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Cost efficiency and technological gap in Western European banks: A stochastic metafrontier analysis

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ABSTRACT

This paper compares the cost efficiencies of banks in Western European countries using a new stochastic metafrontier Fourier flexible cost function for the period 1996–2010. One salient feature of our method is that the TGR can be linked with country-specific environmental variables. Results show that the average TGRs in these countries are close to one another, implying that banks operating in this integrated market undertake analogous technology. Moreover, the TGR and MCE exhibit a gradual upward trend during 1996–2000, followed by a downward trend especially after the subprime crisis of 2007–2010. The managerial inability constitutes the primary source of inefficiencies.

1. Introduction

The financial services industries in Western European countries have become highly integrated ever since the completion of the Single Market for Financial Services in 1993. Banking industries there have experienced a wide range of fundamental changes in their regulatory and competitive environments, including the reduction or elimination of trade and entry barriers to those markets in the European Union (EU). Banks are soon facing an increasingly competitive atmosphere not only from domestic markets, but also from abroad. Bank managers must adopt the best technologies to date to efficiently produce an array of financial products in order to gain excess profit and to be viable. In this wave of international economic integration, the cost efficiency of the EU banks is a core issue worth to be deeply investigated.

Banks in such an integrated and interconnected market as the EU are more likely to be exposed to global shocks (Camilla, Serlenga & Shin, 2013). As noted by González (2005) and Fiordelisi, Marques-Ibanez, and Molyneux (2011), the growing competition reduces the market power of banks thereby reducing their charter value. Chortareas, Girardone, and Ventouri (2013) point out that excessive financial liberalization tends to provide an incentive for financial institutions to take greater risks, which might incur recent subprime crisis and European crises. How to successfully weather the financial crisis, particularly in the future, appears to be an important topic, and this is intimately associated with banks' production efficiency, since a technically efficient bank is able to offer various financial services to its customers in a lower cost and earn higher profits. This prompts the main motivation for this study, aiming at investigating the efficiency of Western European banking industries.

When dealing with comparisons of efficiencies in a cross-group scenario, Battese, Rao, and O'Donnell (2004) and O'Donnell, Rao, and Battese (2008) propose a mixed two-step approach to find the metafrontier production function that facilitates efficiency comparisons of different groups. Their two-step procedure combines the conventional stochastic frontier approach (SFA) in the first step to estimate the group-specific frontiers with the mathematical programing technique in the second step to estimate the

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metafrontier production function. Clearly, these two steps involve the use of distinct approaches, i.e., the econometric and non-parametric approaches. The former requires specifying a specific functional form with error components, while the latter is function-free and unable to immune from random shocks. One potential limitation on the programming technique is that the parameter estimates are lack of statistical properties due to the linear (or quadratic) programming is deterministic in essence and its estimates are inclined to be confounded with shocks. Although Battese et al. (2004) suggest using simulation and bootstrapping methods to derive standard errors of the coefficient estimates, no statistical inferences about those estimates can be made. Furthermore, to associate environments with banks' efficiency, the programming technique has to rely on, e.g., the two-stage method or three-stage methods (Fried, Lovell, Schmidt & Yaisawarng, 2002). Conversely, the SFA of Battese and Coelli (1995) enables ones to examine the determinants of the efficiency scores in a single step.[1]

To fill up the gap in the literature, the current paper employs the newly developed approach by Huang, Huang, and Liu (2014) to estimate and compare the cost efficiencies of banks in Western European countries. The major difference between the new approach and the mixed two-step approach lies in the second step relating to the estimation of the metafrontier, where the new approach suggests using the SFA, rather than the linear or quadratic programming (QP). In this manner, the parameter estimates and their standard errors have known statistical properties. In addition, the technology gap ratio can be further specified as a set of environmental variables, characterizing the exogenous differences faced by different groups or countries. We can refer the new metafrontier as the stochastic metafrontier (SMF), as opposed to the deterministic metafrontier derived by the mixed approach.

There are two main approaches to examining efficiencies and productivity changes for firms: parametric and non-parametric approaches. These two approaches have their own strengths and weaknesses, and there is no consensus on which is the best method for assessing frontier efficiency (Wang and Huang, 2007). The non-parametric method has the advantage that there is no need to specify a functional form for the boundary of the production technology. However, its weakness is that it constructs a deterministic frontier such that all deviations from the frontier are implicitly attributed to inefficiency. This indicates that non-parametric approach tends to be sensitive to the influences of data noise (e.g., shocks and measurement errors). Although the issue of data noise can be dealt with by the parametric approach, it requires specifying functional forms for the production (cost, profit) function and distributional assumptions on the error components. In other words, the parametric approach suffers from the potential problems of functional form misspecification and invalid distributional assumption.

In a cross-country setting, in order to cope with potential heterogeneity, there is an extensive amount of literature on how different environmental conditions may affect a firm's efficiency. Except for the metafrontier approach, an alternative non-parametric partial frontier method has recently been developed to solve the sensitivity problem of extreme values and outliers. Cazals, Florens, and Simar (2002) first introduce the notion of order-m partial frontiers based on the concept of the expected minimum input (or maximum output) function. Following Cazals et al. (2002), Daraio and Simar (2005, 2007) propose the concepts of a conditional efficiency measure of the order-m. Although the new methods have many advantages and been applied by, e.g., Bonaccorsi and Daraio (2008), De Witte and Dijkgraaf (2009), and Daraio and Simar (2005), disadvantages, such as the issue of bandwidth selection, have also been identified (Balaguer-Coll, Prior & Tortosa-Ausina, 2013).[2] In addition, even though the new methods are able to deal with the problems of outliers and extreme noise, they are in essence still deterministic and assume no noise. Since a firm-level dataset is often subject to being rather noisy, these approaches may be incapable of assessing the true efficiency for firms (Verschelde, Dumont, Rayp & Merlevede, 2016). Furthermore, these methods are heavily dependent on the manual inspection of the data, which is infeasible for large datasets (Chortareas, Girardone & Ventouri, 2011). Given that our sample contains 9189 bank-year observations from 10 Western European countries, the metafrontier approach seems to be a better choice than the non-parametric partial frontier method.

Although the translog (TL) cost function has been widely used by numerous practitioners to characterize the production technology of banking sectors, it is criticized as being merely able to locally approximate a true but unknown cost function. It forces large and small banks to lie on a symmetric U-shaped ray average cost curve, and may produce biased measures of scale economies for banks of various sizes. See, for example, McAllister and McManus (1993), Wheelock and Wilson (2001), and Huang and Wang (2004). In contrast, the Fourier flexible (FF) functional form of Gallant (1982) can globally approximate the underlying cost function as closely as desired in the Sobolev norm. Many empirical studies confirm that the FF function provides a better fit for financial institution data than the TL specification, e.g., McAllister and McManus (1993), Mitchell and Onvural (1996), Berger and Mester (1997), Berger, Leusner, and Mingo (1997), and Huang and Wang (2004). Thus, this study chooses the FF cost function to describe the underlying technology for banks under study.

In summary, the present study attempts to extend the deterministic metafrontier TL cost function to the more general SMF FF cost function that has several advantages. First, since the technology parameters of the SMF are estimated by the maximum likelihood (ML), the conventional statistical inferences for parameter estimates can be directly drawn without relying on simulations or bootstrapping techniques. Second, the technology gaps can be treated as a one-sided error term, which, together with the statistical noise, constitutes the composed error. Finally, macroeconomic environmental conditions can be modeled as the determinants of the technology gaps, like the one proposed by Battese and Coelli (1995). The variance of the one-sided error term is heteroscedastic, as pointed out by Kumbhakar and Lovell (2003), which may be preferable and consistent with reality.

The rest of the paper is organized as follows. Section 2 briefly reviews the literature on metafrontier model and empirical studies

[1] Wang and Schmidt (2002) find evidence supporting the one-step method whenever one is interested in the effects of exogenous variables on efficiency levels, in which their analysis is based on the "scaling property".

[2] Daraio and Simar (2005, 2007) suggest a cross-validation rule to select the appropriate order of the bandwidths, while Bădin et al. (2010) note that the rule fails to have particular optimality properties in finite samples.

for banks' efficiency in Western European countries. Section 3 formulates the metafrontier FF cost function and its estimation procedure. Section 4 introduces the data source and variable definitions. Section 5 conducts empirical study, while the last section concludes the paper.

2. Literature review

The efficiency measurement of banking industries has drawn much attention to academic researchers since this sector has undergone major changes in regulation, globalization, financial innovation, market competition, and operation risks around the world. In the ongoing integration of European financial markets, the structure of banking industries has experienced rapid changes and challenges too. Whether the efficiency scores of European banks tends to be equalized is an interesting issue and worth thoroughly investigated. Many earlier works have already performed cross-country comparisons by estimating a global cost frontier for the commercial banks in this area. Allen and Rai (1996) adopt both SFA and DFA (distribution-free approach) to compare cost efficiency (CE) measures across 15 developed countries (including 11 Western European countries) for the period 1988–1992. They divide those sample countries into universal banking and separated banking countries, corresponding to different regulatory environments. Using the TL specification, evidence is found that universal banks are more efficient than those of non-universal banks, and financial institutions in France, Italy, United Kingdom, and United State are the most inefficient. Altunbaş, Gardener, Molyneux, and Moore (2001a) extends the TL cost frontier to the FF cost frontier and analyze banking efficiency of 15 European countries during the period 1989–1997. Their empirical results suggest that banks can save total costs by reducing managerial and other inefficiencies. The X-inefficiency of EU banks reveals a gradually decreasing secular trend over the sample period.

The above studies attempt to construct a common frontier for all banks from different countries, implicitly assuming that banks from various countries undertake a common production technology. Even though this setting allows for a direct comparison of efficiency levels, it fails to account for potential technology heterogeneity among sample countries and is likely to obtain misleading results. Some researchers stress the importance of environmental variables on the determination of a bank's cost efficiency, e.g., Dietsch and Lozano-Vivas (2000), Cavallo and Rossi (2002), Lozano-Vivas, Pastor and Hasan (2001), Lozano-Vivas, Pastor and Pastor (2002), Beccalli (2004), Beccalli and Frantz (2009), as well as Lee and Huang (2016), who carry out international comparisons among countries using common frontiers that take environmental conditions into account.

Another strand of contemporary literature compares the efficiency of banks across European nations by estimating individual national frontiers. Berger, DeYoung, Genay, and Udell (2000) claim that estimating individual frontiers avoids the comparison problem arising from the environmental differences across nations. They employ the SFA to estimate the cross-border banking efficiency and compare foreign-owned with domestic-owned banks in 4 European countries and the United States for the period 1992–1997. The outcomes show that domestic banks in these countries outperform foreign banks in terms of cost efficiency, confirming the home field advantage hypothesis. Weill (2004) estimates the cost efficiency of banks in 5 major European countries, using various methods of the SFA, DFA, and DEA for the period 1992–1998. It is crucial to note that the efficiency scores obtained by the foregoing two papers are in fact not directly comparable, because these measures are gauged against different group frontiers, rather than a common frontier or metafrontier.

To sum up, all of the aforementioned works that involve cross-country comparisons of efficiency count on either estimating a common frontier or group specific production frontiers, but not both. The common frontier approach requires the imposition of homogeneous technology adopted by all banks from different countries, which is inconsistent with the reality and hence may result in biased parameter estimates and efficiency measures. Moreover, the individual frontiers approach suffers from the problem of incomparability arising from heterogeneous benchmarks for banks from different countries.

Differing from the foregoing studies, Battese et al. (2004) propose the metafrontier model that is constructed to envelope a set of group-specific frontiers. Under this framework, Bos and Schmiedel (2007) use the TL cost function to estimate comparable efficiency measures for 15 Western European commercial banks during the period 1993–2004. Their results support the existence of a single European banking market. Huang, Chiang, and Chen (2011a) extend the metafrontier production function to the metafrontier FF cost function with time-varying technical inefficiency. They conclude that the mean TGRs are generally increasing over time and that European banks are inclined to adopt quite advanced technology during the sample period.

3. Methodology

3.1. The Fourier Flexible cost function

The FF function is a semi-parametric approach that expands the standard TL functional form by adding a set of trigonometric Fourier series. These additional terms consist of various sine and cosine functions that are mutually orthogonal. Gallant (1982) shows that the FF function is capable of approximating the true but unknown function as closely as desired in Sobolev norm. Let $W = (W_1, \ldots, W_N)'$ be an N-vector of input prices and $Y = (Y_1, \ldots, Y_M)'$ be an M-vector of output quantities. The FF cost frontier ($\ln f_t(X_{it})$) of bank i at time t, for a given country (group) j, is formulated as:

$$\begin{aligned}\ln f_t^j(X_{it}) = a_0 &+ \sum_{m=1}^{M} a_m \ln(Y_{mit}) + \sum_{n=2}^{N} \beta_n \ln(W_{nit}) + \phi_1 T + \frac{1}{2}\left[\sum_{m=1}^{M}\sum_{k=1}^{M} \delta_{mk} \ln Y_{mit} \ln Y_{kit} + \sum_{n=1}^{N}\sum_{h=1}^{N} \gamma_{nh} \ln W_{nit} \ln W_{hit} + \phi_{11} T^2\right] \\ &+ \sum_{m=1}^{M}\sum_{n=1}^{N} \rho_{mn} \ln Y_{mit} \ln W_{nit} + \sum_{m=1}^{M} \psi_m \ln Y_{mit} T + \sum_{n=1}^{N} \theta_n \ln W_{nit} T + \sum_{m=1}^{M} [A_m \cos(z_{mit}) + B_m \sin(z_{mit})] \\ &+ \sum_{m=1}^{M}\sum_{n=1}^{M} [A_{mn} \cos(z_{mit} + z_{nit}) + B_{ij} \sin(z_{mit} + z_{nit})] + \varepsilon \end{aligned} \quad (1)$$

where X_{jit} includes all relevant variables in the model, $\ln Y_m$ and $\ln W_n$ are the mth (log)output quantities and the nth (log)input prices, respectively, T represents the time trend. Since the trigonometric function of sine and cosine are defined over 0 and 2π, notation z_m is the re-scaled values of $\ln Y_m$ ($m = 1,\ldots, M$) such that it spans in the interval $[0, 2\pi]$. Notations $\alpha, \beta, \phi, \delta, \gamma, \rho, \psi, \theta, A$, and B signify the technology parameters to be estimated.

The scaled log-output quantities are calculated as $z_m = \lambda_m(\ln Y_m + \ln d_m)$, where $\lambda_m = 6/(\ln Y_m^{\max} + \ln d_m)$, $\ln d_m = 0.00001 - \ln Y_m^{\min}$, and $Y_m^{\max}$ and $Y_m^{\min}$ are the maximum and minimum value of output m in the sample. This transformation formula guarantees the minimum value of $\ln Y_m$ to be slightly greater than zero and the maximum value of $\ln Y_m$ to be equal to 6 that falls short of 2π. See, for example, Gallant (1982), Chalfant and Gallant (1985), Mitchell and Onvural (1996), Berger et al. (1997), Altunbaş, Liu, Molyneux & Seth, (2000), Altunbaş et al. (2001a), Altunbaş, Evans and Molyneux (2001b), Huang et al. (2011a), and Huang, Shen, Chen and Tseng (2011b).

The composed error of $\varepsilon = v + U$ contains a two-sided noise $v \sim N(0, \sigma_v^2)$ and a one-sided error $U \geq 0$ that reflects cost inefficiency of the firm, and v is assumed to be independent of U. Following Battese and Coelli (1995), the inefficiency term is associated with an array of environmental variables, that is:

$$U_{it} = \tau_{it}'\Omega + u_{it} \geq 0 \quad (2)$$

where Ω denotes a collection of environmental variables and τ is the corresponding coefficients, and $u \sim N(0, \sigma_u^2)$.

3.2. Metafrontier FF cost function and technology gaps

Suppose that there are J different countries and each country has N_j banks, facing exogenous input prices and output quantities and attempting to minimize their production costs under the constraint of current technology. The stochastic cost frontier model for each bank i (=1, …, N_j) of country j (j = 1, …, J) at time t (=1, …, T) can be specified as:

$$C_{jit} = f_t^j(X_{jit})e^{\varepsilon_{jit}} \quad (3)$$

Here, C_{jit} is the actual expenditure and composed error $\varepsilon_{jit} = v_{jit} + U_{jit}$, where v_{jit} and U_{jit} are similarly defined as the above. The jth country-specific cost frontier of $f_t^j(.)$ takes the FF form in Eq. (1), which can vary across country and over time.

The measure of country-specific cost efficiency for a bank is defined by the ratio of the minimum feasible cost adjusted by noise, $e^{v_{jit}}$, to observed cost, namely:

$$CE_{it}^j = \frac{f_t^j(X_{jit})e^{v_{jit}}}{C_{jit}} = e^{-U_{jit}} \quad (4)$$

Let $f_t^M(X_{jit})$ be the underlying metafrontier cost function that envelops all country-specific cost frontiers. Since group j's cost frontier must less than or equal to $f_t^M(X_{jit})$ by definition, their relationship can be expressed as:

$$f_t^j(X_{jit}) = f_t^M(X_{jit})e^{U_{jit}^M}, \forall\, j, i, t \quad (5)$$

Here, term $U_{jit}^M \geq 0$ measures the gap between country cost frontiers and the meta- cost frontier. Similar to Battese et al. (2004), the ratio of the metafrontier to the country j's frontier is defined as the technology gap ratio (TGR), i.e.,

$$TGR_{it}^j = \frac{f_t^M(X_{jit})}{f_t^j(X_{jit})} = e^{-U_{jit}^M} \leq 1 \quad (6)$$

Measure TGR evaluates the deviation of the potential cost defined by the metafrontier FF cost function from the country-specific FF cost frontier This ratio reflects how advance is the production technology adopted by the country, which may depend on economic and non-economic factors and, thus, can change across firms and countries and time-variant. The larger the value of the TGR, the more advanced technology the country undertakes, so the country cost frontier is closer to the meta-cost frontier.

Fig. 1 illustrates the relationship between the meta-cost frontier and the country-specific cost frontier, where the stochastic cost frontiers for two countries in the case of a single output are denoted by Frontier 1 and Frontier 2. The meta-cost frontier envelops the two country-specific cost frontiers from below. For a given output level Y_{jit}, say, the difference between a bank's actual cost C_{jit} and the metafrontier $f_t^M(X_{jit})$ consists of three components: the technology gap ratio, $TGR_{it}^j = f_t^M(X_{jit})/f_t^j(X_{jit})$, the cost efficiency, $CE_{it}^j = f_t^j(X_{jit})/f_t^j(X_{jit})e^{U_{jit}} = e^{-U_{jit}}$, as well as the random noise component, $f_t^j(X_{jit})e^{U_{jit}}/C_{jit} = e^{-v_{jit}^M}$. That is,

$$f_t^M(X_{jit})/C_{jit} = TGR_{it}^j \times CE_{it}^j \times e^{-v_{jit}^M} \quad (7)$$

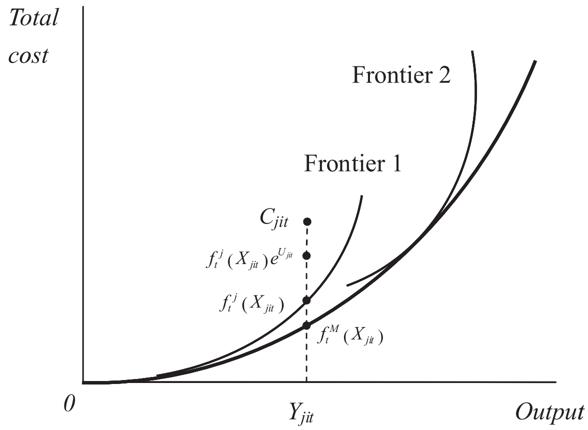

Fig. 1. Metafrontier cost model.

It is noteworthy that although both the technology gap ratio TGR_{it}^j and the firm's cost efficiency CE_{it}^j are bounded from zero to one, the metafrontier $f_t^M(X_{jit})$ does not necessary envelop all banks' observed cost C_{jit}. The unrestricted ratio in Eq. (7) distinguishes the metafrontier modeling using the stochastic frontier analysis (SFA) from data envelopment analysis (DEA). By accounting for the random noise component the decomposition can be expressed alternatively as:

$$MCE_{jit} = \frac{f_t^M(X_{jit})e^{v_{jit}^M}}{C_{jit}} = TGR_{it}^j \times CE_{it}^j \tag{8}$$

where MCE_{jit} is defined as the bank's cost efficiency with respect to the meta-cost frontier as opposed to the bank's cost efficiency CE_{it}^j with respect to the country cost frontiers $f_t^j(X_{jit})$. Eq. (7) states that measure MCE can be decomposed into two components, i.e., TGR and CE.

3.3. Estimation procedure

The conventional mixed procedure suggests using the stochastic frontier approach to estimate the country-specific stochastic frontier of Eq. (3) by the maximum likelihood (ML) in the first step. To estimate the metafrontier function of Eq. (5) in the second step, Battese et al. (2004) and O'Donnell et al. (2008) suggest the use of mathematical programming techniques that are deterministic in essence and likely to be confounded with random shocks, due to their lack of random disturbances. This article introduces the new metafrontier approach, first proposed by Huang et al. (2014), to estimate the metafrontier FF cost function by the ML, rather than programming techniques, under the framework of the SFA that not only incorporates random disturbances, but also allows us to associate the TGR with a set of environmental variables, while programming techniques fail to do so.

After taking the natural logarithm, Eq. (3) becomes a standard stochastic cost frontier with the function of $f_t^j(.)$ being specified as the FF functional form. It can be estimated by the ML and let $\hat{f}_t^j(X_{jit})$ be the corresponding fitted value. Country j's cost efficiency of bank i at time t is evaluated by the following conditional expectation:

$$CE_{it}^j = E(e^{-U_{jit}}|\varepsilon_{jit}) \tag{9}$$

where ε_{jit} will be substituted by its estimate of $\hat{\varepsilon}_{jit} = \ln C_{jit} - \ln \hat{f}_t^j(X_{jit})$.

The true value of $f_t^j(.)$ in Eq. (5) is not observable, which can be related to its fitted value (in terms of logarithms) as:

$$\ln \hat{f}_t^j(X_{jit}) = \ln f_t^j(X_{jit}) + v_{jit}^M \tag{10}$$

where v_{jit}^M is the estimation error. Eq. (5) is also not a regression equation due to its omission of a disturbance term. Substituting Eq. (10) into Eq. (5), we successfully transform Eq. (5) into a regression equation with composed errors:

$$\ln \hat{f}_t^j(X_{jit}) = \ln f_t^M(X_{jit}) + U_{jit}^M + v_{jit}^M \tag{11}$$

Terms U and v form the error components, where we assume that $v_{jit}^M \sim N\left(0, \sigma_{vM}^2\right)$ is a normal random variable with a mean of zero and a heteroskedastic variance (see below) independent of U_{jit}^M. In this manner, Eq. (11) can be treated as a stochastic frontier model and should be estimated by the ML.

Term U_{jit}^M can be specified as a function of environmental variables like Eq. (2). It is noteworthy that the variance of the disturbance term v_{jit}^M is not constant since it contains the residual term $\hat{\varepsilon}_{jit}$. This problem of heteroskedasticity will result in inconsistent estimated covariance matrix of the parameter estimates. Thus, the log likelihood function is referred as the log quasi-likelihood function. The quasi-maximum likelihood (QML) parameter estimates are consistent, but their corresponding standard errors are not and can be corrected by the "sandwich" estimator.[3] See White (1982).

The above proposed two-step stochastic frontier approach ensures that the metafrontier FF cost function lies underneath country-specific cost frontiers. Using the similar formula to Eq. (9), the TGR can be calculated by the following conditional expectation:

$$TGR_{it}^{j} = E\left(e^{-U_{jit}^{M}}|\varepsilon_{jit}^{M}\right) \leq 1 \tag{12}$$

where $\varepsilon_{jit}^{M} = v_{jit}^{M} + u_{jit}^{M} = \ln \hat{f}_t^{j}(X_{jit}) - \ln f_t^{M}(X_{jit})$ are the composite errors of Eq. (11). Note that the TGR is a function of environmental variables via $\tau'_{it}\Omega$ and the variances of $\sigma_{v^M}^2$ and $\sigma_{u^M}^2$.

4. Data description

This paper compiles unconsolidated accounting statements from the BankScope database of BVD-IBCA. The sample contains 1303 commercial banks from 10 Western European countries, i.e., Austria, Belgium, Denmark, France, Germany, Italy, Luxembourg, Spain, Switzerland, and the United Kingdom, spanning 1996 to 2010. The data are scrutinized carefully in order to avoid potential inconsistency and keying errors. Several banks reporting extreme values on the variables of main interest are removed. The final unbalanced panel data contain 9189 bank-year observations. Based on the intermediation approach, banks are assumed to hire three inputs—labor (x_1), physical capital (x_2), and borrowed funds (x_3)—to produce three outputs: total loans (y_1), other earning assets (y_2), and non-interest revenue (y_3).

Because there are quite a few missing values on the number of employees, we select the total assets net of fixed assets to proxy for x_1,[4] and its price (w_1) is calculated as the ratio of personnel expenses to x_1. Physical capital is measured by the amount of fixed assets and its price (w_2) is measured by the ratio of other operating expenses to x_2. Borrowed funds consists of all deposits and borrowed money and its price (w_3) is defined as the ratio of total interest expenses to x_3. Total costs equal the sum of the above three expenses. All of the inputs and outputs are expressed in thousands of real US dollars deflated by the consumer price index of individual countries with base year 2000. Table 1 presents variable definitions.

Table 2 summarizes the descriptive statistics for all variables and the distribution of banks across countries. These statistics show that substantial variation in quantities of inputs and outputs and input prices exists among countries, implying that banks in these countries might adopt dissimilar production techniques and choose heterogeneous operation scales. Such differences justify the use of the metafrontier model for the study of international comparison.

The empirical analysis is conducted under a two-step SF procedure, where the effects of environmental heterogeneity on cost efficiency and TGR can be accounted for in both steps. Specifically, microeconomic variables explaining bank-specific differences and macroeconomic variables reflecting country differences are included in the estimation of group frontiers and the metafrontier, respectively. The micro-level variables are considered to be correlated with regulatory conditions, competitive conditions, and ownership in Eq. (3). The macro-level variables are considered to be associated with nationwide features, characterizing economic conditions and market structure as a whole in Eq. (11).[5]

In the first-step we estimate the FF cost frontier for each sample country. Three environmental variables are considered, i.e., equity to total assets ratio (ETA), average return on assets (ROA), and the ownership structure. To proxy for regulatory conditions faced by individual banking industry, the equity to total assets ratio, is adopted. It is well-known that equity capital provides a buffer against portfolio losses and is regarded as a substitute for deposits and borrowed money to finance loans. A bank with a lower equity level implies that its managers tend to have a higher risk-taking attitude and are willing to conduct a greater leverage. It is often claimed that a well-capitalized bank is more efficient (Berger & Mester, 1997; Lozano-Vivas et al., 2001; Yildirim & Philippatos, 2007).

The ROA is used as an indicator of a bank's profitability that is intimately affected by the competitive condition of the banking industry. To proxy for competitive conditions encountered by different banking industries, the average return on assets in each year is calculated. According to Lozano-Vivas et al. (2001), Cavallo and Rossi (2002), Lozano-Vivas et al. (2002), and Andrieş (2011), the relationship between the profitability ratio and efficiency is expected to be positive. The higher the profitability ratio, the more efficient is the bank.

The relationship between ownership and efficiency has been one of the major research interests. See, for example, Beccalli (2004), Bonin, Hasan & Wachtel, (2005a, b), Fries and Taci (2005), Yildirim and Philippatos (2007), and Huang et al. (2011b), to mention a few. As noted by Berger (2000), there are two main hypotheses pertaining to the effect of ownership. According to the home field advantage hypothesis, domestic private banks are more efficient than foreign-owned banks, because foreign-owned banks incur higher costs and receive lower revenues than domestic banks do. Conversely, the global advantage hypothesis asserts that foreign-owned banks have competitive advantages over domestic banks, resulting in higher efficiency scores. The recent literature supports

[3] Let $\ln L(\theta)$ be the log-likelihood function of Eq. (11). The standard ML estimators of θ, $\hat{\theta}$, have the inverse of the Fisher information matrix $I(\theta) = -E\left(\frac{\partial^2 \ln L(\theta)}{\partial\theta\partial\theta^T}\right)$ as the covariance matrix of $\hat{\theta}$. However, the covariance matrix of the quasi-maximum likelihood estimators has the so-called sandwich form: $I^{-1}(\theta)[S(\theta)S^t(\theta)]I^{-1}(\theta)$, where $S(\theta)=E(\partial \ln L(\theta)/\partial\theta)$ is the score function. Johnston and DiNardo (1997: pp. 428–430) provide a brief discussion of the quasi-maximum likelihood estimation of misspecified models and the derivation of the covariance matrix.

[4] This selection is the same as Altunbaş et al. (2000, 2001b), Weill (2004), and Fries and Taci (2005).

[5] The idea follows Huang et al. (2014) and Huang, Chiang, and Tsai (2015). Since managerial ability and the choice of technology tend to be intimately correlated with each other, our selection of the two sets of environmental variables appears to be acceptable.

Table 1
Summary of variables, descriptions, and data sources.

Variables	Definition	Source
Input and output		
Total Loans (y_1)	Short-term and long-term loans	Bankscope
Other earning assets (y_2)	Other earning assets, including government bonds, corporate securities, and other investments	Bankscope
Non-interest revenue (y_3)	Fee and commission income and other income	Bankscope
Labor (x_1)	Total assets (net of fixed assets)	Bankscope
Physical capital (x_2)	Total fixed assets	Bankscope
Borrowed funds (x_3)	Deposits and borrowed money	Bankscope
Price of labor (w_1)	Total personnel expenses / total assets	Bankscope
Price of physical capital (w_2)	Other operating expenses / total fixed assets	Bankscope
Price of borrowed funds (w_3)	Total interest expenses / total funding	Bankscope
Microeconomic variables		
Equity to asset ratio	The ratio of equity capital to total assets of a bank	Bankscope
Average return on assets	Average ROA of all banks per annum	Bankscope
State-owned banks	State = 1 for state-owned banks and 0 otherwise; foreign banks are the normalization.	Bankscope
Domestic private banks	Private = 1 for private banks and 0 otherwise; foreign banks are the normalization.	Bankscope
Macroeconomic variables		
Real GDP per capita	The ratio of a nation's real gross domestic product to its population	WDI
Population Density	The ratio of inhabitants per square kilometer	WDI
Deposit density	The ratio of deposit per square kilometer	IFS
HHI	The Herfindahl-Hirshmann index	ECB

Notes: WDI, World Development Indicator, World Bank; IFS, International Financial Statistics, IMF; ECB, EU Banking Structures, European Central Bank.

that foreign-owned banks operate more efficient than domestic private banks and state-owned banks. Our sample banks are classified into three ownership types, i.e., state-owned, domestic private, and foreign-owned banks, with the last one arbitrarily chosen as the normalization.

In the second step, the new stochastic metafrontier model is estimated as the benchmark to evaluate the TGRs for each bank of all sample countries. The salient feature of the new model is its capability of linking the TGRs with a set of macroeconomic environmental variables. Four environmental variables that are believed to influence the TGRs are included, i.e., real GDP per capita (GDPPC), population density (PD), deposit density (DD), and Herfindahl-Hirshmann index (HHI).[6]

Variable GDPPC is measured by the ratio of a nation's real gross domestic product to its population, serving as a proxy for the overall macroeconomic conditions. As noted by Dietsch and Lozano-Vivas (2000), Lozano-Vivas et al. (2001), Lozano-Vivas et al. (2002), and Huang et al. (2011b), GDPPC affects both demand for and supply of banking services, such as deposits and loans. An increase in GDPPC raises the demand for loans and the supply of loanable funds fueled by savings, which may stimulate banks' output and profits. In addition, a country with a higher level of GDPPC usually has developed a relatively mature banking system and operated under an advanced technology. Hence, its group frontier is apt to be closer to the metafrontier, corresponding to higher values of the TGR.

Variable PD is defined as the ratio of inhabitants per square kilometer, which may capture the potential that banks develop channels for offering financial services to possible customers. Lozano-Vivas et al. (2002) claim that a higher level of PD results in less expenditures on retail distribution of banking activities. Conversely, the supply of banking services in a market of lower PD are likely to incur higher operating costs and little incentive to increase their efficiency (Radić, Fiordelisi & Girardone, 2012). Thus, the relationship between the PD and TGRs is expected to be positive.

Variable DD is calculated as the ratio of deposit per square kilometer. Although Fries and Taci (2005) and Weill (2007) argue that banks operating in a higher DD market would likely raise funds less costly, this cost saving would be offset by the fact that banks are facing keen competition and have to employ more and higher quality inputs to provide high quality of services to their customers, but still charge competitive prices. As noted by Huang et al. (2011b), this may hinder banks from minimizing their costs of production. Thus, deposit density may widen the gap between country frontiers and the metafrontier.

Variable HHI is defined as the sum of squared market shares (multiplied by 100) of each bank in terms of total assets. The HHI ranges from 0 to 10,000. A value of HHI in excess of 1800 implies that the market is highly concentrated; a value of HHI lying between 1000 and 1800 indicates that the market's degree of concentration is medium; a value of HHI less than 1000 means that the market is highly competitive. One prediction of the quiet life hypothesis (Hicks, 1935) is that an increase in concentration results in a decrease in bank performance. This hypothesis recognizes that monopoly power allows managers to reduce efforts to increase its operating performance. Conversely, the structure-conduct-performance (SCP) paradigm posits the opposite relationship, i.e., increased market power generate collusive behavior leading to higher profitability. In addition, the efficiency structure hypothesis states that the efficient firms have lower cost and are able to increase their market share, which leads to higher concentration

[6] The HHI is taken from the European Central Bank (ECB) annual report on EU banking structures. Switzerland is not included in the ECB report, whose HHI is directly computed from our data.

Table 2
Summary statistics for banking costs, outputs, inputs, and input prices.

	Austria	Belgium	Denmark	France	Germany	Italy	Luxembourg	Spain	Switzerland	United Kingdom
Number of banks	78	53	65	194	205	180	138	81	226	83
Number of observations	584	350	709	1505	1492	783	1060	331	1888	487
Outputs										
Loans	1,836,842	11,381,888	5,007,991	8,863,882	10,376,787	9,856,646	1,376,986	14,615,682	1,815,620	1,329,927
	(5,754,238)	(32,269,660)	(21,894,605)	(38,733,876)	(51,019,992)	(29,710,833)	(3,312,498)	(47,318,860)	(15,063,931)	(3,911,571)
Investments	1,913,226	16,432,494	3,826,540	14,765,455	11,833,355	7,991,604	4,574,350	10,515,667	1,685,843	2,069,733
	(7,040,553)	(52,086,775)	(17,574,719)	(72,505,596)	(63,077,722)	(34,813,286)	(9,467,193)	(42,087,634)	(18,316,783)	(6,130,452)
Non-interest revenue	28,964	119,006	62,500	218,014	196,312	238,371	47,894	195,092	70,822	58,646
	(61,583)	(304,041)	(228,273)	(894,384)	(1,155,556)	(720,893)	(86,438)	(677,966)	(658,622)	(166,601)
Inputs										
Labor (total assets net of fixed assets)	3,920,348	30,794,108	9,939,146	28,687,128	26,607,142	19,011,135	6,196,383	26,001,693	3,947,823	3,758,852
	(12,458,595)	(94,052,505)	(44,696,413)	(141,683,441)	(161,628,058)	(62,845,205)	(12,502,269)	(90,015,368)	(37,574,329)	(9,906,094)
Physical capital	22,047	118,831	41,922	75,699	57,699	128,980	15,544	165,366	30,340	15,692
	(57,269)	(295,292)	(164,687)	(348,922)	(229,518)	(382,291)	(41,155)	(427,165)	(232,340)	(41,171)
Borrowed funds	2,616,737	24,902,029	5,524,243	19,108,835	18,766,116	11,503,018	5,204,744	17,256,080	3,043,267	2,533,470
	(8,560,111)	(74,669,859)	(25,232,494)	(88,335,476)	(102,238,210)	(33,504,383)	(10,515,470)	(53,385,572)	(26,871,978)	(6,841,122)
Input prices										
Price of labor	0.0193	0.0130	0.0206	0.0177	0.0215	0.0151	0.0073	0.0136	0.0248	0.0170
	(0.0270)	(0.0138)	(0.0187)	(0.0147)	(0.0529)	(0.0093)	(0.0081)	(0.0122)	(0.0262)	(0.0348)
Price of physical capital	4.2322	2.9496	3.8986	6.9867	6.4280	5.6058	5.1911	2.9280	3.8473	5.7809
	(9.9925)	(4.0598)	(9.7962)	(17.2573)	(13.2885)	(17.2804)	(8.1797)	(7.7763)	(11.9318)	(9.6462)
Price of funds	0.0387	0.0381	0.0443	0.0504	0.0453	0.0370	0.0552	0.0353	0.0246	0.0443
	(0.0458)	(0.0294)	(0.1793)	(0.0768)	(0.1102)	(0.0423)	(0.0706)	(0.0202)	(0.0211)	(0.0425)
Total cost	166,689	1,096,987	357,662	1,198,405	995,112	788,894	343,162	933,575	150,445	181,263
	(518,882)	(3,162,348)	(1,497,115)	(4,793,454)	(4,841,139)	(2,405,316)	(757,100)	(2,952,333)	(1,405,354)	(430,622)

Notes: All inputs and outputs are expressed in thousands of real US dollars with a base year of 2000. Standard deviations are in parentheses.

Table 3
Summary statistics for environmental variables.

	Austria	Belgium	Denmark	France	Germany	Italy	Luxembourg	Spain	Switzerland	United Kingdom
Microeconomic variables										
Regulatory condition										
Equity to total assets ratio (%)	11.5375	7.1367	11.6300	8.5273	13.2054	11.1126	6.0635	9.8167	16.5417	16.4756
	(12.6925)	(6.1405)	(5.3816)	(9.1156)	(15.4584)	(9.5368)	(6.1860)	(10.1755)	(13.6556)	(12.1250)
Competitive condition										
Average return on assets (%)	0.8437	0.5489	1.1497	0.4869	0.6520	0.4785	0.7227	0.2631	1.2247	0.6920
	(0.6388)	(0.3679)	(0.7917)	(0.5590)	(0.3711)	(0.3430)	(0.2720)	(0.5377)	(0.4971)	(0.6592)
Ownership structure										
State-owned banks	0.0137	0.0114	0.0014	0.0326	0.0617	0.0038	0.0330	0.0423	0.0307	0.0698
	(0.1163)	(0.1064)	(0.0376)	(0.1775)	(0.2406)	(0.0618)	(0.1788)	(0.2016)	(0.1726)	(0.2551)
Domestic private banks	0.5959	0.5829	0.9520	0.6804	0.6193	0.9029	0.1528	0.6918	0.5689	0.4579
	(0.4911)	(0.4933)	(0.2138)	(0.4665)	(0.4857)	(0.2962)	(0.3600)	(0.4624)	(0.4954)	(0.4987)
Macroeconomic variables										
Main economic condition										
Real GDP per capita	24,549	22,733	30,253	21,815	23,296	19,136	47,206	14,771	35,100	26,606
	(1,795)	(1,495)	(1,610)	(1,218)	(1,313)	(703)	(6,220)	(1,317)	(1,821)	(1,976)
Population density	99	343	127	113	236	200	174	85	183	249
	(2)	(7)	(2)	(3)	(1)	(4)	(10)	(5)	(6)	(5)
Deposit density	3,158	10,250	2,520	2,358	7,049	3,837	42,067	2,206	12,036	3,861
	(848)	(3,088)	(1,071)	(708)	(2,259)	(1,320)	(18,433)	(1,299)	(3,562)	(1,412)
Market structure										
HHI	518	1,611	1,190	592	170	254	295	454	2,197	386
	(60)	(498)	(181)	(90)	(44)	(60)	(60)	(92)	(863)	(113)

Notes: Real GDP per capita and deposit density are expressed in thousands of real US dollars with a base year of 2000. Standard deviations are in parentheses.

(Demsetz, 1974). Thus, market structure can have either positive or negative impacts on bank's TGRs.

Table 3 presents the descriptive statistics of all environmental variables mentioned above. These statistics uncover that banks in different countries have different features, caused mainly by distinct regulatory environments, managerial abilities, economic environments, and market structure. Given these fundamental differences, it is critical to take them into account in the efficiency assessment and comparison among distinct groups operating under heterogeneous technologies. This justifies the use of the new metafrontier model that enables the calculation of comparable cost efficiencies and TGR that can be further linked with various determinants.

5. Empirical results and analysis

5.1. Parameter estimates

Software FRONTIER 4.1 is applied to estimate individual country frontiers of Eq. (1). Both the FF and the standard TL cost functions are estimated for the purpose of comparison. These estimates are not shown to save space, but are available upon request for the authors. In summary, more than a half of the parameter estimates in each country frontier reach statistical significance at least at the 10% level. The hypothesis that the parameters of all the Fourier series are joint zero is decisively rejected at the 1% level of significance by the likelihood ratio (LR) test. We, thus, claim that the FF cost function is valid to characterize the sample banks' production technologies and the underlying cost structure.

To better address the statistical problem in a two-stage approach, we further test for the null hypotheses that the coefficients of all macro-level environmental variables are jointly zero by the LR test. The restricted group frontier for each sample country contains only micro-level variables, whose log-likelihood value is denoted by L_R, while the unrestricted group frontier includes both micro- and macro-level variables, whose log-likelihood value is denoted by L_U. If the hypothesis is not rejected by the data, then the restricted model holds, indicating that those macro-level variables can be ignored in the first stage. These estimates are not shown to save space, but are available upon request for the authors. In summary, more than one half of the macro-level parameter estimates in all country frontiers fail to reach statistical significance at the 5% level. The null hypothesis cannot be rejected at the 5% level of significance. We therefore do not take these macro-level environmental variables into account in the first stage.[7]

Table 4 summarizes coefficient estimates of the micro-level environmental variables based on the FF cost function. The outcomes reveal that most of those estimates are significant in each sample country, but their signs differ, caused possibly by the distinct country-specific situations. We focus our attention only on those estimates that attain statistical significance. Variable ETA is negatively associated with the cost inefficiency term for all sample countries, implying that the higher the ETA is, the more efficient is the bank. This result is congruent with many previous studies, such as Fries and Taci (2005), Kumbhakar and Wang (2007), Huang et al. (2011b), and Radić et al. (2012). With some exceptions, the coefficient of ROA is found to be significantly negative, showing that high profitability prompts banks' cost efficiency in these countries. This finding is consistent with Cavallo and Rossi (2002) and Casu and Molyneux (2003). For the ownership dummies, the sign of the coefficient estimate of the state-owned and domestic private banks are significantly positive in most countries. One is led to conclude that foreign-owned banks are more cost efficient than the other two forms of banks. This result is similar to Fries and Taci (2005) and Huang et al. (2011b) and supports the view of global advantage hypothesis.

Before estimating the metafrontier, it is important to test the null hypothesis (H_0) that the sample banks from different countries adopt the same technology. If the hypothesis is not rejected by the data, then all banks of different countries share the same technology, implying that the estimation of the metafrontier is not necessary. A likelihood-ratio test is utilized here. The value of the log-likelihood function for the stochastic cost frontier estimated by pooling the data for all sample countries ($L(H_0)$), which assumes that those banks from different countries undertake the same technology, is equal to 2593.63. See the bottom line of the first column in Table 5. The sum of the values of the log-likelihood functions for the ten cost frontiers ($L(H_1)$) is equal to 3085.38, which assumes that the sample banks from different countries adopt heterogeneous technology. The degrees of freedom for the Chi-square distribution involved are 477, which is the difference between the number of parameters estimated under H_1 and H_0. Since the LR test statistic of 983.51 exceeds the corresponding critical value at the 1% level, the hypothesis is decisively rejected. We conclude that the sample banks from different countries are indeed operating under different technologies, which validates the construction of the metafrontier.

The metafrontier FF cost function is estimated by the SMF model of Eq. (11) and by the quadratic programming technique. Recall that the SMF model allows the one-sided error term of U_{jit}^M to be associated with an array of environmental variables, similar to Battese and Coelli (1995). This model is labeled as SMF95. Moreover, U_{jit}^M can be simply specified as a function of time, like the one proposed by Battese and Coelli (1992), which is formulated as $U_{jit}^M = U_{ji}^M \exp[-\eta(t - T)]$, where $U_{ji}^M \sim N^+\left(\mu, \sigma_{u^M}^2\right)$. This latter model is dubbed SMF92.

Table 5 summarizes the second-step parameter estimates for models SMF95 (column 1), SMF92 (column 2), and QP (column 3). The estimates of the Fourier series are shown in Table A1 of Appendix A. Daraio and Simar (2005, 2007) and Simar and Wilson (2007) point out the statistical problem in the context of the two-stage DEA model. In this regard, the standard errors of Models SMF95 and SMF92 are modified by the use of sandwich-form estimators.[8] The coefficient estimates from the programming technique of QP deviate substantially from those of the SMF95 and SMF92, whereas the estimates of the SMF95 and SMF92 are quite close to each other. In addition, the estimated σ_u^2 and σ_v^2 of both SMF models are significantly different from zero, supporting the presence of error components appearing in the stochastic metafrontier model.

The corresponding parameter estimates of the two SMF models are somewhat close to each other. All of the macroeconomic environmental factors exercise significant influences on the TGRs. As expected, the coefficient estimate of variable GDPPC is significantly negative, implying that better economic conditions foster banks undertaking more advanced production technology, prompting the country specific frontier closer to the metafrontier. Similarly, the significantly negative coefficient of PD uncovers that banks operating in an area with higher PD are inclined to adopt better technology. The variable of DD is found to have a significantly positive coefficient, suggesting that banks in a high DD market tend to adopt inferior technology. The coefficient estimate of the HHI is significantly negative, implying that banks with higher market power are likely to select more advanced technology than those banks running in a less concentrated market.

5.2. Measures of cost efficiency and technology gaps

Table 6 presents the descriptive statistics of the TGR, CE, and MCE measures for all countries of the three models. Note that the estimated CEs are not comparable across countries. The average values (standard deviation) of measure CE vary from roughly 0.812 (0.072) in Spain to 0.930 (0.041) in Germany with an overall average value of 0.891 (0.077). A representative bank in Spain is able to save its production costs by improving its managerial ability up to 19.8%. In contrast, the potential cost saving of an average German bank is merely 7%, whose actual costs lie quite close to the country specific frontier for a given bundle of output. This result falls in the range achieved by previous empirical work on the efficiency of the Western European banking industries. See, for example, Altunbaş et al. (2001a), Schure, Wagenvoort, and O'Brien (2004), Bos and Schmiedel (2007), Huang et al. (2011a).

According to the model of SMF95, the average values (standard deviation) of the TGR range from 0.807 (0.099) in Luxembourg to 0.960 (0.013) in Denmark with an overall mean value of roughly 0.916 (0.070). Banks in Luxembourg are found to assume the least

[7] We are particularly grateful to an anonymous referee who provides us with helpful information.

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sophisticated technology, since its country specific cost frontier deviates the farthest from the metafrontier than other countries' frontiers. This may be attributed to the fact that Luxembourg has the largest value of deposit density (see Table 3), which is negatively correlated with TGR. Conversely, Danish banks take on the most superior technology, whose cost frontier is the nearest to the metafrontier. This is partially ascribable to its having the third lowest value of deposit density. British banks also undertake quite advanced technology. A common feature of these two countries is that both Denmark and the United Kingdom, the member states of the EU, have opt-outs from joining the Eurozone by reasons of economic sovereignty. It is known that both countries have modern, very open and well-developed market economy. They believe that limiting their rights to conduct an independent monetary policy in the European economic and monetary union would be detrimental to their economies.

The average TGRs in these sample countries are quite close to one another, with the exception of Luxembourg. This means that banks operating in such a mature and highly integrated market, like those Western European countries, choose to assume similar and superior technology, making their cost frontiers do not diverge apart from the metafrontier very much. In other words, the integration of the EU economies is beneficial, because liberalization of cross-border trade of financial services stimulates innovation and technological progress. This finding is consistent with, e.g., Bos and Schmiedel (2007).

We can now compare production efficiency among nations on the basis of MCE that is measured against the metafrontier FF cost function. The average values of the MCE of the ten countries range between 0.739 and 0.847, with an overall mean value of 0.816. Banks in Germany (0.847), Switzerland (0.843), and Denmark (0.831) are the top three most efficient, while banks in Spain (0.739), Luxembourg (0.742), and Italy (0.795) are the bottom three least efficient. This finding is consistent with the recent empirical works, e.g., Pastor and Serrano (2006), Apergis and Alevizopoulou (2011), and Camilla et al. (2013). It is interesting to note that previous works, such as Allen and Rai (1996) and Vennet (2002), have found evidence that universal banks are more efficient than separated banks. It is known that Germany and Switzerland are classified as the universal banking system (Rime and Stiroh, 2003; Xie, 2007).

Table 4
Parameter estimates of the environmental variables.

Country	ETA		ROA		State banks		Private banks	
Austria	-0.020	***	-0.153	***	-1.927		-0.589	***
	(0.003)		(0.045)		(1.229)		(0.117)	
Belgium	-0.016	***	-0.006		0.100		-0.046	
	(0.001)		(0.037)		(0.110)		(0.029)	
Denmark	-0.002	*	-0.020	**	-0.725	***	0.002	
	(0.001)		(0.008)		(0.127)		(0.020)	
France	-0.021	***	-0.252	***	0.548	***	0.215	***
	(0.003)		(0.037)		(0.101)		(0.058)	
Germany	-0.001	*	-0.126	**	0.169	*	0.989	***
	(0.001)		(0.054)		(0.095)		(0.035)	
Italy	-0.009	***	-0.306	***	1.633	***	-0.217	***
	(0.001)		(0.028)		(0.143)		(0.039)	
Luxembourg	-0.017	***	0.176		0.327	***	0.058	
	(0.001)		(0.114)		(0.102)		(0.089)	
Spain	-0.011	***	-0.046	***	-0.037		0.109	***
	(0.001)		(0.018)		(0.052)		(0.014)	
Switzerland	-0.018	***	-0.857	***	0.980	***	0.702	***
	(0.001)		(0.053)		(0.123)		(0.058)	
United Kingdom	-0.032	***	-0.094	**	-0.311		0.375	***
	(0.002)		(0.043)		(0.225)		(0.081)	
Expected sign	−		−		+		+	
Estimated sign								
significantly positive	0		0		5		5	
significantly negative	10		8		1		2	
insignificant	0		2		4		3	

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

Table 5
Parameter estimates for various competing metafrontier models (FF).

Independent	SMF95			SMF92			QP	
variables	Coefficient		S.E.	Coefficient		S.E.	Coefficient	S.D.
constant	2.073	***	0.071	1.263	***	0.093	2.387	0.580
$\ln y1$	0.613	***	0.017	0.589	***	0.011	0.441	0.091
$\ln y2$	0.441	***	0.021	0.577	***	0.012	0.385	0.079
$\ln y3$	-0.146	***	0.016	-0.171	***	0.013	-0.089	0.069
$\ln w2$	0.008		0.008	0.108	***	0.007	0.130	0.046
$\ln w3$	0.238	***	0.012	0.121	***	0.009	0.159	0.072
$\ln y1 \times \ln y1$	0.098	***	0.001	0.102	***	0.001	0.086	0.008
$\ln y2 \times \ln y2$	0.135	***	0.003	0.127	***	0.001	0.109	0.009
$\ln y3 \times \ln y3$	0.031	***	0.006	0.020	***	0.002	-0.022	0.013
$\ln y1 \times \ln y2$	-0.117	***	0.001	-0.122	***	0.001	-0.104	0.006
$\ln y1 \times \ln y3$	0.009	***	0.002	0.015	***	0.001	0.022	0.007
$\ln y2 \times \ln y3$	-0.020	***	0.003	-0.016	***	0.001	0.007	0.009
$\ln w2 \times \ln w2$	0.007	***	0.001	0.005	***	0.001	-0.009	0.005
$\ln w3 \times \ln w3$	0.097	***	0.002	0.090	***	0.001	-0.055	0.012
$\ln w2 \times \ln w3$	0.003	***	0.001	0.005	***	0.001	0.032	0.007
$\ln y1 \times \ln w2$	-0.011	***	0.001	-0.014	***	0.001	-0.012	0.004
$\ln y1 \times \ln w3$	0.026	***	0.002	0.032	***	0.001	0.024	0.007
$\ln y2 \times \ln w2$	0.005	***	0.001	0.001		0.001	-0.001	0.007
$\ln y2 \times \ln w3$	-3.59E-05		0.002	0.010	***	0.001	0.040	0.011
$\ln y3 \times \ln w2$	0.011	***	0.001	0.009	***	0.001	0.013	0.006
$\ln y3 \times \ln w3$	-0.021	***	0.004	-0.030	***	0.001	-0.078	0.011
$t \times \ln y1$	0.002	***	2.29E-04	0.003	***	1.83E-04	0.002	0.002
$t \times \ln y2$	-0.004	***	3.45E-04	-0.003	***	2.36E-04	-0.005	0.003
$t \times \ln y3$	2.08E-04		3.04E-04	0.001	***	2.61E-04	-9.75E-05	0.002
$t \times \ln w2$	-0.002	***	1.78E-04	-0.001	***	2.04E-04	-0.001	0.001
$t \times \ln w3$	-0.002	***	0.001	-0.002	***	2.97E-04	0.002	0.003
t	0.033	***	0.003	2.49E-04		0.002	0.078	0.021
t^2	-4.85E-04	**	2.02E-04	-3.05E-04	**	1.22E-04	-0.003	0.001
Constant	9.691	***	1.964	–			–	
$\ln GDPPC$	-1.528	***	0.278	–			–	
$\ln PD$	-0.707	***	0.087	–			–	
$\ln DD$	0.976	***	0.132	–			–	
HHI	-1.09E-04	***	3.05E-05	–			–	
σ_u^2	0.091	***	0.001	0.107	***	0.002	–	
σ_v^2	0.013	***	0.005	0.010	***	0.001	–	
μ	–			-0.338	***	0.023	–	
η	–			0.008	***	0.002	–	
Log-likelihood	4038.648			6497.153			–	

Notes: SMF95, stochastic metafrontier with Battese and Coelli (1995) specification; SMF92, stochastic metafrontier with Battese and Coelli (1992) specification; QP, quadratic programming model. The standard errors of SMF are corrected by sandwich estimators. The standard errors of the QP estimators are obtained from bootstrapping. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Our empirical evidence is congruent with the previous works and validates the current trend of the banking universalization.

It is important to note that the mean values of the TGR in all countries, derived from the QP method, are less than those from the SMF methods, leading to lower average values of the MCE. The programming method underestimates banks' TGR and MCE and gives larger variations of them. This phenomenon is in accordance with the previous studies, in that the use of nonparametric techniques report lower efficiency with lager variations than the use of parametric techniques.[9] Berger and Mester (1997) note that the above result is partially arisen from the inclusion of some random errors into the efficiency score.

As far as the SMF92 model is concerned, the average values (standard deviations) of the TGR range from 0.712 (0.122) in Luxembourg to 0.920 (0.040) in Denmark, with an overall mean value of 0.834 (0.105). The SMF92 is inclined to underestimate the TGR measures and exhibit larger variations. Recall that the macroeconomic environmental conditions are crucial determinants of the technology gap of U_{jit}^{M} in Eq. (11). The exclusion of those macroeconomic environmental variables from the SMF92 causes possibly the problem of misspecification, which may distort the TGR measures. Therefore, the SMF95 is preferable over the SMF92.

[9] See Berger and Humphrey (1997) for a comprehensive survey.

Table 6
Summary statistics of relevant efficiency scores for various competing metafrontier models based on FF specification.

	Stochastic Metafrontier with τ (SMF95)				Stochastic Metafrontier without τ (SMF92)				Metafrontier (QP)			
	Mean	Min	Max	S.D.	Mean	Min	Max	S.D.	Mean	Min	Max	S.D.
Technology gap ratio (TGR)												
Austria	0.924	0.258	1.000	0.085	0.850	0.290	1.000	0.118	0.659	0.085	1.000	0.184
Belgium	0.900	0.559	0.976	0.071	0.814	0.484	0.966	0.116	0.580	0.146	0.876	0.157
Denmark	0.960	0.870	1.000	0.013	0.920	0.760	1.000	0.040	0.720	0.280	1.000	0.107
France	0.933	0.364	1.000	0.047	0.819	0.335	0.990	0.080	0.685	0.030	1.000	0.172
Germany	0.911	0.375	1.000	0.053	0.811	0.348	1.000	0.075	0.649	0.039	0.999	0.141
Italy	0.946	0.399	1.000	0.035	0.919	0.536	1.000	0.063	0.760	0.162	1.000	0.131
Luxembourg	0.807	0.463	1.000	0.099	0.712	0.448	1.000	0.122	0.513	0.044	1.000	0.189
Spain	0.911	0.509	0.980	0.070	0.863	0.436	0.996	0.096	0.662	0.099	0.986	0.181
Switzerland	0.932	0.664	0.978	0.029	0.852	0.505	0.991	0.084	0.687	0.078	1.000	0.172
United Kingdom	0.948	0.578	1.000	0.039	0.859	0.383	1.000	0.099	0.680	0.109	1.000	0.176
All countries	0.916	0.258	1.000	0.070	0.834	0.290	1.000	0.105	0.662	0.030	1.000	0.175
Group-Specific cost efficiency (CE)												
Austria	0.892	0.428	0.979	0.070	0.892	0.428	0.979	0.070	0.892	0.428	0.979	0.070
Belgium	0.901	0.757	1.000	0.044	0.901	0.757	1.000	0.044	0.901	0.757	1.000	0.044
Denmark	0.866	0.682	0.992	0.035	0.866	0.682	0.992	0.035	0.866	0.682	0.992	0.035
France	0.887	0.226	0.983	0.072	0.887	0.226	0.983	0.072	0.887	0.226	0.983	0.072
Germany	0.930	0.286	1.000	0.041	0.930	0.286	1.000	0.041	0.930	0.286	1.000	0.041
Italy	0.840	0.210	1.000	0.122	0.840	0.210	1.000	0.122	0.840	0.210	1.000	0.122
Luxembourg	0.919	0.691	0.983	0.035	0.919	0.691	0.983	0.035	0.919	0.691	0.983	0.035
Spain	0.812	0.684	1.000	0.072	0.812	0.684	1.000	0.072	0.812	0.684	1.000	0.072
Switzerland	0.904	0.120	1.000	0.075	0.904	0.120	1.000	0.075	0.904	0.120	1.000	0.075
United Kingdom	0.845	0.193	1.000	0.112	0.845	0.193	1.000	0.112	0.845	0.193	1.000	0.112
All countries	0.891	0.120	1.000	0.077	0.891	0.120	1.000	0.077	0.891	0.120	1.000	0.077
Metafrontier cost efficiency (MCE)												
Austria	0.824	0.162	0.940	0.099	0.758	0.202	0.956	0.123	0.589	0.053	0.963	0.172
Belgium	0.811	0.528	0.947	0.073	0.734	0.448	0.942	0.117	0.522	0.139	0.837	0.143
Denmark	0.831	0.652	0.955	0.035	0.796	0.617	0.946	0.048	0.623	0.244	0.915	0.094
France	0.828	0.204	0.963	0.077	0.727	0.184	0.948	0.093	0.609	0.028	0.963	0.162
Germany	0.847	0.222	0.982	0.062	0.754	0.199	1.000	0.079	0.604	0.035	0.933	0.135
Italy	0.795	0.202	0.968	0.117	0.772	0.188	0.985	0.123	0.641	0.129	0.954	0.148
Luxembourg	0.742	0.413	0.962	0.098	0.655	0.353	0.962	0.119	0.472	0.043	0.961	0.177
Spain	0.739	0.435	0.975	0.079	0.700	0.390	0.941	0.091	0.538	0.082	0.884	0.152
Switzerland	0.843	0.115	0.943	0.075	0.770	0.098	0.958	0.102	0.622	0.051	0.951	0.170
United Kingdom	0.802	0.178	0.937	0.111	0.728	0.148	0.948	0.134	0.576	0.051	0.960	0.171
All countries	0.816	0.115	0.982	0.090	0.742	0.098	1.000	0.109	0.590	0.028	0.963	0.164

Notes: SMF95, stochastic metafrontier with Battese and Coelli (1995) specification; SMF92, stochastic metafrontier with Battese and Coelli (1992) specification; QP, quadratic programming model.

5.3. Trending of various efficiency measures

Whether the financial integration of the Single Market in the EU helps promote bank efficiencies is an interesting issue.[10] Table 7 summaries the average values of CE, TGR, and MCE, derived from the SMF95, over the sample period and Fig. 2 draws the trends of these efficiency scores. The mean values of CEs exhibit a gradual upward trend varying from 0.887 to 0.904 in the period of 1996 to 2000, followed by a slow downward trend from 0.893 to 0.871 in the period of 2001 to 2010. Measure MCE has a similar trend to CEs, which ranges from 0.813 to 0.838 in the first five years, and then goes down all the way to 0.786, especially after the subprime crisis of 2007–2010. This suggests that a more integrated financial market is able to enhance banking efficiency at the outset. This outcome is in line with, e.g., Casu and Girardone (2004), Weill (2007), and Kondeas, Caudill, Gropper, and Raymond (2008).

Although the financial integration might increase banks' cost efficiency, bank managers might be willing to take more risk to react a higher regulatory burden, which could ultimately affect banks' performance. For example, loose and easy credit conditions, such as during 2002–2008, result in higher risk-taking of lending and borrowing activities. As noted by Fiordelisi et al. (2011), banks with lower levels of efficiency tend to have a moral hazard incentive to undertake risky business, such as the less intensive monitoring of credit in an attempt to boost returns. Moreover, the exposure of higher risk is possibly to hurt a bank's efficiency, because this bank has a higher probability to consume large amounts of resources coping with the increased non-performing loans. The downward

[10] The Single Market for Financial Services in the EU was established in January 1, 1993.

Table 7
Summary statistics of relevant efficiency scores over time (SMF95-FF).

Period	CE		TGR		MCE	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
1996	0.887	0.070	0.918	0.074	0.813	0.082
1997	0.891	0.071	0.922	0.072	0.820	0.085
1998	0.897	0.063	0.922	0.068	0.827	0.081
1999	0.900	0.062	0.924	0.062	0.831	0.076
2000	0.904	0.063	0.928	0.059	0.838	0.076
2001	0.893	0.075	0.930	0.057	0.830	0.083
2002	0.894	0.081	0.924	0.059	0.826	0.088
2003	0.896	0.085	0.917	0.064	0.821	0.093
2004	0.899	0.093	0.913	0.090	0.820	0.091
2005	0.893	0.081	0.920	0.062	0.821	0.088
2006	0.894	0.083	0.914	0.069	0.816	0.095
2007	0.890	0.095	0.905	0.094	0.805	0.093
2008	0.880	0.087	0.902	0.082	0.792	0.098
2009	0.878	0.088	0.896	0.087	0.785	0.101
2010	0.871	0.096	0.903	0.074	0.786	0.099
96–98	0.892	0.068	0.921	0.071	0.820	0.083
99-01	0.899	0.067	0.927	0.060	0.833	0.078
02–04	0.896	0.081	0.918	0.065	0.822	0.091
05–07	0.893	0.080	0.913	0.071	0.814	0.092
08–10	0.877	0.090	0.900	0.081	0.788	0.100
Average	0.891	0.077	0.916	0.070	0.816	0.090

Note: SMF95, stochastic metafrontier with Battese and Coelli (1995) specification.

trends of CEs and MCEs correspond to the recession period of global economies after 2000 and the trends deteriorate ever since the subprime crisis at the late of 2007.

The mean TGRs lies between 0.918 and 0.930 and reveals a tendency toward convergence to the metafrontier of the Western European banking market over the period 1996–2001. A gradual upward trend in first six years indicates that the gaps between country frontiers and the metafrontier shrink over time. The creation of the Single Market appears to benefit these sample banks by improving their production technologies. However, this affirmative trend is reversed particularly during the global economic recession and subprime crisis. This is especially true when comparing our findings with, e.g., those of Camilla et al. (2013) who investigate globalization and technological convergence in the EU. They claim that the technology divergence may be closely related to the foreign direct investment (FDI), an important channel for international technology diffusion. The FDI declines especially after 2000.[11]

Note that different trends are traced out by the other two models, i.e., SMF92 and the QP. Based on the SMF92, Appendix B shows the means of the relevant efficiency scores. Since the estimate of η is significantly positive, this model predicts that the TGRs grow with time, which is confirmed by Fig. B1, with a few exceptions. The foregoing implies that the production technology of sample banks improves during the sample period. Since the SMF92 model ignores other determinants of the TGR, its average TGR value is underestimated and difficult to precisely describe the evolution of technology innovations, occurred in European banking market.

According to Fig. B2, the QP model shows quite different trends from those obtained by the SMF95 and SMF92. Its average MCE and TGR fluctuate synchronously. That is, the mean MCEs (TGRs) exhibit a slow upward trend during 1996–2005 and then turn into a downward trend. It is noteworthy that these results are likely to be confounded with random shocks. As the programming technique is deterministic in essence and is unable to separate random disturbances from the model. In addition, time effects and country heterogeneity cannot be associated with the technology gap.

An interesting question immediately arises, i.e., which element of the CE and TGR plays a more important role in the determination of the MCE. Fig. 2 reflects that the CE component is uniformly lower than the TGR component, implying that the managerial inability constitutes the primary source of inefficiencies, rather than the technology adopted. This suggests that banks should make every effort to enhance their managerial ability in such a way as to reduce their input mix for a given output combination, since the CE is input-oriented. However, if the environmental heterogeneity is overlooked, the average TGR is uniformly lower than the CE, by referring to Figs. B1 and B2, which means that the major source of inefficiencies comes from the adoption of inferior technology, instead of the managerial inability. This validates the importance of environmental variables on modeling the metafrontier.

[11] This trend is also confirmed by the t-test of difference in mean. There exist statistically significant difference in mean at the 1% level between three sub-period averages of 1996–2000, 2001–2007, and 2008–2010.

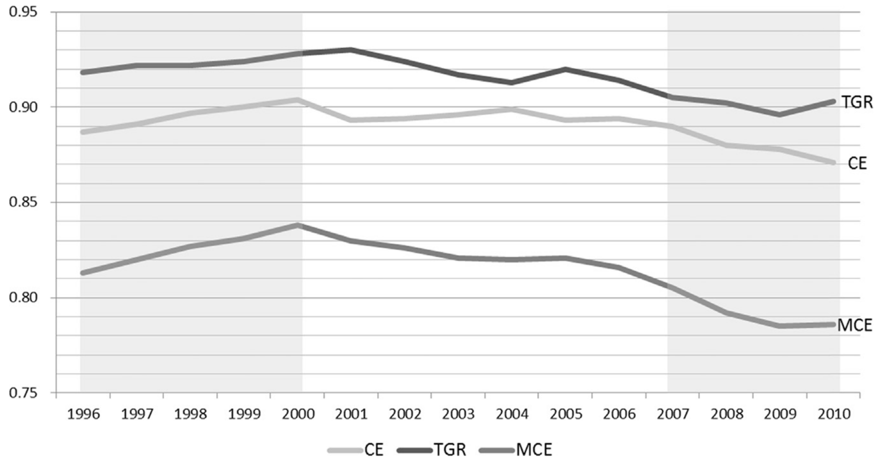

Fig. 2. Trends in CE, TGR, and MCE (SMF95).

6. Conclusion

This paper successfully extends the deterministic metafrontier TL cost function to the more general SMF FF cost function that is known as more flexible than the TL form. Differing from the conventional two-step procedure, proposed by Battese et al. (2004) and O'Donnell et al. (2008), the SMF FF cost function is formulated and applied to estimate the TGR. In this manner, the first and the second step of the approach are consistent. Moreover, the SMF FF cost function is advantageous over the programming techniques due to the former having desirable statistical properties, allowing researchers to draw statistical inferences, and being able to associate the TGRs with a set of country-specific environmental variables. Conversely, estimates from programming techniques are lack of the above traits, in addition to their confounding with random shocks due to their deterministic essence. The environments faced with a bank usually impose some restrictions on bank managers, which may limit their ability to optimize the allocation of resources among alternative uses. This helps identify the sources of a bank's production inefficiency.

Using the newly developed methods, this paper devotes to decompose the overall cost efficiency of Western European banks during the period of 1996 to 2010 in an attempt to accurately compare the sources of cost inefficiency scores among the European banks. We believe that our approach can provide more information to bank managers and government authorities than the conventional one. Our empirical application discloses that the TGR and MCE exhibit gradual upward trends during 1996–2000 and then fluctuate with downward trends, especially after the subprime crisis of 2007–2010. The results show that a single and competitive banking market not only prompts cost efficiency, but also shrinks the technology gap within the member states of the EU during 1996–2000. However, the wave of international economic integration is inevitably accompanied by higher degree of risk exposure. The subsequently downward trends reflect this factor during the global recession period after 2000 and deteriorate after the subprime financial crisis starting from the late 2007.

It is worth-mentioning that the choice of methodology has crucial influences on the estimation results and the implied policy implications. Not only the parameter estimates considerably differ from one another, but also the estimated efficiency scores show dissimilar distribution and patterns. The mathematical programming techniques tend to underestimate the TGR and MCE measures with larger variations, probably due to specification error, i.e., the estimates are likely to confound with shocks and fail to link with environmental variables. Although the SMF92 is capable of incorporating random shocks, it still underestimates the measures of the TGR and MCE with larger variations in comparison to the SMF95. Our SMF specification, i.e., the SMF95 that includes group-specific environmental variables as determinants of the technology gap, appears to be superior and preferable.

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Table A1
Estimates of Fourier series for various competing metafrontier models.

Independent variables	Stochastic Metafrontier with τ (SMF95) Coefficient		S.E.	Stochastic Metafrontier without τ (SMF92) Coefficient		S.E.	Metafrontier (QP) Coefficient	S.D.
cos $z1$	0.092	***	0.009	0.036	***	0.009	-0.070	0.084
sin $z1$	-0.119	***	0.006	-0.006		0.008	-0.358	0.060
cos $z2$	-0.011	*	0.006	0.061	***	0.007	-0.146	0.058
sin $z2$	0.055	***	0.007	0.017	**	0.008	-0.010	0.049
cos $z3$	-0.013	*	0.007	-0.086	***	0.008	-0.029	0.054
sin $z3$	0.047	***	0.005	0.004		0.007	0.235	0.048
cos 2$z1$	-0.064	***	0.004	-0.038	***	0.004	-0.026	0.032
sin 2$z1$	0.033	***	0.003	0.040	***	0.004	0.046	0.037
cos 2$z2$	-0.052	***	0.003	-0.069	***	0.003	0.036	0.026
sin 2$z2$	0.020	***	0.003	0.030	***	0.004	-0.019	0.032
cos 2$z3$	0.001		0.004	-0.011	***	0.004	0.095	0.025
sin 2$z3$	-0.026	***	0.003	-0.013	***	0.003	-0.016	0.024
cos $z1z2$	0.124	***	0.004	0.147	***	0.005	0.019	0.040
sin $z1z2$	-0.031	***	0.004	-0.019	***	0.005	-0.165	0.040
cos $z1z3$	-0.025	***	0.004	-0.055	***	0.005	-0.064	0.045
sin $z1z3$	-0.088	***	0.004	-0.052	***	0.005	-0.088	0.035
cos $z2z3$	0.033	***	0.004	0.026	***	0.004	-0.072	0.040
sin $z2z3$	0.117	***	0.004	0.047	***	0.005	0.186	0.032

Notes: SMF95, stochastic metafrontier with Battese and Coelli (1995) specification; SMF92, stochastic metafrontier with Battese and Coelli (1992) specification; QP, quadratic programming model. The standard errors of the QP estimators are obtained using a bootstrapping method with 1000 replications. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

Appendix A

See Table A1.

Appendix B

See Figs. B1 and B2.

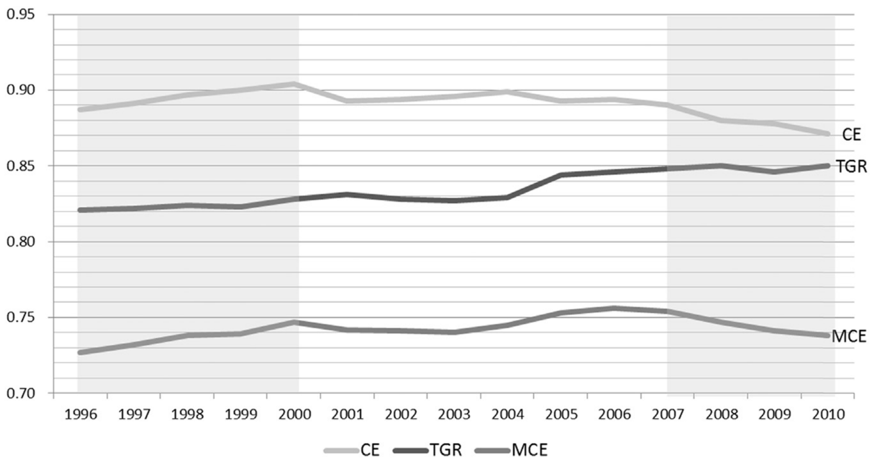

Fig. B1. Trends in CE, TGR, and MCE (SMF92).

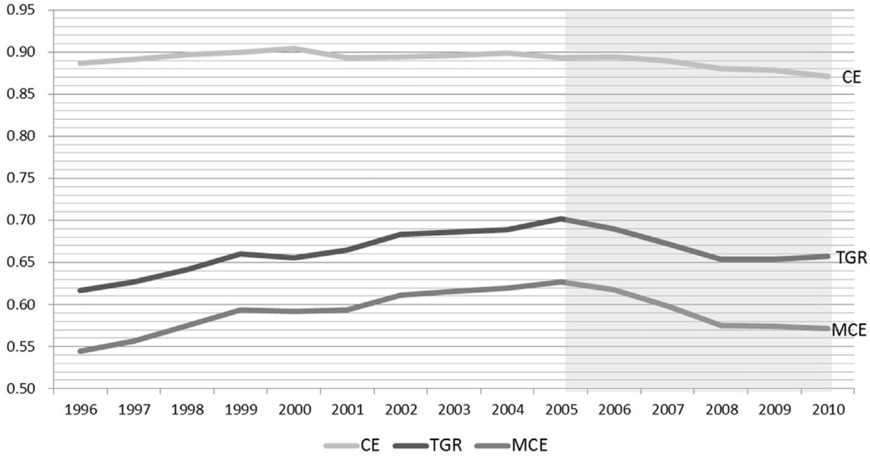

Fig. B2. Trends in CE, TGR, and MCE (QP).

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