An Application of the Meta-frontier Cost Function to the Study of Bank Efficiencies and Technology Gaps in 16 European Countries

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Abstract

This paper investigates the performance of commercial banks across 16 European countries for the years 1994-2003, adopting the newly developed meta-frontier cost function model by Battese et al. (2004). The model enables the decomposition of the meta-cost efficiency into two components: the usual technical efficiency (CE) and the technology gap ratios (TGR). Most of the mean TGR for the sample countries are much less than those of the mean CE, implying that there are quite a few banks utilizing inferior technologies and operating off the meta-cost frontier. Evidence is found that, over time, the average technical efficiency of the financial sectors in Europe's markets improves and the technology gap shrinks. Although technical inefficiencies and technology gaps remain persistent, the current trend toward further de-specialization may prompt a more efficient banking system.

Keywords: meta-frontier cost function; technical efficiency; technology gap ratio

JEL Classification: C23, C61, D24, G21

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1. Introduction

The European Union (EU) was founded in 1992 by the Treaty on European Union (the Maastricht Treaty).[1] The Treaty also set up the European Economic and Monetary Union (EMU), which not only created a single currency, the Euro, but also set forth many economic convergence principles, including exchange rate, inflation rate, public finance, and interest rate stability. Through the endeavor of the EMU, its member states have adopted the new criteria to regulate their financial markets in order to lower barriers to competition among financial institutions, peaking in January 1, 1993 with the establishment of the Single Market for Financial Services. These changes aim at a single, competitive market for financial services.

Under the new regime, a bank can branch freely into other EU countries and will be regulated by its home country, while before the enforcement of the new regulation, cross-border expansions were subject to authorization. By removing substantial barriers to entry, the new legislation has created significant improvements in the competitive conditions of domestic financial markets. In such a more competitive environment, current differences in performance among the banking industries of EMU members will influence each country's banking structure and future competitive viability. Hence, in the ongoing integration of European markets for banking services, it is crucial to understand and to compare the differences or similarities in the banking performance among these countries. This in turn should lead bank managers to better predictions and preparation for an expected increase in cross-border competition.

[1] The Maastricht Treaty was signed on February 7, 1992 in Maastricht by the members of the European Community and entered into force on November 1, 1993 under the Delors Commission.

In recent years the structure of Europe's financial industries has been changing rapidly. The implementation of the Single Banking Market during the 1990s considerably lowered barriers to competition among European banks and prompted the banks to expand branches abroad within the nations of the EU. The financial markets have become so competitive and so integrated that it is necessary to understand the sources of banks' efficiency differences among member states.

There exists many research works applying either a parametric or non-parametric approach to investigate a bank's efficiency. The former mainly includes the stochastic frontier approach (SFA) and the distribution free approach (DFA), which require researchers to specify a particular function form for a production (cost or profit) function. The latter is often referred to as data envelopment analysis (DEA), which involves the use of linear programming methods and is known as being function free. A number of cross-country comparisons with respect to European banking performance have been conducted, using either or both the parametric and non-parametric approaches. Weill (2004) makes an excellent review on country-specific studies for France, Germany, Italy, Spain, United Kingdom (UK), and Switzerland, and cross-country comparisons particularly for European countries. Berg et al. (1993) employ the DEA approach to capture the differences in banking efficiency among Norway, Sweden, and Finland. Berg et al. (1995) follow up the study by adding Denmark to the previous sample. Fecher and Pestieau (1993) and Pastor et al. (1997) utilize the DFA and DEA approaches to eleven OECD countries and eight developed countries, respectively.

Several previous papers, e.g., Allen and Rai (1996), Altunbas et al. (2001), and Vennet (2002) to mention a few, estimate a global cost frontier for all banks from different countries, which implicitly assumes that banks from various countries share a common production technology. This presumption seems not to fit reality well, as national variations in political institutions, law and tax systems, and natural environments exert pressure on bank managers' capabilities and willingness to adopt technical innovation. Applying the DEA method with the adjustment for environment factors, Lozano-Vivas et al. (2001) and Lozano-Vivas et al. (2002) analyze the technical efficiency of ten European countries separately. Following this vein, Weill (2004) estimates individual national frontiers rather than one common frontier for all sample countries in the context of SFA, DFA, and DEA to measure the cost efficiency of banks in five European countries (France, Germany, Italy, Spain, and Switzerland) during the period 1992–1998. However, since each country has its own production frontier, the relative technical efficiency scores of different countries are not directly comparable. This difficulty can be readily solved by applying the meta-frontier technique (see below).

In this paper we attempt to examine the performance of commercial banks across 16 European countries and covering ten years. Recall that the technical efficiency of a bank operating under a type of technology should not be compared with that of other banks operating under a different type of technology. Conventional studies on the comparisons of production efficiency are unable to tell the differences in various technologies employed by the sample banks of distinct countries (industries, groups, or regions). We therefore recommend the use of a meta-frontier technique, recently proposed by Battese et al. (2004), but further extend the investigation from a primal production function to a dual cost function. This technique enables us to calculate technical efficiencies for banks operating under different technologies as well as the technology gap ratios (TGRs), measuring the extent to which the cost frontiers of individual countries deviate from the meta-frontier cost function.

The aforementioned procedure is likely preferable, because it does not impose the same technology on banks from different countries, on the one hand, yet allows for direct comparisons of production efficiencies among banks with differential technologies after adjusting for the TGRs, on the other. The meta-frontier approach to inefficiencies of financial institutions results in a better measure for regulators (lawmakers, supervisory agencies, antitrust authorities, etc.) to use in gauging the costs and benefits to society of distinct policies than the conventional approach to inefficiencies, which does not put value weights on the adoption of inferior technology. The meta-frontier efficiency is a broader concept than the conventional efficiency.

The rest of the paper is organized as follows. Section 2 briefly reviews some related research works. Section 3 develops a meta-frontier cost function and defines a few efficiency concepts. In Section 4 the data and the definitions of input and output variables are described, while in section 5 technical efficiency scores and TGRs for each bank are empirically evaluated under the framework of the meta-frontier cost model. The last section concludes the paper.

2. Literature Review

The first subsection briefly introduces some papers examining the efficiencies of European banking sectors, particularly applying the SFA approach. The next subsection highlights the meta-frontier production function.

2.1 Efficiency Studies Using the SFA Techniques

The SFA was first developed by Aigner et al. (1977) and Meeusen and van den Broeck (1977) nearly simultaneously. Pitt and Lee (1981) and Schmidt and Sickles

(1984) later generalize the techniques to panel data using the maximum likelihood and fixed-effects and random-effects methods. While earlier panel data models all rely on the assumption of time-invariant efficiency, such as Kumbhakar (1987), Battese and Coelli (1988), and Atkinson and Cornwell (1994), the maintained assumption is relaxed by Cornwell et al. (1990) and Lee and Schmidt (1993), whose temporal variation in technical inefficiency is modeled through the intercept of the production frontier. Differing from Cornwell et al. (1990) and Lee and Schmidt (1993), Kumbhakar (1990) and Battese and Coelli (1992) specify alternative time-varying technical inefficiency models through an error component model. Their specifications assume that inefficiency change is the same for all firms, whereby the log-likelihood function and its partial derivatives are derived in their papers.

Stochastic frontier models that allow for firm-specific patterns of temporal change in technical inefficiency have been developed by Heshmati and Kumbhakar (1994), Kumbhakar and Heshmati (1995), and Kumbhakar and Hjalmarsson (1995). These models impose a restriction in that the inefficiency term is identically and independently distributed across individuals and over time, so that the temporal variation of technical inefficiency cannot be tested. Cuesta (2000) proposes a model that allows for firm-specific patterns of temporal change in technical inefficiency using an error component model. Although more flexible in modeling technical inefficiency changes over time, Cuesta’s (2000) approach may suffer from the problem of incidental parameters if the time periods of panel data are finite. Due to a short panel, this article selects to apply the specification of Battese and Coelli (1992) to escape the potential problem.

Vennet (2002) analyzes the cost and profit efficiency of European financial conglomerates and universal banks and finds that the trend toward de-specialization may lead to a more efficient banking system. Kraft and Tirtiroglu (1998), Hasan and Marton (2003), Bonin et al. (2005), and Fries and Tacy (2005) apply the SFA model and Nikiel and Opiela (2002) apply the DFA approach to investigate the bank efficiency in transition countries. Bonin et al. (2005) and Fries and Tacy (2005) reach the conclusion that private banks are more efficient than government-owned banks and that foreign-owned banks are more efficient than other types of banks. Hasan and Marton (2003) find that Hungarian-owned banks report higher inefficiency than their foreign counterparts in both cost and profit categories. Maudos et al. (2002) employ the DFA approach to make cross-country comparisons and discover that there is a wide range of variation in efficiency levels in the banking system of the EU, especially with the variation in profit efficiency being greater than in cost efficiency.

When conducting comparisons of banking efficiencies across countries, we need to estimate a common frontier for all banks of the sample countries under consideration. It is important to take country-specific environmental conditions into account, which influence the efficiency scores of all banks in the same country. If we simply gather all banks across countries together without regard to the potential impacts of the environmental differences on a bank's efficiency, then we are implicitly assuming that all banks from different countries adopt the same production technology and that they are facing the same exogenous shocks. Thus, efficiency differences across banks and states are entirely ascribable to managerial ability to lower costs. Such a strong assumption may lead to biased parameter estimates and the measures of scale, scope, and technical efficiencies.

This paper extends the meta-frontier production function, proposed by Battese et al. (2004), to a meta-frontier cost function, which appears to be preferable as multiple outputs can be easily considered. We argue here for the appropriateness of the meta-cost function for use in the regulatory analysis of financial institutions since cost minimization and profit maximization are possibly suitable behavioral objectives in banking. We elect cost minimization over profit maximization, because it is a well-defined and a more widely specified function in the literature, and because there are problems precisely evaluating some output prices from the Bankscope data bank. It is recommended that future investigations employ and compare both cost and profit specifications, if the data bank contains relevant price data. The meta-cost function allows for the calculation of technical efficiencies for banks operating under different technologies, which are likely to be subject to various environmental restrictions. Another salient advantage of the meta-cost function approach comes from the comparability of the efficiency scores among banks of all countries, since the technical efficiencies are evaluated on the basis of the meta-cost frontier after adjusting for the differences in TGRs.

2.2 The Meta-Frontier Model

Hayami (1969) first proposes the meta-frontier production function to examine the causes of agricultural productivity differences among developed and less developed countries, followed by Hayami and Ruttan (1970, 1971). Hayami and Ruttan (1970, 1971) make a crucial assumption that the technological possibilities available to all agricultural producers in different countries can be characterized by the same production function - namely, the meta-production function. This concept is theoretically attractive, because it is based on the simple hypothesis that all producers in different countries have potential access to the same technology and it allows for the comparisons of production efficiencies among producers operating under different technologies. It is pivotal to note that the framework of the meta-production function does not necessarily imply that all producers operate on a universal production function. The meta-production function, proposed by Ruttan et al. (1978), is an envelope curve of production points of the most efficient countries. Each country may choose to operate on different part of the production possibility curve, depending on its resource endowments, adoption and diffusion of technology, and economic environments.

Following Hayami and Ruttan (1970, 1971), Lau and Yotopoulos (1989) employ the meta-production function approach to compare agricultural productivity across countries. This approach is econometrically advantageous due to its competence to collect data from different countries so that the scope of variations of the dependent and independent variables and the number of observations can be dramatically increased. Moreover, it reduces the possibility of multicollinearity among inputs, as the key inputs are usually changing together. Several limitations exist inherent to this approach. However, the incomparability of data, the differences in the basic economic environment, and the specification of an appropriate production function pose some difficulties.

Battese and Rao (2002) attempt to compare the technical efficiencies of firms in different groups that may not have the same technology on the basis of the stochastic meta-frontier production function. They assume that there are two different data generation mechanisms for the data: one with respect to the stochastic frontier that is estimated using data belonging to that group, and the other with respect to the meta-frontier model that is estimated using entire sample data. The estimation of the technology gap provides information on the ability of the firms in one group to compete with other firms from different groups within an industry (a region or a nation). Battese et al. (2004) modify the above model by assuming that data generation processes are only applied to the frontier models for the firms in the different groups. The meta-frontier production function is an overarching function of a given mathematical form that envelopes the deterministic parts of a set of stochastic frontier production functions for firms that operate under different technologies involved.

3. Methodology

This section first introduces the meta-frontier cost function. Next, it addresses how to assess production efficiency along with technology gap ratios. In the third subsection the concepts of scale and scope economies are concisely described, while the last subsection summarizes the estimation procedures for the meta-frontier cost function. We believe that the investigation of the cost efficiency is an appropriate approach specific to European financial institutions, since Europe's financial markets have become more competitive and highly integrated in the past two decades. Running a business in such a keen competitive atmosphere, bank managers should be devoted to minimizing the production costs incurred by offering a variety of financial services through taking the advantages of scale and scope economies and enhancing their managerial efficiency.

3.1 The Meta-frontier Cost Function

The traditional production efficiency against a cost frontier is evaluated by the extent to which a bank's actual cost deviates from the efficient cost frontier. Suppose that there are R different countries under consideration, and that each country r has N_r banks that face input prices and pursue the cost minimization objective for a given amount of outputs. The stochastic cost frontier model for each bank w

of country r at time t can be written as:

$$C_{wt(r)} = f(X_{wt(r)}, \varphi_{(r)}) e^{V_{wt(r)}+U_{wt(r)}}, \\ w = 1,2,\ldots,N_r;\ t = 1,2,\ldots,T;\ r = 1,2,\ldots,R, \tag{1}$$

where $C_{wt(r)}$ is the realized total expenditure, $X_{wt(r)}$ is a vector of output and input prices, and $\varphi_{(r)}$ is a vector of the unknown technology parameters to be estimated. Terms $V_{wt(r)}$ and $U_{wt(r)}$ are two mutually independent random errors, where the former is a normally distributed two-sided error with mean zero and a constant variance, capturing the statistical noise, while the latter represents a time-variant technical inefficiency to be specified in Section 5. For expository convenience, equation (1) is further formulated as:

$$C_{wt(r)} = e^{X_{wt(r)}\varphi_{(r)}+V_{wt(r)}+U_{wt(r)}}. \tag{2}$$

Following Battese et al. (2004), the model assumes that there is merely one data-generation process for those banks operating under a given technology for each country. The entire cross-country data are individually generated from the respective frontier models in the different countries. The meta-frontier is assumed to take the same functional form as the individual stochastic frontiers in the different countries. Thus, the meta-frontier cost function that envelops country-specific cost frontier is expressed as:

$$C^*_{wt} = f(X_{wt}, \varphi^*) \equiv e^{X_{wt}\varphi^*}, \\ w = 1,2,\ldots,\ N = \sum_{r=1}^{R} N_r;\ t = 1,2,\ldots,T. \tag{3}$$

Here, C^*_{wt} is the optimal expenditure for bank w in year t, incurred by producing a given level of output mix subject to exogenous input prices; φ^* is the corresponding parameter vector associated with the meta-frontier cost function satisfying the restriction of (by construction):

$$X_{wt}\varphi^{*} \le X_{wt}\varphi_{(r)} \ . \qquad (4)$$

The meta-frontier is defined as a deterministic parametric function enveloping the deterministic parts of the individual cost frontiers such that its values must be less than or equal to the deterministic components of the stochastic cost frontiers of the different countries involved. The meta-frontier cost function reflects the minimum possible production cost for producing a given level of output quantities; it is the minimum cost corresponding to the most efficient production technique status quo. The inequality constraint of equation (4) is required to hold for all countries and time periods. The meta-frontier is thus viewed as an envelope curve beneath the individual cost frontiers of the different countries. Figure 1 illustrates how the meta-frontier cost function envelopes the stochastic frontiers of the different countries for the case of a single output.

[Insert Figure 1 Here]

In the figure, Frontier1 to Frontier3 represent three stochastic frontiers corresponding to three national frontiers. The meta-frontier cost function surrounds the three stochastic frontiers from below, indicating that it entails production costs that are no more than the deterministic costs correlated with the stochastic cost frontiers for the respective countries involved. Frontier1 and Frontier2 are arbitrarily chosen to be tangent to the meta-frontier and Frontier3 is not. As will be clear shortly, banks in states 1 and 2 on average adopt higher production technology relative to banks in state 3, because the former two states' cost frontiers are relatively closer to the meta-frontier than Frontier3.

3.2 Efficiency Scores and Technology Gap Ratios

The conventional cost efficiency of a firm is evaluated by the ratio of the minimum cost to its actual cost, reflecting the extent to which the firm's actual cost lies above the cost frontier. Based on this idea, the measure of the meta-cost efficiency ($CE^{*}_{wt(r)}$) for bank w in year t of country r is derived by the ratio of the meta-cost, adjusted by the corresponding random error, to actual cost:

$$CE^{*}_{wt(r)} = \frac{e^{X_{wt}\varphi^{*}+V_{wt(r)}}}{C_{wt(r)}}. \tag{5}$$

Substituting (2) into (5) yields:

$$CE^{*}_{wt(r)} = \frac{e^{X_{wt}\varphi^{*}+V_{wt(r)}}}{e^{X_{wt}\varphi_{(r)}+V_{wt(r)}+U_{wt(r)}}} = e^{-U_{wt(r)}} \times \frac{e^{X_{wt}\varphi^{*}}}{e^{X_{wt}\varphi_{(r)}}}, \tag{6}$$

where the first term on the right-hand side of equation (6) is the conventional input oriented technical efficiency (CE) relative to the stochastic cost frontier of country r, i.e.:[2]

$$CE_{wt(r)} = \frac{e^{X_{wt}\varphi_{(r)}+V_{wt(r)}}}{e^{X_{wt}\varphi_{(r)}+V_{wt(r)}+U_{wt(r)}}} = e^{-U_{wt(r)}}. \tag{7}$$

It must lie between zero and one, because $U_{wt(r)}$ is inherently a non-negative random variable. The second term on the right-hand side of equation (6) is referred to as the technology gap ratio (TGR), i.e.:

$$TGR_{wt(r)} = \frac{e^{X_{wt}\varphi^{*}}}{e^{X_{wt}\varphi_{(r)}}}. \tag{8}$$

The TGR mainly evaluates the size of the technology gap for country r whose currently available technology adopted by its resident firms lags behind the technology available for all countries, represented by the meta-frontier cost function.

We specifically measure the TGR using the ratio of the potentially minimum cost that is defined by the meta-frontier cost function to the cost of the frontier function for

[2] For details please see, for example, Atkinson and Cornwell (1994) and Huang and Kao (2006).

country r, given the observed output and input prices. Apparently, it has a value between zero and one, because of equation (4). The higher the average value of the TGR is for a country, the more advanced the production technology it adopts. Figure 2 illustrates two cases of a national cost frontier, in which Frontier1 is tangent to the meta-frontier, but Frontier1' fails to do so. The technology corresponding to Frontier1' is said to be inferior to that of Frontier1, as the former consumes higher cost than the latter does to produce a given output quantity. Let point a in Figure 2 represent firm a's actual cost. It can easily be seen that under Frontier1, firm a's TGR is measured as $a'''Y_1 / a''Y_1$, which is greater than or equal to $a'''Y_1 / a'Y_1$, corresponding to firm a's TGR but under Frontier1'. The use of inferior technology 1' means the firm has a greater frontier cost.

[Insert Figure 2 Here]

The meta-cost efficiency measure of equation (5) can now be expressed as:

$$CE^{*}_{wt(r)} = CE_{wt(r)} \times TGR_{wt(r)}, \tag{9}$$

indicating that it consists of two elements: one of them is the conventional technical efficiency measuring the deviation of a firm's actual cost from the country specific cost frontier, and the other is a new one measuring the deviation of the country specific cost frontier from the meta-frontier cost function. Term $CE^{*}_{wt(r)}$ certainly ranges from zero to one due to both CE and TGR lying in the same range. The meta-cost frontier efficiency score of an enterprise reflects how well it performs relative to the predicted performance of the best-practice peers that exploit the best technology available for all groups to produce a given output mix. These benchmark firms operate on the meta-cost frontier, i.e., they are employing the best available technology in the production process.

The measure of meta-cost frontier efficiency is preferable for most regulatory and other purposes to the measure of traditional cost frontier efficiency, as the former measure does not impose the strong restriction of homogeneous technology used by different groups. Such a homogeneity restriction often distorts the estimates of production efficiency and leads traditional cost efficiency scores to be higher than meta-cost efficiency scores, all else being equal, since the meta-cost efficiency score sets a more rigorous standard that combines group-specific efficiency, CE, with technology gap ratios, TGRs. It is quite plausible that some banks that are relatively technically efficient with higher CE scores are relatively technologically inefficient with lower TGRs, and vice versa, depending on the relationship between managers' abilities to adopt the best technology and the optimal input combination and their competences to swiftly respond to market signals and institutional breaks.

This negative association between the measures of CE and TGR can be illuminated by Figure 2 and is indeed confirmed by an empirical exercise later. On the basis of Figure 2, there are two firms, a and a', assumed to have the same expenses at point a, say, and they undertake technologies 1 and 1', respectively. The adoption of technology 1 results in the measures of CE, TGR, and CE^* equaling to $a''Y_1/aY_1$, $a'''Y_1/a''Y_1$, and $a'''Y_1/aY_1$, respectively. However, under technology 1', the respective measures are $a'Y_1/aY_1$, $a'''Y_1/a'Y_1$, and $a'''Y_1/aY_1$. Interestingly enough, both technologies produce equivalent estimates of CE^*, since both CE^*s are assessed against the unique standard, i.e., the meta-cost frontier, while the magnitudes of their respective components differ with alternate orders, i.e., $a''Y_1/aY_1 < a'Y_1/aY_1$ and $a'''Y_1/a''Y_1 > a'''Y_1/a'Y_1$. This implies that measure CE tends to be negatively correlated with measure TGR. The foregoing further means that any two firms with equal expenditures but using dissimilar technologies, such as

Frontiers 1 and 1’, are not directly comparable in terms of CE scores due to heterogeneous standards. The comparison is meaningful solely in the context of the meta-cost frontier.

3.3 Formulations of the Scale and Scope Economies

In the case of multiple outputs, a popular measure of scale economies is referred to as ray scale economies (RSE), developed by Baumol et al. (1982), and is widely applied to various industries including the financial industry. It is defined as:

$$RSE = \sum_i \frac{\partial \ln f}{\partial \ln Y_i}, \tag{10}$$

where $\ln Y_i$ is the natural logarithm of the *i*th output produced by a firm and f denotes the cost function. An estimate of RSE less than, equal to, or greater than 1 respectively indicates scale economies, constant returns to scale, or scale diseconomies.

Economies of scope exist when the total cost of a firm jointly producing multiple outputs is lower than the sum of the total costs of specialized firms producing each output separately. In the case of a bank producing three outputs, as suggested by Mester (1987, 1996), the estimate of within-sample scope economies is defined as:

$$SC = \frac{f(Y_1 - 2Y_1^m, Y_2^m, Y_3^m) + f(Y_1^m, Y_2 - 2Y_2^m, Y_3^m) + f(Y_1^m, Y_2^m, Y_3 - 2Y_3^m) - f(Y_1, Y_2, Y_3)}{f(Y_1, Y_2, Y_3)}, \tag{11}$$

where Y_i^m equals 10% of the minimum value of Y_i in the sample. The purpose of using Y_i^m in place of zeros in the equation avoids taking the logarithms of zero in the translog function of the specialists. An estimate of SC greater than or less than zero respectively indicates scope economies or diseconomies.

As recognized by Berger et al. (1993), there are at least two major problems in exploiting the translog specification to compute scope economies. One of them is related to zero predicted costs for each of the specialized banks. The other issue is referred to as the problem of extrapolation. It is well known that most commercial banks provide their entire array of products involved in the cost function. There is virtually a null of data on banks that specialize. Since scope efficiency is not the main theme of the current paper, we choose not to go any further on this issue.[3]

3.4 Estimation Procedure

Following Battese et al. (2004), the estimation procedure is divided into three steps as below.

1. Estimate national cost frontiers for each sample country r by the maximum likelihood to yield technology parameters $\hat{\varphi}_{(r)}$. The stochastic frontier model proposed by Battese and Coelli (1992), allowing for temporal variant technical efficiency, is applied.
2. Obtain the estimate of $\varphi *$ in the meta-frontier cost function using mathematical programming techniques that will be briefly described shortly.
3. According to equations (6)-(11), calculate the cost efficiency (CE), the technology gap ratios (TGR), scale economies, and scope economies, using estimates $\hat{\varphi}_{(r)}$ and $\hat{\varphi} *$ obtained by Steps 1 and 2.

There are two alternative approaches that can be applied to identify the optimal meta-frontier, as proposed by Battese et al. (2004). One relies on the sum of

[3] There are several alternative approaches to solve the recognized problems. For example, Berger et al. (1987), Buono and Eakin (1990), Berger et al. (2000) utilize the level of output in place of the log. In addition, Berger et al. (1987), Berger and Humphrey (1991), and Hunter and Timme (1991) develop a technique of expansion path subadditivity that appears to be able to get rid of the problem of extrapolation. Baumol et al. (1982) propose a concept of weak cost complementarities and demonstrate that weak cost complementarities are a sufficient condition for economies of scope.

absolute deviations of the meta-frontier values from those of the country frontiers, and the other depends on the sum of squares of the same distances.

Minimum Sum of Absolute Deviations

Vector $\hat{\varphi}*$ is obtained by solving the following optimization problem:

$$\min L \equiv \sum_{t=1}^{T}\sum_{w=1}^{N}\left|\ln f(X_{wt},\hat{\varphi}_{(r)}) - \ln f(X_{wt},\varphi^*)\right| \tag{12}$$

$$s.t. \ln f(X_{wt},\varphi^*) \le \ln f(X_{wt},\hat{\varphi}_{(r)}) . \tag{13}$$

It is clear from equations (12) and (13) that the estimated meta-frontier vector minimizes the sum of the absolute logarithms of $f(X_{wt},\hat{\varphi}_{(r)})/f(X_{wt},\varphi^*)$, which represents the reciprocal of the radial distance between the meta-frontier and the frontier of country r, as measured at the observed output and input prices. The weights of the deviations for all firms in the sample are the same. Since all the deviations are positive due to equation (13), all the absolute deviations are exactly equal to the differences. Using equations (2) and (3), we can transform the above optimization problem to the linear programming (LP) problem:

$$\min L \equiv \sum_{t=1}^{T}\sum_{w=1}^{N}\left(X_{wt}\hat{\varphi}_{(r)} - X_{wt}\varphi^*\right) \tag{14}$$

$$s.t. \; X_{wt}\varphi^* \le X_{wt}\hat{\varphi}_{(r)} . \tag{15}$$

It is worth mentioning that the solution to the above problem is tantamount to minimizing the objective function $L^* = -\bar{X}\varphi^*$, subject to linear restrictions (15), where $\bar{X}$ denotes the row vector of the means of the elements for the X_{wt}-vectors of all observations in the dataset. This seems legitimate, as the parameter estimates of the stochastic frontiers for the different countries, $\hat{\varphi}_{(r)}$, r = 1,…, R, are treated as fixed values for the linear programming problem.

Minimum Sum of Squared Deviations

The other approach attempts to minimize the sum of squares of the deviations between the meta-frontier and the frontier of the individual countries. This optimization problem is identical to a constrained least squares estimation. Here, $\hat{\varphi}*$ is estimated by solving a quadratic programming (QP) problem:

$$\min L^{**} \equiv \sum_{t=1}^{T}\sum_{w=1}^{N}\left(X_{wt}\hat{\varphi}_{(r)} - X_{wt}\varphi^{*}\right)^{2} \tag{16}$$

$$s.t.\ X_{wt}\varphi^{*} \leq X_{wt}\hat{\varphi}_{(r)}.$$

What is immediately clear in the objective function is that the larger the technology gap ratio is for a bank, the higher the weight will be that is being assigned to it.

Standard errors of the estimators for the two meta-frontiers cannot be obtained directly by the mathematical programming. They can be deduced by either simulation or bootstrapping methods. Differing from Battese et al. (2004), this paper uses the bootstrapping method, since the underlying data generation process is unknown and the analytic estimates of the standard errors of the estimators are impossible to calculate. The method may be able to provide a better finite sample approximation.

4. Data Source and Variable Definitions

The primary data source comes from the *Bankscope* database over the period 1994-2003 and is supplemented by the *Eurostat* database. We select unconsolidated accounting data for 828 banks in 16 European countries, which have at least three years of data available. The total number of observations is 4977. All the nominal variables have been transformed into real terms by the consumer price index of individual countries with the base year of 1985.

We employ the intermediation approach to define the variables of inputs and outputs. Three output categories are identified: loans, investments, and non-interest revenues. The inputs include labor, physical capital, and borrowed funds. As data on the number of employees are not completely available from the databank, the price of labor is calculated as the ratio of personnel expenses to total assets, which is similar to previous works using the same data source, such as Altunbas et al.(2000, 2001) and Weill (2004). The price of physical capital is defined as the ratio of other non-interest expenses to fixed assets. The price of borrowed funds is measured by the ratio of paid interests to all funding. Finally, total costs are the sum of the above three items of expenditures.

Table 1 summarizes the descriptive statistics and the distributions of the sample banks among countries. These statistics indicate that there are considerable differences among the countries. Banks of different countries may employ inputs of different qualities to provide heterogeneous outputs through dissimilar production techniques. In other words, the performance of banks from different countries is not directly comparable as they are gauged on the basis of various standards. This justifies the use of the meta-frontier model.

[Insert Table 1 Here]

5. Empirical Results

In the first subsection we present the parameter estimates of the stochastic cost frontier for each country. The second subsection measures the cost efficiency and the TGR for each sample bank, while the last subsection calculates the scale and scope economies.

5.1 Parameter Estimates

Each country's cost frontier is specified as a standard translog function form with trends and the inefficiency term follows Battese and Coelli (1992), i.e.:

$$\ln C_{wt} = \alpha_0 + \sum_{j=1}^{4} \alpha_j \ln Y_{jwt} + \sum_{k=1}^{3} \beta_k \ln P_{kwt} + \frac{1}{2}\sum_{j=1}^{4}\sum_{m=1}^{4} \gamma_{jm} \ln Y_{jwt} \ln Y_{mwt}$$

$$+ \frac{1}{2}\sum_{k=1}^{3}\sum_{n=1}^{3} \delta_{kn} \ln P_{kwt} \ln P_{nwt} + \sum_{j=1}^{4}\sum_{k=1}^{3} \rho_{jk} \ln Y_{jwt} \ln P_{kwt} + U_{wt} + V_{wt}\,, \qquad (17)$$

where C_{wt} denotes the real observed total cost of bank *w* at time *t*; Y_1 to Y_3 denote the three outputs, i.e., loans, investments, and non-interest revenues, respectively; $\ln Y_4$ signifies the linear time trend; and P_1 to P_3 represent the three input prices of labor, physical capital, and borrowed funds. The one-sided error of U_{wt} denotes the temporal production inefficiency and is further formulated as:

$$U_{wt} = U_w \exp\left[-\eta\left(t - T\right)\right], \quad t = 1, \ldots, T, \qquad (18)$$

where $U_w \sim N^+(\mu, \sigma_u^2)$ is assumed to be a time-invariant, truncated normal random variable independent of two-sided error $V_{wt} \sim N(0, \sigma_v^2)$ and η is a new parameter to be estimated. Parameters μ, σ_u^2, and σ_v^2 are all country specific, taking different values for different countries. Term U_{wt} decreases at an increasing rate if $\eta > 0$, increases at an increasing rate if $\eta < 0$, or remains constant if $\eta = 0$.

There are a few characteristics deserving specific mention. Microeconomic theory requires that a cost function is homogeneous of first degree in input prices and that it is symmetrical, i.e., $\gamma_{jm} = \gamma_{mj}$ (for all $j \neq m$) and $\delta_{kn} = \delta_{nk}$ (for all $k \neq n$). Other properties can be checked once the parameters have been estimated. After imposing the homogeneity constraint on (17), we rewrite it as:

$$\ln c_{wt} = \alpha_0 + \sum_{j=1}^{4} \alpha_j \ln Y_{jwt} + \sum_{k=2}^{3} \beta_k \ln p_{kwt} + \frac{1}{2}\sum_{j=1}^{4}\sum_{m=1}^{4} \gamma_{jm} \ln Y_{jwt} \ln Y_{mwt}$$

$$+\frac{1}{2}\sum_{k=2}^{3}\sum_{n=2}^{3}\delta_{kn}\ln p_{kwt}\ln p_{nwt}+\sum_{j=1}^{4}\sum_{k=2}^{3}\rho_{jk}\ln Y_{jwt}\ln p_{kwt}+U_{wt}+V_{wt}\,, \qquad (19)$$

where $\ln c_{wt}=\ln C_{wt}-\ln P_{1wt}$, and $\ln p_{kwt}=\ln P_{kwt}-\ln P_{1wt}$, $k=2,3$. In other words, the first input is arbitrarily chosen as the numeraire and its price is used to normalize all the terms involving C, P_2, and P_3. Notations α, β, γ, δ, ρ, η, μ, σ_u^2, and σ_v^2 are unknown parameters of the cost function. Using software Frontier 4.1 (Coelli, 1996), equation (19) can be estimated for each of the 16 countries. The parameter estimates are not shown to save space, but are available upon request to the authors.

The widely used translog cost function is known as being flexible, in the sense that it offers a second-order approximation to the true but unknown function. With a few exceptions, we observe that more than half of the parameter estimates of the country frontiers attain statistical significance at least at the 10% level. Taking these estimated parameters as given, we can examine whether the estimated cost function satisfies the regularity conditions imposed by microeconomic theory. Most of the sample observations are found to be consistent with the theory.[4] Viewed from this angle, one may claim that these coefficient estimates of country frontiers are well representative for an average bank's production technology and cost structure.

Having estimated and analyzed each country's cost frontier, one may ask whether or not banks from different countries operate under a unique type of technology. If all banks share the same technology, then it would be unnecessary to

[4] Specifically, we check all the three cost shares, the marginal costs of the three outputs, the conditional factor demands, and the negativity conditions of the Hessian matrix for each observation and for each country. Most of the sample points are found to have the expected signs. Details are overlooked here, but available upon request to the authors. In their recent survey on the estimation of a cost function, Greene et al. (2004) give an explanation for some observations against the requirements. The inconsistency may come from the exclusion of the share equations in the estimation.

analyze data by a meta-frontier model. A likelihood-ratio (LR) test is performed for the null hypothesis that all countries' stochastic cost frontiers are the same. The value of the LR test statistic is equal to 2295, which is significant even at the 1% level. Hence, the null hypothesis is decisively rejected.[5] Banks from different countries indeed operate under different technologies. This leads us to the next step - the estimation of the meta-frontier cost function.

[Insert Table 2 Here]

In order to compare the meta-frontier cost function with conventional studies, where banking efficiencies are evaluated by simply pooling all the data across countries together without regard to the possible technological differences, we also estimate the translog stochastic cost function with respect to all of the 16 sample countries. The results are reported in the first column of Table 2. The remaining two columns of the table show the parameter estimates obtained by the meta-frontier linear programming and quadratic programming. Standard errors attached to the two sets of the mathematical programming estimators are obtained through bootstrapping methods. Treating the sample as if it were the population, we randomly draw with replacement for 1000 new datasets of the same size as the original sample. For each generated dataset, the new meta-frontier parameters are estimated by linear and quadratic programming. Therefore, there are 1000 parameter estimates for each coefficient. The estimated standard error of a meta-frontier parameter is calculated as the standard deviation of the 1000 new parameter estimates. It is interesting to note that both the LP coefficient estimates and the bootstrapped standard deviations are quite close to those of the QP estimates. However, there are substantial

[5] The LR statistic is distributed as a Chi-square distribution with the degrees of freedom being 480, the difference between the number of parameters being estimated under the alternative and the null hypotheses.

differences between the meta-frontier coefficients and the corresponding coefficients of the SFA for entire sample. Moreover, it is seen that the vast majority of the bootstrapped standard deviations are relatively small to the corresponding coefficients. This implies that the LP and QP coefficients are very precisely estimated and hence well representative of the meta-cost function. The foregoing permits us to just focus our attention to either of the two mathematical programming estimators. In fact, the two sets of meta-frontier parameter estimates lead to quite similar estimates of the TGRs. We therefore arbitrarily elect to present the relevant results calculated using the LP estimates.

[Insert Table 3 Here]

5.2 Cost Efficiencies and Technology Gap Ratios

In this subsection we shift our attention to the estimates of the cost efficiency and the technology gap by persistently applying the LP parameter estimates. Table 3 reports the measures of the TGR, along with the relative cost efficiency to the stochastic frontier for individual countries (CE) and the meta-frontier efficiency score (CE*). For the whole West European banking samples, the mean value of CE is about 0.71. The figure is not far apart from the results that are found by Altunbas et al. (2001) and Vennet (2002), who study the efficiencies of West European banks by pooling all sample points of different countries.[6] The mean values of CE across countries range from 0.47 for Finland to 0.94 for Norway. These figures imply that, on average, the potential cost savings for Finnish banks are about 53% of their actual costs, which may be attributed to the managerial inability to control costs. In

[6] Dietsch (1997) finds that the mean X-efficiency score of French depository banks is equal to 0.707 (truncation at 0.05). Other studies on West European banks yield mean X-inefficiencies estimates ranging from 17% to 35%. See, for example, Schure et al. (2004), Altunbas et al. (2001), Carbo et al. (2002), and Maudos et al. (2002). Weill (2004) obtains mean efficiency scores for five major European states varying from roughly 0.66 to 0.84 when using the SFA approach.

contrast, an average bank in Norway lies quite close to the cost frontier. Norwegian banks' managerial inefficiency is not as serious as that in Finnish banking.

It is noticeable that the reverse is true for Norwegian and Finnish banks in terms of TGRs. Although Norwegian banks have the highest CE scores among all sample states, they appear to adopt inferior production technologies, as the mean value of their TGRs stands at the third lowest. Banks in Portugal, Spain, and Sweden have analogous features, where they have higher country specific mean CE scores and lower mean TGRs than the respective overall averages. Conversely, Finnish banks operate under superior technologies, but at the expense of lower average CE scores, i.e., their actual production costs lie over and farther apart from their own cost frontier. Banks in Italy, Denmark, Switzerland, and Belgium face a similar situation, where they have lower average country specific mean CE scores and higher mean TGRs than the respective overall averages. Banks in UK, Luxembourg, and Netherlands have both lower mean CE scores and TGRs than the respective overall averages, while German banks exhibit both a higher mean CE score and TGR than the respective overall averages. The remaining banks in Austria, France, and Greece show mixed relative mean values of the CE scores and TGRs to the respective overall counterparts.

It is worth taking a closer look at some important features of the technology gaps. The mean values of the TGR vary from roughly 0.1 for UK to 0.55 for Finland, indicating that the average level of production technology adopted by British banks tends to be the lowest among all sample countries. Consequently, British banks can shave their frontier costs by up to 90%, if the potential technology available to all countries, the technology corresponding to the meta-frontier, is adopted. The Finnish banks are in another extreme, employing the most superior production process to provide financial services, because their country frontier is found to be the closest to the meta-frontier. On average, the potential cost savings of Finnish banks are as low as about 45% of their frontier costs.[7] Note that most of the sample countries' cost frontiers, except for Denmark, Luxembourg, Norway, Portugal, and UK, are tangent to the meta-cost frontier, as they all have the estimated values of TGR equaling unity. Four of the five states, with the exception of Denmark, stand at the lowest four average TGRs. It is conceivable that the presence of a tangency between the country frontier and the meta-frontier is a valuable signal of the level of production technology undertaken by a group. Failure to observe such a tangency for a group is apt to yield a lower average value of TGR, implying that the group's technology achievement may be low relative to other groups under study.

Not surprisingly, the mean cost efficiency relative to the meta-frontier, CE*, of Germany stands at first place, followed by Switzerland, Sweden, and Belgium, and the mean CE*s of UK, Luxembourg, and Netherlands are ranked at the bottom, including Finland. The mean values of CE* vary from around 0.07 for UK to 0.36 for Germany, where the component TGR is on average much less than the component CE. This implies that there are quite a few banks operating far beyond the meta-cost frontier. It is suggested that the sample banks take steps to catch up with the potential technology available to all countries so as to substantially shift their frontier cost function down and to be viable in the competitive market.

One of the salient features under the framework of the meta-frontier model is that the model allows for distinguishing the TGR from the CE score and, in turn, gains further insights on banks' production efficiencies. In other words, the model

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[7] It is seen by inspecting Table 1 that British banks on average tend to grant the least loans to their customers, while Finnish banks on average extend the second largest loans. This may be one of the reasons forcing the mean TGR of UK to the lower end and that of Finland to the other end.

renders more information by subdividing the measure of CE* into two elements: CE and TGR. On the basis of this information, bank managers, consultants, and regulatory authorities should be aware of whether the observed inefficiencies could raise the possibility of bank failure considerably, and so this could be used to reallocate scarce resources to where they are most needed. Conversely, without the benefit of such quality information, regulators' decisions may have the unintended consequences of increasing the costs of providing financial services to customers, lowering the quantity or quality of these services, or exposing the banks to systemic risk. Meta-cost frontier efficiency appears to be superior to conventional cost frontier efficiency as it does not require all groups involved to operate under the same technology, which, in turn, offers higher flexibility in describing the characteristics of production and cost and greater accuracy in estimating production efficiency.

[Insert Figure 3 Here]

The frequency distributions of the TGRs for the observed banks could give us a better understanding about the degrees of technology differences among the European countries. Figure 3 shows that there is a good deal of variability in TGRs for banks in the sample countries. It is seen that banks in ten countries, i.e., Austria, France, Germany, Greece, Luxembourg, Netherlands, Norway, Portugal, Spain, and UK, tend to have skew frequency distributions of the TGRs to the right. Banks in the remaining six countries, i.e., Belgium, Denmark, Finland, Italy, Sweden, and Switzerland, are inclined to have symmetrical frequency distributions of the TGRs, centered at around 0.5. The former group of ten countries contains a larger number of banks with lower TGRs. It can be inferred that a country with a symmetrical distribution of TGRs outperforms a country with a positively skew distribution of TGRs, as the former adopts advanced technology.

[Insert Figure 4 Here]

One may ask an important question of whether and what direction the CE scores are correlated with the TGRs. This information offers a potential link between production efficiency and technology achievement. Using the computed means of CE and TGR for the 16 countries shown in Table 3, we obtain their simple correlation coefficient at about -0.45. Figure 4 draws the scatter diagram for the pairs of means CE and TGR. It is observed that the two mean measures are negatively associated with each other in a moderate degree, where the CE-TGR combination from UK exhibits quite a large variability and may be treated as an outlier. Dropping this combination would reduce the simple correlation coefficient to around -0.63.[8] Evidence is found that a higher mean value of TGR corresponds to a lower mean value of CE, and vice versa, which is congruent with the discussion on Figure 2 in Subsection 3.2. This indicates that in a country undertaking more advanced technology (a higher TGR) its banks' actual costs fail to catch up with the downward shifting country frontier, worsening its average CE score. This may be attributed to the presence of quasi-fixed inputs, which hinder banks from instantaneously and optimally selecting an input mix given the output quantities. This form of rigidity appears to be pervasive as the quasi-fixed inputs are virtually present in all sectors of an economy (Ouellette and Vierstraete, 2004).[9]

[Insert Figure 5 Here]

Having access to panel data incorporating both cross-sectional and time series

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8 Battest et al. (2004) appear to attain a similar negative relationship between CE and TGR, in which the region of Jakarta has the lowest mean TE score as well as the highest mean value of TGR among the five regions, while the reverse is true for the region of east Java.

9 Factors, such as regulation, large adjustment costs, transactions and information costs, and the indivisibility of some inputs, constitute the main sources of quasi-fixity. Specifically, core deposits and physical capital are frequently viewed as quasi-fixed with the banking sector by, for example, Flannery (1982), Humphrey (1993), Berger et al. (1993), Noulas et al. (1990), and Hunter and Timme (1995).

properties, we are able to analyze the evolution of the CE and the TGR over the sample period 1994-2003. To remove random shocks from the data, the CE scores and the TGRs are averaged across countries for each year. These cross country averages are used to draw Figure 5, which depicts that both CE and TGR gradually grow with time, from around 0.5 to 0.8 and from around 0.3 to 0.45, respectively. However, the mean values of the TGR slightly decrease after 2001. Generally speaking, the European banks seem to benefit from the establishments of the EU and the Single Market for Financial Services. A single and competitive market for financial services not only improves the banking efficiencies within a member country, but also shrinks the gap between the country's production technology and the potential technology available to all countries.

[Insert Table 4 Here]

5.3 Estimates of Scale and Scope Economies

According to equations (10) and (11), the measures of scale and scope economies for the sample banks are calculated using both parameter estimates of the country cost frontiers and the SFA of Table 2. Table 4 reports the mean values of these measures for each country. Fourteen out of the sixteen mean scale economy measures calculated using the country frontier parameters are in excess of those computed using the SFA parameters. The imposition of a common production technology on the financial industry shared by all sample countries tends to bias the estimates of scale economies downward so that all the banking sectors of the European samples enjoy advantage of increasing returns to scale. The production scale of a representative bank falls short of the optimal size. All banks benefit through augmenting their production scale, since their average costs decline as their sizes expand.

Viewed from the angle of country frontiers, a somewhat different picture can be described. There are five countries, i.e., Austria, Belgium, Norway, Portugal, and Sweden, having estimates of scale economies exceeding 0.96, indicating that the production scale of banks for the five countries, on average, is nearly optimal such that the long-run average cost of these banks attains the minimum.[10] The banks of the remaining 11 countries exhibit increasing returns to scale. They provide various financial products on the decreasing portion of the long-run average cost curve. As the economies of size are not exhausted, banks of these 11 countries can further reduce their average costs by means of expanding their production scale, such as conducting mergers and acquisitions.

Table 4 also shows that there are four countries, i.e., Austria, Greece, Portugal, and Spain, having negative estimates of scope economies, evaluated by the country frontiers. This implies that it is possibly desirable for banks of these four countries to be specialists in offering financial services to their customers. On the contrary, product mix economies exist in the financial industries of the other 12 states. These banks may be able to cut their production costs by further diversifying their line of financial products.[11] The sharing of factors such as labor, computer equipment, and customer information across multiple financial products and risk diversification activities constitute the main source of such potential cost savings.[12] The presence

[10] Vennet (2002) concludes for universal banks and financial conglomerates that there are no significant scale economies nor diseconomies, which is in line with the results of Allen and Rai (1996). However, Cavallo and Rossi (2001) uncover the existence of economies of scale at every production scale and for every bank organizational type. Altunbas and Molyneaux (1996) reach similar results.

[11] As pointed out by Berger et al. (1993), the use of formula (11) may sometimes lead to large estimates of scope economies and diseconomies due to the effects of extrapolation together with the problems of the translog specification, as mentioned in Subsection 3.3. Also see Berger and Humphrey (1991), Pulley and Humphrey (1993), and Mester (1993).

[12] According to Lewellen (1971), the conduct of risk diversification by a bank helps reduce the expected costs of financial distress and allows for greater financial leverage leading the bank to earn higher revenues from risk-sensitive customers who are willing to pay more or accept lower services in return for lower default risk.

of scope diseconomies only in a few countries fails to lend somewhat more support on the prevalence of specialized production. It is preferable for banks in most countries to exercise joint production, which appears to be the favorite path of financial conglomerates.[13] Differing from the country frontiers, the common frontier of the SFA detects two countries, i.e., Finland and Norway, having negative and quite small (in absolute value) measures of product-mix economies, leading to a little stronger evidence of scope efficiency prevailing in the sample countries.[14]

The above results should be interpreted with great care in view of the inherent drawbacks of the translog function. It is seen that estimates of the economies of scope from the country frontier vary dramatically. In contrast, the same estimates of scope economies from the common SFA cost frontier are relatively stable. This dissimilarity may be explained by the fact that the common frontier approach requires using the entire sample to estimate a common cost function, thus increasing the range of variation of the independent variables and the number of observations.

Broadly speaking, European banking industries exhibit both scale and scope economies with a few exceptions. One is led to conclude that it is advantageous for banks to enlarge their production scale and to diversify their financial products through, e.g., a merger with or the acquisition of insurance companies and/or investment firms.

6. Conclusions

[13] Financial conglomerates are financial institutions that provide the entire range of financial services. In the EU, conglomeration and universal banking are permitted by the Second Banking Directive (1989), which has been enforced by all member nations. In this directive the EU has adopted a broad definition of credit institutions, corresponding to the German model of universal banking.

[14] Vennet (2002) finds the presence of unexploited scope economies for the smallest cooperative banks and Lang and Welzel (1996) obtain scope economies for small German cooperative banks. Cavallo and Rossi (2001) also discover the existence of scope economies for six European countries, i.e., France, Germany, Italy, Netherlands, Spain, and UK, over the period 1992-1997. It is crucial to note that the outcomes of Cavallo and Rossi (2001) may confound the measure of scope economies with X-efficiency, since they fail to take the possible X-inefficiency into account. See Berger et al. (1993), Berger and Humphrey (1991), and Mester (1993) for details.

This paper has investigated the performance of commercial banks across 16 European countries for the years 1994-2003, in terms of the cost efficiency and technology gap ratios. In conventional studies, it is shown to be invalid that the efficiency score of a bank employing one type of technology can be compared with that of another bank employing a different type of technology. However, the imposition of a unique production technology on all groups involved tends to bias the various efficiency measures and leads to inappropriate policy implications. The newly developed meta-cost function provides a possible solution to this incomparability problem, since the relevant efficiencies are evaluated and compared on the basis of the common meta-cost function, hence resolving the difficulty of unequal standards.

The component TGR reflects the degree of technology gap for a particular country whose currently available technology adopted by its banks lags behind the technology available for all countries. The average CE scores for the sample countries are found to fall into the range of the previous works and are negatively correlated with the TGRs. This means that a relatively technically efficient bank is usually technologically inefficient and vice versa. Furthermore, most of the mean values of the component TGR for the sample countries are much less than those of the component CE, indicating that there are quite a few banks operating off the meta-cost frontier. The sample banks need to make every effort to keep pace with the potential technology available to all countries so as to be competitively viable.

The empirical outcomes show that banks in European countries are employing versatile forms of technology. The existence of multiple technologies justifies that a meta-frontier model may be a suitable choice for conducting a cross country study. Our findings yield clear evidence regarding the emergence of substantial variability in the technology gap ratios for banks in the 16 countries of our study. Some financial industries are inclined to adopt inferior technologies to produce an array of financial services due possibly to the hiring of considerable quasi-fixed inputs, making their meta-cost efficiency measures very low. As Europe's financial markets have become more competitive and highly integrated after the erection of the EU and the implementation of the Second Banking Directive (1989), evidence is found that the average efficiency of the financial sectors has improved over time and that the technology gap between a country's cost frontier and the potential meta-frontier has shrunk over time.

When the restriction of a common production technology is imposed on our sample, measures of the scale economies are apt to be underestimated such that the financial institutions in all the sample states exhibit increasing returns to scale. However, the same measures evaluated under different technologies, i.e., using the country frontier parameters, result in a somewhat distinct conclusion. The banking industries in 5 of the 16 countries have already reached the optimal plant size, enjoying the minimum long-run average cost. It is impossible for these banks to further reduce their average costs. The banking industries in the remaining 11 countries are located at the decreasing part of their respective long-run average cost curves. These relatively small-scaled banks can achieve benefits by augmenting their production scale through, e.g., mergers and acquisitions. As product-mix economies are present in most of the countries, conglomeration can lower a bank's production costs by sharing inputs in joint production and diversifying risk. The empirical results suggest the option for a strategy of diversification. Although technical inefficiencies and technology gaps remain persistent, the current trend toward further de-specialization may prompt a more efficient banking system.

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Table 1. Descriptive statistics for all countries

Variable	Austria	Belgium	Denmark	Finland	France	Germany	Greece	Italy	Luxembourg	Netherlands	Norway	Portugal	Spain	Sweden	Switzerland	UK
Number of banks	21	24	48	10	156	141	18	121	63	13	12	22	58	11	94	16
Nnumber of observations	137	118	339	48	907	861	121	766	328	94	78	134	361	57	540	88
Total cost	342.0152	770.6157	173.9057	540.3178	624.560138	599.6001	111.5377	441.1900	483.0223	330.7489	363.9005	221.4476	314.8106	870.5152	495.3035	267.3878
	(738.4505)	(1,527.2528)	(525.9168)	(591.5974)	(2,019.2870)	(2,520.6303)	(170.1370)	(1,118.1825)	(592.3419)	(802.8914)	(441.3191)	(298.1052)	(771.0827)	(936.1710)	(2,423.9160)	(635.8698)
Outputs																
Total loans (Y_1)	5752.4089	2870.8298	2476.7888	9512.3615	6536.228037	8575.3611	932.4758	5136.0296	4994.3971	5266.0078	5491.6551	2173.0419	4000.3145	12354.5979	7061.7418	234.6226
	(11,817.7299)	(6,336.7061)	(7,901.5202)	(12,215.2397)	(21,244.2365)	(35,518.4875)	(1,326.9539)	(12,775.2779)	(5,850.4115)	(13,110.8512)	(6,791.2679)	(2,897.7409)	(9,249.4752)	(14,162.7842)	(34,367.5024)	(607.2661)
Total investments (Y_2)	1176.8494	4009.7393	1063.2057	3014.8806	2493.294664	2886.8931	468.0788	1275.4837	2561.5475	723.7700	850.0509	506.1777	1282.3567	4068.7148	2380.9333	985.6606
	(2,678.0225)	(7,776.7153)	(3,947.6852)	(2,954.6339)	(9,530.0935)	(15,369.2916)	(869.8046)	(3,133.7969)	(3,350.8017)	(1,778.5995)	(1,084.5914)	(750.3299)	(4,193.6309)	(4,594.5287)	(14,130.3583)	(2,467.2828)
Non-interest revenue((Y_3)	34.9115	590.3803	39.9994	98.5514	129.1542	121.3604	10.0389	97.6324	47.2918	3.2005	73.3750	110.3945	59.8490	162.9436	167.8554	58.9706
	(57.2138)	(1,202.2564)	(140.0078)	(116.0593)	(527.2182)	(614.4434)	(18.1087)	(227.8687)	(63.4064)	(3.5646)	(95.1664)	(219.4341)	(133.7706)	(159.1530)	(765.6894)	(129.6807)
Input prices (%)																
Price of labor (P_1)	1.4011	1.2963	2.0038	1.0650	1.714248	1.3801	1.8914	1.7582	0.3979	0.7182	0.8862	1.1653	1.5795	1.1866	1.7933	1.0515
	(0.8282)	(0.8605)	(0.8776)	(2.0078)	(1.2502)	(0.9748)	(0.8420)	(1.0022)	(0.3535)	(1.1477)	(0.2894)	(0.6026)	(1.2323)	(0.5498)	(1.7058)	(0.6443)
Price of borrowed funds (P_2)	3.2372	3.9565	2.8996	3.3125	4.867901	4.6322	6.8057	4.1564	6.8547	5.2390	5.1917	6.1672	4.4500	3.2297	3.1456	4.8291
	(0.9282)	(1.0610)	(1.0293)	(1.3383)	(6.0149)	(12.8035)	(3.1665)	(2.8922)	(4.6839)	(2.5897)	(1.2886)	(6.4276)	(8.2275)	(1.6809)	(1.7131)	(2.7948)
Price of physical capital (P_3)	87.3138	568.4903	154.9729	330.4598	400.932894	294.8965	114.5686	138.7337	33.6720	219.2871	114.4839	103.0388	99.2069	744.7346	233.7107	236.3665
	(76.7428)	(694.4088)	(272.9975)	(444.7610)	(578.3759)	(425.2311)	(63.2373)	(212.8516)	(34.8736)	(202.5505)	(372.0884)	(99.7869)	(149.4540)	(855.0085)	(492.3772)	(315.3139)

Note: All values are in millions of real US dollars with a base year of 1985, except for the input prices. Standard deviations are in parenthesis.

Table 2. Maximum-likelihood estimates of the SFA approach and the estimates of the meta-frontier cost function.

Variable	SFA	Meta(LP)	Meta(QP)
Constant	4.1930 (0.1763)	-0.8465 (0.1180)	1.1114 (0.1122)
$\ln Y_1$	-0.1422 (0.0451)	0.6059 (0.0234)	0.2635 (0.0244)
$\ln Y_2$	0.0728 (0.0334)	0.4320 (0.0149)	0.2517 (0.0173)
$\ln Y_3$	0.2636 (0.0279)	-0.0444 (0.0190)	0.2001 (0.0259)
$\ln p_2$	0.5556 (0.0540)	-0.1000 (0.0331)	0.4339 (0.0324)
$\ln p_3$	0.2505 (0.0412)	0.6259 (0.0211)	0.3295 (0.0225)
$\ln Y_4$	-0.0962 (0.0168)	0.1291 (0.0141)	0.0591 (0.0105)
$\ln Y_1 \times \ln Y_1$	0.0605 (0.0084)	-0.0216 (0.0036)	0.0231 (0.0041)
$\ln Y_2 \times \ln Y_2$	0.0247 (0.0057)	-0.0226 (0.0024)	0.0212 (0.0022)
$\ln Y_3 \times \ln Y_3$	0.0451 (0.0014)	0.0086 (0.0024)	0.0165 (0.0025)
$\ln p_2 \times \ln p_2$	0.0242 (0.0133)	-0.4412 (0.0086)	-0.3695 (0.0080)
$\ln p_3 \times \ln p_3$	0.0148 (0.0081)	-0.0023 (0.0022)	0.0065 (0.0028)
$\ln Y_4 \times \ln Y_4$	0.0173 (0.0019)	-0.0050 (0.0012)	-0.0105 (0.0011)
$\ln Y_1 \ln Y_2$	-0.0206 (0.0053)	-0.0349 (0.0018)	-0.0395 (0.0028)
$\ln Y_2 \ln Y_3$	0.0096 (0.0034)	0.0328 (0.0022)	0.0081 (0.0025)
$\ln Y_1 \ln Y_3$	0.0131 (0.0036)	0.0438 (0.0021)	0.0268 (0.0030)
$\ln p_2 \ln p_3$	0.0489 (0.0083)	0.1465 (0.0035)	0.1139 (0.0032)
$\ln Y_1 \ln p_2$	0.0259 (0.0085)	0.1419 (0.0042)	0.0638 (0.0036)
$\ln Y_1 \ln p_3$	-0.0259 (0.0062)	-0.0553 (0.0025)	-0.0244 (0.0024)
$\ln Y_2 \ln p_2$	0.0160 (0.0065)	0.0963 (0.0040)	0.0994 (0.0034)
$\ln Y_2 \ln p_3$	-0.0209 (0.0049)	-0.0601 (0.0019)	-0.0518 (0.0020)
$\ln Y_3 \ln p_2$	-0.0507 (0.0048)	-0.1781 (0.0018)	-0.1424 (0.0017)
$\ln Y_3 \ln p_3$	0.0110 (0.0042)	0.0612 (0.0025)	0.0470 (0.0022)
$\ln Y_4 \ln Y_1$	-0.0016 (0.0025)	0.0243 (0.0018)	0.0288 (0.0014)
$\ln Y_4 \ln Y_2$	0.0036 (0.0021)	0.0097 (0.0014)	0.0145 (0.0012)
$\ln Y_4 \ln Y_3$	-0.0022 (0.0017)	-0.0194 (0.0015)	-0.0251 (0.0010)
$\ln Y_4 \ln p_2$	-0.0254 (0.0029)	-0.0409 (0.0026)	-0.0594 (0.0025)
$\ln Y_4 \ln p_3$	0.0043 (0.0023)	-0.0148 (0.0019)	-0.0027 (0.0015)
Sample size	4977	4977	4977

Note: Numbers in the parentheses of the first column are standard errors and those of the last two columns are bootstrapped standard deviations.

Table 3. Summary statistics of TGRs and CE measures for all sample countries, where the LP estimates are used to calculate the TGRs

Country/Statistic	Mean	Minimum	Maximum	St. Dev.	Country/Statistic	Mean	Minimum	Maximum	St. Dev.
Austria					Luxembourg				
CE	0.7637	0.5514	0.9580	0.0811	CE	0.6188	0.1965	0.9468	0.2052
TGR	0.3588	0.0574	1.0000	0.1691	TGR	0.2153	0.0041	0.9721	0.1802
CE*	0.2732	0.0432	0.8247	0.1322	CE*	0.1289	0.0036	0.7432	0.1124
Belgium					Netherlands				
CE	0.6585	0.4663	0.9518	0.1209	CE	0.6749	0.2397	0.9447	0.1775
TGR	0.4807	0.0294	1.0000	0.2270	TGR	0.3644	0.0007	1.0000	0.2343
CE*	0.3201	0.0168	0.7348	0.1732	CE*	0.2368	0.0004	0.8720	0.1740
Denmark					Norway				
CE	0.6302	0.3321	0.9800	0.1391	CE	0.9435	0.8712	0.9791	0.0265
TGR	0.4807	0.0128	0.9572	0.1951	TGR	0.2781	0.1176	0.8524	0.1386
CE*	0.2930	0.0073	0.7110	0.1168	CE*	0.2626	0.1088	0.8189	0.1315
Finland					Portugal				
CE	0.4731	0.0677	0.9048	0.2525	CE	0.9073	0.5174	0.9944	0.0975
TGR	0.5475	0.0938	1.0000	0.2662	TGR	0.3171	0.0999	0.9073	0.1467
CE*	0.2230	0.0323	0.5939	0.1185	CE*	0.2896	0.0956	0.9016	0.1455
France					Spain				
CE	0.7452	0.1850	0.9857	0.1727	CE	0.8545	0.2048	0.9922	0.1424
TGR	0.4037	0.0004	1.0000	0.1421	TGR	0.3215	0.0258	1.0000	0.1193
CE*	0.3041	0.0002	08824	0.1361	CE*	0.2805	0.0248	0.9785	0.1229
Germany					Sweden				
CE	0.8086	0.1118	0.9913	0.1421	CE	0.8653	0.5120	0.9960	0.1338
TGR	0.4328	0.0078	1.0000	0.1576	TGR	0.4201	0.0413	1.0000	0.2730
CE*	0.3583	0.0072	0.8909	0.1617	CE*	0.3209	0.0427	0.8075	0.1854
Greece					Switzerland				
CE	0.6227	0.3805	0.9071	0.1268	CE	0.6967	0.2590	0.9757	0.1583
TGR	0.4505	0.0846	1.0000	0.1778	TGR	0.4792	0.0160	1.0000	0.1424
CE*	0.2837	0.0615	0.7210	0.1422	CE*	0.3374	0.0113	0.7723	0.1311
Italy					UK				
CE	0.5598	0.1437	0.9668	0.1783	CE	0.6943	0.2768	0.9238	0.1333
TGR	0.5201	0.0108	1.0000	0.1582	TGR	0.1019	0.0035	0.2285	0.0615
CE*	0.2857	0.0100	0.7582	0.1153	CE*	0.0704	0.0027	0.1661	0.0451
Total									
CE	0.7136	0.0677	0.9960	0.1895					
TGR	0.4144	0.0004	1.0000	0.1857					
CE*	0.2923	0.0002	0.9785	0.1485					

Table 4. Mean measures of scale and scope economies using the parameter estimates from the country frontiers and the SFA of Table 2

	Scale economies		Scope economies	
Countries	Country frontier	SFA	Country frontier	SFA
Austria	1.0008	0.6596	-0.8606	0.3754
Belgium	0.9613	0.7263	3.3834	2.0851
Denmark	0.8044	0.5261	17.5990	4.9711
Finland	0.7335	0.8870	1.4067	-0.0068
France	0.8522	0.6197	1.5178	7.3554
Germany	0.9227	0.6089	0.8977	9.5147
Greece	0.7809	0.4772	-0.6414	1.2105
Italy	0.8402	0.6641	104.11	11.6519
Luxembourg	0.7465	0.7322	3.5852	0.0471
Netherlands	0.5352	0.3580	21.4816	32.3907
Norway	0.9622	0.7402	9.2925	-0.0045
Portugal	0.9946	0.6697	-0.7521	0.4000
Spain	0.9323	0.6658	-0.7665	0.7235
Sweden	0.9734	0.7458	53.7467	0.5686
Switzerland	0.9184	0.5938	0.7413	8.1861
UK	0.2046	0.3873	23.1524	2.4414

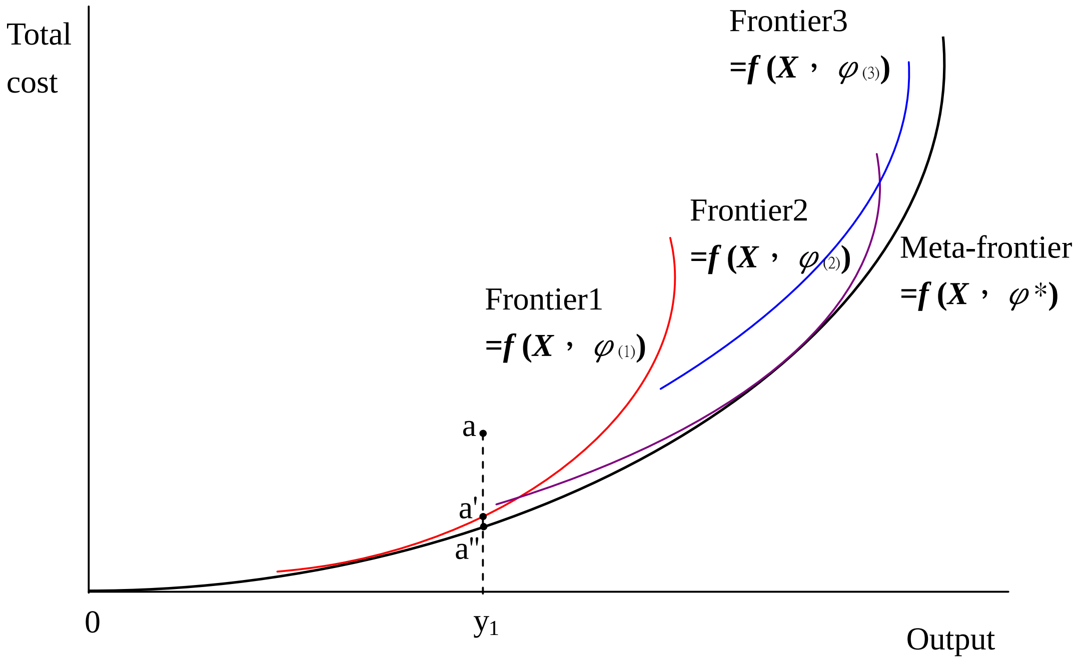


Figure1. Meta-frontier Cost Model

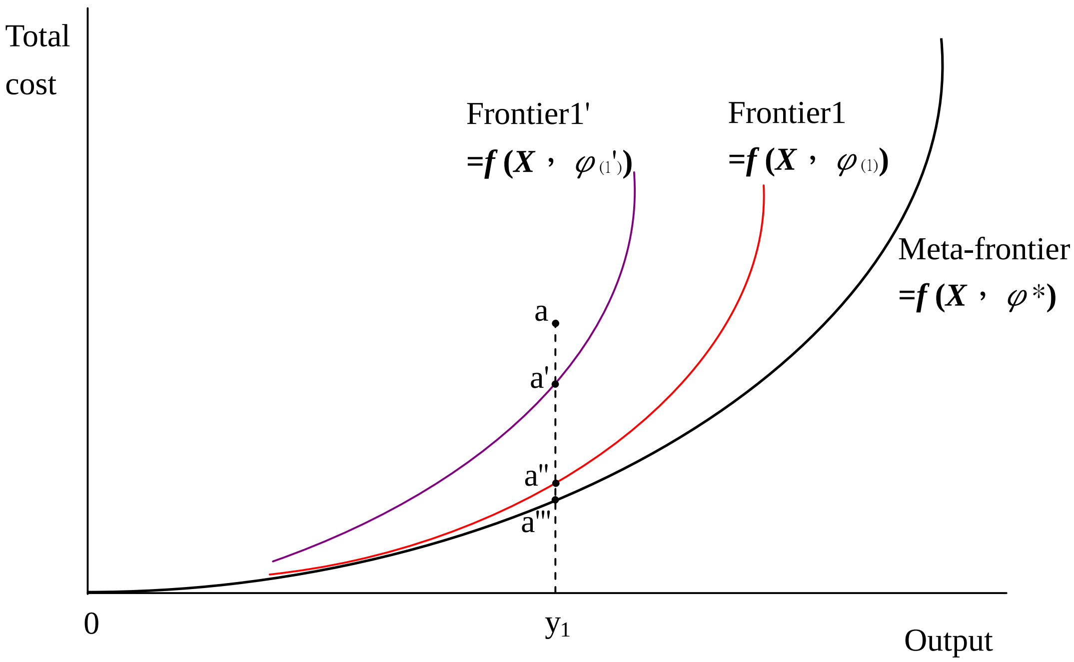
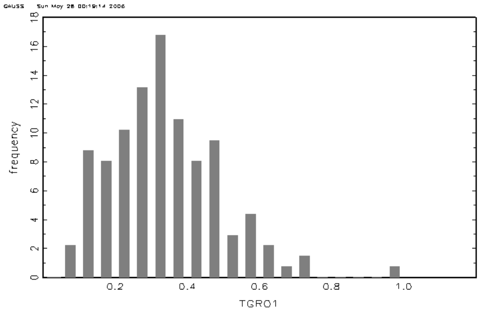
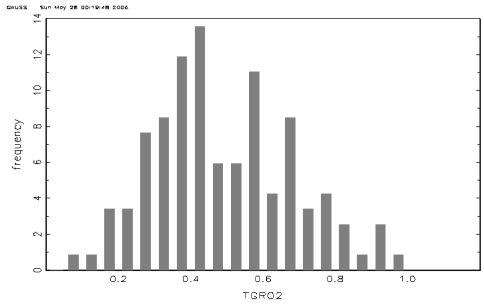


Figure 2. Meta-frontier Cost Model with
Different Levels of Technology



Austria



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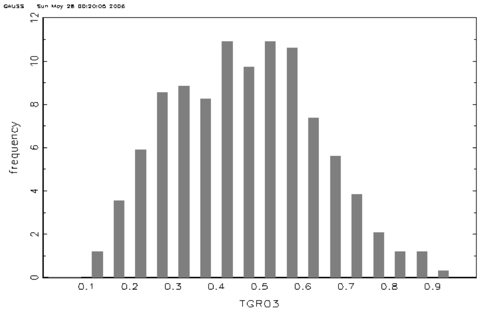
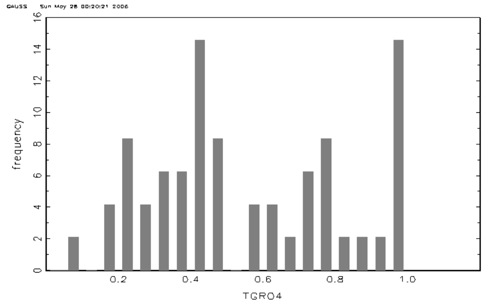
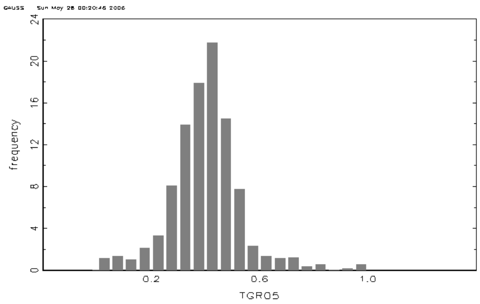


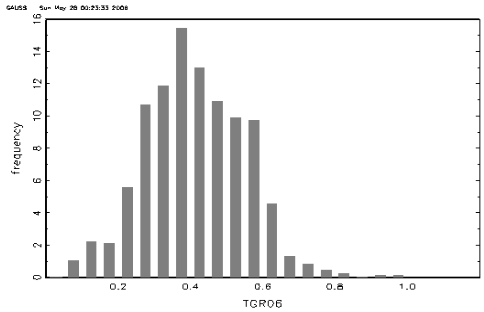
Denmark



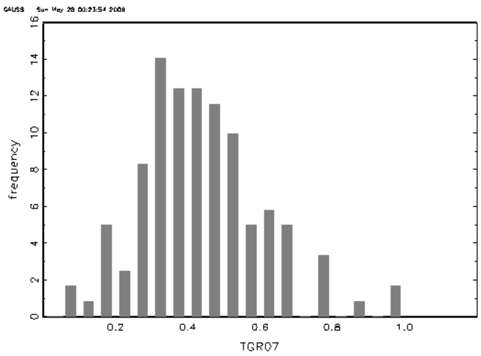
Finland



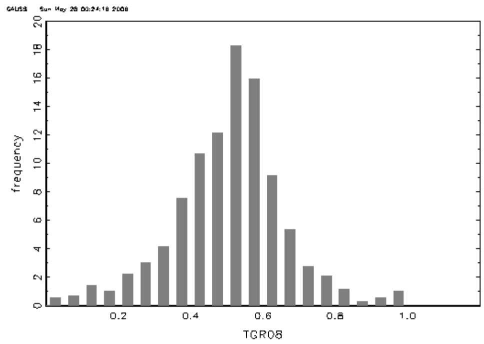
France



Germany

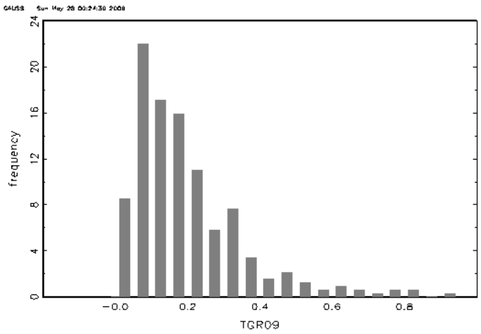


Greece

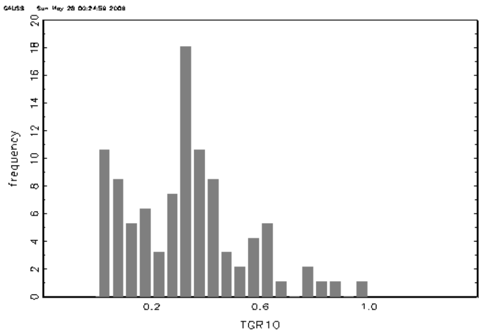


Italy

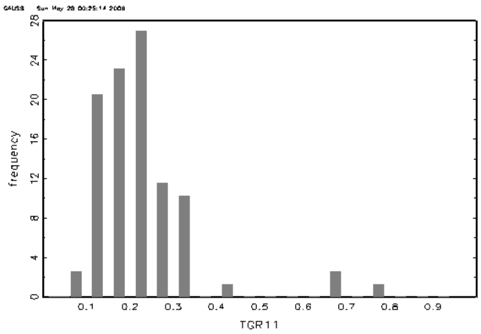
Figure 3. Frequency Distributions of TGRs in Different Countries



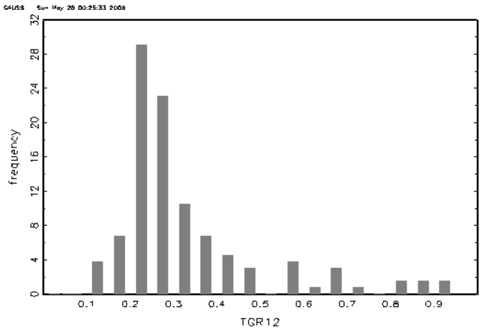
Luxembourg



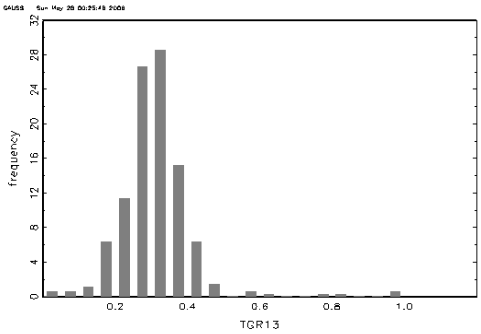
Netherlands



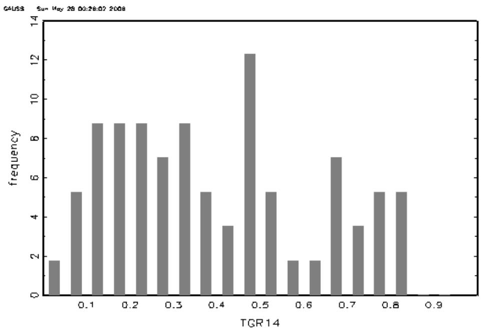
Norway



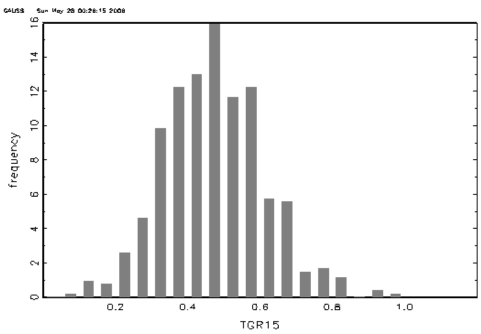
Portugal



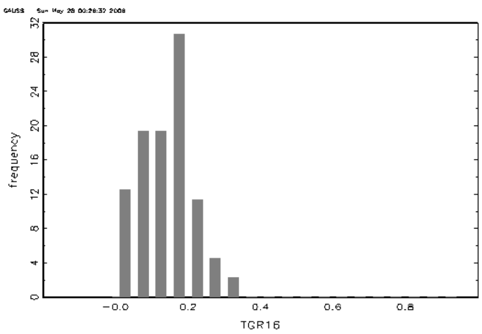
Spain



Sweden



Switzerland



UK

Figure 3. Frequency Distributions of TGRs in Different Countries (cont'd).

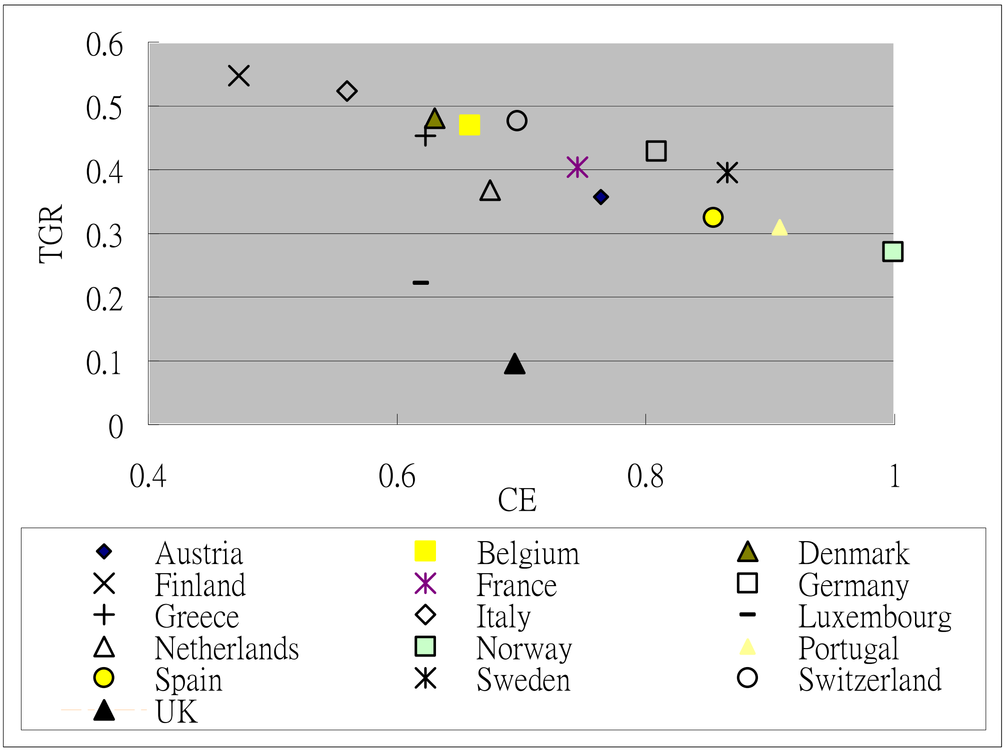
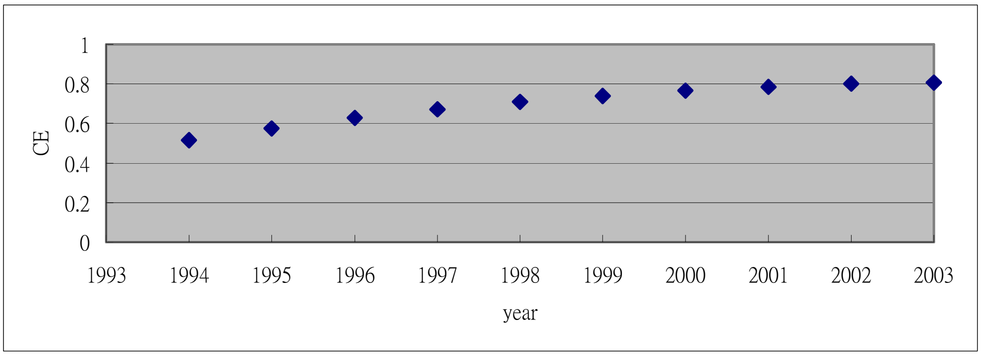


Figure 4. Scatter Diagram Relating the Means of CE to the Means of TGR



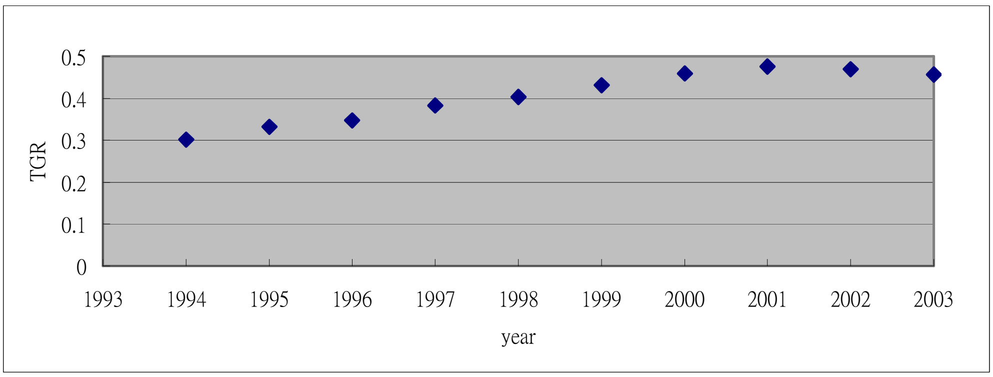


Figure 5. Mean Values of CE and TGR over Time