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Economies of Scale and Efficiency in European Banking: New Evidence

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Notes

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Non-Technical Summary

The recent wave of bank mergers and acquisitions suggests that bankers around the world are attempting to create more lean (cost efficient) and profitable financial institutions by reducing overlapping branches, cutting labour costs, exploiting scope economies and implementing new technology that may need large scale to be effective. This paper investigates whether about 2000 credit institutions across 15 European countries have managed to reduce costs since the implementation of the Second Banking Directive of the European Union in 1993. It reveals whether there is scope for further restructuring and how and where possible economic gains can be achieved.

A cost frontier, i.e. a function which relates the minimum costs incurred for producing a certain mix and level of outputs given the input prices, is estimated using a new econometric technique, the Recursive Thick Frontier Approach (RTFA). This method is discussed in more detail in Economic and Financial Report, 99/02. It is assumed that the frontier applies at the European level, i.e. banks located in any region of the European union can achieve *best practice* as indicated by the frontier, but the cost function discriminates between banks of different legal status and allows for shifts in average costs over time. The econometric approach allows for deviations from the cost frontier that are due to random effects because of measurement errors, unobservable shocks and factors which are beyond the sphere of influence of the banks' management. On the other hand, deviations may also reflect inefficiency due to wasted resources as a result of managerial incompetence in controlling costs.

Scale economies, structural changes in average costs due to, for instance, *technological progress*, costs differences between different *types* of credit institutions and a measure of managerial efficiency or so-called *X-efficiency* are computed on the basis of this cost frontier. Measuring *scope economies* is beyond the scope of this study. In this analysis we adopt the idea that differences in efficiency stem from both wasting of resources due to bad management and unprofitable acquirement of these resources.

New empirical evidence regarding the performance of European banks is obtained by estimating an augmented Cobb-Douglas model, which allows us to disentangle the effects of input prices on average costs from other time-related effects such as technological progress. For our sample period this is important as average costs fell about 20% for the overall European banking industry just because the average interbank rate, which is used to construct the price of the input loanable funds, fell from 8.4% to 4.5%.

To summarise our results, we find that the cost structure and performance of European banks over the period 1993-1997 can be characterised by the following key observations:

We do not find major economic gains from *positive economies of scale* for the overall European banking industry. The picture becomes slightly different when looking only at the saving sector. Our results indicate that cost reductions of about 6% can be achieved for savings banks through larger (or, in some cases, smaller) scale. However, increasing returns to scale do only exist for firms up to a size of EUR 600 million. The average cost curve is clearly U-shaped for saving institutions since the ten largest firms, i.e. with total assets exceeding EUR 50 billion, have significantly higher costs than savings banks in the optimal size class. For commercial banks the optimal size picture is less transparent, which is possibly due to the fact that this group of banks is highly diverse. Some small investment banks that offer a range of products which is substantially different from the average product mix, could belong to this group.

Significant shifts in the cost frontier over time were only detected for saving institutions. The drop of about 9 percent in average costs experienced by the best practice savings banks could be due to technological innovation but may equally well indicate that these banks have reduced their distance to the even more efficient best practice commercial banks by cutting costs in other ways. Indeed, different types of credit institutions are operating on different average cost levels. For instance, when taking into account the full sample of credit institutions, we find that X-efficient commercial banks incur, on average, four per cent lower costs per unit of assets than X-efficient savings banks during the sample period. Mortgage banks, in their turn, have considerably lower costs than commercial banks.

From a cost reduction point of view, one may therefore expect that competitive forces will eventually trigger restructuring of the European banking sector in the form of de-mutualisation of savings banks. On the other hand, in contrast to savings banks, mortgage banks are considerably different from commercial banks in respect of the financial services they offer. It is, thus, very likely that certain types of niche players may flourish while at the same time the bulk of the European financial institutions go in the direction of commercial banking.

In contrast with the relatively modest consequences of size, technology and type, large cost reductions are possible when managers organise their business in a more efficient manner. Our results show that more than 80% of the European banks are not located at their cost frontier and that these banks can reduce the cost per unit of assets with more than 16% on average. The slimming course of the European banking sector has already led to substantial cost cutting across Europe, and X-inefficiency decreased on average by about four percent over our sample period. A remarkable result is that bankers in the UK were able to reduce X-inefficiencies from over 20% to essentially zero in this fairly short time span. Although some countries showed rapid improvement in bank performance, in other countries such as Austria, France, Germany, and Luxembourg, bankers have yet to start their diet. Therefore, considerable differences in cost efficiency still exist across Europe. The most striking outliers are the Greek commercial banks. Although Greek bankers also improved, average X-inefficiency still exceeded 59 per cent in 1997.

Splitting up the sample into large banks, when their total assets exceeded EUR 10 billion in 1997, and smaller ones, reveals some additional interesting results. The 200 big banks of our sample have around 6 per cent lower X-inefficiency than their 1774 smaller peers. To us this result seems somewhat counterintuitive as we would expect that smaller banks are easier to manage. Possibly large banks operate in a more competitive environment which forces them to be more efficient. Another reason can be that managers of large commercial banks are better monitored by shareholders. However, both small and large banks reduced their X-inefficiency over time.

Although the European banking industry is at the beginning of a new era with the introduction of the Euro, one can only guess about the rapidity at which the necessary restructuring will take place. Restrictive labour laws, state ownership and other forms of state intervention, cultural and language barriers to cross border banking and the like may limit the pace of changes in European banking. However, there is plenty of scope to reduce costs and enhance efficiency throughout Europe.

Abstract

This paper investigates the cost efficiency of 1974 credit institutions across 15 European countries over the five-year period following the implementation of the Second Banking Directive in 1993. The Recursive Thick Frontier Approach is employed to estimate a *Augmented* Cobb-Douglas cost frontier that allows banks of different types, in different periods, and belonging to different size categories, to operate at different costs per unit of assets. As size economies are exhausted at a balance sheet total of EUR 600 million, we do not find major economic gains from economies of scale for the overall European banking industry. However, the saving bank sector may reduce average costs with roughly 6% by choosing an optimal size for its institutions. No impact of technological progress on the average costs of the full sample of X-efficient banks could be detected but managerial efficient saving banks reduced average costs with 9% during our sample period. The most important reason for inefficiencies in the European banking is managerial inability to control costs. Although in some countries such as the UK and The Netherlands cost reductions were rapidly achieved, the average level of X-inefficiency of European banks still exceeded 16% in 1997.

JEL Classification Number: G21

Keywords: X-efficiency, Economies of scale, European Banking, Cost Frontier, Recursive Thick Frontier Approach

1. Introduction

The number of studies that evaluate the performance of European banks sink into insignificance beside the voluminous literature on US financial institutions. This paper partially fills this gap by investigating the cost efficiency of almost 2000 credit institutions across 15 European countries.

On the first of January 1993, the Second Banking Directive (1988) of the European Union and a number of the other key EU directives[1] related to the financial service industry were implemented. This heralded a new episode of deregulation, standardised capital requirements and changes in supervision rules and deposit-guarantee schemes. The *single passport* and *mutual recognition* have cleared the road for cross-border banking, while the introduction of the Euro on the first of January 1999 took away one of the last obstacles for a competitive and integrated banking market. The general belief among bankers and academics is that competition has significantly increased in this changing European banking environment. Indeed, the numerous cases of recent mergers and acquisitions in the financial world would indicate that bankers and insurers are trying to reshape their businesses into more profitable and lean (cost efficient) institutions in order to face national and global competitive pressures. Traditional income streams such as interest margins have dried up, whereas new sources of revenues such as brokerage services, investment banking products, risk management and portfolio management have become more and more important. Besides major changes in the regulatory environment, the banking industry will be further modernised by the implementation of new computer technologies.

Given the broad picture sketched above, one may ask whether the performance of European credit institutions over the five years following the implementation of the Second Banking Directive has improved. In this paper we evaluate the performance of banks in this period by looking at cost efficiency, i.e. whether banks minimise the cost incurred per unit of assets. In particular, we analyse how production costs depend on scale economies, managerial efficiency (or so-called X-efficiency), technological progress, and the legal status of the institutions. For this purpose, we estimate a cost frontier of the minimum costs to produce a certain mix and level of outputs given the prices of inputs.

What kind of questions do we not address? Our model is less suitable to measure economies of scope. One of the reasons for this are the restrictions on the substitutability between inputs and outputs that are imposed on the functional form of our cost model. Therefore, we refrain from predicting what will be the economic gains of *universal banking*. In recent efficiency studies, however, only small increasing economies of scope were detected. See Berger, Hunter and Timme (1993), Berger and Humphrey (1997), Berger and Mester (1997), and Berger, Demsetz and Strahan (1998) for comprehensive surveys on empirical findings regarding the existence of scale and scope economies and X-efficiency of financial institutions.

From the duality theorem it follows that the technology of a firm can be described by the parameters of the cost function. However, optimising the level of output given the available resources does not necessarily lead to profit and revenue maximisation in economies that can

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[1] Namely, the Money Laundering Directive, the Own Funds Directive, the Solvency Ratio Directive, the Consolidated Supervision Directive, and the directive on Deposit-Guarantee Schemes. The Large Exposures Directive, the Capital Adequacy Directive and the Investment Services Directive came into force in 1994, 1995 and 1996 respectively. See, among others, Molyneux et al. (1996).

be characterised by, for instance, oligopolistic markets, asymmetric information and risk-averse individuals. In response to this argument, some recent articles (see, among others, Berger and Mester (1997), and Rogers (1998)) consider, besides the traditional cost function, also the profit and revenue frontiers and derive from these functions X-efficiency measures. Although these studies give useful insights in the differences in profitability of banks, a serious problem with these approaches, however, is that market power may obscure the efficiency (in terms of productivity) results. In this study we only focus on cost minimisation, and leave profit or revenue maximisation aside.[2]

This paper innovates with respect to traditional cost frontier analyses in three distinctive ways:

● First, a new econometric technique is employed to estimate the parameters of the cost function. A detailed exposition of the method, the so-called Recursive Thick Frontier Approach (RTFA), is given in Wagenvoort and Schure (1999). The traditional econometric techniques for frontier models, namely the Stochastic Frontier Approach (SFA), the Thick Frontier Approach (TFA) and the Distribution Free Approach (DFA) (see Aigner, Lovell and Schmidt (1977), Berger and Humphrey (1992) and Berger (1993) respectively) have in common that they depend on *a priori* assumptions that are, whether feasible or not, difficult to test. Our approach is based on the assertion that if deviations from the frontier of X-efficient companies are completely random then one must observe for this group of banks that the probability of being located either above or below the frontier is equal to one half. This hypothesis can be tested for panel data sets but requires sorting of the full sample into a group of X-*in*efficient banks and a group of X-efficient banks. The cost frontier is estimated using only the observations of the latter category.

● Second, we present a method to disentangle the effects of input prices on the average costs from other time-related effects such as structural changes caused by innovation in technology and deregulation. In other words, we are able to reveal shifts in the cost frontier over time.

To specify the cost model we choose the Cobb-Douglas function augmented with dummies in order to measure differences in average costs due to the time period, the bank's type (legal status) and its size category. In response to the critique that the standard Cobb-Douglas and Translog cost functions are too restrictive to accurately measure economies of scale[3] we include seven size dummies in the cost function. This way of modelling gives sufficient flexibility with respect to economies of scale, and can include a U-shaped average cost curve. A discussion of the relative merits of this approach is given in section 3.

● Third, our data set allows for a more general definition of X-efficiency than obtained in the usual studies of this type. In traditional cost studies, X-inefficiencies may appear due to wasting of resources. However, differences in performance cannot be caused by inefficient acquisition of the inputs, since every bank is assigned a different input price vector, usually based on the actual cost incurred. For example, the price of labour is defined as the bank's

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[2] An interesting related topic is whether high market concentration or high market shares is a result of better performance or whether it reflects monopoly power. This question is especially relevant for public policy considerations of anti-trust institutions. In this study we do not test this so-called *structure-conduct-performance* relationship (see, among many others, Berger (1995), Goldberg and Rai (1996) and Maudos (1998)).

[3] Therefore, recent stochastic cost frontier studies consider the Fourier Flexible functional form (see Altunbas et al. (1999), Altunbas, Goddard and Molyneux (1999), and Berger and Mester (1997)).

expenses on labour divided by its number of employees. Choosing input prices in this way means that they will differ for each bank in the sample. It is thus implicitly assumed that banks pay the "right" amount for their inputs which may differ in quality. By contrast, in our study we adopt the idea that differences in efficiency stem from both the wasting of resources and because managers acquire these resources inefficiently. In particular, input prices are, as far as possible, constructed from general price indices (for buildings, financial services, wages etc.) instead of the actual expenses of a bank. In our case, input prices are equal for different banks in the same country and the same year.

McAllister and McManus (1993) argue that the traditional way of choosing input prices may bring about the economies of scale puzzle[4] since larger firms have better risk diversification opportunities and thus lower cost of funding than small firms. These so-called *financial* scale economies will also be revealed by our approach. If larger banks pay less than our constructed average price of funds, and thus have lower interest costs, then these banks will have lower average costs than small banks and this will eventually show up in our measure of economies of scale. In most recent cost studies this effect would remain undiscovered.

Our results on the efficiency of European banks can be very briefly summarised as follows: the reported X-inefficiencies, which are on average between 16% and 20%, dominate by far the possible gains from size economies. Although the saving bank sector can reduce the costs per unit of assets by roughly 5% by increasing size, significant scale effects are only found for small institutions (with total assets up to EUR 600 million). For the overall banking industry, economies of scale are negligible with respect to the cost reductions that can be achieved by improving the quality of its managers. For the full sample, technological progress could not be detected. On the contrary, the average costs of X-efficient saving banks were significantly reduced (with 9%) during the sample period 1993-1997, possibly due to technological innovation. Substantial differences in X-efficiencies exist across Europe. In 1997, UK bankers were almost fully efficient, whereas Greek bankers were the most inefficient ones with X-inefficiencies exceeding, on average, the 55% level. A striking result however is that the cost dispersions in some European countries, i.e. Finland, Ireland, Italy, The Netherlands and the UK, were rapidly reduced.

These empirical findings are in accordance with earlier studies on US financial institutions (see, for instance, Berger, Hanweck and Humphrey (1987), McAllister and McManus (1993) and the review article of Berger and Humphrey (1997)) but contradict recent results on the scale efficiency of both American and European financial institutions. Hughes and Mester (1998), and Altunbas and Molyneux (1996) find positive economies of scale for a broader range of size classes for American banks and French and Italian banks respectively, including banks with total assets above USD 3 billion.[5]

There are various reasons that could explain why size economies were not revealed by our study. Hughes and Mester (1998) argue that large banks take more risk due to the financial scale economies mentioned above. As a consequence, the quality of the output mix of larger banks is of a different nature than the quality of the financial products of small credit institutions. Therefore, large banks may incur higher costs per unit of offered financial services and thus measures of output quality must be included in the cost model when

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[4] Empirical studies on US banks in the 1980s and early 1990s do not find large scale economies.

[5] However, Altunbas and Molyneux (1996) do not find significant sale economies for banks above the size of USD 100 million in Germany and Spain.

assessing efficiency. A closely related argument is that big banks may profit from scope economies that could not be revealed by our *augmented* Cobb-Douglas function.

The remainder of this paper is organised as follows: In the next section we enlarge upon the cost frontier methodology by explaining the adopted *intermediation* approach and discussing several problems related to it. Section 3 contains a thorough exposition of our cost model and introduces various efficiency measures. The econometric method is briefly explained in Section 4, whereas the data sources, variable definitions, and some summary statistics are presented in Section 5. Section 6 contains the results, while Section 7 concludes. Finally, Appendix A1 and Appendix A2, with detailed information on price data and the tables containing the regression results respectively, are attached.

2. The Method

When assessing efficiency one can be interested in *X-efficiency* --i.e. whether banks use their available inputs efficiently, *scale efficiency* --i.e. whether banks produce the right amount of outputs, and *scope efficiency* – i.e. whether banks choose an efficient combination of outputs. All types of efficiencies shed light on a different aspect of the production technology of banks. As was mentioned in the introduction, this paper addresses X-efficiency and scale efficiency.

Since we study the production technology of banks it seems natural to establish estimates of their production function. This, however, immediately leads to a difficulty. A bank normally has multiple outputs rather than a single one, so a statistical model of the production function would have multiple endogenous variables and is hence difficult to estimate. For this reason bank efficiency studies usually focus on the banks' cost function or profit function. This is a valid approach, as, by the Duality Theorem, we know that a cost function summarises all the relevant information of a firm's technology.[6] By concentrating on the cost function we are left with only one endogenous variable: total costs.

By definition a cost function gives the minimum costs to produce a specific set of outputs for given input prices. Therefore, when establishing an equation relating total costs to an output vector and input prices we can only call this a cost function when assuming that some of the banks in the data set indeed minimise costs. In our analysis we make this assumption.[7]

A cost function relates costs to outputs –or *production*-- and input prices. However, it is not at all trivial what is meant by the outputs and inputs of a bank. As an illustration, bank efficiency studies have adopted entirely different definitions of the production of a bank. Berger and Humphrey (1992) distinguish three approaches to defining bank outputs. For instance, the *Asset Approach* defines the assets of a bank as outputs and the liabilities as inputs. The *User Cost Approach* treats assets or liabilities that increase the value of the banking firm as outputs, and the remaining assets and liabilities as inputs. We view the bank as a *producer of services* such as screening projects, monitoring borrowers, enforcing contracts, portfolio selection, hedging risks, providing brokerage services, keeping deposits and other claims liquid, providing repayment insurance, etc. By defining services as the banks' production implies that we adopt what Berger and Humphrey (1992) call the *Value-*

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[6] The Duality Theorem can be found in any standard micro textbook such as for example Varian (1992).

[7] To be more precise we assume this to be true for banks on the *efficient frontier* (see the next section).

Added Approach in defining a bank's production.[8] All services which are needed to generate the value-added are defined as our inputs. For example, man-power and office space are inputs as they are needed for the service production of a bank. A detailed description of the outputs and input prices we chose in this study can be found in Section 5.

Measuring the service production of a bank is a problem in itself. How are for example the services offered to account holders quantified? Ideally one would like to have data on the number of transactions processed, the number of account statements sent to customers and the like. Unfortunately these data are not available. And for other outputs, such as the 'amount' of contract enforcement and the 'amount' of risk hedged, the problems get even worse. In the Value-Added Approach these problems are by-passed by assuming that the amount of services produced are proportional to various variables on the balance sheet and the profit and loss account. Variables which are recognised to imply service production are then used as proxies for the amount of services produced and plugged in the statistical model. As an example, loans are considered to be an output because when offering loans, services are supplied, such as screening the projects, monitoring borrowers, enforcing contracts, and diversifying risks. Another output could be deposits, as deposits imply services such as processing of transactions, production of account statements, etc. It is less clear that assets such as government bonds are production as normally purchasing government bonds does not imply much screening effort or contract enforcement. Some of these assets provide liquidity and thus, beside having some output characteristics, are an input in the form of loanable funds, though this is not considered here.

Variables on the balance sheet and profit and loss account often vastly overstate the actual flow of services produced. However, this is simply a scaling problem. So the product of the amount of loans and its concomitant parameter estimate will still correctly represent the contribution of loan services on total costs.

What is a problem in case of panel data, though, is that the values of certain variables may not imply an equal proportion of service production in different years. For example, if deposits of a bank in a specific year are twice as high as in the preceding year, this need not imply that the amount of deposit services have also doubled. That is, if inflation has been substantial, then a deflator must be employed to keep outputs in different years comparable. Yet, we do not know of any panel data study that addresses this issue. In this paper we attempt to keep outputs in different years comparable by *scaling* the output variables. The details of this and an econometric argument for it are presented in the next section.

A more fundamental problem with this study, and many other bank efficiency studies, is that amounts of certain variables of different banks may not be comparable.[9] Take the example of customer loans on the balance sheet. Customer loans are heterogeneous and different banks may supply different types of loans which require a different amount of service production. It may hence be that, without being inefficient, one bank incurs higher costs per unit of loans. As a result, this bank will incorrectly be judged as being inefficient in supplying loans. In our study this problem is potentially severe. Namely, as our focus is on the European Union we will have to assume that within this area output proxies can be compared. Although the

[8] Viewing banks as intermediators of financial services is traditionally called the "intermediation approach" (see Sealey and Lindley (1977)).

[9] Mester (1996) attempts to address this problem by including the average volume of non-performing loans as a measure for the quality of the loan portfolio.

implementation of the Second Banking Directive on 1 January 1993 implied a considerable harmonisation of the EU banking laws, it is clear that there are still large structural differences between EU member states. We must bear this in mind when interpreting the results in section 6.

3. The Cost Frontier

3.1 Background

Cost frontiers for banking industries are usually estimated by regressing the natural logarithm of total costs on a particular function with outputs and input prices (or their logs) as its arguments:

$$\ln TC_{ti} = f_t(y_{ti,1},\ldots, y_{ti,K}, p_{t1},\ldots, p_{tJ}) + \varepsilon_{ti}. \qquad (1)$$

In equation (1) TC_{ti} represents the total cost of firm i in period t. K and J represent the number of outputs produced by firm i and the number of its inputs, respectively. The amount of output of type k is denoted by $y_{ti,k}$, $k = 1,\ldots,K$; the price of input *j* by p_{tj}, $j = 1,\ldots,J$; and the disturbance term by ε_{ti}.

The functional form of $f_t(\cdot)$ is usually chosen to be a second-order Taylor approximation in logs of a general cost function, the so-called translog cost function. The translog cost function provides a fairly general specification of a bank's technology. Some recent cost frontier studies using a translog cost function are Altunbas and Molyneux (1996), Berger (1995), Berger and Hannan (1998), Goldberg and Ray (1996), Lang and Welzel (1996), Hughes and Mester (1998), Maudos (1998), Mester (1996), Rogers (1998), and Vander Vennet (1996). Other studies choose the Cobb-Douglas function [Cooper (1980), Fanjul and Maravall (1985)] or the Fourier Flexible form [Altunbas (1997), DeYoung and Hasan (1998)] to model the banks' technology. A disadvantage of the Cobb-Douglas specification with respect to the other two is that it implies a stronger restriction on the set of technologies which can be borne out by the data. For example, the elasticity of substitution between inputs is restricted to equal one for a Cobb-Douglas specification. Furthermore, it imposes restrictions on the substitutability between outputs and it does not allow for U-shaped average cost curves. For these reasons, the standard Cobb-Douglas functional form is less suitable to measure for instance economies of scope or scale.

Despite its disadvantages we choose the Cobb-Douglas specification in this study. There are two reasons for this choice. First, taking the adjusted R-squared as a measure, the translog cost function specification does not better explain our data than the Cobb-Douglas specification. Yet, the results of the translog specification are far more difficult to interpret.[10] Second, due to price changes in the time period which we consider, it appears necessary to distinguish between the effect of price developments on costs and other effects such as changes in technology. As we will see below we found an appealing solution for this problem, but one which is not suitable for the translog specification.

[10] As an example, using the translog cost function we obtained one significantly negative price coefficient and two which exceeded one.

In the remaining part of this section we discuss how the unknown parameters of relationship (1) can be consistently estimated. The discussion takes the Cobb-Douglas cost function as example but would also apply to other specifications. Then we proceed with explaining how to interpret results from the regressions. In particular, we address how technological progress could be identified[11], how X-efficiency is measured, and how to determine scale economies. For expositional simplicity we take the number of our regressors as those used in our regressions, so we have 5 output variables ($K = 5$), 3 input prices ($J = 3$), 5 time periods ($T = 5$) and 4 different types of banks.

3.2 Specification

3.2.1 Scaling the outputs.

A first problem encountered when estimating equation (1) is that the regressors and the error term are likely to be dependent. Consequently, standard regression results will be invalid. To see this, note that a bank which is operating on a large scale, i.e. with relatively high values of the output variables, has in general relatively high costs. In case this bank is inefficient and given a certain per unit output inefficiency, it will deviate in absolute terms to a larger extent from the efficient frontier than a small inefficient bank. For an inefficient bank, the inefficiency component of ε_{ti} will depend, among other things, on the bank's operating scale. In other words, the disturbances are not orthogonal to the regressors in model (1) and we cannot get consistent estimates without resorting to instrumental variable estimation or appropriately scaling the model. We propose to follow the latter solution and suggest scaling by dividing the left-hand side and the right-hand side of equation (1) by total assets, which is a proxy for size. Scaling has two advantages. First, we fulfil the fundamental orthogonality condition referred to above. Second, a cost function requires the outputs to be in physical units, rather than nominal values. Without scaling our output proxies are nominal quantities which might imply that in different years they are not comparable. Scaling will reduce this output measurement problem.

3.2.2 Economies of Scale.

There are three reasons for including dummy variables in model (1) for different size classes. First, scaling may not necessarily fully solve the problem of non-orthogonality of the error terms. Inefficiency may depend on size in a non-linear way. In this case, including size dummies further reduces the under-estimation of the unknown parameters in relationship (1). Second, by inserting 7 size dummies we allow for a fairly general form of the average cost curve that encompasses the U-shaped average cost function. The Cobb-Douglas function with size dummies can exhibit decreasing, increasing or constant returns to scale in any order. Third, economies of scale can be directly observed from the computed regression coefficients associated with the size dummies. In other efficiency studies it is common to compute economies of scale by differentiating the cost function.

[11] Strictly speaking, we are only able to detect shifts in the cost frontier over time. These shifts over time can also have different causes than changes in technology. Examples are regulatory changes, structural developments or other factors that determine the optimal cost of a bank, but are not incorporated in the cost function.

We split our sample of European banks into 8 non-overlapping size groups.[12] For example, the size dummy (s_1) for the group of smallest banks is defined according to $s_{1,ti} = 1$ if $TA_{ti} \leq$ EUR 100 million, $s_{1,ti} = 0$ otherwise. TA_{ti} are the total assets of bank i in period t.

3.2.3 Price changes versus changes in the frontier over time.

In a panel data framework, the functional form f must take into account that the frontier may change over time due to technological progress, changes in regulation or other structural developments. In equation (1) this has been made explicit by adding a subscript t to the functional form f. To allow for these shifts of the efficient frontier we include time dummies in our model. Specifically, as we consider a time period of 5 years we include $T-1=4$ time dummies in regression equation (1). Unfortunately, this gives rise to a problem with the interpretation of the estimated parameters. In particular, input prices can show general time patterns in which case the time dummies are correlated with the price variables. For example, for our data set the price of funds decreased in time whereas the price of buildings and labour steadily increased. As a consequence the time dummies will not only pick up the effects of technological progress and the like, but also these price changes.

A solution to this econometric problem is obtained by first regressing each input price on a constant and the time dummies. In other words, before estimating model (1) we perform the following three auxiliary regressions:

$$\ln p_{tj} = \eta_{0j} + t_1\eta_{1j} + t_2\eta_{2j} + t_3\eta_{3j} + t_4\eta_{4j} + dp_{tj}, \quad j = 1,..,3 \qquad (2)$$

Here $\eta_{0j}, \eta_{1j}, \eta_{2j}, \eta_{3j}, \eta_{4j}$ are the unknown parameters of the constant and the four time dummies $t_1,..,t_4$, respectively, and $dp_{tj}, t = 1,..,T$ are the errors. These errors can be interpreted as the deviation of the prices from their time pattern in Europe. At first glance regression (2) looks strange as the notation suggests that we have five observations and as many unknown parameters. However, for each country we have different price observations, so that the equation detects a general (EU-15) time pattern in each price. Subscripts indicating the relevant price in each country are omitted for notational clarity. Estimation of (2) yields:[13]

$$dp^*_{tj} = \ln p_{tj} - \eta^*_{0j} - t_1\eta^*_{1j} - ... - t_4\eta^*_{4j}, \quad j = 1,..,3 \qquad (3)$$

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[12] Group 1: total assets ≤ 100 million ECU

Group 2: 100 million ECU < total assets ≤ 300 million ECU

Group 3: 300 million ECU < total assets ≤ 600 million ECU

Group 4: 600 million ECU < total assets ≤ 1 billion ECU

Group 5: 1 billion ECU < total assets ≤ 5 billion ECU

Group 6: 5 billion ECU < total assets ≤ 10 billion ECU

Group 7: 10 billion ECU < total assets ≤ 50 billion ECU

Group 8: 50 billion ECU < total assets.

In the remainder of the text we will write EUR instead of ECU, although the basket of currencies that constitutes the ECU is slightly different from the one that constitutes the Euro.

[13] In the next equation and later sections, parameters with superscript * represent estimated values.

By construction, the estimated deviations in the prices, after taking into account time effects, are orthogonal to the time dummies. Therefore, price effects on total costs can be separated from other effects such as technological progress and the like by substituting equation (3) in model (1) (see equation (5) below). In the case of the translog cost function, however, the number of explanatory variables in the resulting regression equation explodes. As we mentioned above this was one consideration for choosing the more restrictive Cobb-Douglas specification in this paper.

3.2.4 Type dummies.

Different types of banks can have different cost structures. This can be due to the fact that different types of banks operate on different market segments which require a more costly or less costly treatment of the financial products offered. Also it may be that differences in the regulatory environment faced by the various types of banks affect their costs. Finally, some types of banks may simply be X-inefficient. In the first two cases it is appropriate to add type dummies to the cost frontier. Indeed, in these cases differences in costs are beyond control of the managers of the banks and hence have nothing to do with a difference in X-efficiency. In the latter case, instead, one should not add type dummies.

We have chosen to include three type dummies in order to distinguish between four different types of banks. Cost differences between the various bank types are thus detected by looking at the estimated coefficients of the type dummies in the model. Needless to say, it is up to the researcher to judge how the type dummy coefficients are to be interpreted. One can think that type differences imply different cost structures for banks. Alternatively one can suspect that cost differences between bank types are due to differences in X-efficiency.[14]

3.2.5 The model.

After scaling total costs and the output variables, and inserting all the dummies introduced above, the Cobb-Douglas cost function becomes:

$$\frac{TC_{ti}}{TA_{ti}} = \gamma_0 \left(\frac{y_{ti,1}}{TA_{ti}}\right)^{\beta_1} \cdots \left(\frac{y_{ti,5}}{TA_{ti}}\right)^{\beta_5} p_{t1}^{\alpha_1} p_{t2}^{\alpha_2} p_{t3}^{\alpha_3} \sigma_1^{s_{1,ti}} \ldots \sigma_7^{s_{7,ti}} \delta_1^{t_1} \ldots \delta_4^{t_4} \gamma_1^{d_{1i}} \gamma_2^{d_{2i}} \gamma_3^{d_{3i}} + \varepsilon_{ti} \qquad (4)$$

In equation (4), $d_{1i},..,d_{3i}$ are the values of the type dummies of bank i. Let $w = (\gamma_0, \beta_1,.., \beta_5, \alpha_1, \alpha_2, \alpha_3, \sigma_1,..., \sigma_7, \delta_1,.., \delta_4, \gamma_1, \gamma_2, \gamma_3)$ be the vector of parameters to be estimated. Under the null hypothesis of no economies of scale, no technological innovation or other structural changes and equal cost structures across different types of institutions the parameters $(\sigma_1,.., \sigma_7, \delta_1,.., \delta_4, \gamma_1,.., \gamma_3)$ are all equal to one.

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[14] Besides economic considerations, there are two econometric arguments for putting in type dummies. First, in the presence of substantial efficiency differences between the various types of banks, the number of banks on the cost frontier might become too small to generate reliable parameter estimates. Second, if it were the case that X-efficiency and types are correlated then by omitting type dummies we obtain significant correlations between the error term and the regressors (assuming that different types of banks have a different output mix). This invalidates the regression results.

Taking logs of both sides of equation (4) and using the equations in (3) gives[15]:

$$\ln\left(\frac{TC_{ti}}{TA_{ti}}\right) = c + \beta_1 \ln\left(\frac{y_{ti,1}}{TA_{ti}}\right) + ... + \beta_5 \ln\left(\frac{y_{ti,5}}{TA_{ti}}\right) + \alpha_1 dp^*_{t1} + ... + \alpha_3 dp^*_{t3}$$

$$+ s_{1,ti}\kappa_1 + ... + s_{7,ti}\kappa_7 + t_1\lambda_1 + ... + t_4\lambda_4 + d_1\pi_1 + d_2\pi_2 + d_3\pi_3 + \eta_{ti} \quad (5)$$

where

$$c = \ln(\gamma_0) + \eta^*_{01}\alpha_1 + \eta^*_{02}\alpha_2 + \eta^*_{03}\alpha_3 \quad (6)$$

$$\kappa_k = \ln(\sigma_k),\ \ k = 1,...,(K-1) = 7 \quad (7)$$

$$\lambda_1 = \ln(\delta_1) + \eta^*_{11}\alpha_1 + \eta^*_{12}\alpha_2 + \eta^*_{13}\alpha_3 \quad (8)$$

$$\lambda_2 = \ln(\delta_2) + \eta^*_{21}\alpha_1 + \eta^*_{22}\alpha_2 + \eta^*_{23}\alpha_3 \quad (9)$$

$$\lambda_3 = \ln(\delta_3) + \eta^*_{31}\alpha_1 + \eta^*_{32}\alpha_2 + \eta^*_{33}\alpha_3 \quad (10)$$

$$\lambda_4 = \ln(\delta_4) + \eta^*_{41}\alpha_1 + \eta^*_{42}\alpha_2 + \eta^*_{43}\alpha_3 \quad (11)$$

$$\pi_l = \ln(\gamma_l),\ \ l = 1,...,3 \quad (12)$$

η_{ti} is the new error term. (13)

For each cost function the sum of the input price elasticities, or α_j in the model, equals unity. We therefore estimate model (5) under the restriction:

$$\sum_{j=1}^{3} \alpha_j = 1 \quad (14)$$

The parameters of interest given by vector w can be reconstructed using relationships (6)-(12) once the parameter estimates of the regression models (3) and (5) are obtained. Computing the variances of the parameters of interest sometimes causes more difficulties. For the parameter estimates of the type dummies, γ^*_j, exact standard errors can be computed since $\exp(\pi_l)$ is log-normally distributed if π_l is normally distributed.[16] However, in the case of the estimates of the constant, γ^*_0, and the time dummies, δ^*_t, standard errors can only be approximated. A way to do this is given in Kmenta (1986, p.487). Let in the next formula

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[15] The number 1 is added to TC_{ti} and $y_{ti,j}$, $j = 1,..,5$ in order to have a well-defined logarithmic function.

[16] Let $x \sim N(\mu, \sigma^2)$. The variance of a log-normally distributed random variable y=exp(x) equals $\text{var}(y) = \exp(2\mu + \sigma^2)(\exp(\sigma^2) - 1)$.

α^* be a function of K other estimators $\beta_1^*,..,\beta_K^*$, i.e. $\alpha^* = f(\beta_1^*,..,\beta_K^*)$. Then, for large samples, the variance of α^* can be approximated using a Taylor expansion:

$$\mathrm{var}(\alpha^*) \approx \sum_k \left(\frac{\partial f}{\partial \beta_k}\right)^2 \mathrm{var}(\beta_k^*) + 2\sum_{j<k}\left(\frac{\partial f}{\partial \beta_j}\right)\left(\frac{\partial f}{\partial \beta_k}\right)\mathrm{cov}(\beta_j^*,\beta_k^*);\ j,k = 1,2,...,K \qquad (15)$$

We used formula (15) to approximate the standard errors of $\gamma_0^*,\delta_1^*,\delta_2^*,\delta_3^*,\delta_4^*$ where we assume that $\mathrm{cov}(\eta_{0i}^*,\eta_{0j}^*) = 0$ if $i \neq j$ and $\mathrm{cov}(\alpha_i^*,\eta_{ji}^*) = 0$ for $i = 1,2,3,$ and $j = 0,...,4$.[17] Furthermore, we approximated $\mathrm{cov}(\eta_{1i}^*,\eta_{1j}^*)$, $i \neq j$; $\mathrm{cov}(\eta_{2i}^*,\eta_{2j}^*)$, $i \neq j$; $\mathrm{cov}(\eta_{3i}^*,\eta_{3j}^*)$, $i \neq j$; and $\mathrm{cov}(\eta_{4i}^*,\eta_{4j}^*)$, $i \neq j$ by $\mathrm{cov}(\eta_i^*,\eta_j^*)$ where $\eta_i^* = (\eta_{1i}^*,\eta_{2i}^*,\eta_{3i}^*,\eta_{4i}^*)$.

3.3 Interpretation and Efficiency

In the next section it is explained how model (5) under restriction (14) is estimated. Here we will address how the estimates of the parameters of interest can be interpreted, and how the estimation results can be used to find measures of scale and X-efficiency.

Parameter estimates for the size dummies, σ_i^*, $i = 1,...,7$, indicate general cost differences of the banks in the respective size class with respect to the banks in the reference class. In particular, estimates σ_i^*, which are significantly smaller (larger) than unity, indicate that, accounting for all other aspects incorporated in the model, banks falling in size class i have significantly lower (higher) costs per unit of assets than banks in the reference class. Likewise, parameter estimates for the time dummies indicate developments of the cost frontier over time. An attractive interpretation of this would be technological progress. In our study we consider the time period 1993-1997. Then, taking the reference time period to be 1993, estimates δ_j^* which are significantly smaller than unity might indicate that technological progress leads to a cost reduction of efficient banks in the sample period. Finally, parameter estimates of type dummies, d_j, which are significantly larger (smaller) than unity show that efficient banks of the corresponding type have higher (lower) total costs over total assets than efficient banks in the benchmark class.

The regression results give also insight in other aspects concerning the efficiency of the banks in the sample. Let us first address X-efficiency, the degree to which banks use their

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[17] Note that:

$\mathrm{cov}(\alpha_1^*,\alpha_3^*) = -\mathrm{var}(\alpha_1^*) - \mathrm{cov}(\alpha_1^*,\alpha_2^*),$

$\mathrm{cov}(\alpha_2^*,\alpha_3^*) = -\mathrm{var}(\alpha_2^*) - \mathrm{cov}(\alpha_1^*,\alpha_2^*),$

$\mathrm{var}(\alpha_3^*) = \mathrm{var}(\alpha_1^*) + \mathrm{var}(\alpha_2^*) + 2\,\mathrm{cov}(\alpha_1^*,\alpha_2^*),$

$\mathrm{cov}(c,\alpha_3^*) = -\mathrm{cov}(c,\alpha_1^*) - \mathrm{cov}(c,\alpha_2^*),$ etc.

available resources efficiently. Define $TC_{ti}^{\min}$ to be the estimated cost level of bank i in year t if it were on the efficient frontier:

$$TC_{ti}^{\min} = \left(\frac{TC_{ti}}{TA_{ti}}\right)^{*} TA_{ti}.$$

A measure for X-efficiency would be given by the fraction $TC_{ti}^{\min} / TC_{ti}$. X-*in*efficiency represents the distance of a particular firm to the efficient frontier, or

$$X - ineff_{ti} = \left(1 - \frac{TC_{ti}^{\min}}{TC_{ti}}\right). \tag{16}$$

As was explained in Section 2, efficiency may also differ because some banks do not operate at a right size. Let us define $\sigma^{\min} = \min\{1, \sigma_1, ..., \sigma_7\}$, i.e. $\sigma^{\min}$ represents the value of the size dummy of banks in the size class with minimum costs. Then a useful measure of *size-inefficiency* is defined as:

$$S - ineff_{ti} = \left(1 - \frac{\sigma^{\min}}{\sigma_1^{s_{1,ti}} ... \sigma_7^{s_{7,ti}}}\right). \tag{17}$$

We note that formula (17) is only applied to those banks which are member of a size class with *significantly* higher costs then the optimal size group of banks. If, on the contrary, the respective size dummy is not significantly different from the optimal scale dummy, then $S - ineff_{ti} = 0$.

4. The Estimation Technique

Estimating the cost frontier (equation (5)) requires non-standard regression techniques instead of OLS or its generalisations. The reason for this is that we look at the minimum cost incurred instead of the average costs. One could employ Data Envelopment Analyses (see among others Charnes et al. (1994)) in order to find the close fitting frontier which envelops all data points. In this case, deviations from the frontier represent inefficiencies by definition. On the other hand, in this paper we adopt an estimation method which takes into account that deviations from the frontier may emerge due to inefficiency but also due to other temporary bank specific reasons (for example, re-organisation costs) or simply bad and good luck. In this section we briefly explain why our method is different from other so-called *stochastic* or *thick* frontier approaches.[18] A thorough exposition of our new method, the so-called Recursive Thick Frontier Approach (RTFA), is given in Wagenvoort and Schure (1999).

A standard technique for stochastic frontier analysis (SFA) was introduced by Aigner, Lovell and Schmidt in 1977. This method decomposes the disturbance η_{ti} of model (5) into two components. One component is assumed to represent the noise term (usually modelled by the normal distribution) and the other component reflects the inefficiency part (usually modelled by the half-normal or exponential distribution). The Maximum Likelihood procedure is used

[18] See, for instance, Berger and Humphrey (1992).

to estimate the model. Although it is common in efficiency studies to adopt SFA, it is open to three main criticisms. First, it remains unclear how the distributional assumptions can be tested. The outcomes of recent efficiency studies crucially depend on these *a priori* distributional assumptions. Second, adding a half-normal or exponential component to the disturbances of the regression model does not appear to be an adequate way of treating the inefficient banks differently compared to the efficient ones. We find for our sample of banks that SFA gives parameter estimates which are close to the OLS estimates. Indeed, the regression residuals are approximately normally distributed. This would suggest that all deviations from the regression line are due to bad and good luck instead of differences in performance. At the same time, one suspects that some banks in the sample are more efficient than others since relatively many banks are always located below the regression line whereas many other banks are always located above the regression line. It is highly unlikely that this can be put down to bad and good luck. Third, SFA is highly sensitive to outlying observations.

The method that we propose is less vulnerable to the criticisms mentioned above. Regarding the first two arguments, instead of making the usual distributional assumptions we assume that the probability of an efficient bank of being at either side of the cost frontier is equal to one half. This assumption can be tested for a selected sample of X-efficient companies. We therefore consider a selection criterion that sorts the sample into a group of X-efficient and a group of X-inefficient banks. The cost frontier is estimated using only the observations of the former group. If this group of banks is still too large, i.e. our test statistic rejects that on average the probability for a bank to be above or below the regression line is 0.5, then we reduce this group of banks by eliminating those banks which are relatively far positioned above the regression line (i.e. banks with relatively high costs). Our method is only suitable for panel data. The time dimension of panel data enables to require information on the persistence of some banks of having lower cost than others, and this is obviously not available when taking into account only single cross-sections. Therefore, we argue that it will be always difficult to distinguish between luck or efficiency if only single cross-sections are used to estimate the frontier.

Regarding the third criticism, note that our RTFA approach is less sensitive to outlying observations than SFA. First, the parameters of the cost frontier are estimated by considering only the observations associated with the X-efficient companies. Outliers in the observations associated with the X-inefficient banks thus cannot spoil the cost frontier regression. Evidently, outliers may also occur in the group of banks with relatively low costs. We therefore employ the one-sided trimmed least squares estimator when estimating model (5) for the group of X-efficient banks (see Wagenvoort and Schure (1999) for more details).

The last point regarding the estimation of the frontier model (5) relates to the representativity of our sample of banks. Since our full sample of firms contains relatively many German saving banks it could happen that the cost frontier is solely determined by these institutions. Our regression results for the full sample of firms reveal that this problem does not occur. For the separate regression including only saving banks, however, German saving and cooperative institutions put their stamp on the shape of the cost frontier. We therefore repeated the regression for a smaller sample of saving banks which included, besides all the saving banks in the other EU countries, only 150 German saving banks. The latter ones were randomly chosen among 673 German saving institutions. Needless to say, when computing size and X-inefficiencies all German saving banks were taken into account.

5. The Data

5.1 Bank Selection

Our main data source is 'BankScope' of Bureau van Dijk, a data set with bank data from annual reports and rating agencies. Also we made use of the 1998 edition of 'Bank Profitability' of the OECD, the International Financial Statistics of the IMF (IFS), Datastream International, and the CRONOS data set of Eurostat. Below we will describe how we selected our data from BankScope, and how we defined the variables for the cost function estimation.

The focus of our study is on *credit institutions*, as defined in the two European Economic Community (EEC) Council Directives on the "business of credit institutions". Both these so-called *Banking Directives* define a credit institution as "an undertaking whose business is to receive deposits or other repayable funds from the public and to grant credits for its own account" (First banking Directive, 1977). To translate this in practical BankScope terms, we selected "Commercial Banks", "Savings Banks", "Cooperative Banks", "Real Estate/Mortgage Banks", "Medium & Long Term Credit Banks", and "Non Banking Credit Institutions". We will use the terms 'banks' and 'credit institutions' interchangeably and they will normally refer to the banks we selected in BankScope.

We took banks in the European Union countries (EU-15) for which yearly data for 1993-1997 is available. We have focused on this period as on 1 January 1993 the Second Banking Directive (1988) came in force implying a large degree of deregulation in the European Union. Also relatively many banks are available in BankScope for this period. The bank set only includes 'living banks'. BankScope calls a bank 'living' when it continues to exist as a legal body.[19] We understand that the focus on living banks implies a sample selection bias. Namely, a potential reason why the banking sector may become more efficient over time is that inefficient banks die. However, including banks that have died leads to missing observations in our sample which are very difficult to deal with econometrically. Of the banks that we thus had obtained, we selected all consolidated statements, unconsolidated statements, and some so-called aggregate statements.[20] Applying all the selection criteria above led to a first group of 2185 banks with data for 5 years.

We put considerable effort into cleaning this first selection of banks. First, some legal entities appeared twice in the data set as BankScope publishes both their consolidated statement and their unconsolidated statement. Often this was no problem when the consolidated balance sheet contained many more assets --and thus is of a different nature-- than the unconsolidated one. However, sometimes the consolidated and the unconsolidated statement looked similar, in which case more or less the same balance sheet had entered the first selection twice. In order to prevent this we eliminated banks for which the total assets on the unconsolidated statements exceeded 70 percent of the total assets on their consolidated balance sheet. We also removed banks which report zero or negative interest expenses or operating expenses in

[19] So a bank dies when it goes bankrupt or when its *activities* are brought in another bank. Ownership structure has little to do with whether a bank is a living bank. In case of a take-over a bank often continues to exist as a legal entity, and therefore remains a living bank.

[20] In BankScope terms, we selected statements with consolidation codes C1, C2, U1, U2 and A1. Aggregated Statements are generated by BankScope by adding up the statements of a group of affiliated banks, which, however, have no financial links between them, nor form a legal entity.

Table 1. Number of credit institutions in the EU-15 analysed in this study

Country (Population in millions in 1995)	Commercial	Savings	Mortgage	Long-term and Non-bank	Total
Austria (8.05)	20	21	8	1	50
Belgium (10.14)	33	19	1	16	69
Denmark (5.23)	47	28	2	5	82
Finland (5.11)	5	1	0	1	7
France (58.15)	171	86	3	35	295
Germany (81.64)	156	673	49	8	886
Greece (10.46)	17	0	0	0	17
Ireland (3.58)	5	0	0	2	7
Italy (57.29)	57	129	0	8	194
Luxembourg (0.4)	86	5	1	5	97
Netherlands (15.45)	28	2	2	3	35
Portugal (9.9)	18	3	1	2	24
Spain (39.21)	66	55	1	3	125
Sweden (8.83)	5	0	5	2	12
United Kingdom (58.26)	59	3	1	11	74
EU-15 (371.7)	773	1025	74	102	1974

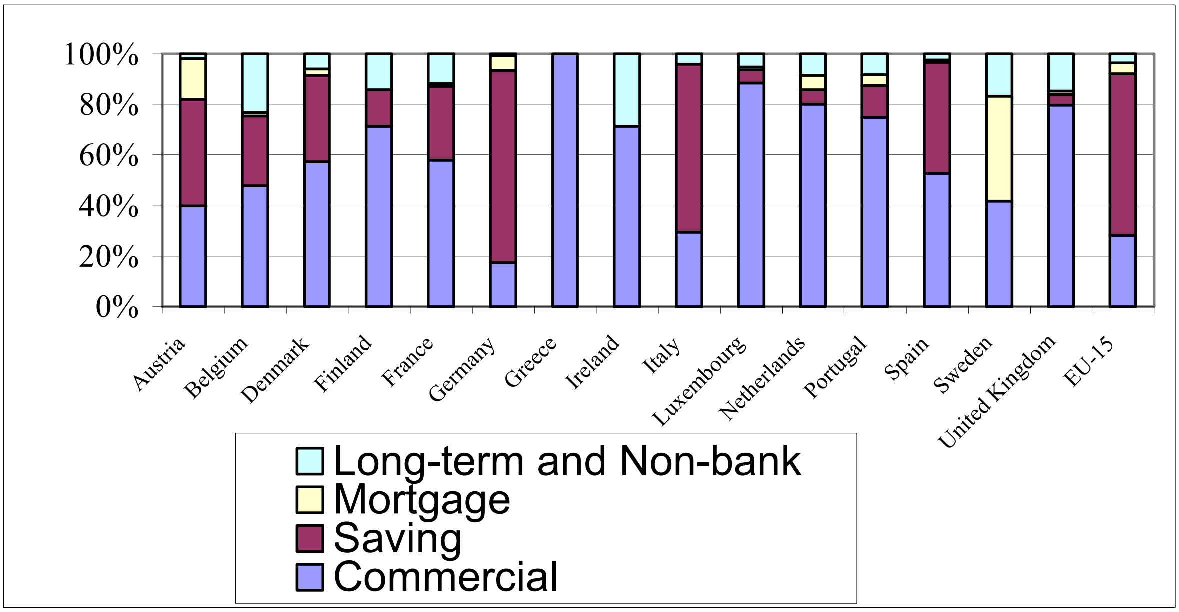
Sources: IFS and BankScope.

one or more years.[21] Third, we removed two banks for which we found that individual balance sheet items exceeded the balance sheet totals (erroneous data). Fourth, we left out some outlier observations. In particular, we omitted banks reporting an amount of 'off-balance sheet items' of more than twice the balance sheet total, and a bank which reported the regular operating and interest expenses to be more than 2½ times the balance sheet total in a particular year. While we recognise that the data for these few banks was not necessarily wrong, these bank would have formed 'leverage points' which could have seriously distorted the regression results.

Table 1 reports the country of origin and the type of the 1974 banks which were left over after cleaning the data. In the table we have grouped the banks into four categories: Commercial Banks (Commercial), Savings Banks and Cooperative Banks (Savings), Real Estate/Mortgage Banks (Mortgage), and Medium & Long Term Credit Banks and Non Banking Credit Institutions (Long-term and Non-bank). We will follow this classification throughout the rest of the paper. From this table, which fairly well covers the overall European banking industry, and Figure 1 it can be seen that the structure of the banking sectors of the EU-15 countries varies considerably. In particular, Austria, Germany, Italy and Spain have relatively many savings banks (more than 40% of the total). On the other hand, in Ireland, Greece, Luxembourg, The Netherlands, Sweden and the UK, less than 10% of the credit institutions of our sample are savings banks. Although these numbers slightly change when including all banks which reside in Europe, the broad picture holds true for the whole European banking sector. For instance, while not in our data set, there are a few savings banks in Sweden and Greece.

[21]Sometimes the data suggest that in a particular year interest expenses may indeed have been zero. In this case we left the bank in the sample.

Figure 1. Percentages of banks of different legal status in the European Union



Source: Bankscope.

Another striking fact from Table 1 is that Austria, Belgium, Denmark, France, Germany and, last but not least, Luxembourg have relatively many banks. In these countries there are more than 5 banks per 1 million of inhabitants whereas the median in Europe is only about 3.2 banks per 1 million people.

5.2 Definition of the Variables

All data for total costs and output comes from Bankscope. The banks' total costs are defined as the sum of 'interest expense', 'total operating expense' and 'commission expense'.

We have defined 5 output variables: customer deposits, loans, equity investments, off-balance sheet items, and other services. *Customer deposits* comprise demand, savings and time deposits.[22] The variable *loans* is created by taking 'total loans' in BankScope and subtracting 'loans to municipalities / government' and 'loans to group companies / associates'. The latter two variables are subtracted as we suspect that relatively few actions need be undertaken when offering loans to these groups of borrowers and thus these assets do not significantly incur additional costs. We share the opinion that mortgages may also imply a different amount of services per unit than other loans and therefore should be treated as an separate output variable. However, unfortunately for most countries BankScope data does not separate mortgages from loans. *Equity investments* are obtained by adding up 'equity investments' and 'other investments'. These items comprise the book value of participations and shares in companies with related business and shares in other non-financial affiliates. Here we have to remark that in many cases this latter output can be substantially under-valued since its book value, as taken from Bankscope, is usually determined on the basis of historic costs instead of its market value. However, this does not necessarily pose as a problem in measuring financial services as long as banks use similar accounting techniques.

[22] As we were not sure whether demand and saving deposits on the one hand and time deposits on the other represent the same amount of service production per unit, we attempted to create two output variables rather than one. Unfortunately, however, the data for German banks do not allow for such an analysis.

Evidently, there is a potential danger of mis-measurement of the level of the output variable equity investments for our bank set. We have included this variable as we suspect that equity investments imply activities such as the selection of the shares and active monitoring and risk-management. *Off-balance sheet items* correspond to 'off-balance sheet items' in BankScope which contains contingent liabilities arising from guarantees, irrevocable letters of credit, irrevocable facilities, discounted bills, etc. Derivatives are not included in this item. Like loans, off-balance sheet items force the bank to screen and monitor projects and hence provide services. Finally, the variable *other services* is equal to the variable 'commission revenue'. In order to keep the commission revenues in different years comparable we divide through a price index for banking services.[23] Appendix A1 explains how this price index is created. Contrary to all other output variables, which are stock variables on and off the balance sheet, other services is a flow variable taken from the profit and loss account.

In our opinion the remaining earning and non-earning assets on the banks' balance sheet, such as securities, treasury and other bills, bonds, certificates of deposits, cash balances, and the like, do not require the provision of a significant amount of services and are hence not included in the output vector.[24]

Three input prices have been defined: the price of loanable funds, the price of labour and the price of buildings.[25] The *price of funds* is obtained by taking a weighted average of the average 3-month interbank rate and the deposit rate. This data is obtained from Datastream International and IFS, respectively. The weights are determined by the amount of deposit funding as part of total funding (total assets) of each bank. The *price of labour* represents the average wage rate in the banking sector in each country. The data needed to construct an index for the price of labour is taken from BankScope and the OECD. The *price of buildings* is created by taking an appropriate price index for newly delivered buildings and correcting it for the relative price levels in each country. A detailed description on these calculations is given in the Appendix A1.

The prices we use are fundamentally different from most other bank efficiency studies. Normally the price of funds is defined as the ratio of the interest expenses to the total amount of funds. The wage rate is normally taken to equal the labour expenses of the bank over the number of its employees. Finally, the price of a unit of capital is normally defined by dividing the net expenses for fixed asset by the average value of fixed assets. In other words,

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[23] Obviously, changes in prices of the other output variables can be relevant too. Unfortunately no adequate data on these prices are available. As mentioned in section 3, we minimise this problem by *scaling* all the output variables, including the deflated commission revenue, and total costs by total assets. One could argue that, in the special case of the output variable *other services*, this scaling is redundant since we already divide through a price index. Recall however that there is also an econometric argument for it since scaling reduces the problem that the model errors are not orthogonal to the regressors in a cost model specification and on that score the fundamental orthogonality condition is not fulfilled. Division through price indices cannot solve the latter problem.

[24] Adding these items to the output vector and leaving it up to the regression to decide whether they should be treated as production leads to invalid regressions. Namely, in this case there will be a strong dependency between the output variables since their sum equals the balance sheet total. Even if this were not an econometrical problem, it would give problems interpreting the parameter estimates.

[25] The reader could correctly point out that banks face more prices when acquiring their inputs. We think, though, that the three prices we have included are the most important input prices. Also, our assumption here is not so much that the bank faces only these three prices, but that a linear combination of these can sufficiently well approximate the prices that the bank might face. Other bank efficiency studies typically also include up to three prices.

in other studies the prices faced by a particular bank are usually defined using data on the actual expenses of that bank. When these expenses are unnecessarily high this is not measured as being inefficient. As a result efficiency differences only stem from differences in the production of outputs.

We recognise that both approaches have advantages and disadvantages. For instance, if different banks require different skilled labour then some banks may have on average a higher or lower wage bill than others without necessarily being inefficient. Nevertheless, we think our approach is more appropriate when studying bank efficiency as we suspect many efficiency differences arise exactly because some banks acquire their inputs inefficiently.

5.3 Some Descriptive Statistics

We will now present some descriptive statistics on the banks in the data set. Figure 2 shows that across Europe there are also considerable differences in the cost levels. Average costs, i.e. the ratio of costs over total assets, range for most countries between 4% and 8%. Besides the striking outlier of Greece, average costs are also relatively high in France, Italy, Luxembourg and Portugal when compared with the EU-15 average (of 6.6% in 1997).[26] In all European countries, however, costs per unit of assets substantially decreased. Figure 3 shows that for the overall European banking industry, average costs fell about 25% during the period 1993-1997.

It would be premature to conclude from Figure 2 and Figure 3 that Greek banks are more inefficient than other European banks or that the performance of European banks has improved over time. For testing these kinds of hypotheses we have to take into consideration changes in the input prices and changes in the level and mix of the outputs. For example, it is notable that the interbank fund rate in 1997, on average, is only 47% of the prevailing rate in 1993. Indeed, our cost frontier regression (presented in the next section) gives a fund price elasticity of about 40% with respect to average costs. This means that average costs of X-efficient banks decreased with roughly 20% just because the fund rate fell from 8.4% to 4.5%. Figure 3 to Figure 6 show this relationship between average costs and the fund rate for the EU-15, Italy, Germany, and the UK respectively. Evidently, given the sharp fall in the price of funds in Europe one may expect substantially lower average costs for banks in general. Whether banks have actually improved in efficiency terms can only be detected by careful interpretation of the cost frontier regression results.

Substantial differences across the banking industry are also revealed by looking at the banks' output structure in the respective European countries. Figure 7 shows the decomposition of the earning assets. Equity investments are relatively small compared to other earning assets. On average, equity investments are less than 2% of total assets, whereas 50% of the balance total consists of loans and mortgages. Luxembourg and Greece have relatively many 'other assets'. As mentioned before, these assets, such as treasury and other bills, are not included as outputs in our cost model since they do not significantly incur additional costs. In the special case of Luxembourg, however, this assumption could be too restrictive. This means that the results presented in section 6 have to be interpreted with some caution.

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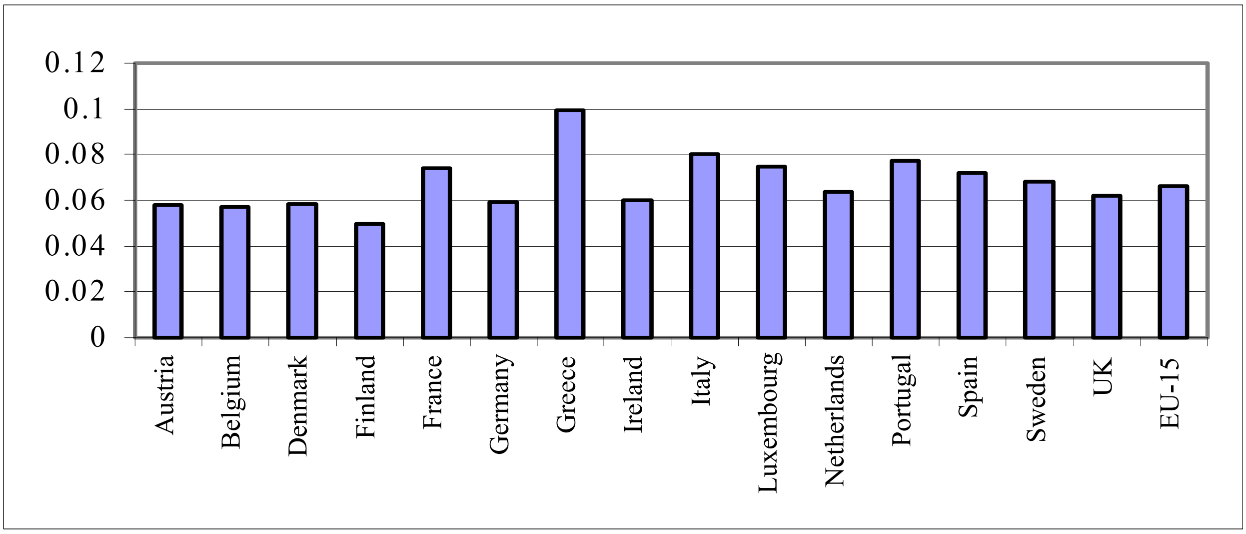
[26] The EU-15 averages in figures 1 to 10 are constructed by applying country weights on the basis of the share of each country in total European assets.

Figure 2. Costs over total assets in the European Union, full sample



Three other outputs are included in the cost model: deposits, off- balance sheet activities, and services related to other activities (brokerage services). The ratio of deposits over total assets also reveals remarkable differences in country output structures (see Figure 8). According to the *Value-Added Approach* adopted in this paper, deposits have output features besides providing input in the form of loanable funds. Because the differences in the relative amount of deposits are substantial, including this output variable in the cost model is important for a fair comparison of banks in different countries. Both the ratio of off-balance sheet items to total assets, and the ratio of brokerage services to total assets, reveal two outliers with respect to financial product mix. In 1997, Belgium and Swedish banks report relatively high off-balance sheet activities (see figure 9). Furthermore, brokerage services are relatively high in Ireland and the UK (see figure 10). Note that for Greece earned brokerage fees are not reported in BankScope. We should bear these facts in mind when discussing the cost efficiency of banks in the next section.

Figure 3. Costs over total assets and the interbank rate in the EU-15

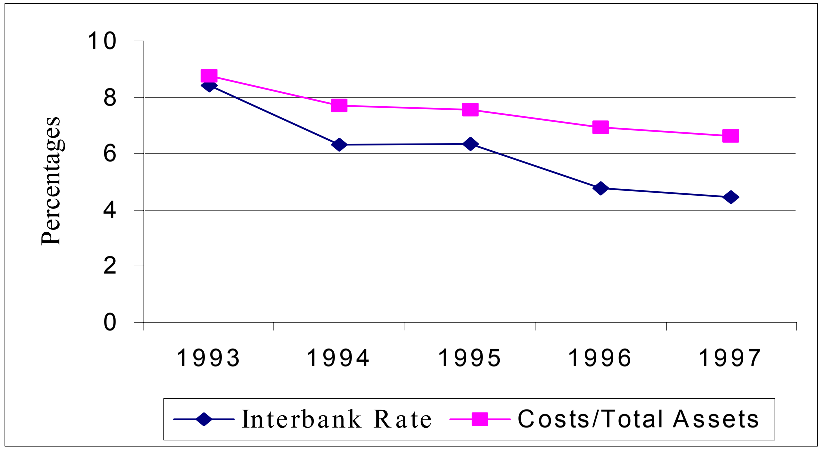


Figure 4 Cost over total assets and the interbank rate in Italy

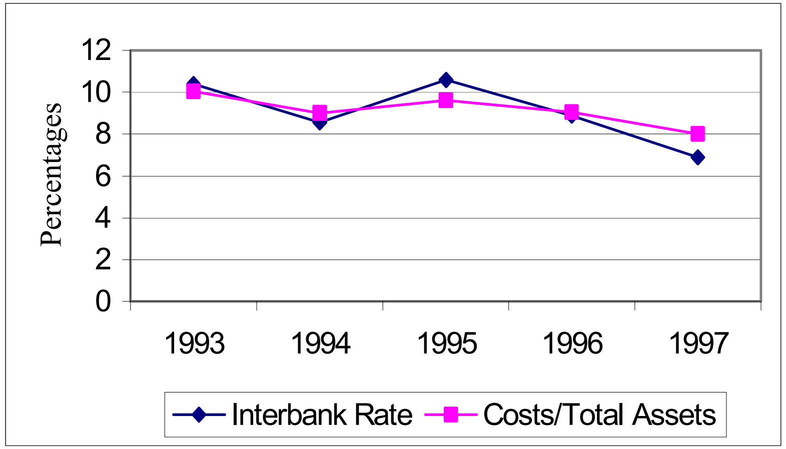


Figure 5 Costs over total assets and the interbank rate in Germany

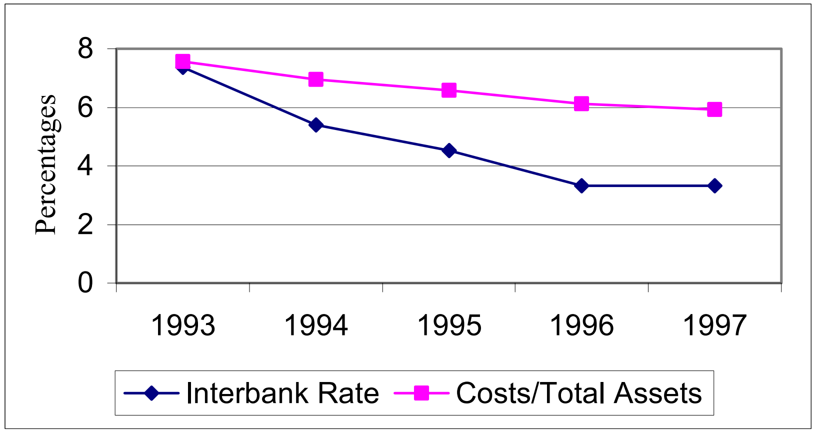


Figure 6 Costs over total assets and the interbank rate in the UK

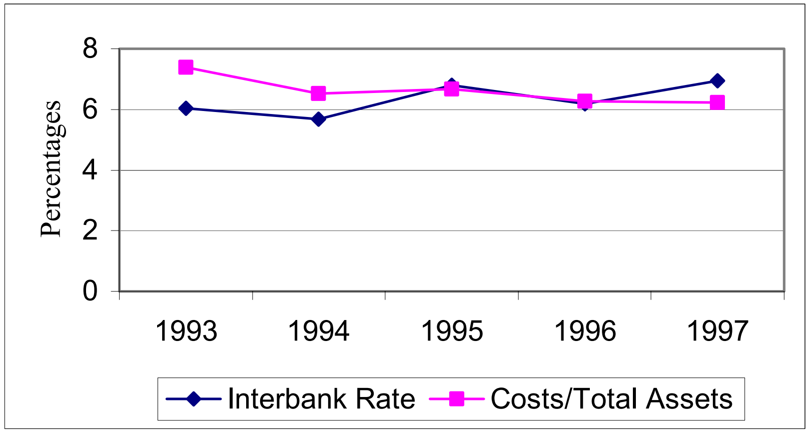


Figure 7 Decomposition of earning assets (outputs over total assets), 1997

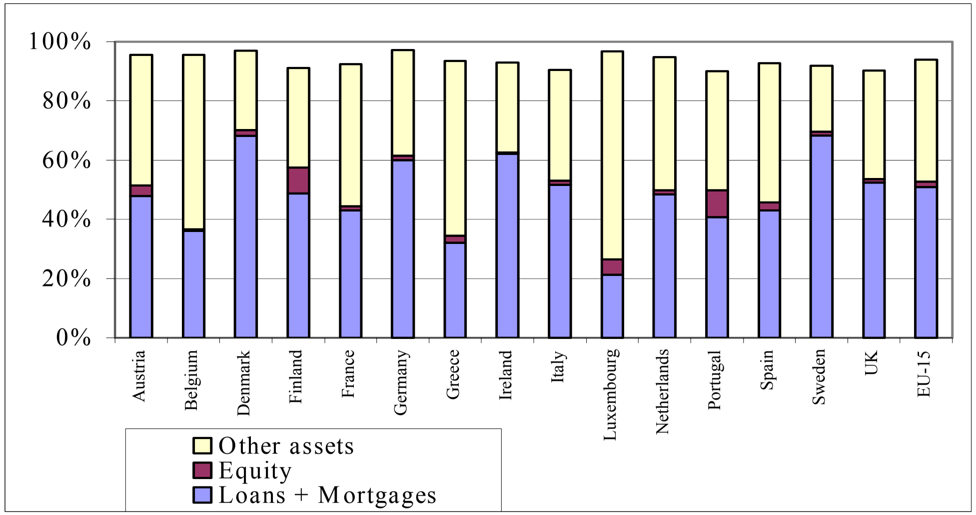
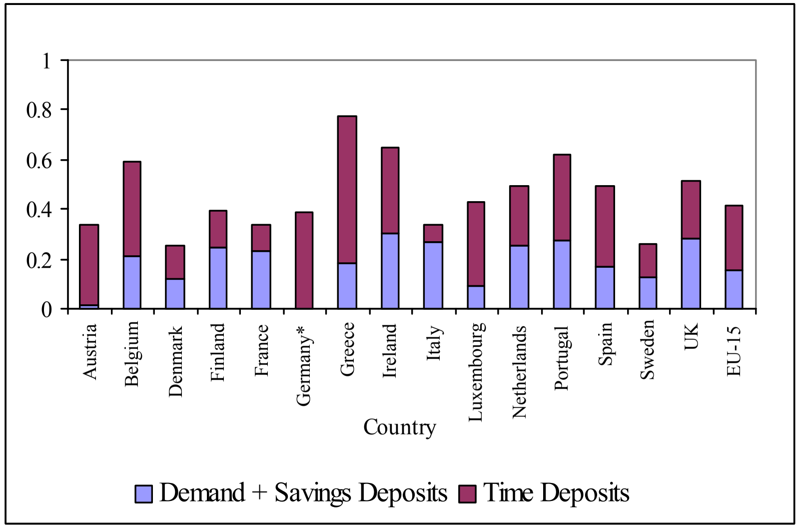


Figure 8 deposits over total assets, 1997



Note: The fixed capital stock, which contains for example buildings, is not explicitly shown in this graph. This explains why the columns do not add up to 100 percent.

Figure 9 Off-balance sheet activities over total assets, 1997

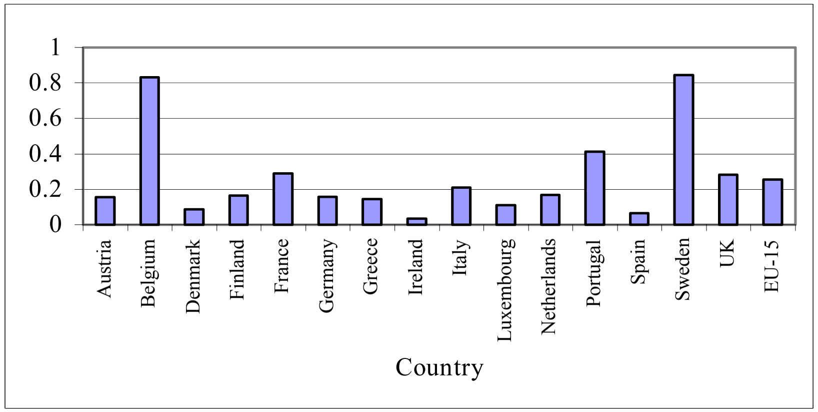
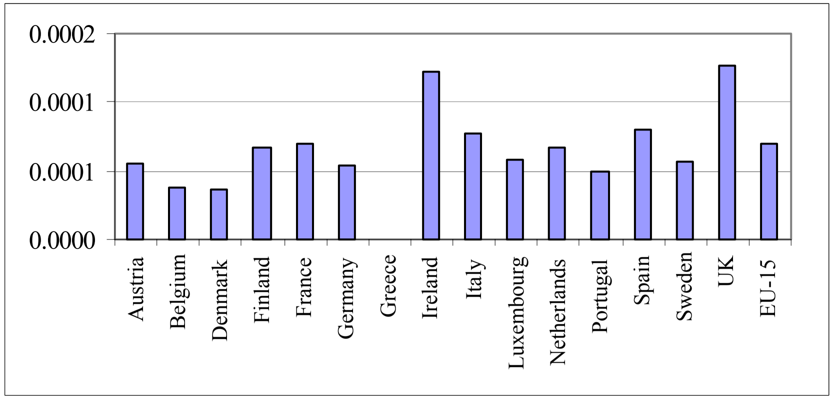


Figure 10 Earned brokerage fees over total assets, 1997



6. Empirical Evidence Regarding the Efficiency of European Banking

We performed separate regressions for the full bank sample, for commercial banks, and the sample of savings banks. Due to data limitations we could not perform separate regressions for mortgage banks or long-term and non-bank credit institutions. However, before turning to the regression results several remarks are in order. The first remark relates to how well our Cobb-Douglas specification manages to explain the data. Taking Theil's adjusted R^2 as our measure of fit, we see that the model best explains the data of savings banks. In this case, our model explains 81% of the variation of total costs over total assets, compared to 49% and 38% for the full sample and the commercial banks, respectively. Table A2.3 and Table A2.6 of Appendix A2 contain the results for the full sample and the commercial banks respectively while Table 4 in the main text shows the results for the savings banks. The differences in explanatory power might be explained by the fact that savings banks make up a more homogeneous group of banks. Besides that the group of commercial banks is more heterogeneous, within this category, some banks possibly exploit better economies of scope than others, leading to cost differences which the Cobb-Douglas specification is unable to detect.

Based on R^2, it is difficult to judge whether our model explains the data well compared to other studies. In recent efficiency studies of banks it is not unusual to report an adjusted R^2 exceeding 0.95. However, as we have mentioned before, in these studies the regression model is not scaled by total assets. Hence, to a considerable extend the high R^2 of these models is due to the fact that 'big' banks face higher costs.

Related to the reliability issue of the regression results is how many banks are found to lie on the cost frontier. For the full sample we find that 340 out of 1974 credit institutions in Europe are on their cost frontier, 173 of which are German.[27] This implies that the cost frontier is based on 340*5=1700 observations. From the point of view of degrees of freedom, the regression results are thus reliable.

A second remark is that one should be careful when interpreting our parameter estimates. Especially the estimated coefficients of the input prices and the outputs are not necessarily the impact on the bank's average costs of changing the variable in which one is interested (i.e. the partial effect). The reason is that some input prices and outputs may be significantly cross-correlated. [28] To give an example, it is likely that both the price of labour and the price of buildings are correlated to inflation. The same can be true for some outputs. It may well be that the outstanding amount of loans of (commercial) banks is strongly related to their off-balance sheet activities.

A related remark is that in such cases insignificant parameter estimates need not imply that the impact of the corresponding variable is insignificant. For instance, for commercial banks we find that the parameter estimate of the price of labour is not significant in the regression which includes the time-dummies. However, this does not necessarily indicate that the price of labour is irrelevant to the costs of a bank. A significant correlation between the price of labour and the price of buildings may drive this result.

[27] Table A2.1 reports exactly how many banks are on the frontier and which are their home countries for the full sample, the commercial banks and the savings banks.

[28] If, by contrast to the situation sketched above, a particular variable is little correlated to the remaining variables in model (5), the corresponding parameter estimate can be interpreted as an elasticity. This is a standard feature of log-linear models.

A final remark is made about model reduction. In the cases of the full sample and the group of commercial banks, none of the time dummies are significantly different from 1 on the 95 percent confidence level as can be verified in the tables A2.3 and A2.6. We therefore repeated the regressions without including time dummies in model (5). The results of which are reported in tables 2 and 3 respectively. The parameter estimates of the complete model for the savings banks are shown in Table 4.

6. 1 Input Prices and Costs

It becomes immediately clear from Table 2, which gives the estimated cost frontier for the full sample of banks, that the most important input price of banks is the price of loanable funds. This confirms our impression of a close relationship between costs per asset and the price of funds (shown in figures 3 to 6). For the full sample we get a coefficient of 0.43 and we believe that this figure can well be interpreted as the fund price elasticity of total costs over assets.[29]

We notice from tables 3 and 4 that the costs of commercial banks are more sensitive to changes in the fund rate than the costs of savings banks. The price elasticities of loanable funds are 0.56 and 0.37 respectively. An explanation for the considerable difference in these estimates may be that savings banks rely more on long-term finance than commercial banks while our price of funds is based on two short-term rates.

We conclude with a key point. Given the big impact of the price of funds it is of crucial importance to take the correct price for this variable. If a price is taken which is inappropriate for a specific country, we will have incorrect estimates for the X-efficiency measures for the banks in that country.

In the full sample the coefficients of the price of labour and the price of buildings are 0.23 and 0.34 respectively. When splitting up the sample these estimates change substantially. We believe this is due to the high correlation between the two prices (they may both be driven by inflation). We therefore refrain from any interpretation of these results.

6.2 Bank Outputs and Costs

We will first discuss the relationships that we observe between the production of different outputs and average costs for the full sample of banks (Table 2). Then we pinpoint some differences in output elasticities between commercial and savings banks (Table 3 and Table 4).

For the full sample, brokerage and loans are the most important outputs. These explanatory variables enter the cost frontier with significant parameter estimates equal to 0.099 and 0.069 respectively. Although the estimate of deposits over total assets is smaller (0.025), deposits do also contribute significantly to explaining the bank’s cost. This confirms our view that deposits have output characteristics. Equity investments appear with a positive significant coefficient of small magnitude (0.011).

It is striking that off-balance sheet items enter the regression equation with a significant negative coefficient (-0.008). This result is due to a strong positive correlation between loans

[29] We did a regression of the price of funds on the other two prices and found that in the sample period there was very little correlation between the price of funds and the other two prices.

Table 2 The estimated Cobb-Douglas cost frontier for the period 1993–1997, full sample

	Parameter Estimate	t-value
Constant	0.0016*	5.92
Deposits over Total Assets	0.0248*	9.75
Loans over Total Assets	0.0693*	20.31
Equity Investments over Total Assets	0.0114*	7.65
Off-balance Sheet over Total Assets	-0.0075*	-4.91
Brokerage over Total Assets	0.0993*	26.57
Price of Funds	0.4256*	46.25
Price of Labour	0.2345*	9.64
Price of Buildings	0.3398*	13.79
Dummy, Total Assets ≤ 100 Million ECU	1.0745*	3.42
Dummy, 100 Million < Total Assets ≤ 300 Million	1.0601*	3.17
Dummy, 300 Million < Total Assets ≤ 600 Million	1.0147	0.76
Dummy, 600 Million < Total Assets ≤ 1 Billion	1.0236	1.18
Dummy, 1 Billion < Total Assets ≤ 5 Billion	1.0248	1.35
Dummy, 10 Billion < Total Assets ≤ 50 Billion	1.0614*	2.70
Dummy, 50 Billion < Total Assets	1.0436	1.71
Dummy Commercial Banks	0.9620*	-4.63
Dummy Mortgage Banks	0.8052*	-6.25
Dummy M-LT & NB Credit Institutions	0.7958*	-8.19
Adjusted Coefficient of Determination	0.44	
Binomial Test	3.73	
Number of banks on the cost frontier	321	

Notes:
(1) The regressand is 'total costs over assets'.
(2) Brokerage is scaled by the annual average index of the price of banking services in the respective countries.
(3) Type dummies are defined with respect to savings and cooperative banks.
(4) Time dummies are defined with respect to the year 1993.
(5) Size dummies are defined with respect to the class: 5 Billion < Total Assets ≤ 10 Billion ECU.
(6) We have adopted the RTFA method. The "Binomial Test" statistic asymptotically converges to a Chi-squared distribution with one degree of freedom.
(7) The price of funds is computed as the weighted average (according to the relative amount of deposits in total assets) of the (yearly average of the) 3-months LIBOR and the deposit rate.
(8) $\chi^2_{0.01}(1) = 6.63$, and $t(\infty)_{0.025} = 1.96$. Significant parameters at the 95% confidence level are marked with an asterisk.

Table 3 The estimated Cobb-Douglas cost frontier for the period 1993–1997, commercial banks

	Parameter Estimate	t-value
Constant	0.0076*	3.42
Deposits over Total Assets	0.0045	1.61
Loans over Total Assets	0.0525*	7.92
Equity Investments over Total Assets	0.0156*	6.46
Off-balance Sheet over Total Assets	-0.0154*	-6.18
Brokerage over Total Assets	0.1618*	22.02
Price of Funds	0.5602*	32.87
Price of Labour	0.1413*	3.57
Price of Buildings	0.2985*	7.99
Dummy, Total Assets $\leq 10^8$ (ECU)	0.7748*	-7.28
Dummy, $10^8 <$ Total Assets $\leq 3*10^8$	0.9126*	-3.87
Dummy, $3*10^8 <$ Total Assets $\leq 6*10^8$	0.9412*	-2.58
Dummy, $6*10^8 <$ Total Assets $\leq 10^9$	1.0119	0.46
Dummy, $0.5*10^{10} <$ Total Assets $\leq 10^{10}$	0.9013*	-3.10
Dummy, $10^{10} <$ Total Assets $\leq 0.5*10^{11}$	1.1015*	4.21
Dummy, $0.5*10^{11} <$ Total Assets	0.9798	-0.76
Adjusted Coefficient of Determination	0.43	
Binomial Test	5.10	
Number of banks on the cost frontier	143	

Notes:
(1) The regressand is 'total costs over assets'.
(2) Brokerage is scaled by the annual average index of the price of banking services in the respective countries.
(3) Type dummies are defined with respect to savings and cooperative banks.
(4) Time dummies are defined with respect to the year 1993.
(5) Size dummies are defined with respect to the class: 1 billion < Total Assets ≤ 5 billion.
(6) We have adopted the RTFA method. The "Binomial Test" statistic asymptotically converges to a Chi-squared distribution with one degree of freedom.
(7) The price of funds is computed as the weighted average (according to the relative amount of deposits in total assets) of the (yearly average of the) 3-months LIBOR and the deposit rate.
(8) $\chi^2_{0.01}(1) = 6.63,$ and $t(\infty)_{0.025} = 1.96.$ Significant parameters at the 95% confidence level are marked with an asterisk.

Table 4 The estimated Cobb-Douglas cost frontier for the period 1993–1997, savings and cooperative banks

	Parameter Estimate	t-value
Constant	7.21E-05*	4.35
Deposits over Total Assets	0.0299*	4.31
Loans over Total Assets	0.2119*	21.87
Equity Investments over Total Assets	0.0090*	4.53
Off-balance Sheet over Total Assets	-0.0012	-0.87
Brokerage over Total Assets	0.0369*	9.58
Price of Funds	0.3718*	27.73
Price of Labour	0.6355*	20.88
Price of Buildings	-0.0073	-0.37
Dummy, Total Assets $\leq 10^8$ (ECU)	1.1599*	10.40
Dummy, $10^8 <$ Total Assets $\leq 3*10^8$	1.0314*	2.73
Dummy, $3*10^8 <$ Total Assets $\leq 6*10^8$	1.0471*	4.23
Dummy, $10^9 <$ Total Assets $\leq 0.5*10^{10}$	1.0168	1.63
Dummy, $0.5*10^{10} <$ Total Assets $\leq 10^{10}$	1.0015	0.11
Dummy, $10^{10} <$ Total Assets $\leq 0.5*10^{11}$	1.0130	0.96
Dummy, $0.5*10^{11} <$ Total Assets	1.1169*	5.97
Dummy 1997	0.9102*	-2.61
Dummy 1996	0.9483	-1.45
Dummy 1995	0.9538	-1.33
Dummy 1994	0.9819	-0.51
Adjusted Coefficient of Determination	0.81	
Binomial Test	6.53	
Number of banks on the cost frontier	147	

Notes:
(1) The regressand is 'total costs over assets'.
(2) Brokerage is scaled by the annual average index of the price of banking services in the respective countries.
(3) Type dummies are defined with respect to savings and cooperative banks.
(4) Time dummies are defined with respect to the year 1993.
(5) Size dummies are defined with respect to the class: $6*10^8 <$ Total Assets $\leq 10^9$.
(6) We have adopted the RTFA method. The "Binomial Test" statistic asymptotically converges to a Chi-squared distribution with one degree of freedom.
(7) The price of funds is computed as the weighted average (according to the relative amount of deposits in total assets) of the (yearly average of the) 3-months LIBOR and the deposit rate.
(8) $\chi^2_{0.01}(1) = 6.63$, and $t(\infty)_{0.025} = 1.96$. Significant parameters at the 95% confidence level are marked with an asterisk.

and off-balance sheet items. Namely, when loans were left out from the model we found that the sign of the coefficient for off-balance sheet items reversed. A possible economic explanation for the reported negative coefficient of the off-balance sheet variable could be that a bank with many off-balance sheet items incurs less production costs per unit of loans relative to other banks. This could be for two reasons. First, the production costs per unit of a large loan is probably lower than the production costs of one unit of credit supplied to small lenders. Banks with a high level of credit commitments and guarantees are usually larger and may also have larger clients. Therefore, they provide loans of larger volume compared to banks with few off-balance sheet items. Second, off-balance sheet items contain many credit commitments. The loans provided by banks with many off-balance sheet items often stem from these credit commitments and these are usually only made to customers with an unviolated payment record. This means that the screening and monitoring expenses incurred are lower.

The results regarding the effects of output on cost become interesting once we compare the parameter estimates of the separate regressions for commercial and savings banks. The positive relationship between brokerage and costs is much more pronounced for commercial banks than for savings banks. For commercial banks the parameter estimate for brokerage services is 0.162 whereas for savings banks we find a value of 0.04. On the other hand, loans are more important for the cost function of a savings bank. For savings banks and commercial banks we find significant parameter estimates of 0.212 and 0.053, respectively. Finally, the coefficient for deposits is substantially lower for the commercial banks than for savings banks and not even significant. All these differences in output elasticities can be explained by the fact that commercial banks offer more credit lines and market related services such as security trading, risk management, underwriting of assets, etc.

6.3 Cost Differences Between Different types of Credit Institutions

The full sample regression results reveal that mortgage banks and long-term and non-bank credit institutions operate at significant lower costs than savings banks. In both cases the ratio of costs to total assets is about 20% lower than for savings banks. Structural differences between different credit institutions may underlie this result. For example, the nature of the outputs or the institutional environment of mortgage banks and long-term and non-bank credit institutions may fundamentally differ from savings banks. For this reason the cost differences mentioned above need not reflect differences in X-inefficiencies.

Our analysis also suggests that on average commercial banks operate at 4% lower costs than savings banks (see Table 2). Again this can be due to differences in structure or X-efficiency. For example, a difference in X-efficiency could occur when managers of savings banks have more discretion over the use of the bank's cash-flow. If this were the case, demutualisation of savings and cooperative banks would lead to lower costs.

6.4 Technological Progress

Has the cost frontier shifted over time in the sample period? In Table A2.3 we see that for the full sample the parameter estimates corresponding to time dummies gradually increase over time, indicating the opposite. However, none of the t-values of the time dummies are significant. We have, therefore, no evidence that the cost level of a typical efficient bank changes over time in the period 1993 – 1997. We find the same result for the commercial banks [see Table A2.6]. By contrast, we see that costs over assets of an average efficient savings bank decreases over time. In particular, for X-efficient banks we find a steady reduction in the costs over total assets of about 2% each year. To be more precise, in the period 1993 – 1997 efficient savings banks reduced their costs by 9 percent.[30]

With our limited study we are not in the position to judge what are the driving forces behind the drop in costs for savings banks, and why this effect did not occur for commercial banks. One can think however of several explanations. As was mentioned above, saving banks are on average less efficient than commercial banks. The reduction in the cost per unit of assets of the group of managerial efficient savings banks, could simply reflect that these banks have reduced their distance to the even more efficient commercial banks. The possible reasons for observing such a rise in X-efficiency are numerous. For instance, small saving banks may reduce costs by centrally organising the acquisition of funds on the money markets or the portfolio management of securities. Within this view, German "sparkassen" provide an illustrative example. Cost reductions can possibly also be ascribed to the implementation of new (computer) technology that facilitates data processing, data communication with other institutions, credit risk evaluation and decision-making. It is not unlikely that savings banks were slower in adopting the latest technology in comparison with commercial banks since the latter group of banks are usually more market orientated. Commercial banks may have started earlier with exploiting new technology in comparison with saving banks, but the returns have faded away or were offset by other structural changes. That does not mean that technological innovation such as Internet banking will have no impact on commercial banks in the future. However, for our sample period, technological progress was statistically irrelevant for commercial banks.

6.5 Size Inefficiencies

From the parameter estimates of the size dummies in Table 2 we find initially increasing returns to scale and afterwards constant returns to scale. The estimates for the size dummies initially decrease in the size class. For very large banks the dummy increases again and becomes significantly different from unity only for the size class with total assets between 10 and 50 billion but is insignificant for the largest banks in the sample with total assets above 50 billion. It therefore seems that only very small banks face higher costs than the reference class of banks. In particular, banks with less assets than EUR 100 million have approximately 7.5 percent higher costs per asset and banks with assets between EUR 100 and 300 million have approximately 6.0 percent higher costs per asset.

Turning to Table 4 for savings banks we clearly find a U-shaped average cost curve. This indicates that small savings banks face increasing returns to scale while very large banks have decreasing returns to scale. Savings banks with less assets than EUR 100 million have approximately 16 percent higher costs per asset than the savings banks falling in the reference class. Also the next two smaller size groups have significantly higher costs per asset of roughly 3 percent and 5 percent, respectively. After that there are constant average costs until we arrived at the ten very large savings banks with total assets exceeding EUR 50 billion. These banks have roughly 10 percent higher costs over assets than the medium-sized reference class. Summarising, small and very large savings banks can improve efficiency by choosing their total assets between EUR 600 million and EUR 50 billion.

For the group of commercial banks the size picture is much less transparent, as costs seem to jump up and down with increasing size class. In our view these rather strange results are due to the fact that commercial banks form a very diverse group of banks. Some small investment

[30] See the value of the 1997 time dummy in Table 4.

Table 5 Weighted average of the estimated size inefficiencies in the European Union (percentages, number of banks in each country given in parentheses)

Country	1997	1996	1995	1994	1993
EU-15	0.03	0.04	0.04	0.05	0.05
Austria (50)	0.02	0.03	0.04	0.05	0.04
Belgium (69)	0.02	0.02	0.02	0.03	0.03
Denmark (82)	0.14	0.15	0.16	0.17	0.15
Finland (7)	0.00	0.00	0.00	0.00	0.00
France (295)	0.01	0.02	0.02	0.02	0.02
Germany (886)	0.06	0.07	0.08	0.09	0.10
Greece (17)	0.03	0.01	0.03	0.12	0.12
Ireland (7)	0.00	0.00	0.00	0.00	0.00
Italy (194)	0.02	0.02	0.03	0.03	0.03
Luxembourg (97)	0.05	0.07	0.06	0.08	0.08
Netherlands (35)	0.01	0.01	0.01	0.01	0.02
Portugal (24)	0.00	0.00	0.00	0.01	0.00
Spain (125)	0.01	0.02	0.02	0.02	0.03
Sweden (12)	0.00	0.00	0.00	0.00	0.01
United Kingdom (74)	0.01	0.01	0.01	0.01	0.01

Note: This table is derived using the results in Table 2. The weight of each bank is obtained from its total asset amount.

banks that offer a range of products which is substantially different from the average product mix, could belong to this group. This could also be taken as evidence that there is scope for niche players to play an important role in the banking industry.

Using the results above we can determine to which extent the banking sector may improve its performance by exploiting the increasing returns of scale. The European banking sector as a whole hardly would improve efficiency by choosing the right scale of operations as shown in Table 5. This is because small banks, although there are more than 800 credit institutions in Europe which are smaller than EUR 600 million measured in balance total, account for a small fraction of the of the European banking sector's assets (see Table A2.2). By contrast Table 6 shows that savings banks do have scope for improvement. By choosing the right scale, savings banks can reduce costs per asset by approximately 6 percent. This empirical finding is driven by France and Germany where cost reductions of approximately 8% and 6% are attainable.[31] Indeed, most of the European savings banks are based in these two countries and many of them are either small or very large.

[31] Lang and Welzel (1996) also find moderate size economies for all size classes of German cooperatives using 1989-1992 data.

Table 6 Weighted average of the estimated size inefficiencies in the European Union, savings and cooperative banks (percentages, number of banks given in parentheses)

Country	1997	1996	1995	1994	1993
EU-15	6.1	6.2	5.9	5.9	5.8
Austria (21)	1.2	1.2	1.2	1.5	1.5
Belgium (19)	5.4	4.8	1.3	4.7	5.1
Denmark (28)	3.5	3.5	3.8	4.3	4.1
France (86)	8.0	8.1	7.7	7.7	7.8
Germany (673)	6.4	6.7	6.6	6.5	6.5
Italy (129)	1.1	1.2	1.2	1.3	1.3
Luxembourg (5)	1.3	1.3	1.3	1.3	1.3
Spain (55)	3.2	3.2	3.2	3.2	1.1
Finland (1)	1.7	1.7	1.7	1.7	1.7
Greece (0)	--	--	--	--	--
Ireland (0)	--	--	--	--	--
Netherlands (2)	11.5	11.4	11.4	11.4	11.5
Portugal (3)	1.2	1.3	1.3	1.3	1.3
Sweden (0)	--	--	--	--	--
United Kingdom (3)	1.1	1.2	1.3	1.3	1.3

Note: This table is derived using results in Table 4. The weight of each bank is obtained from its total asset amount.

Other studies using European data (see, for instance, Altunbas and Molyneux, 1996) tend to find positive economies of scale also for larger size classes (in some cases up to a level of total assets of EUR 10 billion). Our results are more in line with previous US evidence. Hence, in our view, it remains unclear whether there are greater economies of scale in Europe than in the US.

A final remark has to be made for savings banks in countries such as Germany where there is a very high degree of cooperation between the, from a legal point of view, independent mutual organisations. One could argue that all the small savings banks in Germany constitute one large saving institution. Given such an interpretation, measuring scale economies for this group of banks makes no sense. Our results would then indicate that relatively small savings banks and the ten mega savings banks are much more X-inefficient than the others.

6.6 X-efficiency

As we have shown in Section 3 we can construct a measure for X-inefficiency using our estimation results of the cost frontier. Basically the X-inefficiency of a particular bank is measured by the difference of the realised costs of that bank and the cost frontier. In tables 7, 8 and 9 we have computed country averages of X-inefficiency in each year for the full sample, commercial and savings banks respectively. In constructing these averages we weight the X-inefficiencies of a particular bank by its total assets as a percentage of the total

Table 7 Weighted average of the estimated X-inefficiencies in the European Union full sample (percentages, number of banks in each country given in parentheses)

Country	1997	1996	1995	1994	1993
EU-15	16	20	19	19	20
Austria (50)	11	16	18	14	7
Belgium (69)	13	23	18	16	20
Denmark (82)	20	25	27	37	32
Finland (7)	10	17	11	28	32
France (295)	22	21	21	22	22
Germany (886)	16	19	14	14	10
Greece (17)	59	63	64	67	67
Ireland (7)	21	35	33	35	31
Italy (194)	14	18	26	22	24
Luxembourg (97)	22	20	19	11	20
Netherlands (35)	13	24	21	21	28
Portugal (24)	30	33	36	36	41
Spain (125)	22	24	25	23	29
Sweden (12)	28	30	23	35	39
United Kingdom (74)	-4	8	10	13	20

Note:This table is derived using the results in Table 2. The weight of each bank is obtained from its total asset amount.

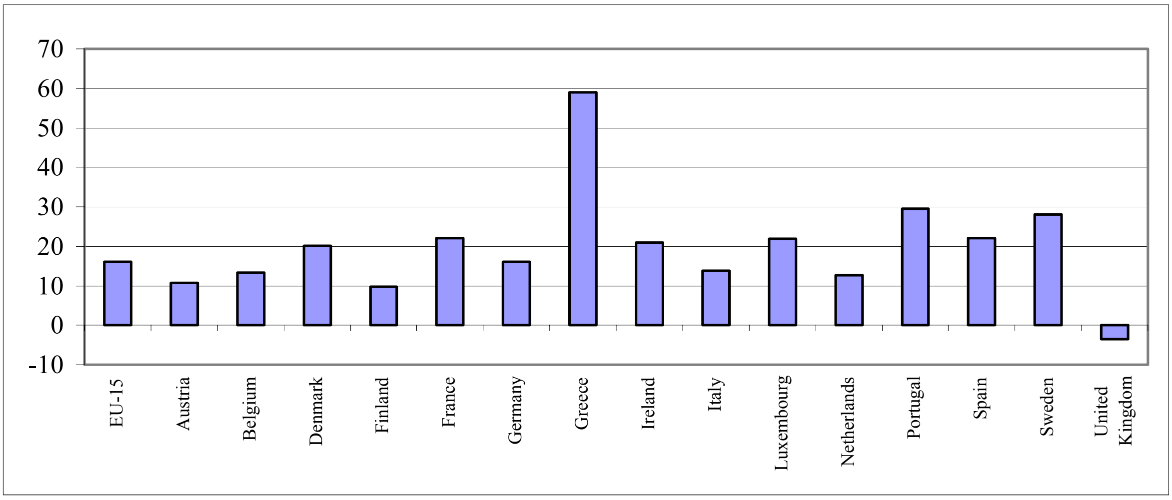
assets of the banks in the respective country. In the same way we also created averages for the European Union. In order to reduce the influence of severe outlying observations we ignore those banks with X-inefficiencies that are tremendously large or small. This can be revealed by means of a (two-sided) trimmed least squares regression of $X - ineff_{ti}$ on a constant and country dummies. We evaluate whether the absolute value of the standardised residuals from this regression exceed the cut-off value 5.[32]

Since inefficiency stemming from the sources discussed above is modest, it is clear that the largest cost reductions in the European banking industry can be achieved by improving management skills, i.e. by improving X-efficiency. In Table 7 we find that for the full sample of banks the average X-inefficiency in the sector is of the order 15-20 percent throughout the sample period. This figure is similar to what has been found for the US. Average X-inefficiencies within the European Union considerably fell from about 20 percent in 1996 to 16 percent in 1997. There remains, however, plenty of scope for improving the banking sector.

Who are Europe's efficient bankers? There are some striking differences in X-efficiency in Europe that are worth mentioning. These are also illustrated in Figure 11. In the UK, bankers were able to reduce their managerial inefficiency from approximately 20 percent in 1993 to full X-efficiency in 1997. On the other hand Greek banks appear to be the most inefficiently managed in Europe. Although Greek bankers improved, average X-inefficiency still exceeded 59 percent in 1997. Like the UK, the Netherlands and Finland show considerable gain in X-efficiency in the sample period. Conversely, Austria, France, Germany and Luxembourg did not improve over time or even worsened. The other differences we observe

[32] We scale the regression residuals by a robust estimate of the standard deviation. For this purpose the Medium Absolute Deviation (MAD) estimator is employed (see, among others, Rousseeuw and Leroy (1987), p.45).

Figure 11. X-inefficiency (in percentages) of European banks in 1997



are less pronounced and sometimes do not match with the prior views that one may have. For example, Sweden is found to have a relatively inefficient banking sector with X-inefficiency ranging between 39 percent (1993) and 28 percent (1997). In Italy on the other hand, which many think is still at an early stage in restructuring, the banking sector is found to be relatively efficient (X-inefficiency fell from 24 percent in 1993 to 14 percent in 1997).

Although differences in X-efficiency across countries are substantial in many cases, we have to be somewhat careful in distinguishing between the performance of banks steering a middle course. The variance of the computed X-inefficiencies corresponding to the companies on the frontier is quite large. Therefore it may happen that average X-inefficiency even becomes negative for a particular country. Managerially efficient banks incur between 10 percent higher costs and 14 percent lower costs than the predicted optimal costs at the 95 percent confidence interval.[33] The "thickness" of the cost frontier, that is the band around the cost function wherein the average cost of X-efficient firms fluctuate, is relatively small in comparison with the dispersion of the inefficient banks. These latter banks are highly inefficient with an average X-efficiency of 77%. In this case, the corresponding 95% confidence interval spans from 57% to 97%. The overlapping part of these two 95% confidence intervals indicate a "twilight zone" where banks are close to optimal performance but not fully cost efficient. The conclusion that can be drawn from these findings is that sometimes X-inefficiencies are extremely high but for other cases there are not enormous differences, all things considered.

Splitting up the sample into commercial banks and savings banks reveals some additional interesting results. Looking at the EU averages in tables 8 and 9 it is clear that commercial banks have higher average X-inefficiencies (around 13%) than savings banks (around 7 percent), when each type is compared to its respective cost frontier. Recall from section 6.3 however that X-efficient savings banks have on average roughly 4 per cent higher costs than X-efficient commercial banks. In other words, it is unlikely that savings institutions on average are much more efficient than their commercial peers when looking at the cost frontier associated with the whole European banking industry.

[33] Our estimation method, RTFA, guarantees that X-efficient banks are not systematically located above or below the frontier.

Table 8 Weighted average of the estimated X-inefficiencies in the European Union, commercial banks (percentages, number of banks given in parentheses)

Country	1997	1996	1995	1994	1993
EU-15	13	18	14	14	13
Austria (20)	19	25	16	3	-10
Belgium (33)	23	33	26	20	20
Denmark (47)	-2	2	3	8	4
Finland (5)	5	12	-2	20	20
France (171)	24	23	15	19	16
Germany (156)	17	21	14	10	1
Greece (17)	66	69	69	69	70
Ireland (5)	15	29	23	26	13
Italy (57)	14	15	20	18	18
Luxembourg (86)	26	25	19	8	14
Netherlands (28)	17	25	23	22	27
Portugal (18)	23	25	26	23	27
Spain (66)	20	15	10	8	10
Sweden (5)	1	0	-7	2	9
United Kingdom (59)	-16	4	3	8	15

Note:This table is derived using results in Table 3. The weight of each bank is obtained from its total asset amount.

Table 9 Weighted average of the estimated X-inefficiencies in the European Union, savings and cooperative banks (percentages, number of banks given in parentheses)

Country	1997	1996	1995	1994	1993
EU-15	9	6	7	7	7
Austria (21)	8	4	14	11	9
Belgium (19)	13	11	15	1	1
Denmark (28)	7	13	19	20	27
France (86)	13	4	10	11	11
Germany (673)	4	4	0	3	-3
Italy (129)	6	7	16	8	11
Luxembourg (5)	2	6	3	-4	13
Spain (55)	21	23	22	24	30
Finland (1)	23	23	38	42	53
Greece (0)	--	--	--	--	--
Ireland (0)	--	--	--	--	--
Netherlands (2)	-1	-1	-1	0	18
Portugal (3)	29	29	30	30	36
Sweden (0)	--	--	--	--	--
United Kingdom (3)	41	36	34	24	33

Note: This table is derived using results in Table 4. The weight of each bank is obtained from its total asset amount.

Table 10 Weighted average X-inefficiency of small and large banks (percentages).

Year	Large	Small
1997	14	20
1996	18	25
1995	18	24
1994	18	24
1993	19	24

Note: A bank is defined to be 'large' when its total assets in 1997 exceeded ECU 10 billion. Small banks had a balance sheet total which was smaller than ECU 10 billion. In our sample there are 200 big banks and 1774 small ones.

We also investigated whether there are differences in X-efficiency between small and large banks. Here we defined a bank to be 'large' when its 1997 total assets amount exceeded EUR 10 billion. The other banks were defined as 'small'. In our data set there are 200 big banks and 1774 small ones. Table 10 shows that, on average, large banks have around 6 percent lower X-inefficiency than small banks. To us this result seems somewhat counterintuitive as we would expect that smaller banks are easier to manage. Possibly large banks operate in a more competitive environment which forces them to be more efficient. Another reason can be that managers of large commercial banks are better monitored by shareholders. It is interesting to note that both small and large banks reduced their X-inefficiency over time.

Conclusion

This paper investigated economies of scale and efficiency in European banking. For this purpose, a cost frontier was estimated. It is assumed that the frontier applies at the European level, i.e. banks located in any region of the European union can achieve *best practice* as indicated by the frontier, but the cost function discriminates between banks of different legal status and allows for shifts in average costs over time. In comparison with the numerous analyses of the performance of American banks, the number of analyses that have considered European banking is few.

New empirical evidence was obtained by estimating an augmented Cobb-Douglas model, which allows us to disentangle the effects of input prices on average costs from other time-related effects such as technological progress. Furthermore, an innovative regression technique, the so-called Recursive Thick Frontier Approach, was also used. RTFA sorts the full sample into a group of X-efficient banks and a group of X-*in*efficient banks and proceeds with testing whether the banks, which are supposed to be managerial efficient, are randomly distributed around the frontier. The advantages of the new method, compared to the traditional econometric frontier techniques, are the following: First, the basic underlying assumptions of the model can be tested. Second, RTFA is less sensitive to outlying observations. However, the number of firms that are relatively close to the frontier must be sufficiently large in order to successfully apply this technique.

To summarise our results, we find that the cost structure and performance of European banks over the period 1993-1997 can be characterised by the following key observations:

The gains from *positive economies of scale* are "scanty" for the overall European banking industry. The picture becomes slightly different when looking only at the saving sector. Our results indicate that cost reductions of about 6% can be achieved for savings banks through larger (or, in some cases, smaller) scale. However, increasing returns to scale do only exist for firms up to a size of EUR 600 million. The average cost curve is clearly U-shaped for saving institutions since the ten largest firms, i.e. with total assets exceeding EUR 50 billion, have significantly higher costs than savings banks in the optimal size class. For commercial banks the optimal size picture is less transparent, which is possibly due to the fact that this group of banks is highly heterogeneous.

Significant shifts in the cost frontier over time were only detected for saving institutions. The drop of about 9 percent in average costs experienced by the best practice savings banks could be due to technological innovation but may equally well indicate that these banks have reduced their distance to the even more efficient best practice commercial banks by cutting costs in other ways. Indeed, different types of credit institutions are operating on different average cost levels. For instance, when taking into account the full sample of credit institutions, we find that X-efficient commercial banks incur, on average, four per cent lower costs per unit of assets than X-efficient savings banks during the sample period. Mortgage banks, in their turn, have considerably lower costs than commercial banks.

From a cost reduction point of view, one may therefore expect that competitive forces will eventually trigger restructuring of the European banking sector in the form of de-mutualisation of savings banks. On the other hand, in contrast to savings banks, mortgage banks are considerably different from commercial banks in respect of the financial services they offer. It is, thus, very likely that certain types of niche players may flourish while at the same time the bulk of the European financial institutions go in the direction of commercial banking.

In contrast with the consequences of size, technology and type, large cost reductions are possible when managers organise their business in a more efficient manner. Our results show that more than 80% of the European banks are not located at their cost frontier and that these banks can reduce the cost per unit of assets with more than 16% on average. The slimming course of the European banking sector has already led to substantial cost cutting across Europe, and X-inefficiency decreased on average say about four percent over our sample period. A remarkable result is that bankers in the UK were able to reduce X-inefficiencies from over 20% to essentially zero in this fairly short time span. Although some countries showed rapid improvement in bank performance, in other countries such as Austria, France, Germany, and Luxembourg, bankers have yet to step on the scales. Therefore, considerable differences in cost efficiency still exist across Europe.

Although the European banking industry is at the beginning of a new era with the introduction of the Euro, one can only guess about the rapidity at which the necessary restructuring will take place. Restrictive labour laws, state ownership and other forms of state interference (promoting national champions etc.), cultural and language barriers to cross border banking and the like may set the pace of changes in European banking. However, there is plenty of scope to reduce costs and enhance efficiency throughout Europe.

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Appendix A1 Price Data

In the main text we have mentioned three input prices and a price index for banking services. In this appendix we give a detailed description of how we created these data.

The *price of funds* is obtained by taking a weighted average of the 3-month interbank offered rate and the deposit rate. The weight of the deposit rate is taken to be the value of deposits over the total amount of liabilities. The weight of the interbank rate is taken to be one minus the deposit rate weight. The deposit rates are extracted for each country from the IFS data set [Line 60l in the IFS data set of the IMF]. For some countries, we missed data on the last quarter in 1997 in which case we constructed the 1997 value to be the average of the rates in the first three quarters of 1997. The interbank rate was retrieved from Datastream International. We downloaded monthly data on the 3-month interbank offered rates in the EU-15 countries and from these we created year averages. The interbank rates which were thus created are given in Table A1.1.

The *price of labour* was constructed using BankScope data and OECD data. As wages in each country differ, we created 15 different wage rates. The 1996 and 1997 observations in each country are constructed using BankScope. We added up all labour expenses of all banks in the sample in a given country and divided the sum by the number of workers employed by these banks. A considerable number of banks report the necessary data. Only in case of Ireland we had few banks [in 1996, three banks (out of seven), and in 1997, four]. As employment data prior to 1996 is normally not found in BankScope we could not generate wage rates for 1993 – 1995 in this way. However, in the 1998 issue of 'Bank Profitability' of the OECD there is data for 1993 –1996 both on labour expenses in the banking sector, and on the total number of employees.[34] With this we had data for the entire period 1993 – 1997, with double data for the year 1996. Unfortunately, for a few countries the 1996 values of the BankScope calculations differed considerably from the OECD data, and we decided to base the price of labour in 1996 and 1997 on the BankScope data. Data for 1993, 1994 and 1995 was obtained by extrapolating the 1996 observation from BankScope using the OECD data to compute changes in the wage rate in the period 1993 – 1996. The results are given in Table A1.2. The *price of buildings* is created by taking a price index for newly delivered buildings and correcting it for the relative price levels in each country.

The data on newly delivered buildings is obtained from the CRONOS data set of Eurostat (/theme4/ construc/ isti08a/ i8aa ind, see Table A1.3), and relative price levels are constructed from data of CRONOS and the IFS of the IMF. We used Purchasing Power Parities (PPPs) with respect to Germany. In WEFA we found exchange rates to the German Mark for the EU-15 currencies.[35] In CRONOS we found monthly purchasing power parities from Jan 1993 until Nov 1995 (/theme2/ price/ ppa/ ppam). Dividing the exchange rates by the PPPs we obtained monthly data on the relative price level in Jan 1993 – Nov 1995. The observations from December 1995 onwards could be generated using IFS. In particular, we downloaded monthly data on the 'real effective exchange rate' (i.e. series r*eu)* for Nov 1995 – Dec 1997 and used this index to extrapolate the previous data. From the monthly relative price levels in the EU-15 we created yearly averages [see Table A1.4]. The relative price

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[34] That is, for some countries the data is not available for the banking sector as a whole. In that case the OECD gives data for the commercial banks (Greece, Luxembourg, Portugal, Sweden and the UK) or for commercial plus savings banks (Denmark).

[35] These are given by the series L00RF.M; e.g. for the UK (country code is M112) the series was 'M112L00RF.M'.

Table A1.1 Interbank rates in the EU-15 countries in 1993 – 1997, percentages

Country	Datastream Code	1993	1994	1995	1996	1997
Austria	ASVIB3M(IO)	7.05	5.14	4.57	3.38	3.50
Belgium	BIBOR3M(IO)	8.30	5.78	4.85	3.30	3.50
Denmark	CIBOR3M(IO)	10.83	6.32	6.13	4.02	3.73
Finland	FNIBC3M(IO)	7.81	5.37	5.70	3.63	3.24
France	PIBOR3M(IO)	8.76	5.88	6.52	3.95	3.48
Germany	FIBOR3M(IO)	7.36	5.40	4.53	3.32	3.33
Greece[a]	GDIBK3M(IO)	21.50	30.49	16.46	13.85	14.20
Ireland[b]	EIRED3M(IR)	9.56	5.94	6.25	5.41	6.06
Italy[c]	ITIBK3M(IO)	10.39	8.57	10.57	8.87	6.89
Luxembourg[d]	BIBOR3M(IO)	8.30	5.78	4.85	3.30	3.50
Netherlands	HOLIB3M(IO)	6.88	5.20	4.37	3.01	3.32
Portugal[a]	LISBO3M(IO)	13.42	11.27	9.90	7.39	5.71
Spain	ESMIB3M(IO)	11.88	8.09	9.33	7.58	5.46
Sweden	SIBOR3M(IO)	8.88	7.63	8.80	6.04	4.44
United Kingdom	LDNIB3M(IO)	6.04	5.67	6.80	6.18	6.95

Notes:

[a] We missed some observations for Portugal and Greece. For Portugal we missed two observations: 31/12/92 and 31/1/93, so we averaged the other 1993 observations to come to the 1993 rate. Our first Greek observation is the 29/04/1994 one, so we missed little more than a year. For the last of these missing observations we found a good substitute, the 3 month deposit offered rate in Greece. We established our 1994 average as the average of these three observations and the 9 interbank rates we had for 1994. The 1993 average we took to be 21.5 percent, a rough guess based on extrapolating the three 3 month deposit rates we had for Greece.

[b] Datastream has no interbank rates for Ireland, so we took the 3-Month money middle rate [EIRED3M(IR)].

[c] Italy's first 4 monthly observations were taken from the series 'Italy Atic Interbank 3-month (history) - offered rate'.

[d] The Luxembourg data series is the same as the Belgium one [BIBOR3M(IO)].

levels in Table A1.4 were used to correct the price indices of buildings of Table A1.3 for price differences between the EU countries. The price index which resulted from this is the *price of buildings* as used in the study [see Table A1.5].

The price index for *banking services* is obtained from the CRONOS data set of Eurostat. We followed the link /theme2 /price /hicp /haind and selected time series hicp_idx, 125a ('banking services n.e.c.'). Unfortunately CRONOS only has data from 1995 onwards, if at all. To solve this problem, we took the 1993 and 1994 levels to be equal to the 1995 level. The results are given in Table A1.6.

Table A1.2 Annual wage rate per employee in ECU in the EU-15 countries, 1993 – 1997

	1993	1994	1995	1996	1997
Austria	46062	48002	52913	53827	52115
Belgium	54898	56704	58765	60161	60880
Denmark	43418	45000	47797	49986	51744
Finland	29898	32664	33069	37554	35054
France	51956	51591	52848	54946	57509
Germany	43606	44837	48627	49813	52923
Greece	19439	20788	22758	25555	27602
Ireland[a]	31696	31696	31696	34384	35350
Italy	55323	54966	50784	59409	58476
Luxembourg	54579	60460	64095	64284	63916
Netherlands	36635	40006	44601	47943	55438
Portugal	27731	27605	30322	32380	33905
Spain	39615	36296	37686	40203	37389
Sweden	39919	40048	46305	53385	55883
United Kingdom	41193	40452	40571	39950	42023

[a] For the years 1993 and 1994 no data was available. Wages in these years we have assume to be equal to the 1995 wages.

Table A1.3 Cost of buildings, price indices for the EU-15 (Source: CRONOS, Eurostat)

Country	CRONOS Code	1993	1994	1995	1996	1997
Austria	Prin_out, b100 [a]	95.2	97.7	100.0	101.7	103.3
Belgium	CPI [f]	96.3	98.6	100.0	102.0	103.7
Denmark	Prin_inp, b110 [d]	94.5	96.4	100.0	103.1	106.0
Finland	Prin_inp, b100 [c]	97.3	98.8	100.0	98.9	101.3
France	Prin_out, b110 [b]	99.9	100.1	100.0	101.8	104.2
Germany	Prin_out, b110 [b]	95.4	97.6	100.0	99.9	99.3
Greece	Prin_out, b110 [b]	87.9	94.4	100.0	106.0	111.5
Ireland	Prin_inp, b900 [e]	94.4	96.6	100.0	100.7	104.7
Italy	Prin_inp, b110 [d]	94.7	98.1	100.0	101.8	104.3
Luxembourg	Prin_out, b110 [b]	97.0	98.2	100.0	100.9	102.4
Netherlands	Prin_out, b110 [b]	94.1	96.4	100.0	102.3	106.1
Portugal	CPI [f]	91.2	96.0	100.0	103.1	104.9
Spain	Prin_inp, b100 [c]	92.3	95.4	100.0	102.8	104.7
Sweden	CPI [f]	95.4	97.5	100.0	100.5	101.0
United Kingdom	Prin_out, b110 [b]	92.1	95.4	100.0	102.0	107.1

Notes:
[a] Output price index of the building sector (national currency)
[b] Output price index for residential buildings (national currency)
[c] Construction cost index of the building sector (national currency)
[d] Construction cost index of residential building (national currency)
[e] Construction cost index of building and civil engineering sector (national currency)
[f] Consumer price index

Table A1.4 Price levels in EU-15 relative to German prices, year averages for 1993 – 1997.

	1993	1994	1995	1996	1997
Austria	0.99	1.01	1.02	1.02	1.06
Belgium	0.90	0.91	0.91	0.93	0.96
Denmark	1.16	1.16	1.16	1.20	1.27
Finland[a]	1.00	1.00	1.00	0.94	0.96
France	0.92	0.91	0.90	0.91	0.94
Germany	1.00	1.00	1.00	1.00	1.00
Greece	0.69	0.69	0.69	0.75	0.83
Ireland	0.78	0.77	0.74	0.74	0.76
Italy	0.75	0.73	0.66	0.76	0.84
Luxembourg	0.84	0.85	0.86	0.87	0.90
Netherlands	0.91	0.92	0.92	0.91	0.92
Portugal	0.63	0.62	0.61	0.64	0.67
Spain	0.75	0.72	0.70	0.74	0.78
Sweden[a]	1.00	1.00	1.00	1.06	1.07
United Kingdom	0.74	0.74	0.68	0.73	0.95

[a] For Sweden and Finland we missed data for Jan 1993 - Nov 1995. In these months the relative price levels have been taken to be 1.

Table A1.5 Price index buildings (Germany 1995 = 100)

	1993	1994	1995	1996	1997
Austria	94.5	99.1	101.5	103.5	109.7
Belgium	86.6	89.7	91.0	94.9	99.6
Denmark	109.7	111.7	116.3	123.3	135.2
Finland	97.3	98.8	99.9	93.2	97.1
France	91.4	91.4	89.7	92.5	97.5
Germany	95.4	97.6	100.0	99.9	99.3
Greece	60.7	65.2	68.5	79.1	92.7
Ireland	73.9	74.8	73.8	74.8	79.5
Italy	71.4	71.7	66.0	77.6	87.5
Luxembourg	81.8	83.7	85.5	88.2	92.4
Netherlands	86.0	88.4	91.8	93.5	97.8
Portugal	57.8	59.1	61.1	65.9	70.6
Spain	69.7	68.2	69.9	76.2	81.2
Sweden	95.4	97.5	100.1	106.2	108.3
United Kingdom	67.9	70.4	68.2	74.4	101.3

Table A1. 6 Price index for banking services (Source: CRONOS, Eurostat)

Country	1993	1994	1995	1996	1997
Austria[b]	100	100	100	100	100.1
Belgium[a]	95.5	95.5	95.5	100	100.5
Denmark[a]	98.5	98.5	98.5	100	102.8
Finland[a]	102.5	102.5	102.5	100	101.1
France[b]	100	100	100	100	100.3
Germany[a]	97.5	97.5	97.5	100	102.4
Greece[c]	100	100	100	100	100
Ireland[a]	89.2	89.2	89.2	100	103.8
Italy[a]	93.6	93.6	93.6	100	109.9
Luxembourg[a]	94	94	94	100	112
Netherlands[a]	100.9	100.9	100.9	100	99.7
Portugal[a]	94.5	94.5	94.5	100	105.8
Spain[a]	97	97	97	100	118.7
Sweden[a]	98.1	98.1	98.1	100	114.4
United Kingdom[b]	100	100	100	100	101.2

Notes:

[a] Missing values in CRONOS for 1993 and 1994.

[b] Missing values in CRONOS for 1993, 1994 and 1995.

[c] Missing values in CRONOS for all years.

Appendix A2 Regression Results

Table A2.1 The number of banks which are on the cost frontier in the European Union

Country	Full Sample (Concomitant Table A2.3)	Commercial Banks (Concomitant Table A2.6)	Savings Banks (Concomitant Table 4)
Austria	8	0	8
Belgium	5	1	5
Denmark	13	3	5
Finland	0	0	0
France	59	23	36
Germany	173	26	51
Greece	0	0	--
Ireland	1	1	--
Italy	32	13	38
Luxembourg	25	17	3
Netherlands	3	5	1
Portugal	1	2	0
Spain	5	9	0
Sweden	2	2	--
United Kingdom	13	13	0

Table A2.2 Number of observations in each size class for the three regressions

Size Class	Full Sample (9870)	Commercial Banks	Saving Banks
Total Assets ≤ 100 million (ECU)	569	316	204
100 million < Total Assets ≤ 300 million	2013	680	1259
300 million < Total Assets ≤ 600 million	1551	557	919
600 million < Total Assets ≤ 1 billion	1197	457	658
1 billion < Total Assets ≤ 5 billion	2901	980	1649
5 billion < Total Assets ≤ 10 billion	638	304	233
10 billion < Total Assets ≤ 50 billion	703	348	158
50 billion < Total Assets	298	223	45

Table A2.3 The estimated Cobb-Douglas cost frontier for the period 1993–1997, full sample

	Parameter Estimate	t-value
Constant	0.0018*	4.84
Deposits over Total Assets	0.0065*	3.33
Loans over Total Assets	0.0782*	24.25
Equity Investments over Total Assets	0.0099*	6.91
Off-balance Sheet over Total Assets	-0.0105*	-7.62
Brokerage over Total Assets	0.0990*	28.44
Price of Funds	0.5050*	35.38
Price of Labour	0.2455*	9.18
Price of Buildings	0.2496*	12.53
Dummy, Total Assets ≤ 100 Million ECU	1.0789*	3.94
Dummy, 100 Million < Total Assets ≤ 300 Million	1.0650*	3.79
Dummy, 300 Million < Total Assets ≤ 600 Million	1.0287	1.63
Dummy, 600 Million < Total Assets ≤ 1 Billion	1.0353	1.93
Dummy, 1 Billion < Total Assets ≤ 5 Billion	1.0262	1.59
Dummy, 10 Billion < Total Assets ≤ 50 Billion	1.0424*	1.99
Dummy, 50 Billion < Total Assets	1.0421	1.78
Dummy Commercial Banks	0.9390	-7.70
Dummy Mortgage Banks	0.6867	-9.27
Dummy M-LT & NB Credit Institutions	0.6602	-14.94
Dummy 1997	1.0706	1.53
Dummy 1996	1.0887	1.91
Dummy 1995	1.0171	0.40
Dummy 1994	1.0320	0.75
Adjusted Coefficient of Determination	0.49	
Binomial Test	5.96	
Number of banks on the cost frontier	340	

Notes:
(1) The regressand is 'total costs over assets'.
(2) Brokerage is scaled by the annual average index of the price of banking services in the respective countries.
(3) Type dummies are defined with respect to savings and cooperative banks.
(4) Time dummies are defined with respect to the year 1993.
(5) Size dummies are defined with respect to the class: 5 Billion < Total Assets ≤ 10 Billion ECU.
(6) We have adopted the RTFA method. The "Binomial Test" statistic asymptotically converges to a Chi-squared distribution with one degree of freedom.
(7) The price of funds is computed as the weighted average (according to the relative amount of deposits in total assets) of the (yearly average of the) 3-months LIBOR and the deposit rate.
(8) $\chi^2_{0.01}(1) = 6.63,$ and $t(\infty)_{0.025} = 1.96.$ Significant parameters at the 95% confidence level are marked with an asterisk.

Table A2.4 Weighted average of the estimated X-inefficiencies in the European Union (percentages, number of banks in each country given in parentheses)

Country	1997	1996	1995	1994	1993
EU-15	16	18	20	19	21
Austria (50)	14	17	23	16	7
Belgium (69)	15	24	22	18	21
Denmark (82)	21	23	27	36	29
Finland (7)	14	18	17	31	34
France (295)	23	20	22	23	23
Germany (886)	18	19	19	16	13
Greece (17)	57	59	62	63	65
Ireland (7)	22	35	38	39	33
Italy (194)	10	11	23	19	22
Luxembourg (97)	23	20	21	12	21
Netherlands (35)	14	24	24	22	31
Portugal (24)	29	29	35	33	38
Spain (125)	20	15	18	18	24
Sweden (12)	28	28	22	36	40
United Kingdom (74)	-4	4	11	14	23

Note: This table is derived using the results in Table A2.3. The weight of each bank is obtained from its total asset amount.

Table A2.5 Weighted average of the estimated size inefficiencies in the European Union (percentages, number of banks in each country given in parentheses)

Country	1997	1996	1995	1994	1993
EU-15	0.03	0.04	0.04	0.05	0.05
Austria (50)	0.02	0.03	0.04	0.05	0.05
Belgium (69)	0.02	0.03	0.03	0.04	0.04
Denmark (82)	0.15	0.16	0.17	0.18	0.17
Finland (7)	0.00	0.00	0.00	0.00	0.00
France (295)	0.02	0.02	0.02	0.02	0.02
Germany (886)	0.06	0.07	0.08	0.10	0.11
Greece (17)	0.03	0.02	0.04	0.13	0.13
Ireland (7)	0.00	0.00	0.00	0.00	0.00
Italy (194)	0.02	0.03	0.03	0.03	0.03
Luxembourg (97)	0.05	0.08	0.07	0.09	0.08
Netherlands (35)	0.01	0.02	0.02	0.02	0.02
Portugal (24)	0.00	0.00	0.00	0.01	0.00
Spain (125)	0.01	0.02	0.02	0.03	0.03
Sweden (12)	0.00	0.00	0.00	0.00	0.01
United Kingdom (74)	0.01	0.01	0.01	0.01	0.01

Note: This table is derived using the results in Table A2.3. The weight of each bank is obtained from its total asset amount.

Table A2.6 The estimated Cobb-Douglas cost frontier for the period 1993–1997, commercial banks

	Parameter Estimate	t-value
Constant	0.0126*	2.60
Deposits over Total Assets	0.0095*	2.62
Loans over Total Assets	0.0454*	5.79
Equity Investments over Total Assets	0.0140*	4.82
Off-balance Sheet over Total Assets	-0.0150*	-4.99
Brokerage over Total Assets	0.1627*	18.51
Price of Funds	0.6493*	22.81
Price of Labour	0.0890	1.65
Price of Buildings	0.2617*	5.30
Dummy, Total Assets $\leq 10^8$ (ECU)	0.7714*	-6.08
Dummy, $10^8 <$ Total Assets $\leq 3*10^8$	0.9159*	-3.13
Dummy, $3*10^8 <$ Total Assets $\leq 6*10^8$	0.9168*	-2.97
Dummy, $6*10^8 <$ Total Assets $\leq 10^9$	0.9696	-0.91
Dummy, $0.5*10^{10} <$ Total Assets $\leq 10^{10}$	0.8966*	-2.91
Dummy, $10^{10} <$ Total Assets $\leq 0.5*10^{11}$	1.0814*	2.69
Dummy, $0.5*10^{11} <$ Total Assets	0.9596	-1.26
Dummy 1997	1.1234	1.36
Dummy 1996	1.1272	1.41
Dummy 1995	1.0302	0.37
Dummy 1994	1.0408	0.50
Adjusted Coefficient of Determination	0.38	
Binomial Test	5.68	
Number of banks on the cost frontier	115	

Notes:
(1) The regressand is 'total costs over assets'.
(2) Brokerage is scaled by the annual average index of the price of banking services in the respective countries.
(3) Type dummies are defined with respect to savings and cooperative banks.
(4) Time dummies are defined with respect to the year 1993.
(5) Size dummies are defined with respect to the class: 1 billion < Total Assets ≤ 5 billion.
(6) We have adopted the RTFA method. The "Binomial Test" statistic asymptotically converges to a Chi-squared distribution with one degree of freedom.
(7) The price of funds is computed as the weighted average (according to the relative amount of deposits in total assets) of the (yearly average of the) 3-months LIBOR and the deposit rate.
(8) $\chi^2_{0.01}(1) = 6.63,$ and $t(\infty)_{0.025} = 1.96.$ Significant parameters at the 95% confidence level are marked with an asterisk.

Table A2.7 Weighted average of the estimated X-inefficiencies in the European Union, commercial banks (percentages, number of banks given in parentheses)

Country	1997	1996	1995	1994	1993
EU-15	13	18	19	18	18
Austria (20)	24	29	25	12	1
Belgium (33)	26	35	32	25	25
Denmark (47)	3	5	11	15	10
Finland (5)	7	13	4	24	24
France (171)	26	23	20	23	21
Germany (156)	20	23	21	15	8
Greece (17)	62	64	66	65	67
Ireland (5)	14	28	28	31	17
Italy (57)	12	10	21	20	22
Luxembourg (86)	28	26	25	12	19
Netherlands (28)	20	27	29	25	33
Portugal (18)	19	18	24	19	25
Spain (66)	17	10	11	7	11
Sweden (5)	3	1	-3	4	14
United Kingdom (59)	-19	0	6	12	21

Note: This table is derived using results in Table A2.6. The weight of each bank is obtained from its total asset amount.