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The prediction of bank acquisition targets with discriminant and logit analyses: methodological issues and empirical evidence

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Abstract

This paper uses discriminant and logit analyses to develop prediction models to identify bank acquisition targets. We consider several methodological issues, such as whether the choice of the estimation technique, the selection of variables, the use of raw versus industry relative data, the train-and-test sampling scheme, and the criteria for model evaluation affect the predictive accuracy of the developed models. Both estimation methods generate remarkably similar model performance rankings, while differences are revealed in the relative importance of variables when using raw versus industry relative data. We find that in most cases there is a fair amount of misclassification, consistent with previous studies in non-financial sectors, which is hard to avoid given the nature of the problem.

Keywords: Acquisitions; banks ; discriminant ; logit ; prediction ; targets

JEL classification codes: G21 ; G34

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Abstract

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1. Introduction

Over the last thirty five years or so there has been significant research undertaken to develop classification models for predicting takeover targets, in various countries such as the US (e.g. Espahbodi and Espahbodi, 2003), the UK (e.g. Powell, 2001), Canada (e.g. Belkaoui, 1978), and Greece (e.g. Slowinski et al., 1997). This is not surprising, since the prediction of acquisitions is of major interest to stakeholders, such as investors, creditors, and others in the supply chain that have established relationships with the target firms (Tartari et al., 2003). These studies, however, have traditionally focused on the development of prediction models for non-financial sectors (e.g. manufacturing) and excluded financial institutions such as banks from their analysis, owing to differences in the environment in which they operate and their unique characteristics.[1]

The banking industry has experienced significant consolidation through merger and acquisition (M&A) activity over the past two decades. Yet, in relation to studies that can be found for non-financial sectors, there has been very limited research on developing prediction models to identify potential acquisition targets in the banking industry.[2] Apart from their bank-specific characteristics, it may be argued that the regulatory environment in which banks operate might be an important factor for the dearth of research in this area. In the US, for example, bank M&As were tightly regulated until the Gramm-Leach-Bliley Act of 1999 and so the need for building a prediction model to identify potential bank targets would diminish if regulators were to approve only certain types of mergers.[3] In the European Union banking industry, despite the influence of regulatory control from both the European Commission and national authorities, there was a 23% reduction in the number of banks over the period 1997-2003, and this decrease was to a large extent due to M&As within national boundaries (Campa and Hernando, 2006). Hence, the evidence seems to suggest that it is competitive

[1] Among the unique features of banks in particular, apart from their role in financial intermediation and the provision of financial services, is their unusual structure of financial statements suggesting that certain bank-specific characteristics distinguish them from other corporations (Bauer and Ryser, 2004). Thus many of the empirical proxies typically included in prediction models for non-financial firms, such as current and quick ratio, are not meaningful for banks, which are therefore excluded from the analysis.

[2] With the exception of Pasiouras et al (2007, 2008), none of studies in the literature on developing prediction models for takeover targets have focussed on financial firms for reasons explained above.

[3] We are thankful to an anonymous reviewer for this interesting and relevant comment that motivated us to include this paragraph in the revised version.

environment created by the single financial market rather than the underlying regulatory regime that has driven merger activity in the European banking industry.[4] Nevertheless, it is surprising that research on identifying potential targets in the banking industry has not attracted as much interest as research on other aspects of bank M&As, such as studying the underlying characteristics of bank acquisition likelihood, the assessment of performance gains from mergers, and the importance the environment (including the regulatory framework) in affecting the incentive to merge (see, e.g. Campa and Hernando, 2006).

The goal of this paper is to highlight the methodological issues involved in developing prediction models to identify acquisition targets in the EU banking industry, hoping to encourage research interest and activity in this relatively under-researched area. Although Pasiouras et al. (2007, 2008) have recently examined the development of such models, they focus on the comparison of non-parametric techniques (e.g. multicriteria decision aid and support vector machines) rather than on traditional, parametric methods like discriminant and logit, which dominated research activity in the business of predicting non-financial targets for well over 30 years. Our study complements the aforementioned studies by developing discriminant and logit models of prediction, while undertaking a systematic comparison of the two sets of models by addressing several methodological issues, such as the approach to select variables, the use of raw versus industry relative data, and other issues involved in the evaluation process for predicting bank acquisition targets. The banking sector offers a fertile ground for developing prediction models to help identify potential takeover targets, in response to financial deregulation and greater consolidation activity across the globe recently. In our empirical

[4] Regulatory barriers, among other factors, appear to have hindered cross-border mergers according to the European Commission (2005), as they are subject to investigation by the EC Merger Regulation No. 4064/89 (Council of the European Union, 1989, 2004) if the transaction exceeds the turnover thresholds. Nevertheless, deals which do not raise serious doubts about competition in the single market often get approval. In the case of banks, nation states also have the right to block cross-border deals if they are not satisfied with the soundness and prudence of the acquirer. However, according to Koehler (2007), there have been only three cases so far where regulators have intervened and delayed the merger of banks in the EU. On the other hand, domestic M&As are typically governed by national laws, and these are rarely blocked except in cases where there is serious opposition from anti-trust authorities. Hence, the role of regulatory environment in affecting bank M&As is not clear-cut, and the empirical evidence seems to suggest that the underlying economic environment and the specific characteristics of banks play a more significant role in driving M&As in the European banking industry (see, e.g. Lenine and Vander Vennet, 2007; Hernando et al, 2008).

analysis, we concentrate on EU bank M&As that occurred over the period 1998-2002, which saw the launch of the Euro.

The rest of the paper is organized as follows. Section 2 presents a review of methodological issues. Section 3 addresses the data, sampling and estimation issues, while section 4 discusses the empirical results. Section 5 concludes the paper and offers some directions for future research in the field.

2. Methodological issues

In this section, we discuss a number of issues that are important in predicting acquisition targets, such as the choice of the classification technique, the selection of the variables and the procedure for the evaluation of the models.

2.1. Choice of classification technique

New methods for developing acquisition targets prediction models have recently been introduced including rough sets, neural networks, recursive partitioning, multicriteria decision aid, and support vector machines (e.g. Slowinski et al, 1997; Cheh et al, 1999; Espahbodi and Espahbodi, 2003; Pasiouras et al, 2007, 2008). Nevertheless, multivariate parametric approaches, such as discriminant analysis and logit analysis (hereafter DA and LA) have traditionally dominated the field. However, to our best knowledge there have been only 3 studies in the prediction of acquisition targets that compare and evaluate DA and LA using the same dataset. Zanakis and Zopounidis (1997) report that logit models provide inferior overall predictions compared to those of DA. Barnes (2000) points out that neither technique had any significant success in predicting takeover targets, whereas Espahbodi and Espahbodi (2003) report that LA obtained slightly higher classification accuracies than DA. Thus, the empirical results from these studies are mixed and the present study attempts to provide some further evidence while focusing on the banking sector[5].

[5] The empirical results from studies not concerned with acquisition targets but other applications in finance and accounting are also mixed. Wiggington (1980) finds that LA significantly out-performed DA in terms of relative predictive accuracy in credit risk. Collins and Green (1982) obtain similar results, but find that LA is considerably better at identifying failed firms. On the other hand, in a comparison of the two techniques for corporate bankruptcy prediction, Ohlson (1980) concludes that both are similar.

2.2. Choice of variables

2.2.1. Variables selection

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. However, with a large number of ratios as potential candidates for model development and limited help from financial theories, a question that arises in empirical research is which variables to use. At the same time, one has to consider the trade off-between the level of information that will be captured, input requirements, and over-fitting (Kocagil et al., 2002).

Not surprisingly, variables selection has long been an active research topic in statistics and pattern recognition and various techniques have been proposed. For example, Huberty (1994) suggests the use of: Logical screening (e.g. financial theory and human judgement), statistical screening (e.g. tests of group mean differences), and dimension reduction (e.g. factor analysis). The literature on acquisition targets, has experimented with all these approaches in the past.

For example, some studies start from a large list of variables and reduce them on the basis of stepwise procedures (e.g. Simkowitz and Monroe, 1971). However, Palepu (1986) criticizes the use of stepwise procedures, and argues that this method is arbitrary and leads to the statistical "overfitting" of the model to the sample at hand. Yet, researchers continue to use stepwise procedures not only in the prediction of acquisition targets (e.g. Espahbodi and Espahbodi, 2003), but in other classification problems in finance and accounting as well (e.g. bankruptcy prediction).

Palepu (1986) suggests the selection of a limited set of variables on the basis of the most frequently mentioned takeover hypotheses However, in most cases, models developed using this approach have had rather low predictive ability. Powell (1997) offers two potential explanations for this. First, these models are based upon takeover theories that are prevalent in the literature but have little or no validity. Second, the empirical proxies used fail to capture the implications underlying the theories.

Barnes (2000) starts from a large number of variables covering basic takeover hypotheses and reduces them on the basis of correlation coefficients[6]. Doumpos et al.

[6] Kocagil et al. (2002) argue that using highly correlated ratios without careful attention to address the inherent multicollinearity among the variables can result in imprecise "optimal weights" for a model, which

(2004) follow a similar approach by combining correlation analysis with univariate tests of means differences to pre-select a final set of input variables for model development. Thus, the rule of thumb is to maintain a small set of variables that are statistically significant (in a univariate context) and uncorrelated to each other.

Stevens (1973) applied factor analysis in developing a model for the prediction of acquisition targets, and this practice has been followed by a number of studies (e.g. Tartari et al., 2003). However, Doumpos et al. (2004) argue that while the results of factor analysis indicate the number of distinct factors and how the original data are grouped into these factors, they do not provide any information about the importance of the variables in the specific research problem.

In the light of the above arguments, there is no general agreement in the literature as for the method that should be used to select the input variables for the development of the models. In the present study, we start with a list of 18 variables, initially chosen on the basis of data availability and appropriate theories or motives for acquisitions. Our final set of input variables for model development is based on use of (i) stepwise procedures, (ii) logical screening (i.e. human judgment taking account of prior studies and acquisition theories), (iii) combination of statistical criteria (Kruskal-Wallis and correlation analysis), and (iv) factor analysis. Thus, we compare the different approaches to variables' selection, and attempt to throw light on whether one approach results in higher classification accuracies than another for predicting bank acquisition targets.

2.2.2. Raw versus industry relative data

Following the study by Platt and Platt (1990) on bankruptcy prediction, researchers have used industry relative ratios (e.g. Barnes, 2000) to adjust raw data for industry specific differences[7]. However, the results as to whether industry relative data are better than raw (i.e. unadjusted) data are mixed. Those of Cudd and Duggal (2000) depend highly on the

may result in poor out-of-sample model performance. However, while multicollinearity makes it difficult to interpret the significance of the coefficients, it does not affect the classification accuracy of the models (Etheridge and Sriram, 1997).

[7] In this case, the industry relative ratio is defined as the firm's ratio relative to the corresponding average value in the firm's industry at the same time. Standardizing by industry averages deflates raw values and expresses the variables in terms of proportions to enhance comparability. Also, because ratios are usually computed over different years, standardizing also controls for the mean shift in the ratios from year to year. Platt and Platt (1990) argue that this adjustment results in: (a) more stable financial ratios, (b) more stable coefficient estimates over time, and (c) less disparity between ex ante and ex post forecast results.

distributional characteristics and the definition of a dummy industry disturbance variable; while Asterbo and Winter (2001) find that models with industry-adjusted variables performed worse than with non-adjusted (raw) variables. Finally, Barnes (2000) reports that raw accounting ratios and industry relative ratios based on the same underlying data generate significantly different forecasts using the same statistical techniques. We follow Barnes (2000) and others in using both raw and industry relative data to investigate associated differences in acquisition likelihood and model prediction accuracies.

2.3. Evaluation procedures

2.3.1. Model validation

There appears to be a lack of coherence about the proportion of acquired and non-acquired firms in a train-and-test sampling scheme typically used to develop and validate prediction models. While an equal matched training sample is desirable for efficient estimation, Palepu (1986) criticizes previous studies for using equal matched holdout samples during testing and argue that such samples overestimate the model's ability to predict. However, Palepu's argument may not be as simple as it appears, since the difference in the prediction ability of the model could be attributed to the specific performance measure that was used (i.e. overall accuracy), which is very sensitive to the prevalence of positive cases (e.g. acquired firms, etc) as a percentage of the total sample[8]. Nevertheless, following the criticism of Palepu (1986), some researchers have used unequal matched samples of acquired and non-acquired firms for model validation, while others have continued to use equal matched samples. Our study makes use of both equal

[8] By recalculating the overall accuracy in the study of Stevens (1973), Palepu showed that if Stevens 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). However, Palepu's argument may not be as simple as it appears, since the difference in the prediction ability of the model could be attributed to the specific performance measure that was used (i.e. overall accuracy), which is very sensitive to the prevalence of positive cases (e.g. failed firms, acquired firms, etc) as a percentage of the total sample. More detailed, Palepu (1986) simply assumed that the sample of Stevens (1973) could consist of a total of 1,000 firms, with 40 targets and 960 non-targets, rather than 80 firms with 40 targets and 40 non-targets as used by Stevens. He recalculated the overall accuracy, while keeping the individual group accuracies constant. Hence, while the correct classification accuracy for acquired firms remained 85% and that for non-acquired 55%, the overall accuracy declined from 70% to 56%. However, if one had used the average accuracy (rather than the overall) the results would have remained unchanged.

and unequal holdout samples to provide a coherent and comparative test-bed in evaluating the out-of-sample performance of the prediction models.

2.3.2. Choice of cut-off point

The prediction results are usually reported in the form of a classification table, where firms are classified as acquired or non-acquired on the basis of a cut-off probability point. An approach commonly used in practice is to set the cut-off point equal to 0.5. However, Palepu (1986) criticizes this approach as arbitrary and proposes the use of an optimal cut-off point, where the conditional marginal probability densities for acquired and non-acquired banks are equal, this being determined by minimising the total error rate (or maximizing the total number of correct predictions). As an alternative, Barnes (1998) proposes the use of a weighted cut-off point based on historical data, although his results do not indicate any superiority of the proposed method over Palepu's optimal classification rule[9]. In this study, apart from using various cut-off based classification rules, we also apply the Receiver Operating Characteristic (ROC) curves[10] to provide a more comprehensive analysis of our model evaluation results.

3. Empirical study

3.1. Sample

The sample consists of 168 commercial banks, operating in the EU-15 single market, that were involved in 161 domestic and 7 cross-border acquisitions between 1998 and 2002[11].

[9] In another study, that focuses on the construction of stock portfolios on the basis of takeover predictions, Powell (2001) experiments with different cut-off points to select the portfolio with the highest ratio of targets to the total number of firms. His models predict quite well on average, classifying about 84% of targets and non-targets correctly, hence outperforming those of Palepu (1986). However, Powell (2001) acknowledges that if the same classification rule as in Palepu had been used, it would have resulted in a much lower predictive accuracy (47%) than the one achieved.

[10] ROC curves were initially used by Peterson et al (1954) in signal detection theory, and by Tanner and Swets (1954) in psychology. They were later used in numerous studies in medicine, and more recently Sobehart and Keenan (2001) suggested their use in rating models. Studies in accounting and finance using ROC curves include: Nargundkar and Priestley (2003) for credit risk modelling, Gaganis et al. (2005) for bankruptcy prediction, Rodriguez and Rodriguez (2006) for sovereign debt rescheduling, and Pasiouras et al (2008) for predicting bank acquisition targets.

[11] The acquired banks were identified in Bankscope and Zephyr databases of Bureau van Dijk's company and BANKERSalmanac.com. The acquisition represented the purchase of 50% or more of ownership of the acquired bank. The Bankscope and BANKERSalmanac.com databases provide information only for full

As the ECB (2006) indicates, between 1993 and 2003 the number of domestic M&As accounted for approximately 80% of total consolidation activity. Furthermore, as Walkner and Raes (2005) point out, domestic acquisitions accounted for around 90% in terms of value between 1987 and 2003. Therefore, it is not surprising that cross-border deals account for only 4% in our sample[12]. The 168 acquired banks were combined with 566[13] banks that were not acquired over the same period. Accounting data for all banks were collected from Bankscope.

To ensure the proper evaluation of the model we split the dataset into two distinct samples[14]. The estimation sample includes 137 banks acquired between 1998 and 2001 and an equal number of non-acquired banks matched by fiscal year[15]. Two holdout samples for testing in the future are also formed. Holdout 1 is an equal matched sub-sample consisting of 31 banks acquired during 2002 and 31 non-acquired banks randomly

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acquisitions and, therefore, we had to rely on Zephyr.com for the identification of banks subject to majority acquisitions.

[12] Since there might be differences between domestic and cross-border deals, as a robustness test we also re-estimated some of the models by excluding the 7 cross-border deals from the sample but observed no significant differences in the classification results (see footnote 34 for precise details). Hence, we present and discuss the results for the complete sample in the remainder of the paper, although in doing so we do not imply that domestic and cross-border deals should be treated as homogenous. It is likely that our results are unaffected due to the small proportion of cross-border deals.

[13] These were the total number of banks that met the following requirements: (i) had available data in Bankscope for the period 1996-2001, (ii) were characterized as commercial in Bankscope, (iii) were operating in one of the 15 EU countries.

[14] An alternative technique would be to use a re-sampling technique such as bootstrapping or cross-validation. However, as Espahbodi and Espahbodi (2003) mention while re-sampling techniques reduce the over-fitting bias, by offering an out-of-sample evaluation, they do not provide an out-of-time evaluation and therefore fail to indicate the usefulness of the model in the future. For the development of models for the identification of bank acquisition targets with a cross-validation procedure, see Pasiouras et al (2007). By contrast, the use of testing sample from a future period, as used in the present study, implicitly accounts for the case of a "drifting" population (i.e. over time) and allows us to determine if the variables and their estimated coefficients remain stable over the range of time period considered.

[15] The matching of acquired and non-acquired firms for estimation is common practice in most studies of acquisitions prediction (e.g. Barnes, 1998) and bankruptcy prediction (e.g. Bhargava et al., 1998). There are two primary reasons for following this procedure. The first is to lower the cost of gathering data compared to setting up an unmatched sample (Zmijewski, 1984). The second, and most important, is that a choice based sample provides higher information content than a random sample (Cosslett, 1981). Given that the number of acquisitions is relatively small compared to non-acquisitions, random sampling will consequently result in a sample comprising of many non-acquired firms and only few (if any) acquired firms, which from an estimating perspective is inefficient (Palepu, 1986). Thus it is essential to select the training sample in a way that will ensure that acquired firms 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, while Cosslett (1981) characterizes such a sample as a close-to-optimal design. Similar considerations may apply to holdout samples, although in this case there are stronger arguments for using an unequal sample as the model will be evaluated in a context that more closely resembles the true population (Palepu, 1986).

selected from the 429 non-acquired banks not used for model development. Holdout 2 includes the 31 banks acquired over the period 2002 (same as in Holdout 1) and all the 429 non-acquired banks mentioned above.

Finally, as in most previous studies we use accounting statements from the most recent year prior to the acquisition for our empirical analysis (i.e. the first year before acquisition for the acquired banks and the same fiscal year for the non-acquired ones). The literature on non-financial firms suggests that the prediction of acquisitions is very difficult and hence the models developed seek to predict acquisitions in a given year based on data mainly for the previous year (e.g. Espahbodi and Espahbodi, 2003).

3.2. Variable selection

3.2.1. Financial variables

As mentioned above we start with a list of 18 variables for which data were available in Bankscope. Beyond the main bank-specific financial categories (capital strength, profitability, expenses management and liquidity), we also account for the influence of size, growth and market power of banks. We discuss the variables in more detail below. Our primary justification for considering these variables and the categories they represent is based on emphasizing their connection with the motives for bank M&As[16].

Wheelock and Wilson (2000) find (for the US) that the lower a bank's capitalization, the greater the probability that the bank will disappear by being acquired. They argue that this is so with the acquisition of failing banks prior to insolvency as with the purchase of banks by skillful managers who are able to operate successfully with high

[16] By emphasising the motives for banks M&As, we have omitted the influence of regulatory control, which is found to be important in studies that examine the determinants of acquisitions (e.g. Koehler, 2008). In our context, the influence of regulations is deliberately excluded for a number of reasons. First, as emphasised earlier, our main stance is methodological, and we believe that the incorporation of regulatory variables is unlikely to affect the like to like comparisons that we perform, for example, between models with raw and country-adjusted variables and with different evaluation techniques. Second, the addition of regulatory variables could add unnecessary complexity to our analysis, for instance, in considering whether the approach for the selection of regulatory (or more generally environmental) variables should be consistent with that of financial ratios. Finally, Koehler (2008) examines the impact of merger control as a potential determinant of EU bank acquisitions and finds that transparency of regulation influences the acquisition likelihood in cross-border deals, although not in domestic deals. This final point reinforces our belief that the inclusion of regulatory variables is unlikely to alter our results, given that 96% of the deals in our sample are domestic.

leverage. In our case, capital strength is represented by the following variables:[17] (i) equity to assets (EQAS) ratio that measures the amount of protection offered to the bank by its equity, (ii) equity to loans (EQLOAN) ratio, which measures the equity available to absorb losses on the bank's loan portfolio, (iii) the ratio of equity to customer & short term funding (EQCUST), providing a measure of the amount of permanent funding (i.e. equity) relative to customer deposits and short term funding, (iv) equity to liabilities ratio (EQLIAB), which provides a slightly different picture of the equity funding of the balance sheet, and (v) capital funds to liabilities ratio (CAPLIAB), which adds hybrid capital and subordinated debt to shareholders' equity in the numerator (while the denominator is the same as in EQLIAB).

A major hypothesis in the literature is that acquisitions serve to drive out bad management. Thus, as mentioned by Hannan and Rhoades (1987), poorly managed banks are likely targets for acquirers who think that they can manage more efficiently the assets of the acquired banks and increase profits and value. We consider six measures of managerial performance, from which five represent profitability and one cost efficiency. The profitability measures are: (i) net interest margin (NIM), which is the net interest income expressed as a percentage of earning assets, and reflects the profitability of a bank's interest-earning business, (ii) the ratio of net interest income to average total assets (NIMAS), which is similar to NIM, but expressed as percentage of average total assets rather than earning assets, (iii) the ratio of other operating income to average assets (OTHAS), which indicates to what extent non-interest income represents a greater percentage of bank's operating income, (iv) return on average assets (ROA), calculated as net profit divided by average total assets, and used to measure the overall profitability of a bank, and (iv) return on average equity (ROE), calculated as net profit divided by average shareholders equity, an alternative measure of profitability. Finally, as a measure of efficiency in expenses management, we use COST, which measures overheads as a proportion of income.

Another important bank aspect that can influence the acquisition likelihood is a bank's liquidity position. However, it is difficult to determine a priori what the direction

[17] The considered variables cover slightly different aspects of banks capital strength and are commonly used in many recent studies in banking, although there are risk-weight measures (such as the Tier 1), which could not be considered due to high number of missing values for these observations.

of the influence will be. On one hand, some banks may be acquired because of their good liquidity position (i.e. the size of liquid assets attracts acquirers). On the other hand, it is possible that banks that are particularly illiquid will find it difficult to avoid an acquisition (or they will be willing to be acquired), because they have moved into liquidity problems that are difficult to overcome. We consider three ratios related to liquidity: (i) net loans divided by customers & short term funding (LOANCUST), a measure highlighting the association between comparatively illiquid assets (loans) and moderately stable funding sources (deposits and other short term funding), thus showing the extent to which the bank has lent its deposits in illiquid form; (ii) liquid assets divided by customers & short term funding (LIQCUST), which measures the percentage of latter that could be met almost on demand; and (iii) net loans divided by total assets (LOANS), which indicates the percentage of bank assets that are tied up in loans. The last ratio can also serve as an indicator of loan activity (Hannan and Rhoades, 1987; Moore, 1996). Hannan and Rhoades (1987) suggest that, on the one hand, a high level of loans would seem to indicate aggressive behaviour by the target bank while, on the other, a low level of loans may indicate a bank with conservative or complacent management, which an aggressive acquiring bank could turn around to increase returns.

Bank size may also have an impact on its acquisition likelihood for numerous reasons. First, large banks are more expensive to be acquired. Second, larger banks have greater resources to fight an unwanted acquisition. Third, they are also more difficult to be absorbed into the existing organization of the acquiring bank. Hannan and Rhoades (1987) and Moore (1996) find the effect of size to be insignificant, however, Wheelock and Wilson (2000) report that smaller banks are more likely to be acquired than larger ones. In line with previous studies, we use total assets as a measure of size (SIZE)[18].

As for growth, Kocagil et al. (2002) point out, referring to previous empirical evidence, that some banks whose growth rates were relatively high experienced problems because their management and/or structure were not able to deal with and sustain exceptional growth. It is, in general, possible that a firm constrained in this way could be

[18] In the case of raw data, the logarithm of total assets is used to reduce the outlier bias, making extremely large or small banks less influential. In the case of country-adjusted data, a transformation is accomplished by dividing the total assets of the bank with the average total assets of the corresponding banking industry. Hence, a logarithmic transformation is not considered necessary in the latter case.

an attractive acquisition target for another firm with surplus resources or management available to help (Barnes, 1999). In the present study, we represent the influence of bank growth by the annual change of the bank's total assets (GROWTH).

Finally, a study by the Group of Ten (2001), focusing on the consolidation in the financial services industry, reveals that market power, interpreted as an increase in market share, was among the most important motivating influences on M&A activity. We therefore consider the market share of banks in terms of deposits (DEPSHARE), and loans (LNSHARE).

3.2.2. Industry adjusted variables

The Group of Ten (2001) also points out that the nature of acquisition activity and the dominant motivations for acquisitions may differ between countries. Furthermore, there is greater heterogeneity in the levels of profitability, liquidity, cost efficiency and other aspects of bank's performance across countries. Therefore, as Harris et al. (1982) point out the accounting ratios for individual firms may have little meaning in isolation and their relationship to industry averages can enhance their explanatory power. Using raw data, we therefore derived industry relative (adjusted) ratios using the following formula:

Banks industry relative ratio X_1 in year t = Banks X_1 ratio in year t / Average value of X_1 ratio for the commercial banking industry of the corresponding country in year t[19]

3.2.3. Methodologies

DA seeks to obtain a linear combination of the independent variables. The objective is to classify observations into mutually exclusive groups as accurately as possible by maximizing the ratio of among-groups to within-groups variance. The discriminant function is of the following form:

[19] Country averages were calculated from the Bankscope database for each one of the 15-EU commercial banking industries and for each year over the period 1996-2001. The only variables for which we do not calculate the industry average are market shares, which by definition express the value of a bank relative to the industry in which it operates.

$$Z = b_0 + b_1 x_1 + b_2 x_2 + ... + b_m x_m$$

where x_j is the *j*th independent variable, b_0 is the coefficient for the *j*th independent variable, and Z is the discriminant score that maximizes the distinction between the two groups. A given bank will be classified as a acquired if Z > Zc (the critical Z), and as non-acquired if Z < Zc. Alternatively, a given bank may be classified as acquired or non-acquired based on its posterior (conditional) probability of acquisition. This approach is consistent with the LA model discussed below.

In LA the probability of a bank to be acquired based on a set of independent variables is given by the following function:

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

where

$$Z_i = \ln\left(\frac{P_i}{1 - P_i} \right) = b_0 + b_1 x_1 + b_2 x_2 + ... + b_m x_{m,} + \varepsilon_i$$

is the probability that bank *i* will be acquired, b_0 is the intercept term and b_j (j = 1,…,*m*) represents the coefficients associated with the corresponding independent variables x_j (j= 1,…,*m*) for each bank. The coefficient estimates are obtained by regression, which involves maximizing a log-likelihood function. The model is then used to estimate the group-membership probabilities for all banks under consideration. The bank is classified as acquired (non-acquired) if the posterior probability of acquisition of that bank is greater (lower) than a cut-off probability point.

4. Empirical Results

4.1. Descriptive statistics and preliminary analysis

Table 1 presents summary statistics[20] based on the training sample used for model development, distinguishing between the acquired and non-acquired banks, as well as

[20] All descriptive statistics are after capping extreme values to reduce the influence of outliers in the regressions.

between raw and industry relative data. For both sets of data, the Kruskal-Wallis (K-W) chi-square test reveals significant mean differences for the variables ROA, ROE and COST, which suggests that non-acquired banks were relatively more profitable and cost efficient than acquired banks. Additionally, for industry relative data, the results also indicate that acquired banks were marginally less well capitalized, as revealed by the statistical significance of mean group differences for the capital strength variables EQAS, EQLIAB, CAPLIAB.

[Insert Table 1 Around Here]

On the basis of the statistical screening method, it would be instructive to include the aforementioned six variables in the model development process[21]. Table 2 shows the correlations among the variables appropriately found to be statistically mean-significant in raw and industry relative data. On both sets of data, a high correlation is found between ROA and ROE. This is also, and more so, the case between the industry relative capital ratios EQAS, EQLIAB and CAPLIAB (Panel B). To avoid potential multicollinearity problems, therefore, we select the variables with the highest K-W value among the highly correlated ones[22]. Thus, by this method, ROA and COST are the appropriate variables for model development using raw data, with EQAS added when using industry relative data.

[Insert Table 2 Around Here]

However, while univariate tests suggest specific variables as candidates for model building, in a multivariate setting it may be argued that a collective set of variables might achieve a better degree of discrimination between the two groups of banks. To avoid potential biases, therefore, we supplement our model development process with other methods for variable selection as discussed above, including the use of factor analysis.

[21] Here the rule of thumb is not to include a variable unless its discriminatory power is statistically demonstrated on a univariate basis (Kocagil et al, 2002), although as explained above we also employ other criteria in model development (e.g. human judgment, factor analysis, and stepwise procedure).

[22] Although Judge et al (1988) point out that correlations below 0.8 should not be too harmful as far as multicollinearity is concerned, there are other reasons for not including highly correlated variables within the same category for model development, as explained below. The basis for selecting the one with the highest K-W statistic is because it suggests the highest degree of discriminatory power in distinguishing between the two groups, which is appropriate for model development.

Because of the degree of overlap and high correlation among some variables, factor analysis is used to empirically identify subsets of variables with common characteristics.

Table 3 presents the standardized scoring coefficients (or loadings) of factor analysis conducted on both raw and country-adjusted data. In both cases, we extract five factors (on the basis of eigenvalues greater than unity), which together account for over 80% of the total variance. We present only loadings over 0.6, and the results show that none of the proxies with highest loadings span more than one factor. The proxy with the highest loading is therefore treated as the representative or lead variable for that factor to be included in model estimation. Using this method, it appears that factors with lead variables EQLIAB, LOANS, LNSHARE, ROE and OTHAS are potential candidates for model development using raw data, with NIMAS replacing OTHAS on industry relative data.

[Insert Table 3 Around Here]

4.2. Models' Development

We estimate 4 models as follows: Model 1 with variables selected using a stepwise procedure; Model 2 with variables judiciously chosen by logical screening; Model 3 with variables determined by the statistical screening method explained above; and Model 4 using factors labelled in Table 3. Table 4 presents the estimation results for raw data. All models are statistically significant at the 1% level.

[Insert Table 4 Around Here]

The stepwise DA and LA models (shown as Model 1) developed with raw data show statistical significance of four variables (ROE, COST, SIZE and LNSHARE), these being determined by a process of stepwise elimination of insignificant variables. Under LA, both ROE and SIZE are negatively related, whereas COST and LNSHARE are positively related to acquisition likelihood. The latter two (COST, LNSHARE) have a greater impact than the former (ROE and COST) on both models.

In Model 2, we included variables not picked up by the other selection methods, which we regard as potential candidates on the basis of prior studies and acquisition motives discussed above. In particular, we rely on the use of ROA (as in Model 3) instead of ROE because, as Falkenstein et al. (2000) note, the interpretation of ROE can be "extremely confusing conceptually"[23]. Furthermore, EQAS is preferred among the capital ratios, as it the most commonly used one in banking studies (e.g. Wheelock and Wilson, 2002, 2004). We also include LOANS to proxy for loan activity[24] (e.g. Moore, 1996). In addition, we include a measure of liquidity, relying on LIQCUST rather than on LOANCUST[25]. Finally, as a measure of market power, we use DEPSHARE instead of LNSHARE, because the latter incorporates the influence of loans already included through LOANS. In this model, the statistically significant influences are COST, ROA, SIZE and DEPSHARE, which are consistent with the results of Model 1.

In Model 3, SIZE and DEPSHARE (apart from LOANS, LIQCUST, GROWTH and LNSHARE) are excluded by the statistical screening method, and their effects are seen to manifest into the significance of the intercept term. In Model 4, the factor bearing the effect of ROE is statistically significant and negative, but as Table 5 shows this factor incorporates the influence of COST too. We conclude that, using raw data, both DA and LA models show profitability (ROA or ROE), expenses management (COST), SIZE (log of total assets), and market power (LNSHARE or DEPSHARE) as statistically significant factors influencing bank acquisitions.

Table 5 shows the results of the models estimated using industry relative data (hereafter Models 5-8[26]). The stepwise model 5 (under both DA and LA) now contains just two significant variables, COST and LNSHARE, since the influence of profitability

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[23] The argument is analogous to saying that a negative ratio can result from either negative profits or equity values, and for a ratio to be positive both the numerator and denominator have to be negative or positive. Some studies report a positive effect of this variable on acquisition likelihood (e.g. Palepu, 1986) while others negative (e.g. Cudd and Duggal, 2000). However, our results are consistent in terms of sign whether we use ROA or ROE.

[24] Loans are the largest single item in total assets. 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.

[25] This is partly because the interpretation of LOANCUST might not be straightforward, as it depicts relationship between comparatively illiquid assets (i.e loans) and comparatively stable funding sources (i.e deposits and other short term funding). Therefore the lower this ratio, the more liquid the bank is. On the other hand, a bank that transforms more deposits into loans (i.e. higher LOANCUST) relative to its competitors will probably have higher market share, interest margin, and profits. We rely on LIQCUST also because of its use in previous studies (e.g. Pasiouras and Gaganis, 2007).

[26] Note that Models 5, 7 and 8 are slightly different in their estimated specifications from Models 1, 3 and 4 respectively. Model 5 ends up excluding ROA, which is included in Model 1. Model 8 replaces OTHAS (in Model 4) with NIMAS. Model 7 has EQAS added by virtue of its high discriminatory power in industry relative data, while its mean difference is insignificant in raw data, and so its excluded from Model 3. Model 6 retains the same specification as Model 2.

(ROA) is found insignificant. In Models 6-7, the insignificance of ROA is confirmed, although in Model 8 the factor containing ROE is significant as it also bears the effect of COST. Notably, COST (inefficiency) has a more pronounced and positive effect on acquisitions. Among other variables, SIZE and DEPSHARE are insignificant in Model 6, but LIQCUST is statistically significant at 10% level. However, LNSHARE retains its statistical significance in Model 5. We therefore conclude that, on industry relative data, the statistically significant influences are COST, LNSHARE and LIQCUST.

To summarise, the estimated results reveal some differences in the relative importance of the variables when comparing models on raw versus industry relative data, although both DA and LA estimations obtain qualitatively similar results for each of the four models.

[Insert Table 5 Around Here]

4.3. Models' Validation.

Table 6 presents the classification results for the models based on a cut-off point set equal to 0.5. In each case we present the accuracies for the individual groups (acquired/non-acquired), the overall and average accuracies, as well as Cohen's Kappa and PABAK indices[27]. Panel A reports results for raw data (Models 1-4), and Panel B for industry relative data (Models 5-8). The results are very similar throughout for both DA and LA, as would be expected from the similarity of the estimated variable coefficients.

[27]The individual groups accuracies refer to the percentage of acquired (non-acquired) banks that are correctly classified. The average classification accuracy is classified as the average of the correct accuracies of acquired and non-acquired banks. The overall classification accuracy is calculated as (Number of correctly classified acquired banks + Number of correctly classified non-acquired banks)/Total number of banks. 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. 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. 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. Byrt et al. (1993) proposed a solution to the possible bias of Cohen's Kappa, known as "Prevalence-Adjusted-Bias Adjusted Kappa" (PABAK). 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.

All models achieve better than chance (i.e. 50%) accuracies in the training sample, although a more appropriate basis for evaluation against chance is provided by the results of the Holdout 1 sample. On this sample, the average/overall classification accuracies show that Models 1 and 4 perform below par (i.e. negative Kappa and PABAK), while Model 3 does marginally better than Model 2, by virtue of achieving higher classification accuracy for the acquired group (61.29%). Moving on to comparing the models on the Holdout 2 sample, we observe an increase in overall/average accuracies for all models, mainly as result of the improvement in their ability to correctly classify non-acquired banks. Here Model 2 performs slightly better than Model 3 on average/overall accuracy (i.e. increase in Kappa and PABAK), although Model 3 fares better on correctly classifying acquired banks.

[Insert Table 6 Around Here]

A similar picture emerges from the models estimated with industry relative data, although in this case Models 5, 6 and 7 perform better than chance, while Model 8 falls below par in terms of overall/average classification accuracy achieved on Holdout 1. The main observation here is that all the models correctly classify a higher proportion of acquired banks on holdout samples, with Model 6 slightly out-performing Models 5 and 7 on all the measures. Between the two holdout samples, the improvement in terms of correctly classifying non-acquired banks is not as high for Model 6 (industry relative data) as it is for Model 2 (same model on raw data). Nevertheless, it is clear that the average/overall classification accuracies for all the models are higher in Holdout 2 than in Holdout 1. Thus, while Palepu (1986) shows that the accuracies reported by Stevens (1973) would be lower if tested in an unequal sample, we empirically demonstrate here that classification accuracy increases for the category whose proportion in the sample size increases (i.e. non-acquired banks) as we move from equal to unequal matched sample for testing[28].

[28] Palepu illustrates the bias (overestimate) in the classification error rate by taking into account the relative population values and shows that "the size of the bias is proportional to the difference in the two types of sample error rates as well as the difference in the ratios of population and sample shares of targets and non-

As mentioned earlier, Palepu (1986) suggests the use of an optimal classification rule which requires that the conditional marginal probability of classifying a firm as acquired, if it is actually acquired, should equal or exceed the corresponding marginal probability of classifying the firm as acquired, if it is actually a non-acquired firm. The optimal cut-off point that attempts to balance the probability of committing these Type I and Type II errors is where the two conditional marginal densities are equal. We follow this procedure, and determine the new (optimal) cut-off points[29].

[Insert Table 7 Around Here]

Table 7 presents the classification results when we apply the optimal cut-off points. We observe that as the cut-off point is raised upwards from 0.5, the percentage of acquired banks classified correctly decreases, while the corresponding percentage for non-acquired banks increases, thus implying a trade off between Type I and Type II errors. As a result, on Holdout 1, Models 1's performance is improved and is rated slightly better than Model 2 on average/overall accuracy, and Model 3 is superior only by virtue of correctly classifying a higher proportion of non-acquired banks, while it does worse than the other two in correctly classifying acquired banks. Model 2, however, correctly classifies a higher proportion of acquired banks, and on Holdout 2 it is superior in classifying both groups of banks. Model 4 remains the worst performing model even with the optimal cut-off point (being only slightly higher than 0.5, and so the expected change is marginal).

Evaluating the models on industry relative data (Table 7, Panel B) gives a similar picture as above, except that the higher than 0.5 optimal cut-off point makes Model 5 superior on the average/overall accuracy in Holdout 1, although Models 6 and 7 retain their ability to correctly classify a higher proportion of acquired banks. Despite the associated trade-off in Type I and Type II errors as the cut-off point varies, Model 6 remains superior on Holdout 2. Model 8, with the optimal cut-off at 0.55 achieves

targets" (1986, p. 11). To avoid any ambiguity, we are showing empirically that use of unequal samples does not always lead to lower overall accuracies as might be inferred from Palepu's result.

[29] For brevity of space we do not present the Tables with the calculations here, which are however available from the authors upon request. The estimated optimal cut-off points are as follows: 0.5230 (DA Model 1), 0.5500 (DA Model 2), 0.5500 (DA Model 3), 0.5130 (DA Model 4), 0.5230 (LA Model 1), 0.5569 (LA Model 2), 0.5514 (LA Model 3), 0.5166 (LA Model 4), 0.5584 (DA Model 5), 0.5500 (DA Model 6), 0.4977 (DA Model 7), 0.5500 (DA Model 8), 0.5618 (LA Model 5), 0.5526 (LA Model 6), 0.4944 (LA Model 7), 0.5500 (LA Model 8).

significantly poorer classification results for acquired banks at the expense of improving its ability to correctly classify non-acquired banks (in relation to 0.5 cut-off), and remains inferior on average/overall performance.

The above results indicate, however, a fair amount of misclassification in all categories, ranging between 15-68% in raw data and 30-68% in industry relative data. The higher variability in the predictions for raw data is due to Models 1 and 2 achieving about 85% accuracy in classifying non-acquired banks, in Holdout 2, under the 0.5 classification rule. The range of variability in lower under the optimal classification rule, but correspondingly the average misclassification is higher[30]. While these results are consistent with previous studies (e.g. Espahbodi and Espahbodi, 2003, Pasiouras et al, 2007, 2008), highlighting the difficulties involved in predicting acquisition targets, they clearly demonstrate poor predictive ability of the model that suffers from relatively low explanatory power, due to the omission of significant effects not appropriately taken into account by use of factor analysis or statistical filtering procedures.

Following Barnes (2000), we also evaluated the models using a weighted average cut-off point set to 0.9326 for Holdout 2[31]. Not surprisingly, under this approach, since only those banks with acquisition probability higher than 0.9326 are classified as acquired, all the models ended up classifying correctly all non-acquired banks (100%), while at the same time misclassifying all acquired banks (0%), yielding average/overall accuracies of 50%. The unequal size of Holdout 2 leads to this extreme result and makes the weighted approach to cut-off an uninteresting one in our case.

4.4. An alternative evaluation approach – ROC curves

The above analysis shows that varying the cut-off point changes the classification accuracies because of the trade-off between Type I and Type II errors, and therefore unless there are good prior reasons for selecting an appropriate cut-off point, different classification rules will lead to arbitrary differences in the performance ranking of the

[30] Overall comparisons are complicated by the variety of classification metrics used, apart from the variety of models entertained, the use of two estimation methods, datasets, cut-off rules and holdout samples, but generally the average misclassification (error rate) is high, with raw data showing somewhat greater variability than industry-relative data.

[31] This cut-off point is specific to the holdout sample, determined ex post as follows: [(31 x 0) + (429 x 1)] / 460 = 0.9326. In an equal matched sample the calculation would result in a cut-off point equal to 0.5

models. We therefore follow Pasiouras et al. (2008) and use the ROC curves that offer a comprehensive analysis of all possible errors, and all cut-off points[32]. In addition to schematic presentation of the ROC curves, the area under the curve (AUC) measure, shown in Table 8, can also provide useful information as it averages the misclassification rates over all possible choices of the various cut-off points. Thus, AUC values can be used to compare different classification models when no information regarding the costs or severity of classification costs is available.

We observe that Holdout 2 has higher AUC than Holdout 1, consistent with the increase in the classification accuracies obtained with the 0.5 and optimal cut off points. The model rankings are also similar, with models based on logical screening (i.e. Models 2 and 6) achieving the highest AUC in Holdout 2, and those of the statistical screening method (i.e. Models 3 and 7) slightly out-rank the other models in Holdout 1[33]. We also see a better predictive performance of Models 1 and 2 in Holdout 2, while the use of factor analysis (i.e. Models 4 and 8) achieves the lowest AUC. These results are therefore consistent with the results of Tables 6 and 7.[34]

In Figures 1 and 2, we present the ROC curves for two highest-ranking DA and LA models on Holdout 2 (i.e. Models 1 and 2 for raw data in Figure 1 and Models 6 and 7 for industry relative data in Figure 2)[35], which shows remarkable similarity in the performance of the DA and LA models. While it appears that the high-ranking models show better predictive ability on raw data, it should be noted that this is specific to Holdout 2 and results from the models' ability to predict a high proportion of non-targets. In general, the results of Table 8 show that models using industry relative data tend to

[32] The ROC curve plots the percentage of "hits" (i.e. true positives) of the model on the vertical axis, and the 1-pecificity or percentage of "false alarms" (i.e. false positives) on the horizontal axis. The result is a bowed curve rising above the 45 degree line towards the upper left corner. The sharper the bend and the closer to the upper left corner, the higher the predictive accuracy of the model.

[33] Except in the case of LA model 6 which ranks slightly higher than LA model 7, suggesting that there is little difference in performance between human judgement and statistical screening methods on Holdout 1.

[34] As a robustness test, we re-estimated Models 2, 4, 6, 8 while excluding the 7 cross-border deals from the sample. These models achieved the best (Models 2 & 6) and worst (Models 4 & 8) performance in terms of average classification and AUC values when we evaluated the results in the Holdout 2 sample, which is more representative than Holdout 1. We observed no other significant differences either in the classification accuracies or in the AUC. The results of these four models not reported are available from the authors upon request.

[35] For brevity of space we do not present all the ROC curves. The information is summarized in Table 8.

exhibit less variability in their predictive accuracy across the holdout samples, consistent with the argument that industry adjusted variables are more stable (Platt and Platt, 1990).

[Insert Table 8 and Figures 1 and 2 Around Here]

5. Conclusions

This paper has sought to develop and evaluate prediction models for the identification of banks acquisition targets. Using accounting data for 734 commercial banks in the EU, from which 168 banks were acquired over the period 1998-2002, we examined several methodological issues in model development and prediction. We used discriminant and logit analyses to estimate a variety of models, and utilized a range of criteria to evaluate the predictive accuracy of the models in terms of distinguishing the acquired banks from non-acquired ones.

Starting with a set of 18 variables chosen to represent well-known acquisition motives (takeover hypotheses), and using both raw and industry relative data, we utilized four model selection procedures (stepwise regression, statistical screening, logical screening and factor analysis) to arrive at a final set of input variables for estimation. While these results reveal differences in the use of raw and industry relative data, they are consistent across the range of the discriminant and logit models estimated.

Turning to the predictive performance of the models developed, we tested on both equal (matched) and unequal holdout samples. Several approaches to evaluating model performance were considered, and to the extent that classification accuracies vary with the adjustment in the cut-off point used in computing error rates, the selection of the optimal model depends very much upon the measure used for evaluation. Some models showed better accuracies at classifying acquired banks while others were better at classifying non-acquired banks, the latter more prevalent with the use of raw data. However, in terms of correctly classifying acquired as well as non-acquired banks across the two holdout samples, we found that models based on logical screening delivered more consistent and better performance. Overall, while our results show that the models achieve classification accuracies higher than chance, there is nevertheless a fair amount of misclassification, which suggest difficulties in predicting bank acquisition targets.

In comparing the use of raw and industry relative data, the latter adjusting for country-wide differences in bank level data, the models showed better predictive ability to correctly classify acquired banks with industry relative data, and conversely better at classifying non-acquired banks with raw data. Hence, as shown by the evaluation results obtained with ROC curves, industry relative data seem to offer more stable out-of-sample predictive outcome, highlighting the importance of correcting for industry level disturbances in the data.

Although we base our initial list of variables on prior studies and acquisition motives, the present study is restricted to the use of financial data. Obviously, the efficiency of the prediction model in terms of its discriminatory power may be enhanced by non-financial characteristics. In particular, agency costs theories suggest that managerial incentives and corporate governance mechanisms (e.g. golden parachutes, poison pills, managerial ownership, executive salary, etc) are potentially influential factors in M&As. Unfortunately, data availability for European banks has limited the scope of present study to the use of financial ratios, and it is hoped that future research will incorporate non-financial factors in model development. Another avenue for future research would be to focus on cross-country deals and incorporate the influence of regulatory variables for merger control in the classification models.

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Table 1 – Descriptive statistics and Kruskal-Wallis test

	Raw					Country-adjusted				
	Non-acquired		Acquired		Kruskal-Wallis	Non-acquired		Acquired		Kruskal-Wallis
	Mean	Stdv	Mean	Stdv	χ^2	Mean	Stdv	Mean	Stdv	χ^2
EQAS	8.70	6.60	8.12	6.52	1.52	2.06	1.48	1.82	1.46	5.46**
EQLOAN	32.27	41.27	31.77	40.37	0.37	3.31	4.18	3.17	4.23	0.90
EQCUST	12.26	12.54	11.63	11.56	0.62	2.07	2.02	1.93	1.96	2.50
EQLIAB	10.30	9.50	9.55	9.22	1.63	2.31	2.08	2.03	2.04	5.34**
CAPLIAB	11.50	9.24	10.61	9.06	2.26	1.78	1.44	1.61	1.44	4.64**
NIM	2.68	1.80	2.56	1.55	0.04	1.73	1.15	1.57	1.05	1.32
NIMAS	2.46	1.60	2.36	1.40	0.04	1.77	1.18	1.60	1.08	1.41
OTHAS	1.52	1.20	1.42	1.08	0.31	1.40	1.24	1.20	1.02	0.83
ROA	0.80	0.61	0.49	0.66	17.30***	1.80	1.63	1.05	1.63	18.61***
ROE	11.26	7.33	7.53	7.67	16.94***	0.99	0.71	0.69	0.72	11.34***
COST	62.89	17.14	74.32	21.84	22.46***	0.96	0.25	1.12	0.30	21.42***
LOANS	46.42	24.78	46.24	25.93	0.00	1.04	0.55	0.99	0.54	0.75
LOANCUST	59.28	33.72	60.33	36.06	0.00	0.96	0.55	0.96	0.57	0.00
LIQCUST	37.47	27.71	35.01	29.24	1.08	1.32	0.97	1.22	0.99	1.09
GROWTH	8.19	16.63	6.00	21.64	0.44	-0.12	3.18	-0.76	3.82	0.85
SIZE	3.09	0.73	3.06	0.79	0.36	0.46	0.87	0.56	1.08	0.28
LNSHARE	0.54	1.02	0.77	1.36	0.00	0.54	1.02	0.77	1.36	0.00
DEPSHARE	0.62	1.36	0.90	1.72	0.00	0.62	1.36	0.90	1.72	0.00

Variables are defined in Table 2. ***Statistical significant at the 1% level, ** Statistical significant at the 5% level, *Statistical significant at the 10% level

Table 2 – Correlation analysis

Panel A: Raw variables			
	ROA	ROA	COST
ROA	1.00		
ROE	0.76	1.00	
COST	-0.49	-0.51	1.00

Panel B: Adjusted variables						
	EQAS	EQLIAB	CAPLIAB	ROA	ROE	COST
EQAS	1.00					
EQLIAB	0.99	1.00				
CAPLIAB	0.97	0.99	1.00			
ROA	0.46	0.43	0.41	1.00		
ROE	-0.03	-0.04	-0.04	0.77	1.00	
COST	-0.08	-0.07	-0.06	-0.44	-0.47	1.00

Table 3 – Factor analysis

	Component				
	1	2	3	4	5
Panel A: Raw variables					
EQLIAB	**0.98**				
CAPLIAB	0.97				
EQAS	0.97				
EQCUST	0.96				
LOANS		**0.95**			
LOANCUST		0.92			
LIQCUST		-0.74			
NETINTAS		0.65			
EQLOANS		-0.65			
NIM		0.64			
LNSHARE			**0.97**		
DEPSHARE			0.96		
SIZE			0.79		
ROE				**0.85**	
COST				-0.82	
ROA				0.79	
OTHERAS					**0.71**
GROWTH					
Panel B: Country adjusted variables					
	1	2	3	4	5
EQLIAB	**0.97**				
CAPLIAB	0.97				
EQAS	0.96				
EQCUST	0.95				
LOANS		**0.95**			
LOANCUST		0.92			
LIQCUST		-0.68			
EQLOANS					
LNSHARE			**0.96**		
DEPSHARE			0.95		
SIZE			0.92		
ROE				**0.92**	
ROA				0.84	
COST				-0.70	
NETINTAS					**0.63**
NIM					0.63
GROWTH					
OTHERAS					

Notes: Only loadings above 0.6 (in absolute terms) are shown. With bold is the variable with the highest loading in the component.

Table 4 – Estimation results with raw data

	DA				LA			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Constant	-0.066	0.777	2.081	0.956	-0.015	0.606	-1.307**	0.564
					(0.000)	(0.281)	(4.861)	(2.427)
EQAS		0.010				0.008		
		(0.065)				(0.097)		
EQLIAB				-0.022				-0.013
				(-0.201)				(0.798)
OTHAS				0.232				0.171
				(0.322)				(1.787)
ROA		-0.666	-0.684			-0.512*	-0.446*	
		(-0.426)	(-0.438)			(3.726)	(3.842)	
ROE	-0.055			-0.139	-0.041**			-0.084***
	(-0.412)			(-1.043)	(4.297)			(18.209)
COST	0.033	0.032	0.037		0.024***	0.023***	0.023***	
	(0.638)	(0.630)	(0.722)		(10.006)	(9.223)	(10.019)	
LOANS		-0.011		-0.002		-0.008		-0.001
		(-0.270)		(-0.056)		(1.278)		(0.57)
LIQCUST		-0.013				-0.010		
		(-0.378)				(2.594)		
GROWTH		-0.004				-0.003		
		(-0.154)				(0.165)		
SIZE	-0.674	-0.628			-0.503**	-0.462*		
	(-0.512)	(-0.477)			(3.974)	(3.091)		
LNSHARE	0.645			0.385	0.483***			0.235**
	(0.777)			(0.464)	(8.502)			(4.282)
DEPSHARE		0.394				0.287**		
		(0.610)				(5.726)		
DA								
Wilk's Lambda	0.878	0.880	0.909	0.918				
χ^2	35.204***	34.274***	25.989***	22.961***				
LA								
χ^2					35.570***	34.988***	26.328***	23.415***
Nagelkerke R^2					0.162	0.160	0.122	0.109

Notes: Variables are defined in Table 2. Model 1 is estimated with stepwise procedure. Model 2 is estimated on the basis of logical screening (i.e. previous studies and acquisition theories). Model 3 is estimated with a set of variables selected on the basis of a combination of Kruskal-Wallis and correlation analysis. Model 4 is developed with variables selected on the basis of factor analysis. Values in parentheses correspond to the standardized coefficients in the case of DA and Wald test in the case of LA; ***Statistical significant at the 1% level, **Statistical significant at the 5% level, *Statistical significant at the 10% level.

Table 5 – Estimation results with industry-adjusted data

	DA				LA			
	Model 5	Model 6	Model 7	Model 8	Model 5	Model 6	Model 7	Model 8
Constant	-3.861	-1.781	-2.547	1.662	-2.523***	-1.293*	-1.634***	0.751**
					(23.007)	(2.926)	(7.363)	(5.343)
EQAS		0.049	-0.026			0.036	-0.018	
		(0.072)	(-0.038)			(0.106)	(0.032)	
EQLIAB				-0.165				-0.076
				(-0.340)				(1.279)
NIMAS				-0.031				-0.014
				(-0.035)				(0.010)
ROA		-0.181	-0.231			-0.135	-0.152	
		(-0.295)	(-0.376)			(1.750)	(2.377)	
ROE				-1.307				-0.596***
				(-0.933)				(10.766)
COST	3.498	2.674	2.817		2.289***	1.950***	1.818***	
	(0.966)	(0.738)	(0.778)		(22.849)	(13.213)	(12.271)	
LOANS		-0.477		-0.147		-0.335		-0.063
		(-0.259)		(-0.080)		(1.242)		(0.054)
LIQCUST		-0.411				-0.304*		
		(-0.403)				(3.173)		
GROWTH		-0.070				-0.051		
		(-0.246)				(1.798)		
SIZE		-0.116				-0.092		
		(-0.133)				(0.147)		
LNSHARE	0.350				0.227**			
	(0.415)				(4.238			
DEPSHARE		0.281				0.204		
		(0.382)				(1.295)		
DA								
Wilk's Lambda	0.901	0.881	0.905	0.951				
χ^2	28.347***	34.093***	27.145***	13.573***				
LA								
χ^2					28.371***	34.643***	27.422***	13.779***
Nagelkerke R^2					0.131	0.158	0.127	0.065

Notes: Variables are defined in Table 2. Model 5 is estimated with stepwise procedure. Model 6 is estimated on the basis of logical screening (i.e. previous studies and acquisition theories). Model 7 is estimated with a set of variables selected on the basis of a combination of Kruskal-Wallis and correlation analysis. Model 8 is developed with variables selected on the basis of factor analysis. Values in parentheses correspond to the standardized coefficients in the case of DA and Wald test in the case of LA; ***Statistical significant at the 1% level, **Statistical significant at the 5% level, *Statistical significant at the 10% level.

Table 6 - Classification results (cut-off point equal to 0.5)

		DA			LA		
Panel A: Raw data		Training	Holdout 1	Holdout 2	Training	Holdout 1	Holdout 2
Model 1	Acquired	62.77%	48.39%	48.39%	62.77%	48.39%	48.39%
	Non-acquired	67.88%	48.39%	82.28%	67.88%	45.16%	82.05%
	Average	65.33%	48.39%	65.34%	65.33%	46.77%	65.22%
	Overall	65.33%	48.39%	80.00%	65.33%	46.77%	79.78%
	Cohen Kappa	30.66%	-3.23%	16.16%	30.66%	-6.45%	15.91%
	PABAK	30.66%	-3.23%	60.00%	30.66%	-6.45%	59.57%
Model 2	Acquired	60.58%	51.61%	51.61%	60.58%	51.61%	51.61%
	Non-acquired	70.07%	51.61%	81.82%	67.88%	51.61%	81.12%
	Average	65.33%	51.61%	66.72%	64.23%	51.61%	66.37%
	Overall	65.33%	51.61%	79.78%	64.23%	51.61%	79.13%
	Cohen Kappa	30.66%	3.23%	17.21%	28.47%	3.23%	16.47%
	PABAK	30.66%	3.23%	59.57%	28.47%	3.23%	58.26%
Model 3	Acquired	64.23%	61.29%	61.29%	64.23%	61.29%	61.29%
	Non-acquired	62.04%	51.61%	58.51%	62.04%	51.61%	58.04%
	Average	63.14%	56.45%	59.90%	63.14%	56.45%	59.67%
	Overall	63.14%	56.45%	58.70%	63.14%	56.45%	58.26%
	Cohen Kappa	26.28%	12.90%	5.68%	26.28%	12.90%	5.50%
	PABAK	26.28%	12.90%	17.39%	26.28%	12.90%	16.52%
Model 4	Acquired	62.77%	38.71%	38.71%	62.04%	38.71%	38.71%
	Non-acquired	59.12%	32.26%	50.12%	58.39%	32.26%	50.12%
	Average	60.95%	35.48%	44.41%	60.22%	35.48%	44.41%
	Overall	60.95%	35.48%	49.35%	60.22%	35.48%	49.35%
	Cohen Kappa	21.90%	-29.03%	-2.85%	20.44%	-29.03%	-2.85%
	PABAK	21.90%	-29.03%	-1.30%	20.44%	-29.03%	-1.30%
Panel B: Industry-adjusted data							
Model 5	Acquired	59.85%	64.52%	64.52%	59.85%	64.52%	64.52%
	Non-acquired	64.96%	58.06%	60.84%	64.23%	58.06%	60.61%
	Average	62.41%	61.29%	62.68%	62.04%	61.29%	62.56%
	Overall	62.41%	61.29%	61.09%	62.04%	61.29%	60.87%
	Cohen Kappa	24.82%	22.58%	7.57%	24.09%	22.58%	7.47%
	PABAK	24.82%	22.58%	22.17%	24.09%	22.58%	21.74%
Model 6	Acquired	64.23%	70.97%	70.97%	64.23%	70.97%	70.97%
	Non-acquired	63.50%	51.61%	61.77%	63.50%	51.61%	61.07%
	Average	63.87%	61.29%	66.37%	63.87%	61.29%	66.02%
	Overall	63.87%	61.29%	62.39%	63.87%	61.29%	61.74%
	Cohen Kappa	27.74%	22.58%	9.86%	27.74%	22.58%	9.52%
	PABAK	27.74%	22.58%	24.78%	27.74%	22.58%	23.48%
Model 7	Acquired	60.58%	64.52%	64.52%	61.31%	64.52%	64.52%
	Non-acquired	65.69%	51.61%	62.47%	65.69%	51.61%	61.77%
	Average	63.14%	58.06%	63.49%	63.50%	58.06%	63.14%
	Overall	63.14%	58.06%	62.61%	63.50%	58.06%	61.96%
	Cohen Kappa	26.28%	16.13%	8.32%	27.01%	16.13%	7.99%
	PABAK	26.28%	16.13%	25.22%	27.01%	16.13%	23.91%
Model 8	Acquired	63.50%	58.06%	58.06%	62.77%	58.06%	58.06%
	Non-acquired	51.09%	32.26%	51.98%	51.82%	32.26%	52.91%
	Average	57.30%	45.16%	55.02%	57.30%	45.16%	55.49%

Overall	57.30%	45.16%	52.39%	57.30%	45.16%	53.26%
Cohen Kappa	14.60%	-9.68%	2.58%	14.60%	-9.68%	2.87%
PABAK	14.60%	-9.68%	4.78%	14.60%	-9.68%	6.52%

Table 7 - Classification results (Palepu's cut-off point)

		DA			LA		
Panel A: Raw data		Training	Holdout 1	Holdout 2	Training	Holdout 1	Holdout 2
Model 1	Acquired	61.31%	45.16%	45.16%	61.31%	45.16%	45.16%
	Non-acquired	72.26%	58.06%	84.62%	70.07%	58.06%	84.15%
	Average	66.79%	51.61%	64.89%	65.69%	51.61%	64.66%
	Overall	66.79%	51.61%	81.96%	65.69%	51.61%	81.52%
	Cohen Kappa	33.58%	3.23%	17.18%	31.39%	3.23%	16.62%
	PABAK	33.58%	3.23%	63.91%	31.39%	3.23%	63.04%
Model 2	Acquired	50.36%	48.39%	48.39%	50.36%	48.39%	48.39%
	Non-acquired	78.83%	51.61%	85.08%	78.83%	51.61%	85.31%
	Average	64.60%	50.00%	66.73%	64.60%	50.00%	66.85%
	Overall	64.60%	50.00%	82.61%	64.60%	50.00%	82.83%
	Cohen Kappa	29.20%	0.00%	19.48%	29.20%	0.00%	19.79%
	PABAK	29.20%	0.00%	65.22%	29.20%	0.00%	65.65%
Model 3	Acquired	53.28%	38.71%	38.71%	53.28%	38.71%	38.71%
	Non-acquired	77.37%	67.74%	70.16%	77.37%	67.74%	70.16%
	Average	65.33%	53.23%	54.44%	65.33%	53.23%	54.44%
	Overall	65.33%	53.23%	68.04%	65.33%	53.23%	68.04%
	Cohen Kappa	30.66%	6.45%	3.37%	30.66%	6.45%	3.37%
	PABAK	30.66%	6.45%	36.09%	30.66%	6.45%	36.09%
Model 4	Acquired	60.58%	38.71%	38.71%	59.85%	38.71%	38.71%
	Non-acquired	64.23%	32.26%	53.38%	65.69%	32.26%	54.08%
	Average	62.41%	35.48%	46.04%	62.77%	35.48%	46.39%
	Overall	62.41%	35.48%	52.39%	62.77%	35.48%	53.04%
	Cohen Kappa	24.82%	-29.03%	-2.13%	25.55%	-29.03%	-1.97%
	PABAK	24.82%	-29.03%	4.78%	25.55%	-29.03%	6.09%
Panel B: Industry-adjusted data							
Model 5	Acquired	49.64%	51.61%	51.61%	48.18%	51.61%	51.61%
	Non-acquired	79.56%	67.74%	68.07%	80.29%	67.74%	68.30%
	Average	64.60%	59.68%	59.84%	64.23%	59.68%	59.96%
	Overall	64.60%	59.68%	66.96%	64.23%	59.68%	67.17%
	Cohen Kappa	29.20%	19.35%	6.96%	28.47%	19.35%	7.08%
	PABAK	29.20%	19.35%	33.91%	28.47%	19.35%	34.35%
Model 6	Acquired	51.09%	61.29%	61.29%	48.91%	61.29%	61.29%
	Non-acquired	73.72%	54.84%	67.60%	74.45%	54.84%	67.83%
	Average	62.41%	58.06%	64.44%	61.68%	58.06%	64.56%
	Overall	62.41%	58.06%	67.17%	61.68%	58.06%	67.39%
	Cohen Kappa	24.82%	16.13%	9.96%	23.36%	16.13%	10.09%
	PABAK	24.82%	16.13%	34.35%	23.36%	16.13%	34.78%
Model 7	Acquired	61.31%	64.52%	64.52%	63.50%	64.52%	64.52%
	Non-acquired	65.69%	51.61%	62.00%	63.50%	51.61%	60.14%
	Average	63.50%	58.06%	63.26%	63.50%	58.06%	62.33%
	Overall	63.50%	58.06%	62.17%	63.50%	58.06%	60.43%
	Cohen Kappa	27.01%	16.13%	8.10%	27.01%	16.13%	7.26%
	PABAK	27.01%	16.13%	24.35%	27.01%	16.13%	20.87%
Model 8	Acquired	45.99%	38.71%	38.71%	45.26%	38.71%	38.71%
	Non-acquired	72.26%	58.06%	69.46%	72.26%	58.06%	69.70%
	Average	59.12%	48.39%	54.09%	58.76%	48.39%	54.20%
	Overall	59.12%	48.39%	67.39%	58.76%	48.39%	67.61%

Cohen Kappa	18.25%	-3.23%	3.05%	17.52%	-3.23%	3.16%
PABAK	18.25%	-3.23%	34.78%	17.52%	-3.23%	35.22%

Table 8- Area Under the Curve (AUC)

	Raw			Adjusted	
	Holdout 1	Holdout 2		Holdout 1	Holdout 2
		Discriminant analysis			
Model 1	0.484	0.798	Model 5	0.604	0.639
Model 2	0.532	0.802	Model 6	0.619	0.683
Model 3	0.558	0.601	Model 7	0.623	0.651
Model 4	0.403	0.503	Model 8	0.491	0.579
		Logit Analysis			
Model 1	0.483	0.798	Model 5	0.603	0.639
Model 2	0.529	0.800	Model 6	0.624	0.683
Model 3	0.555	0.600	Model 7	0.623	0.650
Model 4	0.404	0.504	Model 8	0.491	0.579

Models 1 and 5 are estimated with stepwise procedure. Models 2 and 6 are estimated on the basis of logical screening (i.e. previous studies and acquisition theories). Models 3 and 7 are estimated with a set of variables selected on the basis of a combination of Kruskal-Wallis and correlation analysis. Models 4 and 8 are developed with variables selected on the basis of factor analysis. For models 1-4 (5-8) raw (adjusted) data are used. Holdout 1 is an equally matched holdout sample that consists of 31 acquired and 31 non-acquired banks. Holdout 2 is an unequal holdout sample that consists of the 31 acquired banks of Holdout 1 and 429 non-acquired banks.

Figure 1 – ROC Curves of Models with raw data and highest AUC

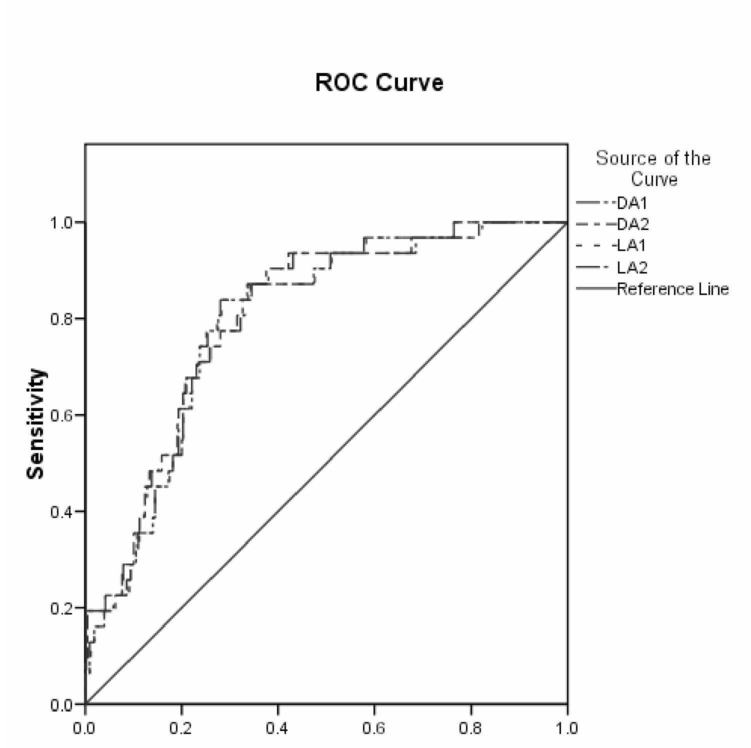

Figure 2 –ROC Curves of Models with adjusted data and highest AUC