Costs, Competitiveness
and the
Changing Structure of European Banking

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1. Introduction

The forces acting to mold European banking into a single market are increasing. A major factor supporting the convergence process is the Second Banking Directive, which went into effect in January 1993. The Directive allows financial institutions that are licensed in one EU country to operate in other member countries, thereby obviating the need to obtain a license from the regulatory authorities in the guest country. Non-EU countries are also affected by the Directive as non-EU institutions operating or seeking to establish a subsidiary in the EU must also comply with the Directive in order to receive a Single Banking License. In addition, their home countries must grant reciprocal banking arrangements to EU countries in which non-EU institutions operate. Further impetus to the integration process has come through the introduction of the Euro, which increased price transparency and created a single, large capital market in Europe.

The increasing cross-border competition accompanying the convergence process raises the question as to the future structure of European banking. Will large, universal banks come to dominate the industry, or will small, specialized banks find greater opportunity? Since, as a rule (cf. PANZAR, 1989), the most cost effective market structure prevails under free competition (a natural monopoly being a case in point), the effect increased competition will have on the future development of individual institutions and the industry as a whole depends to a large extent on the sources of cost variation among banks.

Cost variations across firms emanate essentially from two sources: inefficient operation, representing deviations from a best-practice frontier (frontier inefficiency[1]), and unexploited economies of scale and scope, which the best-practice frontier may provide. Scale and scope economies confer cost advantages on large, diversified banks or - in the case of diseconomies - on small, specialized firms, whereas frontier inefficiency is not, as a rule, linked to firm size or output mix. If unexploited economies of scale and scope were the main source of cost variation across banks in Europe, then one could expect large, full-service banks to eventually dominate the industry. Increased concentration would be the consequence.

1 Frontier inefficiency is sometimes loosely termed X-inefficiency, an expression coined by Leibenstein. However as originally conceived, X-inefficiency only pertained to technical efficiency, which refers to the excessive use of factor inputs to achieve a given output level (deviations from a production frontier), and excluded allocative efficiency, which pertains to the use of factor combinations that conflict with relative factor prices. Together, technical and allocative inefficiency constitute deviations from a minimum cost frontier (LEIBENSTEIN, 1966).

Knowledge of the size and sources of cost variation among banks is important for policy makers. Such information helps them to understand the forces lying behind the current restructuring in banking and to anticipate future changes, thus aiding them in forging appropriate policies. For example, if frontier inefficiency were the main source of cost variation among banks, then this could point to insufficient competition suggesting policies geared to decreasing regulation and fostering competition. If, on the other hand, unexploited economies of scale and scope underlay these cost differences, then this could signal increasing concentration, perhaps suggesting policies aimed at tightening regulation.

To assess the relative efficiency of banks across Europe, cross-country studies are needed. National studies are useless because efficiency is a relative concept, pertaining solely to the banks in a given sample. Unfortunately, few international studies exist. Of the 130 bank efficiency studies that BERGER and HUMPHREY (1997) cite in their survey, only six are cross-country and, of these, three pertain solely to Scandinavian countries.

The following study attempts to right this imbalance by exploring the cost efficiency of a sample of 1783 commercial and savings banks that were operating in the EU, Norway or Switzerland (i.e. Western Europe) in the period 1993-97. This spans the years directly following the introduction of the Second Banking Directive, which is thought to have provided added support to the integration process. The study employs a non-parametric frontier method, data envelopment analysis (DEA), and incorporates recent methodological advances in the bank efficiency literature with respect to the handling of revenues and risk.

Three questions stand in the forefront of this study:

- How large is the cost differential among banks in Europe?
- What are the sources of the cost differential?
- What implications do the results have for future structural change and policy stance?

The study unfolds as follows. Section 2 provides a brief overview of the current state of research, concentrating in particular on cross-country studies. Section 3 develops our empirical approach. Section 4 describes the data. Section 5 presents and interprets our results. Section 6 summarizes our findings and discusses policy implications.

2. Previous Work

2.1. General Overview

Cost studies have a long tradition in the banking literature. The first studies appeared in the 1950s[2] and attempted to determine whether the average cost curve in banking exhibited a U-shaped form by plotting banks' cost-asset ratios against their total assets. The results were mixed. Since then, the level of sophistication of bank cost studies has risen appreciably.

The first generation of econometric studies following these early attempts sought to analyze the presence of scale and scope economies by estimating ever more flexible cost functions for banks. This line of research culminated in the study by BERGER ET AL. (1987) on US banking. First-generation cost studies have a decided drawback, however: they implicitly assume that banks always produce on their minimum cost frontiers, i.e., that frontier inefficiency does not exist. This assumption has since been invalidated by a study by BERGER and HUMPHREY (1991), who discovered in a sample of US banks that frontier inefficiency not only existed, but that it exceeded the cost advantages that economies of scale and scope could provide. This implied that banks had more to gain by improving their efficiency at their given scale and product mix than by adjusting their scale or scope to their optimal levels.

The discovery by Berger and Humphrey ushered in a second generation of studies, so-called frontier estimation models, that take frontier inefficiency explicitly into account. These studies show that Berger and Humphrey's fundamental finding holds true both in other time periods and countries.

Two basic approaches to estimating best-practice frontiers exist: parametric and non-parametric methods.[3] The parametric approach imposes a particular functional form on the efficient frontier and employs regression analysis to estimate the frontier parameters, whereas non-parametric techniques merely demand that the data fulfill general regularity conditions implied by axiomatic production theory and utilize linear programming methods. Unlike parametric approaches, non-parametric methods do not allow for stochastic noise in the left-hand variable.

In recent years a third generation of bank efficiency studies has begun to emerge that, along with cost, also take revenues and risk into account. Consideration of reve-

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[2] For example, ALDAHEFF (1954).

[3] LEWIN and LOVELL (1993) provide an in-depth comparison of the two approaches.

nues is intended to control for differences in service and product quality not captured in the accounting data typically used in bank efficiency studies. These omissions cause banks that accept higher costs to produce high-quality services to appear cost inefficient. Incorporating revenues tends to ameliorate the problem since higher quality should generate higher revenues, which offset the extra expenses.

Parametric frontier studies that take revenue into account often do so simply by replacing profits for costs as the left-hand variable in a standard minimum cost regression equation. This approach, inspired by BERGER and MESTER (1997), yields a so-called alternative profit function, which differs from a standard profit function in that output quantities substitute for output prices. This is thought to control for non-competitive elements in product markets, which invalidate the perfect competition assumption underlying the standard profit function. Studies that have taken revenues and profits into account generally find that measured frontier efficiency increases. In addition, they detect either a statistically insignificant or negative relationship between cost and profit efficiency (BERGER/HUMPHREY, 1997). These results suggest that the quality of bank services does indeed vary, that supplying higher-quality services does raise costs and that customers are willing to pay higher prices for these services. Hence, ignoring revenues runs the risk of obtaining misleading results.

The reasons for considering risk in bank efficiency studies are basically twofold. For one, finance theory implies that there is a trade-off between risk and returns. Consequently, if differences in tastes for risk are not taken into account, more risk-adverse banks that accept lower returns for greater security will appear less efficient, even though they may operate optimally given their risk preferences. Secondly, managing risk is factor intensive and hence generates costs, which will seem to represent inefficiency if risk is ignored.

Bank efficiency studies control for risk in several ways. Some authors[4] include loan loss provisions or non-performing loans. Others use bank capital[5], arguing that the level of equity is closely linked to risk. MCALLISTER and MCMANUS (1993) proxy the costs of risk with the hypothetical capital costs a bank would incur if it were to meet a given uniform insolvency risk. This seems the most convincing approach of the three.

4 Among others CHARNES ET AL. (1990), BERG ET AL. (1992) and CHU/LIM (1998) in non-parametric studies, and HUGHES/MESTER (1993) and BERGER/DEYOUNG (1997) in parametric investigations.

5 Among others MESTER (1996) and BERGER/MESTER (1997).

The problem with loan loss provisions is, for one, that current problem loans are more a result of monitoring and screening costs incurred in the past than of those currently generated. On the other hand, problem loans also create costs of their own, stemming from the expenses connected to loan recovery. However, including problem loans in this case has the perverse effect of rewarding banks that are inefficient in customer screening and loan monitoring. A further problem is that banks' loan losses represent realizations of a random variable (credit risk). As such, they do not provide a reliable measure of how much risk a bank has actually taken on. After all, even AAA bonds sometimes fail, and not every junk bond need default.[6]

Bank capital too is problematical, because, taken alone, it is an unreliable measure of risk: risk also depends on the level and volatility of returns. As a result, it is quite possible that high capital-assets ratios are more than offset by high return volatility so that the banks with the most capital are actually the riskiest.

According to current research, controlling for risk appears to increase measured cost economies of scale (BERGER/HUMPHREY, 1997). MCALLISTER and MCMANUS (1993) explain this finding by arguing that larger banks have more opportunities to diversify, which lowers their risks and thus reduces the amount of costly financial capital they must hold.

Accounting for risk seems to affect the level of measured efficiency as well. BERGER and HUMPHREY (1997) report that the inclusion of a risk variable decreases measured cost and profit inefficiency. This should come as no surprise in the case of parametric studies, however, since the inclusion of an additional regressor has to reduce residual variation, from which measured inefficiency stems. Controlling for risk in a non-parametric setting also has to reduce measured inefficiency since the inclusion of risk introduces an additional constraint, which necessarily narrows the scope for efficiency improvement.

2.2. Cross-Country Studies

As mentioned in the introduction, few cross-country studies on bank efficiency exist. *Table 1* offers a selected survey. The table characterizes the studies with respect to

[6] For this reason, it seems rather futile to try, as PASTOR (1999) does, to distinguish between discretionary and non-discretionary loan losses by controlling for environment (exogenous factors). The winnings of players on a roulette table generally vary too, even though they submit themselves to the same external environment and odds. To deem net winners more efficient than net losers, as Pastor's approach would do, does not seem appropriate.

methodology, specification of inputs and outputs, degree of coverage and the results achieved. As is plain to see, the surveyed studies differ in several respects.

With respect to methodology, BERG ET AL. (1993) and PASTOR ET AL. (1997) are the sole studies that employ non-parametric frontier analysis. Among the parametric studies, only VANDER VENNET (1994) uses a non-frontier approach (NFA), which rules out the presence of frontier inefficiency from the beginning. The parametric frontier studies apply three different approaches: the stochastic frontier (SFA), thick-frontier (TFA) and distribution-free frontier approach (DFA). SFA imposes a parametric structure on an unobserved composite error term which encompasses both frontier inefficiency and any random noise in the left-hand variable. In contrast, TFA and DFA refrain from imposing a parametric structure on the error term. Instead, DFA assumes that the random noise of each bank averages out to zero over the sample period so that the average residual of a bank can be interpreted as an estimate of its, by assumption, constant level of frontier inefficiency. The use of DFA obviously requires panel data. TFA, on the other hand, estimates separate cost frontiers for high and low-cost banks and interprets the distance between the frontiers as frontier inefficiency, and the variation about the frontiers as random noise.

Most of the studies cited in *Table 1* estimate cost frontiers. DIETSCH ET AL. (1998) and VANDER VENNET (1999) also estimate alternative profit frontiers. BERG ET AL. (1993), on the other hand, estimate a production frontier, which considers only input and output quantities. Hence, they measure technical efficiency, which represents just one component of cost efficiency.

The definition of bank inputs and outputs varies as well across studies. The choice of definition depends essentially on what a researcher pictures a bank to be. The so-called production approach views the main function of banks as servicing accounts, both deposit and loan accounts. Accordingly, output is defined as the number of accounts, and input as bank operating costs. The so-called intermediation approach, on the other hand, emphasizes the role of the bank as an intermediary between depositors and borrowers. Thus output is defined as loans and investments, both measured in money volumes; and inputs are set equal to operating costs and deposits. A recent research finding has led to a departure from this simple dichotomy, however. According to a study by HUMPHREY (1992), almost one half of operating expenses incurred by US commercial banks result from servicing demand and savings accounts, which would suggest treating these deposits as outputs. Yet the intermediation approach

Table 1: Survey of Cross-Country Bank Efficiency Studies

study	methodology			data					countries	results	
				inputs or prices	**outputs**	**banks**	**bank type**	**source**		**efficiency**	**scale**
Allen/Rai (1996)	SFA, DFA	cost	panel 1988-92	labor, borrowings, fixed assets	loans, securities	194	commercial	Com-pustat	**A**, AUS, B, CH, CN, **D**, **DK**, ES, *F*, FIN, *I*, JP, **S**, *UK*, US	0.82	60
Berg et al. (1993)	DEA	produc-tion	cross section 1990	labor, fixed assets	loans, deposits, branches	779	all	official	*FIN*, *N*, **S**	0.60	
Dietsch et al. (1998)	DFA	cost, profit	panel 1992-96	labor, purchased funds, deposits	loans, time deposits, demand deposits, earning assets	661	commercial, mutual, savings	IBCA	*A*, B, D, **DK**, **ES**, *F*, I, L, NL, *POR*, **UK**	0.88, 0.70	
Dietsch, Vivas (1998)	DFA	cost	panel 1988-92	labor, borrowings, fixed assets	loans, deposits, earning assets	324	commercial, savings	?	*ES*, **F**	0.58	
Pastor et al. (1997)	DEA	cost	cross section 1992	labor costs, other non-interest costs	loans, deposits, earning assets	400	commercial	IBCA	**A**, **B**, **D**, *ES*, *F*, **I**, *UK*, US	0.86	
Ruthenberg Elias (1996)	TFA	cost	panel 1989-90	labor, fixed assets, loan share	total assets	65	5 largest	official	B, CH, D, DK, ES, F, FIN, GR, I, IRE, ISR, NL, POR, S, UK	0.70	50
Vander Vennet (1994)	NFA	cost	cross section 1991	labor & fixed assets (& deposits)	loans & deposits (or investments)	1504	no investment	IBCA	B, D, DK, ES, I, L, NL, POR, UK		3-10
Vander Vennet (1999)	SFA	cost, profit	cross section 1995-96	labor, fixed assets, deposits	loans & securities (or interest & non-interest income)	2375	no investment	?	A, B, CH, D, DK, ES, F, FIN, GR, I, IRE, L, N, NL, POR, S, UK	0.80, 0.68	5-50

views them as inputs. To avoid this obvious contradiction, even intermediary approaches increasingly include demand and savings deposits as outputs. This procedure resembles the so-called value-added approach initiated by HANCOCK (1991), which considers items on either side of the balance sheet as potential output candidates if they contribute to value-added. In the case of demand and savings deposits this requirement seems fulfilled since customers are apparently willing to incur account charges and accept lower interest rates for the services these accounts provide.

The choice of bank categories to investigate also varies across the studies cited in *Table 1*. Common to all studies, however, is the inclusion of commercial banks and, with perhaps the exception of BERG ET AL. (1993), the exclusion of investment banks.

Despite their differences, most cross-country studies come to similar conclusions with respect to the average[7] level of measured frontier efficiency. Broader-scope cross-country studies suggest that the average cost efficiency ranges from 0.70 (RUTHENBERG/ELIAS, 1996) to 0.80 (ALLEN/RAI, 1996 and VANDER VENNET, 1999), which is roughly in line with the results from US studies (BERGER/HUMPHREY, 1997). Less agreement with US studies exists, however, with regard to profit efficiency. As the table shows, international studies which consider both cost and profit efficiency find the latter to be lower. The opposite holds true for US studies (BERGER/HUMPHREY, 1997). The lower value of profit efficiency yielded by cross-country studies implies that bank customers pay lower prices for cost-intensive outputs, suggesting that these added costs do not contribute to service and output quality in the eyes of customers.

Less unanimity exists among the cross country studies with regard to the optimal, cost minimizing size of a bank (column "scale" in the table), as measured by total assets. Findings range from 3 (VANDER VENNET, 1994) to 60 billion US dollars (ALLEN/RAI, 1996). The studies also arrive at somewhat varying results with respect to the countries with the highest and lowest cost-efficient banks. The former appear in bold print in the table, the latter in italics.[8] For example, DIETSCH ET AL. (1998) and PASTOR ET AL. (1997) come to opposite conclusions with regard to the relative efficiency of banks in Austria (A), Spain (ES) and the United Kingdom (UK) although both studies sample similar bank types from the same data source. The contradiction

[7] The reported efficiency scores for DIETSCH ET AL. (1998) represent median values. The second value, when given, pertains to profit efficiency

[8] Only European banks are considered in this breakdown. The last three studies cited in *Table 1* do not present evidence allowing a country ranking.

results possibly from the use of different frontier approaches: DEA in the case of PASTOR ET AL. (1997) and DFA in the case of DIETSCH ET AL. (1998).

3. Methodology

The following study measures the cost and profit efficiency of a sample of European banks employing DEA. The natural way of proceeding in this case is to first define a production technology set T on the sample of banks which exhibits strong disposability[9] of inputs and outputs

$$T = \{ (\mathbf{x}, \mathbf{y}) : \mathbf{Y}\boldsymbol{\lambda}_i \geq \mathbf{y}_i \,,\ \mathbf{X}\boldsymbol{\lambda}_i \leq \mathbf{x}_i \,,\ \boldsymbol{\lambda}_i \geq 0 \,,\ i = 1, ..., I\}, \qquad (1)$$

where
- $\mathbf{Y}$ = M x I matrix of bank outputs ($\mathbf{Y} \geq 0$),
- $\mathbf{X}$ = N x I matrix of bank inputs ($\mathbf{X} \geq 0$),
- $\mathbf{y}_i$ = M x 1 vector of the outputs of a given bank i,
- $\mathbf{x}_i$ = N x 1 vector of the inputs of the bank,
- $\boldsymbol{\lambda}_i$ = I x 1 vector of so-called intensity weights, and
- I = sample size.

Then, depending on the orientation (cost or profit), one would either minimize total costs

$$\mathbf{w}_i'\mathbf{x}_i \qquad (2)$$

or maximize profits

$$\mathbf{p}_i'\mathbf{y}_i - \mathbf{w}_i'\mathbf{x}_i \qquad (3)$$

for each of the I banks in the sample, subject to the constraints imposed by the technology set T, where **w** represents an N x 1 vector of factor prices and **p** an M x 1 vector of output prices.[10] Proceeding in this way would yield the following two linear programming problems:

[9] Strong disposability of inputs and outputs implies that inputs and outputs can be freely disposed of, i.e., that it is always possible to produce a given output level with more inputs or to produce less output with a given quantity of inputs. In short, strong disposability rules out "backward bending" isoquants and transformation curves.

[10] Vectors and matrices appear in bold print throughout.

in the case of cost minimization

$$\mathbf{w}_i'\mathbf{x}_i \xrightarrow[\mathbf{x}_i,\boldsymbol{\lambda}_i]{} \min \tag{4}$$

$$\begin{aligned} \text{s.t.} \quad & \mathbf{Y}\boldsymbol{\lambda}_i \geq \mathbf{y}_i \\ & \mathbf{X}\boldsymbol{\lambda}_i \leq \mathbf{x}_i \\ & \boldsymbol{\lambda}_i \geq 0 \end{aligned}$$

and in the case of profit maximization

$$\mathbf{p}_i'\mathbf{y}_i - \mathbf{w}_i'\mathbf{x}_i \xrightarrow[\mathbf{x}_i,\mathbf{y}_i,\boldsymbol{\lambda}_i]{} \max \tag{5}$$

$$\begin{aligned} \text{s.t.} \quad & \mathbf{Y}\boldsymbol{\lambda}_i \geq \mathbf{y}_i \\ & \mathbf{X}\boldsymbol{\lambda}_i \leq \mathbf{x}_i \\ & \boldsymbol{\lambda}_i \geq 0, \end{aligned}$$

which are solved for each of the I banks in succession. The optimal input $\mathbf{x}_i$* and output $\mathbf{y}_i$* vectors for a given bank i yielded by the solutions to the two problems would then be used to calculate the following cost and profit efficiency measures for the bank:

$$\frac{\mathbf{w}_i'\mathbf{x}_i^*}{\mathbf{w}_i'\mathbf{x}_i} = \frac{\text{frontier costs}}{\text{observed costs}} \tag{6}$$

$$\frac{\mathbf{p}_i'\mathbf{y}_i - \mathbf{w}_i'\mathbf{x}_i}{\mathbf{p}_i'\mathbf{y}_i^* - \mathbf{w}_i'\mathbf{x}_i^*} = \frac{\text{observed profits}}{\text{frontier profits}} \tag{7}$$

As (4) and (5) indicate, proceeding in this manner requires data on both quantities (x, y) and prices (w, p). Unfortunately, reliable price data are rarely available for banks. Prices used in bank efficiency studies often must be constructed as the ratios of flows (say, interest costs or interest revenues) to stocks (in this case, deposits and loans). As stock aggregates used in these calculations are quite heterogeneous, the prices they yield tend to be inaccurate and to produce misleading results. To avoid this problem, we treat costs and revenues as scalars, i.e., we do not distinguish between their price and quantity dimensions. In such instances it is customary in the literature[11] to replace (4) and (5) with the following linear optimization problems:

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[11] In the case of scalar costs see for example FÄRE and GROSSKOPF (1985) and for scalar revenues and costs compare PASTOR (1999).

cost minimization

$$\theta_i \xrightarrow[\theta_i,\boldsymbol{\lambda}_i]{} \min \tag{4a}$$

$$\begin{aligned} \text{s.t.} \quad & \mathbf{Y}\boldsymbol{\lambda}_i \geq \mathbf{y}_i \\ & \mathbf{C}\boldsymbol{\lambda}_i \leq \theta_i \mathbf{c}_i \\ & \boldsymbol{\lambda}_i \geq 0 \end{aligned}$$

profit maximization

$$\pi_i \xrightarrow[\pi_i,\boldsymbol{\lambda}_i]{} \min \tag{5a}$$

$$\begin{aligned} \text{s.t.} \quad & \mathbf{R}\boldsymbol{\lambda}_i \geq \mathbf{r}_i \\ & \mathbf{C}\boldsymbol{\lambda}_i \leq \pi_i \mathbf{c}_i \\ & \boldsymbol{\lambda}_i \geq 0 \end{aligned}$$

where $\mathbf{R}$ = M x I matrix of bank revenues ($\mathbf{R} \geq 0$)

$\mathbf{C}$ = N x I matrix of bank costs ($\mathbf{C} \geq 0$)

$\mathbf{r}_i$ = M x 1 vector of the revenues of bank i,

$\mathbf{c}_i$ = N x 1 vector of the costs of the bank.

θ and π measure the degree to which the observed costs of a bank correspond, respectively, to their cost minimizing and profit maximizing levels. Due to the nature of the linear optimization problem, θ and π = (0, 1]. In this sense, the parameters correspond to measures (6) and (7). However in contrast to these measures, θ and π represent radial measures, i.e., they measure the amount of cost contraction that appears possible, holding cost shares constant (proportional cost reduction). FÄRE and GROSSKOPF (1985) discuss further the relationship between (6) and θ.

The advantage of proceeding in accordance to (4a) and (5a) is that price data are not required, which - given that unreliability of bank price data - should yield more robust results. This procedure has a drawback, however, in that it does not allow one to distinguish between technical and allocative efficiency. Hence, it remains unknown to what degree measured frontier inefficiency is due to excessive input usage and/or to factor combinations that conflict with relative factor prices.

In essence, (4a) and (5a) search for a linear combination of banks that (i) requires no greater costs than bank i to generate no less output or revenue than i and that (ii) minimizes the measured efficiency of i. The linear combination fulfilling these requirements defines the section of the best-practice frontier against which the efficiency of bank i is measured. If no linear combination, other than bank i itself, can be found, then λ_{ij} equals 1 for i = j and 0 for i ≠ j, θ_i or $\pi_i = 1$, and the bank is deemed efficient, i.e., as lying on the best-practice frontier.

To obtain efficiency measures for the other banks, the linear programming problems must be solved a total of I times, once for each bank in the sample. Proceeding in this manner results in a piecewise linear envelopment of the data set, from which the procedure DEA draws it name.

Although (4a) and (5a) place no parametric strictures on the frontier technology, they nevertheless do impose certain restrictions on it. The first N+M constraints, as previously noted, impose strong disposability on **C**, **Y** and **R**, and the last I constraints linear homogeneity (constant returns-to-scale) on the best-practice frontier. BANKER ET AL. (1984) show that the linear homogeneity constraint can be relaxed by appending the convexity restriction[12] $\boldsymbol{\lambda}_i'\mathbf{e} = 1$ to (4a) and (5a), which allows for variable returns-to-scale[13] (VRS). GROSSKOPF (1986) terms the ensuing best-practice frontier a convex frontier to contrast it with the linear frontier associated with constant returns to scale (CRS).

A convex efficiency frontier envelops the data set more tightly than a linear frontier. Consequently, the efficiency measure θ_{VRS} (or π_{VRS}) based on a convex frontier will always equal or exceed the corresponding measure θ_{CRS} (or π_{CRS}) based on a linear frontier. Moreover, a linear frontier nests a convex frontier. Based on these relationships, FÄRE and GROSSKOPF (1985) suggest the following measure for scale efficiency

$$SE = \frac{\theta_{CRS}}{\theta_{VRS}} \quad , \tag{8}$$

where $0 < SE \leq 1$ since $\theta_{VRS} \geq \theta_{CRS}$. SE gives the factor of proportionality by which the efficiency of a bank falls short of the efficiency it would exhibit if it had optimal size. Note that equation (8) can also be interpreted as dividing the total inefficiency

12 **e** denotes the unit vector.

13 This does not allow for an S-shaped matching frontier, however, as this would violate the convexity constraint. The convexity constraint restricts the returns-to-scale to being first increasing, then constant and then decreasing.

θ_{CRS} of a bank into a component SE, due to non-optimal scale, and a component θ_{VRS}, arising from frontier inefficiency.

SE does not indicate whether scale inefficiency is due to sub- or superoptimal size, however. Distinguishing between these two cases requires analyzing the sum $\boldsymbol{\lambda}_i'\mathbf{e}$ based on the solution values for $\boldsymbol{\lambda}$ from (4a) and (5a), which assume a linear reference technology. BANKER (1984) shows that this sum is less than, equal to, or greater than one depending on whether the frontier technology exhibits increasing, constant, or decreasing returns-to-scale, respectively. This insight, together with (8), provides the basis for investigating the presence of increasing returns-to-scale in this study.[14] Unfortunately, whether economies of scale are due to the greater efficiency of large-scale production or to large-scale price advantages cannot be determined in our approach due to the use of scalar profits and costs.

4. Data

The data used in this study stem from the Fitch-IBCA database BankScope. We consider only commercial and savings banks to keep the size of the linear programming problems manageable.[15] Most studies cited in *Table 1* also include these bank groups. Besides, with the exception of the thousands of cooperative banks in Germany, the banks in most countries in our sample fall into one of these two categories anyway.

The sample consists of the 1783 commercial and savings banks that (i) operated in the EU, Norway or Switzerland at some point over the period 1993-97, (ii) were contained in the BankScope database and (iii) offered the data needed for our study. The data were extracted from the unconsolidated bank income and balance sheet accounts and converted into US dollars at prevailing exchange rates. We employ period averages (cross-section perspective).

We differentiate among the following costs, outputs, and revenues:

costs (c_n)

- c_1 = interest costs
- c_2 = personnel costs
- c_3 = commissions, fees and trading expenses
- c_4 = other operating and administrative expenses
- c_5 = probability of insolvency

14 FERRIER ET AL. (1993) provide a simulation method for determining the presence of scope economies with the help of DEA results. The method is quite cumbersome and has yet to find its way into the mainstream DEA literature. Because of the awkwardness of the procedure, we have chosen not to implement it.

15 Note the size of the matrices in the constraints to (4a) and (5a).

outputs (y_m)

y_1 = net loans

y_2 = other earning assets

y_3 = off-balance-sheet items

y_4 = deposits

revenues (r_m)

r_1 = interest income

r_2 = commissions, fees, trading and other operating income

A number of variable definitions deserve comment. The insolvency risk (c_5) of a bank i is defined as:

$$\left[\frac{E(ROA)_i + CAR_i}{\sigma(ROA)_i}\right]^{-2}, \tag{9}$$

where E(ROA) represents the expected rate of return on assets (ROA), σ(ROA) the standard deviation or volatility of ROA, and CAR the capital-asset ratio. The fraction in (9) gives the distance between the insolvency threshold (= -CAR) of a bank and its expected rate of return on assets, measured in standard deviations. According to the Chebychev inequality, the probability that ROA will fall outside the interval E(ROA) ± [E(ROA)+CAR] is less than or equal to the square of the reciprocal of this fraction, no matter how ROA is distributed. The square of the reciprocal is what appears in (9). Technically speaking, (9) overestimates the true probability inasmuch as only negative deviations from E(ROA) lead to default. Assuming that ROA is distributed symmetrically about its expected value, we could halve (9) to obtain a truer picture of the actual upper bound on a bank's probability of default. Since halving (9) would have no influence on the results, as DEA measures relative efficiency, we refrain from doing so. The probability of insolvency was chosen over loan losses or bank capital for the reasons given in section 2.

To obtain E(ROA), which we need to calculate (9), we ran separate pooled regressions for commercial and savings banks by regressing a bank's ROA in year t (t = 1993, ..., 1997) on its size (total assets), its portfolio structure (ratio of loans, investments, fixed assets and off-balance-sheet items to total assets, respectively), all first-order interactions of these five variables (to pick up possible non-linearities) and on a full set of country dummies. The estimated coefficients were then applied to the period-average regressor values of each bank to calculate its E(ROA) for 1993-97. We utilized the same procedure to obtain σ(ROA), replacing the left-hand variable in the re-

Table 2: Inputs and Outputs by Country (average values)

		INPUTS					OUTPUTS					
	Banks	C_1	C_2	C_3	C_4	C_5	y_1	y_2	y_3	y_4	r_1	r_2
Austria	38	26.8	8.4	7.2	6.5	0.029	369.9	247.4	100.7	535.6	40.6	12.6
Belgium	41	51.1	8.4	6.0	5.4	0.035	305.7	716.2	483.0	975.5	71.7	7.1
Denmark	54	46.1	15.5	1.0	8.7	0.010	601.6	516.9	166.5	869.2	80.5	8.7
Finland	1	441.7	8.2	6.8	8.1	0.020	4345.3	4270.7	971.2	80.0	529.0	1.0
France	159	95.7	18.0	4.9	11.7	0.114	626.6	1274.7	368.1	1584.3	127.2	16.8
Germany	898	58.0	17.0	5.3	10.2	0.016	777.8	562.6	155.3	1202.4	96.1	10.9
Greece	10	93.9	23.6	4.5	12.9	0.048	358.9	641.4	162.1	952.2	124.3	1.2
Ireland	1	8.0	0.3	0.1	0.1	0.001	184.6	339.0	1970.6	223.4	19.7	0.2
Italy	117	143.2	52.0	13.1	25.6	0.013	1278.3	1145.7	305.0	1633.9	227.1	40.7
Luxembourg	116	183.3	7.9	4.2	6.2	0.063	638.4	2087.8	1405.8	2459.6	203.4	15.2
Netherlands	16	271.6	4.3	3.2	2.3	0.023	3432.5	884.9	187.8	1612.8	291.6	2.1
Norway	11	19.4	4.8	5.7	3.0	0.032	355.1	88.0	35.6	390.8	32.7	4.7
Portugal	4	74.7	16.5	25.2	11.4	0.012	796.6	203.6	1057.3	972.3	111.9	30.4
Spain	57	80.2	24.1	7.3	13.3	0.035	714.4	712.4	74.7	1363.9	134.5	16.8
Sweden	3	160.7	3.0	1.0	2.0	0.040	1527.8	195.6	1565.5	554.6	178.4	3.8
Switzerland	231	36.8	12.1	7.3	9.5	0.053	586.9	394.6	230.2	766.5	49.4	23.4
United Kingdom	26	50.0	10.5	3.6	6.8	0.037	369.6	578.9	247.4	806.4	61.6	12.1
Total	1783	74.0	17.7	5.9	10.7	0.055	752.3	743.2	286.1	1254.4	108.8	15.2

gression equation with the absolute value of the residuals from the first regression model. All ex-post estimates of σ(ROA) proved to be positive. MCALLISTER and MCMANUS (1993) use a similar approach.

The inclusion of off-balance-sheet items (y_3) as an output is based on the observation that the Basle Accord on capital adequacy assigns these items risk weights that equate them with loans, implying that they generate similar screening, monitoring and control costs (BERGER/MESTER, 1997).

The choice of deposits (y_4) as an output is made under the assumption that these are proportional to payment transactions and other services flowing to customers. Demand and savings deposits would have been more appropriate, but such detailed information was only available for a small sample of the banks considered in this study. We also include deposits as an output in the measurement of profit efficiency to ensure that we control sufficiently for the costs they generate. This procedure is somewhat unconventional, since it mixes stocks with flows, but it is not without precedent.[16]

Revenues used in this study represent pre-tax income to avoid the distorting effect of different national tax rates.

Table 2 presents the averages of the cost, output and revenue variables of the banks in our sample, broken down by country. Monetary values appear in millions of US dollars. As the table indicates, the majority of the banks studied are located in France, Germany, Italy, Luxembourg and Switzerland, as is to be expected given the size of their economies or the national importance of banking[17]. Note that the relative size of the dollar values appearing in the table depends on the average size of the banks in a country and should not be taken as a sign, say, of high or low-cost banking.

Of particular interest is the size of the insolvency risk of an average bank in the different countries. According to *Table 2*, French banks are the riskiest on average. *Table 3* explains why. It presents the components upon which our risk measure rests. Note that in accordance with (9), banks with a low capital-asset ratio and a low expected and volatile rate of return on assets have a high probability of default. In the case of French banks, it appears that the deciding factor is the high volatility of their

16 See, e.g., BERGER/DEYOUNG (1997) and RESTI (1997).
17 The banking sector in Switzerland, for example, contributes roughly 10% to GDP.

returns. The returns of Danish banks also appear to be relatively volatile, but this is offset by high level returns and a thick capital cushion, both of which French banks lack. Banks in Finland, Germany and the Netherlands, on the other hand, achieve relatively low returns and hold below-average levels of capital, but compensate for this with lower return volatility. Note that according to *Table 3*, no monotonic relationship exists between insolvency risk and the amount of capital a bank holds. In fact, Swiss and British banks hold a relatively large amount of capital and yet are still among the riskier. Hence, bank capital would be a poor proxy for risk in our sample.

Table 3: Components of Insolvency Risk

	E(ROA)	σ(ROA)	CAR	Risk
Austria	0.0391	0.0217	0.0903	0.0285
Belgium	0.0305	0.0161	0.0880	0.0347
Denmark	0.0562	0.0165	0.1305	0.0099
Finland	0.0000	0.0117	0.0831	0.0198
France	0.0345	0.0272	0.0852	0.1136
Germany	0.0340	0.0095	0.0590	0.0157
Greece	0.0466	0.0224	0.0689	0.0480
Ireland	0.0283	0.0177	0.5518	0.0009
Italy	0.0529	0.0146	0.1039	0.0130
Luxembourg	0.0189	0.0126	0.0501	0.0630
Netherlands	0.0153	0.0067	0.0770	0.0228
Norway	0.0438	0.0138	0.0817	0.0317
Portugal	0.0458	0.0165	0.1099	0.0118
Spain	0.0461	0.0227	0.1028	0.0352
Sweden	0.0167	0.0068	0.0514	0.0403
Switzerland	0.0532	0.0344	0.1514	0.0526
United Kingdom	0.0289	0.0203	0.1440	0.0365
Total	0.0377	0.0161	0.0826	0.0547

Table 4 presents information on the average size, scope and engagement in retail banking of the banks in our sample. According to the figures presented, the banks in Finland, Italy, Luxembourg and the Netherlands are the biggest on average.[18]

Table 4: Indicators of Scale and Scope

	Total Assets	Scope	Retail
Austria	652.4	0.701	0.731
Belgium	1058.6	0.638	0.867
Denmark	1167.5	0.841	0.902
Finland	9336.5	0.882	0.998
France	1994.3	0.745	0.819
Germany	1397.1	0.689	0.884
Greece	1110.0	0.865	0.990
Ireland	530.8	0.434	0.991
Italy	2683.5	0.780	0.827
Luxembourg	2816.3	0.473	0.872
Netherlands	4539.7	0.606	0.938
Norway	485.1	0.344	0.879
Portugal	1121.5	0.601	0.730
Spain	1547.3	0.618	0.872
Sweden	1782.5	0.764	0.955
Switzerland	1058.6	0.458	0.709
United Kingdom	1058.7	0.669	0.868
Total	1577.5	0.655	0.848

Scope is based on the Herfindahl index, here defined as

$$-\ln \sum_{k=1}^{3} \left(\text{portfolio share}_k\right)^2 . \tag{10}$$

The minus sign is added so that the value of the scope measure increases with the degree of diversification. Portfolio shares pertain to loans, investments and off-balance-

[18] Note, however, that our sample contains only one Finnish bank.

sheet items. According to the scope variable, the banks in Denmark, Finland and Greece are relatively broadly diversified, while those in Ireland[19], Norway and Switzerland are the least so.

The variable termed "Retail" is defined as the ratio of interest income to total operating income and is intended to serve as a proxy for the degree of specialization in retail banking. A large value means a strong emphasis on retail banking. The variable can also be viewed as a proxy for the degree to which a bank serves as an intermediary. In this regard, the banks in Austria and Switzerland appear to fit this role the least, reflecting perhaps the importance of asset management in both countries.

The variables in *Table 4* are used in the next section as regressors to investigate the sources of efficiency difference among the banks in our sample.

5. Results

5.1. Frontier Efficiency

This section reports the efficiency results based on a convex reference technology, which allows for variable returns to scale (VRS). In other words, the results pertain to frontier inefficiency. Scale inefficiency, resulting from operating at a non-optimal size, and scale economies are viewed in the next section.

Table 5: Cost and Profit Frontier Efficiency (VRS)

	Cost		Profit	
	no risk	risk	no risk	risk
minimum	0.099	0.099	0.234	0.234
median	0.394	0.523	0.558	0.627
mean	0.452	0.539	0.598	0.652
maximum	1.000	1.000	1.000	1.000
coefficient of variation	0.415	0.360	0.268	0.267

Table 5 presents summary statistics for the cost and profit frontier efficiency of the banks in our sample. The coefficient of variation measures the relative dispersion of frontier efficiency about the common mean. As the table indicates, the average effi-

[19] Note here too that our sample includes just a single bank from Ireland.

ciency across all banks varies between 0.45 and 0.65, depending on the perspective (cost or profit) chosen and/or whether risk is included. This implies that that an average bank in our sample could lower its costs to between 45 and 65% of its current level and still maintain its output and revenue levels. The median values are somewhat lower than the average values, indicating that slightly more banks lie below than above the mean.

The average efficiency levels appearing in the table are less than those previous cross-country studies have yielded (*Table 1*). This could be due to any number of causes, as our study differs from previous work in several ways. The main source, however, is probably the use of DEA in this study. DEA tends in general to generate lower average efficiency scores than parametric approaches (BERGER/HUMPHREY, 1997).

As *Table 5* points out, the average level of measured frontier efficiency increases and the degree of dispersion decreases when we switch from a cost to a profit perspective. In other words, when outputs (y) are replaced by the income streams (r) they generate, measured efficiency rises and the efficiency differential across banks declines. The increase in measured efficiency suggests that the output variables (loans, investments, deposits and off-balance-sheet items) fail to capture cost-intensive differences in product quality, which apparently generate higher revenues, as profit efficiency exceeds cost efficiency. Note that the increase in measured efficiency that a switch from a cost to a profit perspective engenders agrees with US results but conflicts with previous cross-country findings.

The inclusion of risk raises measured efficiency as well, but then it must since introducing risk adds a further constraint, which by necessity reduces the scope for improvement and thus inefficiency.[20] The inclusion of risk also reduces the efficiency variation across the banks in our sample, but only within a cost perspective, not within a profit perspective. This latter finding suggests that the differences in profit efficiency among the banks in our sample are not due to differences in their tastes for risk but rather to differing abilities of their portfolios and services to generate income.

Table 6 measures the rank correlation between the efficiency scores based on different risk and cost/profit perspectives. As the correlation coefficients indicate, the

[20] It is not an issue in this paper, but note that by including and excluding risk in a DEA framework, one could estimate the shadow price of risk in terms of a cost-saving potential. FÄRE ET AL. (1999) apply this insight to measure the cost of capital-adequacy regulations.

inclusion of risk does not have a great effect on the efficiency ranking of the banks in our sample. The coefficient values range from 84 to 88% depending on whether a cost or profit perspective is chosen. A switch from a cost to a profit standpoint, on the other hand, does have a marked effect on the relative efficiency rankings of the banks, the degree of correlation between the two sets of results falling to 49 and 58%. In another cross-country study, DIETSCH ET AL. (1998) report an even lower rank correlation coefficient of 26% between measured cost and profit efficiency (cf. *Table 1*). US studies yield still lower correlations between cost and profit efficiency: there the degree of correlation is either statistically insignificant or negative (BERGER/HUMPHREY, 1997). These lower values stem from parametric studies, suggesting that the source of the difference may be methodological. Nevertheless, the fact that the degree of correlation between cost and profit efficiency is at best low and at worst negative indicates that the relative efficiency of banks depends critically on the choice of a cost or profit perspective.

Table 6: Rank Correlation Coefficients between Frontier Efficiency Scores (VRS)

cost excluding risk vs. cost including risk	0.839
profit excluding risk vs. profit including risk	0.879
cost excluding risk vs. profit excluding risk	0.491
cost including risk vs. profit including risk	0.575
cost excluding risk vs. profit including risk	0.432

Table 7 presents summary statistics for measured cost and profit efficiency, broken down by country, i.e., it represents a country-specific version of *Table 5*. "Var" denotes the coefficient of variation. As *Table 7* indicates, depending on the choice of orientation and the inclusion of risk, the average frontier efficiency of banks varies from 0.16 in Greece (cost perspective, ignoring risk) to 1.00 in Ireland. Note again, however, that our sample only contains one Irish bank, so the result can hardly be taken as being representative of all Irish banks.

Irrespective of the perspective chosen or the treatment of risk, the banks in Denmark, Finland, France, Ireland, Luxembourg, and Sweden appear generally to be the most frontier efficient, while those in Greece, Italy, Portugal, Spain, and the UK appear to be the least so. Greek and Portuguese banks are without question the least efficient. Even the most efficient banks ("max") in these two countries lie far from the

Table 7: Average Cost and Profit frontier Efficiency by Country (VRS)

	Cost								Profit							
	excluding risk				including risk				excluding risk				including risk			
	min	mean	max	var	min	mean	max	var	min	mean	max	var	min	mean	max	var
Austria	0.156	0.473	1.000	0.423	0.174	0.560	1.000	0.417	0.344	0.607	1.000	0.282	0.344	0.656	1.000	0.289
Belgium	0.224	0.442	1.000	0.446	0.253	0.488	1.000	0.391	0.398	0.601	1.000	0.290	0.401	0.615	1.000	0.277
Denmark	0.289	0.523	1.000	0.355	0.293	0.614	1.000	0.319	0.465	0.778	1.000	0.173	0.465	0.796	1.000	0.176
Finland	0.805	0.805	0.805	0.000	0.828	0.828	0.828	0.000	0.942	0.942	0.942	0.000	0.942	0.942	0.942	0.000
France	0.099	0.469	1.000	0.455	0.099	0.498	1.000	0.449	0.272	0.649	1.000	0.276	0.272	0.656	1.000	0.279
Germany	0.124	0.422	1.000	0.321	0.128	0.536	1.000	0.267	0.320	0.585	1.000	0.215	0.326	0.652	1.000	0.227
Greece	0.117	0.162	0.260	0.332	0.117	0.186	0.310	0.391	0.318	0.485	0.752	0.237	0.318	0.485	0.754	0.238
Ireland	1.000	1.000	1.000	0.000	1.000	1.000	1.000	0.000	1.000	1.000	1.000	0.000	1.000	1.000	1.000	0.000
Italy	0.155	0.281	1.000	0.519	0.172	0.363	1.000	0.409	0.324	0.548	1.000	0.316	0.331	0.648	1.000	0.283
Luxembourg	0.151	0.540	1.000	0.442	0.152	0.617	1.000	0.415	0.354	0.704	1.000	0.285	0.414	0.752	1.000	0.268
Netherlands	0.244	0.508	1.000	0.416	0.326	0.731	1.000	0.347	0.381	0.631	1.000	0.286	0.532	0.789	1.000	0.229
Norway	0.261	0.534	0.737	0.283	0.261	0.693	0.980	0.348	0.403	0.489	0.585	0.105	0.403	0.590	0.702	0.142
Portugal	0.173	0.289	0.479	0.458	0.190	0.346	0.525	0.454	0.390	0.520	0.719	0.309	0.406	0.579	0.877	0.366
Spain	0.114	0.343	1.000	0.467	0.126	0.396	1.000	0.399	0.274	0.605	1.000	0.297	0.274	0.646	1.000	0.312
Sweden	0.231	0.514	0.950	0.746	0.299	0.634	0.950	0.514	0.544	0.764	1.000	0.299	0.553	0.851	1.000	0.303
Switzerland	0.116	0.607	1.000	0.311	0.126	0.648	1.000	0.309	0.234	0.537	1.000	0.315	0.234	0.572	1.000	0.330
United Kingdom	0.207	0.482	1.000	0.411	0.239	0.552	1.000	0.398	0.343	0.603	1.000	0.222	0.344	0.646	1.000	0.255
Total	0.099	0.452	1.000	0.415	0.099	0.539	1.000	0.360	0.234	0.598	1.000	0.268	0.234	0.652	1.000	0.267

best-practice frontier. Otherwise, almost every country has at least one bank on the efficiency frontier.

Previous cross-country studies also find Danish and Swedish banks to be among the most cost efficient and the Portuguese banks to be among the least so. Otherwise though, not a great deal of agreement exists with previous work in this respect, although of course previous cross-country studies themselves do not present a very uniform picture.

The switch from a cost to a profit perspective has a marked effect on the measured efficiencies of the banks in the Netherlands, Norway and Switzerland. From a cost perspective, the banks in Norway and Switzerland are among the most efficient on average. However, from a profit perspective they are among the least efficient. The opposite holds true for the banks in the Netherlands: from a cost viewpoint they are among the least efficient, whereas from a profit viewpoint they are among the most efficient. This suggests that an average Dutch bank achieves a decidedly higher value-added per unit cost than a typical Norwegian or Swiss bank. The strong change in rankings of the banks of these countries when the perspective changes is probably the cause of the low rank correlation between cost and profit efficiency (*Table 6*).

Note that no efficiency differential should exist among banks in an integrated banking market in competitive equilibrium. Hence, national banking markets in which efficiency dispersion (coefficient of variation) across banks is well-below average should be more highly integrated and lie closer to a competitive equilibrium than others. Viewed from this perspective, the banking markets in Denmark, Germany and Norway seem to come closest to meeting this "ideal", while the banks in Italy, Portugal, Spain, Sweden and Switzerland (with respect to profit efficiency) do so the least. This could be a sign of structural change (state of larger disequilibrium) as well as of non-competitive elements. Note too that banking markets that are more integrated tend to be more frontier efficient on average, supporting the view that increased integration and hence competition increase efficiency.

Finally note that the inclusion of risk has little effect on the efficiency rankings of the national banking industries. This was to be expected given the higher degree of correlation between efficiency scores based on different treatments of risk (*Table 6*).

Table 8 takes a closer look at the possible causes of the re-ranking of banks that occurs when the chosen perspective changes. The table reports the results of regress

Table 8: Effects of Varying Orientation on the Efficiency Rankings of Banks (OLS)

Variable	(1)	(2)	(3)
constant	0.406***	0.035	0.396***
	(0.085)	(0.030)	(0.088)
Austria	-0.053	0.018	-0.027
	(0.053)	(0.025)	(0.054)
Belgium	0.008	-0.032	-0.009
	(0.040)	(0.028)	(0.041)
Denmark	0.006	-0.046**	-0.037
	(0.028)	(0.019)	(0.031)
Finland	-0.317***	-0.008	-0.278***
	(0.033)	(0.019)	(0.034)
France	0.033	-0.063***	0.012
	(0.029)	(0.011)	(0.029)
Greece	0.597***	-0.014	0.600***
	(0.094)	(0.044)	(0.095)
Ireland	-0.297***	-0.040***	-0.284***
	(0.022)	(0.010)	(0.022)
Italy	0.359***	0.078***	0.454***
	(0.026)	(0.015)	(0.028)
Luxembourg	0.096***	0.109***	0.170***
	(0.034)	(0.026)	(0.036)
Netherlands	-0.066	0.313***	0.175**
	(0.062)	(0.100)	(0.089)
Norway	-0.209***	0.043	-0.122
	(0.080)	(0.030)	(0.083)
Portugal	0.386*	0.048	0.430**
	(0.220)	(0.100)	(0.199)
Spain	0.300***	0.008	0.306***
	(0.041)	(0.019)	(0.042)
Sweden	0.120	0.192	0.225
	(0.205)	(0.117)	(0.229)
Switzerland	-0.347***	-0.034***	-0.329***
	(0.020)	(0.009)	(0.021)
United Kingdom	-0.054	0.049	-0.001
	(0.062)	(0.030)	(0.063)
Scale x 10^{-4}	-0.079***	-0.125***	-0.124***
	(0.026)	(0.017)	(0.026)
(Scale x $10^{-4})^2$	0.004*	0.010***	0.007***
	(0.003)	(0.002)	(0.003)
Scope	0.466***	0.115*	0.536***
	(0.133)	(0.065)	(0.137)
Scope^2	0.044	0.078	0.013
	(0.115)	(0.062)	(0.119)
Intermediation	-1.660***	-0.164	-1.550***
	(0.262)	(0.102)	(0.271)
Intermediation^2	1.354***	0.112	1.217***
	(0.208)	(0.087)	(0.217)
Savings Bank	0.003	0.222***	0.136***
	(0.015)	(0.009)	(0.016)
adj. R^2	0.499	0.446	0.523
$\ln L(\beta_0)$	-561.86	371.84	-458.93
$\ln L(\beta^*)$	66.14	909.36	8.85
$-2[\ln L(\beta_0)-\ln L(\beta^*)]$	1256.01***	1075.04***	935.55***

Asterisks denote statistical significance with a risk of error of less than 10% (*), 5% (**), or 1% (***).
HEC standard errors appear in parentheses.

ing (with OLS) the log of the ratios of two of a bank's efficiency measures on a set of country dummies and a set of variables describing the bank's size ("scale"), degree of asset diversification ("scope"), emphasis on retail banking ("retail") and type (commercial or savings). The variables in parentheses are described in *Table 4*. All of the efficiency ratios serving as left-hand variables have the same denominator, namely the cost efficiency of a bank not controlling for risk (column 1 in *Table 5*). The first column of *Table 8* compares this efficiency measure with that yielded by a profit perspective, continuing to ignore risk (column 3 in *Table 5*); column 2 in *Table 8* compares the identical efficiency score with the measure yielded by a cost perspective in which risk is considered (column 2 in *Table 5*); and the last column in *Table 8* compares this same efficiency measure with that obtained from a profit perspective in which risk is included (column 4 in *Table 5*). The last column in *Table 8* thus investigates the combined effect of changing from a cost to a profit perspective and including risk, the other two columns analyze these effects separately. A positive (negative) sign in *Table 8* means that banks exhibiting a large value with respect to the given variable benefit (suffer) from the orientation change to which the specific column refers.

Take, as an example, the signs of the dummy variable for Switzerland. We see that all are negative, indicating that Swiss banks suffer from every form of change in orientation. Moreover, comparing the estimated values of the coefficients indicates that this is particularly true with respect to a switch from a cost to a profit perspective. This we knew of course from *Table 7*. The purpose of the regressions is another: (i) to investigate whether the non-dummy variables ("scale", "scope", "retail", "savings"), i.e., the different compositions of the national banking industries can explain the shift in the country rankings caused by a shift in orientation and (ii) to discover what types of banks gain (positive sign) or suffer (negative sign) from a shift of orientation.

We start with the first issue. It is clear from the regression results that the different compositions of the national banking industries, as measured by the non-dummy regressors, cannot explain the shift in rankings. Roughly a half of the coefficients of the country dummies are still statistically significant at the 10% level. When running the regressions without the non-dummy variables[21], 36 of 48 country dummies are statistically significant, while with the non-dummy variables the ratio falls to 25:48, indicating that our composition variables can explain about a third (11/36) of the switches in country rankings caused by a change in orientation. The explanatory power of our composition variables is particularly large with respect to the inclusion

[21] These results are not reported to conserve space.

of risk (column 2 in *Table 8*). In this case, 6 of the country dummies lose their explanatory power when composition variables are included in the regression equation. This is not surprising in view of the fact that the composition variables principally describe the structure of a bank's portfolio, which is a determining factor of risk.

The signs of the estimated coefficients of the composition variables indicate that the efficiency rankings of large scale banks fall, albeit at a decreasing rate, when the orientation changes from a cost to a profit perspective and/or when risk is included. In other words, the relative ranking of the smaller banks in our sample improves. Note that this does not mean that small banks are more efficient than large banks, but merely that their relative position vis-à-vis large banks improves, which can mean moving, say, from last to second-to-last place.

With respect to scope, we find that the relative efficiency rankings of the more diversified banks gain from a change from a cost to a profit orientation and/or from the inclusion of risk. The effect seems to be greater with respect to a switch to a profit perspective than with regard to including risk.

The relative efficiency positions of financial institutions with a relatively strong presence in retail banking appear, on the other hand, to suffer, albeit in decreasing amounts, from a switch from a cost to a profit orientation. Their relative rankings seem to be immune to the consideration of risk, however.

The opposite holds true for the relative ranking of savings banks vis-à-vis commercial banks. Their relative position is unaffected by a change from a cost to a profit perspective, while it improves through the introduction of risk.

In contrast to *Table 8*, which investigates which banks' <u>relative</u> efficiency gains or loses from a change in orientation, *Table 9* examines which types of banks are more frontier efficient than others. The table presents the results of regressing a bank's measured frontier efficiency on the same set of variables appearing in *Table 8*. However, since in the present case the left-hand variable is bounded from above, a Tobit model is used and estimated with maximum likelihood (MLE). Note once again that, ideally, the estimated coefficients of all country-specific dummies should be statistically insignificant, indicating that the heterogeneity of banks of different countries can explain the efficiency differential across national banking industries. That this is not case is an indication that country-specific differences with regard to regulatory, institutional or competitive conditions are relevant as well.

Table 9: Determinants of Cost and Profit Frontier Efficiency, Tobit Model (MLE)

	cost		profit	
Variable	**excluding risk**	**including risk**	**excluding risk**	**including risk**
constant	0.833***	0.852***	1.112***	1.122***
	(0.037)	(0.042)	(0.032)	(0.037)
Austria	0.065***	0.095***	0.041**	0.066***
	(0.023)	(0.027)	(0.020)	(0.023)
Belgium	-0.003	-0.020	-0.001	-0.013
	(0.022)	(0.026)	(0.019)	(0.022)
Denmark	0.161***	0.161***	0.241***	0.225***
	(0.020)	(0.023)	(0.017)	(0.020)
Finland	0.146	0.137	-0.039	-0.074
	(0.139)	(0.159)	(0.117)	(0.137)
France	0.042***	0.017	0.053***	0.036***
	(0.013)	(0.015)	(0.011)	(0.013)
Greece	-0.239***	-0.267***	-0.160***	-0.164***
	(0.045)	(0.052)	(0.038)	(0.045)
Ireland	1.337	1.440	1.061	1.191
	(43.48)	(49.81)	(36.78)	(43.04)
Italy	-0.135***	-0.142***	-0.024**	0.029**
	(0.014)	(0.016)	(0.012)	(0.014)
Luxembourg	-0.005	0.066***	0.041***	0.103***
	(0.015)	(0.018)	(0.013)	(0.016)
Netherlands	0.019	0.235***	-0.015	0.163***
	(0.036)	(0.042)	(0.031)	(0.037)
Norway	0.028	0.099**	-0.083**	-0.036
	(0.042)	(0.048)	(0.036)	(0.042)
Portugal	-0.143**	-0.139*	-0.018	0.011
	(0.069)	(0.079)	(0.059)	(0.068)
Spain	-0.113***	-0.126***	0.002	0.008
	(0.019)	(0.022)	(0.016)	(0.019)
Sweden	0.077	0.160*	0.141**	0.266***
	(0.080)	(0.092)	(0.070)	(0.089)
Switzerland	0.120***	0.117***	-0.064***	-0.049***
	(0.012)	(0.014)	(0.010)	(0.012)
United Kingdom	0.053*	0.090***	0.026	0.065**
	(0.028)	(0.032)	(0.024)	(0.028)
Scale x 10^{-4}	0.342***	0.261***	0.432***	0.473***
	(0.017)	(0.040)	(0.015)	(0.020)
(Scale x $10^{-4})^2$	-0.024***	0.032	-0.029***	-0.032***
	(0.002)	(0.031)	(0.002)	(0.002)
Scope	-0.503***	-0.416***	-0.240***	-0.196***
	(0.062)	(0.072)	(0.053)	(0.062)
Scope^2	0.166***	0.161***	0.131***	0.117**
	(0.053)	(0.061)	(0.045)	(0.053)
Intermediation	-0.644***	-0.749***	-1.756***	-1.788***
	(0.113)	(0.130)	(0.097)	(0.115)
Intermediation^2	0.486***	0.559***	1.358***	1.352***
	(0.090)	(0.104)	(0.077)	(0.091)
Savings Bank	-0.013	0.096***	-0.013*	0.072***
	(0.009)	(0.010)	(0.007)	(0.009)
σ	0.137***	0.158***	0.116***	0.136***
	(0.002)	(0.003)	(0.002)	(0.002)
$\ln L(\beta_0)$	-1039.61	-826.32	-1277.05	-1032.64
$\ln L(\beta^*)$	-893.83	-611.78	-1171.63	-833.16
$-2[\ln L(\beta_0)-\ln L(\beta^*)]$	291.56***	429.08***	210.84***	398.96***
LRI $(1-\beta^*/\beta_0)$	0.140	0.260	0.083	0.193

Asterisks denote statistical significance with a risk of error of less than 10% (*), 5% (**), or 1% (***). Estimated standard errors in parentheses.

It is important to note, however, that the variation of frontier efficiency is greater within than across countries. This is confirmed by the fact that R^2 ranges from 9 to 21% when we estimate the four models in *Table 9* with OLS, excluding all but the country dummies. It thus appears that the national banking markets in Europe themselves are not highly integrated or at least that they are not in a state of competitive equilibrium. The results presented in *Table 7* suggested the same.

The regression results pertaining to the country dummies basically confirm the findings presented in *Table 7*. For example, *Table 9*, in full agreement with *Table 7*, shows that Swiss banks belong to the more cost efficient (positive signs) on the one side, and to the less profit efficient (negative signs) on the other. The fact that the signs of the estimated coefficients are statistically significant indicates that this finding cannot be explained by the uniqueness of Swiss banks with respect to the non-dummy variables considered here.

According to the results in *Table 9* pertaining to bank characteristics, the efficiency of banks increases with scale and decreases with scope[22], albeit in decreasing amounts, irrespective of the perspective chosen and/or the inclusion of risk. This implies that large and/or specialized banks are more cost and profit efficient than small and/or diversified banks, i.e., that the former operate closer to the best-practice frontier than the latter. This finding suggests that large, specialized banks would suffer less from increased competition than small, diversified financial institutions.

Banks oriented more towards retail banking are also at a disadvantage in this respect. According to *Table 9*, banks with a strong emphasis on retail banking are both less cost and profit efficient. Yet on the other hand, savings banks, which typically specialize more in retail banking, are more profit efficient than commercial banks, all else equal.

5.2. Scale Economies

We turn now to the question as to whether the banks in our sample display increasing returns to scale and if so, how large the optimal bank size is. At issue is no longer the degree of deviation from a best-practice frontier, but rather the shape of the frontier itself. We begin with *Table 10*, which presents summary statistics of the scale elas-

[22] BERGER and HUMPHREY (1997) note that this finding is common in US studies.

ticity measure (SE), defined in equation (8)[23], and indicates the number of banks exhibiting increasing (IRS), constant (CRS) or decreasing returns to scale (DRS). The results are differentiated according to cost or profit perspective and the inclusion of risk.

Taking first a look at the last three rows in *Table 10*, we see that, except from a profit perspective excluding risk (column 3), the majority of banks operate at a scale that exhibits increasing economies. This implies that the greater share of banks in our sample are sub-optimal in size. The median values point in the same direction since, with the exception of the third column, they all equal or exceed one.

Table 10: Indicators of Economies of Scale

	Cost		Profit	
SE	no risk	risk	no risk	risk
minimum	0.267	0.381	0.361	0.418
median	1.000	1.016	0.958	1.002
mean	0.987	1.063	0.911	0.997
maximum	3.454	3.559	2.420	2.503
IRS	901	1241	633	959
CRS	32	51	37	63
DRS	850	491	1113	761

Interestingly, the inclusion of risk increases the number of banks operating at a sub-optimal scale. This implies that increasing scale, in that it reduces risk, decreases costs and increases revenues. MCALLISTER and MCMANUS (1993) report a similar finding in a cost study of US banks. To explain this phenomenon, which they term financial returns to scale, they point to the greater opportunities that large banks have

[23] To ease interpretation, the reciprocal of SE is used in *Table 10* for banks exhibiting increasing returns to scale. In this way, one can differentiate between scale inefficiency due to sub-optimal scale (SE > 1) and that owing to super-optimal scale (SE < 1). Roughly speaking, the SE to which *Table 10* pertains corresponds to the reciprocal of the more familiar scale elasticity.

to diversify, allowing them to lower risk and to reduce their need for costly financial capital.

Table 11: Banks Operating under Increasing (IRS), Constant (CRS) or Decreasing (DRS) Returns to Scale by Country

	Cost						Profit					
	excluding risk			including risk			excluding risk			including risk		
	IRS	CRS	DRS	IRS	CRS	DRS	IRS	CRS	DRS	IRS	CRS	DRS
Austria	29	2	7	29	4	5	21	1	16	24	2	12
Belgium	26	2	13	25	1	15	20	2	19	20	2	19
Denmark	48	2	4	49	3	2	47	3	4	46	5	3
Finland	0	0	1	0	0	1	0	0	1	0	0	1
France	81	6	72	86	7	66	57	4	98	58	4	97
Germany	379	4	515	639	7	252	259	8	631	512	14	372
Greece	8	0	2	9	0	1	1	0	9	1	0	9
Ireland	0	1	0	0	1	0	0	1	0	0	1	0
Italy	41	1	75	87	1	29	16	3	98	50	5	62
Luxembourg	59	5	52	65	16	35	25	5	86	34	17	65
Netherlands	11	1	4	11	1	4	8	1	7	10	1	5
Norway	8	0	3	11	0	0	7	0	4	7	0	4
Portugal	3	0	1	3	0	1	2	0	2	2	0	2
Spain	23	2	32	35	1	21	12	2	43	19	2	36
Sweden	2	0	1	3	0	0	0	1	2	1	1	1
Switzerland	164	5	62	170	8	53	142	5	84	159	7	65
United Kingdom	19	1	6	19	1	6	16	1	9	16	2	8
Total	901	32	850	1241	51	491	633	37	1113	959	63	761

On the other hand, a switch from a cost to a profit perspective appears to have an opposite effect on optimal scale. The number of banks operating at sub-optimal scale decreases, suggesting that, in general, revenues do not keep pace with costs as the size of a bank increases.

Comparing the first and last column of *Table 10* gives an indication of which of these two opposing forces dominates. It appears that financial returns to scale exceed profit diseconomies slightly, since SE and the number of banks operating at sub-optimal scale are larger in the last column than in the first.

Table 11 breaks down the figures in the last three rows in *Table 10* by country. It shows the number of banks in each country that operate under increasing, constant or decreasing returns to scale, differentiating between orientation and controlling for risk. Comparing the figures, we observe that a large majority of Danish and Swiss banks in our sample are too small, operating under increasing returns to scale. This holds true irrespective of perspective and control for risk. To a lesser extent, the same is true of banks in Austria. In contrast, the majority of French banks appear to be too big from a profit perspective. German banks, on the other hand, present a very mixed picture. If risk is considered, the great majority of German banks in our sample appear to be too small; and if risk is ignored, the large majority appear to be too big. This implies that financial returns to scale are particularly strong in Germany. Large scale, by reducing risk, appears to reduce costs significantly there.

Table 12 takes the previous table and breaks it down by size instead of country. This allows us to investigate which bank size, measured in total assets and in millions of US dollars, is optimal. The size classes in *Table 11* represent deciles. Hence each size class contains roughly the same number of banks (178). Based on the point at which parity between the number of banks operating under increasing and decreasing returns to scale holds approximately, optimal scales appears to lie in the range between roughly 0.5 and 1.5 billion US dollars in total assets, depending on the perspective chosen and control for risk. This result suggests a decidedly smaller optimal bank size than previous cross-country studies (*Table 1*) and probably stems in large part from our use of a non-parametric frontier approach.

5.3. Frontier Inefficiency versus Scale Inefficiency

In this section we turn to the question as to which of the two forms of inefficiency, frontier inefficiency or scale inefficiency, is the greater in our sample of European

Table 12: Banks Operating under Increasing (IRS), Constant (CRS) or Decreasing (DRS) Returns to Scale by Size

	Cost						Profit					
	excluding risk			including risk			excluding risk			including risk		
$millions	IRS	CRS	DRS	IRS	CRS	DRS	IRS	CRS	DRS	IRS	CRS	DRS
8-104	153	7	18	152	9	17	142	12	24	152	13	13
105-204	158	1	19	160	2	16	158	1	19	163	2	13
205-311	165	0	13	168	0	10	154	2	22	156	2	20
312-445	160	2	16	170	3	5	121	2	55	131	3	44
446-621	129	3	46	162	3	13	40	2	136	87	3	88
622-860	72	2	104	152	3	23	15	4	159	57	5	116
861-1208	39	1	138	125	2	51	1	1	176	71	3	104
1209-1792	18	4	156	86	6	86	2	3	173	77	4	97
1793-3218	5	5	168	55	6	117	0	3	175	59	9	110
3219-129552	2	7	172	11	17	153	0	7	174	6	19	156
Total	901	32	850	1241	51	491	633	37	1113	959	63	761

banks. *Table 13* provides an answer. It presents geometric means of the measured frontier efficiency of the banks in our sample, based, in the one instance, on a linear or constant-returns (CRS) frontier and, in the other, on a convex or variable-returns (VRS) frontier. The measured efficiency based on a VRS frontier was the object of analysis in section 5.1. SE, on the other hand, was viewed in the previous section and corresponds to the ratio of CRS-efficiency to VRS-efficiency presented in equation (8). Given the definition of SE, the values in the last row in *Table 13* must equal the product of the other two. Consequently, the efficiency scores in the final row give the average degree of efficiency when both frontier and scale inefficiency are taken into account. Hence, if the banks if the banks in our sample were to eliminate their scale inefficiency completely, total efficiency (CRS) would rise on average to the figures appearing in the top row (VRS) of the table, in other words, but not very much. If the banks were to eliminate their frontier inefficiency instead, then total efficiency would climb to the figures appearing in the middle row, i.e., by a large amount. Taking logs of the values in *Table 13* indicates that roughly 10% of the efficiency variation across European banks stems from scale inefficiency. In other words, the main source of cost and profit variation across banks in Europe is not unexploited economies of scale, but rather inefficient operation. Hence, the banks in our sample would have much more to gain from improving the efficiency of their operations at given scale than from adjusting their size to optimal scale.

Table 13: Frontier Efficiency versus Scale Efficiency

	Cost		Profit	
	no risk	risk	no risk	risk
VRS	0.418	0.504	0.578	0.629
SE	0.889	0.906	0.845	0.904
CRS	0.372	0.457	0.488	0.569

A further question arises in regard to the cost and profit differential among the banks in our sample. At issue is whether there is a trade-off between frontier efficiency and scale efficiency. Do banks that are frontier inefficient tend to be scale efficient and vice versa? If so, this would suggest a flatter efficiency differential across banks than the results in section 5.1 suggest. *Table 14* seeks an answer to this question by investigating whether a correlation exists between a bank's ranking with respect to frontier efficiency and its ranking with regard to scale efficiency. The reported rank correlation coefficients are statistically significant, given the size of our sample, but the relationship is anything but tight. Hence, we can conclude that frontier inefficiency (efficiency) and scale efficiency (inefficiency) generally do not offset one another. Nor do they potentiate one another, for that matter.

Table 14: Rank Correlation between Frontier Efficiency and Scale Efficiency

cost excluding risk	0.046
cost including risk	0.030
profit excluding risk	-0.038
profit including risk	0.082

6. Conclusions

The creation of a single European market in banking should increase cross-border competition driving out inefficient banks and leveling the efficiency differential across financial institutions. Viewed from this perspective, the European banking industry is a long way from constituting a single market.

Our investigation of a large sample of European banks indicates that in the period 1993-97 average efficiency, defined as a bank's proximity to a best-practice frontier, varied more within European countries than across their national borders, implying either that national banking industries themselves are not fully integrated, that they are in a state of greater disequilibrium due to restructuring or that the relevant banking market is delineated along other lines than national borders.

The average frontier efficiency of European banks appears to be relatively low, ranging from 45% from a cost perspective to 65% from a profit standpoint. According to our results, the average efficiency of banks is highest in Denmark, France, Luxembourg and Sweden, and lowest in Greece, Italy, Portugal, Spain and the UK. Large, specialized and/or less retail-oriented banks are more efficient. In other words, frontier efficiency seems to increase with scale and decrease with scope.

Optimal scale, estimated to be in the range of 0.5-1.5 billion US dollars in total assets, was found to be of secondary importance. Merely 10% of the efficiency variation across European banks results from non-optimal scale, implying that banks have far more to gain from improving efficiency at their given scale than from adjusting their size to optimal scale. Although achieving optimal size has only modest gains to offer, Danish and Swiss banks nevertheless appear to be too small on average, and French banks too big.

In light of our results, policy makers need not fear that the emergence of a single European banking market will lead to a high degree of concentration in the industry. The economies of scale are simply not there: neither with respect to costs, to profits nor to risk diversification. The large variation of efficiency across European banks implies, however, that market convergence and increased competition would engender a major shake out in the industry. Since measured efficiency increases with size and decreases with scope, large and/or specialized banks would be at an advantage.

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