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Abstract

Various measures of efficiency are calculated using the non-parametric data envelopment approach (DEA), for a sample of 255 European Union banks over the period 2005 to 2010. The results clearly indicate a fall in efficiency across the sample during the period analysed. The findings also suggest that the crisis had a differentiated impact across countries and across bank specialisations. Banks from Sweden and Denmark were the most efficient over the sample period, while the banks worst affected by the crisis were from Belgium and Denmark, followed by Ireland and Greece. Additionally, the results indicate that commercial banks were the most heavily affected in comparison to other specialisations.

JEL Classification: G01, G21
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1. Introduction

Over the last two decades, European banking systems have become increasingly liberalised and integrated. The observed financial integration has been enhanced by greater deregulation and technological change, leading to increased competition between financial institutions. These progressive changes have encouraged banks to improve the efficiency of their operations. However, as banks strive for greater operational efficiency, the increased level of competition can lead them to take on excessive risk (Hellman et al., 2000). For this reason, we have seen financial regulators stressing the importance of capital adequacy in order to offset such risk-taking incentives.

Although there is a well established literature on European banking efficiency, reviewed in the following section, there has been little attempt to investigate its behaviour during the period that encompasses the global financial crisis that started in late-2007. Accordingly, in this paper, we employ the frontier estimation technique 'data envelopment analysis' to measure the efficiency of banks in 15 European Union countries (EU-15) for the period from 2005 to 2010.[1] This is done in order to determine whether banking efficiency was adversely affected across the sample by the financial turmoil.

There are two widely-used methodologies for measuring banking efficiency; namely, stochastic frontier analysis and non-parametric data envelopment analysis. In this study, we opted for the latter. In Section 3 of the paper we explain in detail the advantages and disadvantages of each approach and the reasons behind our choice. We also describe in detail the non-parametric data envelopment analysis approach. In Section 4 we provide a description of our data which covers 255 banks from EU-15.

We begin by analyzing banking efficiency for the whole period and our results are consistent with those found by other researchers. Then, we compare efficiency scores for the pre-crisis two-year period 2005-2006 with corresponding scores for the post-crisis two-year period 2009-2010.[2] We find that overall efficiency has dropped by approximately 12 per cent with three quarters of this fall attributed to a drop in input-orientated technical efficiency. This

[1] The EU-15 comprises of Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and the United Kingdom.

[2] Of course, what started as a banking crisis has been transformed into a global macroeconomic crisis and eventually into a sovereign debt crisis. Nevertheless, our results provide a preliminary assessment of the impact of the crisis on banking efficiency levels. We would expect that as the crisis unfolded during 2007 and 2008, banks were reacting to events beyond their immediate control and for this reason we have not included these time periods into our comparisons.

indicates that banks were unable to utilise their resources efficiently which was reflected by various financial market freezes (Acharya et al., 2012). Furthermore, the impact of the crisis was not uniform across the EU area. Banks from Belgium and Denmark were worst affected by the crisis, followed by financial institutions from Ireland, Greece, Finland and the Netherlands. We also find that the crisis had a differentiated impact on efficiency across specialisations. In particular, the biggest drop is observed in the efficiency of commercial banks followed by savings banks and real-estate banks, while cooperative banks were the least affected. We present all our empirical results in Section 5. Finally, Section 6 concludes.

2. Literature Review

In comparison to the vast literature on US banking efficiency (see Mitchell and Onvural, 1996; Berger and Humphrey, 1997; Berger, 2007), the level of empirical research conducted on European banking is still relatively small. However, the level of interest in European banking has increased over the last decade due to the rapidly changing structure and competitive nature of financial markets in the region. These changes have consequently increased the demand for greater efficiency from banking institutions.

There have been several country specific studies in European markets, with the majority of the attention focused on banks from France, Germany, Spain and the United Kingdom. More recently, there appears to be a shift of attention towards Transition European economies and the new developing members of the European Union. The literature highlights the need for more cross-country comparisons of banking efficiency. In this section we review the most relevant literature regarding banking efficiency in the original 15 European Union countries (EU-15) analysed in this study. The majority of the studies on banking efficiency utilise either the stochastic frontier approach (SFA) or the data envelopment analysis (DEA) approach.[3] There are some interesting observations about earlier empirical research which is worth pointing out.

Firstly, there is a wide variation of average efficiency scores across all studies. However, this does not come as a complete surprise when the disparity in estimation techniques, time periods and samples used are taken into account. In general, the average efficiency scores when using DEA and SFA were approximately 65 and 77 per cent, respectively. This

[3] Our observation is also consistent with Berger and Humphrey (1997) who find an almost perfect 50/50 split between the two approaches.

outcome is in line with the findings of Berger and Humphrey (1997), who observe that US studies using SFA exhibit significantly larger efficiency scores than those using DEA.

Secondly, the findings with regard to cross-country comparisons are considerably dispersed, with no concrete consensus on which country's banks are the most efficient. Nevertheless, there are some trends that run through the literature. Banks from Germany were most frequently found to be the most efficient in comparison to other countries (Allen and Rai, 1996; Altunbas et al., 2001; Carbo et al., 2002; Cavallo and Rossi, 2002; Casu and Molyneux, 2003), followed by banks from Austria and Denmark (Allen and Rai, 1996; Altunbas et al., 2001; Carbo et al., 2002). Conversely, banks from the UK were most frequently found to be least efficient relative to other countries (Allen and Rai, 1996; Altunbas et al., 2001; Cavallo and Rossi, 2002; Weill, 2004), followed by financial institutions from France (Allen and Rai, 1996; Lozano-Vivas et al., 2002; Weill, 2004) and Italy (Allen and Rai, 1996; Lozano-Vivas et al., 2002; Casu and Molyneux, 2003).

Lastly, a few studies that compare banking efficiency levels by specialisation conclude that cooperative and savings banks tend to exhibit higher levels of efficiency than commercial banks (Lang, 1996; Dietsch and Weill, 1999). In contrast, Cavallo and Rossi (2002) find that real-estate banks are considerably more efficient than other banking specialisations. However, the analysis conducted by Weill (2004) finds no clear indication that a specific bank type has an advantage over others with regard to efficiency.

3. Methodology

3.1 Efficiency measurement

The two main approaches employed in academic studies to determine banking efficiency are the parametric stochastic frontier approach (SFA), and the non-parametric technique, data envelopment analysis (DEA). The widely used SFA approach, initially proposed by Aigner et al. (1977), is a statistical or parametric method of estimating efficiency levels, which when modelled requires the specification of a particular functional form. On the other hand, the non-parametric approach DEA does not require this prior specification, instead forming a piecewise linear frontier by enveloping all observed data points. Hence, the DEA approach does not depend on any functional form like its parametric counterpart.

The accuracy of estimates using the parametric SFA approach depends on the accuracy of the approximation of the true cost and production functions by the chosen functional forms

(Drake and Hall, 2003). This functional form accuracy is, in turn, dependent on the accuracy of labour input prices, that rely on the availability of accurate data on employee numbers. However, the number of employees for banks in the EU-15 countries is not readily available and hence labour input prices would be subjected to possible inaccuracy or bias, highlighting a potential drawback of the SFA approach for the current sample. Another reason against using SFA is that in many cases, as pointed out by Berger and Humphrey (1997), the measurement of SFA is sometimes approximated by the use of a translog function. While this choice greatly increases the flexibility of the frontier giving it the ability to more closely represent the data it is also susceptible to poor estimates when analysing banking data (McAllister and McManus, 1993; Mitchell and Onvural, 1996). In contrast, DEA does not impose such a structure on the efficient frontier, nor does it require the assumption that all banks face an identical unknown production technology. The only requirement is that a rational and comprehensive set of inputs and outputs are specified to produce relative efficiency measurements.

It is important to note that the DEA approach does not allow for a random error term to account for statistical noise. Therefore, any deviation from the efficient frontier is linked to inefficiency within the bank and, thus, there is a potential for DEA to overstate efficiency measurements (Berger and Mester, 1997; Grosskopf, 1996). On the other hand, SFA does allow for a random error term, which accounts for external influences on the bank or imperfections in the specification of the model. However, a disadvantage of SFA is that any non-random error that causes a deviation from the frontier is the result of both technical and allocative efficiency, which are hard to separate. In this study we focus on technical and scale efficiencies, measured using the non-parametric DEA method which is discussed in more detail in the next sub-section.

3.2. Data Envelopment Analysis (DEA)

The concept of frontier estimation was first proposed by Farrell (1957), who suggested the decomposition of relative efficiency levels into categories. However, it wasn’t until Charnes et al. (1978) that the term data envelopment analysis (DEA) was first used. DEA constructs a non-statistical or non-parametric frontier which takes each individual bank, known as a decision making unit (DMU) in turn and envelopes the data points of the DMUs, constructing a ‘best practice’ frontier. The firms with the highest levels of relative efficiency make up the efficient frontier, while the inefficiency of the remaining banks is measured as a ratio of the their costs to the costs incurred by the ‘best practice’ DMUs. Subsequently, each DMU in the sample is assigned an efficiency score between 0 and 1, with higher scores indicating better efficiency, relative to other firms.

Farrell (1957) stated that the overall productive efficiency of a firm is composed of overall technical efficiency and allocative efficiency. This categorisation of efficiency can be better explained with the use of Figure 1 which presents a single output isoquant (yy) which is made up of varying combinations of two inputs (x_1 and x_2), producing the single output. The DMU at point A is overall efficient in choosing the cost minimising production process given the relative input prices represented by the tangent line ZZ, which represents the cost minimisation plane to the efficient frontier. The DMU at point C is allocatively inefficient in choosing an appropriate input mix, where allocative efficiency reflects the ability of a firm to use the factors of production in optimal proportions, given their respective prices. The DMU at point D is both allocatively and technically inefficient, because it requires higher levels of inputs, x_1 and x_2, while producing the same level of output as the DMU at point C.

[Please insert Figure 1. around here]

Furthermore, numerical measures for the overall productive inefficiency of the DMU at point D can be obtained by splitting the inefficiency into allocative and technical efficiency. The allocative inefficiency of firm D is measured by the ratio OB/OC which reflects the choice of an inappropriate input mix. In other words, the costs at point B are equal to the costs in the overall productively efficient point A, but lower than at point C. Therefore the ratio of OB/OC measures the possible input saving that can be made. The overall technical inefficiency of firm D is measured by the ratio OC/OD which compares the minimum input required for production of one unit to the observed input usage by firm D. In other words, the ratio measures the proportion of inputs that could be saved without reducing the firm’s output.

The use of the unit isoquant output to measure overall technical efficiency in Figure 1 is valid under the assumption of constant returns to scale (CRS). Charnes et al. (1978) has imposed the CRS assumption which presupposes that there is no significant relationship between the scale of operation and efficiency. It presents efficiency wholly as overall technical efficiency. The CRS assumption is only justifiable when all DMUs are operating at an optimal scale. In practice however, firms might face either economies or diseconomies of scale, due to such factors as imperfect competition and constraints on finance (Casu and Molyneux, 2003).

Thus, if one makes the assumption of CRS when not all of the DMUs are operating at optimal scale, the computed measure of technical efficiency will be contaminated with scale inefficiencies.

Consequently, the DEA model was further developed by Banker et al. (1984) by relaxing the CRS assumption. The new model assesses the efficiency of DMUs characterised by variable returns to scale (VRS); whether they are increasing returns to scale at lower output levels or decreasing returns to scale at higher output levels. Under the VRS assumption the model provides a measurement for pure technical efficiency, which is a measurement of the overall technical efficiency devoid of the scale efficiency effect. Therefore, if there appears to be a difference between the overall technical and pure technical efficiency scores of a particular DMU, then this indicates the existence of scale inefficiency. This is summarised in Figure 1 where the overall technical efficiency ratio OC/OD can be further decomposed into scale efficiency represented by the ratio OS/OD, and pure technical efficiency represented by the ratio OC/OS, where point C represents a DMU exhibiting constant returns to scale. More formally:

$$\text{Overall productive efficiency} = \text{Allocative efficiency} \times \text{Scale efficiency} \times \text{Pure technical efficiency}$$

$$OB/OD = [OB/OC] \times [OC/OS] \times [OS/OD] \quad (1)$$

Where pure technical efficiency (PTE) represents the efficient transformation of a firm's adopted inputs to give maximum output, without assuming efficiency of scale. Therefore, inefficiency can occur when more of each input is used than should be required to produce a given level of output. This occurrence is more difficult to explain, but is typically attributed to weak competitive forces and the unproductive use of resources which tend to be under the control of, and result from the behaviour of the management (Evanoff and Israilevich, 1991). Alternatively, scale efficiency (SE) corresponds fairly closely to the microeconomic definition of economies of scale. Therefore, banks can be categorised as operating at either optimal scale (CRS); or conversely suboptimal scale, whether it be due to increasing or decreasing returns to scale. Scale efficient firms will have an input-output combination which reflects constant returns to scale. In other words, changes in the output level are a result of proportional changes in costs. Consequently, the overall technical efficiency (OTE) can be formally described as:

$$\text{OTE} = \text{PTE} \times \text{SE} \tag{2}$$

As mentioned earlier, accurate and complete data on input prices is unavailable for the sample of EU-15 banks analysed in this study, hence it is not possible to analyse the issue of allocative efficiency. Nevertheless, within the DEA model, it is legitimate and appropriate to focus on OTE and its decomposition into PTE and SE. Unlike the parametric SFA model which explicitly requires that efficiency is a composite of allocative and pure technical efficiency. Therefore, while concentrating on technical efficiency, Farrell suggests constructing a piecewise linear approximation to the isoquant model. However, this produces a relative measure of efficiency rather than an absolute one, since the DMU's which are the most efficient relative to the sample make up the piecewise efficient frontier.

To obtain a measure for technical efficiency using the VRS method, we need to separately calculate its components, i.e. PTE and SE. In a sample of n DMUs, the measurement of each DMU's pure technical efficiency requires the measurement of the ratio between observed inputs (x) and outputs (y), which are weighted accordingly with each DMU having a different weighting vector λ. The industry inputs and outputs are represented by the column vectors X and Y respectively. Each firm's PTE is then calculated by finding its corresponding lowest multiplicative factor, θ, which is applied to its use of inputs (x) to make sure that it remains a part of the input requirement set. Thus, we choose:

$$\{\theta, \lambda\} \text{ to: } \min \theta \text{ such that: } \theta x \geq \lambda' X,$$

$$y \leq \lambda' Y,$$

$$\lambda i \geq 0, \quad \sum \lambda i = 1, \quad i = 1, \ldots, n. \tag{3}$$

The approach described in program (3) forms a convex hull of intersecting planes which tightly envelope the data points. After determining each firm's PTE, the next step is to calculate each DMU's scale efficiency. SE is calculated by resolving the technical efficiency problem presented in program (3), but this time without the constraint that the input requirement set must be convex, given by $\sum \lambda i = 1$. The loosening of the constraint allows for combinations of inputs which have been scaled up or down to be included in the DMU's production possibility. This is illustrated in Figure 2 which shows the case for a single input (x) and a single output (y). The boundary set by OC represents the constant returns to scale frontier, which indicates that any DMU to the right of the boundary is part of the production possibility set and is acting at optimum scale or CRS. However, due to the introduction of the convexity constraint, $\sum \lambda i = 1$, the area of production possibility becomes the area to the right of the boundary VV. This boundary represents the piecewise linear frontier which does not assume CRS, instead it allows for increasing or decreasing returns to scale (VRS) depending on the output level of the DMU.

[Please insert Figure 2. around here]

To further illustrate this, a DMU at point K in Figure 2 is technically inefficient under both the CRS and VRS assumptions. The OTE of a firm at point K under the CRS assumption is given by the ratio FG/FK, while under VRS, the PTE would only be given by the ratio FH/FK. Therefore, the lowest multiplicative factors regarding overall technical efficiency, θ_o, and pure technical efficiency, θ_p, can be gleaned by solving program (3) without imposing the convexity constraint $\sum \lambda i = 1$. Whereas, the multiplicative factor corresponding to scale efficiency, θ_s, is calculated by applying the convexity constraint. Consequently, by extending the explanation used to determine the ratio of equation (2), scale efficiency is measured as the ratio of the two results and can be rewritten as:

$$\text{SE} = \text{OTE} \,/\, \text{PTE} \tag{4}$$

SE is a very useful analytical tool as it provides information on the level of inefficiency resulting from deviations from the firm’s optimum scale or from operating at CRS; in other words, whether a DMU is operating on its minimum efficient scale (MES) or not. Even though SE provides us with this information, it does not inform us on whether the DMU is operating at increasing or decreasing returns to scale, i.e. whether the bank is operating above or below its MES. Therefore, to determine whether a DMU is exhibiting increasing or decreasing returns to scale, requires that the technical efficiency program (3) is run again, but this time with the assumption of non-increasing returns to scale rather than VRS. If it is observed that the two measures of PTE differ, then we can conclude that the bank is operating at increasing returns to scale, whereas, if the two measures coincide then the bank is operating at decreasing returns to scale.

A final point of consideration is that DEA has the option of expressing the VRS technical efficiency in either an input- or output-orientated method. The input-orientation is associated with cost minimising behaviour, whereas the output-orientation is related to revenue maximising activities (Kumbhakar et al, 2007). The choice of orientation has both theoretical and practical implications. In some industries, the method of orientation is clear, such as if the emphasis of the industry is to control costs, the input-orientated method should be utilised. With regards to banking however, the evidence is less clear. Although the majority of studies use the input-orientated model, arguing that in banking the primary decision variables are the inputs, there is significant evidence to suggest that restricting attention to a particular orientation may neglect major sources of technical efficiency in the other direction (Casu and Molyneux, 2003; Berger et al., 1993). For this reason, we present technical efficiency measured using both orientation methods. However, it is important to note that the same frontier is calculated regardless of orientation and that the same set of DMUs make up the 'best practice' frontier. The difference comes when measuring the relative technical efficiency of the inefficient DMUs with respect to the efficient frontier.

Therefore, the analysis in Section 5 utilises the piecewise efficiency frontier of DEA for a sample of banks from across the EU-15 countries and analyses the relative efficiency levels between the various types of banks used in this study.

4. Data

4.1 Description of sample and data sources

The sample used in this study consists of data from 255 banks of varying asset size from across the original 15 European Union countries (EU-15) during the period 2005-2010.[4] The data with regard to the sample was drawn from the Bankscope International Bank Database (2011).[5]

When choosing a sample in order to analyse quantitative bank data, it is important to ensure that the sample is homogeneous, i.e. that the types of banks in the sample under analysis have similar features. Therefore, the cross-section of banks used is made up of *retail banks,* including commercial banks, cooperative banks, real-estate & mortgage banks and savings banks.[6] These financial institutions were chosen as they share a common business structure. In particular, their primary purpose is to accept deposits, which are pooled and utilised to provide credit. Meanwhile, other non-retail banks, such as investment banks are excluded

[4] A full list of the banks used in this study is available from the author upon request.
[5] Bankscope is jointly owned by Fitch International Bank Credit Analysis (IBCA) and Bureau van Dijk, offering a comprehensive financial database, and providing detailed raw data on over 10,000 international banks.
[6] These bank types are recommended for further research by Williams (2004) who only analyses savings banks.

from the sample due to the variation in banking structure, technology and aims of the institutions (Al-Muharrami et al., 2006).

To ensure consistency in the data, only banks which disclosed their financial data via consolidated income statements and balance sheet data were included in the sample. Additionally, the sample was thoroughly checked and any missing values were excluded. The reference currency is US Dollars (USD) and all reported data has been appropriately deflated to real 2005 terms by utilising individual country GDP deflators.[7]

The sample of banks under analysis is summarised in Table 1 which presents some descriptive statistics. It is clear that the mean total assets of banks in France, Germany and the UK are substantially larger than those in other countries. For example the average French bank is approximately three times larger than banks in Ireland and Italy and six times larger than those in Portugal and Greece. Moreover, it is clear that the average size of a commercial bank is nearly twice that of an average cooperative bank and around five times as large as a real-estate or savings bank. Such variation in size regarding bank specialisation may be explained by different regulation conditions implemented on the different types of banks within the sample (Dietsch and Weill, 1998).

[Please insert Table 1. around here]

4.2 Input and output variables

There is no consensus on how the bank production function should be modelled to measure efficiency using DEA. This study follows the intermediation approach proposed by Sealey and Lindley (1977), which has been widely used in recent studies (see Drake et al., 2009; Drake and Hall, 2003; Casu and Molyneux, 2003) to measure the flow of services provided by financial institutions. Under the intermediation approach, the primary function of a financial institution is to intermediate between savers and investors by turning deposits and other liabilities into loans and other assets. Therefore, the main consequence of the intermediation approach is to consider deposits as an input; whereas the alternative production approach considers deposits as an output. This definition of banking very closely reflects the behaviour of the banks chosen to be analysed in this study. Additionally, Berger and Humphrey (1997) point out that the intermediation approach may be more appropriate when evaluating the efficiency of entire financial institutions. This is due to the inclusion of

[7] GDP deflators were sourced from the Economic and Social Data Service International database (ESDS, 2011).

interest expenses which make up a significant proportion of costs. Whereas, the production approach is more appropriate for evaluating the efficiencies of branches of financial institutions. Therefore, the DEA model estimated reflects the standard intermediation approach and consists of four inputs (*total deposits, fixed assets, total operating expenses* and *loan loss provisions*) and three outputs (*total other earning assets, total other income* and *total loans*).

The first input, *total deposits* is comprised of total customer deposits, total money market funding and total other funding, including short-term borrowing. *Fixed assets* is a proxy for the capital input. *Total operating expenses* represents the labour input, and is made up of personnel expenses plus other operating expenses. This input accounts for non-traditional business activities undertaken by the bank. Ideally, the labour input would be represented by the number of employees, but due to the lack of data, the input on expenses is the best proxy. However, it is argued that this may lead to a bias against banks that hire high quality staff, i.e. high cost staff. Fortunately, this problem appears to solve itself, as banks with high quality staff would be expected to achieve higher levels of output, removing any such bias and ensuring that such banks don't show up to have a relative efficiency disadvantage (Drake and Hall, 2003). *Loan loss provisions* are expenses set aside for the allowance of problem loans, and is utilised in the context of the DEA model as a proxy for the risk of default on lending. Banking risks such as problem loans are a crucial factor that must be taken into account when measuring efficiency. Akhigbe and McNulty (2003) and Drake and Hall (2003) both find that there is a significant impact on relative efficiency scores when risk is not accounted for. Subsequently, when accounting for risk, we are assuming that problem loans have an exogenous impact on the bank, in other words, they are outside the control of the management (Berger and Humphrey, 1997).

With regards to outputs, *total other earning assets* are included to capture the business operations of banks. However, it would be inappropriate to focus exclusively on *total other earning assets*, as this would not account for the complete operations of modern banking (Drake and Hall, 2003). Hence, the output, *total other income* is included, which is made up of net commissions, fees, trading and other operating income, and is essential in the analysis as it reflects the diversification of banking operations around the margin. It is also important because it takes into account any non-traditional business activities, which is reflected by more banks putting an increased emphasis on off-balance sheet trading (Drake et al., 2009). Lastly, *total loans* can be defined as the sum of total customer loans and total other lending.

Table 2 reports the average values of inputs and outputs by year for the entire sample of banks from 2005 to 2010. It is clear that there is a significant increase in the level of *total deposits*, *total loans* and *total other earning assets* beyond 2006. Interestingly, the level of *loan loss provisions* remains steady until 2007; however, from 2008 onwards there is a great increase in the level of provisions set aside by banks. This represents a significant rise in the level of the default risk faced by banks, and is most likely due to the credit crisis which begun in late-2007.

[Please insert Table 2. around here]

5. Empirical Results

The entire sample of banks in the EU-15 countries during the period of 2005 to 2010 is run through DEA simultaneously, creating a common efficient frontier for all of the DMUs in the sample. This allows us to compare the efficiency scores from the banks across the EU-15 countries over the sample period against a common benchmark. This section initially examines the efficiency results derived from the various measures using DEA; but subsequently, concentrates on the more sophisticated VRS measures of efficiency, namely, the input- and output-orientated pure technical efficiency scores. Accordingly, this section firstly, analyses the general banking efficiency performance of the sample. Secondly, cross-country comparisons are made with regard to efficiency during the sample period. Lastly, efficiency is analysed with regard to bank specialisation, looking at whether particular bank types perform better within the European banking environment.

5.1 Efficiency results

The efficiency performance of all banks in the sample from the EU-15 countries over the period of 2005 to 2010 are summarised in Table 3. It can be observed from Table 3 that the mean overall technical efficiency, which assumes constant returns to scale, over the sample period is 62.1 per cent, indicating that overall, the banks in the EU-15 countries could make cost savings of up to 37.9 per cent which is a considerably large amount. This finding matches the average efficiency levels found in previous literature using DEA (see Lozano-Vivas et al., 2002; Casu and Molyneux, 2003; Weill, 2004). [8] Most interesting, however, is that the mean OTE falls dramatically from 65 per cent to 58.5 per cent between 2007 and 2008, indicating that the global financial crisis, which is widely agreed to have hit in late-

[8] Efficiency scores regarding each individual bank in the sample are available from the authors upon request.

2007 seems to have considerably affected banking efficiency in Europe. Moreover, there appears to be a drop in efficiency during this period across all measures of efficiency. Given that the crisis struck in late-2007 and carried through 2008 we compare banking efficiency performance before and after the global financial shock by calculating the mean efficiency of the two years prior to the crisis (2005 and 2006), and comparing this level with the mean of the two years following the crisis (2009 and 2010). Clearly, during 2007 and 2008 efficiency measures were severely affected by events outside the direct control of banks. By concentrating in the period after the crisis, we can get a better idea about the impact of the financial shock on bank operations.

[Please insert Table 3. around here]

We observe that overall technical efficiency falls from a mean level of 68.4 per cent to 56.1 per cent, indicating a substantial reduction in efficiency of 12.3 per cent. The majority of this fall can be attributed to the variation in input-orientated pure technical efficiency which falls by 8.9 per cent over the same period. Hence, from the definition of input-based PTE, it can be said that the management of the banks in the sample were unable to fully utilise their resources after the crisis had struck. This observation would seem sensible as it is likely that the level of inter-bank lending fell due to banks being insecure about investing in each other. Additionally, the level of *loan loss provisions* increased as we observe in Table 2 due to the increase in the level of problem loans and the likely deterioration in the quality level of assets some banks were holding.

Generally, the average level of scale efficiency for European Union banks is 86.7 per cent, indicating scale economies of 13.3 per cent. This finding is larger than the 7 per cent scale inefficiency reported by Altunbas et al. (2001), when analysing a sample of European banks during the 1990s. However, the results in Table 3 also suggest a steep drop in the level of scale efficiency, with an average pre-crisis measure of 90.2 per cent falling to 83.5 per cent post-crisis. Thus, indicating that the existence of diseconomies of scale increased due to the financial crisis. This finding is not surprising, considering that many banks decreased with regard to size and capital following the crisis.

The level of average output-orientated pure technical efficiency is relatively high compared to the input-based measure, with a score of 86.2 per cent which is similar to the finding of Beccalli et al. (2006). The finding indicates that European banks are particularly efficient at maximising their outputs, i.e. loans and other operating income given a set level of inputs.

Moreover, in contrast to the other measures of efficiency, the output-orientated PTE doesn't fall as dramatically, demonstrating a 3 per cent fall over the period analysed.

5.2 Cross-country comparisons

In order to assess efficiency in more detail, this section compares each individual country's performance against the common efficient frontier. Tables 4 and 5 present annual variable returns to scale efficiency scores for the 15 European Union banks analysed in the sample.

[Please insert Table 4. around here]

[Please insert Table 5. around here]

In line with the findings of Allen and Rai (1996) and Carbo et al. (2002), the input-orientated efficiency measure finds banking institutions from Sweden and Denmark to be the most efficient over the sample period, followed by banking institutions from the UK, France and Germany. The output-based method also shows the performance of banks in Sweden and Denmark to be superior to those of the other EU-15 countries. However, unlike the input-based measure which shows a variation of efficiency levels across countries, the output method shows a bunching up effect, with seven of the countries performing at efficiency levels between 85 and 90 per cent. On the other hand, both methods of measurement indicate that banks from Greece and Belgium performed least well in terms of efficiency. Meanwhile the input-based method also indicates that financial institutions from Italy, Portugal, Spain, Finland and Ireland perform only slightly better which is consistent with earlier research into European banking efficiency.

However, the mean efficiency scores over the sample period do not tell the full story, as banks from some countries suffered more than others from the global financial crisis. For this reason, Table 6 exhibits the changes in banking efficiency between the periods before and after the crisis. It is immediately clear that the efficiency levels of banks from across the EU-15 were adversely by the financial crisis. Furthermore, it appears that banks from Belgium and Denmark were worst affected by the crisis, followed by financial institutions from Ireland, Greece, Finland and the Netherlands.

[Please insert Table 6. around here]

The falls in efficiency scores may be explained by the Belgian subsample being heavily affected by two of the largest banks experiencing severe difficulty raising liquidity funds in the immediate aftermath of the crisis.[9] Dutch banks also had large investments in Belgian banks, with close relationships between the troubled Belgian Fortis bank and the Dutch bank ABN Amro, which required capital injections of its own. Furthermore, a large government cash injection was required to stabilise the Danish banking industry in the years following the start of the crisis. Moreover, it is likely that these countries had considerable exposure to Icelandic banks which suffered from the collapse of the entire banking system. Meanwhile, Ireland experienced a property bubble crash of their own, spurring the need for recapitalisation of three of their largest commercial banking institutions and their largest real-estate bank (Goddard et al., 2009).[10]

It also appears that the banks from the larger EU economies seem to be relatively less affected by the shock, especially in terms of the output-based measure. In particular, banks from France, Germany, the UK, Italy and Spain seem to come through the crisis healthier relative to banks from their European counterparts. This finding is likely to be attributed to the diverse nature of the financial systems in the larger European countries. The finding for UK banks, which is surprising given the extent to which they were exposed to the crisis, might be explained by the prompt government response (Acharya and Sundaram, 2009).

5.3 Banking efficiency by specialisation

The analysis of banks according to their specialisation has grown in importance due to the significant market share enjoyed by cooperative, real-estate and savings banks in Europe today. As mentioned in Section 2, previous literature has found that cooperative and savings banks tend to operate at higher efficiency thresholds than commercial banks (see Lang, 1996; Dietsch and Weill, 1999). The efficiency scores of the current study with regard to specialisation are summarised in Table 7 and Figure 3. Table 7 shows that average overall technical efficiency scores for cooperative and savings banks do indeed outperform commercial banks. This difference appears to be explained by the lower levels of scale efficiency of commercial banks relative to other bank types. Furthermore, real-estate and mortgage banks clearly outperform all other bank types with an overall technical efficiency

[9] The Belgian Fortis bank and Dexia bank both required considerable government capital injection packages to escape insolvency. These two banks made up a quarter of the entire Belgian sample.
[10] The Bank of Ireland, Allied Irish Banks, Anglo-Irish Bank and the real-estate bank Depfa all required large capital injections post-2007.

score of 80.2 per cent, supporting the finding by Cavallo and Rossi (2002). However, a closer inspection of the input-orientated pure technical efficiency scores suggests that this finding is not robust across all approaches, as commercial banks are found to be more efficient than cooperative and savings banks.

[Please insert Table 7. around here]

[Please insert Figure 3. around here]

The performance and reaction of banks to the global financial crisis can be examined with respect to specialisation by looking at pure technical efficiency scores preceding and following the period of 2007-2008. It emerges that although the mean efficiency scores of banks vary due to specialisation, they are all adversely affected by the financial crisis in a similar way. In particular, the efficiency of commercial banks falls the most (-8.85%), followed by savings banks (-8.65%) and real-estate banks (-7.85%), while cooperative banks come out least affected (-5.80%).[11] The smaller impact on cooperative banks may be described by the nature of their long-term outlook business model, which is characterised by stable income and high capitalisation. Additionally, cooperative banks are orientated around the needs of their customers and members; hence they are expected to have invested less in structured financial products than commercial or savings banks. Therefore, although some cooperative banks suffered substantial losses, on average they were more stable through the period of financial instability (Groeneveld and Bouke de Vries, 2009).

6. Conclusions

In this study, the level of various measures of efficiency are calculated using the non-parametric frontier approach DEA, for a sample of 255 European Union banks over the period 2005 to 2010. Unlike previous studies, this study allows for a fresh perspective by using efficiency measures derived from DEA, rather than SFA. Furthermore, a brand new sample is used, which is specifically selected to offer an insight into the performance of European banks during the recent financial crisis, which began in late-2007.

The results clearly indicate a fall in efficiency during the period analysed. The sharpest drop is observed between 2007 and 2008, indicating that the crisis was instrumental in the fall of

[11] Although the crisis is widely credited to the practice of subprime mortgage lending, it appears that European real-estate and mortgage banks were no more exposed to the subprime mortgages and their derivatives than any other bank specialisation.

banking efficiency. The cross-country efficiency comparisons reveal that banks from Sweden and Denmark were the most efficient over the sample period, followed by banking institutions from the UK, France and Germany. Meanwhile, the banks worst affected by the crisis were from Belgium and Denmark, followed by financial institutions form Ireland, Greece, Finland and the Netherlands. The results measuring efficiency by specialisation indicated that real-estate banks were the most efficient, while cooperative banks were the least affected by the credit crisis.

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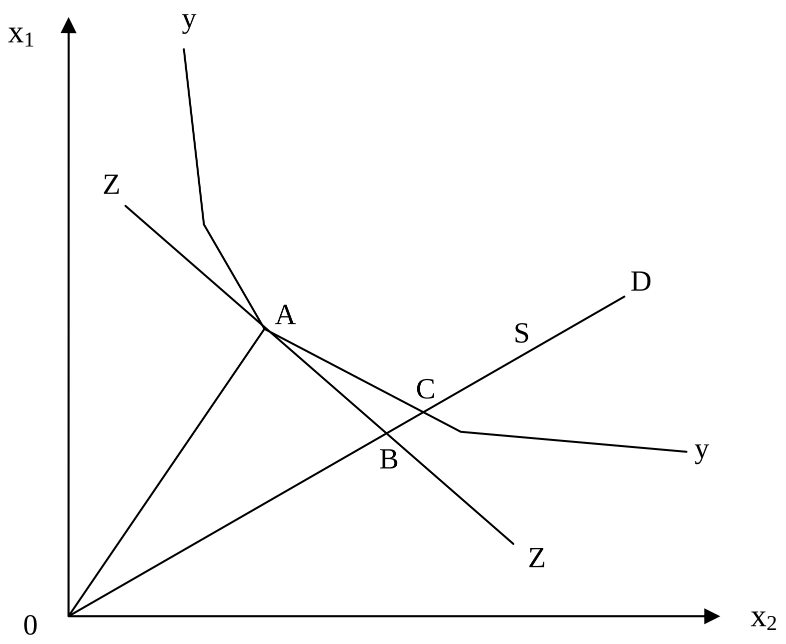

Figure 1: DEA frontier - Farrell efficiency

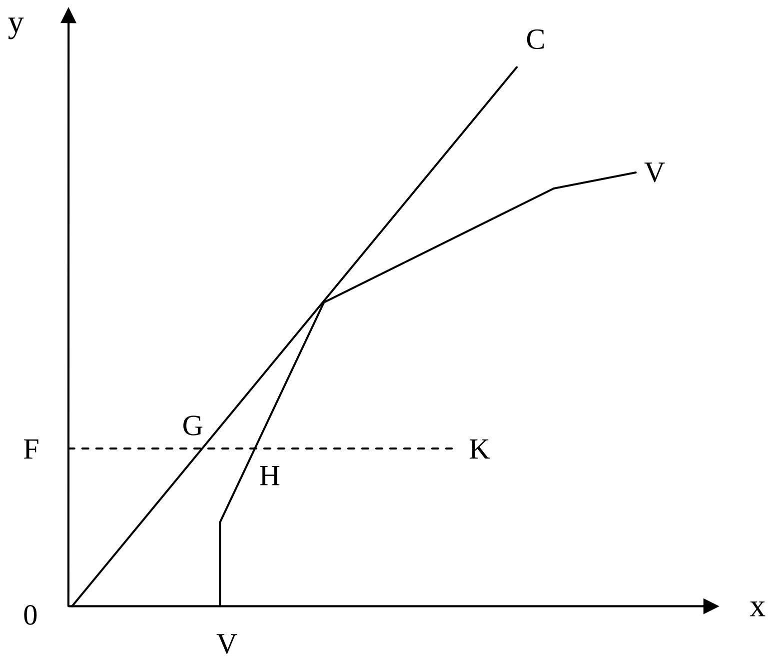

Figure 2: Scale and technical efficiency

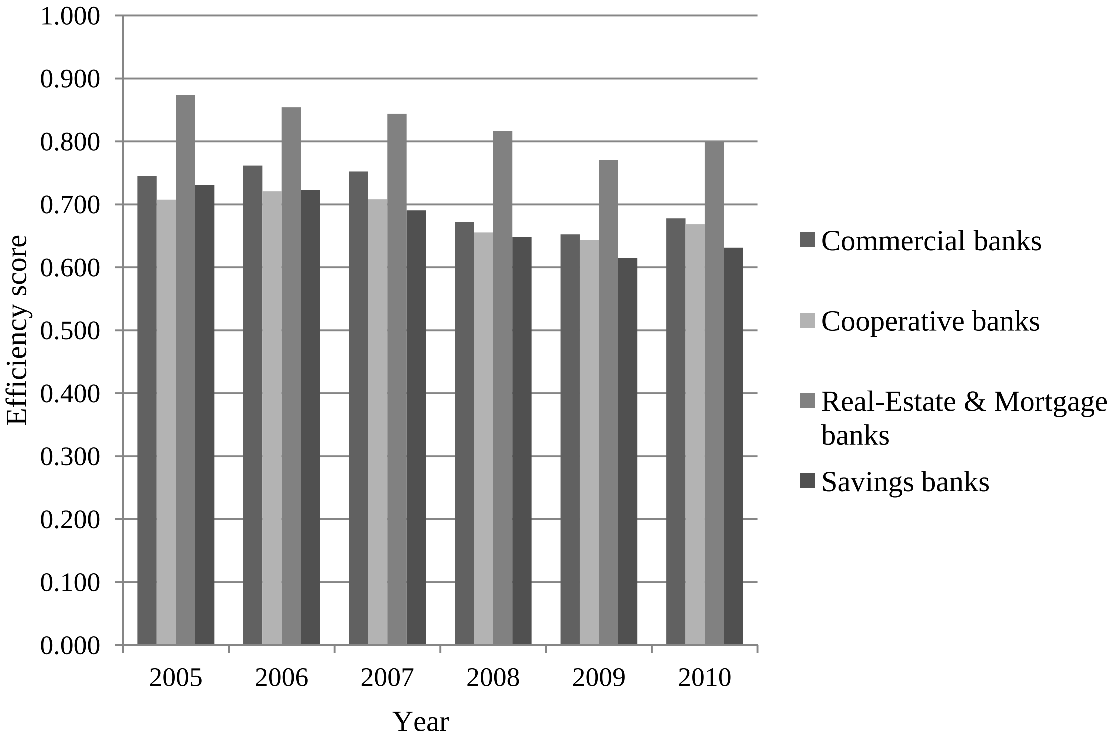

Figure 3: Input-orientated pure technical efficiency scores with respect to bank specialisation

Table 1
Average total assets in billion USD (2005-2010)

Country	No. of banks	Mean	Median	Stdev	Min	Max
Austria	20	35.80	11.30	64.21	0.36	257.95
Belgium	6	238.37	269.60	169.16	14.37	464.95
Denmark	16	72.42	8.29	145.65	0.40	572.55
Finland	4	144.44	80.27	143.39	34.95	382.26
France	43	311.00	29.63	639.57	0.96	2669.91
Germany	13	355.74	65.59	644.23	3.08	2546.27
Greece	13	46.46	29.57	48.38	3.65	161.34
Ireland	8	109.39	98.80	79.99	16.21	223.77
Italy	34	97.94	15.82	252.62	2.37	1241.97
Luxembourg	5	28.64	19.67	22.28	6.20	58.03
Netherlands	9	260.94	30.75	440.79	4.67	1246.76
Portugal	10	53.24	16.88	59.60	2.67	168.17
Spain	27	138.22	28.70	329.72	0.95	1626.80
Sweden	4	230.92	288.33	126.29	22.14	324.88
UK	43	272.62	30.03	547.66	0.52	2332.56
EU-15	255	180.52	28.70	426.11	0.36	2669.91

Specialisation	No. of banks	Mean	Median	Stdev	Min	Max
Commercial banks	147	244.16	40.08	482.52	0.36	2669.91
Cooperative banks	50	148.09	19.62	448.03	2.37	2312.73
Real-Estate & Mortgage banks	31	46.54	15.65	79.69	0.52	306.00
Savings banks	27	47.85	14.64	85.72	0.67	381.78

Table 2
Descriptive statistics for inputs and outputs across EU-15 in billion USD

		2005	2006	2007	2008	2009	2010
Inputs							
Total Deposits	Mean	59.35	77.98	96.55	93.36	97.41	94.12
	Med	10.35	13.08	16.45	17.82	19.31	18.33
	Stdev	130.31	171.74	214.71	197.29	211.98	206.13
Fixed Assets	Mean	0.79	0.94	1.12	1.07	1.18	1.12
	Med	0.11	0.13	0.16	0.14	0.14	0.13
	Stdev	2.12	2.52	2.88	2.89	3.32	3.06
Operating Expenses	Mean	1.35	1.80	2.15	2.08	2.22	2.21
	Med	0.25	0.31	0.37	0.36	0.36	0.34
	Stdev	3.08	4.29	5.07	4.85	5.27	5.44
Loan Loss Provisions	Mean	0.14	0.20	0.27	0.54	1.17	0.86
	Med	0.02	0.02	0.04	0.08	0.13	0.08
	Stdev	0.39	0.56	0.76	1.45	3.22	2.39
Outputs							
Total Loans	Mean	49.77	65.24	82.98	83.90	85.97	85.07
	Med	9.60	13.12	15.99	18.05	18.47	17.57
	Stdev	104.35	133.48	172.64	169.07	176.62	178.08
Other Earning Assets	Mean	54.97	73.64	91.03	99.58	86.49	83.43
	Med	4.22	5.15	6.30	6.02	6.44	6.12
	Stdev	147.65	208.83	269.40	316.90	243.65	240.19
Total Other Income	Mean	1.69	2.47	2.87	1.84	2.38	2.40
	Med	0.27	0.39	0.42	0.29	0.34	0.34
	Stdev	4.15	6.30	7.26	4.64	6.22	6.24

Table 3
Evolution of efficiency for the whole EU-15 sample over the period 2005-2010

	2005	2006	2007	2008	2009	2010	Mean
Overall technical efficiency							
Mean	0.688	0.679	0.650	0.585	0.537	0.585	0.621
Median	0.703	0.698	0.674	0.603	0.535	0.586	
Standard deviation	0.206	0.206	0.206	0.222	0.239	0.222	
Minimum	0.243	0.196	0.186	0.176	0.128	0.176	
Maximum	1.000	1.000	1.000	1.000	1.000	1.000	
Input-orientated pure technical efficiency							
Mean	0.751	0.761	0.748	0.684	0.661	0.684	0.715
Median	0.750	0.764	0.750	0.682	0.647	0.688	
Standard deviation	0.170	0.171	0.174	0.191	0.201	0.191	
Minimum	0.376	0.257	0.257	0.217	0.197	0.217	
Maximum	1.000	1.000	1.000	1.000	1.000	1.000	
Output-orientated pure technical efficiency							
Mean	0.875	0.881	0.875	0.844	0.843	0.853	0.862
Median	0.899	0.894	0.891	0.862	0.859	0.873	
Standard deviation	0.108	0.104	0.105	0.121	0.122	0.116	
Minimum	0.509	0.559	0.552	0.457	0.482	0.461	
Maximum	1.000	1.000	1.000	1.000	1.000	1.000	
Scale efficiency							
Mean	0.912	0.892	0.872	0.857	0.813	0.857	0.867
Median	0.981	0.972	0.959	0.964	0.931	0.944	
Standard deviation	0.150	0.169	0.183	0.207	0.237	0.207	
Minimum	0.313	0.289	0.258	0.194	0.189	0.194	
Maximum	1.000	1.000	1.000	1.000	1.000	1.000	

Table 4
Input-orientated pure technical efficiency scores (x-PTE) by individual country

	2005	2006	2007	2008	2009	2010	Mean
Austria	0.738	0.760	0.726	0.686	0.670	0.685	0.711
Belgium	0.704	0.704	0.698	0.487	0.448	0.539	0.596
Denmark	0.920	0.943	0.914	0.748	0.680	0.760	0.828
Finland	0.697	0.797	0.709	0.563	0.557	0.650	0.662
France	0.761	0.787	0.784	0.727	0.718	0.746	0.754
Germany	0.707	0.749	0.779	0.687	0.700	0.713	0.723
Greece	0.589	0.558	0.553	0.496	0.445	0.393	0.506
Ireland	0.767	0.757	0.749	0.658	0.575	0.585	0.682
Italy	0.724	0.701	0.672	0.611	0.630	0.633	0.662
Luxembourg	0.794	0.835	0.800	0.669	0.712	0.767	0.763
Netherlands	0.790	0.783	0.798	0.740	0.650	0.682	0.741
Portugal	0.681	0.718	0.673	0.645	0.665	0.670	0.675
Spain	0.707	0.714	0.696	0.680	0.613	0.660	0.678
Sweden	0.874	0.958	0.987	0.849	0.871	0.873	0.902
United Kingdom	0.805	0.793	0.792	0.758	0.732	0.756	0.773

Table 5
Output-orientated pure technical efficiency scores (y-PTE) by individual country

	2005	2006	2007	2008	2009	2010	Mean
Austria	0.893	0.894	0.879	0.852	0.865	0.875	0.876
Belgium	0.730	0.755	0.765	0.625	0.601	0.661	0.689
Denmark	0.970	0.979	0.965	0.906	0.903	0.916	0.940
Finland	0.818	0.865	0.825	0.739	0.778	0.815	0.806
France	0.878	0.894	0.895	0.864	0.864	0.879	0.879
Germany	0.829	0.856	0.862	0.815	0.827	0.824	0.835
Greece	0.803	0.784	0.764	0.738	0.732	0.713	0.756
Ireland	0.860	0.860	0.869	0.837	0.762	0.793	0.830
Italy	0.875	0.865	0.849	0.820	0.847	0.845	0.850
Luxembourg	0.890	0.914	0.896	0.832	0.851	0.865	0.875
Netherlands	0.897	0.897	0.897	0.874	0.841	0.861	0.878
Portugal	0.834	0.848	0.831	0.813	0.839	0.848	0.835
Spain	0.869	0.876	0.868	0.858	0.837	0.852	0.860
Sweden	0.908	0.971	0.992	0.910	0.923	0.923	0.938
United Kingdom	0.900	0.896	0.896	0.887	0.879	0.887	0.891

Table 6
Comparison of pre- and post-crisis efficiency measures by country

	Input-orientated pure technical efficiency			Output-orientated pure technical efficiency		
	Pre-crisis	Post-crisis	Difference (%)	Pre-crisis	Post-crisis	Difference (%)
Austria	0.749	0.678	-7.13	0.894	0.870	-2.40
Belgium	0.704	0.493	-21.04	0.743	0.631	-11.16
Denmark	0.932	0.720	-21.14	0.974	0.909	-6.50
Finland	0.747	0.603	-14.39	0.841	0.796	-4.52
France	0.774	0.732	-4.23	0.886	0.871	-1.49
Germany	0.728	0.707	-2.17	0.842	0.826	-1.67
Greece	0.574	0.419	-15.45	0.794	0.722	-7.14
Ireland	0.762	0.580	-18.18	0.860	0.778	-8.23
Italy	0.712	0.632	-8.05	0.870	0.846	-2.38
Luxembourg	0.814	0.739	-7.51	0.902	0.858	-4.42
Netherlands	0.786	0.666	-12.02	0.897	0.851	-4.62
Portugal	0.700	0.668	-3.18	0.841	0.844	0.28
Spain	0.711	0.636	-7.42	0.872	0.845	-2.76
Sweden	0.916	0.872	-4.41	0.939	0.923	-1.60
UK	0.799	0.744	-5.46	0.898	0.883	-1.51

Note: Pre-crisis measure is equal to the mean of the efficiency scores of 2005 and 2006; Post-crisis measure is equal to the mean of the efficiency scores of 2009 and 2010.

Table 7
Mean efficiency scores with regard to bank specialisation

	2005	2006	2007	2008	2009	2010	Mean
Commercial banks							
Overall technical efficiency	0.664	0.658	0.627	0.543	0.492	0.531	0.586
Input-orientated pure technical efficiency	0.745	0.762	0.752	0.672	0.652	0.678	0.710
Output-orientated pure technical efficiency	0.861	0.872	0.867	0.827	0.825	0.837	0.848
Scale efficiency	0.889	0.864	0.839	0.814	0.760	0.788	0.826
Cooperative banks							
Overall technical efficiency	0.647	0.642	0.620	0.573	0.530	0.560	0.595
Input-orientated pure technical efficiency	0.707	0.721	0.708	0.655	0.643	0.669	0.684
Output-orientated pure technical efficiency	0.866	0.874	0.868	0.840	0.848	0.858	0.859
Scale efficiency	0.915	0.897	0.885	0.884	0.830	0.843	0.876
Real-Estate & Mortgage banks							
Overall technical efficiency	0.857	0.830	0.813	0.790	0.751	0.769	0.802
Input-orientated pure technical efficiency	0.874	0.854	0.844	0.817	0.771	0.800	0.827
Output-orientated pure technical efficiency	0.953	0.942	0.938	0.934	0.920	0.929	0.936
Scale efficiency	0.979	0.970	0.959	0.967	0.971	0.961	0.968
Savings banks							
Overall technical efficiency	0.702	0.689	0.644	0.600	0.546	0.575	0.626
Input-orientated pure technical efficiency	0.730	0.723	0.690	0.648	0.615	0.631	0.673
Output-orientated pure technical efficiency	0.880	0.876	0.857	0.842	0.847	0.845	0.858
Scale efficiency	0.953	0.945	0.926	0.917	0.882	0.903	0.921