Efficiency and Scale Economies in European Banking: A Cross-Country Comparison

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Abstract:
The increased cross-border competition in banking that European integration should engender raises the question as to the future structure of banking in Europe. The study addresses this issue by exploring the cost and profit structure of a large sample of European commercial and savings banks over the period 1993-97, using non-parametric frontier analysis and controlling for risk. The results indicate that large, specialized and/or less retail-oriented banks are both more cost and profit efficient, putting them at an advantage under increased competition. Optimal scale, estimated to be in the range of 0.5-1.5 billion US dollars in total assets, explains merely 10% of the efficiency variation across European banks, implying that banks have more to gain from raising efficiency at their given scale than from adjusting scale to its optimal level, and that scale economies do not provide a strong rationale for the current wave of bank mergers and acquisitions in Europe. In addition, efficiency varies more within countries than across national borders, suggesting that national banking markets themselves are not fully integrated or at least not in a state of competitive equilibrium.

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1. Introduction

The competitive environment in European banking is changing. The Second Banking Directive, which went into effect in January 1993, removed a number of obstacles which have hindered cross-border competition among banks in the past. For example, financial institutions that are licensed in one EU country can now operate throughout the EU without applying for a separate license in the host country. Non-member countries such as Norway and Switzerland are also affected by the Directive as they must comply to its statutes and grant reciprocity in order to receive a banking license within the EU. The introduction of the single currency Euro in 1999 should also increase cross-border competition by increasing price transparency and by creating a single capital market in Europe. As a result, underwriting, trading activities, and fund management should cease being the preserve of local financial institutions.

The increased cross-border competition that the integration process should engender 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/or 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 institutions, whereas frontier inefficiency is not necessarily 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.

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1 Frontier inefficiency has come to be termed X-inefficiency, an expression coined by LEIBENSTEIN (1966). However as originally conceived, X-inefficiency only pertained to technical inefficiency, which refers to the excessive use of factor inputs to achieve a given output level (deviations from a production frontier), and excluded allocative inefficiency, which pertains to the use of factor combinations at odds with relative factor prices. Together, technical and allocative inefficiency constitute deviations from a minimum cost frontier. In the following, we bow to convention and use the terms frontier inefficiency and X-inefficiency interchangeably.

Knowledge of the size and sources of cost variation among banks should be of interest to policy makers, since information of this sort helps in understanding the forces lying behind current restructuring in banking and to anticipate future changes, thus providing a basis for forging appropriate policy responses. For example, if frontier inefficiency were the main source of cost variation among banks, then this would suggest insufficient competition and support policies geared to decreasing regulation and to fostering competition. If, on the other hand, unexploited economies of scale and scope were the principle cause of cost differences, then this could foretell an impending increase in concentration and perhaps favor policies aimed at tightening regulation.

To assess the relative efficiency of banks across Europe, cross-country studies are needed. Results from national studies are of little use because measured efficiency is relative, pertaining solely to the banks in the given sample and hence not suited for cross-country comparisons. 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 few cross-country bank efficiency studies that do exist almost all focus exclusively on cost efficiency and ignore risk and revenues. Concentrating solely on cost can lead to an overestimation of the true level of frontier inefficiency, however. Failure to consider risk, for example, discriminates against banks that choose to adopt cost-intensive measures to reduce their exposure, making them appear inefficient although they may be operating optimally given their risk preferences. Likewise, ignoring revenues causes banks that choose to incur additional expenses in order to increase product quality and income to seem inefficient. The following paper breaks with this tradition by considering revenues and risk along with cost. In so doing, it represents the first cross-country bank efficiency study that systematically examines the impact of including risk and revenues on measured efficiency.

The analysis is based on a sample of 1783 commercial and savings banks that were operating in the EU, Norway or Switzerland during the period 1993-97, in which the Second Banking Directive was in effect. The study employs a non-parametric frontier estimation method termed data envelopment analysis (DEA).

The results of our study indicate that large, specialized and/or less retail-oriented banks are both more cost and profit efficient, putting them at an advantage under increased competition. However, optimal scale, estimated to be in the range of 0.5-1.5

billion US dollars in total assets, explains merely 10% of the efficiency variation across European banks, implying that banks have more to gain from raising frontier efficiency than from adjusting scale, and that scale economies do not provide a strong rationale for the current wave of bank mergers and acquisitions in Europe. In addition, the results show that efficiency varies more within countries than across national borders, suggesting that national banking markets themselves are not fully integrated or at least not in a state of competitive equilibrium.

Our results confirm that it is important to consider revenues and risk along with costs when assessing the efficiency of banks. Including risk and/or revenues raises the level of measured efficiency, implying that part of measured cost inefficiency is due to the costs associated with measures that banks take to reduce risk and increase revenues. Optimal scale is affected too. Controlling for risk raises optimal size, implying that larger banks – perhaps due to greater diversification possibilities – can manage risks at less cost, while including revenues lowers optimal scale, suggesting that revenues fail to keep pace with costs as the size of a bank increases.

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. Short Overview

The first generation of econometric studies of efficiency in banking concentrated on scale and scope economies by estimating ever more flexible cost functions. This line of research culminated in the study by Berger et al. (1987) of US banking. First-generation cost studies have a decided drawback, however, in that they implicitly assume that banks always produce on their minimum cost frontiers, i.e., that frontier inefficiency does not exist. This assumption was called strongly into question by the results of a study by Berger and Humphrey (1991) that showed that X-inefficiency not only existed, but that it clearly exceeded the cost advantages that economies of scale and scope could provide. As previously mentioned, this implies that banks would profit more from improving their efficiency at their given scale and product mix than from 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 X-inefficiency explicitly into account. These studies show time and again that Berger and Humphrey's fundamental finding holds true both for other sample periods and countries.

Two basic approaches for estimating best-practice frontiers exist: parametric and non-parametric methods (cf. FRIED ET AL., 1993). 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 (DEA) merely require the data to fulfill general regularity conditions implied by axiomatic production theory and utilize linear programming methods. The two methodologies differ in a more fundamental sense, however. The parametric approach estimates the frontier by attempting to fit a regression plane through the center of the data, whereas DEA tries to envelope the data with a piecewise linear surface from below (cost frontier) or above (profit frontier). From the standpoint of a frontier, DEA seems intuitively more appealing since it bases its estimate on extreme observations, where one would expect the majority of efficient firms to lie. Yet concentrating on extreme values makes the results more susceptible to outliers stemming from measurement error. The parametric approach, on the other hand, controls for measurement error in the dependent variable, yet runs the risk of misspecifying the frontier since it centers its frontier estimate around firms in the middle of the data where one would not await many efficient banks. In short, neither approach is without its weaknesses. By way of preview, we choose the non-parametric approach in this study and try to ameliorate the problem of measurement error by using period averages.

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 revenues 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 in order to provide high-quality services to appear cost inefficient. Incorporating revenues lessens the problem since higher quality should generate higher revenues to offset the extra expenses.

Parametric frontier studies of banks 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[2] that have taken revenues and profits into account generally find that cost and profit efficiency are either weakly positive or negatively correlated, implying that high-cost banks make up for higher expenses through higher revenues. Ignoring revenues thus runs the risk of overstating the true level of frontier inefficiency.

The reasons for considering risk in bank efficiency studies, on the other hand, 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. For another, managing risk is factor intensive and hence generates costs, which will appear as inefficiency if the sources of these additional costs are ignored.

Bank efficiency studies control for risk - explicitly or implicitly - basically in two ways: either by introducing a variable such as bank capital[3] that is connected to current risk exposure, or by including a variable like loan loss provisions or non-performing loans[4], which capture risk-generated costs. All of these measures suffer from a number of weaknesses, however.

Loan loss provisions and non-performing loans are problematical, for one, because they can depend more on past risk exposure than on the exposure generating current returns, thereby introducing measurement error. For another, the use of these variables favors banks that skimp on customer screening and loan monitoring and discriminates against those that choose to incur costs to avoid these losses. Finally, loan loss provisions and non-performing loans represent realizations of a random variable, which may not be representative of the true underlying risk. After all, even AAA bonds sometimes fail, and not every junk bond need default.[5]

For these reasons, proxies for current risk exposure seem to be a better solution. Bank capital is deficient in this role as the risk posture of a bank also depends on the level and volatility of its returns. It is quite possible that more highly capitalized banks

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2 BERGER and HUMPHREY (1997) survey the literature.
3 E.g., MESTER (1996) and BERGER/MESTER (1997).
4 E.g., 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 approaches.
5 Recent bank efficiency literature (e.g., BERGER/DEYOUNG, 1997) often distinguishes between endogenous and exogenous risk in addressing these latter two weaknesses of loan-associated risk measures.

are actually more at risk because their thick equity cushions are more than offset by low mean returns and high return volatility.[6] MCALLISTER and MCMANUS (1993) use a more complete measure of risk which is based on the probability that a bank will suffer bankruptcy. By way of preview, we follow their example and use an estimate of a bank's probability of failing as our risk measure.

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, thereby lowering their risks and hence 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 in their survey 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. Incorporating risk in a non-parametric setting also must reduce measured inefficiency since including risk introduces an additional constraint, which necessarily narrows the scope for efficiency improvement. We take that effect into account in this study.

2.2. Cross-Country Studies

As mentioned in the introduction, relatively few cross-country studies on bank efficiency exist. *Table 1* offers a selected survey. The table characterizes the studies with respect to 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 regard to methodology, BERG ET AL. (1993), CASU/MOLYNEUX (1999) and PASTOR ET AL. (1997) are the only 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 X-inefficiency from the start. The paper is included here because it represents the first large-scale cross-country study on bank efficiency. The parametric frontier studies, on the other hand, apply four different methodologies: the stochastic frontier (SFA), thick-frontier (TFA) and distribu-

[6] ESTRELLA ET AL. (2000) find bank capital alone to be a good predictor of bank failure in the US during the period 1989-93, but this result need not hold universally for the reasons given above. Theoretical models (cf. SHELDON, 1996) also give reason to question the universality of their result.

tion-free frontier approaches (DFA) along with the fixed-effects model (FE). SFA imposes a parametric structure on an unobserved composite error term which encompasses both X-inefficiency and any random noise in the left-hand variable. In contrast, TFA, DFA and FE refrain from imposing a parametric structure on the residual. 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. FE too assumes that a firm's level of X-inefficiency is constant over the sample period, but does not require random error to average to zero in finite samples. The use of DFA and FE obviously requires panel data. TFA, on the other hand, does without panel data. It 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), MAUDOS ET AL. (1999) and VANDER VENNET (1999) also estimate alternative profit frontiers. ALTUNBAȘ/CHAKRAVARTY (1998) and 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 also varies 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 typically 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 views them as inputs. To avoid this conflict, 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

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, CND, **D**, **DK**, E, *F*, FIN, *GB*, *I*, J, **S**, USA	0.82	60
Altunbaş/ Chakravar-ty (1998)	SFA	producti on	panel 1988-95	n.a.	n.a.	13,603	all	n.a.	EU	0.75	
Berg et al. (1993)	DEA	produc-tion	cross section 1990	labor, fixed assets	loans, deposits, branches	779	all	official	*FIN*, *N*, **S**	0.60	
Bikker (1999)	SFA	cost	panel 1989-97	none	loans, time deposits, demand deposits, other income	3,085	all	IBCA	**B**, **CH**, D, *E*, *F*, GB, *I*, **L**, NL	0.38	
Casu/Moly-neux (1999)	DEA	cost	panel 1993-97	costs, deposits	loans, securities	750	commercial, savings, mortgage	IBCA	*E*, F, **D**, **GB**, I	0.65	
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**, **E**, *F*, **GB**, I, L, NL, *P*	0.88, 0.70	
Dietsch, Vivas (2002)	DFA	cost	panel 1988-92	labor, borrowings, fixed assets	loans, deposits, earning assets	324	commercial, savings	n.a.	*E*, **F**	0.58	
Maudos et. al. (1999)	SFA, DFA, FE	cost, profit	panel 1993-96	labor, loanable funds, fixed assets	loans, deposits, other assets	879	all	IBCA	A, B, D, E, F, FIN, *GB*, **I**, L, NL, *P*	0.47, 0.50	

Table 1: Survey of Cross-Country Bank Efficiency Studies (cont.)

study	methodology			data					countries	results	
				inputs or prices	outputs	banks	bank type	source		efficiency	scale
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**, *E*, *F*, *GB*, **I**, USA	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, E, F, FIN, GB, GR, I, IL, IRL, NL, P, S	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, E, GB, I, L, NL, P		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	n.a.	A, B, CH, D, DK, E, F, FIN, GB, GR, I, IRL, L, N, NL, P, S	0.80, 0.68	5-50

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 investigated also varies across the studies cited in *Table 1*. Common to most studies, however, is the inclusion of commercial banks and the exclusion of investment banks. Note, too, that most studies use the Fitch-IBCA database, probably due to the fact that it is one of the few databases that provides financial statement data from financial institutions in different countries using internally consistent accounting definitions.

Despite their differences, most cross-country studies come to similar conclusions with respect to the average[7] level of measured frontier efficiency. Results from studies based on a broad set of countries suggest that the average cost efficiency ranges from 0.70 (RUTHENBERG/ELIAS, 1996) to about 0.80 (ALLEN/RAI, 1996 and VANDER VENNET, 1999), which is roughly in line with the results from US studies (BERGER/HUMPHREY, 1997). Agreement with US investigations also exists with regard to profit efficiency. With the exception of MAUDOS ET AL. (1999), international studies which consider both cost and profit efficiency find the latter to be lower, as do US studies (BERGER/HUMPHREY, 1997). The lower value profit efficiency yields need not imply that added costs do not succeed in achieving correspondingly higher revenues since the denominators of the two efficiency measures usually differ: observed costs in the one case and efficient profits in the other. Our approach avoids this problem.

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) in assets. In contrast, US investigations usually yield values lying between 0.1 and 10 billion US dollars (cf. BERGER ET AL., 2000).

International 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] According to BIKKER (1999), "experts" generally claim that banks in France, Germany, and particularly southern Europe are less efficient on average than banks in the rest of West Europe. The reasons proffered are more severe regulation, public policy and financial conservatism in the case of Ger-

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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. Some studies do not present results that allow a national ranking. Countries are denoted by national license plate codes.

many (D), strong interference by the government in France (F) and Italy (I), and lagging economic development in Greece (GR), Spain (E) and Portugal (P). The results presented in the table roughly support these priors, but exceptions are not rare. Moreover, some studies come to opposite conclusions even though they cover similar countries and time periods. 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, and the United Kingdom (GB) although both studies sample similar bank types from the same data source. The contradiction possibly results 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).

With the exception of BERG ET AL. (1993), all of the studies cited in *Table 1* estimate common efficiency frontiers cross national banking markets. This approach has come under attack recently[9] because it neglects environmental factors such as market conditions, market structures and regulations, which may differ across countries. Imposing a common frontier may thus set too high a standard for countries with non-conducive environments, giving one the false impression that the banks in these countries are generally less efficient. Several methods exist to combat this problem within a non-parametric frontier analysis, while still maintaining the ability to make cross-country comparisons. For example, one could, as BERG ET AL. (1993), estimate separate frontiers for each country and then compare the national frontiers with the help of a Malmquist index. However, this requires making pairwise comparisons of all the national frontiers in the sample, which is hardly manageable in a broad international study like the following one. Alternatively, one could estimate separate frontiers for each country, project the banks on their national frontiers and then conduct DEA on the resulting pooled sample of inefficiency-adjusted banks. CHARNES ET AL. (1981) appear to have developed this method. To our knowledge, this approach has not yet been applied to bank data. A third possibility is to use a two stage approach in which the efficiency scores obtained in a first stage on the basis of a common cross-country frontier are then regressed on variables which capture national environmental differences. This is the more common approach (cf. BERGER ET AL., 2000) and will be employed in this study.

9 See, for example, ALTUNBAŞ/CHAKRAVARTY (1998), BERGER ET AL. (2000) and DIETSCH/VIVAS (2000).

3. Methodology

The following study measures the cost and profit efficiency of a sample of European banks with DEA. The conventional approach chosen in the literature in this case is to first define a production technology set T on the sample of banks which exhibits strong disposability[10] of inputs and outputs

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

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 i-th 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 either minimizes total costs

$$\mathbf{w}_i'\mathbf{x}_i \tag{2}$$

or maximizes profits

$$\mathbf{p}_i'\mathbf{y}_i - \mathbf{w}_i'\mathbf{x}_i \tag{3}$$

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 given factor prices and **p** an M x 1 vector of exogenous output prices.[11] Treating factor and product prices as given is of course tantamount to assuming perfect competition in factor and product markets, respectively. Proceeding in this way yields the following two linear programming problems:

[10] 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.

[11] 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

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

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

Each problem is 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 are then 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, applying this approach 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 the aggregates used in these calculations are far from homogenous, the prices they yield tend to be inaccurate and may 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 dimension. In such instances it is customary in the literature[12] to replace (4) and (5) with the following linear optimization problems:

[12] 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 same bank.

The efficiency scores θ and π measure the degree to which the observed costs of a bank correspond, respectively, to their (constrained) 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).

Equations (4) and (4a) are nevertheless quite similar in spirit. Both present output-constrained cost minimization problems. However, (4) holds factor prices constant, while (4a) imposes no such constraint. Hence, the two equations will only yield equivalent results when all banks face common factor prices. If that is not the case, then higher cost efficiency could simply reflect factor price advantages. For example, banks in Luxembourg and Switzerland could possibly attract foreign funds at lower cost as a result of banking secrecy, low or non-existent taxes on income from wealth for non-inhabitants, and a stable currency. Under these conditions, banks in Luxembourg and Switzerland would tend to appear more cost efficient on the basis of (4a).

Whether the same banks also achieve correspondingly higher profits is another matter altogether, however. Equation (5a) addresses this issue. In essence, (5a) is a revenue-constrained version of (4a). It is profit-oriented since it compares a bank's revenues to its costs, yet it differs from profit maximization (5) as it precludes a bank's expanding its revenues to achieve higher profits. In this sense, (5a) is similar in spirit to the alternative or output-constrained profit function employed in parametric efficiency studies to allow for non-perfect competition in product markets. In addition, not requiring factor price data, (5a) also has another advantage over the alternative profit function. Since the efficiency scores θ and π have the same denominator (i.e., observed costs) they can be directly compared, which does not hold true for (6) and (7).

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, while θ_i or $\pi_i = 1$. In this case the bank is deemed efficient, i.e., to lie 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 leads to 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**, while the last I constraints instill 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[13] $\boldsymbol{\lambda}_i'\mathbf{e} = 1$ to (4a) and (5a), which allows for variable returns-to-scale[14] (VRS). GROSSKOPF (1986) terms the ensuing best-practice frontier as being convex to contrast it with the linear frontier associated with constant returns to scale (CRS).

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[13] **e** denotes the unit vector.

[14] This does not allow for an S-shaped frontier, however, as this would violate the convexity constraint, which restricts the returns-to-scale to being first increasing, then constant and finally decreasing.

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

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

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) implies that the total inefficiency θ_{CRS} of a bank is the product of a component SE, due to non-optimal scale, and a component θ_{VRS}, arising from X-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 $\lambda_i'\mathbf{e}$ based on the solution values for λ 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 our study.[15] Unfortunately, whether economies of scale are due to the greater efficiency of large-scale production or to the price advantages enjoyed by large banks cannot be determined in our approach due to the use of scalar revenues and costs. However, the difference is essentially irrelevant with respect to future market structure, since both forms of size advantage, price and large-scale production, make market concentration financially attractive for the individual firm.

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

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[15] FERRIER ET AL. (1993) provide a simulation method for determining the presence of scope economies with the help of DEA. The method requires the presence of banks that do not provide all outputs. Unfortunately, too few banks fulfilled this requirement in our sample to implement the procedure.

problems manageable.[16] Most studies cited in *Table 1* also include these bank groups. Moreover, with the exception of the thousands of cooperative banks in Germany, the majority of 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 included in the BankScope database and (iii) contained 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). Should random error average out in a finite time period as DFA assumes, then the use of period averages should ameliorate the problem of measurement error which plagues DEA studies.

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

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 require comment. The insolvency risk (c_5) of a bank i is defined as:

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

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[16] Note the dimensions of the matrices in the constraints to (4a) and (5a).

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) overstates 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) in (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 each bank's average regressor values to calculate its E(ROA) for 1993-97. We utilized the same procedure to obtain σ(ROA), replacing the left-hand variable in the regression 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) employ 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 include deposits as an output in the measurement of profit efficiency too to ensure that we control sufficiently for the costs they generate. This procedure is some-

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

what unconventional, since it mixes stocks with flows, but it is not without precedent.[17]

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 relative size of their economies or banking sectors[18]. 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.

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

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

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 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, unlike in the study by ESTRELLA ET AL. (2000), bank capital would be a poor proxy for risk in our sample.

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

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.[19]

Scope is based on the Herfindahl index, here defined as

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

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-sheet items. According to the scope variable, the banks in Denmark, Finland and Greece are relatively broadly diversified, while those in Ireland[20], 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 indicates a strong emphasis on retail business. 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 section 5.1 as regressors in an analysis of the sources of efficiency variation 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 solely to X-inefficiency. Scale inefficiency, resulting from operating at a non-optimal size, and scale economies are viewed in section 5.2.

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

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[19] Note, however, that our sample contains only one Finnish bank.
[20] Note here too that our sample includes just a single bank from Ireland.

frontier efficiency about the overall mean. As the table indicates, the average efficiency of all banks taken together 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 their 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.

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

The average efficiency levels appearing in the table fall below 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. DEA tends in general to generate lower average efficiency scores than parametric approaches (BERGER/HUMPHREY, 1997).

As *Table 5* indicates, 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.

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. To avoid this effect, we concentrate on the impact of introducing risk on the variation of efficiency across banks and on the banks' rankings in the efficiency hierarchy (*Table 6*). With respect to cost, we see that incorporating risk reduces the efficiency variation across banks, while leaving the efficiency rankings of banks relatively unchanged. The rank correlation between the cost efficiency scores based, respectively, on the exclusion and inclusion of risk equals 0.839 (cf. *Table 6*). The decrease in variation combined with an unchanged rank order implies that introducing risk improves the cost efficiency of the initially less efficient banks more, suggesting that some of the higher costs that these seemingly less efficient banks incur is directed towards lowering risk. In other words, lowering risk is not costless. Hence, failing to control for it will make risk-adverse banks appear less cost efficient.

The introduction of risk in a profit perspective yields a somewhat different pattern. The efficiency ranking of banks again remains relatively unchanged (*Table 6*), but so does the variation of efficiency across banks. This lack of impact suggests that the differences in profit efficiency among the banks in our sample are not due to differences in the banks' tastes for risk, but simply to differing abilities of their portfolios and services to generate income.

Turning in *Table 6* now to the rank correlation between the efficiency scores based on a cost or profit perspective, we see that a switch from a cost to a profit orientation has a marked effect on the banks' efficiency rankings, the degree of correlation between the two sets of results falling to between 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. There the degree of correlation is either statistically insignificant or negative (BERGER/HUMPHREY, 1997). These lower values stem from parametric studies, however, suggesting that the source of the difference may be methodological. Nonetheless, the fact that the degree of correlation between cost and profit efficiency is generally 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 contains only one Irish bank, so the result can hardly be taken as being representative of all Irish banks.

Irrespective of the perspective chosen or the inclusion 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 best-practice frontier. Otherwise, almost every country has at least one bank on the efficiency frontier.[21] With the exception perhaps of France and the UK, these results agree with "expert" opinion (cf. section 2.2).

Previous cross-country studies (cf. *Table 1*) 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 research 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 orientation 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 standpoint they are among the least so. The opposite holds true for the banks in the Netherlands: from a cost perspective they are among the least efficient, whereas from a profit viewpoint they are among the most so. 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 shift in the rankings of the banks of these countries when the orientation changes is probably the cause of the low rank correlation between cost and profit efficiency (*Table 6*).

[21] It should be noted that country rankings do not indicate how banks of one country would perform as foreign-owned entities in other national markets. See BERGER ET AL. (2000) on this issue.

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

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 in the sense used here tend to be more frontier efficient on average, supporting the view that increased integration and hence competition increase efficiency.

Finally observe 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 provides 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 regressing (with OLS) the log of the ratios of two of a bank's efficiency measures on a set of country dummies[22] 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 impact 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.

[22] The reference country is Germany.

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 change 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 fully, since roughly a half of the coefficients of the country dummies are still statistically significant at the 10% level after controlling for differing banking structure. Ideally, the estimated coefficients of all country-specific dummies would lose their statistical significance if different banking structures were the main source of shifts in national ranking. When running the regressions without the non-dummy variables[23], 36 of all 48 country dummies are statistically significant, while with the non-dummy variables the ratio falls to 25 out of 48, suggesting 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 the composition variables is particularly large with respect to the inclusion of risk (column 2 in *Table 8*). In this case, six of the country dummies lose their statistical significance 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. This holds true for the other bank attribute variables as well.

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

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
$lnL(\beta_0)$	-561.86	371.84	-458.93
$lnL(\beta^*)$	66.14	909.36	8.85
$-2[lnL(\beta_0)-lnL(\beta^*)]$	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.

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 position of savings banks vis-à-vis commercial banks. Their ranking 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' efficiency position gains or loses from a change in orientation, *Table 9* examines which types of banks are more frontier efficient than others for a given perspective. 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 again that, ideally, the estimated coefficients of all country-specific dummies should be statistically insignificant if differing banking structures alone could 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.

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* suggest the same.[24]

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*,

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[24] This finding tends to qualify somewhat the results of studies (e.g., ALTUNBAŞ/CHAKRAVARTY, 1998 and DIETSCH/VIVAS, 2000) that conclude that environmental factors are decisive in explaining efficiency differences across national banking sectors. If this were true, one would expect less efficiency variation within than across national borders.

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.

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[25], 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 frontier 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 elasticity measure (SE), defined in equation (8)[26], and also 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

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

[26] 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.

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

By contrast, 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 appear to be too small, operating under increasing returns to scale. This holds true irrespective of perspective and control for risk. To a lesser ex-

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

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

	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

tent, 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 millions of US dollars in total assets, 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. The lower bound happens to coincide roughly with the median size of the banks in our sample, and the upper bound to their average size (cf. *Table 4*). Our finding suggests a decidedly smaller optimal bank size than previous cross-country studies (*Table 1*) and may stem in 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 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 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) in 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 reinforce 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 decreasing the efficiency differential across financial institutions. Viewed from this perspective, our results suggest that 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 X-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 lines other 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, which - with perhaps the exception of France and the UK - roughly agrees with "expert" opinion. Large, specialized and/or less retail-oriented banks are more X-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 scale to its optimal size. Although achieving optimal size has only modest gains to offer, the Danish and Swiss banks in our sample nonetheless appear to be too small on average, and French banks too large.

Our failure to discover major cost and profit advantages from large-scale and broad-scope banking, even when controlling for risk, may seem to run counter to the large number of mergers and acquisitions now taking place in European banking.[27] However, the contradiction is more apparent than real. Innumerable empirical studies of bank mergers exist which fail to find systematic gains in value or performance from

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[27] CYBO-OTTONE and MURGIA (2000) report that mergers and acquisitions in European banking jumped to 50-90 deals per year between 1986 and 1994, after averaging 15 deals per year until then. In fact, according to INZERILLO ET AL. (2000), mergers and acquisitions were the most important cause of the reduction in the number of banks in Europe in the 1990s.

bank consolidation.[28] Our results merely confirm these previous findings. Moreover, there are good reasons to believe that scale and scope detract from economic efficiency. For one, offering a wide range of products and services increases coordination and administration costs, which could more than offset any revenue gains such measures may engender. For another, a sufficient number of bank customers may prefer to be served by smaller banks and specialists and be willing to pay prices for such services that well outweigh any added costs. After all, banking is based on individual trust, which may flourish less in an impersonal environment. Finally, reasons other than gains in efficiency may be the motivating force behind the current wave of mergers and acquisitions in Europe. The desire to increase market power in order to extract higher prices, management goals linked to size, and government intervention could all serve as possible causes of increased consolidation.[29] The importance of these additional motives was not investigated in this study.

Nonetheless, our results do not suggest that policy makers need fear that the emergence of a single European market will lead to a high degree of concentration in the banking 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 could engender a major shake out in the industry. Since measured efficiency increases with size and decreases with scope, large and/or specialized banks should be at an advantage.

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[28] See the broad survey from PILLOFF and SANTOMERO (1998) on US results as well as the short overview in BERGER ET AL. (2000) on more recent research results, also applying to Europe.

[29] BERGER ET AL. (2000) review the theoretical arguments and empirical evidence on these alternative motives.

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