second model used industry-relative ratios, where industry-weighted values were scaled by economy-weighted values. The variables employed in estimating the models were the same as in Powell (1997), corresponding to the same takeover theories.

The within sample total classification accuracy of the first model (Model 1) was between 50.35% and 58.31% depending on the cut-off point, while corresponding accuracies for Model 2 were between 51.39% and 59.12%. For Model 1, the highest G-ratio (0.66) was achieved using a cut-off point equal to 0.55 that resulted in correct classification accuracy equal to 56.35% in total, and 62.89% of targets in the portfolio. The latter (% of targets in the portfolio) corresponds to the number of target firms correctly classified by the model divided by the total number of firms in the portfolio. For Model 2, the highest G-ratio (0.67) was achieved using a cut-off point equal to 0.64 that resulted in correct classification accuracy equal to 51.96% in total, and 67.06% of targets in the portfolio.

The predictive ability of the developed models was tested using the population of firms on 1st January 1996, the day the portfolios of predicted targets were formed. The sample used consisted of 971 non-targets and 29 targets. To "beat the market", the portfolios were formed by applying the previously determined cut-off probabilities, nevertheless for comparison purposes portfolios were also formed using Palepu's rule of minimising the total error rate. The models predicted quite well on average predicting about 84% of targets and non-targets correctly, with Model 2 outperforming Model 1. Both models outperform those of Palepu (1986) whose best model correctly predicted only 46% of firms in the population. However, Powell (2001) acknowledges that if the same classification rule as in Palepu had been used in his study, it would have resulted in a much lower predictive accuracy (47%) than the one achieved. On this basis, the models failed to clearly identify target firms from the total population. For example, of the 209 firms predicted as targets in Model 1, only 7 were in fact targets (3.24%). This percentage was even lower in the case of the Model 2 (2.08%).

Despite the low predictive ability of the models, Powell (2001) examines whether abnormal returns could be earned from the predicted takeovers. Abnormal returns were measured in two ways: (1) as the difference between the return on a firm and the return on the market portfolio (the Market Adjusted Model or MAM), and (2) as the difference between the return on a firm and the return on a control portfolio matched by firm size (the Size Adjusted Model or SAM). Ten portfolios were formed and held for a 12-month holding period. The buy and hold abnormal returns calculated on the basis of both MAM returns and SAM returns suggested that it was not possible to earn significant positive abnormal returns by investing in firms predicted by the models to be potential takeover targets. Using the method similar to Palepu also produced negative abnormal returns, however these were smaller in magnitude compared to the method followed by Powell (2001) using the G-ratio as the optimal cut-off.

There are two issues that should be raised at this point, as they could had lead to higher abnormal returns. First, Powell characterised as targets only those firms that were successfully acquired. However, as Bartley and Boardman (1990) point out, investors can earn abnormal returns from predictions of takeover attempts irrespective of their success. Second, although not explicitly mentioned, only full acquisition or acquisitions above 50% were considered in his study. Nevertheless, in the context of developing a predictive model that can be used by investors, large investment attempts that do not seek a controlling ownership interest need also to be considered (Bartley and Boardman, 1990), based on evidence that positive abnormal returns are produced by investment attempts for as little as 5% of a company's outstanding stock (Bradley et al., 1983; Harris and Risk, 1983). As the purpose of Powell's study was also to examine abnormal returns, these issues could turn out to be critical.

3.2.3 Studies with Non-parametric and various techiques

Slowinski, Zopounidis, Dimitras (1997)

A new approach to the prediction of a firm's acquisition was proposed by Slowinski et al. (1997). This method, based on the rough set theory, does not need any assumption about data prior to the analysis, unlike parametric methods such as discriminant or logit analysis. The information about the firms is organised in a financial information table, where the financial characteristics of the firms correspond to condition attributes and the classification is defined by a decision attribute indicating whether a firm has been acquired or not. With the rough set approach one can determine minimal subsets of conditional attributes (financial ratios) ensuring an acceptable approximation of the classification of the firms analysed and to obtain decision rules from the information table, which can be used to distinguish between acquired and non-acquired firms.

A sample of 30 acquired Greek firms over the period 1983-1990 as well as 30 non-acquired firms matched by asset size, sales volume, and number of employees, from various sectors (excluding the service sector) were used to develop the model. Ten financial ratios were initially chosen and calculated for up to three years prior to the takeover both for acquired and non-acquired firms. The initial information table was reduced from ten to five columns corresponding to: (1) two profitability ratios: (i) earnings before interest and taxes divided by total sales and (ii) cash flow divided by total assets, (2) two debt capacity ratios: (i) (long term debt plus current liabilities) divided by total assets, and (ii) net worth divided by (net worth plus long-term debt), and (3) one liquidity ratio: quick assets divided by current liabilities which were used to derive decision rules using data from one year prior to the acquisition. From the 24 decision rules, 13 rules classified acquired firms and 14 classified the non-acquired firms.

The predictive ability of the model was tested using the same firms but data from 2 years and 3 years prior to the acquisition instead of data from 1 year before the acquisition. The classification accuracy was 75% and 66.7% for 2 and 3 years before the acquisition. The authors compared the new methodology with discriminant analysis, using the same five ratios. They reported that the error rates of the discriminant function for 2 and 3 years before the acquisition were higher than those of the rough set approach, and suggested the rough set approach as a reliable alternative to discriminant analysis.

The new methodology presented in the study of Slowinski et al. offers a promising non-parametric methodology, as it avoids the assumptions of parametric methods and provides good classification accuracies. Nevertheless, the predictive accuracy of the model should have been tested using some kind of holdout sample or resampling technique. Although the authors used data from years 2 and 3 prior to the acquisition, these data were obtained from the same firms that were used for the development of the model. Given that data from year one prior to the acquisition used for the development are not independent from data from years 2 and 3 prior to the acquisition the comparison of the methods should be extended.

Zanakis and Zopounidis (1997)

Zanakis and Zopounidis (1997) offer a comparison of linear and quadratic discriminant analysis and logit models using industrial and commercial Greek firms that were acquired during the period 1983-1990. Two samples, a training sample of 80 firms, and a holdout sample of 30 firms, with equal number of acquired and non acquired firms matched by asset size, sales volume and number of employees, were used to estimate the parameters of the models and test their predictive ability.

For each one of the firms, 16 financial ratios, representing three basic groups, profitability, managerial performance and solvency, were calculated for the three years preceding the takeover. These ratios were chosen after considering i) the data availability, ii) existing empirical studies using similar ratios and iii) their popularity in the financial literature. Factor analysis was used prior to the development of the prediction models to identify any multicollinearity among the financial ratios, which transformed the original ratios into a few uncorrelated factors representing the same financial information. Various discriminant models were developed using a combination of factors and procedures involving stepwise discriminant analysis. In addition, four logit models were obtained using as input the sixteen financial ratios for each year separately and combined.

The authors reported mixed results since most models classified correctly a significant proportion of acquired or non-acquired but not both. They partially supported the findings of Mahmood and Lawrence (1987) on quadratic discriminant analysis being more accurate than linear discriminant analysis in classifying acquired firms and also reported that the logit models provided inferior overall predictions compared to those made by linear discriminant analysis. Their best two models, however, were produced by linear discriminant analysis of six ratios.

The first model had a classification accuracy of 70% for the acquired, 65% for the non acquired and 67.5% in total for the training sample, all significant at the 95% confidence level, while the corresponding accuracies in the holdout sample were 66.7%, 62% and 64.3%. The ratios used in this model were: (Long term debt plus current liabilities) divided by working capital (x_1), (Long Term Debt plus current liabilities) divided by cash flow (x_2), (Long Term Debt plus current liabilities) divided by Working capital (x_3), Inventory to Working Capital (x_4), Earnings to Total Assets (x_5), Current Assets to Current Liabilities (x_6). For this model, ratios x_1 and x_2 were obtained using data one year prior to the acquisition, ratios x_3 and x_4 using data two years prior to the acquisition, while for the last two ratios (x_5 and x_6) data from three years prior to the acquisition were used.

The second model classified correctly 65%, 68% and 66.5% of the acquired, non-acquired and overall respectively, in the training sample, all significant at the 95% confidence level. The predictions in the holdout sample decreased to 63.5%, 61% and 62.3% respectively. This model using data from one year prior to the acquisition utilised the following ratios: Cash Flow to Total Assets (x_1), Fixed Assets to Total Assets (x_2), Net Worth to Total Assets (x_3), Inventory to Working Capital (x_4), (Long Term Debt plus Current Liabilities) to Cash Flow (x_5), Quick Assets to Total Liabilities (x_6).

The authors offered three main reasons for not obtaining better predictions: i) the similarity in the financial ratios between acquired and non-acquired Greek firms, ii) the inclusion of different (non-homogenous) sectors in their sample, which they argued made the predictions more difficult than would have been the case if all firms were from a single sector, iii) the use of takeover data from a less developed country like Greece at that period, were takeover practice had appeared only in recent years, hardly favoured the development of highly predictive models. They concluded that probably Greek takeovers were influenced more by strategic (non-financial characteristics) and such variables should be also considered in future studies.

Fairclough and Hunter (1998)

Fairclough and Hunter employed Neural Networks to discriminate between acquired and non-acquired firms. The sample used consisted of 140 acquired firms and a randomly selected group of non-acquired firms (1480 company years of data) from the period 1987 to 1996 that were listed on the London Stock Exchange. This sample was then divided into the following three sub-samples: (1) A state-based training set of 120 firms, randomly selected for model specification, (2) A cross-validation sample of 150 firms randomly drawn from the remaining observations used to evaluate net performance, and (3) The remaining 1350 observations used as a holdout sample.

Motivated by the findings of Palepu (1986) (whose model could classify correctly 80% of acquired firms but only 45.95% of non-acquired firms) the authors attempted to develop a model that would minimise Type II errors (i.e. the misclassification of non-acquired firms, Type I errors being the misclassification of acquired firms). However, by following such a policy, although the best model achieved an overall classification of 94% in the cross-validation sample and 93.33% in the holdout sample, the differences between type I and type II errors were extremely large. The model classified correct only 12.5% of acquired in the cross-validation sample compared to 98.59% of non-acquired, while the corresponding accuracies in the holdout sample were 4.17% and 98.36%.

The authors also compared their model with discriminant analysis. The model developed using discriminant obtained a classification accuracy of 87.5% for acquired firms and 20.74% for non-acquired firms in the holdout sample, and a total classification accuracy of 24.3%. Based on these results the authors concluded that their artificial neural networks was better at ex-ante classification than the discriminant method. However, considering the differences in their obtained classifications between acquired and non-acquired firms the results of the study should be treated with some caution.

Cheh, Weinberg and Yook (1999)

This is another study that investigates the potential of an artificial neural network (ANN) for identifying potential takeover targets and the possibility of yielding positive abnormal returns from investing in the target stocks. Unlike previous studies which found little to support the claim that it is possible to beat the market, Cheh et al. found that it was possible to earn daily average returns significantly higher than the market average return based on models' predictions.

Two data sets were used. The first data set consisted of 173 acquired and 1,275 non-acquired firms and was used for model development. Firms were selected from the 1985-1987 time period, that were listed on either the New York or the American Stock Exchange and belonged to non-financial or service industries with at least six years of data available. One of the three sampling years was randomly assigned to each one of the non-acquired firms in order to spread them throughout the same sampling period as the acquired firms. The second data set consisted of 186 acquired firms and 1,338 non-acquired firms listed on the 1988 Compustat Industrial File, and used for validation purposes.

Eight financial variables measuring several aspects of a firm's financial condition (size, leverage, liquidity, growth rate, dividend payout, price-earnings ratio, return on equity, q ratio), and one other variable indicating acquisition activity within industry were used.

A standard feedforward, back propagation neural network with one hidden layer was designed to accept as input values eight independent variables for a three year period along with the industry code. Of the total of 1,448 firms available for model development a holdout sample of approximately 10% was set aside to be randomly selected for testing during the training phase. Various network parameters were adjusted and the network repeatedly trained and retrained until a Root Mean Square Error of less than 0.10 was achieved, and comparable performance on the holdout set observed. The trained network was then applied to the validation sample set to test its predictive performance. Various network activation levels or decision thresholds were examined to test the model's overall performance. Firms with network activations below the decision threshold were classified as potential takeover targets and included in the portfolio. Two methods were used to describe the network's performance: (1) its misclassification rates, and (2) investment performance of the model portfolio versus a standard benchmark portfolio.

The results show that although the ANN models were able to achieve low Type I errors (i.e identify a firm to be acquired when it is not actually acquired) at all decision thresholds (0.0075-0.0441), Type II (i.e fail to identify an acquired firm) errors were substantial (0.5860-0.8763). To test further the ability of the model, its accuracy was compared with that of a discriminant model. On one hand, the Type I error of the discriminant model was higher than the ANN model's. However, on the other hand, the Type II error rate of the discriminant was lower. This implies that the discriminant analysis is more likely to misclassify firms as acquired than neural network (higher Type I error), but it misses fewer opportunities (lower Type II error).

The authors also investigated whether predictive performance could be improved if the neural network and discriminant analysis were applied together. Two rules were followed. In the first case, firms were classified as targets, if they were identified as targets by discriminant analysis *and* had neural activation less than the decision threshold. In the second case, firms were classified as acquired if they were either identified as targets by discriminant analysis *or* had neural activation less than the decision threshold. The results were promising since the accuracies obtained following the *and* rule were substantially better than those obtained by either method alone.

Finally, the authors examined the ability to earn excess returns when investing in the stock of the firms identified as targets by the ANN model. Stocks were assumed to be purchased at the beginning of 1989 and held until the firms were acquired (for correctly predicted firms that were actually acquired) or at the end of observation period (1993) for non-acquired firms (misclassified firms). Benchmark portfolios, consisting of equal numbers of stocks as the portfolios suggested by the model, in which all stocks were assumed to earn market return were constructed for comparison reasons. Unlikely previous studies that found that it is not possible to beat the market, Cheh et al. found that daily average return of the portfolios identified by the neural network were significantly higher than market average return. In addition, when the ANN and discriminant analysis were applied together, the daily average returns were even higher.

Barnes (2000)

In his 2000 study, Barnes compares the logit and discriminant methods using the same sample and the 17 accounting variables as in his 1998 study (Barnes, 1998). Two models were estimated using each technique, a model across all industrial classifications based on industry relative ratios and a set of models estimated separately for each industrial sector.

Barnes came up with 3 overall conclusions. First, although the models predicted better than change, provided that the cut-off was properly selected, their overall forecasting ability over-stated their ability to generate excess returns because they were particularly weak at identifying targets. Actually neither the logit industry-specific nor the general models identified a single target using either of the two alternative cut-off points (i.e. weighted average cut-off and maximization of returns), while the discriminant analysis model classified correct approximately 8% of targets in both cases (i.e. general and specific model). Second, the choice of the statistical technique depended on how well the assumptions of the estimation model fitted the statistical nature of the underlying data. Third, the differences between the distributions of forecasts using the general model and the specific model were greater, suggesting that the choice of data form (industry relative or raw accounting data) may be more important than the choice of statistical technique.

Zopounidis and Doumpos (2002)

In a more recent study, Zopounidis and Doumpos (2002) proposed a new technique based on an iterative binary segmentation procedure, known as MHDIS. The proposed method belongs to the Multicriteria Decision Aid (MCDA) family and is a non-parametric approach to study discriminant problems involving two or more ordered groups of alternatives.

The sample consisted of 30 acquired and 30 non-acquired Greek firms and 10 financial ratios covering various aspects of a firm's financial condition were used to develop the model. These ratios were: earnings before interest and taxes divided by total assets (x_1), cash flow divided by total assets (x_2), net income divided by net worth (x_3), cash divided by total assets (x_4), (long term debt plus current liabilities) divided by total assets (x_5), (long term debt plus current liabilities) divided by cash flow, net worth divided by (net worth plus long term debt) (x_7), quick assets divided by current liabilities (x_8), current assets divided by current liabilities (x_9), and working capital divided by total assets (x_{10}).

The model was developed using data from one year prior to the acquisition (year –1) while years two (year –2) and three (year –3) before the acquisition were used to test its discriminating ability. The model classified correct 58.33% and 61.67% of the firms for years 2 and 3 prior to the acquisition respectively. The authors argued that this poor classification could be attributed to the difficulty of predicting acquisition targets in general, and not necessarily to the inability of the proposed approach as a discrimination method.

To test further the proposed technique its classification accuracy was compared with that of discriminant analysis and another multicriteria method, namely UTADIS (for more details on UTADIS and its comparison with MHDIS, see chapter 4). The correct classification accuracy obtained using the proposed method was better for all years compared to the one obtained using discriminant analysis. As opposed to the UTADIS method, the classification accuracy under the proposed approach was significantly higher for year –1, equal for year –2 and slightly higher for year –3.

Based on these results the authors concluded that the iterative binary segmentation procedure is able to provide at least favourable comparable results with the ones provided by UTADIS and outperforms discriminant analysis. Nevertheless, while interpreting the results one should keep in mind that the two MCDA models (MHDIS and UTADIS) have many more parameters to be estimated, resulting in an over fitting in the training sample. Although data from previous years were used for models' validation, these data corresponded to the same firms used for model development.

Espahbodi and Espahbodi (2003)

Another recent study that compared a number of methodologies is that of Espahbodi and Espahbodi (2003). The authors proposed the use of recursive partitioning, a non-parametric technique based on pattern recognition, as an alternative technique to discriminate between targets and nontargets, and compared this method with probit, logit, and discriminant analyses.

The authors used a sample of 133 US firms that were taken over during the last six months of 1997. These firms were matched with up to three control firms at random from all the firms listed on the database, based on the fiscal year-end to eliminate the effect of time and SIC codes to reduce the effects of industry-wide factors. Firms were drawn from various sectors, but excluding utilities and financial institutions due to the different conditions under which firms in these industries operate as well as differences in their financial statements. The authors considered a set of 14 financial variables that were based on market and financial statements data. In addition, 4 other non-financial variables were used: (1) existence of poison pills, (2) existence of golden parachutes, (3) percentage ownership of officers and directors, and (4) state legislation.

Both forward and backward stepwise selection techniques were employed to develop the discriminant and logit modes. The final discriminant and logit models included four variables whose order and overall significance were exactly the same. The Discriminant model classified correctly 63.2% of the targets and 61.3% of the non-targets, while the classification accuracy of the logit was lower with 62.4% and 60.3% accordingly. Since there is no stepwise selection program for probit, the variables that were found to be significant at the logit were used to develop the probit model.

The classification accuracy of the probit model was similar to the other two models with 61.7% of the targets and 61.8% of the non-targets being correctly classified. Table 3.8 presents the coefficients for the three models. The classification accuracies of the recursive partitioning model were 89.5% and 88.1% for the target and non-target groups, thus significantly higher than those of the other three models. The research and development over total firm value, the size, the growth in sales, the price earnings ratio, and the existence of poison pills were the five variables on the basis of which the model separated the acquired and non-acquired firms.

Table 3.8 Coefficients of Discriminant, Logit and Probit Models (Espahbodi & Espahbodi, 2003)

Variables	Discriminant	Logit	Probit
Free Cash Flow over total Assets	1.099	1.428	0.813
	(7.08)	(2.76)	(2.86)
Existence of golden parachutes	0.701	0.612	0.366
	(4.10)	(1.95)	(1.91)
State of Delaware incorporation dummy variable	0.312	0.340	0.204
	(2.26)	(1.61)	(1.65)
Market Value of Equity over total firm value	-0.605	-0.606	-0.353
	(1.72)	(-1.36)	(-1.33)
Constant	0.235	-0.811	-0.508

t-values in parentheses (F-values in the case of discriminant)

The four models were validated using a holdout sample consisting of 38 firms taken over in the first two months of 1998 and a random sample of 200 non-acquired firms. The classification accuracies (respectively for recursive partitioning, discriminant, logit and probit models) were approximately 66%, 53%, 55%, 55% for target firms, and 66%, 51%, 52%, 52% for non-target firms.

Tartari, Doumpos, Baourakis, Zopounidis (2003)

Following recent studies in bankruptcy prediction that attempted to develop integrated prediction models (e.g. Jo and Han, 1996; McKee and Lensberg, 2002), Tartari et al. (2003) were the first to propose such a technique for the prediction of acquisition targets. Although Cheh et al. (1999) had used a simple *and/or* rule to combine ANN with discriminant analysis, Tartari et al. attempt to accomplish such a combination using a more sophisticated approach. Thus, unlike previous studies that have focused on an appropriate methodology to develop a prediction model and in some cases offered a comparison with other techniques to investigate its efficiency, this study by contrast proposes the integration of different methods using a stacked generalisation approach. This is one of the two approaches to integration of models that is described further and employed in our empirical investigation (Chapter 7).

The sample used by Tartari et al. consisted of 48 UK firms, selected from 19 industries/sectors, acquired during 2001 and 48 non-acquired firms matched by principal business activity, asset size, sales volume and number of employees.

Twenty-three financial ratios measuring profitability, liquidity and solvency and managerial performance were calculated for each firm for up to three years prior to the acquisition (1998-2000). Factor analysis was then used to account for any multicollinearity among the financial ratios, which resulted in nine factors explaining more than 77% of the total variance. The following ratios had the highest loadings in the 9 factors and were used further in model development: (1) current assets divided by current liabilities, (2) net income divided by net fixed assets, (3) long-term liabilities divided by (long term-liabilities plus net worth), (4) gross profit divided by total assets, (5) total liabilities divided by working capital, (6) cash flow divided by total assets, (7) inventories divided by current assets, (8) current liabilities divided by net worth, and (9) working capital divided by working capital required.

Four classification methods, namely linear discriminant analysis (LDA), probabilistic neural networks (PNN), rough sets theory, and the UTADIS multicriteria decision aid method, originating from different quantitative disciplines (i.e. statistics, neural networks, rule induction, multicriteria analysis) were used at a first stage to develop individual models. The most recent year (2000) was used as a training sample while the data for the other two years (1998 and 1999) were used to test the generalising performance of the proposed integration approach. An 8-fold cross validation approach was employed to develop the base models using the four methods. The obtained classifications of the firms were then used as a training sample for the development of a stacked generalisation model for the prediction of acquisitions targets. The development of the stacked model was performed using the UTADIS method that combined (at a meta-level) the group assignments of all the four methods considered in the analysis. The use of other methods to develop the combined model was also examined; nevertheless the results were inferior to those obtained with UTADIS. Table 3.9 presents the classification results obtained using the four methods and the stacked model.

Table 3.9 - Classification results (overall correct rate in %) in the study of Tartari et al. (2003)

Methods	2000 (training)	1999	1998
LDA	58.33	50.00	54.17
PNN	100.00	58.33	62.50
Rough Sets	100.00	57.29	58.33
UTADIS	71.87	57.29	55.21
Stacked model	88.54	60.42	63.54

It becomes immediately apparent that the stacked model performed better (in terms of the overall correct accuracy rate) than any of the four methods upon which it was based, throughout all years of the analysis. Furthermore, the results indicated that the stacked model provided significant reductions in the overall error rate compared to LDA, rough sets and UTADIS, although less significant compared to PNN.

The authors concluded that future research needs to be directed to an investigation of the similarities and differences between the assignments made by the models developed using the different classification models and the use of alternative approaches for models integration such as bagging and boosting algorithms. These are issues discussed further in Chapter 7.

Doumpos, Kosmidou, Pasiouras (2004)

Doumpos et al. (2004) illustrate the use of UTADIS multicriteria decision aid technique to develop a model for the prediction of UK acquisition targets. The classification ability of the UTADIS model was compared against the classification ability of models developed using discriminant analysis (DA), logistic regression (LR) and artificial neural networks (ANN).

The sample included 76 firms operating in manufacturing, construction, producing and mining-quarrying-extraction industries that were acquired during the period 2000-2002. These firms were matched by industry and size with 76 non-acquired firms. Thus, the total sample consisted of 152 firms.

Twenty-nine financial ratios were initial candidates for model development, representing profitability, efficiency, activity, financial leverage, liquidity and growth. To avoid problems associated with dimensionality and multicollinearity, the authors sought to reduce the number of variables using a t-test. They argued that although factor analysis provided a reduced number of distinct factors, they do not provide any useful information about the importance of individual variables in a specific research problem. It is possible, using factor analysis, that one may exclude variables that are significant in terms of discriminating the firms between the two groups (acquired and non-acquired). Using the t-test, the following six variables were found to be significant at the 5% level: current ratio, solvency ratio, gearing, debtors collection period, net assets turnover and salaries divided by turnover. The correlation between these six variables were low to moderate, hence allowing the use of all 6 variables in model development.

The UTADIS model was first developed using data drawn from the most recent year prior to the acquisition (i.e. year -1). The results showed that distinction between acquired and non-acquired was primarily based on the gearing ratio, the net assets turnover and the salaries to turnover ratio. The developed model was then applied to data from 2 and 3 years prior to the acquisition (years –2 and –3). The average accuracies were 74.34% and 78.95% respectively.

The models developed using DA, LR and ANN, were tested following the same procedure. More specifically, using the same 6 ratios, the models were developed using the sample data from one year prior to the acquisition and then applied on the data of the years –2 and –3. The specification for the ANN model was achieved through a trial and error process involving several experimentations that led to the use of a back propagation, feed-forward architecture with one hidden layer of six nodes. The results showed that the UTADIS method outperformed both DA and LR, and were found comparable or better than those of ANN when tested using data from years –2 and –3.

While comparing the results of different methods in this study, one should note that UTADIS and ANN approaches are non-parametric and both significantly different from each other as well as from DA and LR methods, resulting in a-priori data fitting superiority in the training sample (year –1). Although the authors assume that by using data from years –2 and –3 for testing they overcome this problem, it is also possible that this a-priory fitting might not be totally eliminated when using such a back-testing analysis to compare the models, as variables come from the same firms used for training. Thus, a more appropriate test would be to use a holdout sample or resampling technique (e.g. cross-validation) for model comparisons.

3.3 Conclusions

This chapter has reviewed a good number of empirical studies that have developed models for the prediction of acquisition targets. A number of conclusions can be drawn.

(1) The majority of these studies have employed discriminant or logit analysis and only more recently have studies emerged employing alternative classification techniques (i.e. neural networks, multicriteria decision aid, rough sets, etc). Consequently, as Espahbodi and Espahbodi (2003) point out, not many have attempted to compare the ability of various classification procedures in predicting corporate takeovers. In this context, our knowledge regarding whether some classification methods may be more effective (in terms of classification accuracy) than others appears to be quite limited. For example, on the basis of our literature review, there are only eight studies that offer a comparison of various methods, of which four compare just two methods while the remaining 4 compare either 3 or 4 methods. At the same time, drawing conclusions among studies is not possible since researchers usually use different independent variables and examine different time periods, industries, countries, etc.; while validation techniques used to access the ability of the models also differ across studies. In order to fill in this gap, we will attempt to answer the question whether model development technique has an impact on prediction ability. To accomplish this task, a number of models will be developed and compared using different classification methods. The present study compares seven different methodologies, which are almost double in number compared to most previous studies did. In addition, two of these methodologies have not been previously employed for the development of acquisition prediction models.

(2) So far, there has been only one study (Tartari et al., 2003) in the literature of the prediction of acquisition targets that has attempted to combine various methods despite the promising results of such integration in similar financial problems like credit scoring (e.g. Doumpos, 2002; Lee et al., 2002) and bankruptcy prediction (e.g. McKee and Lensberg, 2002). As noted earlier, the present study will employ stacked generalisation method of Tartari et al. (2003), as well as an additional technique, the majority voting rule (Huang and Suen, 1993). Thus we will not only examine whether

combining different methods leads to better classification results but also offer a comparison of different methods of combining models for estimation and prediction.

(3) To our best knowledge all studies have developed models for the prediction of acquisition targets in non-financial sectors. However, the financial characteristics of the banking sector are sufficiently different from those of other industries, therefore financial analysis techniques specifically designed to address these differences is necessary. Thus models actually developed for other industries cannot be readily applied for the prediction of bank acquisition targets, and therefore it is necessary to develop M&As targets prediction models specifically for the banking industry.

(4) There appears to be a lack of coherence about the sample used to develop and validate the prediction models. After the criticism of Palepu (1986), many researchers have developed and/or validated their models using unequal samples of acquired and non-acquired firms. At the same time, many researchers continued to use matched samples. It is obvious that both procedures have advantages and disadvantages. However, no study has empirically examined whether the classification accuracy of a model tested in a matched sample is significantly different from that of the same model tested in an unequal sample. The present study will compare the classification ability of the developed models by validating them in equal and un-equal holdout samples.

(5) Finally, all studies reviewed above have examined individual countries, with the majority of them focusing on the US and UK market. To our knowledge there exits no study that seeks to develop models for prediction based on firm level data across countries. By considering banking firms obtained for 15 EU countries, the present study is the first that attempts the development a model with a sample drawn over across countries.

Chapter 4
Methodological Framework for the Development of Acquisition Targets Prediction Model

4.1 Introduction

The prediction of acquisition targets is essentially an application of classification techniques, which classify firms into two groups (i.e. acquired and non-acquired). Other well-known areas of classification in finance are bankruptcy prediction, credit risk assessment, and replication of auditors' opinion. In general in any classification task, there is a set $X = \{x_1, x_2, ... x_n\}$ of n alternatives (e.g. firms) described over a set $g = \{g_1, g_2, ... g_m\}$ of m independent variables (e.g. financial ratios) to be classified into a set $C = \{C_1, C_2, ... C_q\}$ of q predefined groups. The classification problem refers to the development of a model that will assign the alternatives into the predefined groups as accurately as possible. The process is not automatic. As shown in Figure 4.1, the process for the development of acquisition predictions models consists of four main steps (i) construction of an observation set, (ii) selection of input variables, (iii) selection of classification methods to develop the model, and (iv) evaluation of the developed model. This methodological framework is adopted in this study and, consequently, in this chapter we seek to explain each of these steps in detail. Thus, section 4.2 deals with the construction of sample and examines issues such as the definition of acquisition, the splitting of sample into training and testing sub-samples, and the use of equal or unequal sub-samples of acquired and non-acquired firms for training and testing. Section 4.3 explains the procedures for dealing with variables selection and summarises the methods for reducing and selecting input variables from a potentially large data set of candidate variables for model development. Section 4.4 presents methods for developing prediction models for acquisition targets, covering classical statistical and econometric methods, operational research methods, and machine learning methods. Finally, section 4.5 explores issues dealing with the evaluation and assessment of classification methods. It should be noted that some of the issues raised above were already discussed in Chapter 3, but the aim of this chapter is to illustrate the procedures.

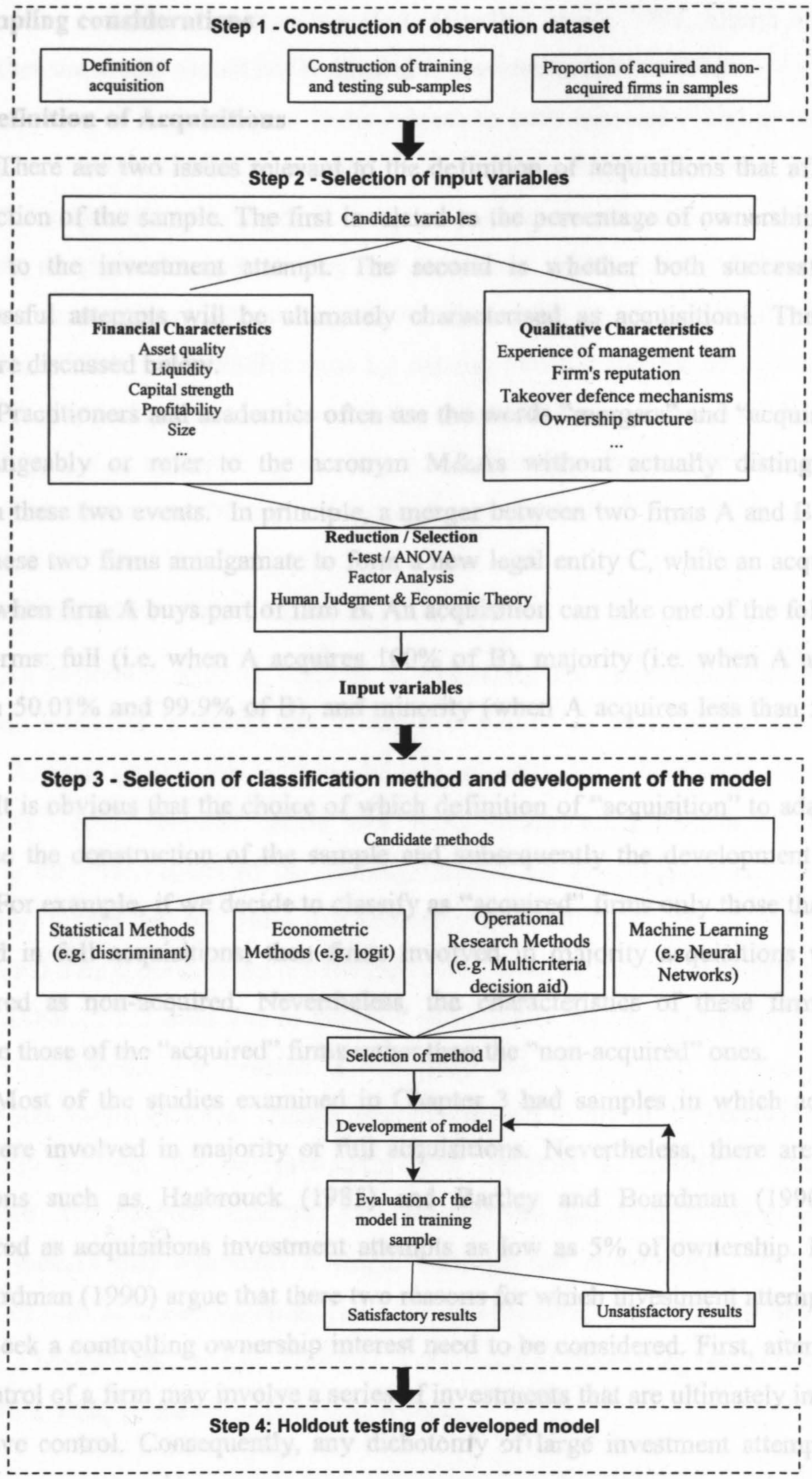

Figure 4.1 – Methodological framework for the development of acquisition targets prediction models

4.2 Sampling considerations

4.2.1 Definition of Acquisitions

There are two issues relevant to the definition of acquisitions that affect the construction of the sample. The first is related to the percentage of ownership that is subject to the investment attempt. The second is whether both successful and unsuccessful attempts will be ultimately characterised as acquisitions. These two issues are discussed below.

Practitioners and academics often use the words "mergers" and "acquisitions" interchangeably or refer to the acronym M&As without actually distinguishing between these two events. In principle, a merger between two firms A and B occurs when these two firms amalgamate to form a new legal entity C, while an acquisition occurs when firm A buys part of firm B. An acquisition can take one of the following three forms: full (i.e. when A acquires 100% of B), majority (i.e. when A acquires between 50.01% and 99.9% of B), and minority (when A acquires less than 50% of B).

It is obvious that the choice of which definition of "acquisition" to adapt will influence the construction of the sample and subsequently the development of the model. For example, if we decide to classify as "acquired" firms only those that were involved in full acquisitions, then firms involved in majority acquisitions will be considered as non-acquired. Nevertheless, the characteristics of these firms may resemble those of the "acquired" firms rather than the "non-acquired" ones.

Most of the studies examined in Chapter 3 had samples in which acquired firms were involved in majority or full acquisitions. Nevertheless, there are a few exceptions such as Hasbrouck (1985) and Bartley and Boardman (1990) that considered as acquisitions investment attempts as low as 5% of ownership. Bartley and Boardman (1990) argue that there two reasons for which investment attempts that do not seek a controlling ownership interest need to be considered. First, attempts to gain control of a firm may involve a series of investments that are ultimately intended to achieve control. Consequently, any dichotomy of large investment attempts and takeover attempts is arbitrary since it is not possible to be confident that an investment attempt, seeking less than 50% ownership is not part of a takeover attempt. Second, if the model is to be used by investors to form portfolios, since there is evidence that positive abnormal returns are produced by investment attempts for as little as five percent of a company's outstanding stock (Bradley et al., 1983; Harris and Risk, 1983), then the model should not be limited to investments above 50%.

Another issue is whether firms subject to both successful and unsuccessful acquisition attempts should be considered as acquired. Most of the studies classify successful acquisitions as acquired and unsuccessful acquisitions as non-acquired. However, some studies (e.g. Bartley and Boardman, 1990; Barnes, 2000) examine attempted acquisitions without regard to their ultimate outcome. Bartley and Boardman (1990) justify their choice by arguing that the success of an acquisition attempt is mostly dependent on factors others than the financial characteristics of the target firm, and a model for predicting successful acquisitions that includes only financial data for successful acquisitions can be miss-specified.

4.2.2 Training and testing samples

An important issue of concern in evaluating the classification ability of a prediction model is to ensure that it has not over-fit on the training (estimation) dataset. As Stein (2002) notes, "A model without sufficient validation may only be a hypothesis". Prior research shows that when classification models are used to reclassify the observations of the training sample, the classification accuracies are "normally" biased upward. Thus, it is necessary to classify a set of observations that are not used during the development of the model, using some kind of testing sample.

Although the measures of model's performance will be discussed in a latter section, it is necessary to examine at this point how we can split the data set into training and testing samples. Taking into account the nature of the problem and the availability of data, the decision maker can consider a number of alternative techniques. The simplest technique for "honestly" estimating error rates is using the holdout method that represents a single train-and-test experiment. Re-sampling techniques such as cross-validation, jackknife and bootstrap also exist that obviate the need for a separate test sample. However, a drawback of resampling techniques is that they cannot take population drifting into account.

4.2.2.1 Holdout sample

As mentioned above, the simplest way of avoiding the bias in the error rate, is to use a holdout sample as considered by Highleyman (1962) among others. Studies in the prediction of acquisition targets have used holdout samples either from the same period (Barnes, 1990) or from a future period (Barnes, 2000; Espahbodi & Espahbodi, 2003). Using a future period entails the case of a drifting population (i.e. change of population over time) and allows determining if the variables in the prediction model and their coefficients remain stable over other time periods[9].

If a holdout sample from the same period is used, then all available cases (or data) are randomly split into training and testing samples. The classification model is developed using the data from the training sub-sample and then tested on the holdout sub-sample.

When a holdout sample from a future period is used, all available cases (data) are first ordered by time. Then the training cases are taken from a given period (up to a specified time), and the testing cases are taken from the following period. The length of the time periods for both training and testing samples depends on the knowledge of the application and the availability of data. Because the population may change with time, this approach provides a closer simulation of the task of prediction, train from the current period to predict a future period.

Generally speaking the larger the training sample, the better the classifier, although the effect begins to diminish after a certain volume of training data. On the other hand, the larger the testing sample, the more accurate is the error rate estimation. Owing to constrained data availability in any real world application, the researchers is therefore faced with the following dilemma: to get a good classification model, by using as much of the data as possible for training or to get a good error estimate by using as much of it as possible for validation. Since a classification model developed with insufficient cases will generally lead to an inaccurate model, the majority of cases are usually used for training and the remainder for testing. Typically 2/3 of the total sample is used for training and 1/3 for testing (Weiss and Kulikowski, 1991).

4.2.2.2 Resampling Techniques

It was mentioned above that three well known resampling techniques are the jackknife, the bootstrap and the *k*-fold cross validation. Quenouille (1949) proposed a

[9] The case of drifting population and its relevance to the prediction of acquisitions will be discussed more detailed in section 4.2.2.3.

technique, latter named the jackknife, to estimate the bias of an estimator by deleting one element each time from the original data set and recalculating the estimator based on the rest of the data. The bootstrap, introduced by Efron (1979) and investigated further in a series of articles (Efron, 1981a,b, 1982, 1983, 1985, 1987, 1990), is an estimation technique that uses sampling with replacement to form the training set. Today it is widely used for the estimation of classification error rates, the selection of classification models, as well as for the comparison of classification methods (Doumpos and Zopounidis, 2002a). There are numerous bootstrap estimators, but the two that so far have yielded the best results for classification are known as the e0 and the .632 bootstrap. Those interested in most detailed explanations and proofs for the jackknife and bootstrap techniques can find an excellent account in Efron (1982), who exhibits the close theoretical relationship between them, as well as Shao and Tu (1995) who provide a systematic introduction to the theory of the jackknife, the bootstrap and other resampling methods.

We now turn to *k*-fold cross validation technique that will be used in the empirical part of the study. One way of almost eliminating the bias in the apparent error rate is through the leave-one-out technique (like jackknife, although the rationale is different) as described by Lachenbruch and Mickey (1968) or through cross validation as discussed in a wider context by Stone (1974) and Geisser (1975). In general, during a *k*-fold cross-validation the complete sample X, consisting of *n* observations (e.g. firms), is initially randomly split into k mutually exclusive sub-samples (folds) $X_1, X_2, \ldots, X_k$ of approximately equal size. Afterwards, *k* models are developed, with each fold in turn used for validation and the remainder left for training (i.e. estimation). The average error rate over all *k* folds is known as the cross-validated error rate. Typically, the number of folds *k* ranges between 1 and 20, although it can also be set equal to *n* (in the case of leave-one-out cross-validation), but the latter can be computationally expensive with large samples. The most widely used value for *k* in cross-validation is 10 (thus known as 10-fold cross-validation). The 10-fold cross validation process is best described as follows (see Abrahams, 2004):

Step 1: The data are randomly split into 10 sub-samples (folds)

Step 2: In each one of the 10 rounds, 9 sub-samples are used for training and one for validation.

Step 3: When all 10 rounds are completed, the average error is used to access the classification accuracy of the developed model. The standard deviation of these estimates can also be calculated to obtain a confidence interval for the overall estimate.

Figure 4.2 provides a schematic presentation of Rounds 1-10:

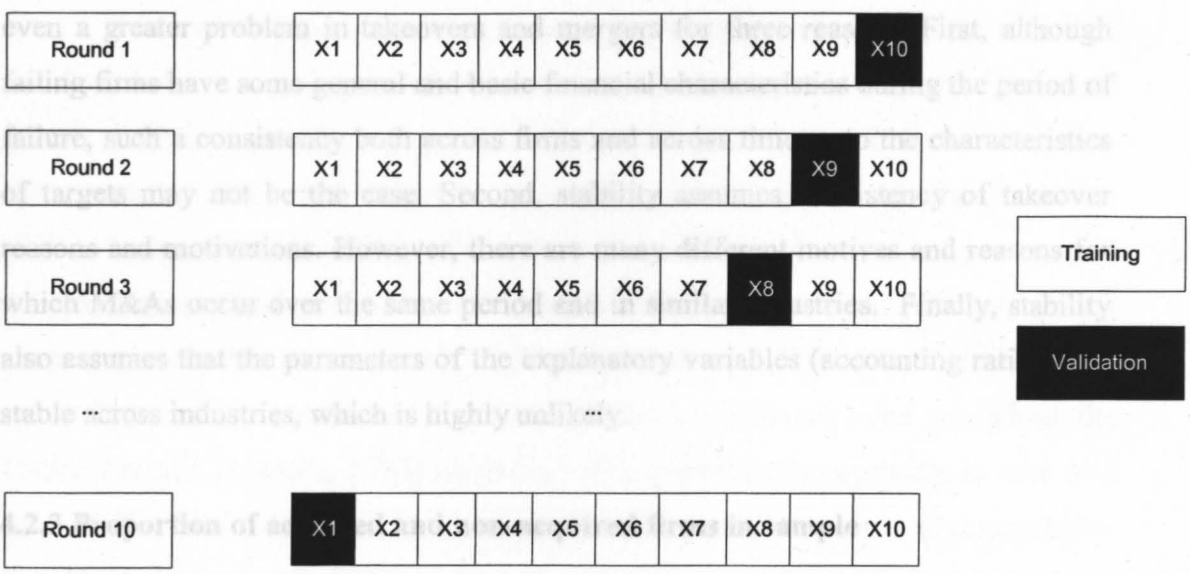

Figure 4.2 - A 10-fold cross validation procedure

4.2.2.3 Population drift

Classification ability is likely to overstate predictive ability as suggested by those studies that use a holdout sample from a latter non-overlapping period (Taffler, 1982). Thus a superior approach would require that the model be validated against a future period, as this approach more closely reflects a "real world" setting. As Espahbodi and Espahbodi (2003) state "After all, *the real test of a classification model and its practical usefulness is its ability to classify objects correctly in the future. While cross-validation and bootstrapping techniques reduce the over-fitting bias, they do not indicate the usefulness of a model in the future*" (p. 571).

If the models are stable then their classification ability will equal their predictive ability (Barnes, 1999). However, there are many reasons why the model may not be stable over time. As Barnes (1990) points out, given inflationary effects, technological and numerous other reasons, including changing accounting policies, it is unreasonable to expect the distributional cross-sectional parameters of financial ratios to be stable over time.

Business failure models have been found to be highly unstable and their predictive accuracy is thereby considerably reduced (Mensah, 1984; Wood & Piesse, 1987; Barnes, 1987; Platt and Platt, 1990). Barnes (1999) suggests that if the stability of the model is a problem in the business failure prediction studies, this is likely to be even a greater problem in takeovers and mergers for three reasons. First, although failing firms have some general and basic financial characteristics during the period of failure, such a consistency both across firms and across time as to the characteristics of targets may not be the case. Second, stability assumes consistency of takeover reasons and motivations. However, there are many different motives and reasons for which M&As occur over the same period and in similar industries. Finally, stability also assumes that the parameters of the explanatory variables (accounting ratios), are stable across industries, which is highly unlikely.

4.2.3 Proportion of acquired and non-acquired firms in sample

We now turn to three other issues, related to sampling, that have received a lot of attention in the acquisitions (and bankruptcy) prediction literature. These are: (a) the proportion of acquired to non-acquired firms (bankrupt/non-bankrupt, respectively) that should be used in the training sample, (b) the proportion of acquired to non-acquired firms that should be used in testing samples, and (c) the criteria on which acquired and non-acquired banks could be matched.

a) *Groups' proportions in training sample*

The majority of the studies on the prediction of acquisitions have used training samples with equal numbers of acquired and non-acquired firms, known as state or choice based sample. There are two primary reasons for following this procedure. The first is the lower cost of gathering data compared to an unmatched sample (Zmijewski, 1984; Bartley and Boardman, 1990). The second and most important is that a state based sample provides higher information content than a random sample (Cosslett, 1981; Palepu, 1986). Given that the number of acquired firms is relatively small compared to non-acquired, random sampling will consequently result in a sample comprising of many non-acquired firms and only a few (if any) acquired firms, which from an estimating procedure perspective, is inefficient[10]. Thus, it is essential to select the sample in a way that will ensure that acquired firms in the training sample represent an adequate proportion. Manski and Lerman (1977) and Manski and McFadden (1981) point out that such a state based sample will provide more efficient estimates than a random sample of the same size, while Cosslett (1981) characterises such a sample as a close-to-optimum design.

However, a state-based sample is not representative of the true population if as mentioned above, non-acquired firms exceed by far the acquired ones. As Zmijewski (1984) and Palepu (1986) point out this will result in biased parameter estimates when the models are developed with estimation techniques that assume random sampling, such as logit and probit analysis. Thus, alternative or adjusted techniques are required to estimate unbiased parameters (Zmijewski, 1984). For example, Palepu (1986) proposed a conditional maximum likelihood estimator in his study. Alternatively, rather than using a conditional maximum likelihood estimator, one can adjust the constant term[11] (Madalla, 1983) or the cut-off probability appropriately to take into account the bias introduced by the state-based estimation sample (Palepu, 1986; Espahbodi & Espahbodi, 2003).

b) *Groups' proportions in testing sample*

Palepu (1986) also criticised previous studies for using equal samples during testing and argued that such samples fail to represent the model's ability to predict targets. He demonstrated that if Stevens (1973) had used an unequal sample for testing, the overall prediction accuracy of his model would have been 56% instead of 70% as reported by Stevens. Palepu's argument, although correct, may not be as simple, as the difference in the prediction ability of the model could be attributed to the performance measure that was used (i.e. overall accuracy), which is very sensitive to the prevalence of positive cases (i.e. targets) as a percentage of the total sample[12].

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[10] See Palepu (1986) and Barnes (1990).

[11] Madalla (1983) has shown that the coefficients are not affected, when a state based sample is being used instead of a random sample. In fact, it is only the constant term that differs by a known value γ. This value can be calculated as follows: $\gamma = \ln P_1 - \ln P_2$, where P_1 and P_2 are the proportions sample from acquired and non-acquired groups respectively.

[12] This and other issues relative to models' performance measures are discussed in more detail in section 4.5.

For example, in the case of Stevens, using the numbers that Palepu assumed[13], the correct classification accuracy for targets remained 85%, as did the correct classification accuracy for non-targets (55%). Thus, if one had used either of these two measures or the average accuracy of two groups (i.e. calculated on a 50:50 sample[14]) the results would have remained unchanged. Of course, one could also argue that these measures remain unchanged because of the assumptions Palepu made.

c) Matching criteria

We now turn to the dilemma of choosing characteristics on which acquired and non-acquired banks should be matched. The matching criteria considered in previous studies were time, size, and industry. Among these, time is considered the most innocuous one (Hasbrouck, 1985) and has been used by almost all the researchers. However, in studies not concerned with merger waves, it seems reasonable to match an acquired firm with a non-acquired firm on the basis of time if observations are likely to be slowly changing or trending. Furthermore, samples for the development and testing of prediction models are usually pooled along many years and, as Barnes (19990) argues, accounting data are rather more volatile particularly around the period of acquisitions.

Many researchers have, in addition to time, matched firms either by industry (e.g. Espahbodi and Espahbodi, 2003) or size (e.g. Stevens, 1973) or both industry and size (e.g. Barnes, 1990), while Hasbrouck (1985) matched cases separately by industry and size. Bartley and Boardman (1990) argue that matching cases by industry, size or other criterion may be an appropriate control technique when the research objective is to examine the statistical significance of individual causal variables, while, additionally, given the lack of a theoretical model, the choice of variables to be matched is inherently arbitrary. Furthermore, as they point out in an earlier study (Bartley and Boardman, 1986) matching firms by industry and size reduces the classificatory power of the discriminant models.

[13] Palepu simply assumed that the sample of Stevens could consist of a total of 1000 firms, 40 targets and 960 non-targets, rather than 40 targets and 40-non targets as used by Stevens, and recalculated the overall accuracy holding the individual groups accuracies constant.
[14] See for example Wilson et al. (1999); Espahbodi and Esphabodi (2003); Doumpos and Pasiouras (2004).

Another important issue, noted by Hasbrouck (1985), is that if a characteristic is used as a matching criterion, then analysis of its effects will not be possible. For example, matching by size prevents analysis of the effects of size on the likelihood of acquisition. In a similar manner, use of an industry-matched sample will exclude from the analysis any industry-specific effects.

4.3 Variables Selection Process

Barnes (2000) points out that the problem for the analyst who attempts to forecast M&As is simply a matter of identifying the best explanatory/predictive variables. Consequently, the second step in the development of an empirical prediction model is the selection of input variables. Unfortunately, financial theories do not offer much by way of discriminating between the numerous variables regarded as potential candidates in model development.

There are, nevertheless, various factors that should be examined, since the reasons that lead firms to merge with or acquire other firms vary. As outlined in Chapter 2, the causes of M&As can be attributed to internal and external factors. Researchers have mainly used financial ratios to account for these reasons and consequently the majority of the acquisition prediction models are based on the financial characteristics of firms. The common assumption underlying these models is that fundamental economic factors (e.g. inflation, interest rates, etc) and the characteristics of the firm (e.g. management quality, sector, ownership, etc) are reflected in firm's financial statements. Similarly to bankruptcy prediction models, the established practice for acquisitions prediction models is to use financial ratios as an input.

A question that emerges when attempting to select financial ratios for empirical research is what ratios, among the hundreds, should be used? Given the large number of possible ratios, it is important to reduce the list of ratios that enter the final model selection process. Variables selection has long been an active research topic in statistics and pattern recognition. It is important that it can simplify the data description, which results in an easier understanding of problems, and better and faster problem solving. However, there is no easy way to determine how many ratios a particular model should contain. Too few and the model will not capture all the relevant information. Too many and the model will be overfitting the training sample, but underperform in a holdout sample, and will most likely have onerous data input requirements. As Hamer (1983) mentioned, the variable set should be constructed on the basis of (a) minimising the cost of data collection and (b) maximising the model applicability.

Huberty (1994) suggests three variable screening techniques that should be used: Logical screening (i.e. financial theory and human judgement), statistical screening (i.e. test of differences of two group means such as ANOVA) and dimension reduction (i.e. factor analysis). All these techniques have been used in past studies and are outlined below.

4.3.1 Financial Theory & Human Judgement

In this case, the selection of variables is based on the most frequently suggested takeover hypotheses. Well-known studies that followed this procedure for variables selection are Palepu (1986), Powell (1997, 2001), Barnes (1998, 2000), Kim and Arbel (1998), Cudd and Duggal (2000). However, in most cases, models developed with variables based on this approach have had rather low prediction ability. Powell (1997) mentions two potential explanations for this. The first is that these models are based upon takeover theories that are prevalent in the literature but have little or no validity. The second is that the empirical constructs used fail to capture the implications underlying the theories. Furthermore, some researchers select the variables on the basis of previous empirical findings (e.g. Belkaoui, 1978; Meador et al., 1996) or upon an effort to cover most aspects of a firm's financial condition (e.g. Cheh et al., 1999; Zopounidis and Doumpos, 2002).

4.3.2 Univariate statistical tests of mean differences

To classify the acquired and non-acquired firms effectively, the predictors (or variables) should be able to discriminate between these two groups. Thus, the aim is to make a determination as to what are the critical factors that distinguish the two groups of banks. In other words, to reveal what is different between an acquired and non-acquired bank?

In practice, statistical tests (e.g. t-test, ANOVA, Kruskal-Wallis) are used to compare, on a univariate basis, the financial characteristics of the two groups of acquired and non-acquired firms. The purpose is to analyse individual ratios to examine the discriminating power of many popular candidates for inclusion in the model. In this case, the rule of thumb is to keep the number of variables small and exclude a variable unless its discriminating power is statistically significant (Kocagil et al., 2002). There are at least two ways of determining the discriminating power of predictors in a univariate context (i.e. parametric or non-parametric statistical tests).

The application of a t-test assumes that the data have been derived from normal distributions with equal variance. If this assumption is not valid (in most cases normality does not hold when using financial ratios), then non-parametric tests could be used instead (which do not make such an assumption).

The Kolmogorov-Smirnov (K-S) test is typically used to test for normality of the underlying distribution. This test compares the cumulative probabilities of values in the data set with the cumulative probabilities of the same values in a specified theoretical normal distribution. If the discrepancy is sufficiently large, the test indicates that the data are not well fitted by the theoretical distribution. In other words, the K-S test examines the null hypothesis that the sample has been drawn from a normal distribution.

Once the variables that differ significantly between the two groups have been identified, a correlation analysis can be employed. If two variables are highly correlated, there is multicollinearity and one of them might be dropped from the analysis. Including highly correlated ratios when estimating the optimal weights for a model without careful attention to address the multicollinearity issue can result in imprecise estimates of the weights, which may result in a poor performance of a model when applied outside of the training sample (Kocagil et al., 2002). After all, if two variables measure essentially the same characteristic, there is no reason to enter both scores into the analysis.

4.3.3 Factor Analysis

The technique of factor analysis was first described by Spearman in 1904. It is a multivariate statistical method, designed to reduce the number of variables to a small number of factors that are linear combinations of the initial variables. Variables that are correlated with one another but largely independent of other subsets of variables are combined into factors. The first factor accounts for as much variation in the data as possible. Each succeeding factor accounts for as much as variation as possible that is not already accounted for by proceeding factors. In general, the univariate correlations between different factors can be expected to be low. By selecting one "representative" ratio from each factor, the choice can be limited to ratios, which depict the information content of the larger set of ratios. The fundamental idea that underlines factor analysis is shown in Figure 4.3, where nine variables are clustered into three separate groups (factors). Variables x_1, x_4, x_5, x_8 are clustered together, which means that they are highly correlated with one another and represent a factor. In a similar manner, variables x_3 and x_7 represent another factor, while x_2, x_6, x_9 define a third factor. Thus, by choosing each factor, the analyst will obtain almost as much information as is inherent in the original nine variables. Of course, the present example may be too simple since in practice the derived factors are not so clear-cut as it is presented in Figure 4.3. The reason is that there might be some overlap between the factors since some of the original variables may have some degree of correlation with some of the other variables. However, factors are distinguished by the fact that the set of variables defining one factor are more highly correlated with each another than they are with the variables defining other factors.

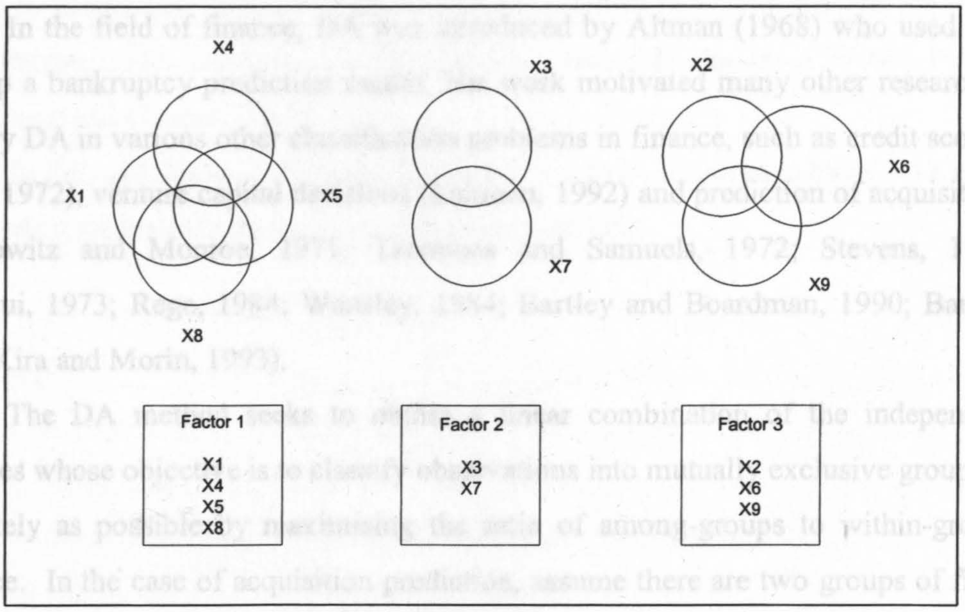

Figure 4.3 – An example of nine variables reduced to three factors

(source: Kachigan, 1991)

Stevens (1973) was the first to apply factor analysis developing a model for the prediction of acquisition targets, followed by Barnes (1990), Kira and Morin (1993), Zanakis and Zopounidis (1997), and Tartari et al. (2003) among others.

4.4 Method selection

A variety of classification methodologies are available for developing prediction models. This section discusses seven different methodologies that are implemented in the empirical study. These methodologies originate from different disciplines; including statistics, econometrics, operational research, and machine learning.

4.4.1 Discriminant Analysis

Discriminant Analysis (DA) was initially proposed by Fisher (1936) in the 1930s and was the first multivariate statistical classification technique. Although the initial study of discriminant analysis involved applications in biological and medical sciences, in recent years it has become increasingly popular in disciplines such as education, engineering, psychology and finance. Consequently, DA has become the most commonly discussed and widely used statistical technique in modeling classification tasks (Lee et al., 1999).

In the field of finance, DA was introduced by Altman (1968) who used it to develop a bankruptcy prediction model. His work motivated many other researchers to apply DA in various other classification problems in finance, such as credit scoring (Lane, 1972), venture capital decisions (Laitinen, 1992) and prediction of acquisitions (Simkowitz and Monroe, 1971; Tzoannos and Samuels, 1972; Stevens, 1973; Belkaoui, 1973; Rege, 1984; Wansley, 1984; Bartley and Boardman, 1990; Barnes, 1990; Kira and Morin, 1993).

The DA method seeks to obtain a linear combination of the independent variables whose objective is to classify observations into mutually exclusive groups as accurately as possible by maximising the ratio of among-groups to within-groups variance. In the case of acquisition prediction, assume there are two groups of firms (acquired and non-acquired), and *m* variables, $g_1, g_2, \ldots, g_m$, for each firm *i*. The DA method therefore estimates a discriminant function of the following form:

$$D_x = p_0 + p_1 g_1 + p_2 g_2 + \ldots + p_m g_m$$

where D_x is the score (for a firm *i*), p_0 is the intercept term and p_j (*j*=1,…,m) represent the slope coefficients associated with the independent variables g_j (*j*=1, …, *m*) for each firm.

A cut-off point is calculated according to the a-priori probabilities of group membership and the costs of misclassification. In the final step, each firm is classified into the acquired or the non-acquired firms group, depending on its score and the cut-off point. Firms with discriminant scores greater than the cut-off point are classified into the one group, while firms with discriminant scores less than the cut-off point are classified into the other group. Alternatively, firms can be classified on the basis of the probability of belonging to one of the groups and a cut-off probability point.

The estimation of the constant term and the discriminant coefficients is based on two major assumptions: (a) the independent variables follow a multivariate normal distribution, and (b) the variance-covariance matrices for all groups are equal. Alternatively, a Quadratic Discriminant Analysis (QDA) can be employed when the covariance matrices of the given populations are not equal.

4.4.2 Logit Analysis

The Logit method that originates from the field of econometrics has been applied to acquisition predictions by various researchers (e.g. Dietrich and Sorensen, 1984; Palepu, 1986; Ambrose and Megginson, 1992; Meador et al., 1996; Powell, 1997; Cudd and Duggal, 2000).

In the logit analysis the probability of a firm to be acquired is based on a set of independent variables is given by the following function:

$$P_i = \left(\frac{1}{1+e^{-Z_i}} \right)$$

where

$$Z_i = \ln\left(\frac{P_i}{1-P_i} \right) = p_0 + p_1 g_1 + p_2 g_2 + \ldots + p_m g_m, + \varepsilon_i$$

is the probability that firm i will be acquired, p_0 is the intercept term and p_j (j = 1,…,m) represents the coefficients associated with the corresponding independent variables g_j (j= 1,…,m) for each firm.

The coefficient estimates are obtained by regression that involves maximising a log-likelihood function (under the usual normality assumption of the random disturbances). The model is then used to estimate the group-membership probabilities for all firms under consideration. The firm is classified as acquired or non-acquired using an optimal cut-off point, attempting to minimise type I and type II errors. For example, in a two group classification problem like the one examined here, one can impose a classification rule of the following form: "classify a firm i into group 1 (acquired) if P_i>cut-off probability, otherwise classify the firm into group 2 (non-acquired). Thus, if the probability of acquisition for a firm is greater than the optimum cut-off point, the predicted firm is classified into the acquired group, otherwise into the non-acquired group. An approach that is commonly used in practice is to set the cut-off point equal to 0.5. Under this classification rule, firms with estimated probability higher than 0.5 are classified as acquired, while those with estimated probability lower than 0.5 are classified as non-acquired. Palepu (1986) proposed the empirical estimation of the optimum cut off point. Under the classification rule of Palepu, the cut-off point is where the conditional marginal probability densities for acquired and non-acquired banks are equal and is equivalent to minimising the total error probabilities. As an alternative Barnes (1998) proposed the use of a maximization of returns cut-off or a weighted cut-off point based on historical data. Finally, Powell (2001) experimented with various cut-off points and selected the one with the highest ratio of number of targets to the total number of firms in the portfolio.

4.4.3 UTilités Additives DIScriminantes (UTADIS)

The UTADIS multicriteria decision aid method employs the framework of preference disaggregation analysis[15] for the development of an additive utility function that is used to score the firms and decide upon their classification. The UTADIS method has been successfully applied in several fields of finance, such as bankruptcy (Zopounidis and Doumpos, 1999a,b; Doumpos and Zopounidis; 2002a), credit risk (Doumpos and Pasiouras, 2004), auditing (Spathis et. al. 2003, Pasiouras et al., 2004a), prediction of acquisitions (Doumpos et al., 2004). We provide a brief

[15] Preference disaggregation analysis (Jacquet–Lagreze & Siskos, 1982, 1983, 2001) refers to the analysis (disaggregation) of the global preferences (judgement policy) of the decision maker in order to identify the criteria aggregation model that underlies the preference result. Preference disaggregation analysis uses common utility decomposition forms to model the decision maker's preferences through regression-based techniques. More detailed, in preference disaggregation analysis the parameters of the utility decomposition model are estimated through the analysis of the decision maker's overall preference on some reference alternatives. The problem is then to estimate the utility function that is as consistent as possible with the known subjective preferences of the decision maker.

description of UTADIS below, drawing upon Doumpos and Zopounidis (2002b) where the reader is referred to for more details.

The developed additive utility function has the following general form:

$$U(x) = \sum_{i=1}^{m} p_i u'_i(g_i) \in [0,1]$$

where $g = \{g_1, g_2, ..., g_m\}$ is the set of the evaluation criteria[16], (which in this case correspond to the financial ratios), p_i is the weight of criterion g_i and $u'_i(g_i)$ is the corresponding marginal utility function normalised between 0 and 1. The criteria weights sum up to 1, i.e. $\sum_{i=1}^{m} p_i = 1$, and indicate the significance of each criterion on the developed classification model. On the other hand, the marginal utility functions $u'_i(g_i)$ are used to consider the partial performance of each alternative on the criterion. In other words, the marginal utility functions provide a mechanism for decomposing the aggregate result (global utility) in terms of individual assessment to the criterion level. To avoid the estimation of both the criteria weights p_i and the marginal utility functions $u'_i(g_i)$, it is possible to use the transformation $u_i(g_i) = p_i u'_i(g_i)$. Since $u'_i(g_i)$ is normalised between 0 and 1, it becomes obvious that $u_i(g_i)$ ranges in the interval [0, x_i]. Hence, the additive utility function is simplified to the following form:

$$U(x) = \sum_{i=1}^{m} u_i(g_i) \in [0,1]$$

The developed utility function provides an aggregate score $U(x)$ for each firm x along all financial ratios[17]. To classify firms in their original group, it is necessary to estimate the utility thresholds $u_1, u_2, ..., u_{q-1}$, defined in the global utility scale (i.e.

[16] In multicriteria decision aid, the term "criteria" is used to denote the independent variables. We therefore follow this terminology when describing UTADIS and MHDIS.

[17] In the case of acquisitions prediction, this score provides the basis for determining whether the firm could be classified in either the group of acquired firms or the group of non-acquired ones.

between 0 and 1) that distinguish the set of q ordered groups $(C_1, C_2, \ldots C_q)$[18]. Comparing the global utilities of a firm a with the utility thresholds, the classification is achieved by using the relations:

$$\left.\begin{array}{ll} U(x) \geq u_1 & \Rightarrow x \in C_1 \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots & \\ u_k \leq U(x) < u_{k-1} & \Rightarrow x \in C_k \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots & \\ U(x) < u_{q-1} & \Rightarrow x \in C_q \end{array}\right\}$$

The estimation of the additive utility model is performed through mathematical programming techniques. More precisely, the following linear programming formulation is employed to estimate the additive utility function and the utility threshold u_1, minimizing the sum of all violations of the above classification rule for all firms:

$$\text{Minimise } F = \sum_{x \in C_1} \sigma^+(x) + \ldots + \sum_{x \in C_k} [\sigma^+(x) + \sigma^-(x)] + \ldots + \sum_{x \in C_q} \sigma^-(x)$$

s.t.

$$\sum_{i=1}^{m} u_i[g_i(x)] - u_1 + \sigma^+(x) \geq 0 \qquad \forall x \in C_1$$

$$\left.\begin{array}{l} \sum_{i=1}^{m} u_i[g_i(x)] - u_{k-1} - \sigma^-(x) \leq -\delta \\ \\ \sum_{i=1}^{m} u_i[g_i(x)] - u_k + \sigma^+(x) \geq 0 \end{array}\right\} \forall x \in C_k$$

$$\sum_{i=1}^{m} u_i[g_i(x)] - u_{q-1} - \sigma^-(x) \leq -\delta \qquad \forall x \in C_q$$

---

[18] The UTADIS as well as the MHDIS, discussed in the next section, make the assumption that the groups are ordered. Therefore C_k is preferred to C_{k+1}, k=1,2,...q. In the case of acquisitions prediction where there are two groups, we can assume that C_1 corresponds to the non-acquired firms and C_2 to the acquired ones, as one of the main hypothesis in the literature is that the acquired are less efficient firms.

$$\sum_{i=1}^{m}\sum_{j=1}^{a_i-1} w_{ij} = 1$$

$$u_{k-1} - u_k \geq s \qquad k = 2, 3, \ldots, q-1$$

$$w_{ij} \geq 0,\ \sigma^+(x) \geq 0,\ \sigma^-(x) \geq 0$$

where:

- a_i is the number of subintervals $[g_i^j, g_i^{j+1}]$ into which the range of values of criterion g_i is divided[19],
- $w_{ij}=u_i(g_i^{j+1})-u_i(g_i^j)$ is the difference between the marginal utilities of two successive values g_i^j and g_i^{j+1} of criterion i ($w_{ij}\geq 0$),
- δ is a threshold used to ensure that $U(x)< u_{k-1}$, $\forall x\in C_k$, $2\leq k\leq q-1$ ($\delta> 0$)
- s is a threshold used to ensure that $u_{k-1}> u_k$ ($s>\delta>0$),
- $\sigma^+(x)$ and $\sigma^-(x)$ are the misclassification errors (over-estimation and under-estimation errors respectively).

After the solution F^* of this linear programming problem is obtained, a post-optimality stage is performed in order to identify, as far as possible, other optimal or near optimal solutions, which could provide a more consistent representation of the decision maker's preferences. In this way the robustness of the developed classification models is examined (Zopounidis and Doumpos, 1999a).

4.4.4 Multi-Group Hierarchical Discrimination (MHDIS)

Zopounidis and Doumpos (2000) developed an alternative MCDA non-parametric approach to use utility functions for discrimination purposes, known as Multi-Group Hierarchical Discrimination (MHDIS) method. Similar to UTADIS, MHDIS has also been successfully applied in classification problems in finance, such as bankruptcy prediction (e.g. Pasiouras et al., 2004b), credit risk (e.g. Doumpos et

[19] A basic assumption of the UTADIS involves the monotonicity of the criteria. As this is rather the exception than the rule in real problems, the most common technique to consider such cases, is to divide the range of criterion values into intervals so that preferences are monotone in each of them.

al., 2002) country risk (e.g. Doumpos and Zopounidis, 2001), auditing (e.g. Pasiouras et al., 2004a), M&A's (Zopounidis and Doumpos, 2002). MHDIS distinguishes the groups progressively, starting by discriminating the first group from all the others, and then proceeds to the discrimination between the alternatives belonging to the other groups.

To accomplish this task, instead of developing a single additive utility function that describes all alternatives (as in UTADIS), two additive utility functions are developed in each one of the q-1 steps, where q is the number of groups. The first function $U_k(x)$ describes the alternatives of group C_k, while the second function $U_{\sim k}(x)$ describes the remaining alternatives that are classified in lower groups $C_{k+1},\ldots,C_q$.

$$U_k(x)=\sum_{i=1}^{m} p_{ki}u_{ki}(g_i) \text{ and } U_{\sim k}(x)=\sum_{i=1}^{m} p_{\sim ki}u_{\sim ki}(g_i),\ k=1,2,\ldots,q-1$$

The corresponding marginal utility functions for each criterion g are denoted as $u_{ki}(g_i)$ and $u_{\sim ki}(g_i)$ which are normalised between 0 and 1, while the criterion weights p_{ki} and $p_{\sim ki}$ sum up to 1, i.e. $\sum_{i=1}^{m} p_{ki}=1$ and $\sum_{i=1}^{m} p_{ki}=1$. Throughout the hierarchical discrimination procedure it is assumed that the marginal utility function $u_{ki}(g_i)$ are increasing functions on the criterion's scale concerning the classification of an alternative in group $C_{k;}$ while on the other hand the marginal utility of a decision concerning the classification of an alternative, according to criterion g_i, into a lower (worse) group than C_k [denoted as $u_{\sim ki}(g_i)$] is a decreasing function on the criterion's scale[20]. Denoting as g_i^j and g_i^{j+1} the two consecutive values of criterion g_i ($g_i^{j+1} > g_i^j$, $\forall g_i \in G$), the monotonicity of the marginal utilities, can be expressed in mathematical terms through the following constraints:

[20] The set of criteria may include both criteria of increasing (i.e. higher values are preferred) and decreasing (lower values are preferred) preference. Without loss of generality the discussion of this section focuses on criteria of increasing preference. Obviously, as Doumpos and Zopounidis (2001) mention, the criteria of decreasing preference can be transformed into increasing preference through sign reversal.

$$u_{ki}(g_i^1)=0 \qquad u_{ki}(g_i^{j+1})>u_{ki}(g_i^j)$$
$$u_{\sim ki}(g_i^{p_i})=0 \qquad u_{\sim ki}(g_i^{j+1})<u_{\sim ki}(g_i^j)$$

These constraints can be simplified by introducing a small positive constant t as the lower bound of the difference between the marginal utilities of the consecutive values g_i^j and g_i^{j+1} as follows:

$w_{kij} \geq t$ and $w_{\sim kij} \geq t$ [21]

where:

$$w_{kij} = u_{ki}(g_i^{j+1}) - u_{ki}(g_i^j)$$
$$w_{\sim kij} = u_{\sim ki}(g_i^j) - u_{\sim ki}(g_i^{j+1})$$

Thus, the marginal utility of criterion g_i at point g_i^j can be calculated as

$$u_{ki}(g_i^j) = \sum_{l=1}^{j-1} w_{kil} \text{ and } u_{\sim ki}(g_i^j) = \sum_{l=j}^{p_i-1} w_{\sim kil}$$

As mentioned above, the model is developed in q-1 steps, where q is the number of groups. In the first step, the method develops a pair of additive utility functions $U_1(x)$ and $U_{\sim 1}(x)$ to discriminate between the alternatives of group C_1 and the alternatives of the other groups $C_2,\ldots,C_q$. On the basis of the above function forms the rule to decide upon the classification of any alternative has the following form:

If $U_1(x) \geq U_{\sim 1}(x)$ then x_j belongs in C_1

Else if $U_1(x) \leq U_{\sim 1}(x)$ then x_j belongs in ($C_2, C_3, \ldots, C_q$)

The alternatives that are found to belong into class C_1 (correctly or incorrectly) are excluded from further analysis.

[21] Upper bounds on the difference between the marginal utilities among the consecutive values g_i^j and g_i^{j+1} can also be set in a similar way (i.e., $w_{kij} \leq \text{upper bound}$ and $w_{\sim kij} \leq \text{upper bound}$).

In the next step, another pair of utility functions $U_2(x)$ and $U_{\sim 2}(x)$ is developed to discriminate between the alternatives of group C_2 and the alternatives of the other groups $C_3,\ldots,C_q$. As in step 1, the alternatives that are found to belong to group C_2 are excluded from further analysis. This procedure is repeated up to the last stage q-1), where all groups have been considered. The overall hierarchical discrimination procedure is presented in Table 4.5:

Table 4.1- The hierarchical discriminant procedure in MHDIS
(Source: Doumpos and Zopounidis, 2002a)

If $U_1(x) \geq U_{\sim 1}(x)$ then $x_j \in C_1$
Else If $U_2(x) \geq U_{\sim 2}(x\ )$ then $x_j \in C_2$
....
Else If $U_{q-1}(x) \geq U_{\sim q-1}(x)$ then $x_j \in C_{q-1}$
Else $x_j \in C_q$

In contrast to the UTADIS method, as Doumpos and Zopounidis (2002) point out, the utility functions in MHDIS do no indicate the overall performance but rather serve as a measure of the conditional similarity of an alternative to the characteristics of group C_k when the choice among C_k and all the lower groups $C_{k+1},\ldots, C_q$ is considered. However, similarly to the UTADIS, the estimation of the weights of the criteria in the utility functions as well as the marginal utility functions is accomplished through mathematical programming techniques. More specifically, at each stage of the hierarchical discrimination procedure, two linear programming and a mixed-integer programming problems are solved to estimate the utility thresholds and the two additive utility functions in order to minimise the classification error, as summarised in Table 4.5.

Table 4.2 Mathematical programming formulations in MHDIS
(source: Doumpos and Zopounidis, 2001)

LP1: Minimising the overall classification error	MIP: Minimising the number of misclassifications	LP2: Maximising the minimum distance
Min $F=\sum e(x)$ s.t. $\sum_{i=1}^{m}\sum_{j=1}^{r_{ai}-1} w_{kij} - \sum_{i=1}^{m}\sum_{j=r_{ai}}^{p_i-1} w_{\sim kij} + e(x) \ge s$, $\forall x\in C_k$ $\sum_{i=1}^{m}\sum_{j=r_{bi}}^{p_i-1} w_{\sim kij} - \sum_{i=1}^{m}\sum_{j=1}^{r_{bi}-1} w_{kij} + e(x) \ge s$, $\forall x\notin C_k$ $e(x)$, $s\ge0$, $t\ge0$.	Min $F=\sum_{\forall x\in MIS}[I(x)]$ s.t. $\left.\begin{array}{l} \sum_{i=1}^{m}\sum_{j=1}^{r_{ai}-1} w_{kij} - \sum_{i=1}^{m}\sum_{j=r_{ai}}^{p_i-1} w_{\sim kij} \ge s,\ \forall x\in C_k \\ \sum_{i=1}^{m}\sum_{j=r_{bi}}^{p_i-1} w_{\sim kij} - \sum_{i=1}^{m}\sum_{j=1}^{r_{bi}-1} w_{kij} \ge s,\ \forall x\notin C_k \end{array}\right\}, \forall x\in COR$ $\left.\begin{array}{l} \sum_{i=1}^{m}\sum_{j=1}^{r_{ai}-1} w_{kij} - \sum_{i=1}^{m}\sum_{j=r_{ai}}^{p_i-1} w_{\sim kij} + I(x) \ge s,\ \forall x\in C_k \\ \sum_{i=1}^{m}\sum_{j=r_{bi}}^{p_i-1} w_{\sim kij} - \sum_{i=1}^{m}\sum_{j=1}^{r_{bi}-1} w_{kij} + I(x) \ge s,\ \forall x\notin C_k \end{array}\right\},$ $\forall x\in MIS$ $s\ge0$, $t\ge0$, $I(x)$ integer.	Max d s.t. $\left.\begin{array}{ll} \sum_{i=1}^{m}\sum_{j=1}^{r_{ai}-1} w_{kij} - \sum_{i=1}^{m}\sum_{j=r_{ai}}^{p_i-1} w_{\sim kij} - d \ge s & \forall x\in C_k \\ \sum_{i=1}^{m}\sum_{j=r_{bi}}^{p_i-1} w_{\sim kij} - \sum_{i=1}^{m}\sum_{j=1}^{r_{bi}-1} w_{kij} - d \ge s & \forall x\notin C_k \end{array}\right\},$ $\forall x\in COR'$ $\left.\begin{array}{ll} \sum_{i=1}^{m}\sum_{j=1}^{r_{ai}-1} w_{kij} - \sum_{i=1}^{m}\sum_{j=r_{ai}}^{p_i-1} w_{\sim kij} \le 0 & \forall x\in C_k \\ \sum_{i=1}^{m}\sum_{j=r_{bi}}^{p_i-1} w_{\sim kij} - \sum_{i=1}^{m}\sum_{j=1}^{r_{bi}-1} w_{kij} \le 0 & \forall x\notin C_k \end{array}\right\}, \forall x\in MIS'$ $d\ge0$, $s\ge0$, $t\ge0$.
$w_{kij}\ge t$, $w_{\sim kij}\ge t$ (monotonicity constraints) $\sum_{i=1}^{m}\sum_{j=1}^{p_i-1} w_{kij}=1$, $\sum_{i=1}^{m}\sum_{j=1}^{p_i-1} w_{\sim kij}=1$ (normalisation constraints)		

Note that each of the three mathematical programming formulations in Table 4.5 incorporates two constraints to ensure the monotonicity of the marginal utilities, as well as to normalise the global utilities in the interval [0,1]. The classification error in LP1 is denoted using the error function *e*. For an alternative $x \in C_k$ such that $U_k(x) \leq U_{\sim k}(x)$ the classification error is $e(x) = U_{\sim k}(x) - U_k(x) + s$. Similarly, for an alternative $x \notin C_k$ such that $U_k(x) \geq U_{\sim k}(x)$ the classification error is $e(x) = U_k(x) - U_{\sim k}(x) + s$. The small positive real constant s is used to ensure the strict inequalities $U_k(x) > U_{\sim k}(x)$ and $U_k(x) < U_{\sim k}(x)$.

If after the solution of LP1, there exist some alternatives for which $e(x)>0$, then these alternatives are misclassified. However, it may be possible to achieve a "re–arrangement" of the classification errors leading to the reduction of the number of misclassifications. In MHDIS this possibility is explored through a mixed-integer programming (MIP) formulation. Since MIP formulations are difficult to solve, especially in cases where the number of integer variables is large, the MIP formulation used in MHDIS considers only the misclassifications that occur through the solution of LP1, while retaining all the correct classifications. This reduces significantly the number of integer variables, which are associated to each misclassified alternative, thus reducing the computational effort required to obtain a solution. In the MIP formulation used in MHDIS, *COR* denotes the set of correctly classified alternatives after solving LP1, and *MIS* denotes the set of misclassified alternatives. The first set of constraints in MIP ensures that all correct classifications achieved by solving LP1 are retained, while the second set of constraints is applied only to alternatives that were misclassified by LP1. The integer error variables *I* indicate whether an alternative is misclassified or not.

Through the solution of LP1 and MIP the "optimal" classification of the alternatives is achieved, where the term "optimal" refers to the minimisation of the total number of misclassified alternatives. However, the correct classification of some alternatives may be "marginal", that is, although they are correctly classified, their global utilities according to the two utility functions developed may be very close. The objective of LP2 is to clarify the obtained classification, through the maximisation of the minimum difference between the global utilities of the correctly classified alternatives achieved according to the two utility functions. Similarly to MIP, COR' denotes the set of correctly classified alternatives after solving LP1 and

MIP, and *MIS′* denotes the set of misclassified alternatives. The first set of constraints in LP2 involves only the correctly classified alternatives. In these constraints *d* represents the minimum absolute difference between the global utilities of each alternative according to the two utility functions. The second set of constraints involves the misclassified alternatives and it is used to ensure that they will be retained as misclassified.

4.4.5 Classification And Regression Trees (CART)

CART (Breiman et al., 1984) has become one of the most popular machine learning approaches in classification problems over the last years. Instead of developing classification functions or network architectures a binary decision tree is developed. The main idea behind CART is simple: at each brand node, the best splitting value for each independent variable is determined, and the sample is split based on the best of these values. This can be accomplished through a set of if-then split conditions that permit accurate prediction or classification of cases. For each parent node, the left child node corresponds to the points that satisfy the condition, and the right child node corresponds to the points that do not satisfy the condition. Figure 4.4 provides a simple hypothetical example of a decision tree involving three independent variables g_1, g_2, g_3 for the classification of a set of firms as acquired (A) and non-acquired (NA).

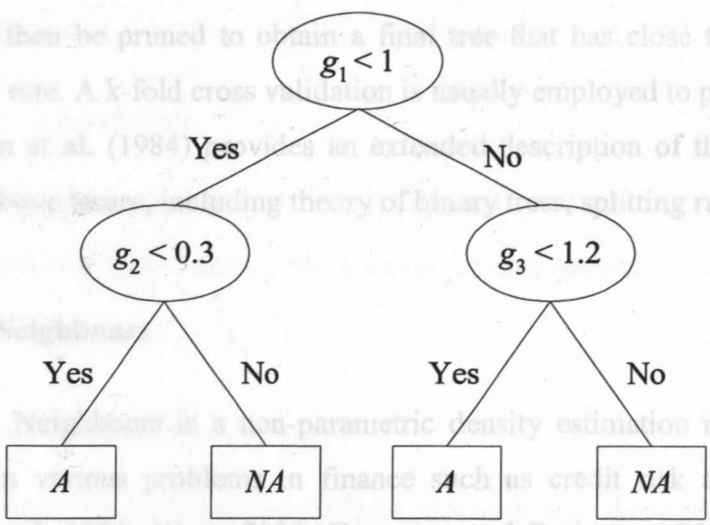

Figure 4.4: An example of a decision tree for classification

Given the hierarchical nature of classification trees, these splits are selected one at a time, starting with the split at the root node (i.e. the top decision node), and continuing with splits of resulting child nodes until splitting stops and the child nodes, which have not been split, become terminal nodes (i.e. points on the tree beyond which no further decisions are made). In general terms, the split at each node will be found that generate the greatest improvement in predictive accuracy. Nevertheless, various split criteria exist such as the Gini, Symgini, Twoing, Ordered Twoing, Maximum Deviance. The Gini index is the measure most commonly used for classification problems and was chosen by Espahbodi and Espahbodi (2003) (also used in the present study). This criterion defines the best splitting value as the one resulting in the smallest node heterogeneity. Consequently, it reaches a value of zero when only one class is present at a node. With priors estimated from class sizes and equal misclassification costs, the Gini index is calculated as the sum of products of all pairs of class proportions for classes present at the node.

Obviously splitting could continue until all cases are correctly classified. However, this would probably result in "overfitting" in a given sample with a reduced ability to classify accurately new observations. One way to control splitting is to continue until all terminal nodes are pure or contain no more than a specified minimum number of cases or objects. An alternative strategy is to continue until all terminal nodes are pure or contain no more cases than a specified minimum proportion of the sizes of one or more classes. The tree obtained from the above procedure can then be pruned to obtain a final tree that has close to the minimum estimated error rate. A k-fold cross validation is usually employed to perform pruning.

Breiman et al. (1984) provides an extended description of this method with discussion of above issues, including theory of binary tress, splitting rules, etc.

4.4.6 Nearest Neighbours

Nearest Neighbours is a non-parametric density estimation method that has been applied in various problems in finance such as credit risk assessment (e.g. Henley and Hand, 1996; West, 2000; Doumpos and Pasiouras, 2004), bankruptcy prediction (e.g. Tam and Kiang, 1992) and interest rate modelling (Nowman and Saltoglu, 2003). The nearest neighbour rule classifies an object (i.e. firm) to the class of its nearest neighbour in the measurement space using some kind of distance measure like the local metrics (Short and Fucunaga, 1980), the global metrics (Fukunaga and Flick, 1984), the Mahalanobis or the Euclidean distance. The latter is the most commonly used one and is also employed in the present study.

The modification of the nearest neighbour rule, the k-nearest neighbour (k-NN) method that is employed in the present study, classifies an object (i.e. firm) to the class (i.e. acquired or non-acquired) more heavily represented among its k nearest neighbours.

Assuming a firm x described by the feature vector $< g_1(x), g_2(x),..., g_m(x)) >$ where $g_r(x)$ is used to denote the values of the r^{th} characteristic of firm x, the distance between two instances x_i and x_j is estimated as follows:

$$d(x_i, x_j) \equiv \sqrt{\sum_{r=1}^{m} (g_r(x_i) - g_r(x_j))^2}$$

Then, the algorithm for approximating a discrete-valued function of the form $f : \Re^n \rightarrow C$, where C is a finite set of classes $\{C_{1,} C_2,..., C_q\}$ proceeds as follows:

Step 1: For each training example (i.e. firm) $< x, f(x) >$, add the firm to the list of training examples.

Step 2: Given a query firm x to be classified, let $x_1, x_2,..., x_k$ denote the k instances from the training examples that are nearest to x.

Step 3: Return $\hat{f}(x) \leftarrow \arg\max_{c \in C} \sum_{i=1}^{k} \delta(c, f(x_i))$, where $\delta(a,b)) = 1$ if $a = b$ and where $\delta(a,b)) = 0$ otherwise.

Thus, the algorithm returns the value $\hat{f}(x)$ as an estimate of $f(x)$, which is the most common value of f among the k training examples nearest to x.

4.4.7 Support Vector Machines (SVMs)

The Support Vector Machines (SVMs) approach has been recently applied in a few financial applications mainly in the areas of time series forecasting (Tay and Cao, 2001, 2002; Kim, 2003; Huang et al., 2005), bankruptcy prediction (Shin et al., 2004) and credit risk assessment (Huang et al., 2004).

SVMs was introduced by Vapnik (1995) and is based on the Structural Risk Minimization (SRM) principle from computational learning theory, that seeks to minimise an upper bound of the generalisation error rather than minimise the training error. A brief description of the SVM approach is given below. A more detailed explanation and proofs can be found in textbooks by Vapnik (1995, 1998) and Cristianini and Shawe-Taylor (2000). SVMs can be used for both regression and classification. Given the purpose of the present study, we will focus on the latter.

SVM uses a linear structure to implement nonlinear class boundaries through extremely non-linear mapping of the input vectors into the high-dimensional space. If the data is linearly separated, SVM finds a special kind of linear model, the optimal separating hyperplane (OSH) that provides the maximum separation between the classes. The training points that are closest to the maximum margin hyperplane are called support vectors. All other training examples are irrelevant for determining the binary class boundaries.

For the linearly separable case, the decision rule defined by an OSH for the binary decision class can be represented by the following equation:

$$y = b + \sum y_i a_i \, \mathrm{x} \bullet \mathrm{x}_i$$

where y is the outcome, y_i is the class value of the training example x_i, and $\bullet$ is the dot product. The vector x corresponds to an input, the vectors x_i are the support vectors and b and a_i are parameters that determine the hyperplane ($a \geq 0$).

From the implementation point of view, Vapnik (1995) showed how training a SVM and finding the parameters b and a leads to a quadratic optimisation problem with bound constraints and one linear equality constraint. This means that the solution of SVMs is unique, optimal and absent from local minima (Tay and Cao, 2001).

Since most real-world problems seem not to be linearly separable, SVMs can work in combination with the technique of "kernels", that automatically realises a non-linear mapping into a feature space. For the nonlinearly separable case, a high-dimensional version of the above equation is given as:

$$y = b + \sum y_i a_i \, K(\mathrm{x}, \mathrm{x}_i)$$

The function $K(\mathrm{x}, \mathrm{x}_i)$ is the kernel function for generating the dot products to construct machines with different types of non-linear decision surfaces in the input space. Any function satisfying Mercer's theorem can be used as the kernel. For constructing decision rules, two typical examples are the polynomial kernel function $K(x_i, x_j) = (x_i \bullet x_j + 1)^d$ where d is the degree of the polynomial kernel, and the Gaussian function with kernel $K(x_i, x_j) = \exp\left(-1/\delta^2 (x_i - x_j)^2\right)$ where δ^2 is the bandwidth of the Gaussian kernel.

In the general non-separable case the development of an SVM model involves two objectives: the maximisation of the separation margin and the minimization of the misclassifications for the training sample. The relative firms in the importance of the two objectives is taken into consideration through a user-defined constant ($C \succ 0$) representing the importance given to the minimisation of the misclassification as opposed to the margin maximisation objective. Implicitly C defines an upper bound on the coefficients a of the separating function.

4.5 Aspects of Model Evaluation

4.5.1 The classification matrix

The outcome of an acquisitions prediction model is between two discrete alternatives, acquired or non-acquired. The model in its classification of firms in the two groups provides a number of correct as well as a number of incorrect predictions. Obviously, the objective of developing an acquisitions prediction model is in fact straightforward: one wants to classify correct as many firms as possible.

The classification results are usually reported in the form of a classification table, often referred to as a confusion matrix. Although there are other measures of evaluation (e.g. Receiver Operating Characteristics - ROC curves), the confusion matrix is almost universally adopted as the standard error report in supervised classification. It is the only method that has been used in previous studies in the prediction of acquisition targets. This matrix is a convenient way to compare the firms' actual group membership versus their predicted group membership. Usually, the column present the number of firms classified in the group while the rows present the number of firms in the actual groups, although the opposite format may be used (i.e. classified in rows and actual in columns). A confusion matrix, using the former format, is shown in Table 4.6

Table 4.3 - The confusion (classification) matrix

		Classified (predicted) by the model		
		Acquired	Non-Acquired	Total
Actual group	Acquired	a	b	$(a+b)$
membership	Non-Acquired	c	d	$(c+d)$
	Total	$(a+c)$	$(b+d)$	N

The notations are defined as:

a: The number of acquired firms that are correctly classified as acquired.

b: The number of acquired firms that are incorrectly classified as non-acquired.

c: The number of non-acquired firms that are incorrectly classified as acquired.

d: The number of non-acquired firms that are correctly classified as non-acquired.

Obviously a perfect model would have zeros for both cells b and c, and the total number of acquired and non-acquired firms in cells a and d respectively, indicating that it perfectly discriminated between the acquired and non-acquired firms.

Based on the differential analysis of elements in the matrix, a number of measures can be computed. Perhaps the most basic tool for understanding the performance of an acquisitions prediction model is the "percentage right". The following are four commonly used measures (calculated as shown on the RHS):

$$\text{Overall correct classification} = (a+d)/N$$

$$\text{Average correct classification} = \{[a/(a+b)] + [c/(c+d)]\}/2$$

$$\text{Acquired firms correct classification} = a/(a+b)$$

$$\text{Non-acquired firms correct classification} = c/(c+d)$$

Alternatively one can focus on classification errors (or misclassifications) as opposed to correct classifications. For example:

$$\text{Overall error rate} = 1 - \text{overall correct classification}$$

or

$$\text{Overall error rate} = (c+b)/N.$$

Before going into more details about the choice of the appropriate evaluation measure, two issues related to model evaluation need to be addressed. These are (i) the absolute comparison performance, and (ii) the comparative performance.

(i) Absolute comparison performance

In general, an absolute evaluation compares the performance of a model to some exogenous metric (i.e. the model should obtain a correct classification accuracy of at least 70% to be characterised as effective). Of course this metric depends highly on the area of application (i.e. for example, bankruptcy prediction models have historically achieved higher accuracies than acquisitions prediction models). Therefore, the most critical question is whether the results of the prediction model are better than the ones that could be obtained by chance assignment. For example, if we had a sample of 50 acquired firms and 50 non-acquired firms, it would be reasonable to expect then, that by using the flip of a coin to decide firm group membership, we could classify about 50% of the firms correctly. The critical question then would be, if by using a classification model we could classify correct more than 50% of the firms.

One way to address this issue is to use the odds ratio. However, this ratio has an unfortunate characteristic of being infinite when either *b* or *c* is 0. Hence, it has the same value when the model is perfect or lacks one type of error. An alternative is to use the Kappa Index (Huberty, 1994).

The Kappa index was initially proposed by Cohen (1960) and is a measure of agreement, which compares the observed agreement to an agreement expected by change between two or several observers or techniques when the judgments are qualitative, contrary to the coefficient of Kendall for example that evaluates the degree of agreement between quantitative judgments. Kappa can therefore express the proportionate reduction in error generated by a classification process, compared with the error of a completely random classification. It can take values between –1 and +1, with 1 indicating perfect agreement and 0 indicating no better than chance agreement. Finally, negative values occur when agreement is weaker than expected by chance. Kappa is often multiplied by 100 to give a percentage measure of classification accuracy. For example, a value of 0.7 would imply that the classification process was avoiding 70% of the errors that a completely random classification would generate.

Kappa can be calculated as follows:

$$\text{Kappa} = (\text{P\_Observed} - \text{P\_Expected}) / (1 - \text{P\_Expected})$$

where P_Observed = $(a+d) / N$
and P_Expected = $(((a+c) * (a+b)) + ((b+d) * (c+d))) / \text{sq}(N)$

Cohen's Kappa can be expressed as:

$$\text{Kappa} = 2\,(ad - bc) / ((a+c)(c+d) + (b+d)\,(a+b))$$

Cohen's Kappa is a widely accepted calculation that, although not commonly used in finance, has been characterised as the touchstone for assessing the quality of diagnostic procedures (Faraone and Tsuang, 1994). An issue that one should consider when evaluating a model with Cohen's Kappa is that when the sample size of one group far exceeds the other Kappa fails and tends to be quite low[22].

Byrt et al. (1994) proposed a solution to the possible bias of Cohen's Kappa, known as "Prevalence-Adjusted-Bias Adjusted Kappa" (PABAK). PABAK has the same interpretation as Cohen's Kappa and can be calculated following the three steps below:

1. Calculate the mean of a and d: $n = (a+d) / 2$
2. Calculate the mean of b and c: $m = (b+c) / 2$
3. Use means m and n from steps 1 and 2, Cohen's Kappa formula and the table below to calculate PABAK.

Table 4.4-Calculation of PABAK

		Predicted	
		Acquired	Non- Acquired
Actual	Acquired	N	M
	Non-Acquired	M	N

[22] The decrease becomes larger especially when the model provides unbalanced classification accuracies between the groups.

PABAK is the value that kappa would take if there were no systematic one-side variations between the ratings and the categories were of equal prevalence.

(ii) Comparative performance

Comparative performance gives an indication of whether model A is better than model B. Obviously, a researcher may be interested in comparing the effectiveness of two classification models using a given dataset. The models may be developed using different classification techniques or the same technique but different predictor variables. For example, in the case of acquisitions prediction, it may be of interest to compare the results of discriminant analysis with those of logit analysis, or to compare the results of using raw with industry adjusted data.

Probably the most important issue when comparing classification models is to use a testing sample. The reason is that some methods such as neural networks, multicriteria decision aid, support vector machines, among others, have different parameters to be estimated compared to each other and significantly more than discriminant and logit, resulting in some of them having an a-priori data fitting superiority in the training sample.

4.5.2 Issues to consider when choosing evaluation measure

We have so far discussed six measures of a model's evaluation performance. It should be mentioned at this point that these measures have different characteristics, and in particular some are sensitive to the prevalence of positive cases (e.g. acquired, bankrupt) as a percentage of the total sample. For example, in the case of acquisition targets prediction, the acquired firms are always much less in the population, and also in the sample, than the non-acquired ones. Tables 4.7 and 4.8 show the effect of prevalence on the measures of evaluation using a hypothetical example. The first table shows the classification of firms obtained by the model. The second shows the six measures for each one of the examples.

Table 4.5 – Hypothetical classification matrices for different prevalence of acquired firms in sample

Example 1 (prevalence = 50%)		Classified (predicted)		
		Acquired	Non-Acquired	Total
Actual	Acquired	60	40	100
	Non-Acquired	20	80	100
	Total	80	120	200
Example 2 (prevalence = 14.28%)				
Actual	Acquired	60	40	100
	Non-Acquired	120	480	600
	Total	180	560	700
Example 3 (prevalence = 1.63%)				
Actual	Acquired	60	40	100
	Non-Acquired	1200	4800	6000
	Total	1260	4840	6100

Table 4.6 – Effect of prevalence on evaluation measures

Prevalence	Example 1 50%	Example 2 14.28%	Example 3 1.63%
Evaluation measure			
Overall correct classification accuracy	70%	77.1%	79.7%
Correct Classification of acquired firms	60%	60%	60%
Correct Classification of non-acquired firms	80%	80%	80%
Average Correct Classification Accuracy	70%	70%	70%
Cohen's Kappa Index	40%	30%	6%
PABAK Index	40%	54.3%	59.3%

It is obvious from Table 4.8 that three measures are not being affected by prevalence while the rest are positively or negatively affected. In particular, the individual correct accuracies for the acquired and non-acquired are not changing. As a result, the average accuracy also remains stable. When the observations in the two groups are equal (i.e. prevalence 50%), the overall accuracy equals the average one. However, the overall correct classification accuracy is negatively related to prevalence. As the number of acquired firms in the sample decreases, the overall correct classification increases. The example could be even more extreme considering that, even if none of the acquired firms had been classified correctly in the third example, the overall classification accuracy would have been 98.37% by assigning all cases to the non-acquired group. Cohen's Kappa and PABAK are positively and negatively related accordingly. As in the case of overall and average accuracies, when the prevalence is 50% these two measures of Kappa are equal. When the prevalence decreases, Cohen's Kappa tends to decrease while PABAK tends to increase.

The selection of the measure of performance depends on the cost of each type of error as well as the prior probabilities. As mentioned above, the error can be used as a measure instead of correct classification. Obviously classification inaccuracies can result in one of two ways, as shown in Table 4.9. First, the model can indicate a firm as acquired, when in fact, it is not acquired (known as Type II error). Second, the model can indicate a firm as non-acquired, when in fact, it is acquired (Type I error).

Table 4.7 – Type I and Type II errors of an acquisition targets prediction model

		Classified by the model	
		Acquired	Non- Acquired
Actual	Acquired	Correct prediction	Type I error
	Non-Acquired	Type II error	Correct prediction

The issue of model error cost is a complex and important one. It is often the case, for example, that a particular model will perform better under one set of cost assumptions, but it will not do so under a different set of assumptions (Provost and Fawcett, 1997; Hoadley and Oliver, 1998). Obviously different users may have different cost structures, making it difficult to present a single cost function that is appropriate across all of them. This leads Altman (1993) to argue that when dealing with costs, one needs to specify exactly who the user is and what costs are relevant. For example, as Cheh et al. (1999) point out, in the context of an investment application (i.e. developing a model to predict acquired targets and form portfolios to earn abnormal returns), there are a number of diversified strategies that an investor could follow by changing the trade-off between type I and type II errors.

Turning to the evaluation measures, for reasons of simplicity, thief the two types of classification inaccuracies (i.e. Type I and Type II errors) incur the exact same loss, as is often assumed, then a single overall classification rate can be used for model evaluation. In that case, the selection of the "best" model is easy, since the one with the highest overall classification rate is selected. However, when the costs are known with some degree of certainty or we simply know that one type of error is more costly than other, but we cannot quantify it, then the best model could be selected based upon the individual classification rates (of the acquired and the non-acquired firms). Consequently, although it is possible for some models to commit less of one type of error than the other, users of models seek to keep the probability of making either type of error as small as possible. Unfortunately, minimising one type of error usually comes at the expense of increasing the other type of error (Sobehart et al., 2000). Thus, as the probability of making a Type II error increases, the probability of a Type I error decreases. For that reason, the average accuracy offers a good alternative that is not affected by prevalence.

Turning to Kappa measures, PABAK is similar to overall accuracy, as it is negatively related to prevalence. Since Cohen's Kappa is positively related to prevalence, a good approach could be to calculate and consider both of them.

It was mentioned above that the prior probabilities should also be considered prior to the selection of the appropriate measure of performance. If the prior probability of one of the two groups is very high, the model will achieve a strong prediction rate if all observations are simply classified into this class. However, when a group has a low probability of occurrence (e.g. acquisition, bankruptcy) it is far more difficult to assign these low probability observations into their correct class. This particular difficulty of accurate group assignments of rare events will not be captured if the overall classification is used as an evaluation method. Therefore, as in the case of costs above, one might prefer to examine the individual group classifications or the average classification.

4.5.3 Out of sample performance – Model's testing

It was mentioned in section 4.2.2 that when classification models are used to reclassify observations of the training sample, the classification accuracies are normally biased upward and the testing of the model in a holdout sample is necessary.

According to Gupton and Stein (2003), the primary goals of testing are to: (1) determine how well a model performs, (2) ensure that a model has not been over-fit and that its performance is reliable and well understood, and (3) confirm that the modelling approach, not just an individual model, is robust through time. Obviously, the same measures are calculated to access the performance of the model in the testing sample. Therefore if the developed model performs satisfactory in the training sample, when evaluated with the other measures discussed above, it can used to decide upon the classification of a set of new alternatives.

4.6 Conclusion

In this chapter we have presented a general methodological framework for the development and the evaluation of an acquisition targets prediction model. The chapter began with a discussion of several sampling issues that should be considered at the early stage of data collection and preparation. We then discussed the reasons and techniques for selecting a small set of input variables among the numerous financial variables that could be included in the model. Three most commonly used techniques for selecting the final set of input variables were discussed. Then, we presented seven well-known classification methodologies, and finally discussed several issues relating to the evaluation of a prediction model. The procedures and issues explained in this chapter will be used in the following chapters for empirical analyses, including the selection and preparation of data as well as the development and evaluation of the prediction models.