EFFICIENCY IN THE EUROPEAN BANKING INDUSTRY: AN EXPLORATORY ANALYSIS TO RANK COUNTRIES

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Abstract

The introduction of the euro in EMU is enhancing international competition between European banks, forcing banks to become more efficient. Which countries will be effected the most? The stochastic cost frontier approach is used to estimate the X-efficiency of the European banks, and a multiproduct translog cost function to compare cost levels. On average, Spanish, French and Italian banks appear to be less efficient than those in Germany, the Netherlands and the UK, while banks in Luxembourg, Belgium and Switzerland are the most efficient. Large differences in average X-inefficiencies and cost-levels between countries exist, Spain being 40% above and Luxembourg 35% below the European average. Large-scale consolidation and rationalisation of the banking industry are expected. Furthermore, the analysis provides strong evidence that X-efficiency estimates from single-country studies, as often found in the literature, can be very misleading.

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1 INTRODUCTION

Many forces of change have affected the competitive environment of the banking industry. This holds
in particular for the European Union, where the adoption of the Second Banking Co-ordination Direc-
tive of 1992 as part of the single European market project has removed institutional obstacles for
banks to operate in foreign markets in the EU. The establishment of the Economic and Monetary
Union and the introduction of one single currency at the beginning of 1999 will also seriously effect
the banking world. Large and transparent euro capital markets are expected to emerge. The
comparative advantages of domestic banks on the domestic markets for bonds and equity in the field
of underwriting and trading activities have diminished since national currencies have been replaced by
the euro. For similar reasons, fund management will no longer be the preserve of local financial
institutions. These developments with respect to international integration will, together with national
deregulation and entry of new types of competitors, further boost competition between banks in the
countries involved. These issues have stirred up the interest in efficiency of banks. Under perfect
competition or market conditions not far from that situation, less efficient banks will be driven from
the market. Eventually, the expected increase in competition is likely to lead to further consolidation
and rationalisation in the European banking sectors. Less efficient banks are more likely to run the risk
of being taken over. Large-scale rationalisation has grave effects on employment. For each of the
European nations, the degree of inefficiency of their banks is vitally important for public policy with
respect to the viability of its banking industry in the near future. The effect of mergers and acquisitions
on efficiency is of crucial importance for individual firms, seeking cost reduction in an increasingly
competitive environment, and for governments, which outline and apply antitrust policies.

In the last decade, the (in-)efficiency of the banking industry has been investigated extensively. In
more recent years, the emphasis of this research area has shifted from scale and scope economies
towards technical and allocative inefficiency. The managerial ability to decide on input and output in
order to minimise cost or maximise revenues is referred to as X-inefficiency. The stochastic cost
frontier approach seeks to measure this type of inefficiency as deviations of the costs from the so-
called efficient frontier, which is the estimated level of costs under optimal behaviour.

This paper applies the stochastic cost frontier approach to the European banking industry in an attempt
to measure its efficiency. To the best of our knowledge, a multicountry study of this kind for Europe is
new. Whereas stochastic cost frontier functions and more statistical approaches, such as the data envelopment analysis, have been applied to the US banking industry manifold, the number of applications to European countries is rather limited. Studies which compare the banking sectors of the major EU countries are lacking (Berger and Humphrey, 1997, Molyneux et al., 1996). Given the recent far-reaching structural changes in the environment of the European banking industry, this limited attention for Europe is fairly remarkable. This may be explained in part by limited availability and unsatisfactory quality of data of the European banks and by particular problems of multicountry studies, among which, technical difficulties and the imperfect international comparability of the data.

The structure of this paper is as follows. Section 2 discusses various definitions of efficiency and presents several often used simple ratios and index numbers for European countries, which are used as a proxy for efficiency. Section 3 introduces the stochastic frontier model, deals with conceptual issues and elucidates basic choices concerning the specification. Section 4 presents the empirical results of European-wide and country-specific estimations. Section 5 reveals some restrictions of the stochastic cost frontier approach in a multicountry setting and presents an alternative measure for efficiency, based on the multiproduct translog cost function, which is also the basic component of the stochastic frontier model. Section 6 refines the estimates by taking the various bank categories into account and reconsider the appropriateness of the frequently applied ratios and index numbers in the light of the refined estimates of efficiency. Section 7 summarises and concludes.

2 PROXIES FOR EFFICIENCY

Farrell (1957) distinguishes two components of the efficiency of a firm: technical efficiency, which reflects the ability of a firm to obtain maximum output from a given set of inputs, and allocative efficiency, which indicates the ability of a firm to use the inputs in optimal proportions, given their respective prices and the production technology. These two measures can be combined to provide a measure of total economic efficiency, or, when cost instead of production is considered, cost efficiency. The optimal or most efficient production, depending on various circumstances such as the scale of the firm in particular, is called efficient frontier. Errors, lags between the choice of the production plan and its implementation, human inertia, distorted communications and uncertainty cause deviations from the efficient frontier, called X-inefficiency (Leibenstein, 1966). Measuring X-inefficiency in the EU banking industry will be the subject of this paper. For the sake of presentation, further on, we will often alternate efficiency and its complement inefficiency, and drop the prefix X where possible.

Studies that compare the efficiency of the banking sectors of European countries are rare or lacking.

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2 In their prominent survey on efficiency of financial institutions, Berger and Humphrey (1997) mention a few multicountry studies for Scandinavian countries or groups of developed countries, but these studies are not
Of course, efficiency cannot be observed directly. Berger and Humphrey (1997) and Molyneux et al. (1996) mention a number of studies that investigate the degree of inefficiency of financial institutions in a number of European countries by applying the stochastic frontier approach, data envelopment analysis or similar methods. However, these studies do not discuss the differences in efficiency between these countries.

Often, efficiency is estimated using related concepts, such as the cost income ratio or the interest rate margin. Table 1 presents a number of more or less well-known proxies of efficiency for nine European countries, investigated further in the remainder of this paper, namely the largest seven EU countries: Belgium, France, Germany, Italy, the Netherlands, Spain and the UK, and two smaller countries with important banking sectors: Luxembourg and Switzerland. The first proxy is the ratio of operating (non-interest rate) expenses and gross income. The interpretation of this ratio is not unambiguous. As proxy of efficiency it is common to assume that a high ratio indicates high efficiency, (forced by) strong competition and (as a result) low average profit rates. This interpretation supposes that tariffs of bank services, such as interest margins, commissions and fees, are more or less fixed due to

directed to Europe as a whole or to the major part of it, nor do they compare countries. Anyhow, these studies are not based on the stochastic cost frontier approach.

The H-value is the sum of input price elasticities of the total interest rate revenue. H is zero in the case of monopoly, 1 in the case of perfect competition and between these extreme values in the case of monopolistic competition.
competition, and hence that, given the output level, revenues are more or less fixed. An alternative view is that inefficiency causes relatively high cost, whereas profits may be seen, to some extent, as accidental or unrelated to cost. This view presumes that tariffs of bank services are not to a greater extent liable to competitive forces, but may be determined by, for instance, a markup on costs. Given the fairly strong competitive conditions in Europe, a certain degree of monopolistic competition, closer to perfect competition than to monopoly (Bikker and Groeneveld, 2000), and in line with the common view, we consider the first interpretation to be the most likely one. Hence, in Table 1, the three highest cost income ratios, indicating the countries among the group of nine with the most efficient banks, are shaded lightly, and the three lowest ratios, referring to the countries with the least efficient banks, are shaded darkly. This kind of shading in order to indicate countries with relatively efficient and inefficient banks is also applied to the other proxies.

The second proxy is the ratio of net interest rate income and the balance sheet total. Low values of this ratio reflect high efficiency, strong competition and low profit rates. This ratio may be distorted by differences in the yield curve between the countries considered, the relative size of equity capital and book-keeping operations, which enlarge or shorten the balance sheet. Other proxies are related to excessive use of labour or branch offices, indicating less developed types of production: labour cost as share of total operating expenses, the number of employees per 10,000 inhabitants, the ratio of the number of employees and balance sheet total, and the number of branches per 10,000 inhabitants. Actually, these indices are rather poor, as they reflect only a minor part of the determinants of efficiency. Finally, we present indices of concentration and competition, which are often assumed to be (positively) related to efficiency. For concentration, the relative balance sheet total of the largest three banks is used and for competition the so-called H-value of Panzar and Rosse as calculated by Bikker and Groeneveld (2000).  

The results in Table 1 are not very helpful in obtaining a ranking of the efficiency of the banking sectors in the nine countries considered. Virtually each country is indicated as efficient at least once, and each country but one is also referred to as inefficient at least once. There are at any rate two reasons for this unsatisfactory result. Firstly, all the employed ratios and indices are, at the best, remotely related to efficiency or reflect one of its many aspects; the majority of them does not directly measure efficiency. Secondly, many proxies are disturbed by measurement errors or special circumstances. For instance, banks in Luxembourg and Switzerland can attract foreign funds at lower cost, due to banking secrecy, the lack of tax on income from wealth for non-inhabitants and the stable currency, and employ a larger part of their countries’ population. Another example is the index of concentration, which tends to be higher in smaller countries. The lower part of Table 1 presents correlations between the ratios and indices, which are expected to be negative in the (very) lightly shaded areas and positive elsewhere. The low values confirm that the proxies do not coincide but (partly) diverge, whereas the
wrong signs even point to opposite pattern. Apparently, at least most of the proxies are unreliable as indicator of efficiency.\(^5\)

Disregarding these shortcomings, the final column of Table 1 presents a plain diffusion index, which just adds plusses (light shading) and minuses (dark shading) to obtain a total score. This indicator suggests that Belgium, France, the Netherlands and Switzerland are rather efficient, whereas Germany, Spain and the UK are relatively inefficient. Based on direct (partial) observation or on in-depth knowledge of the countries’ banking sectors, a certain *communis opinio* states that banks in France, Germany and, in particular, Southern European countries, such as Italy and Spain, are on average less efficient than banks in the other Western European countries. More severe regulation, public policy and financial conservatism (Germany), strong direct interference by the government (France and Italy) and lagging economic development (Greece, Spain, Portugal) are mentioned to explain the diverging (alleged) level of efficiency. We will further refer to this opinion as *experts view*, allowing for the fact that experts can also be completely wrong. In general, this view is not supported by any of the indirect proxies of efficiency of Table 1. From the preceding, it is obvious that there is a need for a much more convincing empirical assessment of the efficiency of the banking sectors in European countries.

### 3 THE STOCHASTIC FRONTIER APPROACH

This section seeks to measure the cost efficiency of banks in the nine European countries considered directly, using the stochastic cost frontier approach. In the last decade, this approach has been applied often in literature on efficiency of the banking industry. Stochastic cost frontier models enable us to calculate the degree of inefficiency for each individual bank in the sample and subsequently to draw general conclusions about X-inefficiencies for a country’s banking industry as a whole. Where stochastic cost frontier functions have been applied to the US banking industry manifold, the number of applications to European countries is rather limited. Multiple countries studies which allow international comparison of inefficiency are rare.

Bank cost efficiency analysis is based on the assumption that the technology of an individual bank can be described by a production function, which links banking outputs to available input factors. Under certain conditions, a dual cost function can be derived from the bank’s decision problem, with output levels and factor prices as arguments. Christensen *et al.* (1973) proposed the translog multiproduct cost function as a second-order Taylor expansion, usually around the mean, of a generic function with

\(^5\) It is remarkable that the correlation between cost-income ratio and interest rate margin even has the wrong sign. This issue will be addressed in Section 6.
all variables appearing in logarithms. The translog cost function is a flexible functional form and is one of the most widely used functions for empirical assessment of efficiency.\(^6\)

The first stochastic frontier function for production was independently proposed by Aigner, Lovell and Schmidt (1977) and Meeseusen and Van den Broeck (1977). Schmidt and Lovell (1979) presented its dual as a stochastic cost frontier function. The standard specification involves a model for cross-section data, which has an error term consisting of two components, one to account for random effects due to the model specification and another to account for cost (in)efficiencies. The model can be written in the following form:

\[
c_{it} = \alpha + \sum_{j} \beta_j x_{ijt} + \sum_{j} \sum_{k} \gamma_{jk} x_{ijt} x_{ikt} + v_{it} + u_{it}
\]

The dependent variable \(c_{it}\) is the logarithm of the cost of production of the \(i\)-th firm (\(i=1, ..., N\)) in year \(t\) (\(t=1, ..., T\)). The two sum terms constitute the multiproduct translog cost function: the independent variables, and their squares and cross-terms. The independent variables \(x_{ijt}\) are the logarithms of the output components (such as loans, saving accounts and demand deposits) and input prices (such as wages and the price level of capital) of the \(i\)-th firm in year \(t\), and \(\beta_j\) and \(\gamma_{jk}\) are the companion unknown parameters. The last two terms form the random part of the stochastic frontier function: the \(v_{it}\)'s are the specification errors of the multiproduct translog cost function, which are assumed to be identically and independently \(N(0, \sigma_v^2)\) distributed and the \(u_{it}\)'s are non-negative random variables, which describe cost inefficiency and are assumed to be identically and independently half-normally \((|N(0, \sigma_u^2)|)\) distributed and independent from the \(v_{it}\)'s. In other words, the density function of the \(u_{it}\)'s is (twice) the positive half of the normal density function. As the traditional half-normal distribution may be too restrictive to draw reliable conclusions, we have used the more general truncated normal distribution \(N(\mu, \sigma^2)\), with zero as truncation point, which provides a rich family of distributions, dependent on the parameters \(\mu\) and \(\sigma^2\), and causes less technical problems than the gamma and exponential distributions.\(^7\)

In applying the stochastic frontier model, the question may arise as to whether this model is a significant improvement of the relatively simple linear regression or translog cost function. The following test is available to address that issue. To simplify the calculation of the numerical maximum likelihood estimation procedure of the stochastic frontier model, Battese and Corra (1977) reparameterise the model: \(\sigma_v^2\) and \(\sigma_u^2\) are replaced by \(\sigma^2 = \sigma_v^2 + \sigma_u^2\) and \(\lambda = \sigma_u^2/(\sigma_v^2 + \sigma_u^2)\). The parameter \(\lambda\) can be employed to test whether a stochastic frontier function is essential at all. Acceptance of the null

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\(^6\) See for an overview, Berger and Humphrey (1997).

\(^7\) See Coelli et al. (1998) for a more comprehensive discussion of this issue.
hypothesis $\lambda = 0$ would indicate that $\sigma_u = 0$ and hence that the term $u_t$ should be removed from the model, so that equation (1) narrows down to the linear regression model.

Finally, we will calculate cost efficiency of a bank relative to the cost frontier estimated by model (1). As $c_{it}$ is expressed in logarithms, costs are defined as $C_{it} = \exp(c_{it})$, where $\exp$ refers to the exponential function. $X$ is the matrix containing all explanatory variables. Cost efficiency is defined as:\(^8\)

$$\text{EFF}_{it} = \frac{E(C_{it} \mid u_{it} = 0, X)}{E(C_{it} \mid u_{it}, X)} = 1/\exp(u_{it})$$

Expressed in words, efficiency is the ratio of the expected costs on the frontier (that is the case where the production would be completely efficient, or $u_{it} = 0$) and the expected costs, conditional upon the observed degree of inefficiency.\(^9\) Note that both nominator and denominator are conditional upon $X$, the given volume of output components and input prices. $\text{EFF}_{it}$ ranges from 0 to 1. An alternative expression is ‘inefficiency’, $\text{INEFF}_{it} = \exp(u_{it})$, the inverse of $\text{EFF}_{it}$, which is bounded between 1 and 8.

The appropriate definition of output in banking has been a topic of discussion in the cost efficiency literature. In the intermediation approach, banks attract deposits and other funds and transform these into loans and investment in securities, using labour and inputs, such as buildings, equipment, information technology and materials. Interest payments are seen as part of the bank's costs and the corresponding dual cost function does not include deposits as an input factor, but the interest rate paid on deposits. Examples of this view are Altunbas et al. (1994, 1995) and Barr et al. (1994). An alternative definition of output is taken by the production approach, which assumes banks to be providers of services related to loans and deposits. In this view, interest payments are not regarded as banking costs. As operating costs were shown to comprise the bulk of cost inefficiency at banks (Berger and Humphrey, 1991), the production approach has become the more common one; examples can be found in Swank (1996), Resti (1997) and Berger and DeYoung (1997). This paper also applies the production approach.

Loans, savings accounts and demand deposits are distinguished as production factors. The number of branches has often also been included in the multiproduct cost function, as an indicator of additional service of a bank to its clients. As our data source did not include sufficient observations of the number of branches, we dropped this variable. Most bank services are related to traditional balance sheet items, such as loans and deposits, but to an increasing extent banks provide other services, for instance, trade in securities, asset management and investment funds for clients, trade on its own ac-

\(^8\) This expression relies upon the predicted value of the unobservable $u_{it}$, which can be calculated from expectations of $u_{it}$, conditional upon the observed values of $v_{it} + u_{it}$ (see Battese and Coelli, 1992, 1993, 1995).

\(^9\) Note that the $E(C_{it} \mid u_{it}, X)$ differs from actual costs, $C_{it}$, due to $v_{it}$. 
count, derivatives, guarantees and credit lines, securitisation, and equity and bond emissions. For the most part, this type of production cannot be related to balance sheet items, whereas other comprehensive information about the amount of these services produced is not reported. Instead of ignoring an increasing part of the banks’ output, we have chosen to describe it in an approximate way and to take ‘other (non-interest) income’ as a proxy for this type of services (see also Resti, 1997).

A dual cost function also includes factor prices as arguments, such as wages and the price of physical capital. For each bank, the wage rate is calculated as the ratio of total wages and the number of employees, and the price of capital is proxied as the ratio of ‘other non-interest expenditure’ and ‘premises and fixed assets’. Both variables are rough approximations as interbank differences in labour productivity and average working time are ignored, while ‘other non-interest expenditure’ also includes outlay on information technology and materials. Moreover, the balance item premises and fixed assets may be rather unreliable, due to book-keeping tricks. Because of this the difference between, for instance, the 5th and 95th percentile of capital prices in our sample appears to be not less than a factor of 15. Apart from these measurement problems, there is also some doubt with respect to content. For the whole approach to yield useable measures, it is necessary to assume competition in the input markets. For Europe, in particular with respect to the labour market, this may not be a reasonable assumption. Furthermore, there is the practical fact that wage rates are not available for the major part of the banks in our sample. For all these reasons, we did not including these input prices in the model (following Swank (1996), who, however, applied the stochastic cost frontier model for one country only, the Netherlands).

4 EUROPEAN-WIDE AND COUNTRY-SPECIFIC ESTIMATIONS

The choice of an adequate translog cost model is central in the specification of the stochastic frontier function. The translog cost model should link the complicated multiproduct output of the various types of banks (and, in principle, the prices of the input factors) as good as possible to the total operating costs (exclusive of interest rate income). There is, of course, the trade-off between the advantage of more output factors, which allow a higher degree of accuracy in explaining costs, on the one hand, and the possible disadvantage of an increase in multicollinearity between these output factors, on the other. After preliminary calculations we have chosen for the output components loans, savings, demand deposits and other income. Berger and Mester (1997) have found that for the US functional form and choice of variables usually make little difference in terms of either average efficiency or the ranking of individual banks.

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10 All input prices are expressed in one currency.
The definitions of the variables are as follows: loans consist of commercial, consumer and mortgage loans, demand deposits include current accounts, savings is made up of saving accounts, saving deposits and time deposits, and non-interest income consists mainly of commission and revenues from financial transactions. The model has been applied to data pertaining to the nine European countries, listed in Table 1. The sample of banks consists of all banking categories (such as listed in the lower part of Table 2), both in foreign and domestic hands, over 1989-1997, as far as included in the IBCA-Fitch database. Any bank-year combination for which at least one dependent or explanatory variable is missing, has been deleted from the sample. This also holds for zero values, which, of course, do not fit into a model with a logarithmic nature. This selection resulted in a sample of 3,085 banks and 14,751 bank-year observations. The second and fourth rows of Table 2 give the distribution of these numbers over the countries.

Table 2 presents an overview of a few country-specific characteristics of the European banks in our sample. For most countries considered, the bulk of banks occurring in the IBCA-Fitch database is included in our sample. However, for a substantial number of banks in Italy and the UK, the database does not record any relevant figures at all, or an incomplete set of data only. By far most of the banks excluded are of minor size. Given the high number of banks and the fact that all available banks are included, we assume that a few general conclusions can be drawn. The number of banks per inhabitant reflects some aspects of the national history of banking evolution in terms of mergers and acquisitions. In Germany, the number of banks is relatively high and, consequently, average bank size is low, reflecting a lagging position in the process of scaling up. For that reason, efficiency of the German banking industry could be lower than in a number of other countries. In the Netherlands and the UK, the number of banks is relatively low\textsuperscript{12} and average bank size is high, indicating lead positions in banking expansion and, possibly, in efficiency. The number of banks is relatively low in Spain too, be it to a lesser degree. In Switzerland, the relative number of banks is high and in Luxembourg even extremely high. However, this is mainly due to the attractive characteristics of the banks in these countries, in particular for foreigners, as mentioned earlier. This phenomenon has resulted in many branches of foreign banks. For Luxembourg, its small population also effects the ratios. Apart from Luxembourg and Switzerland, the balance sheet total per inhabitant provides a rough indication of the development of the financial system. The figures report that Italy and Spain lag somewhat in that respect. For the UK, the - misleading - indication of ‘underdevelopment’ may be due to the above-mentioned under-recording of British banks in the IBCA-Fitch database.

\textsuperscript{11} Anyway, results from additional calculations with a model including these input prices are in line with the outcome of this paper.

\textsuperscript{12} As mentioned, for the UK this low number may also be due to under-recording in IBCA-Fitch.
Cost as share in the balance sheet total is an important indicator of efficiency, even though, of course, costs are explained in part by the output composition. The average cost level is high in Italy and Spain, in line with the ‘expert view’, mentioned in Section 2, but also in Switzerland and the UK, and low in Belgium and Germany and, in particular, Luxembourg. On the whole, the expert view is not confirmed. Loans as share of total assets range from 25 to 60%. Savings and demand deposits vary from 40 to 60%. In all countries, most banks are of the universal ‘commercial’ or ‘co-operative’ type. In Germany and Italy, most banks, and in France many banks, are co-operative banks. This category is hardly found in the other countries. In Germany, Italy and Spain, a substantial share of banks is of the traditional ‘savings bank’ type. Investment banks occur mainly in the Netherlands, the UK and Switzerland. Many of these differences between countries are due to regulatory reasons.

The first column of Table 3 presents estimates of efficiency for Europe as a whole as well as for the individual countries considered. These estimates are based on a European-wide model which, apart from the intercept, consists of 14 explanatory variables: the four output categories and their cross terms (denoted by Eur-14). The stochastic frontier model appears to be a significant improvement of the linear regression model, as the null hypothesis $\beta = 0$ (or $s_u = 0$) is rejected conclusively, see the

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**Table 2  Country-specific characteristics of selected European banks (1989-97)**

<table>
<thead>
<tr>
<th>Country</th>
<th>Belgium</th>
<th>Germany</th>
<th>France</th>
<th>Italy</th>
<th>Luxembourg</th>
<th>Netherlands</th>
<th>Spain</th>
<th>UK</th>
<th>Switzerland</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>no. of banks in IBCA</td>
<td>94</td>
<td>1,826</td>
<td>392</td>
<td>611</td>
<td>128</td>
<td>66</td>
<td>189</td>
<td>317</td>
<td>350</td>
<td>3,979</td>
</tr>
<tr>
<td>no. banks in sample</td>
<td>66</td>
<td>1,661</td>
<td>359</td>
<td>320</td>
<td>89</td>
<td>43</td>
<td>135</td>
<td>115</td>
<td>297</td>
<td>3,085</td>
</tr>
<tr>
<td>idem, per inhabitant</td>
<td>6.5</td>
<td>20.3</td>
<td>6.2</td>
<td>5.6</td>
<td>211.9</td>
<td>2.8</td>
<td>3.4</td>
<td>2.0</td>
<td>42.0</td>
<td>9.4</td>
</tr>
<tr>
<td>no. of observations</td>
<td>247</td>
<td>7,585</td>
<td>1,997</td>
<td>1,624</td>
<td>504</td>
<td>182</td>
<td>515</td>
<td>534</td>
<td>1,563</td>
<td>14,751</td>
</tr>
<tr>
<td>balance sheet total</td>
<td>19.9</td>
<td>6.7</td>
<td>19.9</td>
<td>9.5</td>
<td>8.0</td>
<td>40.2</td>
<td>18.9</td>
<td>39.3</td>
<td>3.9</td>
<td>10.8</td>
</tr>
<tr>
<td>idem, per inhabitant</td>
<td>129</td>
<td>136</td>
<td>122</td>
<td>53</td>
<td>1,700</td>
<td>111</td>
<td>65</td>
<td>77</td>
<td>162</td>
<td>101</td>
</tr>
<tr>
<td>shares in balance sheet total (in %)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>costs</td>
<td>1.5</td>
<td>1.4</td>
<td>1.9</td>
<td>2.7</td>
<td>0.6</td>
<td>2.0</td>
<td>2.5</td>
<td>2.3</td>
<td>2.2</td>
<td>1.9</td>
</tr>
<tr>
<td>loans</td>
<td>30.0</td>
<td>43.8</td>
<td>43.5</td>
<td>50.4</td>
<td>24.1</td>
<td>48.9</td>
<td>47.1</td>
<td>54.7</td>
<td>58.7</td>
<td>45.9</td>
</tr>
<tr>
<td>savings</td>
<td>50.5</td>
<td>32.3</td>
<td>37.3</td>
<td>20.8</td>
<td>31.0</td>
<td>24.7</td>
<td>38.4</td>
<td>26.1</td>
<td>29.8</td>
<td>32.1</td>
</tr>
<tr>
<td>demand deposits</td>
<td>9.5</td>
<td>8.6</td>
<td>9.7</td>
<td>24.1</td>
<td>13.5</td>
<td>26.7</td>
<td>11.3</td>
<td>29.3</td>
<td>20.1</td>
<td>14.7</td>
</tr>
<tr>
<td>other income</td>
<td>0.7</td>
<td>0.5</td>
<td>0.9</td>
<td>1.2</td>
<td>0.3</td>
<td>0.3</td>
<td>1.0</td>
<td>1.3</td>
<td>1.8</td>
<td>0.9</td>
</tr>
<tr>
<td>shares in number of observations (in %)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>commercial banks</td>
<td>63</td>
<td>9</td>
<td>66</td>
<td>25</td>
<td>92</td>
<td>77</td>
<td>57</td>
<td>67</td>
<td>56</td>
<td></td>
</tr>
<tr>
<td>co-operative banks</td>
<td>9</td>
<td>50</td>
<td>25</td>
<td>46</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>0</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>savings banks</td>
<td>10</td>
<td>39</td>
<td>6</td>
<td>25</td>
<td>2</td>
<td>4</td>
<td>36</td>
<td>3</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>investment banks</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>13</td>
<td>2</td>
<td>28</td>
<td>19</td>
<td></td>
</tr>
<tr>
<td>m&amp;l term credit</td>
<td>16</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>real estate/mortg.</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>spec. gov. credit</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>10</td>
<td></td>
</tr>
</tbody>
</table>

*a* Averages, in billions of DM; *b* Balance sheet total of all banks, divided by the number of inhabitants; *c* Medium and long term credit institutions; *d* Real estate and mortgage banks; *e* Specialised government credit banks.

---

13 Other assets such as securities or interbank loans are not included in the model as output components, because there are fewer costs involved. Moreover, we don’t see these activities as typical bank services.

14 In the Netherlands, there is (only) one co-operative bank, but with large market shares.
section above equation (2). This holds also for all other variants of the stochastic frontier model, presented in the remainder of this paper. The banks in France, Italy and Spain are indicated as the least efficient ones and those in Belgium, Luxembourg and Switzerland as the most efficient ones. This ranking of efficiency is rather plausible, that is, in line with the ‘expert view’.

Table 3  European-wide and country-specific estimates of efficiency

<table>
<thead>
<tr>
<th>European-wide estimates</th>
<th>Country-specific estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Efficiency</td>
<td>tcf&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>sfm&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>s&lt;sup&gt;2&lt;/sup&gt;</td>
</tr>
<tr>
<td>Belgium</td>
<td>.431</td>
</tr>
<tr>
<td>France</td>
<td>.261</td>
</tr>
<tr>
<td>Germany</td>
<td>.424</td>
</tr>
<tr>
<td>Italy</td>
<td>.273</td>
</tr>
<tr>
<td>Luxembourg</td>
<td>.560</td>
</tr>
<tr>
<td>Netherlands</td>
<td>.382</td>
</tr>
<tr>
<td>Spain</td>
<td>.242</td>
</tr>
<tr>
<td>Switzerland</td>
<td>.430</td>
</tr>
<tr>
<td>UK</td>
<td>.297</td>
</tr>
</tbody>
</table>

| Weighted avg.           | .381     | .460     | .493     | .615     |

Explanation: Ratios and indices which are shaded lightly indicate countries where the banks are relatively efficient, whereas dark shading point to countries where the banks are relatively inefficient. <sup>a</sup>Tcf is short for translog cost function and sfm for stochastic frontier model.

The estimate of the average level of efficiency is 0.381, which is seen as fairly low. This suggests that costs are at least twice as high as necessary, or that output could be more than doubled without increasing expenses. In general, this average level of efficiency is lower than found often in the literature (see below) and, for the moment, we conclude that our results may underestimate actual efficiency. One cause may be that we did not include input prices, which may have resulted in a more rigid estimation of the frontier. To investigate the average efficiency level further, we extend the European-wide model by eight dummy variables to account for country-specific differences (denoted by Eur-22).<sup>16</sup> These dummies allow the level of cost to diverge over the countries.<sup>17</sup> The inclusion of these dummies indeed raises the average efficiency from 0.381 to 0.460 (Column 2). The statistical description of the model in terms of s, the estimated standard deviation of the random terms, indicates

---

<sup>15</sup> The value of the loglikelihood-test statistic, which has a mixed chi-square distribution (see Lee, 1993), is 11.039, while the critical value is 9.9.

<sup>16</sup> The FRONTIER programme used to estimate the models automatically includes an overall intercept (Coelli, 1996). Therefore, we cannot include dummy variables for all nine countries. The eight dummy variables indicate the difference between each of the corresponding eight countries and the ninth country (here: the Netherlands).

<sup>17</sup> An alternative is to allow all parameters to diverge over the countries, i.e. to apply a separate model for each country, see right-hand side of Table 3.
that inclusion of the country dummies is justified. Adding dummy variables also for the various banking type categories further improves the results slightly, raising the average efficiency to 0.493 (Eur-28 in Column 3). The inclusion of country dummies has also caused a remarkable shift in the efficiency estimates of the countries. Section 5 examines this rather alarming phenomenon further.

Probably, all kinds of banks in nine European countries constitute a very heterogeneous group in terms of production processes. One may expect that, in general, the stochastic frontier approach is less adequate, the more heterogeneous the group of banks is (see Mester, 1996). Where circumstances and bank characteristics vary so widely, it is no surprise that the frontier deviates so much from the mass of the banks. Or, in other words, the estimated frontier of such a heterogeneous collection of banks may not be adequate for the majority of the banks. In order to be able to assess the effect of European-wide comparison, the stochastic frontier model is also applied to the individual countries considered. The last columns of Table 3 present the results of this country-specific estimation. The heterogeneity of the banks in the various countries is illustrated by the standard deviation of the random term in the stochastic frontier model $s$ and of its components, efficiency $s_u$ and specification error $s_v$, which all diverge severely over the countries. This indicates that the chosen model is better suited to describe the cost structure of banks from some countries, such as Germany, and less for others, such as France, or that the collection of banks is more homogeneous in Germany than in France. In line with expectations, the estimates of the efficiency level are higher for most countries, the weighted average being 0.615 instead of 0.493. The average efficiencies of the various countries range from 0.268 for France to 0.781 for Italy.

On the whole, the estimated levels of efficiency are fairly low compared to what has been found in the literature. For the US, Berger and Humphrey (1997) in their survey report average efficiencies typically to be around 0.80 or even higher, but substantially lower levels of even 0.48 have also been observed (Evanoff and Isailevich, 1991, Cebenoyan et al., 1993, Berger, Hancock and Humphrey, 1993). For German banks, Altunbas, Evans and Molyneux (1994) estimate an efficiency level of 0.76, for Italian banks, efficiency estimates range from 0.70 (Resti, 1997) to 0.87 (Altunbas, Molyneux and Di Salvo, 1994), and for British banks an even higher level of efficiency of around 0.90 was found (Altunbas, Maude and Molyneux, 1995).

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18 In the stochastic frontier model, $s$ stands for $(s_u^2 + s_v^2)^{0.5}$, the standard deviation of the whole random term (specification error and inefficiency term). A loglikelihood-ratio test makes clear that the restriction ‘no country dummies’ is rejected.

19 So, there is a trade-off between the advantage of European-wide estimation, which allows the efficiency of banks to be compared with the European-wide best-practice frontier, and the disadvantage of the heterogeneity of such a broad collection of banks, which may prohibit the estimation of an adequate translog cost function.

20 The efficiency of each country is weighted by the number of banks in the sample.
The ranking of the countries in the alternative approaches, respectively inclusion of country dummies and country-specific estimates, raises serious doubts about the reliability of these estimates. In particular, the low efficiency of banks in France and the UK, and the relatively high efficiencies of banks in Germany and Italy are unexpected. The next section examines this issue further.

5 AN ALTERNATIVE ESTIMATE OF COST EFFICIENCY

In the previous section, a remarkable shift in the countries’ levels of efficiency estimates was observed when country dummies were included in the European-wide model. The classification of the efficiency of Belgian banks fell from high to low and the status of Italian banks rose from low to high (Table 3). The ranking of most other countries also changed. This is due to the following technical intricacy of a stochastic frontier model with country dummies. Equation (1) extended with country dummies reads as:

\[ c_{it} = \alpha + \sum_j \beta_j x_{ijt} + \sum_k \gamma_{jk} x_{ikt} + \sum_r \delta_r D_r + v_{it} + u_{it} \] (3)

Dummy coefficient \( \delta_r \) measures the deviation of the level of costs of country \( r \) from the European-wide cost level.\(^{21}\) The OLS estimate of \( \delta_r \) is based on the group averages of the variables (countries seen as groups):

\[
\delta_r = \left( \frac{1}{N_r} \right) \sum_{i,t \in \{R\}} \left( c_{it} - \alpha - \sum_j \beta_j x_{ijt} - \sum_k \gamma_{jk} x_{ikt} \right)
= \left( \frac{1}{N_r} \right) \sum_{i,t \in \{R\}} \left[ (\alpha - \alpha) + \sum_j (\beta_j - \beta_j) x_{ijt} + \sum_k (\gamma_{jk} - \gamma_{jk}) x_{ikt} + v_{it} + u_{it} \right] \] (4)

Estimates are denoted by hats. The summation is over all bank-year combinations of banks from country \( r \), denoted by the set \( \{R\} \), which contains \( N_r \) observations. In panel data analysis, equation (3) is denoted as fixed-effects model and equation (4) is called between estimator, as this estimator is based on variation between observations of banks of country \( r \) only. All other coefficients of equation (3) are based on the within variation of equation (5):

\[
\bar{c}_{it} = \sum_j \tilde{\beta}_j \bar{x}_{ijt} + \sum_k \tilde{\gamma}_{jk} \bar{x}_{ikt} + \bar{v}_{it} + \bar{u}_{it}
\] (5)

where \( \bar{c} \) denotes 'c in deviation from the respective country mean'. Country specific variation is swept away. Note that, via \( \bar{c}_{it} \), the average level of X-inefficiency of country \( r \), which we seek to measure, is

\(^{21}\) Or from the Dutch cost level if \( \delta_{Netherlands} \) is omitted, such as in the empirical application.
one of the determinants of the dummy coefficient of this country and that the average level of X-efficiency of country \( r \) cannot be distinguished separately. In the stochastic frontier approach, the coefficients are not estimated by OLS, but by a numerical procedure, which takes account of the complicated (truncated normal) distribution of \( u_{it} \). The split up of variation in between and within group variation, as expressed above, applies to the estimates of the translog cost model parameters and the specification error \( v_{it} \), but not necessarily to the random term \( u_{it} \), which represents the X-inefficiency. Its truncated-normal-distributed character prohibits a plain and clear view on the effects of the introduction of country dummies on the estimates of X-inefficiency. Nevertheless, it is likely that the measurement of the two concepts, the country's relative cost level and its X-inefficiency, are mixed up in the stochastic frontier model. This is illustrated empirically by the results of Table 3: if dummies are introduced, the estimates of the countries’ average X-inefficiency shift from a plausible ranking to a less convincing ordering.

The ranking of the countries’ X-efficiency levels in Table 3, based on country-specific estimation, shows a strong similarity to the ranking of the European-wide estimation, based on a model with country dummies. This is remarkable as in the European-wide model one frontier is estimated (for all countries), whereas in the country-specific application nine frontiers are estimated, one for each country. This similarity is probably due to the fact that the country-specific model's intercept is estimated just like a dummy coefficient in a European-wide application. Expressed in other words, the effect of country dummies is identical to shifts in the countries' frontiers from the European one. Anyhow, the lack of uniqueness of the estimated country-specific frontier, different from the European-wide one, prohibits a true international comparison of efficiency.

This leads us to the following conclusions. Firstly, efficiencies based on estimation of a stochastic frontier model in a multicountry setting, which includes country dummies, are not adequate for comparison between countries, due to interference between country dummies and average efficiencies. Secondly, efficiency estimates from stochastic frontier models for single countries can be very misleading, as country-specific frontiers may deviate strongly from a European-wide one. For that reason, single-country studies tend to overestimate efficiency. In particular the second conclusion has important consequences, as most of the literature on efficiency is based on single-country studies.

The above analysis indicates that the dummy coefficients in the multiproduct cost function, which constitutes the stochastic frontier model, not only measure differences in the cost level of banks in the various countries in producing identical combinations of financial services, but also reflect differences in average X-efficiency levels. This suggests that these dummy coefficient estimates provide a
straightforward alternative measure of differences in efficiency between the countries. Straightforward, because this alternative is less sophisticated than the X-inefficiency measure of the stochastic frontier model, and because the closely related concepts of deviations in cost level and X-inefficiency are taken together. On the other hand, the cost-function based efficiency estimates are much more precise and tailored than the various rough and sometimes ambiguous proxies presented in Table 1.

Table 4 presents this alternative: coefficients of country dummies, estimated using a European-wide model. The classification of the countries in the categories ‘more efficient’ (light shading), ‘medium efficient’ (blank) and ‘less efficient’ (dark shading) is identical, whether we apply the stochastic frontier model (sfm) or the translog cost function (tcf), or whether we do (Eur-28) or do not (Eur-22) add dummies for types of specialisation. Probably, the estimates of the former model (Eur-28) are more accurate, as that model takes the effects of banking specialisation into account. The classification we find here, corresponds to a certain extent with the ‘expert view’ mentioned earlier: lower efficiency in Italy and Spain, and, thereafter, France, and higher efficiency in the other countries. The high levels of significance of the dummy coefficients indicate that the estimates are rather robust.

Table 4 Efficiency estimated by coefficients of country dummies

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Belgium</td>
<td>-.1251 (18.3)</td>
<td>-.298 (7.8)</td>
<td>-.901 (16.5)</td>
<td>-.209 (5.5)</td>
<td>.40</td>
<td>.89</td>
</tr>
<tr>
<td>France</td>
<td>.302 (8.1)</td>
<td>.049 (1.7)</td>
<td>.365 (9.3)</td>
<td>.101 (3.4)</td>
<td>1.43</td>
<td>1.21</td>
</tr>
<tr>
<td>Germany</td>
<td>.199 (5.4)</td>
<td>-.146 (5.1)</td>
<td>.271 (7.5)</td>
<td>-.097 (3.3)</td>
<td>1.30</td>
<td>.99</td>
</tr>
<tr>
<td>Italy</td>
<td>.569 (14.8)</td>
<td>.066 (2.2)</td>
<td>.656 (16.8)</td>
<td>.130 (4.2)</td>
<td>1.91</td>
<td>1.24</td>
</tr>
<tr>
<td>Luxembourg</td>
<td>-.620 (13.8)</td>
<td>-.544 (16.7)</td>
<td>-.581 (13.1)</td>
<td>-.510 (15.8)</td>
<td>.55</td>
<td>.66</td>
</tr>
<tr>
<td>Netherlands</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>.99</td>
<td>1.09</td>
</tr>
<tr>
<td>Spain</td>
<td>.309 (7.1)</td>
<td>.134 (4.1)</td>
<td>.535 (11.9)</td>
<td>.171 (5.2)</td>
<td>1.69</td>
<td>1.29</td>
</tr>
<tr>
<td>Switzerland</td>
<td>-.158 (4.1)</td>
<td>-.297 (9.7)</td>
<td>-.221 (5.7)</td>
<td>-.272 (8.9)</td>
<td>.79</td>
<td>.83</td>
</tr>
<tr>
<td>UK</td>
<td>.164 (3.8)</td>
<td>-.083 (2.5)</td>
<td>-.047 (1.0)</td>
<td>-.100 (3.1)</td>
<td>.95</td>
<td>.99</td>
</tr>
<tr>
<td>Geometric mean</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>[.51]</td>
<td>[.21]</td>
</tr>
</tbody>
</table>

*Denotes t-values between parenthesis. Ratios and indices which are shaded lightly indicate countries where the banks are relatively efficient, whereas dark shading point to countries where the banks are relatively inefficient.

22 This problem may be less seriously for studies of the US, given its vast size, but appears to be disastrous for studies of countries as large as Germany and Italy.
For comparison, the last column of Table 4 shows the X-efficiency levels as found earlier with the European-wide stochastic frontier model without dummy variables (Eur-14). There is a remarkable close correspondence between its ranking and the ranking according to the dummy coefficients. This confirms the appropriateness of our alternative measure to proxy differences in the countries’ X-efficiency. To assess its qualities further, Table 4 also presents (for Eur-28) the effects of the dummy coefficients on costs, actually the exponent of the dummy coefficients (transforming logarithms back to their natural form), in deviation from their geometric mean. According to the translog cost function, the cost level in Spain and Italy is, respectively, 29 and 21% higher than on average and in Luxembourg 34% lower (controlled for the structure of the banks through the output components). The differences in cost efficiency according to the sfm are substantially larger than according to the tcf, too large to be plausible. Here, again, it appears to be impossible to estimate country dummy coefficients and X-efficiency in the sfm simultaneously, as explained in the beginning of this section. Therefore, we will further restrict ourselves to estimates based on the plain multiproduct translog cost function.

The last column of Table 4 gives an index of the effects of X-efficiency, defined as percentage deviations from its geometric mean. High efficiency corresponds to low costs. The correlation of this index with the alternative measure, the effects of tcf dummy coefficients (the third last column of Table 4), is at 0.924 very high. This proves that two differing measures of efficiency produce fairly coinciding results, and raises confidence in these approaches. The level of the X-efficiency estimates from the EUR-14 model may be too low, their values constitute a reliable ranking of the efficiency of the banking sectors of the countries involved.

Finally, Table 4 also shows the coefficients of the categories of specialisation. Their high t-values indicate that the average cost levels diverge strongly between the categories. The costs of investment, savings and real estate & mortgage banks are significantly and sometimes substantially higher than those of commercial banks, whereas the costs of co-operative banks and medium & long term credit institutions are, respectively, slightly and considerably lower. Apparently, in terms of cost levels, the various categories taken together do not form a homogeneous group.

6 CATEGORY-SPECIFIC ESTIMATES

The production process and the influence of important but omitted determinants, such as other output components or (other) input prices, may diverge substantially between banks of various kinds of

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23 Measured in absolute terms. The correlation with the effects of sfm dummy coefficients is at 0.776 much lower. Also the standard deviation of the index of efficiencies (0.30) is closer to that of the effects of dummy coefficients of the tcf (0.21) than to that of the sfm (0.51).
specialisation, on the one hand, and between these banks and banks with a broad supply of financial services, on the other. We expect the diversity of banking activities to be the major origin for the heterogeneity of our bank sample. Therefore, in this section we seek to further refine the estimation results by estimating efficiency for separate categories.

Table 5 presents specialisation-specific characteristics of the European banks in our sample. Commercial, co-operative and savings banks dominate the sample in terms of numbers of banks or observations. On average, the balance sheet total of commercial banks is four times as large as those of co-operative and savings banks, but smaller than those of some more specialised banks. The shares in the balance sheet total of the four output components considered reflect some of the different activities of the various types of banks. This is illustrated by funding, which diverges over the categories by size and composition. The share of other income, consisting of commission and revenues from financial transactions, is large compared to that of costs for investment banks and medium & long-term credit institutions and much smaller for the others. Cost shares diverge over the categories, but at least in part, they are explained by the composition of output.

The first row of Table 6 presents the average X-efficiencies for the seven bank categories, based on the European-wide stochastic frontier model. The weighted average of these efficiency estimates for separate categories is at 0.622 higher than the efficiency estimate based on a model wherein all categories are taken together (0.493; see Table 3), and also slightly higher than the average over the country-specific estimates (0.615). This holds, in particular, for banking categories with more similar activities, such as savings banks, which have an average efficiency of 0.847, and much less for the largest category, commercial banks, which includes banks with activities, which may diverge strongly. This outcome underlines that splitting the sample in more homogenous groups (i.e. in categories) improves the estimates of efficiency, resulting in more plausible - that is higher –
efficiency levels. On the other hand, some categories, in particular commercial banks, remain rather heterogeneous, hampering - to a certain degree - further progress in estimating efficiency more accurately. This also illustrates that restricting the analyses to one category of banks, e.g. commercial banks, instead of investigating all banks together, may not be very helpful.

### Table 6 European-wide efficiency estimates for separate bank categories

<table>
<thead>
<tr>
<th></th>
<th>all banks</th>
<th>commercial</th>
<th>cooperative</th>
<th>savings</th>
<th>investment</th>
<th>m&amp;l</th>
<th>real estate</th>
<th>spec.</th>
<th>weighted avg.</th>
<th>effects</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>stochastic frontier model</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X-efficiency</td>
<td>.493</td>
<td>.312</td>
<td>.735</td>
<td>.847</td>
<td>.525</td>
<td>.407</td>
<td>.887</td>
<td>.711</td>
<td>.622</td>
<td></td>
</tr>
<tr>
<td>$s^2$</td>
<td>1.183</td>
<td>2.708</td>
<td>.164</td>
<td>.202</td>
<td>.071</td>
<td>2.984</td>
<td>.072</td>
<td>.245</td>
<td>.979</td>
<td></td>
</tr>
<tr>
<td>$s_{c}^2$</td>
<td>.028</td>
<td>.055</td>
<td>.009</td>
<td>.010</td>
<td>.003</td>
<td>.028</td>
<td>.050</td>
<td>.039</td>
<td>.025</td>
<td></td>
</tr>
</tbody>
</table>

| **translog cost function** |           |            |             |         |            |     |             |       |                |         |
| $s^2$                  | .131      | .281       | .032        | .024    | .105       | .163| .064        | .085  |               |         |

**coefficients of country dummies**

<table>
<thead>
<tr>
<th>Country</th>
<th>Belgium</th>
<th>France</th>
<th>Germany</th>
<th>Italy</th>
<th>Luxembourg</th>
<th>Netherlands</th>
<th>Spain</th>
<th>Switzerland</th>
<th>UK</th>
</tr>
</thead>
<tbody>
<tr>
<td>X-efficiency</td>
<td>-.209</td>
<td>-.171</td>
<td>-.115</td>
<td>.325</td>
<td>-.420</td>
<td>-.822</td>
<td>1.916</td>
<td>-</td>
<td>-0.195</td>
</tr>
<tr>
<td>$s^2$</td>
<td>.034</td>
<td>.071</td>
<td>-.351</td>
<td>.921</td>
<td>-.925</td>
<td>-.112</td>
<td>0.160</td>
<td>1.17</td>
<td></td>
</tr>
<tr>
<td>$s_{c}^2$</td>
<td>.009</td>
<td>.011</td>
<td>.514</td>
<td>.797</td>
<td>-.190</td>
<td>1.002</td>
<td>.138</td>
<td>.020</td>
<td>1.02</td>
</tr>
</tbody>
</table>

**Explanations:**

- Ratios and indices which are shaded lightly indicate countries where the banks are relatively efficient, whereas dark shading point to countries where the banks are relatively inefficient.

The lower part of Table 6 presents the country dummy estimates for the various bank categories. To avoid the distortion, caused by simultaneous estimation of country dummy coefficients and X-efficiency, as identified in Section 5, the estimation is based on the translog cost function. The ranking of the countries in terms of average cost level, such as found for all banks, appear to hold also for most of the bank categories. Apart from the small subset ‘real estate & mortgage banks’, where the ranking deviates completely from that of other categories, there are only a few minor deviations from the overall ranking, due in part, to the small number of banks for some combinations of country and category. This picture of a consistent ranking is confirmed by the averages of the dummy coefficients in the last but one column, which are weighted by the corresponding number of observations to take the importance of the categories into account. The last column transforms these outcomes to ‘effects’ on the cost level. The banking industry in Spain appears to be the least efficient, with a level of costs that is 33% above the average. Banks in Italy and France are also rather inefficient, having costs which are, respectively, 27% and 17% higher than on average. Banks in Germany, the Netherlands and the

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24 Also the large value of the translog cost function error term ($s_{c}^2$) for commercial banks suggests that the banks of this category are more heterogeneous, as the model is less able to explain their costs.

25 The dummy coefficients measure the countries’ average cost levels as deviation from the level in the Netherlands. To take account of that, for the calculation of the averages, the dummy coefficients are taken as deviations from their means (per category, over the countries).
UK take a medium position in the ranking, whereas banks in Switzerland, Belgium, and in particular Luxembourg are the more efficient ones at cost levels of, respectively, 15%, 18% and 34% below the average. It should be noted that for Luxembourg and Switzerland, this in part does not reflect efficiency, but the special circumstances mentioned earlier, which, for banks of these countries, makes it easier and, so, cheaper to attract funds. The results reveal that differences in cost levels between European countries are very large and suggest that merging and restructuring activity, as observed in recent years, are most likely to continue or even to speed up.

Table 7  Comparison of various estimates of inefficiency

<table>
<thead>
<tr>
<th></th>
<th>Effects of dummies of bank-category specific models, averages (tcf)</th>
<th>Effects of dummies of European-wide model (tcf)</th>
<th>Index of X-inefficiency (scf)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Belgium</td>
<td>0.82</td>
<td>0.89</td>
<td>0.82</td>
</tr>
<tr>
<td>France</td>
<td>1.17</td>
<td>1.21</td>
<td>1.35</td>
</tr>
<tr>
<td>Germany</td>
<td>1.02</td>
<td>0.99</td>
<td>0.83</td>
</tr>
<tr>
<td>Italy</td>
<td>1.27</td>
<td>1.24</td>
<td>1.29</td>
</tr>
<tr>
<td>Luxembourg</td>
<td>0.66</td>
<td>0.66</td>
<td>0.63</td>
</tr>
<tr>
<td>Netherlands</td>
<td>1.11</td>
<td>1.09</td>
<td>0.93</td>
</tr>
<tr>
<td>Spain</td>
<td>1.33</td>
<td>1.29</td>
<td>1.46</td>
</tr>
<tr>
<td>Switzerland</td>
<td>0.85</td>
<td>0.83</td>
<td>0.82</td>
</tr>
<tr>
<td>UK</td>
<td>1.00</td>
<td>0.99</td>
<td>1.19</td>
</tr>
</tbody>
</table>

Table 7 provides an overview of the results: average effects of the dummy coefficients in the bank-specific models (from Table 6), effects of the dummy coefficients in the European-wide model, and the index of X-efficiency of the stochastic cost frontier model (both from Table 4). For the sake of comparison, the inverse of the latter is shown as index of X-inefficiency. The three measures are highly correlated, as is shown at the bottom of the Table, whereas the ranking of countries in terms of cost efficiency is almost identical. The similarity between the results of the various approaches is striking and raises some confidence with regard to the robustness of the results. On average, the banks in Spain, Italy and France are the less efficient ones and those in Luxembourg, Belgium and Switzerland are more efficient. The 'effects' of the bank-specific model best indicate differences in cost levels, whereas the index of X-efficiency provides a ranking of the frontier-type of X-efficiencies. This index suggests that the range of average X-inefficiencies is even wider than the range of average cost levels: from 46% above the European average (Spain) to 37% below this average (Luxembourg).

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26 For instance, for Spain, the exponent of 0.281 is 1.325.
27 Various alternative specifications and estimations, including splitting the sample over the time period, also provides similar results.
Table 8  Correlations between simple ratios and more sophisticated efficiency estimates

<table>
<thead>
<tr>
<th>sophisticated estimates</th>
<th>ratios: cost income ratio</th>
<th>interest rate margin</th>
<th>labour cost share</th>
<th>labour intensity (bal.sheet) (inhab.)</th>
<th>labour intensity (inhab.)</th>
<th>index of concentration</th>
<th>index of competition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effects dummies of bank spec. model</td>
<td>0.57</td>
<td>0.80</td>
<td>0.63</td>
<td>0.72</td>
<td>-0.72</td>
<td>-0.34</td>
<td>-0.09</td>
</tr>
<tr>
<td>Index of X-inefficiency</td>
<td>0.46</td>
<td>0.68</td>
<td>0.50</td>
<td>0.75</td>
<td>-0.62</td>
<td>-0.28</td>
<td>-0.16</td>
</tr>
</tbody>
</table>

Finally, we compare these more sophisticated indices of efficiency with the easy ratios and indices listed in Table 1, which are often used as a proxy of efficiency. None of these ratios provides a ranking that comes close to the ranking we have found in Table 7. Table 8 presents correlations between these simple ratios and the more sophisticated estimates of efficiency. The correlations in the shaded areas are expected to be negative, whereas the other correlations should be positive. The often-used cost income ratio appears to be totally inappropriate as a yardstick of efficiency, as its correlation even has the wrong sign. Without doubt, this is due to its ambiguous nature as discussed in Section 2. The interest rate margin is the best proxy of differences in cost levels, based on its correlation of 0.80 with effects of the bank-specific model. With a correlation coefficient of 0.72, the labour intensity index related to the balance sheet total is second best. In reversed order, these ratios are also the best proxies of our index of X-efficiencies (correlations are 0.76 and 0.69 for, respectively, labour intensity and interest rate margin). On the whole, the interest rate margin seems to be the best proxy but, nevertheless, with serious shortcomings, as it gravelly overestimates efficiency in France and underestimates efficiency in the UK. In theory, efficiency and competition are closely related. In particular, competition is seen as a condition that forces banks to become efficient. Actually, at the moment, efficiency and competition appear to be rather limited connected phenomena, given the low correlations of around 0.40 between our measures of efficiency and the index of competition. These results underline that none of the popular simple proxies is appropriate, and that there is a need for direct measures of efficiency as proposed in this paper.

7 SUMMARY AND CONCLUSIONS

National deregulation, international integration, entry of new types of competitors and, in particular, the introduction of the euro have seriously affected the competitive environment of the European banking industry. These new developments force banks to become more efficient to avoid being driven from the market. Assessment of the efficiency of the European banking industry and differences in efficiency between countries is of vital importance for public policy with respect to the viability of the banking industry in the near future. As efficiency cannot be observed directly, a number of ratios or index numbers are commonly used as a rough estimate. Rankings of countries based on such

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28 The alternative interpretation, mentioned in Section 2, appears to be more appropriate.
proxies diverge strongly. Apparently, the value of most or all of these ratios and indices as a yardstick of efficiency is fairly poor. The often-used cost-income ratio can be proven to be totally inappropriate as a proxy of efficiency.

This paper applies the stochastic cost frontier approach to measure X-inefficiency, paying particular attention to the differences in efficiency between the banks of the countries considered. European-wide estimation allows the efficiency of banks to be compared to the European-wide best-practice frontier. However, institutional and market conditions and bank characteristics vary so widely that the mass of the banks deviates much from the frontier, running the risk that inefficiency is overestimated (compared to other, single-country studies). Country-specific analyses allow the estimation of more homogenous groups of banks, but diminish the international comparability. Actually, there is strong evidence that efficiency estimates from single-country studies, as often found in the literature, may be very misleading. Two approaches are taken in solving the trade-off problem encountered. Firstly, we conducted European-wide estimation of X-inefficiency separately for each of the various categories of banks in order to reduce the problem of heterogeneity. Secondly, employing a translog cost function, we propose a more straightforward alternative measure of inefficiency, based on dummy coefficient estimates that reflect differences in average cost levels between countries.

The estimates of these two inefficiency measurement approaches are highly correlated and provide a virtually identical ranking of countries with respect to the inefficiency of their banking industries. This similarity raises confidence with regard to the robustness of the results of the two approaches. On average, Spanish banks appear to be the least efficient ones, followed by banks in France and Italy, whereas banks in Luxembourg are most efficient, followed by banks in Belgium and Switzerland. Of course, for banks in Luxembourg and Switzerland, this not only reflects efficiency but also favourable conditions, stemming from bank secrecy and tax regime. On average, banks in Germany, the Netherlands and the UK take a medium position. Cost levels in Spanish banks are estimated to be 33% above the European average and X-inefficiency even 46%. Costs in banks in Luxembourg are 34% below the European average and X-inefficiency 37%. These results can be split up into category-specific efficiency estimates per country.

Of course, the results should be presented with a certain prudence as they may have been affected by, among other things, the heterogeneous nature of the selected banks and their environment, the techniques that are used and the exclusion of input prices. Nevertheless, the overall outcome indicates that differences in average cost-levels and X-inefficiency between EU countries are huge; the average inefficiency is most probably higher than the 20%, found often in the literature. In particular in the countries where banks are less efficient, large-scale consolidation and rationalisation of the banking industry will be unavoidable and also is necessary in order to improve its soundness.
REFERENCES


