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The identification of acquisition targets in the EU banking industry: An application of multicriteria approaches

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Abstract

In this paper we develop classification models for the identification of acquisition targets in the EU banking industry, incorporating financial variables that are mostly unique to the banking industry and originate from the CAMEL approach. Our sample comprises 168 non-acquired banks matching 168 acquired banks over the period 1998-2002, covering 15 EU countries. We compare and evaluate the relative efficiency of three multicriteria approaches, namely MHDIS, PAIRCLAS, and UTADIS, with all models developed and tested using a 10-fold cross validation approach. We find that the importance of the variables differs across the models. However, on the basis of univariate test and the results of the models we could state that in general after adjusting for the country where banks operate, acquired banks are less well capitalized and less cost and profit efficient. The results show that the developed models can achieve higher classification accuracies than a naïve model based on random assignments. Nevertheless, there is fair amount of misclassification that is hard to avoid given the nature of the problem, showing that as in previous studies for non-financial firms, the identification of acquisitions targets in banking is a difficult task.

Keywords: Acquisitions, Banks, Classification, MCDA

JEL: C63, G21, G34

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1. Introduction

The purpose of this study is to evaluate the performance of multicriteria decision aid (MCDA) prediction models developed specifically to identify acquisition targets in the banking industry, an area that is relatively under-researched¹. Of approximately 30 papers that we can identify in the literature which utilised one or more methods for the prediction of acquisition targets, all but one (Pasiouras and Tanna, 2006²) have focused on samples of firms drawn from the non-financial sectors (i.e. manufacturing, retail, hospitality, etc.) and excluded banks from their analysis. One reason for their exclusion is the unusual structure of banks' financial statements suggesting that certain bank specific characteristics distinguish them from other corporations (Bauer and Ryser, 2004). In line with Pasiouras and Tanna (2006) the present paper utilises financial variables that originate from the CAMEL³ approach in developing prediction models that distinguish acquired from non-acquired banks, based on a sample of commercial banks covering 15 EU countries⁴ (the former EU15).

Most of the past studies have used multivariate statistical and econometric techniques such as discriminant analysis (e.g. Stevens, 1973; Barnes, 1990) and logit analysis (e.g. Barnes, 1998; 1999, Powell, 2001) and only more recently the parametric nature and the statistical assumptions/restrictions of those approaches have led researchers to the application of alternative techniques such as artificial neural networks

¹ Most of the previous studies in banks' M&As can be classified in four main categories. These are: (i) studies that examine the consequences of M&As on operating performance (e.g. Cornett and Tehrania, 1992; Berger and Humphrey, 1992; Berger, 1998), (ii) event studies that examine the changes in the share prices of the stock of the merged banks around the M&A announcement date (e.g. Baradwaj et al., 1992; DeLong, 2001), (iii) studies that examine the determinants of the premium paid for the target (e.g. Cheng et al., 1989; Hunter and Wall, 1989; Gart and Al-Jafari, 1999; Henderson and Gart, 1999), and (iv) studies that examine the characteristics of the banks involved in M&As (e.g. Curry, 1981; Wheelock and Wilson, 2000, 2004). Other issues that have been examined are the consequences of banks M&As on small firms lending (e.g. Berger et al., 1998), the arguments for the merger (Went, 2003), the relation of M&As with CEO compensation and managerial incentives (e.g. Anderson et al., 2004), and the determinants of cross-border M&As (e.g. Focarelli and Pozzolo, 2001).

² Pasiouras and Tanna (2006) have used discriminant and logit analysis to re-examine various methodological issues while focusing on the banking industry.

³ CAMEL is an acronym commonly used by bank regulators to assess a bank's financial condition. It refers to the analysis of the five key elements of banks performance (capital adequacy, asset quality, management, earning and liquidity) although we consider, in addition, factors that reflect size, market power and growth of banks as in Wheelock and Wilson (2004) and Pasiouras and Zopounidis (2006).

⁴ The studies that examine the EU banking industry mainly fall in the first (e.g. Vander Venet, 1996; Diaz et al., 2004; Campa and Hernando, 2006) and second (e.g. Tourani Rad and Van Beek, 1999; Cybo-Ottone and Murgia, 2000; Scholtens and Wit, 2004; Valkanov and Kleimeier, 2006; Campa and Hernando, 2006) of the four main categories mentioned above.

(Cheh et al., 1999), rough sets (Slowinski et al., 1997), recursive partitioning algorithm (Espahbodi and Espahbodi, 2003) and multicriteria decision aid (MCDA) (e.g. Doumpos et al., 2004). Some of these studies focused on the search of the best predictive variables (e.g. Bartley and Boardman, 1990; Walter, 1994; Cudd and Duggal, 2000) and others on the search of the most effective empirical method for the development of the prediction models (e.g. Doumpos et al, 2004; Cheh et al., 1999; Slowinski et al., 1997; Espahbodi and Espahbodi, 2003).

The present paper has two overall objectives that cover both categories mentioned above. First, it aims to jointly investigate the efficiency of three MCDA techniques. Second, it attempts to reveal the factors that contribute in the identification of acquisitions targets. The major advantages of the MCDA over the traditional techniques are that they do not make any prior assumptions⁵ about the normality of the variables or the group dispersion matrices (e.g. discriminant analysis), and that they are not sensitive to multicollinearity or outliers (e.g. logit analysis). Furthermore, MCDA techniques can easily incorporate qualitative data, while they are also very flexible in terms of incorporating preferences of the decision maker.

The rest of the paper is as follows. In Section 2 we first describe our sample of EU commercial banks and explain the cross validation procedure for developing and validating the models⁶. We then provide a detailed discussion of the financial variables representing bank-specific characteristics that we consider appropriate for the

⁵Barniv and McDonald (1999) summarize some of the problems related to the use of discriminant, logit and probit. Their argument, based on previous studies, is that Logit and Probit are sensitive to: (a) data properties, such as departure from normality of financial variables (Frecka and Hopwood, 1983; Richardson and Davidson, 1984; Hopwood et al., 1988); (b) overall small sample size (Noreen, 1988; Stone and Rasp, 1991); (c) multicollinearity (Aldrich and Nelson, 1984; Stone and Rasp, 1991). Hopwood et al. (1998) also point out that discriminant analysis (DA) is generally sensitive to departure from normality, and logit and probit are both sensitive to extreme non-normality. DA assumes normality, symmetry and equal covariance matrices, which are usually strong assumptions.

⁶Prior studies that have applied MCDA techniques for the prediction of acquisition of non-financial firms conclude that they can be more efficient than traditional techniques (Zopounidis and Doumpos, 2002; Doumpos et al., 2004). However, the evaluation procedure in these studies has been based on the back testing approach where the models are developed with data from one year prior to acquisition, and tested on data from two or three years prior to the acquisition. Hence, their evaluation approach utilises the dataset that is effectively drawn from the same set of firms used for model development. It has been shown that when classifications models are used to reclassify the observations of the training sample, the classification accuracies are biased upwards (Altman, 1993). In the present study we re-examine the relative efficiency of MCDA techniques using a 10-fold cross validation approach that allows the maximum use of the available data in the training stage and ensures the proper validation of the models.

identification of bank acquisition targets. The three MCDA approaches are described in Section 3, while section 4 discusses the empirical results. Finally, Section 5 presents our concluding remarks on the use of the MCDA models for identifying acquisition targets and highlights some issues for further research.

2. Sample and variables selection

2.1 Sample selection

In order to obtain data and information on commercial bank acquisitions in the EU, certain criteria had to meet. For example, the acquisition represented the purchase of 50% or more of the ownership of the acquired bank, and all banks were classified as commercial banks in Bankscope database⁷. The reason only commercial banks were considered is to avoid comparison problems between other types of banks (e.g. co-operatives, investment, etc.) across the EU countries. Secondly, all financial data have to be available for two years before the year of acquisition. We considered the time span for acquisitions to be 1998-2002, which allowed 168 acquisitions matched by a randomly selected set of 168 non-acquired banks (as of end 2002), resulting in a total sample of 336 banks⁸.

Matching of firms is now common practice when conducting classification studies in finance, such as bankruptcy or acquisitions prediction (e.g. Kira and Morin, 1993; Bhargava et al., 1998; Laitinen and Kankaanpaa, 1999; Neophytou and Mar Molinero, 2004; Charitou et al., 2004; Doumpos et al., 2004; Gaganis et al., 2005). There are two primary reasons for following this procedure, known as choice based sample. The first is the lower cost of collecting data compared to an unmatched sample (Zmijewski, 1984;

⁷ The sources of information for the acquisitions were the Bankscope, BANKERSalamanac.com and ZEPHYR databases of Bureau van Dijk's company, with all financial data collected from the Bankscope database.

⁸ In addition to time, researchers usually match firms on the basis of size. Nevertheless, Bartley and Boardman (1990) argue that "*matching by size or other variables may be an appropriate control mechanism when the research objective is to examine the statistical significance of individual causal variables*" (p.55) and that "*Further, given the lack of a theoretical model, the choice of variables to be matched is inherently arbitrary*" (p. 55). Furthermore, as they point out in an earlier study (Bartley and Boardman, 1986) where firms were matched by industry and size, this procedure reduces the classificatory power of the discriminant models. Another important issue that should be considered is that if a characteristic is used as a matching criterion, its effects will be obviously excluded from the analysis (Hasbrouck, 1985). For example, matching by size prevents analysis of the effects of size on the likelihood of acquisition. Since the literature suggests that size is an important explanatory variable in acquisitions, it was preferred in this study to use size as an independent variable rather as a matching characteristic.

Bartley and Boardman, 1990; Ireland, 2003). The second and most important is that a choice based sample provides higher information content than a random sample⁹ (Cosslett, 1981; Palepu, 1986; Imbens, 1992).

Although the year of acquisition is not common for all banks in the sample, they were all considered as acquired in the year “zero”, referred to as the year of reference. Financial statements for the most recent year prior to the “zero” year were used to obtain the data (i.e. the first or the second year before the year of acquisition, depending on data availability, for the acquired banks and the same fiscal year for the non-acquired ones). Table 1 presents the sample by year and country, distinguishing between the acquired and the non-acquired banks.

[Insert Table 1 Around Here]

An important issue of concern in evaluating the classification ability of a model is to ensure that it has not over-fit to the training (estimation) dataset, as this might affect its out-of-sample performance. This raises the question of how to appropriately validate the model, given that “a model without sufficient validation may only be a hypothesis” (Stein, 2002). Evaluating the model’s performance on the training data set is obviously not adequate, as prior research indicates that this tends to bias the classification accuracies upwards (Altman, 1993). Therefore, using some kind of a holdout-testing sample is appropriate.

The simplest technique for estimating the error rates is a holdout sample that involves a single train-and-test procedure. However, insufficient data on acquired banks can lead to problems when constructing an appropriate holdout sample. Furthermore, in implementing such an approach the number of acquired banks to be included in the training and holdout samples is a crucial point: if too many acquired banks are left out of

⁹ 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 (Palepu, 1986; Barnes, 1990; Ireland, 2003). Thus, it is essential to select the sample in a way that will ensure that acquired firms in sample represent an adequate proportion. Manski and Lerman (1977) and Manski and McFadden (1981) point out that such a choice based sample will provide more efficient estimates than a random sample of the same size, Cosslett (1981) characterizes such a sample as a close-to-optimum design, while Imbens (1992) concludes that the equal share sample is significantly better than random sampling to the extent that controlling with an equal share sample gives more relevant information.

the training sample (in-sample data) then over-fitting becomes likely, whereas if too many acquired banks are left out of the testing sample (out-of-sample data) then it would be difficult to estimate the true performance of the model (Sobehart et al., 2000). To mitigate this problem, a re-sampling technique such as the jackknife, bootstrap or cross validation can be used, thus obviating the need for a separate test sample and ensuring maximum use of the data. Shao and Tu (1995) provide a useful introduction to the use of resampling techniques, and Bartley and Boardman (1986, 1990), Kira and Morin (1993), and Fairclough and Hunter (1998) apply such techniques to the prediction of acquisition targets.

In the present study, we adopt a 10-fold cross validation approach to develop and evaluate the models. Under this approach, the total sample of 336 banks is initially randomly split into 10 mutually exclusive sub-samples (i.e. non-overlapping folds of approximately equal size). Then, 10 models are developed in turn, using nine folds for training and leaving one fold out each time for validation. Thus, in each of the 10 replications, the training sample consists of 302 (or 303) banks, whereas the validation (holdout) sample consists of not-the-same 34 (or 33) banks. The average error rate over all the 10 replications is the cross-validated error rate.

2.2 Choice of Variables

Mergers and Acquisitions (M&As) between banks occur for various reasons and the underlying motives suggest a variety of financial characteristics possessed by the ideal target bank. In a pan-European setting, the need for comparable data across different countries sets obvious restrictions on the type of variables one can use. To minimize possible bias arising from different accounting practices, broad variable definitions as provided by Bankscope are used. We select 8 variables that cover most aspects of banks performance and serve as proxies for the basic motives behind banks M&As¹⁰. Table 2

¹⁰ Palepu (1986) criticized previous studies that typically started with a large number of financial ratios and then, simply on a step-wise basis determined which ratios to retain. He formulated six hypotheses of acquisition likelihood and chose a single representative ratio. Barnes (1998), Cudd and Duggal (2000) and Powell (1997, 2001) followed the same approach and is the one employed in the present study too. The variables we choose reflect some aspects of the CAMEL characteristics (except management capacity) although we relate our discussion to the underlying motives for bank M&As.

presents a list of the variables while the discussion that follows briefly outlines their relation to the motives for banks M&As.

[Insert Table 2 Around Here]

Capital strength

The fact that financial regulators require commercial banks to sustain a minimum amount of capital reflects the importance of defense against the risk of bank insolvency. Studies in the US that examined the relation between capital strength and the acquisition likelihood of a bank have in general found a negative relationship although not statistically significant in all cases (e.g. Hannan and Rhoades, 1987; Moore, 1996; Wheelock and Wilson, 2000). There are two possible explanations for this finding. First, a lack of financial strength tends to attract buyers who can infuse capital into the acquired banks (Moore, 1996). Second, banks attract buyers with skillful managers who are able to operate successfully with high leverage (Hannan and Rhoades, 1987; Wheelock and Wilson, 2000). By contrast, while investigating the role of regulatory capital in bank M&As, Valkanov and Kleimeir (2006) find that US targets have, on average, significantly higher pre-merger Total and Tier 1 capital ratios capitalized?? than their non-acquired peers, although this not the case in the EU. However, the authors mention that their results do not necessarily contradict those of the above mentioned US studies and the differences might be due to the measure used to assess capital strength (i.e. capital to assets ratio versus risk-weighted ratios). In the present study we measure bank's capital strength by its equity to asset ratio¹¹ (EQAS), following its use in numerous recent studies (e.g. Cyree et al., 2000; Wheelock and Wilson, 2000, 2004; Pasiouras and Zopounidis, 2006; Campa and Hernando, 2006).

Inefficient management

¹¹It might be argued that the employment of risk-weighted ratios, such as the Tier 1 ratio, is more appropriate, especially when considering the argument of Valkanov and Kleimeier (2006). However, due to many missing values for Tier 1, we rely on the use of equity to assets ratio. Furthermore, Estrella et al. (2000), in a study of bank default prediction, illustrate that simple leverage ratios predict as well as much more complex risk-weighted ratios over one or two year horizons.

The inefficient management hypothesis (Manne, 1965) argues that if the managers fail to maximize their firm's value, then the firm is likely to be acquired so that inefficient managers will be replaced. Thus, according to this hypothesis acquisitions are motivated by a belief that the acquiring bank's management can handle better the recourses of the acquired bank (Hannan and Rhoades, 1987). Hannan and Rhoades (1987) found no evidence to support the hypothesis, while the results of Curry (1981) are mixed. However, Moore (1996), Focarelli et al. (1999), Wheelock and Wilson (2000) and Pasiouras and Gaganis (2006) found that less efficient banks (either in terms of profitability or expenses management or both) are more likely to be acquired. We use two measures, the return on average assets (ROAA) and the cost/income ratio (COST) to access the efficiency of managers in terms of profits and costs.

Size

Size is related to both synergy and agency motives for M&As and therefore can influence acquisitions through several channels. More detailed, economies of scale and scope are probably the most well known synergy motives associated with size. Nevertheless, there could be diseconomies associated with size and this could negatively influence a target bank's acquisition likelihood, not least because large banks are generally more expensive to be acquired, have greater resources to fight unwanted acquisitions and are more difficult to be absorbed within the organization of the acquiring bank. Furthermore, agency conflicts between shareholders and managers could lead to M&As that are motivated by managers' self interest. In the latter 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. In the present study, as in most studies in banking, we measure size with bank's total assets (SIZE).

Loan activity

Data from the European Central Bank report (2004) on the stability of the EU banking sector indicate that the share of total loans in total assets was approximately 67% in 2003, highlighting the importance of loans for EU banks. Therefore loan activity may be

another factor influencing the decision to acquire a bank. Hannan and Rhoades (1987) argue that, on the one hand, a high level of loans would seem to indicate aggressive behaviour by the target bank and a strong market penetration with important established customer relationships that would make it an attractive target; whereas, on the other hand, a low level of loan activity may indicate a bank with conservative or complacent management, which an aggressive acquiring bank could turn around to increase returns. While most of the studies suggest a negative relationship (Curry, 1981; Hannan and Rhoades, 1987; Moore, 1996; Pasiouras and Zopounidis, 2006), this is not significant in all cases. The results in Wheelock and Wilson (2000, 2004) are also mixed with total loans to total assets, being negatively related but not statistically significant in some instances and positively related but not always statistically significant in other instances, depending on the specification of the estimated model. We follow previous studies in banking (Curry, 1981; Hannan and Rhoades, 1987; Moore, 1996; Wheelock and Wilson, 2000, 2004), and measure the level of loan activity with the total loans to total assets ratio (LOANS).

Liquidity

Without the necessary liquidity and funding to meet obligations, a bank may fail unless external support is given (Golin, 2001). Therefore liquidity management is important for bank managers and may also have an influence on the attractiveness of a bank as a target. On the one hand, banks may be acquired because of their good liquidity position (i.e. the size of their liquid assets attracts acquirers). On the other hand, banks may be acquired because they have run into liquidity problems that are difficult to resolve. In the present study, we measure liquidity with the ratio liquid assets to customer & short term funding¹² (LIQ). This ratio shows the percentage of customer & short term funding that could be met if they were suddenly withdrawn and the higher it is the more liquid the bank is.

¹² Liquid assets are generally short-term assets that can be easily converted into cash (e.g.. cash itself, deposits with the central bank, treasury bills, other government securities and interbank deposits). The use of the value of customer & short term funding on the denominator is motivated by the fact that data from the European Central Bank report (2004) indicate that the share of customers and other credit institutions deposits in total liabilities was 62.29% in 2003.

Growth

Growth can affect bank acquisition in two opposing ways. On the one hand, as Kocagil et al. (2002) point out, empirical evidence suggests that some banks with relatively high growth rates experience problems because their management and/or structure is not able to deal with and sustain exceptional growth. Hence, it is possible that a faster growing firm could be an attractive acquisition for a firm with surplus resources or management available to help (Barnes, 1999). On the other hand, Moore (1996) finds a negative relationship between a bank's growth rate and the acquisition probability to lend support to his argument that a slow growing firm may attract a buyer seeking to accelerate its growth rate and thereby increase its market value. In line with previous studies, we use the annual change in bank's total assets to measure growth¹³ (GROWTH).

Market Power

Market power, interpreted as an increase in market share, has been quoted as one of the most important motivating factors for within-country, within-segment mergers in the financial sector (Group of Ten, 2001). Moore (1996) points out several channels through which market share could influence the decision to acquire a bank. First, regulatory concerns about anticompetitive effects could reduce the probability of acquisition of banks with high market share. Second, there may not be acquirers large enough to take over a bank with considerable market share. Third, a bank's small share could reflect a lack of success in the market and therefore, consistent with the inefficient management hypothesis, this bank would be a potential target for banks with more efficient management. In the present study, we measure market share by dividing the deposits of the bank with the total deposits of the banking sector in which it operates¹⁴ (MSHARE).

¹³As an anonymous reviewer suggested, focused versus unfocused growth could make a difference along with the industry targeted group. More precisely, it has been suggested that retail versus commercial growth may make a difference in returns given the economic environment and management abilities. Unfortunately, data availability has not allowed us to empirically examine this issue, and we hope that future research will improve upon this.

¹⁴As correctly suggested by an anonymous reviewer, total assets could also have been used as a measure of market power. Furthermore, market share in terms of loans is another measure that could be used. However, since we have already considered total assets as a measure of size and we have accounted for bank's loans to a large extent through the inclusion of LOANS (i.e. total loans/total assets) and/or SIZE (i.e. as mentioned above loans accounted for more than 65% of total assets in the EU in 2003) we

Industry-relative financial variables

In a recent study on mergers and acquisitions in the financial sector, the Group of Ten (2001) points out that the nature of acquisition activity and the dominant motivations for acquisitions may differ between countries. For example, the motives or the opportunities for acquisitions, and hence the characteristics of the acquired banks, are likely to be different in a country where a number of acquisitions have already occurred than in one where there has been little acquisition activity. Furthermore, the levels of profitability, liquidity, cost efficiency and other aspects of bank's performance vary across EU countries. Therefore, as Harris et al. (1982) point out, financial ratios for individual firms may have little meaning in isolation and their relationship to industry averages can enhance the explanatory power of financial ratios.

For the purposes of the present study, we use industry relative variables calculated as follows¹⁵ :

Banks Industry relative Ratio X_1 in year $t = \text{Banks } X_1 \text{ ratio in year } t / \text{Average value of } X_1 \text{ ratio in the commercial banking industry of the corresponding country in year } t$

This is done for each of the 15 EU countries, and for every year between 1996 and 2001. Standardizing by country average deflates raw values and expresses the variables in terms of percentages to enhance comparability. Also, because the values of the ratios were computed over different years, standardizing controls for the mean shift in the ratios from year to year (Barnes, 1990; Platt and Platt, 1990).

3. Multicriteria Decision Aid methods

The problem considered in the present study is a classification one that in general involves the assignment of a set of m alternatives $A = \{\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_m\}$, evaluated along a set of n criteria g_1, g_2, \dots, g_n , to a set of q classes C_1, C_2, \dots, C_q . In our case the alternatives are the banks in the sample, the criteria correspond to the eight financial

considered deposits, as an alternative measure of market power often used in the literature, to provides a slightly different picture.

¹⁵ The only variable for which we do not calculate the industry average is market share, which by definition expresses the value of a bank relative to the industry in which it operates.

variables and there are two classes, the non-acquired banks (class C_1) and the acquired banks (class C_2). Hence, in what follows we consider the simple two-class case, while details on the multi-class case, and how they can be handled with multicriteria techniques, can be found in Doumpos and Zopounidis (2002) and Zopounidis and Doumpos (2002).

The present study employs three techniques, namely UTADIS, MHDIS, and PAIRCLAS. The first two originate from the preference disaggregation approach while the latter one adopts pairwise comparisons¹⁶. UTADIS and MHDIS have been used in other classification problems in finance and accounting (e.g. bankruptcy, credit risk, auditing) in the past and so will be described only briefly here. We provide a more extended discussion for PAIRCLAS as this method is relatively new.

3.1 UTADIS

The UTADIS approach implies the development of an additive utility function that is used to score the firms and decide upon their classification. The utility function has the following general form:

$$U = \sum_{i=1}^n w_i u'_i(g_i) \in [0,1] \quad (1)$$

where w_i is the weight of criterion g_i (the criteria weights sum up to 1) and $u'_i(g_i)$ is the corresponding marginal utility function normalized between 0 and 1. 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 and the marginal utility functions, it is possible to use the transformation $u_i(g_i) = w_i u'_i(g_i)$. Since $u'_i(g_i)$ is normalized between 0 and 1, it becomes obvious that $u_i(g_i)$ ranges in the interval $[0, w_i]$. In this way, the additive utility function is simplified to the following form:

¹⁶In the case of the preference disaggregation approach the problem is to develop a criteria aggregation model based on absolute judgments, which provides a rule for the classification of the alternatives on the basis of their comparison to some reference profiles (cut-off points) that distinguish the classes. The alternative approach adopted in PAIRCLAS is based on pairwise comparisons between the alternatives that need to be classified and some other reference alternatives (training sample) that constitute typical examples of each class.

$$U(\mathbf{a}) = \sum_{i=1}^n u_i(g_i) \in [0,1] \quad (2)$$

The developed utility function provides an aggregate score $U(\mathbf{a})$ of each bank along all criteria. In the case of acquisitions prediction, this score provides the basis for determining whether the bank could be classified in either the group of non-acquired or acquired ones. The classification rule in this case is the following (C_1 and C_2 denote the group of non-acquired and acquired banks respectively, while u_1 is a cut-off utility point defined on the global utility scale, i.e. between 0 and 1):

$$\left. \begin{array}{l} U(\mathbf{a}) \geq u_1 \\ U(\mathbf{a}) < u_1 \end{array} \right\} \Rightarrow \mathbf{a} \in C_1 \left. \begin{array}{l} \\ \\ \end{array} \right\} \Rightarrow \mathbf{a} \in C_2 \quad (3)$$

The estimation of the additive value function and the cut-off threshold is performed using linear programming techniques so that the sum of all violations of the classification rule (3) for all the banks in the training sample is minimized. A detailed description and derivation of this mathematical programming formulation can be found in Doumpos and Zopounidis (2002).

3.2 MHDIS

In contrast to UTADIS, 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 into 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 $U_k(\mathbf{a})$ describes the alternatives of group C_1 , while the second function $U_{\sim k}(\mathbf{a})$ describes the remaining alternatives that are classified in lower groups C_{k+1}, \dots, C_q .

$$U_k(\mathbf{a}) = \sum_{i=1}^n w_{ki} u_{ki}(g_i) \text{ and } U_{\sim k}(\mathbf{a}) = \sum_{i=1}^n w_{\sim ki} u_{\sim ki}(g_i), \quad k = 1, 2, \dots, q-1 \quad (4)$$

The corresponding marginal utility functions for each criterion g_i are denoted as $u_{ki}(g_i)$ and $u_{\sim ki}(g_i)$ which are normalized between 0 and 1, while each set of the

criterion weights w_{ki} and $w_{\sim ki}$ sum up to 1. In the formulation above, the model is developed in q-1 steps. Obviously, with two groups, the procedure consists of only one stage during which a pair of additive utility functions $U_1(\mathbf{a})$ and $U_{\sim 1}(\mathbf{a})$ are developed to discriminate between the alternatives of group C_1 and the alternatives of group C_2 . In that case the rule to decide upon the classification of any alternative has the following form:

$$\begin{aligned} \text{If } U_1(\mathbf{a}) \geq U_{\sim 1}(\mathbf{a}) \text{ then } \mathbf{a} \text{ belongs in } C_1 \\ \text{Else if } U_1(\mathbf{a}) \leq U_{\sim 1}(\mathbf{a}) \text{ then } \mathbf{a} \text{ belongs in } C_2 \end{aligned} \quad (5)$$

As with UTADIS, the estimation of the criteria weights and the marginal utility functions is accomplished through mathematical programming techniques. More specifically, in this case the formulation involves solving three programs, two linear and a mixed-integer one, to minimize the classification error and estimate optimally the criteria weights in the two additive utility functions. Further details of this mathematical programming formulation can be found in Zopounidis and Doumpos (2002).

3.3 PAIRCLAS

In this method the alternatives and their classification provide representative examples on the way the decision-maker implements his judgment policy and the system of preferences. The alternatives of the estimation set provide the basis to which any alternative $\mathbf{a}_k \notin A$ is compared in order to decide upon its classification. Within this decision-making context, given a set of classification decisions made by the decision-maker (reference set), a decision for a new alternative can be made through its comparison to the reference alternatives already judged by the decision-maker. In particular, the classification of any \mathbf{a}_k is decided on the basis of the pairwise comparisons $(\mathbf{a}_k, \mathbf{a}_i)$, for all $\mathbf{a}_i \in A$. The results of these comparisons lead to the estimation of the outranking and the outranked character of \mathbf{a}_k as opposed to the reference alternatives.

In outranking relation methods developed for ranking and choice problems (such as in most of the ELECTRE methods (Roy, 1991) and the PROMETHEE methods (Brans and Vincke, 1985)), this information is used to rank the alternatives from the best to the worst ones or to select a limited set of the most preferred alternatives. In the proposed

methodology this information is used for classification purposes. In particular, the alternatives are organized in a valued outranking graph, as in the PROMETHEE II method (Brans and Vincke, 1985). For the reference alternatives that belong to class C_1 ($\mathbf{a}_i \in A \cap C_1$) only the arcs entering node \mathbf{a}_k are considered (i.e., the arcs $\mathbf{a}_i \rightarrow \mathbf{a}_k$). Each arc $\mathbf{a}_i \rightarrow \mathbf{a}_k$ is associated with a preference index $P_{ik} \in [0, 1]$ representing the intensity of preference of the decision-maker for the alternative \mathbf{a}_i over \mathbf{a}_k . Values of P_{ik} close to 1 indicate strong preference for \mathbf{a}_i over \mathbf{a}_k . On the other hand, for the reference alternatives that belong to class C_2 ($\mathbf{a}_i \in A \cap C_2$) only the arcs leaving node \mathbf{a}_k are considered (i.e., the arcs $\mathbf{a}_k \rightarrow \mathbf{a}_i$). Each arc $\mathbf{a}_k \rightarrow \mathbf{a}_i$ is associated with the preference index P_{ki} representing the intensity of preference of the decision-maker for the alternative \mathbf{a}_k over \mathbf{a}_i .

The preference index P_{ik} is specified as the weighted average of the preference of \mathbf{a}_i over \mathbf{a}_k on each criterion g_j :

$$P_{ik} = \sum_{j=1}^n w_j p_j(\mathbf{a}_i, \mathbf{a}_k) \quad (6)$$

where $w_j \in [0, 1]$ is the weight of criterion g_j representing the significance attributed to the criterion by the decision-maker in the pairwise comparisons between the alternatives. The preference function $p_j(\mathbf{a}_i, \mathbf{a}_k) \in [0, 1]$ indicates the strength of the preference of the decision-maker for \mathbf{a}_i over \mathbf{a}_k defined on the basis of the performances of the two alternatives on the criterion g_j (denoted as g_{ij} and g_{kj} , respectively). In the case where $g_{ij} < g_{kj}$ it is assumed that no preference can be established for \mathbf{a}_i over \mathbf{a}_k on the basis of g_j , i.e., $p_j(\mathbf{a}_i, \mathbf{a}_k) = 0$. On the other hand, if $g_{ij} \geq g_{kj}$ the decision-maker has some degree of preference for \mathbf{a}_i over \mathbf{a}_k (i.e., $p_j(\mathbf{a}_i, \mathbf{a}_k) \geq 0$), which is an increasing function of the difference $d_j^{ik} = g_{ij} - g_{kj}$. Therefore, each preference function $p_j(\mathbf{a}_i, \mathbf{a}_k)$ can be defined as follows:

$$p_j(\mathbf{a}_i, \mathbf{a}_k) = \begin{cases} 0 & \text{if } d_j^{ik} < 0 \\ h_j(d_j^{ik}) & \text{if } d_j^{ik} \geq 0 \end{cases} \quad (7)$$

Values of $p_j(\mathbf{a}_i, \mathbf{a}_k)$ close to 1 indicate a strong preference for \mathbf{a}_i over \mathbf{a}_k on the basis of criterion g_j , whereas values close to 0 indicate weak preference. Generally, the preference functions p_j may have different forms depending on the form of the functions

h_j . For example, it is possible to consider the six forms of preference functions (generalized criteria) proposed by Brans and Vincke (1985) for the PROMETHEE methods that require the specification of some preferential parameters such as the preference and indifference thresholds. However, in a real-world situation it may be difficult for the decision-maker to specify which specific form of preference function is suitable for each criterion and to determine the parameters involved. To avoid this problem, instead of using a pre-specified form of preference functions, in the proposed methodology the form of these functions is induced from the information provided by the reference alternatives (Doumpos and Zopounidis, 2004).

The preference indices P_{ik} for the pairwise comparisons ($\mathbf{a}_i, \mathbf{a}_k$) constitute the basis for the development of a rule that can be used to decide on the classification of \mathbf{a}_k . The classification rule used is based on the difference between the leaving and entering flow for the alternative (node) \mathbf{a}_k . This difference defines a net flow f_k for \mathbf{a}_k :

$$f_k = \frac{1}{m_2} f_k^+ - \frac{1}{m_1} f_k^- = \frac{1}{m_2} \sum_{\mathbf{a}_i \in A \cap C_2} P_{ki} - \frac{1}{m_1} \sum_{\mathbf{a}_i \in A \cap C_1} P_{ik} \quad (8)$$

The leaving flow f_k^+ represents the outranking character of \mathbf{a}_k over all reference alternatives that belong to class C_2 , whereas the entering flow f_k^- represents the outranked character of \mathbf{a}_k over all reference alternatives that belong to class C_1 . The net flow is estimated as a weighted average of these leaving and entering flows. The weights used ($1/m_1$ and $1/m_2$) are defined on the basis of the number of reference alternatives belonging to each class (m_1, m_2 denote the number of reference alternatives belonging to classes C_1 and C_2 , respectively). The use of this weighting scheme eliminates the effects that possible significant differences among the number of references alternatives in each class may have on the estimation of the net flow f .

The net flow ranges in the interval $[-1, 1]$. A net flow $f_k \approx -1$ indicates that the alternative \mathbf{a}_k does not outrank the reference alternatives from class C_2 (i.e., $f_k^+ \approx 0$), while being strongly outranked by all reference alternatives from class C_1 (i.e., $f_k^- \approx m_1$). Similarly, a net flow $f_k = 1$ indicates that \mathbf{a}_k strongly outranks all reference alternatives from class C_2 (i.e., $f_k^+ \approx m_2$), while not being outranked by any reference alternative from class C_1 (i.e., $f_k^- \approx 0$). Finally, the case $f_k \approx 0$ indicates an ‘‘average’’ alternative, i.e.,

an alternative that in some sense is “between” C_1 and C_2 and its classification can only be made marginally (i.e. the classification is not clear enough).

Within this context an alternative that belongs into class C_1 is expected to have a high leaving flow f^+ and a low entering flow f^- , whereas an alternative that belongs into class C_2 is expected to have a low leaving flow f^+ and a high entering flow f^- . Intuitively, this means that: (1) an alternative from the class C_1 is expected to have a high outranking character over the alternatives of class C_2 (i.e. it strongly outranks the reference alternatives of class C_2) and a low outranked character by the alternatives of class C_1 (i.e. it is weakly outranked by the reference alternatives of class C_2), and (2) an alternative from the class C_2 should have a high outranked character by the alternatives of class C_1 and a low outranking character over the alternatives of class C_2 . This leads to the following classification rule:

$$\begin{aligned} f_k > z &\Rightarrow a_k \in C_1 \\ f_k < z &\Rightarrow a_k \in C_2 \end{aligned} \quad (9)$$

where z is a cut-off point (which can be either specified by the decision-maker or estimated from the data that the estimation alternatives provide).

On the basis of these rules, the parameters of the preference model (i.e., the criteria weights w_j , the preference functions p_j and the cut-off point z) can be determined using linear programming techniques that seek to minimize the classification errors for the reference alternatives (Doumpos and Zopounidis, 2004).

4. Empirical results

Table 3 presents descriptive statistics (mean, median, standard deviation) and the results of the Kruskal-Wallis test for mean differences in the variables between the two groups of banks (acquired and non-acquired). The results of this chi-square test suggest that after adjusting for the country where banks operate, the differences in the mean values for the acquired versus the non-acquired banks are significant for the first three of the eight variables, representing capital strength and management performance.

The results indicate that non-acquired banks were better capitalized, on average, over the period 1998-2002. This might suggest that acquired banks were characterized by a lack of financial strength that attracted buyers capable of infusing capital (Moore, 1996; Wheelock and Wilson, 2000) or that they had skilful managers capable of operating successfully with high leverage, thus making them attractive targets (Wheelock and Wilson, 2000). However, the lower profit efficiency (as measured by return on average assets) and the higher cost inefficiency (as measured by the cost to income ratio) of the acquired banks appear to lend support to the inefficient management hypothesis indicating that acquisitions serve as a mean to remove inefficient managers.

[Insert Table 3 Around Here]

Despite the fact that only the first three variables in Table 3 appear to be significantly different between the two groups of banks, we include all eight variables in the development of the MCDA models. This is based on the presumption that while univariate tests may discriminate an individual variable, in a multivariate setting the collective set of variables may achieve a better degree of discrimination overall.

The results presented in Table 4 are the average weights (in %) over 10 replications of the model development and testing process described in section 2. In the case of UTADIS and PAIRCLAS, there is only one function categorising all banks in sample, hence only a single set of weights are determined. By contrast, in the case of MHDIS, there are two additive utility functions, U_1 characterizes the non-acquired banks, and U_{-1} characterizes the acquired ones, hence giving two sets of weights.

[Insert Table 4 Around Here]

The results indicate that, in the case of the UTADIS model, the first three variables (EQAS, ROAA, COST) account for nearly 88% of the total weighting, which is consistent with the univariate test results shown in Table 3. In the case of PAIRCLAS, the three most important variables (ROAA, COST, GROWTH), together account for just over 78%. In the case of MHDIS, the weights are more balanced and all the variables

contribute to some degree in the classification of the firms, with the first (EQAS) being the most important and the last (MSHARE) being the least important.

While there is no reason why the importance of the variables differs across the three models, such differences have been observed in past studies as well. For example, Espahbodi and Espahbodi (2003) found that coefficients and therefore the significance of the variables tended to differ across models developed through discriminant, logit, probit analyses and recursive partitioning algorithm. Barnes (2000) also used discriminant and logit analyses and found different variables to be important. One possible explanation is that, although all methods attempt to classify correct as many firms as possible, they consider different ways of processing the same information in the dataset. Another explanation specific to multicriteria models is that, while UTADIS and PAIRCLAS develop only one utility function characterizing all banks, MHDIS develops two functions, each describing one of the two groups. Whether the weights attributed by one method are intuitively more appealing than those selected by another method is a matter of subjective judgment, although it would appear from the results below that a balanced set of weights may result in better classification accuracies.

Turning to the evaluation of the models in terms of their classification ability, Panel A in Table 5 shows the average classification accuracies obtained at the training stage by the 10 fold cross-validation process explained earlier, i.e over the data set used for model development. In this case, MHDIS obtains the highest classification accuracy, achieving 70.6% for the acquired and 72.2% for the non-acquired groups of banks (giving an overall classification accuracy of 71.4%); whereas the corresponding accuracies for PAIRCLASS are 54.4% and 73.3% (overall 63.9%), and for UTADIS are 56.9% and 75.0% (overall 66.0%) respectively. However, since these results refer to the training sample, the potential upward bias should be kept in mind and appropriately, therefore, the out-of-sample efficiency of the models should be examined.

[Insert Table 5 Around Here]

Panel B presents the average classification results obtained over the 10 rounds at the validation sub-samples (i.e over the data set not used for model development). The

highest overall accuracy is again achieved by MHDIS, with 68% of the acquired and 63.3% of the non-acquired banks classified correctly (implying an overall classification rate of 65.7%). PAIRCLAS also achieves marginally better classification accuracies than UTADIS, and its ability to classify correct the non-acquired banks (75%) is even higher than MHDIS (72.2%). It should be noted that UTADIS does better than PAIRCLASS in the training stage, but ends up slightly worse in the validation stage. However, MHDIS performs better than others in both the training and the validation stages. This might be attributed to the balanced overall weightings obtained under MHDIS and the development of separate utility functions for characterizing acquired and non-acquired banks.

The results do indicate a fair amount of misclassification, however, ranging between 30-45% for all methods. This is not inconsistent with previous studies that have in general found the prediction of acquisitions to be a difficult task¹⁷ (e.g. Palepu, 1986; Barnes, 1998, 1999, 2000; Powell, 2001; Espahbodi and Espahbodi, 2003). As Barnes (1999) notes perfect prediction models are difficult to develop even in the bankruptcy prediction literature, where failing firms have definitely inferior or abnormal performance compared to healthy firms. The problem with the identification of acquisition targets is that there are potentially many reasons for acquisitions, while at the same time managers do not always act in a manner which maximizes shareholder returns (i.e. hubris, agency motives). It is more reasonable, therefore, to compare the performance of the models with chance assignments (Barnes, 2000). The results in Table 5 show that all the models perform better than a naïve model based on random assignments¹⁸.

5. Concluding remarks and future directions

¹⁷ A direct comparison with the results of previous studies is not appropriate because of differences in the datasets (Kocagil et al., 2002; Gupton and Stein, 2003), the industry under investigation, the methods used to validate the models, and so on. Nevertheless, a tentative comparison indicates that the range of accuracy in our study is comparable to other studies in acquisitions prediction that employed re-sampling techniques. Bartley and Boardman (1986) achieved a classification accuracy equal to 64% while in a later study (Bartley and Boardman, 1990) they obtained classification accuracies between 69.9% and 79.9%. Similarly, the classification accuracy in the study of Kira and Morin (1993) was equal to 66.17%.

¹⁸ In a sample with equal number of acquired and non-acquired banks like the one used in the present study, such a naïve approach would achieve an overall classification accuracy of 50%.

In this study we developed MCDA classification models for the identification of acquisition targets of commercial banks operating in the EU. The sample consisted of 336 banks operating in the EU, of which 168 were acquired between 1998 and 2002.

Eight variables most of which originate from the CAMEL model (and representing seven potential motives for banks acquisitions) were selected for inclusion in the models. Since the sample was drawn from 15 EU countries, the individual banks' ratios were transformed to industry-relative ratios (by dividing the values of the variables of the individual banks with the corresponding average values of the commercial banking industry in the country where the banks operated).

The models were developed using three multicriteria decision aid techniques, namely MHDIS, PAIRCLAS and UTADIS. A 10-fold cross validation approach that allows the maximum use of the available data while it ensures the proper evaluation of the models, was used to develop and validate the models. The ability of the models was assessed by comparing their classification accuracies, in terms of the percentage of banks correctly classified in each group.

Such models can prove 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 acquisition target. Furthermore, as Curry (1981) mentions, bank regulators might be interested in the development of such models, which could be useful in forecasting the degree of competition in the market. Obviously, the efficiency of the model depends not only on the specifications and flexibility of the classification technique, but also on whether acquired banks have unique characteristics that distinguish them from non-acquired banks.

Our results indicate that the characteristics that can be useful in identifying the acquisition targets may differ across the techniques used to develop the models. However, this is not surprising and has been the case in past studies as well. One possible explanation is that, although all methods are using the same information (i.e. in terms of the data set and variables employed) and they have the same objective (i.e. correct classification), each one of them processes the information differently, due to differences in the procedures for solving the problem. For example, while UTADIS and PAIRCLAS

develop only one utility function characterizing all banks, MHDIS develops two functions, each describing one of the two groups. Furthermore, UTADIS solves one linear programming while MHDIS solves three mathematical programming formulations (i.e. two linear and one mixed-integer). Finally, PAIRCLAS operates on the basis of pairwise comparisons rather than the preference disaggregation approach. On the basis of the contribution of the criteria (in terms of weights) in the three models and the univariate results we could conclude that after adjusting for the country where banks operate, non-acquired banks were better capitalized. We also found evidence to support the inefficient management hypothesis, as acquired banks were characterized by lower profitability and less efficiency in expenses management. Liquidity and loan activity also appeared to be important in characterizing acquired banks in the MHDIS model, while GROWTH was more important in PAIRCLAS.

Turning to the classification ability of the models, the average results over the 10 replications in the validation set showed that all models performed better than a naïve model based on random assignment to outcomes based on prior probabilities (i.e. 50% in an equal sample). Nevertheless, there is fair amount of misclassification, which is hard to avoid given the nature of the problem. The highest overall classification accuracy was obtained by MHDIS (65.7%), followed by PAIRCLAS (63.8%), and UTADIS (61.6%). However, it should be noted that the superiority of any classification procedure may be context or sample specific (Espahbodi and Espahbodi, 2003). Nevertheless, the non-parametric MCDA approaches have certain advantages over the parametric approaches, in that they do not require any assumptions and can easily incorporate qualitative variables, which leads us to conclude that they can be considered as a reliable alternative to the traditional statistical techniques.

One potential shortcoming of the study, as is the case in many classification problems in finance (e.g. bankruptcy, credit risk), is that the usefulness of the model might be limited to the countries for which it was developed¹⁹ (i.e. EU-15). In our case, the problem might be even more serious since, as previously mentioned, the nature of acquisition activity and the dominant motivations for acquisitions may differ across

¹⁹ We would like to thank an anonymous reviewer for a relevant comment that motivated us to include this paragraph in the revised version of the paper.

countries. However, it should be emphasized that the overall framework (i.e. variables selection process, selection of classification techniques, development and evaluation process) can be easily adopted while using data from other countries (e.g. US, Asia) by re-estimating the criteria weights in our models.

Future research could extend the present study towards various directions such as the inclusion of additional non-financial variables (i.e. ownership type, manager's experience or technological capacity), the testing of the usefulness of the models for other countries, the employment of and comparison with alternative techniques (i.e. multidimensional scaling, neural networks, etc), and the combination of MCDA and other techniques into integrated models.

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Table 1 – Acquired and non-acquired banks in sample by year and country

	1998		1999		2000		2001		2002	
	Acq	NAcq	Acq	NAcq	Acq	NAcq	Acq	NAcq	Acq	NAcq
Austria	2	1	0	1	0	3	1	2	1	1
Belgium	3	3	0	1	3	1	0	1	3	2
Denmark	0	0	2	3	2	8	3	1	3	2
Finland	0	0	0	0	1	0	1	0	0	0
France	10	4	9	9	7	15	3	8	6	7
Germany	3	3	3	2	4	12	5	3	1	4
Greece	0	0	3	0	4	0	0	0	1	0
Ireland	0	1	1	1	0	0	0	1	0	1
Italy	1	0	5	4	14	4	3	2	9	3
Luxembourg	1	3	1	2	7	6	7	4	2	1
Netherlands	0	4	1	0	1	1	0	0	0	4
Portugal	0	1	0	0	4	0	2	0	0	3
Spain	3	2	3	2	6	4	1	1	4	2
Sweden	0	0	0	0	0	0	1	0	0	0
UK	1	2	1	4	3	2	1	4	1	2
Total	24	24	29	29	56	56	28	28	31	31

Table 2 – List of independent variables

Category	Definition	Calculation
Capital Strength	EQAS	Equity divided by total assets
Inefficient Management	ROAA	Return on average assets
	COST	Cost to income ratio
Loan activity	LOANS	Total loans divided by total assets
Liquidity	LIQ	Liquid assets divided by customer & short term funding
Growth	GROWTH	Total assets annual change
Size	SIZE	Total assets
Market Power	MSHARE	Deposits market share

Table 3 – Descriptive statistics and Kruskal Wallis test

	Acquired			Non-acquired			Kruskal Wallis test
	Mean	Median	Stdv	Mean	Median	Stdv	Chi-square
EQAS	1.856	1.319	2.441	2.329	1.578	2.727	5.968*
ROAA	-0.205	0.772	10.284	2.166	1.219	3.749	15.945**
COST	1.175	1.112	0.533	0.946	0.977	0.430	25.907**
LOANS	1.023	1.000	0.585	1.044	1.060	0.572	0.263
LIQ	1.297	1.035	1.796	1.517	1.166	2.324	2.142
GROWTH	3.321	0.213	74.897	0.810	0.361	20.533	2.351
SIZE	0.887	0.091	2.472	1.208	0.128	4.773	0.647
MSHARE	1.366	0.110	3.599	1.444	0.130	5.488	0.066

Notes: *Significant at the 5% level, ** Significant at the 1% level; Variables are defined in Table 2

Table 4 - Average weights of the variables (in %) over the 10 replications

	UTADIS	PAIRCLAS	MHDIS	
			U1	U-1
EQAS	42.8%	3.5%	26.5%	19.5%
ROAA	36.5%	27.1%	6.8%	7.0%
COST	8.3%	25.8%	12.6%	10.8%
LOANS	1.1%	3.4%	16.0%	20.0%
LIQ	2.2%	8.6%	16.6%	19.2%
GROWTH	2.1%	25.3%	4.6%	7.1%
SIZE	2.3%	3.1%	13.9%	10.8%
MSHARE	4.8%	3.2%	3.1%	5.7%

Note: Variables are defined in Table 2

**Table 5 – Correct Classifications
(Average results over 10 replications)**

	Acquired	Non-acquired	Overall
Panel A: Training Sample			
MHDIS	70.6%	72.2%	71.4%
PAIRCLAS	54.4%	73.3%	63.9%
UTADIS	56.9%	75.0%	66.0%
Panel B: Validation Sample			
MHDIS	68.0%	63.3%	65.7%
PAIRCLAS	55.4%	72.3%	63.8%
UTADIS	53.7%	69.5%	61.6%