Assessing Bank Performance with Operational Research and Artificial Intelligence Techniques: A Survey

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Assessing Bank Performance with Operational Research and Artificial Intelligence Techniques: A Survey

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Abstract

This paper presents a comprehensive review of 179 studies which employ operational research (O.R.) and Artificial Intelligence (A.I.) techniques in the assessment of bank performance. We first discuss numerous applications of data envelopment analysis which is the most widely applied O.R. technique in the field. Then we discuss applications of other techniques such as neural networks, support vector machines, and multicriteria decision aid that have also been used in recent years, in bank failure prediction studies and the assessment of bank creditworthiness and underperformance.

Keywords: Artificial Intelligence, Banks, Data Envelopment Analysis, Operational Research, Literature review

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1. Introduction

Banks play a central role in the economy. They keep the savings of the public and finance the development of business and trade. Furthermore, numerous studies argue that the efficiency of financial intermediation affects economic growth while others indicate that bank insolvencies can result in systemic crises which have adverse consequences for the economy as a whole.[1]

Thus, the performance of banks has been an issue of major interest for various stakeholders such as depositors, regulators, customers, and investors. While bank performance has been traditionally evaluated on the basis of financial ratios, advances in operational research (O.R.) and artificial intelligence (A.I.) have resulted in a shift towards the use of such state-of-the-art techniques. Of course, this is not surprising, since O.R. has been extensively applied to finance during the last half century (Board et al., 2003). This paper presents a comprehensive review of the use of OR and AI techniques in the assessment of bank performance.

The rest of the paper is structured as follows. Section 2 positions the survey within the existing literature and discusses our framework. Section 3 discusses applications of data envelopment analysis (DEA) in the estimation of bank efficiency and productivity growth. Section 4 presents applications of other O.R. and A.I. techniques in the prediction of bank failure and the assessment of bank creditworthiness and underperformance. Section 5 summarizes our conclusions.

2. Scopus and framework

There are several interesting reviews that are related to our survey. For example, Cook and Seiford (2009) review the methodological developments of DEA over the last thirty years. However, they do not discuss applications of DEA. Zhou and Poh (2008) provide a recent survey of DEA applications but they focus on energy and environmental studies. Dimitras et al. (1996) discuss applications of various techniques in the prediction of business failures but they focus on industrial firms. Smith and Gupta (2000) provide a discussion of the application of neural networks in business problems. Board et al. (2003) survey O.R. applications in the financial markets. Thus, the above surveys are either quite general or they do not focus on applications in banking.

[1] See Levine (2005) for a discussion of the theoretical and empirical discussion of the literature on finance and growth. See Caprio and Klingebiel (2003) for banking crises and the associated costs.

Berger and Humphrey (1997) review studies that examine the efficiency of financial institutions. However, their coverage is limited to efficient frontier techniques (e.g. DEA, stochastic frontier analysis). Furthermore, the survey is now more than ten years old and since that time, numerous papers have been published. Berger (2007) discusses more recent applications of frontier techniques but his survey focuses only on studies that provide international comparisons of bank efficiency. Finally, Ravi Kumar and Ravi (2008) discuss applications of statistical and A.I. techniques in bankruptcy prediction. The applications that they survey were published until 2005, and although a few of them focus on the banking sector most of the studies deal with non-financial firms.

We differentiate our review from the above surveys by discussing applications of O.R. and A.I. techniques over the period 1998-2008 while focusing on bank performance.[2] We searched for papers in Scopus, which is considered to be one of the largest abstract and citation databases. We consider only journal articles and we do not include working papers, monographs, dissertations, or other publication outcomes. Furthermore, our search is limited to articles written in English. We use a combination of various keywords such as "bank efficiency", "bank and data envelopment analysis", "bank performance", "bank and neural networks", "bank and artificial intelligence", "bank and operational (or operations) research". A few additional studies were identified from cross-referencing and were manually collected.

We reviewed a total of 179 studies. DEA is by far the most commonly used O.R./A.I. technique in assessing bank performance and we identified 136 studies that use DEA-like techniques to estimate various measures of bank efficiency and productivity growth, and 28 studies that provide similar estimates at the branch level.[3] We also identified 15 studies that use classification techniques such as neural networks, support vector machines, multicriteria decision aid, decision trees, nearest neighbours to predict bank failure or assess bank creditworthiness, and bank underperformance. These studies were published in a total of 67 journals, however, around 56% of them appeared in just eleven journals. As shown in Table 1, the most

[2] Some of the studies were still in press at the time of the writing of this review, but we included them in our discussion as they were already publicly available since 2008 (i.e. 2008 DOI).

[3] Our survey focuses on studies that examine banking institutions as a whole; however, we also discuss studies on branch efficiency in section 3.2.7 as one could argue that the efficiency of individual branches can influence the performance of banks as a whole.

frequent sources of publication are the *European Journal of Operational Research* (18) and the *Journal of Banking and Finance* (15), followed by *Applied Financial Economics (13)*, *Applied Economics (9), Expert Systems with Applications (9),* and the *Journal of Productivity Analysis (9)*. In the sections that follow we discuss various issues surrounding these studies, while additional information is available in Appendices I to III.

[Insert Table 1 Around Here]

3. DEA and bank-efficiency

DEA is a mathematical programming technique for the development of production frontiers and the measurement of efficiency relative to these frontiers (Charnes et al., 1978). The best-practice production frontier for a sample of banks is constructed through a piecewise linear combination of actual input-output correspondence set that envelops the input-output correspondence of all banks in the sample (Thanassoulis, 2001). Each bank is assigned an efficiency score between 0 and 1. The scores are only relative to the banks in the sample, with higher scores indicating a more efficient bank.

One of the well-known advantages of DEA is that it works relatively well with small samples. Other advantages of DEA are that it does not require any assumptions to be made about the distribution of inefficiency and it does not require a particular functional form on the data in determining the most efficiency banks. However, DEA is also subject to few limitations. Two of the best known shortcomings are that DEA assumes data to be free of measurement error, and that it is sensitive to outliers. Coelli et al. (2005) also point out that: (i) having few observations and many inputs and/or outputs will result in many firms appearing on the DEA frontier, (ii) treating inputs/outputs as homogenous commodities when they are heterogeneous may bias the results, (iii) not accounting for differences in the environment may give misleading results, (iv) standard DEA does not control for multi-period optimization or risk managerial decision making.

Our survey shows that recent DEA studies have examined almost all the banking sectors around the world. A few recent studies provide cross-country evidence. Most of them examine banks from the large EU banking sectors (Pastor, 2002; Casu and Molyneux, 2003; Beccalli et al., 2006). Lozano-Vivas et al. (2002)

examine ten EU countries, Bergendahl (1998) focuses on Nordic countries, while Pasiouras (2008a) examines an international dataset.

3.1. Methodological issues

3.1.1. Efficiency measures

Most of the studies focus on the technical efficiency of banks (e.g. Lozano-Vivas et al., 2002; Drake et al., 2006; Pasiouras, 2008a,b). This efficiency measure indicates whether a bank uses the minimum quantity of inputs to produce a given quantity of outputs or maximizes the output quantity given a certain quantity of inputs.

However, when price data for the inputs and/or outputs are available one can also estimate cost and/or profit efficiency measures.[4] Cost efficiency is the product of technical efficiency and allocative efficiency. The latter refers to the ability of a bank to use the optimum mix of inputs given their respective prices. Consequently, cost efficiency shows the ability of a bank to provide services without wasting resources as a result of technical or allocative inefficiency. Appendix I shows that around 35 studies present measures of DEA cost efficiency (e.g. Tortosa-Ausina, 2002a,b,c; Isik and Hassan, 2002, 2003a).

Pastor and Serrano (2006) propose the decomposition of cost inefficiency into composition inefficiency and intra-specialisation inefficiency. The first component indicates the part of inefficiency due to the composition of specialisations of the banks in each banking sector. The second component reveals the inefficient use of resources within each of the specialisation selected. Prior (2003) also deviates from the above studies by calculating measures of short and long-run cost inefficiency as well as capacity inefficiency for Spanish banks. The first refers to the case that a subset of inputs are fixed and impossible to modify in the short-run. Long-run inefficiency estimates are obtained under the assumption that inputs are variable and under the control of the company. Finally, capacity inefficiency, obtained by the ratio of long-run to short-run inefficiency, refers to excess in costs as a result of inappropriate level in fixed inputs. Similar concepts along with an application in the Indian banking sector are discussed in Sahoo and Tone (2008).

[4] One can also estimate revenue efficiency which is similar to profit efficiency. In both cases, both inputs and output prices are required. The difference is that in the former measure the aim is to maximize revenues rather than profits (i.e. revenues minus costs). We are no aware of DEA studies focusing on revenue efficiency so we do not discuss this issue further. Readers interesting in revenue efficiency could see Coelli et al. (2005) for further details.

Estimations of profit efficiency with DEA are rather limited in the literature. One potential reason is the difficulty in collecting reliable and transparent information for output prices. Furthermore, the decomposition of profit efficiency into technical and allocative efficiency is not straightforward (Coelli et al., 2005). Fare et al. (2004) propose the solution of two sets of linear programmes. In the first, a profit maximising DEA is solved to measure profit efficiency. In the second DEA problem, technical efficiency is measured on the basis of a directional distance function that allows the simultaneous adjustment of inputs and outputs. Kirkwood and Nahm (2006) also estimate profit efficiency, although they use input prices only. Therefore, in a sense they calculate a measure of efficiency that is similar to Berger and Mester's (1997) "*alternative profit*" efficiency which is commonly used in the stochastic frontier analysis literature. The studies of Maudos and Pastor (2003) and Ariff and Can (2008) provide estimates of both *standard* and *alternative* profit efficiency.

Finally, around 30% of the studies obtain estimates of total factor productivity (TFP) growth (e.g. Sathye, 2002; Casu et al., 2004).[5] This measure is usually decomposed further into technological change (i.e. shift in the best practice frontier) and technical efficiency change. Furthermore, in most cases, technical efficiency change is disaggregated into pure technical efficiency change and scale efficiency change under the variable returns to scale assumption discussed below.

3.1.2. Constant vs Variable Returns to scale

DEA can be implemented by assuming either constant returns to scale (CRS) or variable returns to scale (VRS). In their seminal study, Charnes et al. (1978) proposed a model that had an input orientation and assumed CRS. This model returns a score that indicates the overall technical efficiency (OTE) of each bank. Banker et al. (1984) suggested the use of variable returns to scale (VRS) that decomposes OTE into product of two components, pure technical efficiency (PTE) and scale efficiency (SE). The former relates to the ability of managers to utilize firms' given resources, while the latter refers to exploiting scale economies by operating at a point where the production frontier exhibits CRS.

[5] Almost all the studies use the DEA-like Malmquist index. Zen and Baldan (2008) use the Luenberger Indicator that is a generalization of the Malmquist Index.

In most of the recent papers, DEA models are estimated using the assumption of VRS, while arguing that CRS is only appropriate when all firms are operating at an optimal scale.[6] Nevertheless, other studies argue in favour of CRS rather than VRS. For example, Noulas (1997) points out that the assumption of CRS allows the comparison between small and large banks. He claims that in a sample where a few large banks are present, the use of VRS framework raises the possibility that these large banks will appear as being efficient for the simple reason that there are no truly efficient banks (Berg et al., 1991). Avkiran (1999) also mentions that under VRS each unit is compared only against other units of similar size, instead of against all units. Hence, the assumption of VRS may be more suitable for large samples. Soteriou and Zenios (1999a) argue that caution is necessary when using the VRS formulation. First, because the model orientation (i.e. input minimization or output maximization) becomes important. Second, because the use of the weights restriction in the VRS assessment may lead to some other problematic results (Allen, 1997). Consequently, many studies report the results obtained under both CRS and VRS assumptions (e.g. Canhoto and Dermine, 2003; Casu and Molyneux, 2003).

3.1.3. Output-input orientation

Technical Efficiency can be estimated under either an input-oriented or output-oriented approach.[7] As Coelli et al. (2005) point out, the input-oriented technical efficiency measures address the question: "*By how much can input quantities be proportionally reduced without changing the output quantities produced*?" (p. 137). In contrast, the output-oriented measures of technical efficiency address the question: *"By how much can output quantities be proportionally expanded without altering the input quantities used?"* (p. 137).

By far, studies in banking obtain efficiency estimates under the input-oriented approach.[8] This is most likely due to the assumption that bank managers have higher

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[6] Reasons that may not allow a firm to operate at optimal scale include among others imperfect competition, government regulations, constrains on finance, *etc.* (Coelli et al., 2005).

[7] If price data are available, then under the under cost minimization objective (i.e. cost efficiency) one obtains input-oriented measures of technical efficiency and input-mix allocate efficiency. Revenue maximization (i.e. revenue efficiency), results is output-oriented technical efficiency and output-mix allocative efficiency measures. In the case of profit maximization (profit efficiency), technical efficiency can be obtained under either the input or output-oriented assumption (Coelli et al., 2005)

[8] Additional information is available in Appendix I. In contrast to efficiency estimates, productivity measures are in several cases obtained using an output-oriented Malmquist index. However, as discussed in Coelli et al. (2005, p. 80), although the values of the components, and consequently their

control over inputs (e.g. personnel, expenses) rather than outputs (e.g. loans, income, etc). However, there are also some studies that adopt the output-oriented approach (e.g. Ataullah et al., 2004; Ataullah and Le, 2006) or report the results from both (e.g. Casu and Molyneux, 2003; Beccalli et al., 2006). It should be mentioned that the input-oriented and output-oriented measures always provide the same value under CRS but they are unequal when VRS is assumed. However, Coelli et al. (2005) mention that since linear programming does not suffer from statistical problems the choice of an appropriate orientation is not as important as in the case of econometric approaches. Furthermore, in many instances, the choice of orientation has only a minor influence upon the scores obtained (Coelli and Perelman, 1996).

3.1.4. Selection of Inputs and Outputs

There is an on-going discussion in the banking literature regarding the proper definition of inputs and outputs. In the words of Bergendahl (1998): *There have been almost as many assumptions of inputs and outputs as there have been applications of DEA*" (p. 235).

Berger and Humphrey (1997) identify two main approaches for the selection of inputs and outputs. These are the "*production approach*" and the "*intermediation approach*". The first assumes that banks produce loans and deposits account services, using labour and capital as inputs, and that the number and type of transactions or documents processed measure outputs. The second approach perceives banks as financial intermediaries between savers and investors. Berger and Humphrey (1997) argue that neither of these two approaches is perfect because they cannot fully capture the dual role of financial institutions as providers of transactions/document processing services and also being financial intermediaries. They point out that the production approach may be somewhat better for evaluating the efficiencies of bank branches and the intermediation approach may be more appropriate for evaluating financial institutions as a whole. Furthermore, there are difficulties in collecting the detailed transaction flow information required in the production approach. As a result, the intermediation approach is the one favoured in the literature.

However, there is a controversy even within this approach concerning the role of deposits (Berger and Humphrey, 1997). Consequently, some studies use only

contribution to overall productivity change may differ, the overall TFP change measure will be the same regardless of the orientation (i.e. input or output) that is imposed.

earning assets as outputs, a selection that is in line with the asset approach of Sealey and Lindley (1977) while others consider deposits as an additional output, a selection that is more closely related to the so-called value-added approach. We find around eighty applications in bank efficiency where the monetary value of deposits is part of the input vector and twenty applications where deposits are part of the output vector.[9] Around thirty studies use interest expenses as an input without using the stock of deposits (e.g. Sathey, 2002; Weill, 2004). In another eight applications, the stock of deposits is used as an output and the interest expense paid on deposits constitutes an input (e.g. Maudos et al., 2002; Saha and Ravisankar, 2000; Chen et al., 2005). Furthermore, around five studies use time deposits and saving deposits as input and demand deposits as output (e.g. Bauer et al., 1998; Gilbert and Wilson, 1998; Sathye, 2001). Finally, in a few applications the deposits are included as both an input and an output (e.g. Tortosa-Ausina, 2002a).

More recently, some studies have adopted another variation of the intermediation approach. This is the so-called profit-oriented (or operating) approach which defines revenue components (e.g. interest income, non-interest income, *etc.*) as outputs and cost components (e.g. personnel expenses, interest expenses, *etc.*) as inputs.[10] Drake *et al.* (2006) mention that *"from the perspective of an input-oriented DEA relative efficiency analysis, the more efficient units will be better at minimizing the various costs incurred in generating the various revenue streams and, consequently, better at maximizing profits"* (p. 1451). They also argue that this approach can be more appropriate in capturing the diversity of strategic responses by financial firms in the face of dynamic changes in competitive and environmental conditions. Furthermore, Luo (2003) calculates a measure of "*marketability*" efficiency in an attempt to capture the value of the bank in the stock market. In this case, revenue and profits are considered inputs whereas market value, earnings per share, and stock price are outputs.

As discussed before, with the exception of deposits there is a general agreement about the main categories of inputs and outputs, however, this does not

[9] This discussion refers to banks as a whole and not branches. The number of applications does not match the number of studies as in several cases there are numerous models developed in each study. Furthermore, in some cases deposits or non interest expenses are not considered in the analysis. In one case (Prior, 2003), the output was the number of current and saving accounts rather than the monetary value of deposits (i.e. stock).

[10] See Chu and Lim (1998), Avkiran (1999), Sturm and Williams (2004), Das and Ghosh (2006), Drake et al. (2006), Ataullah and Le (2006), Pasiouras (2008b), Pasiouras et al. (2008).

necessarily imply that there is consistency with respect to the specific inputs/outputs used in various studies. For instance, the traditional inputs are fixed assets, personnel[11], and in many cases deposits (e.g. Isik and Hassan, 2002; Maudos and Pastor, 2003; Casu and Girardone, 2004; Havrylchyk, 2006). However, some studies use branches (e.g. Chen, 2001), loan loss provisions (e.g. Drake, 2001; Drake et al., 2006; Pasiouras, 2008b) and equity (e.g. Chu and Lim, 1998; Mukherjee et al., 2001; Sturm and Williams, 2004; Pasiouras, 2008a) as additional or alternative inputs. Chen (2001) disaggregates deposits into current deposits and time deposits, while Das and Ghosh (2006) use demand, savings and fixed deposits. Casu and Girardone (2006) and Beccalli et al. (2006) use total costs as a single input while Casu and Molyneux (2003) use two inputs namely total costs, and total deposits (i.e. customers and short term funding).

Several studies use two outputs, usually, loans and other earning assets (e.g. Casu and Molyneux, 2003; Casu and Girardone, 2004; 2006).[12] However, some studies disaggregate loans into various categories such as housing loans, and other loans (e.g. Sturm and Williams, 2004), real estate loans, commercial loans and personal loans (e.g. Mukherjee et al., 2001; Fare et al., 2004) or short-term and long-term loans (Isik and Hassan, 2002). Others disaggregate other earning assets into investments and liquid assets (Tsionas et al., 2003) or investment in government securities and investments in public and private enterprises (e.g. Chen, 2001). Canhoto and Dermine (2003) use the number of branches as an additional output under the assumption that it represents an additional value for retail customers. Finally, recent studies include non-interest income or off-balance-sheet items as additional outputs (e.g. Isik and Hassan, 2002, 2003a; Sturm and Williams, 2004; Tortosa-Ausina, 2003, Havrylchyk, 2006; Pasiouras, 2008b).[13]

Finally, Halkos and Salamouris (2004) propose an approach that deviates from the above literature. They use an output vector that consists of five financial ratios and no inputs. Their underlying hypothesis is that inputs are considered similar and equal

[11] Some studies use the number of personnel (e.g. Drake, 1999; Sathye, 2001; Maudos and Pastor, 2003; Pasiouras, 2008b). However, due to data unavailability others rely on personnel expenses (e.g. Bergendahl, 1998; Tortosa-Ausina, 2002; Lozano-Vivas et al., 2002; Drake et al., 2006).

[12] Other earning assets normally include various items such as government securities, investment securities, trading securities, other securities, equity investments, and other investments.

[13] Isik and Hassan (2003a) mention among others that ignoring such non-traditional outputs may penalize banks that are heavily involved in these activities. The reason is that while the resources used to produce these non-traditional outputs are part of the input vector, the outputs generated using these inputs are not included in the output vector.

for all banks as they operate in the same markets for money and service. The comparison with standard DEA models developed under either CRS or VRS assumptions shows that the DEA ratio model has the highest discrimination power.

3.1.5. Adjusting for the environment

Coelli et al. (2005) discuss four approaches that can be used to incorporate environmental variables in DEA applications.[14] The first method, by Banker and Morey (1986), requires the environmental variables to be ordered from the least to the most harmful ones for efficiency. Then, the efficiency of a given firm is compared with those firms in the sample that have a value of the environmental variable which is less than or equal to the given firm. This ensures that banks are not compared with peers operating in a more favourable environment. The second method, by Charnes et al. (1981), requires the investigator to: (i) divide the sample into sub-samples and solve DEA problems for each sub-sample, (ii) project all observed data points into their prospective frontiers, and (iii) solve a single DEA using the projected points and assess any difference in the mean efficiency of the two sub-samples. According to Coelli et al. (2005) the following two problems are common in both methods: (i) by splitting up the sample they reduce the comparison set, and (ii) only one environmental variable can be considered in each case thereby limiting the scope of the analysis.

Under the third method, the environmental variables are included directly into the DEA problem as non-discretionary inputs (if it is believed to have a positive effect on efficiency) or outputs (if they have a negative effect on efficiency). The disadvantage of this approach is that one must know *a priori* the direction of the influence, a shortcoming that is also applicable in the case of the first method. Alternatively, the environmental variables can be included as non-discretionary neutral variables using an equality form. The shortcoming of this approach is that it can reduce the reference set for each firm. Recent applications of the above approaches in banking can be found in Pastor (1999) and Lozano-Vivas et al. (2001, 2002).

[14] According to Coelli et al. (2005) environmental variables can include ownership differences, location characteristics, labour union power and government regulations and in a sense any factors that can influence the efficiency of the firm without being traditional inputs or under the control of managers.

The fourth method that is discussed in Coelli et al. (2005) is the two-stage approach. This involves a DEA problem with traditional inputs and outputs in the first stage. In the second stage, the efficiency scores obtained are regressed on the environmental variables. While this approach has been frequently used in the banking literature with numerous applications, it fails to adjust the efficiency measures. Therefore, it is more suitable when the objective is to examine the correlations of efficiency with various factors (see Section 3.2.1.) rather than provide the basis for absolute comparisons across different environments.

Finally, Pastor (2002) and Drake et al. (2006) adjust the bank efficiency scores for risk and external environmental factors respectively, using a multi-stage DEA (see Fried et al, 1999, 2002). In this case, the application starts with the estimation of a DEA model with traditional inputs and outputs. Then, using the slacks from the DEA model they quantify the effect of the operating environment, and adjust the initial dataset inputs and/or outputs. Finally, they re-run the initial DEA model using the adjusted data.

3.2. Topics of interest

3.2.1. Determinants of efficiency

Several studies attempt to investigate the factors that influence the efficiency of banks. Some studies examine only bank-specific factors and others examine both bank-specific attributes and environmental determinants.

Commonly found bank-specific factors are size, profitability, capitalisation, loans to assets (Casu and Molyneux, 2003; Casu and Girardone, 2004; Ataullah and Le, 2006; Ariff and Can, 2008). Isik and Hassan (2003a) examine additional characteristics such as the educational profile of bank personnel and CEO-Chairman affiliation. Some studies examine whether age is related to efficiency (e.g. Isik and Hassan, 2003a; Canhoto and Dermine, 2003; Isik, 2008). Furthermore, Isik and Hassan (2002), Casu and Girardone (2004) and Pasiouras (2008b) examine the international presence of Turkish, Italian, and Greek banks, respectively.

Country-specific factors include market concentration, presence of foreign banks, ratio of private investments to GDP, fiscal deficits to GDP, GDP growth, (Hauner, 2005; Ataullah and Le, 2006). More recently, Pasiouras (2008a) examined the relationship between technical efficiency and regulations related to capital adequacy, private monitoring, banks' activities, deposit insurance schemes, supervisory power and bank entry into the industry.

These studies use the two-stage approach discussed above. First, they use DEA to obtain efficiency estimates. Then, in a second stage, the DEA scores are regressed on a number of explanatory variables using Tobit (e.g. Hauner, 2005), OLS (Ataullah and Le, 2006), GMM (Ataullah and Le, 2006), or GLS (Isik and Hassan, 2003a) regression. The rationale to use Tobit lies on the fact that the efficiency scores are bounded between 0 and 1, and hence non-censored estimates will be biased. Ataullah and Le (2006) among others, mention that it is not necessary to use Tobit as long as the efficiency scores can be transformed by taking the natural logarithm of [efficiency score / (1-efficiency score)].

Whether or not censored regression is used, the most important argument comes from Simar and Wilson (2007) who pont out that the covariates in the second-step regression are obviously correlated with the one side error terms from the first-step as otherwise there would be no need for the second step-regression. Furthermore, the covariates in the second-step are likely to be (highly) correlated with the covariates in the first-step. This means that the errors and the covariates in the first-step cannot be independent. Thus, Simar and Wilson conclude that the likelihood that is maximized is not the correct one, unless one takes account of the correlation structure. Casu and Molyneux (2003) present an early attempt to account for the problems that can emerge in the two-stage DEA method using a bootstrap approach. However, Simar and Wilson (2007) mention that the simple bootstrap is not enough to overcome the drawbacks pointed out above. They propose an algorithm that uses a double bootstrap procedure, and they present an application to U.S. banks. Brissimis et al. (2008) adopt this approach to examine the determinants of efficiency in the new EU banking sectors.

3.2.2. Stock returns and efficiency

Following the work of Ball and Brown (1968) the relationship between stock returns and publicly available information has attracted considerable attention in the accounting and finance literature. Whilst most of the studies examine whether earnings reflect some of the information in stock prices, recent research has, however, shifted towards the use of additional data such as accruals, revenues, economic value added and efficiency to understand how they affect stock prices and returns. DEA applications that were published over the period of our survey and investigate the relationship between bank efficiency and stock returns examine Australia (Kirkwood and Nahm, 2006), Greece (Pasiouras et al., 2008), Malaysia (Sufian and Majid, 2006), Singapore (Chu and Lim, 1998; Sufian and Majid, 2007), Turkey (Erdem and Erdem, 2008), and Spain (Guzman et al., 2008). Furthermore, in a cross-country setting, Beccalli et al. (2006) provide evidence from France, Germany, Italy, Spain, UK, that is, the five principal EU banking sectors. In most cases, the results of these studies indicate a positive relationship between stock returns and efficiency changes. Furthermore, Becalli et al. (2006) reveal that the explanatory power of the model with DEA scores is higher than that of a model that uses the return on equity (ROE) as a measure of performance.

3.2.3. Bank ownership

A number of studies compare the efficiency of banks across different ownership types. One approach used in the literature is to split the sample and compare the means of the different ownership groups. Another approach is to incorporate dummy variables in a second stage analysis as the one described in Section 3.2.1.

Some studies compare domestic and foreign banks. Havrylchyk (2006) finds that greenfield banks are more efficient than domestic banks in Poland, whereas foreign banks that acquired domestic ones have not successfully increased their efficiency. Sturm and Williams (2004) report that foreign banks in Australia are more efficient than domestic ones. Isik and Hassan (2003a) find that foreign banks are more efficient than private domestic Turkish banks while Isik (2008) reports similar results for TFP growth estimates. However, Ataullah and Le (2004) find that prior to the financial liberalization of 1991-1992, foreign banks where less efficient than domestic ones in India and Pakistan; nevertheless, the opposite picture emerged after this period.

Other studies examine the efficiency of state-owned banks. Many of them find that state-owned banks are less efficient than other banks. For instance, Garcia-Cestona and Surroca (2008) find that Spanish banks controlled by insiders (i.e. managers and workers) are more efficient than the ones controlled by public administrations. Ariff and Can (2008) find that joint-stock banks in China are more cost- and profit-efficient than state-owned banks. Chen (1998) in Taiwan, and Mercan et al. (2003) in Turkey also report that the efficiency of privately-owned banks is higher than that of state-owned banks. Similarly, Isik (2008) focuses on TFP growth and finds that the growth of private banks is more than double that of state banks. In contrast, other studies report that the efficiency of private banks is lower than that of state-owned banks in Turkey (Isik and Hassan, 2003a), India (Sathye, 2003), and Austria and Germany (Hauner, 2005).

3.2.4. Corporate events and efficiency

Another part of the literature relates DEA efficiency estimates to corporate events such as mergers and acquisitions and/or bankruptcy. Some of the studies compare the efficiency of acquirers and their targets and examine whether mergers improve efficiency. Avkiran (1999) reports that acquiring banks are more efficient than acquired Australian banks. However, the results of this study also indicate that acquiring banks do not always maintain their pre-merger efficiency and there is mixed evidence on the extent to which the benefits of efficiency are passed to the public. The results of Al-Sharkhas et al. (2008) indicate that merged U.S. banks are on average more technically efficient and that they experience higher productivity growth than non-merged banks. Hahn (2007a) finds evidence that Austrian banks, which engaged in domestic merger deals, achieved a higher productive efficiency level than banks which did not participate in such deals. The results also show that merger gains remain significant over a longer period of time (more than five years) but there is slight tendency to level off. Sherman and Rupert (2006) also focus on the efficiency gains from bank mergers but they concentrate on the branch rather than the bank-level. They find that there are opportunities to reduce operating costs. Such benefits, however, are not realised until four years after the merger.

Kohers et al. (2000) follow a different approach to test whether X-efficiencies influence the market's assessment of bank mergers. They find that that the abnormal returns of bidders around the announcement period were associated with both the target bank's profit efficiency and cost efficiency as well as the difference between the average peer cost efficiency score and the corresponding target's cost.[15] Wheelock and Wilson (2000) also relate efficiency with bank acquisitions. However, in their

[15] Only cost efficiency was estimated with DEA in this study. Profit efficiency was estimated using stochastic frontier analysis. As in previous studies, Kohers et al. (2000) also provide comparisons of efficiency across different groups. They find that acquiring U.S. bank holding companies (BHCs) are less cost-efficient compared to their targets. Also industry peers operate with greater cost efficiencies that then bidder and target BHCs.

case DEA efficiency scores are used as an input in hazard models that capture the acquisition and failure likelihood. They find that inefficiency increases the risk of failure while reducing the probability of a U.S. bank's being acquired. Using a sample of 245 U.S. banks, Luo (2003) also reports that overall technical efficiency can be useful in predicting bank failures.

3.2.5. *Regulatory reform/liberalization and efficiency*

A number of studies examine the impact of regulatory reform and liberalization initiatives on bank efficiency and productivity. The studies that we review seem to indicate a positive relationship in most countries including India and Pakistan (Ataullah et al., 2004), Australia (Avkiran, 1999; Sturn and Williams, 2004), US (Mukherjee et al., 2001), China (Chen et al., 2005), Greece (Tsionas et al., 2003; Rezitis, 2006), Taiwan (Wang and Huang, 2007), Korea (Gilbert and Wilson, 1998), Turkey (Isik and Hassan, 2003b), and the new EU countries (Brissimis et al., 2008). However, Hauner (2005) finds no evidence that productivity is related to deregulation in Germany and Austria, while Sathye (2002) argues that there can be a "*limit of deregulation*" after which no further productivity gains could be possible due to deregulation.

Some other interesting observations can be summarized as follows. The banking sector reform in the newly acceded EU countries had a positive impact on bank efficiency, while the effect of reform on TFP growth was significantly only toward the end of the reform process (Brissimis et al., 2008). The implementation of financial liberalization programmes may enable foreign banks to overcome the liability of "foreignness" and enhance their resource utilization (Ataullah and Le, 2004). The impact of deregulation will not necessarily be the same across different bank ownerships such as state, domestic, foreign (Isik and Hassan, 2003b).

3.2.6. Comparison of frontier techniques

A few studies compare alternative frontier techniques over the period of our survey. Bauer et al. (1998) use a sample of US banks to compare DEA, SFA, TFA (thick frontier approach), and DFA (distribution-free approach) over six consistency criteria. They find that DEA yields much lower average efficiencies, ranks the banks differently, and identifies the best and worst banks differently from parametric methods. Furthermore, compared to DEA the parametric measures were more highly correlated with the traditional (non-frontier) performance measures. Huang and Wang (2002) provide another comparison of SFA, DFA and DEA using data from Taiwanese banks. They also argue that the choice of the frontier approach can result in different conclusions. Weill (2004) provides more recent evidence using a sample from five European countries. However, this cross-country setting does not alter the main conclusion of lack of robustness across different approaches, confirming the results of the previous two studies. Delis et al. (2008) provide further support to these findings using a dataset of Greek banks. The study of Beccalli et al. (2006) also provides useful insights for the differences of SFA and DEA. While this study does not focus on the comparison between these two methods, it finds that while changes in the stock prices of banks reflect percentage changes in DEA cost efficiency scores, this trend is less clear with SFA efficiency estimates. In contrast, Fiordelisi (2008) reports that SFA cost efficiency estimates explain better the variations in shareholder value creation than those derived from DEA.

Casu et al. (2004) compare productivity growth estimates obtained through parametric and non-parametric approaches. Their study seems to indicate that in this case the differences are not as large as in the efficiency studies. They conclude that although the alternative methodologies produce, in some cases, opposing findings, as for the sources of productivity for individual years, in general they do not yield noticeably different results in terms of identifying the components of the productivity growth of EU banks during the period of their study.

3.2.7. Efficiency of bank branches

While most of the above studies focus on the efficiency of banking institutions as a whole, a related strand of the literature examines the efficiency of bank branches.[16] In general, branches are predominantly regarded as production units (see Camanho and Dyson (1999, 2005, 2006), Zenios et al. (1999), Soteriou and Zenios (1999b), Golany and Storbeck (1999), Athanassopoulos and Giokas (2000) and Hartman et al. (2001)) where output is measured by the number of various accounts and/or transactions as contrast to the intermediation approach employed by Portela and Thanassoulis (2005, 2007), Portela et al. (2003), Giokas (2008a) where branches are seen as intermediaries, and thus outputs are measured in monetary terms.

[16] See Appendix II for information on branch efficiency studies.

There are studies which consider the changing role of bank branches from a predominantly transaction-based one to a sales-oriented role. Cook et al. (2000) and Cook and Hababou (2001) distinguish sales and services (transactions) functions of bank branches in a Canadian Bank where inputs are usually shared between these two functions. To model the shared resources, Cook et al. (2000) extend the usual methodology to develop a model which incorporates the best resource split and optimises the aggregate efficiency score. Further, Cook and Hababou (2001) model the shared resources concept by adopting the Additive DEA model. In a recent novel application, Portela and Thannasoulis (2007) assess the branches of a Portuguese bank in terms of their performance in their new roles by specifying efficiency measures which consider sales, transactional activities as well as bank branch profit efficiency.

Service quality is also a significant dimension of bank branches performance. Two different ways are developed in empirical applications to consider service quality. For instance, Soteriou and Zenios (1999b), Golany and Storbeck (1999); Athanassopoulos and Giokas (2000) include quality variables in efficiency analysis whereas Portela and Thannasoulis (2007) use a post-hoc analysis to compare service quality index with efficiency measures. They find that service quality is positively related with operational and profit efficiency.

The diversity of environments in which the branches are operating is also considered in the literature. Paradi and Schaffnit (2004) considered the role of the environmental parameters that are outside the management control in the commercial branches of a large Canadian bank and incorporated risk and economic growth rate of the region, as two non-discretionary factors. On the other hand, Camanho and Dyson (2006) assess the impact of environmental factors and regional managerial policies on branches' productivity through the construction of an index that reflects the relative performance of bank branches operating in four different regions in Portugal. Das et al (2007) introduce the concept of spatial efficiency for each region relative to the nation and thus, measure the effects of differences in the regional characteristics on the efficiency of bank branches across four metropolitan regions in India.

Some interesting observations can be summarised as follows. In general, the existing studies of bank branch efficiency use data on a small number of branches of non-US banks and mostly employ DEA. There are studies however, which evaluate bank branch performance with DEA and compare the results with other methodologies, i.e. FDH (Portela et al. 2003), Malmquist indices (Camanho and

Dyson, 2006), log-linear frontier method (Giokas 2008b), ABC Plus (Kantor and Maital, 1999), OCRA (Parkan and Wu, 1999), Neural Network Model (Wu et al. 2006), Quasi-concave DEA, FDH, and Parametric Frontier models (Dekker and Post, 2001). Most of the studies which were reviewed use technical and operational efficiencies as estimated measures. Recent studies examine the allocative profit efficiency (see Portela and Thanassoulis, 2005, 2008), and cost efficiency (Camanho and Dyson, 2005, 2008) aspects of bank branches.

4. Other O.R. and A.I. techniques and bank performance

In this section, we review 15 recent studies that develop classification models used in the prediction of bank failure (9), bank underperformance (2), and credit ratings (4). Canbas et al. (2005) point out that the study of bank failure is important for at least two reasons. First, an understanding of the reasons beyond the failure allows regulatory authorities to manage and supervise banks more efficiently. Second, the ability to differentiate between healthy and troubled banks can reduce the expected cost of bank failure, either by taking actions to prevent failure or by minimizing the costs to the public (Thomson, 1991). As discussed in Gaganis et al. (2006) while many of the failure prediction models achieve very promising classification accuracies, one common drawback is that they concentrate on the assignment of banks in two groups, failed and non-failed. However, the classification of banks as "bad" or "good" reduces the usefulness of the model. Obviously, the classification into more groups relates to another strand of the literature that deals with credit risk modelling and attempts to replicate the ratings assigned by the credit agencies. In the following sub-sections, we provide a brief description of the methodologies, the employed variables, and the classification results.[17] A summary of the main characteristics of these studies is available in Appendix III.

4.1. Methodologies

Neural network (NN) modelling is an intelligence technique that follows a process similar to the human brain. As in other classification models, the parameters of a NN model need to be estimated before the network can be used for prediction purposes. There are numerous NN architectures, learning methods, and parameters.

[17] To conserve space we keep our discussion on methodologies short. Detailed information is available in the corresponding applications and/or devoted textbooks.

Generally speaking, NN architectures can be either feedback or feedforward. In a feedback network, nodes can receive inputs from nodes in any other layer in the network, whereas in a feedforward network inputs are only received from previous layers. The multi-layer preceptor (MLP-NN), competitive learning neural networks (CL-NN), self-organizing map neural networks (SOM-NN), back-propagation neural networks (BP-NN), and probabilistic neural networks (PNN) are alternative approaches employed in the studies under review (e.g. Chen and Shih, 2006; Boyacioglu et al, 2008).

The approach of Support Vector Machines (SVMs), used in Boyacioglu et al. (2008), Chen and Shih (2006) and Huang et al. (2004), was introduced by Vapnik (1995). It is based on the Structural Risk Minimization (SRM) principle from computational learning theory. This seeks to minimise an upper bound of the generalisation error rather than minimise the training error. SVMs use a linear structure to implement nonlinear class boundaries through extremely non-linear mapping of the input vectors into the high-dimensional space. If the data are linearly separated, SVM uses a special kind of linear model, the optimal separating hyperplane, that provides the maximum separation between the classes. The training points that are closest to the maximum margin hyperplane are called support vectors. All other training examples are irrelevant for determining the binary class boundaries. From the implementation point of view, Vapnik (1995) showed how training a SVM and finding the parameters leads to a quadratic optimisation problem with bound constraints and one linear equality constraint. This means that the solution of SVMs is unique, optimal and absent from local minima (Tay and Cao, 2001).

Nearest Neighbours is a non-parametric estimation method that has been applied in various problems in finance. The nearest neighbour rule classifies an object (i.e. bank) to the class of its nearest neighbour in the measurement space using some kind of distance measure like the local metrics, the global metrics, the Mahalanobis or the Euclidean distance. The modification of the nearest neighbour rule, the k-nearest neighbour (k-NN) method that is employed in Zhao et al. (2008), classifies an object (i.e. bank) to the class (i.e. failed or non-failed) more heavily represented among its *k*-nearest neighbours.

In the case of decision trees that originate from machine learning, instead of developing classification functions or network architectures, a binary decision tree is developed. This can be accomplished through a set of if-then split conditions that lead to the accurate classification of cases (e.g. banks). Commonly used algorithms are CART (e.g. Ravi et al., 2008), and C4.5 (e.g. Zhao et al., 2008).

The UTilités Additives DIScriminantes (UTADIS) multicriteria decision aid (MCDA) method, used in Gaganis et al. (2006), employs the framework of preference disaggregation analysis for the development of an additive utility function that is used to score the firms and decide upon their classification. The estimation of the additive utility model is performed through mathematical programming techniques.

The Multi-Group Hierarchical Discrimination (MHDIS) method, used in Pasiouras et al. (2007), is another MCDA approach that uses utility functions for discrimination purposes. MHDIS distinguishes the groups progressively, starting by discriminating the first group from all the others, and then proceeds to the discrimination between the alternatives belonging to the other groups. To accomplish this task, instead of developing a single additive utility function that describes all alternatives (as in UTADIS), two additive utility functions are developed in each one of the n-1 steps, where n is the number of groups. At each stage of the hierarchical discrimination procedure, two linear, and a mixed-integer, programming problems are solved to estimate the utility thresholds and the two additive utility functions in order to minimise the classification error.

As discussed in Kolari et al. (2002) and Lanine and Vander Vennet (2006) trait recognition is another non-parametric approach, under which individual traits are initially developed from different segments of the distribution of each variable and the interactions of these segments with one or more other variables' segmented distributions. When all possible traits of the variables are tabulated for all banks, trait recognition uses a search routine to cull traits that do not discriminate between failed and non-failed banks. Trait recognition uses two sets of discriminators, the safe traits (associated with non-failed banks) and the unsafe traits (failed banks), known as features. Then these features are used to vote on each bank and classify it as failed or non-failed. Lanine and Vander Vennet (2006) argue that the general rule of classifying safe and unsafe cells and assigning default probabilities works poorly when the number of banks falling into mixed cells is high. To avoid this problem they suggest a formula to compute the probability of default directly without preliminary classification of cells as safe or unsafe.

Some researchers use soft computing approaches with the aim of synthesizing the human ability to tolerate and process uncertain, imprecise and incomplete information during the decision-making (Tung et al., 2004). Soft computing usually integrates various techniques that may originate from different disciplines such as fuzzy logic[18], neural networks, machine learning, etc. in various combinations that will allow the researcher to exploit the strengths of individual techniques (Ravi Kumar and Ravi, 2008). A popular approach is the integration of neural network and fuzzy sets to develop a neural fuzzy network. For example, Tung et al. (2004) propose a Generic Self-organizing Fuzzy Neural Network (GenSoFNN) based on the compositional rule of inference (CRI) to predict bank failure.

Multiple discriminant analysis (MDA) and logistic regression analysis (LRA) are two traditional techniques that are commonly used as benchmarks in classification studies (e.g. Swicegood and Clark, 2001; Pasiouras et al., 2007; Kosmidou and Zopounidis, 2008). In contrast, Tung et al. (2004) benchmark their models against Cox regression which estimates the dependence of the risk of failure on bank's characteristics and of the evolution of that risk over time.

4.2. Variables

In most of the cases, the variables are selected on the basis of the CAMEL model and include measures for Capital strength, Asset quality, Earnings, and Liquidity.[19] The number of variables differs significantly among studies. Some researchers start from a large list of variables and then use statistical screening (e.g. Kruskal-Wallis) or dimension reduction (e.g. factor analysis) to end up with a reduced set of variables. In addition to the financial variables, some studies include additional characteristics related to ownership (e.g. % of shares held by the government), market information (e.g. stock price in previous year), auditing, and country (e.g. Heritage index).

4.3. Classification results

Many of the studies in Appendix III report quite satisfactory classification accuracies, and in several cases, the proposed O.R. and A.I. methods outperform the traditional techniques (i.e. MDA, LRA, Cox regression). Furthermore, the studies that focus on bankruptcy prediction, in general, perform more accurately than those that deal with

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[18] The theory of fuzzy sets, proposed by Zadeh (1965) provides a mathematical approach to emulate human cognitive process. The fuzzy set theory aims to classify subjective reasoning and assign degrees of possibilities in reaching conclusions. Fuzzy logic can also be used to obtain fuzzy "if-then" rules.

[19] *M* in CAMEL refers to management quality, and it is rarely used in empirical studies due to difficulties in assessing management quality.

credit ratings. However, this is not surprising for two reasons. First, while classifying the banks in more groups is more informative, it becomes more difficult to discriminate among groups in the intermediate categories. Second, credit ratings may incorporate additional qualitative information and human judgment that cannot be captured by the conventional variables used in most studies.

In any case, comparisons across different studies should be treated with extreme caution. One reason is that different studies make different assumptions about the prior probabilities of group membership as well as misclassification costs. A second reason is that different studies use different approaches to validate the developed models. For instance, some researchers simply split the total sample in training and holdout datasets without accounting for the stability of models over time; others use resampling techniques (e.g. *k-fold cross-validation*), and others use a holdout sample from a future period. However, it should kept in mind that classification ability is likely to overstate predictive ability. Thus, a superior approach would require that the model be validated against a future period, as this approach more closely reflects a "real world" setting.

5. Concluding remarks

We have presented a comprehensive review of applications of operational research and artificial intelligence techniques in the assessment of bank performance, by discussing a total of 179 studies published between 1998 and 2008. We have classified the studies in two main categories.

The first uses DEA and the DEA-like Malmquist index to estimate the efficiency and productivity growth of banks and bank branches. We have discussed various methodological issues such as the estimated measures of efficiency, the underlying assumptions of the estimated models, and the selection of inputs and outputs. We also discussed the main topics of interest including the relationship between ownership and efficiency, stock returns and efficiency, the determinants of efficiency, the efficiency of bank branches, amongst others. Three of the main conclusions are that: (i) profit efficiency and capacity efficiency have received quite limited attention in DEA studies in banking (ii) most studies that use a two-stage DEA do not employ appropriate bootstrapping techniques, and their results may be biased (iii) there is much diversity among studies with respect to the selection of input and outputs. As in the case banks as a whole, cost and profit efficiency has received considerably less attention in branch efficiency studies. Furthermore, an area of research deserving attention would be the estimation of bank branches efficiency over successive time periods.

Studies falling into the second category, attempt to develop classification models to predict failure, the credit ratings of banks, and identify underperformers. We have found both country-specific and cross-country studies and applications of techniques that originate from various disciplines. Most of the studies rely heavily on financial information although in some cases non-financial variables are also used. Given the differences in the approaches employed to validate the models, comparisons of classification accuracies across studies should be treated with caution. We find only a few studies that propose the combination of the predictions of individual models into integrated meta-classifiers, and we believe that this is an area of research that is worthy of further attention.

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Table 1 – Surveyed studies by publication outlet

	Bank Efficiency - productivity	Branch Efficiency - productivity	Bank Bankruptcy – ratings - underperformance	Total
European Journal of Operational Research	12	7	0	19
Journal of Banking and Finance	15	0	0	15
Applied Financial Economics	13	0	0	13
Applied Economics	9	0	0	9
Journal of Productivity Analysis	5	4	0	9
Expert Systems with Applications	2	1	6	9
Journal of Economics and Business	6	0	1	7
Managerial Finance	5	2	0	7
Omega	0	5	0	5
Applied Economics Letters	4	0	0	4
Interfaces	0	4	0	4
Other	65	5	8	78
Total	136	28	15	179

Appendix I – Studies in bank efficiency and productivity change

Authors (Publication year)	Country	Sample	Period	Input/Output Oriented	Treatment of deposits	Estimated measures	2nd Stage regression
Akhtar (2002)	Pakistan	40 banks	1998	Input	Input	OTE, AE, OE	n.a.
Al-Sharkas et al. (2008)	US	440 bank mergers & peer group of non-merged banks	1986-2002	Input	Input	OTE, PTE, SE, AE, CE, Productivity (and APE using SFA)	n.a.
Ariff & Can (2008)	China	28 banks; 230 obs	1995-2004	Input CE, Output PE	Input	CE, APE, SPE	Tobit
Asmild et al. (2004)	Canada	5 banks	1981-2000	Input	Output	OTE, Productivity	n.a.
Ataullah et al. (2004)	India, Pakistan	n.a.	1988-1998	Output	Interest expense: input	OTE, PTE, SE	n.a.
Ataullah & Le (2006)	India	566 Obs	1992-1998	Output	Interest expense: input	PTE	OLS, GMM
Ataullah & Le (2004)	India, Pakistan	n.a.	1987-1998	Input	Deposits: Output, Financial expenses: input	PTE	n.a.
Avkiran (1999)	Australia	16-19 banks	1986-1995	Input	Interest expense: input in Model 1; Deposits: input in Model 2	OTE	n.a.
Aysan & Ceyhan (2008)	Turkey	466 obs	1990-2006	Input	Input	PTE, Productivity	FE regression
Barr et al. (2002)	US	n.a.	1984-1998	Input	Interest expense: input	OTE	n.a.
Bauer et al. (1998)	US	683 banks	1977-1988	Input	Demand deposits: output; Time & saving deposits: input	CE	n.a.
Beccalli et al. (2006)	France, Germany, Italy, Spain, UK	11-29 banks per country; 90 banks in total	1999-2000	Both	Interest expenses - part of single input (i.e. total cost)	PTE* (and CE with SFA)	n.a.
Bergendahl (1998)	Denmark, Finland, Norway, Sweden	48 banks	1992-1993	Input	Output	OTE, PTE	n.a.

Bergendahl & Lindblom (2008)	Sweden	85-88 banks	1997-2001	Input	Output	OTE*	n.a.
Brissimis et al. (2008)	10 new EU countries	364 banks; 4368 obs.	1994-2005	Input	Input	PTE, Productivity	double bootstrap two-stage least squares truncated
Canhoto & Dermine (2003)	Portugal	20 banks	1990-1995	Input	Output	OTE, PTE, SE, Productivity	n.a.
Casu & Girardone (2004)	Italy	36-48 banks; 168 obs	1996-1999	Input Ef., Output Prod	Input	PTE, AE, CE, Productivity	Logistic
Casu & Molyneux (2003)	France, Germany, Italy, Spain, UK	530 banks	1993-1997	Both	Input	OTE, PTE	Bootstrap-Tobit
Casu et al (2004)	France, Germany, Italy, Spain, UK	2,086 banks	1994-2000	Output	Cost of deposits as input	Productivity	n.a.
Casu & Girardone (2006)	EU-15	11,000 obs	1997-2003	Input	Interest expenses - part of a single input (i.e. total cost)	PTE*	n.a.
Casu & Girardone (2005)	France, Germany, Italy, Spain, UK	2,086 banks	1994-2000	Output	Cost of deposits: input	Productivity	n.a.
Chang & Chiu (2006)	Taiwan	26 banks	1996-2000	Input	Input	OTE, AE, CE	Tobit
Chen (2001)	Taiwan	41 banks	1988-1997	Both	Input	OTE	n.a.
Chen (1998)	Taiwan	34 banks	1996	Input	Deposits: input in 2 Models; Interest expenses: input in 6 models	OTE, PTE, SE	Type of regression not specified
Chen (2002a)	Taiwan	41 banks	1998	Output	n.a.	OTE	n.a.
Chen (2002b)	Taiwan	39 banks; 273 obs.	1994-2000	Input	Input	OTE	Regression

Chen (2004)	Taiwan	44 banks	1994-2000	Input	Input	CE,OTE,PTE,SE,AE	n.a.
Chen &Yeh (2000)	Taiwan	34 banks	1995-1996	Input Ef., Output Prod	Input	OTE,PTE,SE	n.a.
Chen et al. (2005)	China	43 banks	1993-2000	Input	Price of deposits: input; Deposits: output	PTE, AE, CE	n.a.
Chen et al. (2004)	Taiwan	49 banks	2000-2002	Input Ef., Output Prod.	Input	OTE, PTE,SE, Productivity	n.a.
Chiu et al. (2008)	Taiwan	46 banks	2000-2002	Input Ef., Output Prod	Input	PTE, productivity	
Chu & Lim (1998)	Singapore	6 banks	1992-1996	Both	Interest expenses: input	OTE*, PTE, SE	n.a.
Cook et al. (2005)	Tunisia	10 banks; 69 obs	1992-1997	Input	Interm. App: Interest expenses (Input) Product. App: Deposits (Input)	OTE	Regression
Damar (2006)	Turkey	35-38 banks	2000-2003	Input	Interest expense: input; Deposits: output	OTE, PTE, SE	Type of regression not specified
Das & Ghosh (2006)	India	74-98 banks	1992-2002	Input	3 models in total: Interest expense: input in 2 models, Deposits: output in 1 model	OTE, PTE, SE	Tobit
Debasish & Mishra (2007)	India	93 banks	2000-2007	Output	Input	OTE	n.a.
Delis et al. (2008**)	Greece	14-23 banks; 244 obs	1993-2005	Input	Input	CE (and PE using SFA)	n.a.
Devaney & Weber (2000)	US	3391 - 4146 banks	1990-1993	Output	Input	OTE, PTE, SE , Productivity	SUR
Dogan & Fauesten (2003)	Malaysia	16-18 banks	1989-1998	Output	Deposits: output; Interest expenses: input	OTE, Productivity	FE linear model
Drake (2001)	UK	9 banks	1984-1995	Input	Input in Models 1 and 1a; Output in Models 2 and 2b	OTE, PTE, SE, Productivity	n.a.
Drake et al. (2006)	Hong Kong	47-66 banks; 413 observations in total	1995-2001	Input	n.a. in model 1, output in model 2	PTE	Tobit
Drake & Hall (2003)	Japan	149 banks	1997	Input	Input	OTE, PTE, SE	n.a.

Erdem & Erdem (2008)	Turkey	10 banks	1998-2004	Input	Input	OTE, AE, CE*	n.a.
Fare et al. (2004)	US	858-938 banks	1990-1994	Both	Transaction deposits: Output; Non-transaction deposits: input	TE, AE, SPE	n.a.
Fiordelisi (2008)	France, Germany, Italy, UK	Varies from 68 (UK, 1997) to 2,183 (Germany, 2002)	1997-2002	Input	Output	PTE, SE, AE, CE (and PE using SFA)	n.a.
Fukuyama & Weber (2005)	Japan	110-141 banks (1073 obs)	1992-1999	Output TE, Input AE	Input	Luenberger & Farrell PTE, AE	n.a.
Fukuyama & Weber (2002)	Japan	138-141 banks	1992-1996	Both (Input TE & Output AE; Output TE & Input AE)	Input - part of funds from customers	Productivity	n.a.
Fung (2006)	US	135 banks; 1,080 obs	1996-2003	Input	Input	PTE, SE, Productivity	OLS
Garcia-Cestona & Surroca (2008)	Spain	226 Obs.	1998-2002	Output	Output	IP, AE*, IPR	n.a.
Gilbert & Wilson (1998)	Korea	15-25 banks	1980-1994	Output	Demand deposits: output; Time & savings deposits: input	TE, Productivity	n.a.
Guzman & Reverte (2008)	Spain	14 banks	2000-2004	Both	Input	OTE, PTE, Productivity	n.a.
Habibullah et al. (2005)	Malaysia	37 banks	1988-1993	Input	Input	OTE,SE,PTE, Congestion Efficiency	Granger causality
Hahn (2007a)	Austria	Around 800 banks	1996-2002	Input	n.a. in Model 1; Input in Model 2	PTE	Tobit (Bootstrapped)
Hahn (2007b)	Austria	More than 800 banks	1995-2002	Input	Profit oriented: n.a Int. App.: Input	PTE	Tobit
Halkos & Salamouris (2004)	Greece	15-18 banks	1997-1999	Output	n.a. in basic model; Interest expense: input in benchmark model	OTE, PTE, SE (and superefficiency measures)	n.a.
Hauner (2005)	Germany, Austria	97 banks; 485 obs	1995-1999	Input	Input	PTE, SE, AE, CE, Productivity	Tobit
Havrylchyk (2006)	Poland	247 Obs	1997-2001	Input	Input	OTE, PTE, SE, AE, CE	Tobit
Hu et al. (2008**)	Taiwan	14 banks	2007	Input	n.a.	OTE, PTE, SE	n.a.

Huang et al. (2008)	Taiwan	42 banks	2001-2004	Output	Input	Productivity	Regression
Huang & Wang (2002)	Taiwan	22 banks	1982-1997	Input	Input	CE	n.a.
Isik (2008)	Turkey	794 obs	1981-1996	Input	Input	OTE, PTE, SE, Productivity	n.a.
Isik (2007)	Turkey	51 banks; 439 obs.	1981-1990	Output	Input	Productivity	GLS
Isik & Hassan (2003c)	Turkey	54 banks	1992-1996	Input Ef., Output Prod	Input - part of loanable funds	OTE, PTE, SE , Productivity	n.a.
Isik & Akcaoglu (2006)	Turkey	28 banks	1981-1990	Output	Input - part of loanable funds	Productivity	n.a.
Isik & Hassan (2002)	Turkey	36 banks in 1998, 50 banks in 1992, 53 banks in 1996	1988, 1992, 1996	Input	Input	OTE, PTE, SE, AE, CE (also CE, PE from SFA)	GLS
Isik & Hassan (2003a)	Turkey	39, 54, 56 banks	1988, 1992, 1996	Input	Input	OTE, PTE, SE, AE, CE	GLS, Tobit
Isik & Hassan (2003b)	Turkey	38-56 banks; 458 obs.	1981-1990	Input Ef., Output Prod	Input	OTE, PTE, SE, Productivity	n.a.
Isik & Uysal (2006)	Turkey	439 obs.	1981-1990	Output	Input - part of loanable funds	Productivity	n.a.
Kao & Liu (2004)	Taiwan	24 banks	2000	Input	Input	OTE	n.a.
Kao & Liu (2008**)	Taiwan	25 banks	1997-2001	Both min. & max. problems	Purchased funds: input; Demand deposits: output	OTE	n.a.
Kirkwood & Nahm (2006)	Australia	10 banks	1995-2002	Input	Input	PTE, SE, AE, CE, APE, Productivity	n.a.
Kohers et al. (2000)	US	94 bidder, 94 targets, 8960 obs peers	1990-1995	Input	Input & Output	CE	n.a.
Krishnasamy et al. (2003)	Malaysia	10 banks	2000-2001	Output	Output	Productivity	n.a.
Kumar & Gulati (2008)	India	27 banks	2004/2005	Input	Loanable funds: input	OTE, Super eff.	Regression
Kuosmanen & Post (2001)	EU	453 banks	1997	Input	Debt capital: input	TE, AE, CE	n.a.
Kyj & Isik (2008)	Ukraine	150 banks; 883 obs.	1998-2003	Input	Input - part of loanable funds	OTE, PTE, SE	GLS
Laurenceson & Qin (2008)	China	65 banks	2001-2006	Input	Interest expenses: input; Deposits: output	CE	Tobit
Leightner & Lovell (1998)	Thailand	31 banks	1989-1994	Input	n.a.	Productivity	n.a.

Lim & Randhawa (2005)	Hong Kong & Singapore	19 banks	1995-1999	Input	Production: output Intermediation: input	OTE, PTE,SE	n.a.
Lin et al. (2007)	Taiwan	37 banks	2002-2003	Output	Interest expenses: input	OTE, Productivity	n.a.
Liu (2008**)	Taiwan	24 banks	2000	Input	Input	OTE	n.a.
Lozano-Vivas et al. (2002)	10 European	612 banks	1993	Input	Output	PTE	n.a.
Lozano-Vivas et al. (2001)	10 EU countries	612 banks	1993	Input	Output	PTE	n.a.
Luo (2003)	US	245 banks	2000	Input	n.a.	OTE, PTE, SE	n.a.
Maghyereh (2004)	Jordan	14 banks	1984-2001	Input	Input	OTE, PTE, SE, Productivity	Tobit
Maudos et al. (2002)	Spain	1666 Obs.	1985-1996	Input	Price of loanable funds: Input; Loanable funds: output	CE	Tobit
Maudos & Pastor (2003)	Spain	50-77 savings; 75-98 national	1985-1996	Input CE, Output PE	Input	CE, APE, SPE	n.a.
Mercan et al. (2003)	Turkey	545 obs.	1989-1999	Input	n.a.	OTE	n.a.
Mostafa (2007b)	GCC-Gulf Coopn. Council	43 banks	2005	Output	n.a.	PTE,OTE,SE	n.a.
Mostafa (2007a)	Arab banks	85 banks	2005	Output	n.a.	PTE,OTE,SE	n.a.
Mukherjee et al. (2003)	India	27 banks	1997-2000	Output	Output	PTE	n.a.
Mukherjee et al. (2001)	US	201 banks	1984-1990	Input	Input	OTE, PTE	GLS
Neal (2004)	Australia	12-26 banks	1995-1999	Input Ef., Output Prod	Demand deposits: output; Term deposits, certificates of deposits, other deposits: input	PTE, SE, AE, CE, Productivity	n.a.
Noulas (2001)	Greece	19 banks	1993-1998	Input	Interest expense: input	OTE	n.a.
Olgu & Weyman-Jones (2008)	EU-12 and EU-10	164 banks	1997-2001	Output	Input	Productivity	n.a.
Pasiouras (2008b)	Greece	12-18 banks; 78 obs	2000-2004	Input	Deposits: Input in Models 1-4; Interest expense: input in Model 5	PTE, SE	Tobit

Pasiouras (2008a)	95 countries	715 bank	2003	Input	Input	OTE, PTE, SE	Tobit
Pasiouras et al. (2008)	Greece	10 banks	200-2005	Input	Interest expense: input	OTE, PTE, SE	n.a.
Pastor (1999)	Spain	n.a.	1985-1995	Input	n.a.	OTE, PTE, SE	n.a.
Pastor (2002)	Spain, Italy, Frane, Germany	2598 Obs.	1988-1994	Input	Output	CE	Tobit, Logistic
Pastor & Serrano (2006)	10 European	540 banks, 3,780 obs	1992-1998	Input	Input	CE, COMPE, ISPE	n.a.
Paul & Kourouche (2008)	Australia	10 banks 90 obs	1997-2005	Input	Interest expense: input	OTE,PTE,SE	n.a.
Prior (2003)	Spain	n.a.	1986, 1990, 1995	Input	Number of current & savings accounts: output	SRCE, LRCE,CAPE	n.a.
Ramanathan (2007)	GCC	55 banks	2000-2004	Input	Input	OTE, PTE,SE, Productivity	n.a.
Ray & Mukherjee (1998)	US	201 banks	1984-1990	Input	Transaction deposits: Input	PTE,SE,SZE	Tobit
Resti (1998)	Italy	67 merger deals	1987-1995	Input	Output	PTE, Extra efficiency	n.a.
Rezitis (2006)	Greece	6 banks	1982-1997	Output	Input	OTE, PTE, SE, Productivity	Tobit
Rizvi (2001)	Pakistan	37 banks	1993-1998	Both	Output	OTE,PTE,SE Productivity	n.a.
Saha & Ravisankar (2000)	India	25 banks	1992-1995	Input	Interest expense: input; Deposits: output	OTE	n.a.
Sahoo & Tone (2008**)	India	78 banks	1997-2001	Both	Input	PCU, TE, RECU, OCI	n.a.
Sathye (2003)	India	94 banks	1997-1998	Input	Interest expense: input in Model 1; Deposits: input in Model 2	PTE	n.a.
Sathye (2001)	Australia	29 banks	1996	Input	Time & saving deposits: input; Demand deposits: output	OTE, AE, CE	Type of regression not specified
Sathye (2002)	Australia	17 banks	1995-1999	Output	Interest expenses: input	Productivity	Type of regression not specified
Seiford, Zhu (1999)	US	55 banks	1995	Output oriented, Input	n.a.	OTE, PTE	

				congestion			
Simar & Wilson (2007)	US	322 banks; 6,955 banks	Q4 2002	n.a.	Input	TE	Double Bootstrap truncated regression
Stavarek (2006)	EU-11 countries	122-126 banks	2001-2003	Input	Input	PTE, SE	n.a.
Sturm & Williams (2004)	Australia	10-26 banks; 273 obs. In total	1988-2001	Input	Input	OTE, PTE, SE, Productivity	n.a.
Sueyoshi & Kirihara (1998)	Japan	136 banks	n.a.	Input	n.a.	OTE	n.a.
Sufian (2008**)	Malaysia	33-36 banks; 171observations	1995-1999	Input	Model 1: input, Model 2: output with interest expense as input, Model 3: interest expense input	OTE, PTE, SE	Tobit
Sufian (20007)	Singapore	141 banks	1993-2003	Input	Input	OTE,PTE,SE	n.a.
Sufian & Majid (2007)	Singapore	6 banks	1993-2003	Input	Input	PTE*	n.a.
Sufian & Majid (2006)	Malaysia	9 banks	2002-2003	Both	Interest expenses: input	OTE*, PTE, SE	n.a.
Tortosa-Ausina (2002c)	Spain	116-121 banks	1986-1995	Input	Model 1: Input; Model 2: savings & time deposits: output, savings deposits, other deposits and interbank deposits: input	CE	n.a.
Tortosa-Ausina (2002a)	Spain	104 banks	1985-1997	Input	Model 1: Input; Model 2: Input & Output	CE	n.a.
Tortosa-Ausina (2002b)	Spain	104 banks	1985-1997	Input	Input	CE	n.a.
Tortosa-Ausina (2003)	Spain	120-162 banks	1986-1997	Input	Input	CE	n.a.
Tortosa-Ausina et al. (2008)	Spain	n.a.	1992-1998	Output	Both	OTE, Productivity	n.a.
Tsionas (2003)	Greece	17-19 banks	1993-1998	Input Ef., Output Prod	Input	OTE, PTE, SE, AE, CE, Productivity	n.a.
Valverde et al. (2007)	Spain	77 banks; 1540 obs	1992-2001	Input	Input	OCE, ICE	n.a.

Wang & Huang (2007)	Taiwan	22 banks	1982-2001	Input	Input	OTE, OTE-QFI, AE, CE,	AR, GMM, Correlation, Markov
Webb (2003)	UK	6-8 banks	1982-1995	Input	Input	OTE, PTE, SE	n.a.
Weill (2004)	France, Germany, Italy, Spain, Switzerland	688 banks	1992-1998	Input	Interest expense: input	CE	Correlation
Wheelock & Wilson (2000)	US	1316-2555 banks	1984-1993	Both	Input	PTE (and CE with SFA)	n.a.
Yildirim (2002)	Turkey	38-59 banks; 594 obs	1988-1999	Input	Input	OTE, PTE, SE	n.a.
Zen & Baldan (2008)	Italy	121 banks	2001-2005	Input	Output	PTE, Productivity	n.a.
Zhao et al. (2008)	India	65 banks 845 obs	1992-2004	Input	Input - part of loanable funds	OTE ,PTE,SE, Productivity	n.a.

Notes: ** Classified in 2008 on the basis of doi; OTE = Overall Technical Efficiency (i.e. CRS), PTE = Pure Technical Efficiency (i.e. VRS), SE = Scale Efficiency, AE= Allocative Efficiency, CE = Cost Efficiency, APE = Alternative Profit Efficiency, SPE = Standard Profit Efficiency, Productivity = Various Productivity Growth Measures, SRCE = Short-run cost efficiency, LRCE = Long-run cost efficiency; CAPE = Capacity efficiency, PCU = Physical capacity utilization, RECU = Ray economic capacity utilization, OCI = Optimal capacity idleness, IP = Performance index of PTE (result of private negotiations among stakeholders), AE* = A proxy of Allocative Efficiency (calculated without including input prices), IPR = Index of Efficiency with preferences revealed by the legislator (IPR = AE* x IP), COMPE = Composition efficiency, ISPE = Intra-specialization efficiency, OCE = Operating cost efficiency, ICE = Interest cost efficiency, OTE-QFI = OTE in the presence of quasi-fixed inputs, SZE = Size efficiency, PTE* & OTE* = these studies report measures which they label as P-efficiency or cost efficiency simply on the basis of some inputs/outputs that they use but they do not include inputs/output price inputs so in a sense they present measures of technical efficiency.

Appendix II – Studies in branch efficiency and productivity growth

Authors	Inputs	Outputs	Input/Output Oriented	Approach for input/output selection	Estimated measures	Sample size & Country
Portela & Thannasoulis (2007)	**INPUT SET1** -TRANSCT EFF 1. Number ETMs (ATMs + CATs) 2. Rent 3. No. clients not registered **INPUT SET2**-OPRTNL EFF 1. Number of staff 2. Rent **INPUT SET3**-PROFIT EFF 1. Number of staff 2. Supply costs	**OUTPUT SET1**- TRANSCT EFF1. No. new registrations for internet use 2. No. transactions in CATs 3. No. deposits in ETMs **OUTPUT SET2**- OPRTNL EFF 1.number of clients 2. Value current accounts 3. Value other resources 4. Value titles deposited 5. Value credit by bank 6. Value credit by associates 7. Number transactions **OUTPUT SET3**-PROFIT EFF1. Value current accounts 2. Value other resources 3. Value credit over bank 4. Value credit associates	Output except profit efficiency (non-oriented DEA)	Intermediation	Transactional, Operational, Profit	57, Portugal
Portela & Thannasoulis (2005)	1)Number of staff 2)Supply costs	1)Value current accounts 2)Value other resources 3)Value credit by bank 4)Value credit associates	Non-oriented	Intermediation	Overall profit efficiency; technical profit efficiency; allocative profit efficiency scale and mix effects.	57, Portugal
Portela et al. (2003)	1)staff costs 2)other operating costs	1. Value of current accounts 2.Value of credit 3. Interest revenues	Non-oriented	Intermediation	PTE	24, Portugal
Camanho & Dyson (2008)	1)Number of branch and account managers 2)Number of administrative and commercial staff 3)Number of tellers 4)Operational costs (excluding staff costs) And input prices	1) Total value of deposits 2) Total value of loans 3) Total value of off-balance sheet business 4) Number of general service transactions.	Input DEA	Production	OTE, Allocative efficiency and Farrell CE measures, market efficiency and economic efficiency	39, Portugal

Camanho & Dyson (2006)	1)Number of branch employees(including branch and account managers, administrative and commercial staff and tellers)2) Operational costs (excluding staff costs).And input prices	1) Total value of deposits 2) Total value of loans 3) Other revenue 4) Number of general service transactions.	Input DEA	Production	Overall regional performance, within region efficiency spread and frontier productivity	n.a., Portugal
Camanho & Dyson (2005)	1) Number of branch and account managers 2) Number of administrative and commercial staff 3)Number of tellers 4)Operational costs (excluding staff costs).	1)Number of general service transactions	Input DEA	Production	OTE, Farrell CE, Optimistic CE and Pessimistic CE	144, Portugal
Camanho & Dyson (1999)	1) Number of employees in the branch 2) Floor space of the branch 3) Operational costs (costs of supplies and other services). 4) Number of external ATMs.	1)Number of general service transactions performed by branch staff 2)Number of transactions in external ATMs 3) Number of all types of accounts at the branch 4) Value of savings 5)Value of loans	Both	Production	PTE, SE	168, Portugal
Das et al. (2007)	1)# of different categories of employees	1)value of deposits 2)value of credit 3)noninterest income	Input DEA	Intermediation	Labor use efficiency, Regional or spatial efficiency	222, India
Giokas (2008a)	1)Personnel costs 2)Running costs 3)Operating expenses	1)Value of loans 2)Value of deposits 3)Non-interest income	Input DEA	Intermediation	Operating efficiency	171, Greece
Giokas (2008b)	**INPUT SET1-Production efficiency** 1)Personnel costs 2)Running and other operating costs **INPUT SET2-** Transaction efficiency 1)Personnel costs 2)Running costs and other operating costs **INPUT SET3** Intermediation efficiency 1)Interest costs 2)Non-interest costs	**OUTPUT SET1** 1)Value of loan portfolio 2)Value of deposits 3)Non-interest income **OUTPUT SET 2** 1)Loan transactions 2)Deposit transactions 3)Remaining transactions **OUTPUT SET 3** 1)Interest income 2)Non-interest income	Input DEA	Production & Intermediation	Production, transaction & Intermediation specific efficiency	44, Greece

Porembski et al. (2005)	1. #of Employees 2. Office space	1)Private demand deposits 2)Business demand deposits 3)Time deposits 4)Saving deposits 5)Credits 6)Bearer securities 7)Recourse guarantees 8)Bonds 9)Investment deposits10) Insurances (contracts) 11)Contributions to a building society (contracts)	Input DEA	Production	PTE, SE	141, German
Paradi & Schaffnit (2004)	**INPUT SET** 1 **Model 1 Production model** 1)staff, 2)information technology, 3)premises, 4)other non-interest expenses **INPUT SET 2** Model 2 Strategic model 1)staff, 2)information technology, 3)premises, 4)other non-interest expenses 5)nonaccrual loans Environmental factors - Growth factor & risk rating incorporated into Models	**OUTPUT SET1** 1)Deposits2)Loans3)Fee income4)Maintenance activities **OUTPUT SET2** 1)Deposits 2)Loans 3)Fee income4) Deposit spread 5) Loan spread	Both	Intermediation	OTE, PTE, Effectiveness, Cost effectiveness	90, Canada
Sowlati & Paradi (2004)	1)FTE sales 2)FTE support 3)FTE other	1)Loans 2)Mortgages 3)RRSPs 4)Letters of Credit	Input DEA	Production	PTE	79, Canada
Athanassopoulos & Giokas (2000)	**INPUT SET 1** 1)labor hrs, 2)branch size 3) computer terminals 4)operating expenditure **INPUT SET 2** 1)labor costs, 2)operating expenses, 3)running costs of the building;	**OUTPUT SET1** 1st Stage1)Group A transactions 2) Group B transactions 3)Group C transactions 4)Group D transactions 2nd stage 1)Credit transactions 2) Deposit trans. 3) Foreign receipts OUTPUT SET 2 1)savings deposits,2)current deposits, 3)demand deposits,4)time deposits, 5)total loans, 6)non-interest income.	Input DEA	Intermediation	Production, Intermediation &market efficiency	47, Greece
Cook, Hababou & Tuenter (2000)	1)FSE # service staff2) FSA # sales staff 3)FSU # support staff 4)FOT # other staff	1)MDP # counter level deposits 2) MTR # transfers between accounts 3)RSP # retirement savings plan openings 4)MOR # mortgage accounts opened		Production	Aggregate, Sales & Service efficiencies	20, Canada

Cook & Hababou (2001)	**Service :** 1)FSE—total number of full time equivalent service staff **Sales** : 1)FSA—total number of full time equivalent sales staff Shared : 1)FSU—total number of full time equivalent support staff 2)FST—total number of full time equivalent “other” staff	**Service** : 1)TOTMENU—total number of menu account transactions 2)VISA—number of Visa cash advances 3) CAD—number of commercial deposit transactions **Sales** : 1)RSP—number of RSP account openings 2)MORT—number of mortgages transacted 3)BPL—number of variable rate consumer loans transacted	Input DEA	Production	Sales & service efficiency	20, Canada
Golany & Storbeck (1999)	1)Teller Labor 2)Non-Teller 3)Labor Retail Sq. Feet 4)Marketing 5)Employment rate	1)Total Loans 2)Total Deposits 3)Depth 4)Satisfaction	Output DEA	Production	Operational efficiency	182, USA
Hartman et al. (2001)	1)No. of staff 2)No. of computer terminals3)square meters of premises	1)Amount of deposits 2)amount of loans 3)Amount of house mortgages Non-discretionary variables: no. of customers	Input DEA	Production	OTE, PTE & AE	50, Sweden
Kantor & Maital (1999)	INPUT SET 1 **Customer services** 1)Labor costs (MS—including social benefits); 2)services; 3)area (square meters), for services only **INPUT SET 2** Bank transactions 1)Labor costs (MS—including social benefits);2) transactions only; 3)area (square meters),	**OUTPUT SET 1** 1)number of demand deposit accounts; 2)weighted output index—customer service transactions; 3)queue-replacing actions **OUTPUT SET 2** 1)Credit cards, regular and "gold"; 2)weighted output index—transactions;3) commissions on import and export, commercial accounts; 4)savings accounts, activity	DEA	Production	customer service efficiency & transaction efficiency	250, n.a
Parkan & Wu (1999)	**Cost** (1)salaries, (2) staff benefits, (3) electronic data processing expenses, (4) occupancy, (5) temporary staff expenses(6) printing and stationary	**Revenue** (1) LC (letter of credit) advice, (2) LC confirmation, (3) LC issuance, (4) guarantee, (5) acceptance, (6) negotiation and (7) net interest revenue.	Input DEA	Intermediation	DEA scaled inefficiency	24, Hong Kong
Wu et al. (2006)	1)Personnel 2)Other general expenses	1)Deposits 2) Revenues 3) Loans	Input DEA	Intermediation	DEA efficiency & DEA-NN efficiency	142, Canada

Dekker & Post (2001)	1)Front office personnel 2)Facilitating personnel	Total revenue	Input DEA	Intermediation	Revenue generating efficiency	314, Netherlands
Soteriou & Zenios (1999)	**INPUT SET 1 Operational efficiency** 1st Set of Inputs 1.Managerial personnel 2.Clerical personnel 3.Computer terminals 4.Space 2ndset of inputs1.Current accounts 2.Savings accounts 3.Foreign currency and commercial accounts 4.Credit applications 5. Commissions **INPUT SET2** Service Quality Efficiency Model 1st Set of Inputs 1.Managerial personnel 2.Clerical personnel 3.Computer terminals 4.Space 2ndset of inputs1.Current accounts 2.Savings accounts 3.Foreign currency and commercial accounts 4.Credit applications 5. Commissions **INPUT SET3** Profitability efficiency 1st Set of Inputs 1.Managerial personnel 2.Clerical personnel 3.Computer terminals 4.Space 2ndset of inputs1.Current accounts 2.Savings accounts 3.Foreign currency and commercial accounts 4.Credit applications 5. Commissions	**OUTPUT SET 1** Total amount of work produced **OUTPUT SET 2** The level of service quality achieved [i.e. Operational (Internal) & Marketing(Perceived) measures] **OUTPUT SET** 3 Profit	Both	Production	Operational efficiency; Service Quality Efficiency; Profitability Efficiency	144, Cyprus
Zenios et al. (1999)	**INPUT SET1** 1.Managerial personnel 2.Clerical personnel 3.Computer terminals 4.Space **INPUT SET 2** 1.Current accounts 2.Savings accounts 3.Foreign currency 4.commercial accounts Credit applications	Total amount of work produced	Input DEA	Production	Operating efficiency	144, Cyprus
Sherman & Rupert (2006)	Personnel (FTE's) 1. Platform 2.Teller3.Manager 4.Operating Expenses: Supplies, Telephone, Travel, Postage	1. Teller Transactions: Deposits, Withdrawals, Checks, Cashed Bank, Checks, Loan Payments, Bonds - Sold, Redeemed, Coupons 2.Marketing:New Accounts 3.Night Deposits 4.Safe Deposit Visits 5.ATMs Serviced	Input DEA	Production	OTE	217 branches from 4 merged banks, USA

		6.Loans - Mortgage & Consumer: Referrals, Applications, Closings				
Howland & Rowse (2006)	1)Non-sales FTE2)sales FTE 3) Size in total square feet 4)City employment rate	1)Loan volume 2) Deposit volume 3) Average number of products/customer 4) customer loyalty	Both	Production	PTE	162, Canada
Sherman & Zhu (2006)	1)Platform FTSe 2) Teller FTEs 3)Management FTEs 4) Postage, supplies, telephone, travel expenses	1)Deposits, withdrawals, checks cashed 2)Bank checks 3)Bond transactions 4)Night deposits 5)Safe deposits visits 6)New accounts 7)Mortgage and consumer loans 8 ATMs Quality measure-mystery shopper scores	Input DEA	Production	OTE	225, US
Noulas et al. (2008)	Value of 1)Personnel costs 2)Other operating expenses	Value of 1)Deposits 2)Financial products 3)Loans 4) Other loans	Input DEA	Intermediation	OTE	58, Greece

Appendix III – Studies in bank bankruptcy, credit rating and underperformance (Part A)

Authors	Subject	Country	Training sample	Period covered	Techniques Used
Alam et al. (2000)	BF	US	Training: 3 failed, 17 extreme performance, 80 healthy; Validation: not specified, although the authors mention that they repeat their analysis in a second sample of another 100 obs. with qualitatively similar results	1992	FC, CL-NN, SOM-NN
Boyacioglu et al. (2008)	BF	Turkey	Training: 14 failed, 29 non-failed; Validation: 7 failed, 15 non-failed	1997-2003	MLP-NN, CL-NN, SOM-NN, LVQ-NN, SVMs, MDA, CA, LRA
Chen & Shih (2006)	CR	Taiwan	Training: twAA & higher ratings (16), TwA (25), TwBBB (26), tw (BB) & lower ratings (6); Validation: twAA & higher ratings (6), TwA (9), TwBBB (9), tw (BB) & lower ratings (2)	1998-2003	SVMs, BP-NN, LR
Gaganis et al. (2006)	CR	79 countries	Training: Fitch ratings: A & B (466), C (214), D & E (214): Validation: 10-fold cross-validation	2004	UTADIS, MDA, OLR
Huang et al. (2004)	CR	US, Taiwan	Training: Taiwan: AAA (8), AA (11), A (31), BBB (23), BB (1); US: AA (20), A (181), BBB (56), BB (7), B (1); Validation: 10-fold cross-validation; leave-one-out cross-validation	Taiwan: 1998-2002; US: 1991-2000	SVMs, BP-NN, LRA
Kolari et al. (2002)	BF	US	Training: 2 samples from 1989; Failed banks: 18, Non-failed banks: 1012 & 1061; Validation: Various samples from 1990, 1991, 1992; Failed banks: 6 - 18; Non-failed banks: 1053 - 1178	1989-1992	TR, LRA
Kosmidou & Zopounidis (2008)	BF	US	Training: 4 samples from 1993-1999; Failed banks: 19-89; Non-failed banks: 90-455; Validation: 2000-2003; Failed banks: 23; Non-failed banks: 112	1993-2003	UTADIS, MDA
Lanine & Vander Vennet (2006)	BF	Russia	Training: 4 samples from January 1997-March (or August) 2000; Failed banks: 58-78; Non-failed banks: 290-390; Validation: 4 samples from April (or September) 2000 to November 2003 or January (or June) 2004	1997-2004	MTR, TR, LRA
Ng et al. (2008)	BF	US	Training: 20% of total sample (Failed: 358-548, Non-failed: 2,555-2,585); Validation: 80% of total sample (Failed: 358 - 548, Non-failed: 2,555 - 2,585)	1980-2000	FCMAC-CRIS(S), GenSoFNN-CRIS(S), Cox's hazard model
Pasiouras et al. (2007)	CR	9 Asian countries	Training: Fitch ratings: A & A/B (4), B & B/C (31), C & C/D (69), D & D/E (77), E (34); Validation: 10-fold cross-validation	2004	MHDIS, MDA, LRA

Ravi et al. (2008)	BU	US	Training: 640 adequate performance & 160 poor performance banks; the 160 poor performance banks where then duplicated to produce a total of 640 poor performance cases; Validation: 200 banks	1993	MLFF-BP, PNN, RBFN, SVM, CART, FRBC, PCA-MLFF-BP,
Ravi & Pramodh (2008*)	BF	Turkey, Spain	Training: Turkey: 40, Spain: 66; Validation: 10-fold cross-validation	n.a.	PCNN, PCA-TANN, PCA-BPNN, TANN, BPNN
Swicegood & Clark (2001)	BU	US	Small-community banks: Adequate performance 480 (training) & 320 (validation), Underperformance: 120 (training) & 80 (validation); Large-regional banks: Adequate perf. 356 (training) & 237 (validation), Underperformance: 89 (training) & 59 (training)	1993	NN, MDA
Tung et al. (2004)	BF	US	Failed: 548, Non-failed: 2,555; Training: 20%; Validation:80%.	1980-2000	GenSoFNN-CRI, Cox
Zhao et al. (2008*)	BF	US	Training: 240 failed & 240 non-failed; Validation: 10-fold cross-validation	1991-1992	LRA, C4.5 decision tree, BP-NN, k-NN
Notes: BF = Bank Failure, CR = Credit ratings; BU = Bank under-performance, FC = Fuzzy clustering; MLP-NN = Multi-layer perception neural networks, CL-NN=Competitive learning NN, SOM-NN = Self-organizing map NN, LVQ-NN= Learning vector quantization NN, SVMs= Support Vector Machines, MDA = Multivariate discriminant analysis, CA = k-means Cluster Analysis, LRA = Logistic Regression Analysis, TR = Trait Recognition, MTR = Modified Trait Recognition, BP-NN = Back-propagation NN, LR = Linear regression, GenSoFNN-CRI = Generic Self-organising Fuzzy Neural Networks-CRI Scheme, k-NN = k-nearest neighbour, UTADIS= UTilités Additives DIScriminantes, MHDIS = Multi-Group Hierarchical Discrimination					

Appendix III – Studies in bank bankruptcy, credit rating and underperformance (Part B)

Authors	Variables considered	Classification resuls
Alam et al. (2000)	(1) Net income to total assets, (2) Net Loan losses to Adjusted assets, (3) Net loan losses to total loans, (4) non-performing loans to total assets, (5) (net loan losses + provisions) to net income	n.a.
Boyacioglu et al. (2008)	(1) Shareholder's equity / total assets, (2) shareholder's equity / total loans, (3) (shareholder's equity + net profit) / (total assets + off-balance sheet commitments), (4) permanent assets/ total asses, (5) total loans/total assets, (6) loans under follow-up/total loans, (7) specific provision/total loans, (8) specific provision/loans under follow-up, (9) personnel expenses/ average assets, (10) net profit/average assets, (11) net profit/average shareholder's equity, (12) income before taxes/average assets, (13) interest income/total operating income, (14) non-interest expenses/total operating income, (15) liquid assets/total assets, (16) total loans/total deposits, (17) trading securities/total assets, (18) FX assets/FX liabilities, (19) net interest income/average assets, (20) net on balance sheet position/total shareholder's equity; Note: reduced or normalized sets of variables were used in some models.	Correct accuracies: MLP-NN (95.50%), CL-NN (68.18%), SOM-NN (63.63%), LVQ-NN (100%), SVMs (90.90%), MDA (68.18%), CA (81.81%), LRA (81.81%)
Chen & Shih (2006)	(1) % of shares held by the government, (2) % of shares held by major shareholders (above 10%), (3) average stock price in previous year, (4) total assets, (5) liabilities, (6) shareholder's equity, (7) net sales, (8) operating income (loss), (9) liabilities to assets, (10) deposits to net worth, (11) fixed assets to net worth, (12) current reverse ratio, (13) total assets turnover (times), (14) deposit to loan, (15) non-performing loan ratio, (16) interest payments to annual average balance of deposits ratio, (17) interest income to annual average balance of credit extension ratio, (18) average amount of business income per employee, (19) average amount of profit per employee, (20) return on total assets, (21) return on shareholder's equity, (22) operating income to paid-in capital, (23) net profit to sales, (24) EPS, (25) cash flow adequacy ratio; Note: some models use subsets of these variables	Correct accuracies: SVMs (73.08%-84.62%), BP-NN (50%-65.38%), LR (23.08%-50%)
Gaganis et al. (2006)	(1) Equity/Total assets, (2) Loan loss provisions / net interest revenue, (3) Return on average assets, (4) Cost to income ratio, (5) Liquid assets / Customer & short term funding, (6) Log (total assets), (7) Number of subsidiaries, (8) Number of institutional shareholders, (9) Whether the banks is listed on a stock exchange or not, (10) Whether the country is developed or developing	UTADIS: 68.91%, MDA: 65.06%, OLR: 62.88%
Huang et al. (2004)	(1) Total assets, (2) Total liabilities, (3) Long-term debts / total invested capital, (4) Debt ratio, (5) Current ratio, (6) EBIT/interest, (7) Operating profit margin, (8) (Shareholders' equity + long-term debt) / fixed assets, (9) Quick ratio, (10) Return on total assets, (11) Return on equity, (12) Operating income/received capitals, (13) Net income before tax / received capitals, (14) Net profit margin, (15) EPS, (16) Gross profit margin, (17) Non-operating income / sales, (18) Net income before tax / sales, (19) Cash flow from operating activities / current liabilities, (20) (cash flow from operating activities / (capital expenditures +increase in inventory + cash dividends)) in last 5 years, (21) (cash flow from operating activities – cash dividends) / (fixed assets + other assets + working capitals); Note: Some models were developed with sub-sets of these variables	Correct accuracies: SVMs (Taiwan: 75.68% - 79.73%; US:78.87% - 80.38%), BP-NN (Taiwan: 74.32% - 75.68%; US: 75.68% - 80.75%), LRA (Taiwan: 70.27% - 75.68%; US: 75.09% - 76.98%),
Kolari et al. (2002)	(1) Total assets (millions), (2) Net interest income/total assets, (3) Net income after taxes/ total assets, (4) Total equity/total assets, (5) Allowance for loan losses/total assets, (6) Provisions for loan losses/total assets, (7) Net loan charge-offs / total assets,	Correct accuracies: TR: around 85%; LRA: slightly

	(8) Total securities / total assets, (9) Nondeposit liabilities / total liabilities, (10) Certificates of deposit / total deposits, (11) Total loans & leases / total assets, (12) Sum of key asset accounts / total assets, (13-24) maximum change in each preceding ratio / mean of corresponding ratio, (25) Maximum change in loans past due at least 90 days/mean of numerator, (26) Bank Holding Co. total assets (millions), (27) Bank total assets / BHC total assets, (28) Maximum change in total assets / mean change in total assets	better than chance
Kosmidou & Zopounidis (2008)	26 variables were initially considered. After a combination of correlation analysis, ANOVA, Kruskal-Wallis, Mann-Whitney the following 9 variables were used: (1) Return on current assets, (2) Financing of current assets, (3) Operating income / current assets, (4) Income before taxes & exceptional outcome & provisions for loan losses / net depreciations, (5) Asset per employee, (6) Provisions for precarious loans / overdue loans, (7) loans / internal deposits, (8) Tier 1 ratio, (9) Ratio of precarious capital	Correct accuracies: UTADIS: 75.75% - 85.44%; DA: 75.75%-79.35%; Combined model: 83.6%
Lanine & Vander Vennet (2006)	(1) Net income/total assets, (2) Liquid assets/total assets, (3) Government debt securities/total assets, (4) Capital / total assets, (5) Overdue loans + overdue promissory notes)/ total loans, (6) Total loans/total assets, (7) Log (total assets)	Mean Square Error: TR (0.091 - 0.167), MTR (0.072 - 0.149), LRA (0.098 - 0.138); AUC-ROC: TR (0.570 - 0.745), MTR (0.539 - 0.906), LRA (0.511 - 0.752)
Ng et al. (2008)	(1) Average total equity capital / average total assets, (2) Average (accumulated) loan loss allowance / average gross total loans and lease (3) (Average (accumulated) loans 90 + days late) / average gross total loans & leases, (4) Annual loan loss provision / average gross total loans and leases, (5) Non-interest expense / operating income, (6) (total interest income – interest expense) / average total asset, (7) (net after tax income + applicable income taxes) / average total equity capital, (8) (average cash + average federal funds sold) / (average total deposit + average fed funds purchased + average banks' liability on acceptance + average other liabilities), (9) % change in Annual Gross total loans & leases; Note: Additional models with 3 selected variables were also developed	FCMAC-CRIS(S)-9 inputs: 82.07% (year -3) to 91.11% (year -1), FCMAC-CRIS(S)-3 inputs: 83.76% (year -3) to 95.28% (year -1) GenSoFNN-CRIS(S), Cox vs FCMAC-CRIS-various scenarios as for misclassification costs of failed vs survived banks: FCMAC better in minimizing Error I (i.e. classiyfing a failed bank as survived); FCMAC vs GenSoFNN: no difference in year -1; error rate of GenSoFNN almost double in years -2 & -3
Pasiouras et al. (2007)	19 financial variables were initially considered. Using factor analysis the following 5 financial variables were selected: (1) Equity / Customer & short term funding, (2) Net interest margin, (3) Liquid assets / Total deposits & borrowings, (4) Net loans / Total deposits & borrowings, (5) Return on average equity. In addition, the following 5 non-financial variables were used: (6) Number of institutional shareholders, (7) Number of subsidiaries, (8) Auditor's opinion, (9) Whether the bank is listed or not, (10) Heritage	Correct accuracies: MHDIS (66.03%), MDA (53.73%), LRA (47.55%)

	banking-finance index	
Ravi et al. (2008)		
Ravi & Pramodh (2008*)	Turkey: (1) Interest expenses / average profitable assets, (2) Interest expenses / average non-profitable assets, (3) (Shareholders' equity + total income)/(deposits + non-deposit funds), (4) Interest income / interest expenses, (5) (Shareholders' equity + total income) / total assets, (6) (Shareholders' equity + total income)/(Total assets + contingencies & commitments), (7) Networking capital / total assets, (8) Salary & employees' benefits + reserve for retirement)/ no. of personnel, (9) Liquid assets / (deposits + non-deposit funds), (10) Interest expense / total expenses, (11) Liquid assets / total assets, (12) Standard capital ratio; Spain: (1) Current assets / total assets, (2) (Current assets – cash) / total assets, (3) Current assets / loans, (4) Reserves / loans, (5) Net income / total assets, (6) Net income / total equity capital, (7) Net income / loans, (8) Cost of sales / sales, (9) Cash flow / loans; Note: in the case of Spain (Turkey) 6 (7) variables are selected when feature subset selection algorithm is used	Correct accuracies: PCNN-WOFS-LTF (Spain: 96.6%, Turkey: 97.5%), PCNN-WFS-LTF (Spain: 92.5%, Turkey:100%), TANN (Spain: 91.6%, Turkey: 92.5%), PCA-TANN (Spain: 97.5%, Turkey: 97.5%), PCA-BPNN (Spain: 84.1%, Turkey: 85%), BPNN (Spain: 81.67%, Turkey: 87.5%), PCNN-WOFS-STF (Spain: 82.4%, Turkey: 92.5%), PCNN-WFS-STF (Spain: 86.6%, Turkey: 90%)
Swicegood & Clark (2001)	(1) Earning assets / Total assets, (2) Total securities / Total assets, (3) Total loans / Total asses, (4) Nonperforming assets / Total assets, (5) Allowance for loan losses / Total loans, (6) Asset growth, (7) Core deposits / Total assets, (8) Volatile liabilities / Total liabilities, (9) Total equity / Total assets, (9) Noninterest income / Total assets, (10) Interest income / Total assets, (11) Gains (Losses) from sale of securities / Total assets, (12) Salary / Total assets, (13) (Noninterest expense – Salary)/Total assets, (14) Total interest expense / Total assets, (15) Provision expense/ Total loans, (16) Off balance sheet commitments / Total assets, (17) Regional geographic location, (18) Charter, (19) Holding company affiliation, (20) Federal Reserve Bank member, (21) Branch or Unit bank, (22) Deposit insurance	Correct accuracies: NN (Large – Regional: Underperformance = 66.1%, Adequate performance = 85.2%; Small – Community: Underperformance = 60.0%, Adequate performance = 82.8%); MDA (Large – Regional: Underperformance = 50.8%, Adequate performance = 95.3%; Small – Community: Underperformance = 28.7%, Adequate performance = 92.1%)
Tung et al. (2004)	Average total equity capital / average total assets, (2) Average (Accumulated) loan loss allowance / average gross total loans and leases, (3) Average (accumulated) loans 90 plus days late / average gross total loans and leases, (4) Annual loan loss provisions /	Equal error rates: GenSoFNN-CRI: 8.17% -

	average gross total loans and leases, (5) Non-interest expense / operating income, (6) (Total interest income – interest expense)/ average total assets, (7) (Net income (After tax) + applicable income taxes) / average total equity capital, (8) (Average cash + average federal funds sold)/(average total deposits + average fed funds purchased + average banks' liability on acceptances + average other liabilities), (9) % change in annual Gross total loans and leases	36.10%; Errors under different misclassification costs: Cox - Type I error: 6% - 54%, Cox - Type II error: 3.10% - 83.6%; GenSoFNN-CRI - Type I error: 0% - 0.69%, GenSoFNN-CRI - Type II error: 45.45% - 100%
Zhao et al. (2008*)	93 raw accounting variables; 26 fianancial ratios: (1) Total equity / total assets, (2) Gross loans / total assets, (3) Commercial loans / gross loans, (4) Individuals loans / gross loans, (5) Real estate loans / gross loans, (6) Late loans (90 days) / gross loans, (7) Not accruing loans / gross loans, (8) Loan loss provisions / gross loans, (9) Charge-off loans / gross loans, (10) Loan allowance / gross loans, (11) Total loans net-off unearned / total equity, (12) Net income / operating income, (13) Net income / total assets, (14) Operating expenses / total assets, (15) Operating income / total assets, (16) Interest income / interest expenses, (17) Operating income / operating expenses, (18) Net income / total assets, (19) Net income / total equity, (20) Interest expenses for deposits / Total deposits, (21) Interest income from Loans / Gross loans, (22) Interest income / operating income, (23) Cash / total assets, (24) (Cash + Securities) / Total assets, (25) (Cash + Federal funds sold + US Treasury + US Government Obligations)/ total assets, (26) Gross loans / total deposits	Misclassifications costs under different prior probabilities and cost ratios: With raw accounting items (LRA:0.087-0.287; Tree: 0.076-0.298; BP-NN: 0.091-0.417; k-NN: 0.071 - 0.297), With financial ratios (LRA: 0.053 - 0.199; Tree: 0.063 - 0.257; BP-NN: 0.057 - 0.240; k-NN: 0.057 - 0.272)