The Manchester School Vol 79 No. 4 839–860 July 2011
doi: 10.1111/j.1467-9957.2010.02178.x

AN EMPIRICAL STUDY OF BANK EFFICIENCIES AND TECHNOLOGY GAPS IN EUROPEAN BANKING*

by
TAI-HSIN HUANG
National Chengchi University, Taiwan
LI-CHIH CHIANG
Hsing Wu College, Taiwan
and
KUAN-CHEN CHEN
National Chengchi University, Taiwan

This paper extends the established literature on modeling the cost structures of Europe's banking sectors by combining the Fourier flexible cost function with time-varying technical efficiency (TE) under the framework of the meta-frontier, as proposed by Battese *et al.* (*Journal of Productivity Analysis*, Vol. 21 (2004), pp. 91–103) and O'Donnell *et al.* (*Empirical Economics*, Vol. 34 (2008), pp. 231–255). We find multiple technologies prevail in the nine sample countries, justifying the use of the meta-cost frontier. Measures TE and technology gap ratios are found to be positively correlated with each other, implying that a relatively technically efficient bank is possibly technologically efficient and vice versa.

1 Introduction

The European Union (EU) was established in 1992 by the Treaty on European Union (the Maastricht Treaty). On the basis of the treaty, the European Economic and Monetary Union (EMU) was set up as well, which put 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. During the 1990s, banks in the EU countries faced dramatic structural changes, and the number of them in operation has since decreased dramatically. 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.

In the ongoing integration of European markets for banking services, it is crucial to understand and to compare the differences or similarities in

* Manuscript received 27.5.09; final version received 9.11.09.

Published by Blackwell Publishing Ltd, 9600 Garsington Road, Oxford OX4 2DQ, UK, and 350 Main Street, Malden, MA 02148, USA.

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. The implementation of the Single Banking Market during the 1990s considerably lowered barriers to competition among European banks and prompted them to expand branches abroad within the nations of the EU. As noted by Goddard *et al.* (2007), the banks' reactions to the shifting competitive environment consist of undertaking strategies of diversification, vertical product differentiation and consolidation. European integration has influenced the extent of competition in banking markets and the associations between ownership structure, technological change and bank efficiency. The financial markets have now become so competitive and so integrated that it is necessary to understand the sources of banks' efficiency differences among member states.

There exists a substantial amount of literature that applies either a parametric or non-parametric approach to investigate a bank's efficiency. The former group mainly includes the stochastic frontier approach (SFA) and the distribution-free approach (DFA).[1] A few cross-country comparisons with respect to European banking performance have been conducted, using either or both the parametric and non-parametric approaches. Weill (2004) made an excellent review on country-specific studies for France, Germany, Italy, Spain, the UK and Switzerland, and cross-country comparisons particularly for European countries. In particular, he noted that the average efficiency scores in the five European countries range from 0.8 to 0.9 in many cases and are relatively dispersed due to the dissimilarity of samples and time periods under consideration.

The SFA was initially developed by Aigner *et al.* (1977) and Meeusen and van den Broeck (1977) nearly simultaneously in the context of cross-section data. Schmidt and Sickles (1984) suggested using panel data to conduct an estimation of technical efficiency (TE) in an attempt to avoid some difficulties with cross-sectional stochastic frontier models. Earlier panel data models all relied on the assumption of time-invariant efficiency. The maintained assumption was relaxed by Cornwell *et al.* (1990), whose temporal variation in technical inefficiency (TI) is modeled through the intercept of the production frontier. The time-varying TI model proposed by Battese and Coelli (1992) is particularly adopted by this paper.

Several previous papers, e.g. Allen and Rai (1996), Altunbas *et al.* (2001) and Vennet (2002) to mention a few, estimated a global cost frontier for all

[1]The DFA approach was introduced by Berger (1993) based on a translog system of cost and input share equations. This approach avoids imposing specific assumptions on the distributions of the composed error terms like the SFA does. It only assumes that efficiencies are stable over time while random error tends to average out. Although having a balanced panel data set from US commercial banks, spanning 1980 to 1989, Berger (1993) estimated the translog cost function by ordinary least squares for each period and averaged the 10 residuals for each bank in an attempt to cancel out random errors. In this manner, he obtained an estimate of the X-efficiency factor for each sample bank.

banks from different countries, implicitly assuming that banks from various countries share a common production technology. This presumption likely overlooks the fact that national variations in, for example, economic systems, regulatory conditions and natural environments, affect bank managers' capabilities and willingness towards swiftly responding to market conditions and adopting technical innovations. Weill (2004) estimated individual national frontiers rather than one common frontier for all sample countries in the context of SFA, DFA and DEA (data envelopment analysis) in order to measure the TE of banks in five European countries (France, Germany, Italy, Spain and Switzerland) during the period 1992–98. Since each country has its own production frontier, the relative TE scores of different countries are not directly comparable. This difficulty can be at least partially solved by applying the meta-frontier technique.

This paper attempts to examine the performance of commercial banks across nine European countries and covering 10 years. Recall that the TE 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 fail to tell the differences in the various technologies used 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 and Rao (2002) and Battese *et al.* (2004), but further extend the investigation from a primal production function to a dual cost function. A cost function is known as allowing for the consideration of multiple outputs, a desired characteristic of financial systems, rather than a single output. This technique enables us to calculate TEs for banks operating under different technologies as well as the technology gap ratios (TGRs), which measure the extent to which the cost frontiers of individual countries deviate from the meta-frontier cost function. O'Donnell *et al.* (2008) showed how a meta-frontier model can be estimated using non-parametric (DEA) and parametric methods and applied the model to estimate cross-country agricultural sector data.

Although the translog functional form has been widely used for studies of economies of scale and scope, mergers and acquisitions, and technical and allocative efficiencies, it is frequently criticized as being merely able to locally approximate a true but unknown cost function. Specifically, McAllister and McManus (1993) found that the translog function forces large and small banks to lie on a symmetric U-shaped ray average cost curve.[2] They argued that fitting a single parametric cost function across all sizes of banks may bias estimates of scale economies. We instead adopt the Fourier flexible (FF) function form, initiated by Gallant (1981, 1982), due to its ability at globally

[2]Following Baumol *et al.* (1982), the ray average cost of producing an array of outputs $Y \neq 0$ is defined by $C(Y)/\Sigma_{h=1}^{H} Y_h$, where $C(Y)$ is the cost function and H denotes the number of outputs.

approximating the true function as closely as desired in Sobolev norm.[3] The FF function has been extensively applied by, for example, Mitchell and Onvural (1996), Berger and DeYoung (1997), Berger *et al*. (1997), Berger and Mester (1997), DeYoung *et al.* (1998), Altunbas *et al*. (2000, 2001) and Huang and Wang (2004), specific to the investigation of financial institutions.

We argue here for the appropriateness of the cost function for use in the regulatory analysis of financial institutions, because cost minimization and profit maximization are possibly suitable behavioral objectives in banking. We particularly select cost minimization over profit maximization, because it is a well-defined function and because there are problems precisely evaluating some output prices from the Bankscope data bank along with possible negative profit levels.[4] The cost frontier approach to inefficiencies of financial institutions results in a better measure for regulators (lawmakers, supervisory agencies, antitrust authorities etc.) to use when gauging the costs and benefits to society from distinct policies versus the conventional approach to inefficiencies based on a production frontier. This arises from the fact that an estimation of a production frontier requires that producers produce a single output without using information on input prices and total expenditure on the inputs used. Moreover, the adoption of the cost function implicitly assumes the exogeneity of the output variables, which is perhaps reasonable since banks offer a variety of financial products to their customers and these products are primarily exogenously determined beyond the control of individual banks.

The rest of the paper is organized as follows. Section 2 introduces a meta-frontier cost function and defines a number of efficiency concepts. Section 3 describes the data and the definitions of input and output variables, while in Section 4 the TE scores and TGRs for each bank in each sample country are empirically evaluated under the framework of the meta-frontier cost model. The last section concludes the paper.

[3]The following definition of Sobolev norm is taken from Gallant (1982). A flexible function $g_K(x|\theta)$ is able to achieve close approximation to the true function $g(x)$ in Sobolev norm, if it is possible to choose a sequence of coefficients $\theta_1, \theta_2, \ldots, \theta_K, \ldots$, where the length of the vector θ_K may be dependent on K such that:

$$\|g - g_K(\theta)\|_{l,p,\mu} = o\left(K^{-m+l+\varepsilon}\right) \qquad \text{as } K \to \infty$$

for any $\varepsilon > 0$. Integer m denotes the number of times that g is differentiable and l is the largest-order partial derivative regarded as being important in the approximation. Notation '$o(K^{-m+l+\varepsilon})$ as $K \to \infty$' means:

$$\lim_{K\to\infty} K^{m-l-\varepsilon} \|g - g_K(\theta)\|_{l,p,\mu} = 0$$

[4]For example, to highlight the trend of financial systems in Europe to universal banking, we define non-interest revenues as a type of financial product that does not allow for calculating its price. Bos and Schmiedel (2007) estimated both profit and cost functions on data covering 15 European countries, where the independent variables of the profit equation are the same as those of the cost equation—i.e. the profit equation is specified as a function of output quantities and input prices.

2 Methodology

2.1 The FF Cost Function

The FF function form includes a standard translog and the first-order and the second-order trigonometric terms. Under the framework of the SFA, it is formulated as

$$\begin{aligned}\ln C_{it} &= \alpha_0 + \sum_{h=1}^{H}\alpha_h \ln Y_{hit} + \sum_{j=1}^{J}\beta_j \ln W_{jit} \\ &\quad + \frac{1}{2}\left(\sum_{h=1}^{H}\sum_{k=1}^{H}\delta_{hk}\ln Y_{hit}\ln Y_{kit} + \sum_{j=1}^{J}\sum_{m=1}^{J}\gamma_{jm}\ln W_{jit}\ln W_{mit}\right) \\ &\quad + \sum_{h=1}^{H}\sum_{j=1}^{J}\rho_{hj}\ln Y_{hit}\ln W_{jit} + \sum_{h=1}^{H}[a_h\cos(z_{hit}) + b_h\sin(z_{hit})] \\ &\quad + \sum_{h=1}^{H}\sum_{k=1}^{H}[a_{hk}\cos(z_{hit}+z_{kit}) + b_{hk}\sin(z_{hit}+z_{kit})] + U_{it} + V_{it} \qquad (1)\end{aligned}$$

Here, C_{it} is the actual costs of bank i at time t, Y_h ($h = 1, \ldots, H$) denotes the hth output and W_j ($j = 1, \ldots, J$) is the jth input price. Notation z_h is the re-scaled values of the logarithm of output h such that it spans the interval [0, 2π].[5] For details please see, for example, Berger *et al.* (1997) and Altunbas *et al.* (2001). In addition, U_{it} denotes the TI and is further specified as $U_{it} = U_i \exp[-\eta(t - T)]$, where U_i is distributed as $|N(\mu, \sigma_u^2)|$ with μ as an unknown and time-invariant parameter, and V_{it} signifies a two-sided error term that is identically and independently distributed as $N(0, \sigma_v^2)$. Both V_{it} and U_i are assumed to be mutually independent.[6]

Notations α, β, δ, γ, ρ, a and b are unknown parameters to be estimated. Battese and Coelli (1992) derived the log-likelihood function of the composed error term $\varepsilon_{it} = U_{it} + V_{it}$ and hence it is ignored here. Software Frontier 4.1 (Coelli, 1996) is used to estimate equation (1) later. The software provides coefficient estimates, standard errors, estimated variance–covariance matrix and efficiency scores for each firm over time. The parameter estimates of equation (1) will be used to compute the overall scale economies (OSE), defined as

[5]The output variables are rescaled by letting $z_h = \lambda_h(\ln Y_h + \ln d_h)$, where $\lambda_h = 6/(\ln Y_h^{\max} + \ln d_h)$, $h = 1, \ldots, H$, $\ln d_h = 0.00001 - \ln Y_h^{\min}$, and $Y_h^{\max}$ and $Y_h^{\min}$ are the maximum and minimum values of output h in the sample, respectively. The λ_h s are chosen to force the largest observations of each scaled log-output variable to be equal to 6, falling short of 2π, while $\ln d_h$ s are limited to make the smallest observations slightly greater than zero.

[6]Bos and Schmiedel (2007) assumed that U_{it} is distributed as a standard truncated normal and treated the data set as if it were cross-sectional.

$$\text{OSE} = \frac{\sum_{i=1}^{3} Y_h C_h(W, Y)}{C(W, Y)} \tag{2}$$

where C_h denotes the partial derivative of C with respect to the hth output. Returns to scale are increasing, constant or decreasing, as OSE is less than, equal to or greater than unity, respectively.

2.2 Meta-frontier FF Cost Function and Technology Gaps

Suppose that there are R different countries in the sample and that each country r has N_r banks which face exogenous input prices and output quantities and attempt to optimize the cost which is entailed in manufacturing the outputs. The stochastic cost frontier model for each bank i of country r at time t can be given as

$$\begin{aligned} &C_{it(r)} = e^{X_{it(r)}\varphi_{(r)} + V_{it(r)} + U_{it(r)}} \\ &i = 1, 2, \ldots, N_r \qquad t = 1, 2, \ldots, T \qquad r = 1, 2, \ldots, R \end{aligned} \tag{3}$$

where $C_{it(r)}$ presents the total costs, $X_{it(r)}$ is a vector of output quantities and input prices, $\varphi_{(t)}$ is the corresponding unknown technology parameter vector to be estimated, and $V_{it(r)}$ and $U_{it(r)}$ are defined above. Term $X_{it(r)}\varphi_{(r)}$ takes exactly the FF form shown in equation (1).

The meta-frontier is assumed to have the same functional form as the stochastic frontiers in the different countries. In this manner, the meta-frontier cost function for all banks is given by

$$\begin{aligned} &C_{it}^{*} = e^{X_{it}\varphi^{*}} \\ &i = 1, 2, \ldots, \qquad N = \sum_{r=1}^{R} N_r \qquad t = 1, 2, \ldots, T \end{aligned} \tag{4}$$

where C_{it}^{*} is the minimum expenditure incurred by bank i at time t, and φ^{*} is the corresponding parameter vector associated with the meta-frontier FF cost function such that

$$X_{it}\varphi^{*} \le X_{it}\varphi_{(r)} \tag{5}$$

The meta-frontier FF function is defined as a deterministic parametric function such that its values must be less than or equal to the deterministic components of the stochastic FF cost frontier of the different countries involved. The inequality constraint of equation (5) holds for all countries and time periods. Figure 1 draws the stochastic FF cost frontiers for three countries in the case of a single output and are denoted by Frontier 1, Frontier 2 and Frontier 3. A meta-frontier FF function is drawn as an envelope curve which surrounds the three stochastic frontiers from below, indicating that it entails production costs that are no more than the deterministic costs

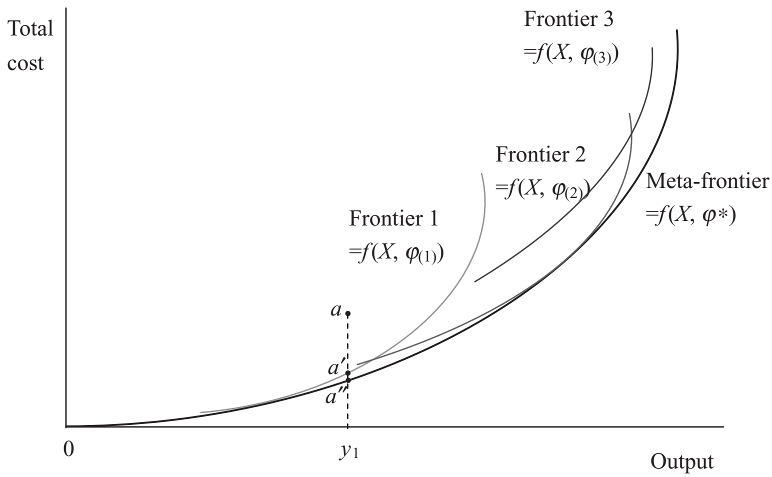

FIG. 1 Meta-frontier Cost Model

correlated with the stochastic cost frontiers for the respective countries involved. Frontier 1 and Frontier 2 are arbitrarily chosen to be tangent to the meta-frontier, whereas Frontier 3 is not.

TE is evaluated by the extent to which a bank's actual cost exceeds its efficient country-specific cost frontier. The measure of overall technical efficiency (OCE*) for bank i at time t in country r is formulated by the ratio of the minimum cost, evaluated by the meta-frontier cost, to the observed cost and adjusted by the corresponding random error:

$$\mathrm{OCE}^{*}_{it(r)} = \frac{e^{X_{it}\varphi^{*}+V_{it(r)}}}{C_{it(r)}} \tag{6}$$

Substituting equation (3) into (6), we obtain

$$\mathrm{OCE}^{*}_{it(r)} = \frac{e^{X_{it}\varphi^{*}+V_{it(r)}}}{e^{X_{it}\varphi_{(r)}+V_{it(r)}+U_{it(r)}}} = e^{-U_{it(r)}} \times \frac{e^{X_{it}\varphi^{*}}}{e^{X_{it}\varphi_{(r)}}} \tag{7}$$

The first term on the right-hand side of equation (7) is the conventional TE relative to the stochastic frontier of country r, denoted by TE. The second term is defined by the TGR, i.e.

$$\mathrm{OCE}^{*}_{it(r)} = \mathrm{TE}_{it(r)} \times \mathrm{TGR}_{it(r)} \tag{8}$$

The TGR mainly measures the degree of technology gap for country r whose currently available technology adopted by its banks is inferior to the technology available for all countries. We assess the TGR using the ratio of the potential cost that is defined by the meta-frontier FF function to the cost for the frontier FF function for country r, holding the observed outputs and input prices constant. It must have a value between zero and one due to restriction equation (5), leading the OCE measure to lie between zero and one as well. The OCE 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 in order to produce a given output mix. These benchmark firms operate on the meta-cost frontier, i.e. they use the best available technology in the production process.

Let point *a* of Fig. 1 represent bank *a*'s actual cost in country 1, and its TE with reference to the country-specific cost frontier is measured by $\mathrm{TE}_{it(1)} = a'y_1/ay_1$. Bank *a*'s TGR is evaluated by $\mathrm{TGR}_{it(1)} = a''y_1/a'y_1$. Using equation (8), its OCE measure is equal to $\mathrm{OCE}^*_{it(1)} = \mathrm{TE}_{it(1)} \times \mathrm{TGR}_{it(1)} = a''y_1/ay_1$.

In line with Battese *et al.* (2004), there are two alternative ways to identify the benchmark technology.

I. Minimum sum of absolute deviations
$\hat{\varphi}^*$ is yielded by solving the optimization problem:

$$\min L^* \equiv \sum_{t=1}^{T}\sum_{i=1}^{N}|\ln f(X_{it}, \hat{\varphi}_{(r)}) - \ln f(X_{it}, \varphi^*)| \tag{9}$$

$$\text{subject to} \quad \ln f(X_{it}, \varphi^*) \le \ln f(X_{it}, \hat{\varphi}_{(r)}) \tag{10}$$

Equations (9) and (10) state that the estimated meta-frontier minimizes the sum of absolute logarithms of $f(X_{it}, \hat{\varphi}_{(r)})/f(X_{it}, \varphi^*)$, which represents the reciprocal of the radial distance between the meta-frontier and the frontier of country *r*.

II. Minimum sum of squares of deviations
$\hat{\varphi}^*$ is estimated by solving a quadratic programming (QP) problem:

$$\min L^{**} \equiv \sum_{t=1}^{T}\sum_{i=1}^{N}(X_{it}\hat{\varphi}_{(r)} - X_{it}\varphi^*)^2 \tag{11}$$

$$\text{subject to} \quad X_{it}\varphi^* \le X_{it}\hat{\varphi}_{(r)} \tag{12}$$

Standard errors of the estimators for the two meta-frontier functions are obtained by bootstrapping methods. The advantage of the bootstrap is that one does not need to know the underlying data generation process, unlike the Monte Carlo simulation. The bootstrap is frequently exploited by applied econometric researchers when an analytic estimate of the standard error of an estimator is hardly calculated, like the case in this paper.

3 Data Source and Variable Definitions

Similar to Altunbas *et al.* (2001), Weill (2004) and Bos and Schmiedel (2007), the main data source is compiled from the Bankscope database spanning 1994 to 2003. As this paper aims to compare similar banks operating in different markets, we pay attention to commercial banks. Table 1 presents that the characteristics of our sample banks are close to those of the aforementioned papers. We use unconsolidated accounting data for 689 commercial banks in nine European countries, i.e. Austria, Belgium, Denmark, France, Germany, Italy, Portugal, Spain and Switzerland, after deleting incomplete observations.[7] Those banks with at least three years of observed data are selected, making the sample unbalanced panel data. The total number of observations is 4220. All the nominal variables have been transformed into real terms by the consumer price index of individual countries with base year 1995.

This paper follows the popular intermediation approach, which views a bank as an intermediary between depositors and borrowers, in order to define a bank's outputs and inputs. Specifically, three output categories can be identified: loans (Y_1), investments (Y_2) and non-interest revenues (Y_3). The first two outputs are commonly used in the literature, while the last output is used to reflect the importance of a bank's non-traditional activities. We identify three inputs, i.e. physical capital (X_1), borrowed funds (X_2) and labor (X_3), which are quite standard in the literature. The price of physical capital (W_1) is computed as the ratio of other non-interest expenses to fixed assets. The price of borrowed funds (W_2) is measured by the ratio of paid interest to all funding. As data on the number of employees are missing for quite a few banks, the price of labor (W_3) is defined as the ratio of personnel expenses to total assets. Altunbas *et al*. (2000, 2001), Weill (2004), Bos and Schmiedel (2007) and others used similar definitions, except for Y_3. Total costs are the sum of the above three types of expenditure.

Table 1 summarizes descriptive statistics and the distributions of the sample banks among countries. The sample contains small- to large-scaled banks such that most of the variables have quite large standard deviations relative to their sample means. Moreover, there are considerable differences across the sample nations.

[7]We have tried to extract data from the other West European countries. The resultant data contain a relatively small number of observations and hence are ignored, because the FF cost function involves extra trigonometric terms that require a larger sample size in order to have enough degrees of freedom. One of the characteristics owned by a FF cost function is that the number of the trigonometric terms is dependent upon the sample size. More specifically, Chalfant and Gallant 1985), Eastwood and Gallant (1991) and Mitchell and Onvural (1996) recommended that the number of coefficients equals the number of effective sample points raised to the two-thirds power for the sake of producing bias-minimizing and asymptotically normal estimates. Eastwood (1991) proposed an upward F test truncation rule to determine the number of parameters to be estimated so that the estimators are consistent and asymptotically normal. Also see Huang and Wang (2004) for an application of both rules. This paper chooses the number of trigonometric terms up to the second order, as shown in the last line of equation (1). Although terms involving higher orders are legitimate, the price is the loss of the degrees of freedom.

Table 1
Descriptive Statistics

Variable	*Austria*	*Belgium*	*Denmark*	*France*	*Germany*	*Italy*	*Portugal*	*Spain*	*Switzerland*
Total number of banks	21	30	48	155	141	120	22	58	94
Total number of observations	137	187	339	904	858	762	134	362	537
Total cost[a]	342.0152	1167.265	173.9057	624.3617	601.6766	441.7648	221.4476	314.2474	498.0184
	(738.4505)	(3675.096)	(525.9168)	(2021.889)	(2524.793)	(1118.801)	(298.1051)	(770.0886)	(2430.416)
Outputs									
Total loans (Y_1)[a]	5752.409	7225.775	2476.789	6359.059	8570.908	5146.058	2173.042	3993.13	7100.584
	(11817.73)	(16277.07)	(7901.521)	(20593.39)	(35254.7)	(12781.83)	(2897.741)	(9237.666)	(34459.6)
Total investments (Y_2)[a]	1176.849	3416.71	1063.206	2463.28	2853.299	1278.187	506.1777	1280.924	2393.666
	(2678.022)	(7215.941)	(3947.685)	(9506.188)	(15127.12)	(3135.284)	(750.3299)	(4187.907)	(14168.81)
Non-interest revenue (Y_3)[a]	47.04695	521.167	39.99939	129.5784	121.7847	97.76005	110.3945	59.68363	168.7931
	(75.09649)	(1150.097)	(140.0078)	(528.0417)	(615.476)	(227.9904)	(219.4341)	(133.6222)	(767.7259)
Input prices									
Price of physical capital (W_1)	0.0873138	5.33596	1.549729	4.018975	2.956362	1.388497	1.030388	0.992091	2.344001
	(0.767428)	(6.232226)	(2.729975)	(5.790903)	(4.257878)	(2.129666)	(0.997869)	(1.492468)	(4.935645)
Price of borrowed funds (W_2)	0.032372	0.076208	0.028996	0.048651	0.04636	0.041598	0.061672	0.044517	0.031389
	(0.009282)	(0.122387)	(0.010293)	(0.060233)	(0.128257)	(0.028925)	(0.064276)	(0.082162)	(0.017107)
Price of labor (W_3)	0.014011	0.022089	0.020038	0.017111	0.013804	0.017592	0.011653	0.015757	0.018001
	(0.008282)	(0.035197)	(0.008776)	(0.0124)	(0.009764)	(0.010026)	(0.006026)	(0.012327)	(0.017082)

Note: [a]All values are in real millions dollars, with base year 1995. Standard deviations are in parentheses.

4 Empirical Results

4.1 Parameter Estimates

We estimate both the FF cost function of equation (1) and the standard translog cost function for each of the nine countries. Table 2 merely summarizes the translog part of the parameter estimates of the FF cost function, and the parameter estimates of the trigonometric part are overlooked to save space. Parameter estimates of the standard translog cost function are not shown to save space, but available upon request to the authors. According to Table 2, more than one-half of the parameter estimates of each country frontier (except for Austria) attain statistical significance at least at the 10 per cent level. The null hypothesis—that the coefficients of the Fourier series (the trigonometric terms) are joint zero—is decisively rejected in each country using the likelihood ratio test. One is led to infer that the FF cost function is more relevant than the translog form in representing an average bank's production technology and underlying cost structure.

Evidence is found that seven countries have significant estimates of η, implying that the TI evolves with time in most of the sample states. Five out of the seven significant η estimates are negative, suggesting that banks' TEs in Austria, Belgium, France, Spain and Switzerland deteriorate over time at an increasing rate. In other words, those banks' actual production costs deviate away from their respective country frontiers, which themselves shift over time due to the presence of technological advancement. Banks' TEs in Denmark and Italy improve over time, as their η estimates are positive. Banks' actual production costs in the two nations move closer to their respective country frontiers, which shift over time as well. The remaining η estimates fail to attain statistical significance, meaning that banks' TEs in Germany and Portugal are potentially time-invariant during the sample period.

Table 3 uses the acronyms SFA-POOL, MF-LP and MF-QP to represent three models, in which SFA-POOL is the FF cost frontier estimated by the maximum likelihood by pooling all observations of the nine countries together, and MF-LP and MF-QP are the meta-frontier FF cost functions estimated by, respectively, solving the linear and quadratic mathematical programming problems using the same data. Similar results from the standard translog counterparts are not shown. It is noteworthy that the estimates of the SFA-POOL model are regarded as a mixture of the corresponding estimates in Table 2 across the nine states, since the model is estimated using the entire sample points without imposing constraint like equation (10) or (12).

The estimation of the pooled model of SFA-POOL permits us to formally test for the differences among the group-specific frontiers. A likelihood ratio test can now be performed to check for the null hypothesis that all country-specific FF cost frontiers are the same. Since the value of the likeli-

TABLE 2
PARAMETER ESTIMATES OF THE FF COST FRONTIERS FOR THE SAMPLE COUNTRIES

Variable	*Austria*	*Belgium*	*Denmark*	*France*	*Germany*	*Italy*	*Portugal*	*Spain*	*Switzerland*
Constant	9.0943**	0.5749	13.8479*	0.5857	–3.8755***	1.0755***	1.2045	3.0265	2.6850*
	(4.1115)	(0.9301)	(8.0320)	(0.9474)	(0.9582)	(0.3997)	(0.9608)	(5.6858)	(1.4955)
ln Y_1	–0.6644	0.4017	–0.5148	0.6323***	–0.0966	0.5724***	0.2565	0.9787***	0.7253*
	(1.3155)	(–0.2782)	(0.4292)	(0.2783)	(0.4885)	(0.1621)	(0.4765)	(0.4000)	(0.4274)
ln Y_2	0.1616	1.4838***	0.6744***	0.5144***	3.4704***	0.5321***	0.7589	0.5335***	–0.0781
	(1.1601)	(–0.1637)	(0.2468)	(0.0745)	(0.5241)	(0.1138)	(0.5693)	(0.2075)	(0.2814)
ln Y_3	0.8359	0.1206	–1.0535*	0.1533**	0.1539	0.1751*	0.2918	0.0804	–0.0795
	(1.1572)	(0.2827)	(0.6536)	(0.0630)	(0.5325)	(0.0908)	(0.5358)	(0.5205)	(0.2147)
ln W_2	1.1995**	0.4076***	0.3308***	0.4370***	0.9407***	0.2183***	–0.5121	–0.0581	0.1676**
	(0.5347)	(0.0898)	(0.1001)	(0.0326)	(0.1583)	(0.0496)	(0.4711)	(0.0890)	(0.0862)
ln W_3	0.2723	0.6567***	0.4277***	0.4026***	0.1219	0.7208***	0.7608*	0.9189***	0.7614***
	(0.4676)	(0.0765)	(0.0743)	(0.0254)	(0.1235)	(0.0417)	(0.4132)	(0.0777)	(0.0795)
ln Y_1 ln Y_1	0.0552	0.0531***	0.1716***	0.0666***	0.0784*	0.0764***	0.0977**	0.0440	0.0558***
	(0.0869)	(0.0221)	(0.0357)	(0.0174)	(0.0421)	(0.0137)	(0.0506)	(0.0329)	(0.0254)
ln Y_2 ln Y_2	0.0015	–0.0245**	0.0442**	0.0229***	–0.2093***	0.0485***	0.0529	0.0391**	0.0955***
	(0.1101)	(0.0128)	(0.0209)	(0.0065)	(0.0431)	(0.0126)	(0.0613)	(0.0184)	(0.0229)
ln Y_3 ln Y_3	–0.1367	–0.0238	–0.1578	0.0025	0.0338	–0.0048	–0.0824	–0.0557	0.0144
	(0.1757)	(0.0325)	(0.1273)	(0.0080)	(0.0548)	(0.0143)	(0.0736)	(0.0927)	(0.0187)
ln Y_1 ln Y_2	–0.0234	–0.0862***	–0.1631***	–0.1050***	–0.1066***	–0.1174***	–0.1531***	–0.1225***	–0.1119***
	(0.0849)	(0.0225)	(0.0210)	(0.0056)	(0.0227)	(0.0082)	(0.0419)	(0.0162)	(0.0256)
ln Y_1 ln Y_3	0.0024	0.0114	–0.0058	–0.0310***	0.0270	–0.0209***	–0.0224	–0.0511	–0.0170
	(0.1009)	(0.0417)	(0.0317)	(0.0051)	(0.0177)	(0.0074)	(0.0452)	(0.0390)	(0.0211)
ln Y_2 ln Y_3	–0.0175	–0.0321	0.0374	0.0221***	0.0211	–0.0122*	0.0405	0.0329*	–0.0017
	(0.0856)	(0.0334)	(0.0257)	(0.0040)	(0.0161)	(0.0064)	(0.0328)	(0.0197)	(0.0170)
ln W_2 ln W_2	–0.0519	0.1298***	0.0979***	0.0764***	–0.0397**	0.0579***	0.0826**	0.0578***	0.1047***
	(0.0817)	(0.0079)	(0.0141)	(0.0032)	(0.0192)	(0.0068)	(0.0446)	(0.0126)	(0.0122)
ln W_2 ln W_3	0.0563	–0.2796***	–0.1998***	–0.1250***	0.0831***	–0.1189***	–0.2882***	–0.1186***	–0.2122***
	(0.1539)	(0.0129)	(0.0218)	(0.0046)	(0.0318)	(0.0105)	(0.0553)	(0.0160)	(0.0212)
ln W_3 ln W_3	0.0018	0.1596***	0.0865***	0.0542***	–0.0050	0.0788***	0.0926***	0.0642***	0.1130***
	(0.0937)	(0.0065)	(0.0104)	(0.0030)	(0.0164)	(0.0062)	(0.0306)	(0.0083)	(0.0113)
ln W_2 ln Y_1	–0.0103	–0.0830***	–0.0195	0.0175***	–0.0400*	0.0208**	0.0264	0.1310***	0.0252
	(0.1357)	(0.0175)	(0.0189)	(0.0066)	(0.0227)	(0.0084)	(0.0549)	(0.0181)	(0.0209)

$\ln W_2 \ln Y_2$	–0.1102	–0.0272***	0.0370**	0.0164***	0.1453***	0.0183***	0.0682**	–0.0148	–0.0134
	(0.1159)	(0.0109)	(0.0169)	(0.0040)	(0.0192)	(0.0071)	(0.0370)	(0.0106)	(0.0140)
$\ln W_2 \ln Y_3$	0.1527*	0.0976***	–0.0113	–0.0234***	–0.0295**	–0.0316***	–0.0216	–0.0867***	0.0037
	(0.0913)	(0.0206)	(0.0201)	(0.0054)	(0.0147)	(0.0092)	(0.0346)	(0.0161)	(0.0184)
$\ln W_3 \ln Y_1$	–0.0232	0.1083***	0.0287*	0.0106*	0.0507***	0.0197***	–0.0477	–0.1002***	–0.0144
	(0.1530)	(0.0120)	(0.0166)	(0.0059)	(0.0187)	(0.0069)	(0.0404)	(0.0176)	(0.0198)
$\ln W_3 \ln Y_2$	0.0706	0.0489***	–0.0353**	–0.0235***	–0.1394***	–0.0241***	0.0201	0.0054	0.0160
	(0.0934)	(0.0084)	(0.0161)	(0.0036)	(0.0153)	(0.0058)	(0.0318)	(0.0085)	(0.0136)
$\ln W_3 \ln Y_3$	–0.1643	–0.1501***	0.0166	0.0104**	0.0527***	0.0046	–0.0380*	0.0685***	–0.0017
	(0.1115)	(0.0152)	(0.0166)	(0.0050)	(0.0136)	(0.0071)	(0.0226)	(0.0152)	(0.0176)
T	–0.2067*	–0.0084	0.0287	0.0071	–0.1124***	0.0370***	–0.1537*	–0.0436*	–0.0003
	(0.1144)	(0.0222)	(0.0209)	(0.0101)	(0.0354)	(0.0152)	(0.0880)	(0.0265)	(0.0200)
T^2	0.0049	–0.0016*	–0.0026***	0.0007	0.0042**	0.0012*	–0.0045*	–0.0017	–0.0022*
	(0.0069)	(0.0009)	(0.0008)	(0.0006)	(0.0022)	(0.0007)	(0.0026)	(0.0013)	(0.0012)
$T \ln W_2$	–0.0460*	–0.0007	–0.0073*	–0.0037*	–0.0258***	0.0047	–0.0262**	–0.0180***	0.0022
	(0.0231)	(0.0042)	(0.0041)	(0.0019)	(0.0073)	(0.0036)	(0.0133)	(0.0062)	(0.0056)
$T \ln W_3$	0.0269	0.0016	0.0026	0.0047***	0.0227***	–0.0003	–0.0174	0.0216***	–0.0143***
	(0.0226)	(0.0039)	(0.0034)	(0.0016)	(0.0062)	(0.0031)	(0.0134)	(0.0047)	(0.0053)
$T \ln Y_1$	0.0159	0.0188***	–0.0004	–0.0032*	0.0224***	–0.0011	–0.0010	0.0161***	–0.0131***
	(0.0217)	(0.0053)	(0.0043)	(0.0019)	(0.0055)	(0.0032)	(0.0135)	(0.0057)	(0.0050)
$T \ln Y_2$	0.0037	–0.0095***	–0.0004	0.0046***	–0.0016	–0.0030	0.0041	0.0008	–0.0019
	(0.0250)	(0.0033)	(0.0029)	(0.0011)	(0.0050)	(0.0021)	(0.0120)	(0.0030)	(0.0039)
$T \ln Y_3$	–0.0096	–0.0088	0.0018	–0.0054***	–0.0213***	0.0021	0.0103	–0.0119***	0.0093**
	(0.0234)	(0.0073)	(0.0050)	(0.0018)	(0.0043)	(0.0028)	(0.0092)	(0.0055)	(0.0041)
σ^2	0.1758***	0.1458	0.0079***	0.0348***	1.1830***	0.0354***	0.0062***	0.0812***	0.0549***
	(0.0539)	(0.2010)	(0.0021)	(0.0027)	(0.0217)	(0.0051)	(0.0009)	(0.0246)	(0.0048)
$\sigma_u^2/(\sigma_u^2+\sigma_v^2)$	0.8983***	0.9874***	0.7318***	0.8441***	0.8561***	0.8096***	0.0158	0.9024***	0.8153***
	(0.0444)	(0.0175)	(0.0646)	(0.0143)	(0.0026)	(0.0270)	(0.0254)	(0.0333)	(0.0276)
μ	0.0775	–0.7589	0.0446	0.3430***	–2.0128***	–0.3387***	–0.0198	–0.5414***	0.4230***
	(0.6466)	(1.3246)	(0.0348)	(0.0331)	(0.6255)	(0.0634)	(0.0504)	(0.1322)	(0.0885)
η	–0.1849**	–0.1353***	0.0922***	–0.0507***	0.0250	0.1061***	0.3392	–0.0687*	–0.1162***
	(0.0857)	(0.0222)	(0.0226)	(0.0087)	(0.0201)	(0.0162)	(0.2667)	(0.0396)	(0.0176)

Note: Standard errors are given in parentheses. ***, ** and *denote statistical significance at the 1 per cent, 5 per cent and 10 per cent levels, respectively.

Table 3
Maximum Likelihood Estimates of the FF Cost Function Using Pooled Data, Together with the Parameter Estimates of the Meta-frontier FF Cost Functions

Variable	*SFA-POOL*		*MF-LP*		*MF-QP*	
Constant	1.8187	(0.9165)	0.5693	(0.4577)	0.4966	(0.4919)
$\ln Y_1$	0.0476	(0.3893)	1.0026	(0.1539)	1.1766	(0.1694)
$\ln Y_2$	0.4733	(0.1609)	0.7445	(0.1063)	0.2587	(0.1021)
$\ln Y_3$	−0.0650	(0.0852)	−0.6682	(0.1226)	−0.2609	(0.0922)
$\ln W_2$	0.3110	(0.0417)	−0.2742	(0.1971)	0.1699	(0.1581)
$\ln W_3$	0.5016	(0.0373)	0.8511	(0.1335)	0.5573	(0.1103)
$\ln Y_1 \ln Y_1$	0.0583	(0.0284)	−0.0616	(0.0166)	−0.0743	(0.0166)
$\ln Y_2 \ln Y_2$	0.0092	(0.0152)	−0.0241	(0.0102)	−0.0032	(0.0093)
$\ln Y_3 \ln Y_3$	0.0117	(0.0131)	−0.1096	(0.0165)	−0.0184	(0.0245)
$\ln Y_1 \ln Y_2$	−0.0913	(0.0084)	−0.1052	(0.0181)	−0.0540	(0.0227)
$\ln Y_1 \ln Y_3$	0.0418	(0.0088)	0.1909	(0.0195)	0.1120	(0.0184)
$\ln Y_2 \ln Y_3$	0.0271	(0.0077)	0.1074	(0.0195)	0.0467	(0.0186)
$\ln W_2 \ln W_2$	0.0239	(0.0054)	−0.1509	(0.0282)	−0.0861	(0.0205)
$\ln W_2 \ln W_3$	−0.0733	(0.0087)	0.2017	(0.0334)	0.1154	(0.0256)
$\ln W_3 \ln W_3$	0.0489	(0.0048)	−0.0816	(0.0147)	−0.0419	(0.0130)
$\ln W_2 \ln Y_1$	0.0490	(0.0083)	0.1561	(0.0331)	0.0767	(0.0332)
$\ln W_2 \ln Y_2$	0.0395	(0.0057)	0.1787	(0.0303)	0.1362	(0.0228)
$\ln W_2 \ln Y_3$	−0.0744	(0.0065)	−0.2516	(0.0274)	−0.1398	(0.0218)
$\ln W_3 \ln Y_1$	−0.0361	(0.0079)	−0.1577	(0.0212)	−0.0758	(0.0255)
$\ln W_3 \ln Y_2$	−0.0477	(0.0053)	−0.1138	(0.0200)	−0.1122	(0.0169)
$\ln W_3 \ln Y_3$	0.1012	(0.0059)	0.2239	(0.0198)	0.1636	(0.0157)
T	−0.0833	(0.0123)	−0.0567	(0.0323)	−0.0232	(0.0361)
T^2	0.0051	(0.0007)	−0.0021	(0.0016)	−0.0057	(0.0022)
$T \ln W_2$	−0.0197	(0.0026)	−0.0429	(0.0099)	−0.0387	(0.0076)
$T \ln W_3$	0.0169	(0.0021)	0.0344	(0.0069)	0.0300	(0.0058)
$T \ln Y_1$	0.0100	(0.0021)	0.0158	(0.0049)	0.0255	(0.0052)
$T \ln Y_2$	0.0047	(0.0017)	0.0073	(0.0049)	0.0004	(0.0051)
$T \ln Y_3$	−0.0084	(0.0018)	−0.0145	(0.0043)	−0.0196	(0.0041)

hood ratio is equal to 6951.94, the hypothesis is decisively rejected even at the 1 per cent level with degrees of freedom being 368. We conclude that the group-specific frontiers are heterogeneous, i.e. banks of different countries operate under distinct types of technology. It is noticeable that the translog results lead to the same conclusion on the heterogeneity of group-specific frontiers. The foregoing justifies the use of the meta-frontier model.[8]

Bootstrapping methods are used to obtain the standard errors attached to the estimates of MF-LP and MF-QP with 10,000 replications. The same applies to the translog case. The estimated standard error of a meta-frontier parameter is calculated as the standard deviation of the 10,000 bootstrapped parameter estimates. It is interesting to note that the coefficients of MF-LP are somewhat close to those of the MF-QP. However, there are relatively larger differences between both the meta-frontier coefficients and the corresponding coefficients of the SFA-POOL. The vast majority of the

[8]Although they did not use a formal test like us, Bos and Schmiedel (2007) reached an analogous result.

bootstrapped standard deviations are relatively small to the corresponding coefficients, implying that the MF-LP and MF-QP coefficients are quite accurately estimated. Since the two sets of meta-frontier parameter estimates give rise to very close estimates of the TGRs, we therefore arbitrarily select to show the relevant results calculated using the MF-QP estimates so as to save space.

4.2 TEs and TGRs

According to Table 4, the mean (standard deviation) TEs of the country frontiers lie in scope from 0.733 (0.197) in Germany to 0.978 (0.023) in Portugal during the 10-year period with an overall average value of 0.825 and a standard deviation of 0.146. This result falls in the range achieved by past bank efficiency studies for West European banks—e.g. Schure *et al*. (2004), Altunbas *et al*. (2001), Carbo *et al*. (2002), Maudos *et al*. (2002) and Weill (2004). These averages show that a representative bank in Germany is capable of cutting its current expenditure by up to roughly 27 per cent, which is ascribable to the managerial inability to optimize costs, while still producing the same output mix. In other words, the best practice bank in Germany incurs 73 per cent of a representative bank's cost in providing the same output levels. The potential cost savings for an average Portuguese bank are around 2.2 per cent, whose actual cost is quite close to the country's cost frontier. Although the TI appears to be small in some countries, it is nevertheless pervasive in the banking sectors of the sample states.

As far as the TGR is concerned, its mean value (standard deviation) ranges from about 0.509 (0.136) in Denmark to 0.627 (0.182) in Belgium with an overall mean value of roughly 0.558 (0.180). Belgian banks are found to adopt the most advanced technology in order to offer a variety of financial services to their customers, and their cost frontier is relatively closer to the meta-cost frontier than other countries' cost frontiers. Belgium banks can on average cut their frontier costs by up to about 37 per cent, if the potential technology available to all countries—the technology corresponding to the meta-frontier—is undertaken. In contrast, Danish banks use the most inferior production process to offer financial services, as their country frontier lies the farthest away from the meta-frontier. The potential cost savings of an average Danish bank are as high as 49 per cent of their frontier costs.

Note that as the standard deviations of the TE measures are less than those of the corresponding TGRs for each country, variable TE is more narrowly distributed around its mean value than is variable TGR. The average values of TE and TGR obtained by Bos and Schmiedel (2007) are equal to 0.805 and 0.991, respectively. However, their TGRs are found to be more tightly distributed around the mean values than are TE measures, based on their translog cost function. This may be attributed to the differences of the functional form, variable definitions, and the assumption on the

TABLE 4
SUMMARY STATISTICS FOR THE THREE EFFICIENCY MEASURES ACROSS THE NINE COUNTRIES

Country	*Mean*	*Minimum*	*Maximum*	*St. Dev.*	*Country*	*Mean*	*Minimum*	*Maximum*	*St. Dev.*
Austria					Italy				
TE	0.8387	0.3947	0.9851	0.1299	TE	0.9283	0.6280	1.0000	0.0614
TGR	0.5202	0.1272	1.0000	0.2125	TGR	0.5159	0.0612	0.9422	0.1397
OCE*	0.4294	0.1110	0.9722	0.1819	OCE*	0.4784	0.0595	0.9208	0.1308
Belgium					Portugal				
TE	0.9213	0.5776	0.9934	0.0771	TE	0.9784	0.8413	0.9973	0.0229
TGR	0.6270	0.0826	1.0000	0.1817	TGR	0.6169	0.2417	1.0000	0.1739
OCE*	0.5787	0.0711	0.9299	0.1758	OCE*	0.6027	0.2382	0.9905	0.1675
Denmark					Spain				
TE	0.8949	0.7014	0.9918	0.0643	TE	0.9311	0.6095	0.9894	0.0616
TGR	0.5085	0.0028	1.0000	0.1364	TGR	0.5562	0.0010	1.0000	0.1487
OCE*	0.4557	0.0026	0.9110	0.1300	OCE*	0.5149	0.0010	0.9851	0.1315
France					Switzerland				
TE	0.7501	0.3796	0.9891	0.0937	TE	0.7571	0.4451	0.9859	0.1026
TGR	0.6027	0.0061	1.0000	0.1735	TGR	0.5549	0.0866	1.0000	0.1902
OCE*	0.4501	0.0042	0.8905	0.1338	OCE*	0.4213	0.0764	0.8483	0.1581
Germany					Total				
TE	0.7331	0.1264	1.0000	0.1967	TE	0.8246	0.1264	1.0000	0.1456
TGR	0.5521	0.0029	1.0000	0.2123	TGR	0.5580	0.0010	1.0000	0.1797
OCE*	0.4007	0.0028	0.9592	0.1792	OCE*	0.4574	0.0010	0.9905	0.1591

Note: The quadratic programming parameter estimates are used to compute the TGR and OCE*.

inefficiency term between theirs and this paper. They asserted that differences between country-specific frontiers and a European meta-frontier are rather small for the single European banking market.

Portuguese banks have the highest TE scores among all sample states and also adopt superior production technologies, as their mean TGR (about 0.617) stands at the second highest. Belgian banks have a similar situation, where they have both higher mean TE and TGR scores than the respective overall averages. Conversely, German and Swiss banks exhibit both lower mean TE and TGR scores than the respective overall averages. The remaining banks in Austria, Denmark, Italy and Spain have above-average country-specific mean TE scores accompanied by below-average mean TGRs, while French banks have lower average country-specific mean TE scores along with higher mean TGRs than the respective overall averages. French banks use somewhat superior production technology to provide financial services at the expense of having larger production inefficiency.

The mean values of OCE* vary from around 0.401 to 0.603 with an overall mean value of 0.457. Their standard errors are all small due possibly to the small standard errors of the TGRs. A representative bank is able to shave up to 54 per cent of its current production cost for the given level of outputs.[9] All countries' component TE is on average much higher than component TGR, implying that the main source of inefficiencies stems from undertaking inferior technology, instead of managerial inefficiency. As expected, the mean overall technical efficiency scores relative to the metafrontier, OCE*, of Portugal and Belgium stand at first and second place, respectively, and the mean OCE* of Germany ranks last, tightly close to Switzerland and Austria. The foregoing confirms the argument that the existence of different technologies should be properly taken into account, especially when a researcher attempts to make comparisons of efficiencies in a cross-border scenario.

We also estimate the standard translog cost frontier using the same data set and the estimated coefficients are not shown. Analogous to the findings of Huang and Wang (2004), the TE scores of individual countries obtained from the FF cost frontiers exceed the corresponding TE scores obtained from the translog counterparts.[10]

It might be interesting to explore whether the TE scores are correlated with the TGRs. This relationship provides additional information on the potential link between production efficiency and technology achievement. Using the sample means of TE and TGR for the nine countries shown in Table 4, we calculate their simple correlation coefficient as 0.1055. This

[9]Note that as the ratio of 54 per cent is calculated against the potentially most efficient cost frontier for all sample countries, the potential per cent of cost savings tends to be high.

[10]It is quite interesting to note that our average TE scores of the FF function are also greater than the mean TE score of the translog function yielded by Bos and Schmiedel (2007), despite that the difference is not large.

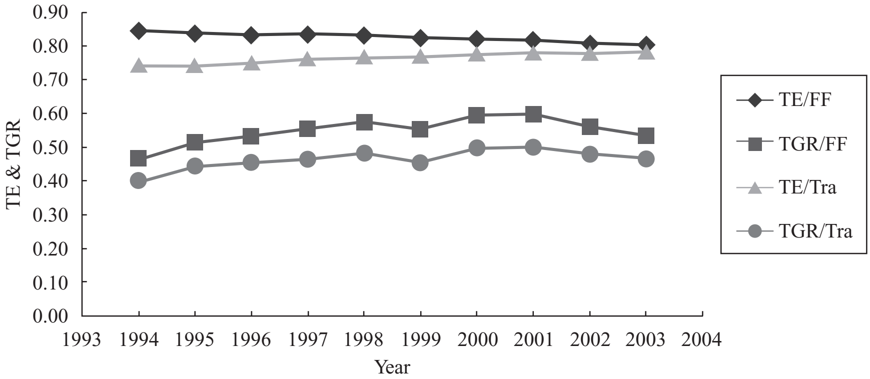

Fig. 2 Mean Values of the TE and TGR over Time (FF versus Translog)

suggests that a higher mean value of TE is accompanied by a higher mean value of TGR, implying that in a country operating under a more advanced technology (a higher mean TGR) its banks' realized costs tend to get closer to its country frontier, leading to a higher average TE score. In contrast, a strong negative relationship is found by the translog cost function since the simple correlation coefficient is calculated as high as –0.8139.[11] Evidence is found by the translog model that banks on average, which are relatively technically efficient with higher TE scores, are relatively technologically inefficient with lower TGRs, and vice versa.

We next attempt to analyze the trending of the TE and the TGR during the sample period. Figure 2 draws the mean values of the TE and TGR. The mean TE scores derived from the FF function slightly decrease with time, from around 0.85 to 0.80, while the mean TGRs vary from around 0.47 initially up to 0.60 and later down to 0.53. A similar time path was traced out by Bos and Schmiedel (2007) for the mean TE scores. The secular trend of the mean TGRs appears to be upward sloping, in spite of being not uniformly increasing. This finding is inconsistent with Bos and Schmiedel (2007). One thus may conclude that Europe's banking markets have become more alike over the sample period, as the gaps between country-specific frontiers and the meta-frontier shrink during the sample period. The same trending of the mean TE scores derived from our translog function is dissimilar, where its mean TEs gradually grow with time, from 0.74 to 0.79, while its mean TGRs exhibit a similar trending to the one deduced from the FF function, from 0.40 up to 0.50 for the first eight years and then down to 0.47 in the last year. Recall that our data do not support the adequacy of the translog form. The conclusion drawn from the translog model—that the mean TE improves over

[11]Battese *et al.* (2004) yielded a similar negative relationship between TE and TGR, using a translog production function.

time in a tardy way—may be doubtful. In any event, Fig. 2 paints a picture characterizing the gradual evolution process, to which a firm's efficiency measure is expected so.

We finally outline the estimated measures of scale economies. The scale economy estimates for the country-specific frontiers are about unity, implying that the representative bank is operating close to constant returns to scale. This outcome is congruent with previous studies, such as Vennet (2002), Cavallo and Rossi (2001), Altunbas and Molyneaux (1996) and Allen and Rai (1996). The mean scale economy measures from the SFA-POOL are much less than unity, which is likely to be caused by the invalid imposition of a common production technology on the financial industry across countries, leading to inconsistent parameter estimates. The use of these parameter estimates seems to underestimate the measures of scale economies. It is found that an average bank of the sample states, except for Austria, exhibits increasing returns to scale. The translog model reaches similar results.

5 Concluding Remarks

The application of the newly developed meta-cost function solves the incomparability problem to some extent, when one attempts to compare the TE scores for banks across countries, due to the fact that those banks potentially operate under different technologies. The existence of multiple technologies justifies the use of the meta-cost frontier, under which the relevant TEs are evaluated against the common cost frontier.

It is crucial to note that the meta-frontier model offers insightful information by subdividing the measure of OCE* into measures of TE and TGR. Informed by this underlying information, both bank managers and regulators know the sources of a bank's measured performance, enabling them to redistribute scarce resources to where they are most needed and productive. Lacking such valuable information, managers' and regulators' decisions may lead to undesirable consequences of raising the production costs and the selling price, which in turn distort resource allocation. The meta-cost frontier approach helps facilitate researchers in characterizing a bank's production process and provides a common standard against which banks' efficiencies in different countries can be correctly compared with one another.

The mean TE scores for the sample countries are detected to fall into the range of prior works and are positively correlated with the TGRs. This implies that a relatively technically efficient bank is also technologically efficient and vice versa. To be more specific, a bank that is producing closer to (farther away) the production frontier is apt to adopt more (less) advanced technology in order to provide various financial services. It is beneficiary for a bank to adopt new innovations quickly since its TE can be promoted at the same time. Most of the average TGRs for the sample countries are much less than those of the average TE scores. Sample banks should be devoted to promoting their production technology. Since the secular trend of the mean TGRs is upward sloping, one is led to conclude that European banks tend to adopt similar and more advanced technology during the sample period. The convergence in technology is potentially induced by the integration in EU banking as banks must undertake innovations quickly to lower their production costs. By doing so, they can survive in such a more competitive atmosphere.

References

Aigner, D. J., Lovell, C. A. K. and Schmidt, P. (1977). 'Formulation and Estimation of Stochastic Frontier Production Function Models', *Journal of Econometrics*, Vol. 6, pp. 21–37.

Allen, L. and Rai, A. (1996). 'Operational Efficiency in Banking: an International Comparison', *Journal of Banking and Finance*, Vol. 20, pp. 655–672.

Altunbas, Y. and Molyneaux, P. (1996). 'Economies of Scale and Scope in European Banking', *Applied Financial Economics*, Vol. 6, pp. 367–375.

Altunbas, Y., Liu, M. H., Molyneux, P. and Seth, R. (2000). 'Efficiency and Risk in Japanese Banking', *Journal of Banking and Finance*, Vol. 24, pp. 1605–1628.

Altunbas, Y., Gardener, E. P. M., Molyneux, P. and Moore, B. (2001). 'Efficiency in European Banking', *European Economic Review*, Vol. 45, pp. 1931–1955.

Battese, G. E. and Coelli, T. J. (1992). 'Frontier Production Functions, Technical Efficiency and Panel Data: with Application to Paddy Farmers in India', *Journal of Productivity Analysis*, Vol. 3, pp. 153–169.

Battese, G. E. and Prasada Rao, D. S. (2002). 'Technology Gap, Efficiency and a Stochastic Meta-frontier Function', *International Journal of Business and Economics*, Vol. 1, pp. 1–7.

Battese, G. E., Rao, D. S. P. and O'Donnell, C. J. (2004). 'A Metafrontier Production Function for Estimation of Technical Efficiencies and Technology Gaps for Firms Operating under Different Technologies', *Journal of Productivity Analysis*, Vol. 21, pp. 91–103.

Baumol, W. J., Panzar, J. C. and Willig, R. D. (1982). *Contestable Markets and the Theory of Industry Structure*, New York, Harcourt Brace Jovanovich.

Berger, A. N. (1993). 'Distribution-free Estimates of Efficiency in the U.S. Banking Industry and Tests of the Standard Distributional Assumptions', *Journal of Productivity Analysis*, Vol. 4, pp. 261–292.

Berger, A. N. and DeYoung, R. (1997). 'Problem Loans and Cost Efficiency in Commercial Banks', *Journal of Banking and Finance*, Vol. 21, pp. 849–870.

Berger, A. N. and Mester, L. J. (1997). 'Inside the Black Box: What Explains Differences in the Efficiencies of Financial Institutions?', *Journal of Banking and Finance*, Vol. 21, pp. 895–947.

Berger, A. N., Leusner, J. H. and Mingo, J. J. (1997). 'The Efficiency of Bank Branches', *Journal of Monetary Economics*, Vol. 40, pp. 141–162.

Bos, J. W. B. and Schmiedel, H. (2007). 'Is There a Single Frontier in a Single European Banking Market?', *Journal of Banking and Finance*, Vol. 31, pp. 2081–2102.

Carbo, S., Gardener, E. P. M. and Williams, J. (2002). 'Efficiency in Banking: Empirical Evidence from the Savings Banks Sector', *The Manchester School*, Vol. 70, pp. 204–228.

Cavallo, L. and Rossi, S. P. S. (2001). 'Scale and Scope Economies in the European Banking Systems', *Journal of Multinational Financial Management*, Vol. 11, pp. 515–531.

Chalfant, J. A. and Gallant, A. R. (1985). 'Estimating Substitution Elasticities with the Fourier Cost Function: Some Monte Carlo Results', *Journal of Econometrics*, Vol. 28, pp. 205–222.

Coelli, T. J. (1996). 'A Guide to FRONTIER Version 4.1: a Computer Program for Stochastic Frontier Production and Cost Function Estimation', *CEPA Working Paper*.

Cornwell, C., Schmidt, P. and Sickles, R. C. (1990). 'Production Frontiers with Cross-sectional and Time-series Variation in Efficiency Levels', *Journal of Econometrics*, Vol. 46, pp. 185–200.

DeYoung, R., Hasan, I. and Kirchhoff, B. (1998). 'The Impact of Out-of-state Entry on the Efficiency of Local Banks', *Journal of Economics and Business*, Vol. 50, pp. 191–203.

Eastwood, B. J. (1991). 'Asymptotic Normality and Consistency of Semi-nonparametric Regression Estimators Using an Upwards F Test Truncation Rule', *Journal of Econometrics*, Vol. 48, pp. 151–181.

Eastwood, B. J. and Gallant, A. R. (1991). 'Adaptive Rules for Semi-nonparametric Estimators that Achieve Asymptotic Normality', *Econometric Theory*, Vol. 7, pp. 307–340.

Gallant, A. R. (1981). 'On the Bias in Flexible Functional Forms and an Essentially Unbiased Form: the Fourier Flexible Form', *Journal of Econometrics*, Vol. 15, pp. 211–245.

Gallant, A. R. (1982). 'Unbiased Determination of Production Technologies', *Journal of Econometrics*, Vol. 20, pp. 285–323.

Goddard, J., Molyneux, P., Wilson, J. O. S. and Tavakoli, M. (2007). 'European Banking: an Overview', *Journal of Banking and Finance*, Vol. 31, pp. 1911–1935.

Huang, T. H. and Wang, M. H. (2004). 'Comparisons of Economic Inefficiency between Output and Input Measures of Technical Inefficiency Using the Fourier Flexible Cost Function', *Journal of Productivity Analysis*, Vol. 22, pp. 123–142.

McAllister, P. H. and McManus, D. (1993). 'Resolving the Scale Efficiency Puzzle in Banking', *Journal of Banking and Finance*, Vol. 17, pp. 389–406.

Maudos, J., Pastor, J. M., Perez, F. and Quesada, J. (2002). 'Cost and Profit Efficiency in European Banks', *Journal of International Financial Markets, Institutions and Money*, Vol. 12, pp. 33–58.

Meeusen, W. and Van Den Broeck, J. (1977). 'Efficiency Estimation from Cobb–Douglas Production Functions with Composed Error', *International Economic Review*, Vol. 18, pp. 435–444.

Mitchell, K. and Onvural, N. M. (1996). 'Economies of Scale and Scope at Large Commercial Banks: Evidence from the Fourier Flexible Function Form', *Journal of Money, Credit and Banking*, Vol. 28, pp. 178–199.

O'Donnell, C. J., Prasada Rao, D. S. and Battese, G. E. (2008). 'Metafrontier Frameworks for the Study of Firm-level Efficiencies and Technology Ratios', *Empirical Economics*, Vol. 34, pp. 231–255.

Schmidt, P. and Sickles, R. C. (1984). 'Production Frontiers and Panel Data', *Journal of Business and Economic Statistics*, Vol. 2, pp. 367–374.

Schure, P., Wagenvoort, R. and O'Brien, D. (2004). 'The Efficiency and the Conduct of European Banks: Developments after 1992', *Review of Financial Economics*, Vol. 13, pp. 371–396.

Vennet, R. V. (2002). 'Cost and Profit Efficiency of Financial Conglomerates and Universal Banks in Europe', *Journal of Money, Credit, and Banking*, Vol. 34, pp. 254–282.

Weill, L. (2004). 'Measuring Cost Efficiency in European Banking: a Comparison of Frontier Techniques', *Journal of Productivity Analysis*, Vol. 21, pp. 133–152.