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ABSTRACT

This paper specifies an empirical framework for estimating both technical and allocative efficiency, which is applied to a large panel of European banks over the years 1996 to 2003. Our methodology allows for self-consistent measurement of technical and allocative inefficiency, in an effort to address the issue known in the literature as the Greene problem. The results suggest that, on average, European banks exhibit constant returns to scale, that technical and allocative efficiency are close to 80% and 75% respectively, and that overall economic efficiency shows a clearly improving trend. We also show through the comparison of various estimators that models incorporating only technical efficiency tend to overestimate it.

Keywords: Technical and allocative efficiency; Translog cost function; Maximum likelihood; European banking
JEL classification: C13; G21; L2

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1. Introduction

It has been established that banks, in their role as financial intermediaries, contribute significantly to economic activity in a number of ways. During the last two decades the banking sector has experienced major transformations worldwide in its operating environment. Both external and domestic factors have affected its structure, efficiency and performance. An efficient banking sector is better able to withstand negative shocks and contribute to the stability of the financial system. Therefore, the efficiency of banks has attracted the interest of international research.

Several studies have estimated bank efficiency using either parametric or non-parametric frontiers.[1] Yet, few studies have attempted to offer a cross-country comparison of the efficiency of the European banking system and none, to our knowledge, has jointly estimated its technical and allocative efficiency. Studies that estimate the efficiency of European banks, using standard techniques, include Pastor *et al*. (1997), Dietsch and Weill (1998), Altunbas *et al.* (2001), Altunbas and Chakravarty (2001), Maudos *et al.* (2002), Bikker (2002) and Casu and Molyneux (2003).

Use of Data Envelopment Analysis (DEA) to estimate bank efficiency presents well-known difficulties in incorporating a stochastic component in the statistical model. Similarly, the decomposition of overall cost efficiency into its technical[2] and allocative[3] components using flexible functional forms has proved to be problematic, since the implied production function cannot be derived. For this reason, researchers have been content to either ignore allocative inefficiency or impose *ad hoc* restrictions to integrate it in an empirical model.

The novel feature of the present paper is that it extends the existing literature by modeling both technical and allocative inefficiency of European banks within a stochastic frontier framework, using the implications of the relationship derived in

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[1] There are three main parametric frontier approaches to measuring efficiency, namely the stochastic frontier approach (SFA), the distribution free approach (DFA) and the thick frontier approach (TFA). Data envelopment analysis (DEA) is the most common among the non-parametric approaches, which also include the free disposal hull (FDH). For a thorough description of these approaches, see Berger and Humphrey (1997). A limited number of studies use distance functions to measure efficiency (e.g. English *et al*.).

[2] Technical efficiency (TE) reflects the ability of a firm to obtain maximal output from a given set of inputs.

[3] Allocative efficiency (AE) reflects the ability of a firm to use the inputs in optimal proportions, given their respective prices. The product of TE and AE is overall economic efficiency (EE).

Kumbhakar (1997). Unlike Kumbhakar and Tsionas (2005) who use a relatively complex Bayesian approach, we present an approximate solution that is relatively easy to implement since we provide a log-likelihood function for this model in closed form. We obtain technical and allocative inefficiency for individual banks at each point in time, by applying a cross sectional maximum likelihood estimation method to a panel of European banks, and then, for expositional brevity, present averages on a country-specific basis and for the European banking system as a whole.

The results suggest that, on average, European banks are characterized by constant returns to scale, although the conventional estimation methods tend to slightly underestimate the magnitude of scale efficiencies. Most importantly, models that include only technical inefficiency significantly overestimate it (strong evidence for this is found for countries like Ireland, the Netherlands and Sweden). However, both technical and allocative efficiency (TE and AE, respectively) have shown a tendency to improve in recent years, as banks apply better managerial practices in order to enhance their overall performance.

The rest of the paper is organized as follows: Section 2 presents a brief review of the literature, followed in Section 3 by the theoretical model. Section 4 deals with the estimation methodology. Section 5 discusses the data and the empirical results and, finally, Section 6 concludes the paper.

2. Brief review of the literature

Greene (1980) defined allocative inefficiency as the departure of the actual cost shares from the optimum shares, failing, in such a context, to derive the relationship between allocative inefficiency and cost increases from such inefficiency (Greene problem). Since then, the literature has proposed an approximate relationship to model allocative inefficiency in the fashion of Schmidt (1984) who modeled the cost of allocative inefficiency as the product of the errors in the cost share equations and a specified positive semi-definite matrix. However, this approximate relationship is not free of problems, as it may lead to inconsistencies that bias the results by unknown magnitudes and in unknown directions.

Kumbhakar (1997), in an important contribution that followed the definition of allocative inefficiency in Schmidt and Lovell (1979), used a translog cost function and established an exact relationship between allocative inefficiency in the cost share equations and in the cost function. Empirical estimation of this model has been restricted to panel datasets in which technical and allocative inefficiency are either assumed to be fixed parameters or functions of the data and unknown parameters (Maietta, 2002). Application of such a model in banking has been limited to Kumbhakar and Tsionas (2005). Their model reduces to a nonlinear seemingly unrelated regression with nonlinear random effects, which they estimate using panel data on U.S. commercial banks. They show that the inclusion of allocative inefficiency in the model produces some notable differences from simple models of technical efficiency, since failure of banks to efficiently allocate their inputs leads to further increases in costs.

A number of studies offer a European cross-country comparison of bank efficiency, using standard efficiency estimation methods.[4] Pastor *et al.* (1997) used a DEA technique to define a common frontier for EU countries that incorporated the effect of differences in the economic environment across countries. Their results indicate that countries like Germany, Denmark, Spain, Luxembourg and France had high efficiency scores, although inclusion of the country-specific control variables significantly lowered them. A similar approach was employed by Lozano-Vivas *et al.* (2002). Dietsch and Weill (1998) used unconsolidated data from 11 EU countries covering the years 1992-1996 to model efficiency using cost and profit frontiers. Their results show a mixed picture across countries, which is sometimes at odds with the rest of the literature, and their most important finding is that European integration has had a positive effect on bank efficiency.

Bikker (2002) used a panel of banks from the 15 EU member states over the years 1990-1997 and stochastic frontier methods, which clearly show an increasing trend in efficiency over time and large efficiency and cost differences among countries, with Luxembourg, Germany, the UK and Denmark being the most efficient and Belgium, Greece and Italy at the other end. Altunbas *et al.* (2001) and Altunbas and Chakravarty (2001), used both the translog and the flexible Fourier functional forms to suggest that scale economies are widespread for small banks (even though the trend is declining), with inefficiencies ranging between 20 and 25%, while banks reduced total cost by around 3% per annum between 1989 and 1997 due to technical

[4] For a thorough review of these studies see Molyneux et al. (2001).

progress (which mainly affects larger banks). Most recently, Casu and Molyneux (2003) applied DEA to five EU countries, whereby they identified a trend toward higher efficiency and reported that the banking systems of Germany and the UK are the most efficient.

While the above literature provides significant evidence on European bank efficiency, no attempt has been made to model allocative inefficiency within a framework that offers an empirical solution to the Greene problem. This paper aims to add to the existing literature in this direction and extend the time frame of the dataset beyond 1997.

3. Theoretical model

In this section we follow Kumbhakar (1997), who derived an exact relationship between allocative inefficiency and cost therefrom in the context of the translog cost function. Assume ξ_j represents (time-invariant) allocative inefficiency for the input pair $(j,1)$ so that the relevant input price vector (often labeled as shadow price vector) to the firm is ($w^* \equiv (w_1, w_2^*,..., w_M^*)$ = (w_1, $w_2 \exp(\xi_2)$,…, $w_J \exp(\xi_J)$)), where $\xi_2,...,\xi_J$ are random variables. Kumbhakar (1997) showed that the translog system (with a single output) can be written as follows.[5]

$$\ln C_{it}^a = \ln C_{it}^* + \ln G_{it} + v_{it} + u_i \,,\; i = 1,...,n \,,\; t = 1,...,T \tag{1}$$

$$S_{j,it}^a = S_{j,it}^0 + \eta_{j,it} \,,\; j = 1,...,J \,, \tag{2}$$

where C_{it}^a, $S_{j,it}^a$, $S_{j,it}^0$, v_{it} and u_i are actual cost, actual shares, a two-sided disturbance and a non-negative disturbance representing technical inefficiency. C^* represents a minimum cost function, with arguments w^* and y (the firm's output), derived from a simple cost minimization problem. We assume, for the time being, only a cross sectional dimension i. $\eta_{j,i}$ and $\ln G_i$ are functions of allocative inefficiency, $\xi_2,...,\xi_J$ defined below. We rewrite the actual cost function as $\ln C_i^a = \ln C_i^0 + \ln C_i^{AL} + v_i + u_i$, where $\ln C_i^{AL}$ ($= \ln C_i^* - \ln C_i^0 + \ln G_i$) can be interpreted as the percentage increase in

[5] The multiple output generalization of this result is straightforward.

cost due to allocative inefficiency and $\ln C_i^0$ is the translog cost frontier.[6] For a translog functional form we obtain

$$\begin{aligned}\ln C_i^0 &= \alpha_0 + \sum_j \alpha_j \ln w_{j,i} + \gamma_y \ln y_i + \tfrac{1}{2}\gamma_{yy}\left(\ln y_i\right)^2 + \tfrac{1}{2}\sum_j\sum_k \beta_{jk} \ln w_{j,i} \ln w_{k,i} \\ &\quad + \sum_j \gamma_{jy} \ln w_{j,i} \ln y_i + \alpha_t t + \tfrac{1}{2}\alpha_{tt} t^2 + \beta_{yt} \ln y_i t + \sum_j \beta_{jt} \ln w_{j,i} t,\end{aligned} \tag{3}$$

$$S_{j,i}^0 = \alpha_j + \sum_k \beta_{jk} \ln w_{k,i} + \gamma_{jy} \ln y_i + \beta_{jt} t, \tag{4}$$

$$\begin{aligned}\ln C_i^{AL} &= \ln G_i + \sum_j \alpha_j \xi_{j,i} + \sum_j\sum_k \beta_{jk}\xi_{j,i} \ln w_{k,i} + \tfrac{1}{2}\sum_j\sum_k \beta_{jk}\xi_{j,i}\xi_{k,i} + \sum_j \gamma_{jy}\xi_{j,i} \ln y_i \\ &\quad + \sum_j \beta_{jt}\xi_{j,i} t\end{aligned} \tag{5}$$

$$G_i = \sum_j S_{j,i}^* \exp(-\xi_{j,i}), \tag{6}$$

where

$$S_{j,i}^* = \alpha_j + \sum_k \beta_{jk} \ln w_{k,i}^* + \gamma_{jy} \ln y_i + \beta_{jt} t \equiv S_{j,i}^0 + \sum_k \beta_{jk}\xi_k \;. \tag{7}$$

Finally,

$$\eta_{j,i} = \frac{S_{j,i}^0\left\{1 - G_{it}\exp(\xi_{j,i})\right\} + \sum_k \beta_{jk}\xi_k}{G_{it}\exp(\xi_{j,i})} \;. \tag{8}$$

Thus, $\eta_{j,i}$ are the deviations of the actual cost shares from their optimum values, and are non-linear functions of allocative inefficiency, $\xi_2,...,\xi_J$, and data.

4. Estimation

The system to be estimated is

$$\ln C^a = \ln C^0 + \ln C^{AL}(\xi) + v + u \tag{9}$$

$$S_j^a = S_j^0 + \eta_j(\xi),\; j = 1,...,J-1, \tag{10}$$

[6] This is non-negative given strict concavity of the cost function. See also Kumbhakar (1997).

where the definitions of $\ln C^{AL}(\xi)$ and $\eta_j(\xi)$ have been given above, and $u \geq 0$ represents input-oriented technical inefficiency. Since $\ln C^{AL}(\xi)$ and $\eta_j(\xi)$ are highly complicated functions of ξ, estimation of this model is challenging, a problem known in the literature as the Greene problem (Bauer, 1990). As we already mentioned, although Kumbhakar (1987) presented the model, he did not provide an estimation technique, while Kumbhakar and Tsionas (2005) presented a Bayesian approach, which rests on the introduction of additional error terms in the share equations. Here, we provide an approximate solution that can be easily implemented in practice, since we provide a log-likelihood function for this model in closed form. More specifically, we consider a first order Taylor series expansion of the cost function and the share equations about $\xi = 0_{J-1}$, whose details have been presented before in Kumbhakar and Tsionas (2005) and are reproduced in the appendix for convenience. It is shown there that, to first order of approximation, $\ln C^{AL}(\xi) \simeq 0$, and $\eta_j(\xi) \simeq \sum_{j=1}^{J} A_{jh}\xi_h$, where

$$A_{jh} = \begin{cases} \beta_{jj} - S_j^0(1 - S_j^0),\ j = h \\ \beta_{jh} + S_j^0 S_h^0,\ j \neq h. \end{cases} \tag{11}$$

Denoting $A_i = [A_{i,jh}]$, which is a $(J-1)\times(J-1)$ symmetric matrix for the i^{th} observation, we have, to first order of approximation,

$$\ln C_i^a \simeq \ln C_i^0 + v_i + u_i \tag{12}$$

$$S_{j,i}^a \simeq S_{j,i}^0 + A_i\xi_i,\ j = 1,\ldots,J-1, \tag{13}$$

$i = 1,\ldots,n$.

It should be noted that $A_i = B + S_i^0 S_i^{0\prime} - diag(S_i^0)$, where $B = \left[\beta_{jh}\right]$. A_i is precisely the matrix whose negative semi-definiteness implies concavity of the translog cost function (Diewert and Wales, 1987, p. 48) and it can be shown that its elements are the elasticities of substitution. It is also remarkable that a *first order* expansion makes the cost function independent of ξ_is, a fact that will be of considerable use in formulating the likelihood function of the model.

To proceed with estimation, we assume that $v_i \sim N(0,\sigma_v^2)$, $u_i \sim N_+(0,\sigma_u^2)$, $\xi_i \sim N_{J-1}(0,\Sigma)$. All the error terms are assumed to be i.i.d., mutually independent, and independent of the predetermined variables (prices, outputs *etc*). Under these assumptions it is clear that $\eta_i = A_i\xi_i \sim N_{J-1}(0,\ A_i\Sigma A_i)$. The implication of modeling allocative inefficiency along the lines of Kumbhakar (1987) is that the error terms of the system, namely the η_i s, are no longer i.i.d.; in particular *they have to exhibit heteroscedasticity* of a special form. Notice that heteroscedasticity here depends on β through the dependence of A_i on the derived shares, S_i^0.

We will estimate the model using the method of ML. The likelihood function is given by

$$L(\beta,\lambda,\sigma,\Sigma) = (2\pi)^{-n(J-1)/2}\prod_{i=1}^{n}|A_i\Sigma A_i|^{-1/2}\exp\left[-\tfrac{1}{2}\sum_{i=1}^{n}\eta_i'(\beta)(A_i\Sigma A_i)^{-1}\eta_i(\beta)\right]\cdot \left(\tfrac{2}{\sigma}\right)^n\prod_{i=1}^{n}\left[\varphi(v_i(\beta)/\sigma)\Phi(\lambda v_i(\beta)/\sigma)\right], \tag{14}$$

where $\eta_i(\beta) = S_i^a - S_i^0$, $v_i(\beta) = \ln C_i^a - \ln C_i^0$, $\sigma^2 = \sigma_v^2 + \sigma_u^2$, $\lambda = \sigma_u/\sigma_v$, and φ, Φ denote the standard normal density function and distribution function respectively. The second part of this expression is the familiar likelihood function of a half-normal cost frontier.[7]

Taking logarithms and concentrating out Σ, we get the estimator[8]

$$\hat{\Sigma}(\beta) = n^{-1}\sum_{i=1}^{n}\xi_i(\beta)\xi_i'(\beta), \tag{15}$$

where $\xi_i(\beta) = A_i^{-1}\eta_i(\beta)$. Substituting in $\ln L(\beta,\lambda,\sigma,\Sigma)$ we get the concentrated log-likelihood function

$$L_C(\beta,\lambda,\sigma) = \text{constant} -\sum_{i=1}^{n}\ln\|A_i\| - \tfrac{n}{2}\ln|\hat{\Sigma}(\beta)| - n\ln\sigma - \tfrac{1}{2\sigma^2}\sum_{i=1}^{n}v_i(\beta)^2 + \sum_{i=1}^{n}\ln\Phi(\lambda v_i(\beta)/\sigma) \tag{16}$$

[7] See Kumbhakar and Lovell (2000, p. 76-77).
[8] In the derivation it is useful to notice that matrices A_i and Σ are symmetric.

Relative to a cost-share system with technical inefficiency, the additional term $-\sum_{i=1}^{n} \ln \| A_i \|$ reflects the heteroscedasticity in the share equation residuals that must be accounted for in estimation by ML. Since this term depends on β it is not possible to obtain consistent estimators of β by estimating a cost-share system with homoscedastic error terms in the share equations. It is possible to get an estimator that accounts for the Jacobian term by assuming that shares are close to zero, in which case we obtain $\sum_{i=1}^{n} \ln \| A_i \| \simeq n \ln \| B - I_{J-1} \|$. This approximation makes the additional term independent of the particular observation so the log-likelihood function can be easily programmed in standard econometric software. In the case of three inputs, for example, this term is simply $n\left[\beta_{11}\beta_{22} - \beta_{12}^2 - \beta_{11} - \beta_{22} + 1\right]$. In our empirical work we use the exact log-likelihood function given above without resorting to this approximation. The reason is that this approximation, although simple to use, is inconsistent with the presence of heteroscedasticity in the share equation residuals.

Given parameter estimates derived from ML, it is possible to obtain measures of bank-specific technical and allocative inefficiency. Bank-specific technical inefficiency can be obtained using

$$\hat{u}_i = E\left(u_i \mid \text{data}\right) = \sigma_* \left[\frac{\varphi(\lambda v_i(\beta)/\sigma)}{\Phi(\lambda v_i(\beta)/\sigma)} + \lambda v_i(\beta)/\sigma \right], \tag{17}$$

where $\sigma_*^2 = \sigma_v^2 \sigma_u^2 / \sigma^2$, see Kumbhakar and Lovell (2000, p. 78).

Given the share equation residuals $\eta_i(\beta)$, we obtain the price distortions as $\xi_i(\beta) = A_i^{-1}\eta_i(\beta)$ from which we can obtain the cost of allocative inefficiency as

$\ln \hat{C}_i^{AL} = \ln C^{AL}(\xi_i(\beta))$. Estimated parameter values are substituted for β, λ, and σ above.

ML estimation has proved difficult primarily because numerical derivatives are not accurate enough, at least in our application, and/or because obtaining the log of the normal cdf is dangerous for large negative values of the argument. For this reason we have used a Nelder-Mead simplex maximization technique which does not require derivatives. Derivatives are, however, needed to obtain the standard errors of the parameters. To obtain standard errors we have resorted to a Metropolis-Hastings Markov Chain Monte Carlo technique (Tierney, 1994) to draw a sample from the posterior distribution of the model and use the estimated standard errors of the parameter draws to gain an appreciation of the curvature of the log-likelihood around its mode. [9] We have used flat priors to obtain the posterior, which we call $p(\theta \mid Y)$, and Y denotes the data.

The particular version of the Metropolis-Hastings scheme used is as follows. Given the estimated covariance matrix $\tilde{V}$ of a cost-share system with technical but no allocative inefficiency, we draw a proposal $\theta^* \sim N\left(\theta^{(i)},\, h\tilde{V}\right)$, where h is a positive parameter. That means we consider this model a reasonable approximation to the model that has both technical and allocative inefficiency. With probability $\alpha\left(\theta^{(i)}, \theta^*\right) = \min\left\{1,\ \dfrac{p(\theta^{(i)} \mid Y)}{p(\theta^* \mid Y)}\right\}$, we accept the proposal, and set $\theta^{(i+1)} = \theta^*$, else we set $\theta^{(i+1)} = \theta^{(i)}$. We use $\theta^{(0)} = \tilde{\theta}$ as the starting value – where $\tilde{\theta}$ is the ML estimate in the model with both technical and allocative inefficiency – and we tune the parameter h to obtain an acceptance rate between 20% and 30%. We have used 15,000 iterations, the first 5,000 of which were discarded to mitigate the impact of start-up effects. The sample $\left\{\theta^{(i)}, i = 1,\ldots,M\right\}$ converges to the distribution whose density is proportional to the posterior kernel $p(\theta \mid Y)$. The posterior mean is estimated by $\bar{\theta} = M^{-1}\sum_{i=1}^{M}\theta^{(i)}$, and the posterior covariance matrix is estimated using $\bar{V} = M^{-1}\sum_{i=1}^{M}\left(\theta^{(i)} - \bar{\theta}\right)\left(\theta^{(i)} - \bar{\theta}\right)'$. The square roots of the diagonal elements of this matrix can be used as standard errors associated with the ML estimate of the model that we obtained via the Nelder-Mead procedure. Since the posterior means derived from the Bayesian approach are very close to the ML parameter estimates, we only report the latter.

[9] We have also tried the inverse of the numerical Hessian and the BHHH approximation as well as the Gill-Murray generalized Cholesky decomposition of the generalized inverse of the Hessian (Gill and King, 2004) without success.

5. Data and empirical results

5.1 Data

The proposed method is applied to a sample of European commercial banks for the period 1996 to 2003. We choose to limit the empirical analysis to the unconsolidated statements of commercial banks in order to reduce the possibility of introducing aggregation bias in the results. All necessary data is obtained from the BankScope database and includes 13 of the 15 EU countries.[10]

The first problem encountered in bank efficiency studies is the definition and measurement of output. The two most widely used approaches are the 'production'[11] and the 'intermediation'[12] approaches. While we acknowledge that it would probably be best to employ both approaches to identify whether the results are biased when using a different set of outputs, sufficient data to perform such an analysis on European banks is generally unavailable. Hence, this study uses the 'intermediation approach' for two main reasons: First, this approach is inclusive of interest expenses that usually account for over one-half of total costs and second the BankScope database lacks the necessary data for implementation of the production approach.

Having defined the methodological approach to be followed, we focus our attention on the selection of variables. Table 1 reports the variables to be used, along with some descriptive statistics. We use a dual approach that captures both the input and output characteristics of deposits, in the sense that interest expenses include interest paid on deposits, while deposits are associated with a substantial amount of liquidity and payment services provided to depositors (see Berger and Humphrey, 1997). We generate input prices by dividing all their respective costs by total assets, given that BankScope does not include comprehensive information on input quantities.[13]

[10] Greece and Finland are excluded from the analysis due to data limitations.
[11] Under this approach output is measured by the number of transactions or documents processed over a given time period (see Berger and Humphrey, 1997).
[12] Under this approach output is measured in terms of values of stock variables (such as loans, deposits, etc.) appearing in bank accounts.
[13] Clearly, it is possible that defining the price of inputs in terms of output could result in some bias against e.g. those banks, which hire high quality and, therefore, relatively high cost staff. This potential bias is mitigated, however, given that banks with higher quality staff should expect to see some benefit in terms of output. Hence, providing that the high quality staff is sufficiently productive, such banks will not be disadvantaged from a relative efficiency point of view.

Finally, following the literature (e.g. Altunbas *et al.*) the analysis includes a time trend (T) and a capital variable (E). The time trend is intended to capture technological change in the period examined; thus, the partial derivative of cost with respect to T gives the impact of technical change. The capital ratio (equity/assets) serves as a proxy for capital adequacy, included in the cost function to control for risk.[14]

5.2 Empirical results

So far we have presented the model for technical efficiency with a single output. We rewrite it here for the three output-three input case[15] using the translog functional form:

$$\begin{aligned}\ln C_{it}^{a} &= a_0 + \sum_j a_j \ln w_{j,it} + \sum_m \gamma_m \ln y_{m,it} + \frac{1}{2}\sum_m\sum_q \gamma_{mq} \ln y_{m,it} \ln y_{q,it} \\ &+ \frac{1}{2}\sum_j\sum_k \beta_{jk} \ln w_{j,it} \ln w_{k,it} + \sum_j\sum_m \gamma_{jm} \ln w_{j,it} \ln y_{m,it} + a_t t \\ &+ \frac{1}{2} a_{tt} t^2 + \sum_m \beta_{mt} \ln y_{m,it} t + \sum_j \beta_{jt} \ln w_{j,it} t + a_E E + \frac{1}{2} a_{EE} E^2 + \\ &+ \sum_m \beta_{mE} \ln y_{m,it} E + \sum_j \beta_{jE} \ln w_{j,it} E + v_{1,it} + u_i\end{aligned} \tag{18}$$

and

$$\begin{aligned}S_{j,it}^{a} &= a_j + \sum_k \beta_{jk} \ln w_{k,it} + \sum_m \gamma_{jm} \ln y_{m,it} + \beta_{jt} t + \beta_{jt} E + v_{j+1,it} \\ m,q &= 1,2,3 \quad j,k = 1,2\end{aligned} \tag{19}$$

The assumptions about the noise components and the technical inefficiency component (u) are the same as before. The model incorporating allocative inefficiency is the above system of equations amplified with the system comprised of equations (9) and (10). The methodology described in Section 4 provides efficiency estimates for each cross sectional unit (bank) at each point in time. In other words, we are able to get efficiency estimates equal to the number of observations. Due to space

[14]Berger (1995) suggests that relaxation of the perfect capital markets assumption allows an increase in capital to raise expected earnings, by reducing the expected costs of financial distress. Clearly, a well-capitalized bank is better able to absorb unexpected credit losses and provide safety for depositors and creditors. On the other hand, too much capital reduces the bank's ability to maximize returns.

[15] We impose homogeneity by dividing all inputs by physical capital (the third input).

considerations we calculate and present country as well as year averages, based on these estimates.

In Table 2 we report estimation results with five different methods: The first is a simple OLS regression on the translog cost function, the second is a SUR on the translog cost share system, the third is a SUR on the translog cost share system with technical efficiency (SUR_T) followed by a ML estimate obtained from Nelder-Mead simplex as described in Section 3, and finally estimation of approximate translog cost share system with both technical and allocative inefficiency ($SUR_{T\&A}$).

A first comment regarding the results is that the capital ratio is negatively and significantly correlated with total cost. This implies that the perfect capital markets assumption may not hold. This result is consistent with most of the literature that examines such a relationship, including Berger (1995) and models of the so-called Structure-Conduct Performance hypothesis (SCP) (for a review of these models see Goddard *et al.*, 2001).

We estimate scale economies[16] for all banks and report their temporal variation (by averaging the bank-specific values across years) and overall mean obtained from the four estimation methods (Table 3). The results suggest that, in general, constant returns to scale are prevalent in the European banking system. The evidence of the lack of scale economies, on average, is generally consistent with most of the recent literature on bank efficiency of developed banking systems (for example see Humphrey and Vale, 2004). On the other hand, Altunbas *et al.* (2001) identify positive returns to scale for a large sample of European banks spanning an earlier period (1989-1997).[17] The results obtained from the different estimation methods present small differences among themselves. The model without allocative inefficiency seems to slightly underestimate overall scale economies. On average, there is a trend toward decreasing returns to scale in European banking (although the overall change is smaller than 1%). These findings are consistent with the belief that

[16] Scale economies are obtained by differentiating the cost function in each of the four models, i.e. the simple OLS on the translog (OLS), the SUR on the translog cost share system (SUR), the SUR on the translog cost share system with technical efficiency (SUR_T) and the SUR on the translog cost share system with both technical and allocative efficiency ($SUR_{T\&A}$), with respect to output.

[17] Additionally, the European Commission (1997), investigating the cost characteristics of various European banking sectors, reported that as banking systems approach a higher level of sophistication in terms of technology and productivity, opportunities from exploiting economies of scale may be quite limited. Nevertheless, for a better analysis of scale economies one should distinguish between differently-sized banks.

the European banking system has exploited whatever returns to scale were available and that recently the drive to improved performance has come from greater efficiency.

Some average efficiency measures are given in Table 4 and are illustrated in Figures 1 through 5, showing significant variation between countries and over time.[18] Table 4 shows that the model without allocative inefficiency (i.e. column 1) overestimates the overall TE by a considerable amount (approximately 9%). Furthermore, SUR_T reports a fall by roughly 2% in TE during the sample period, while $SUR_{T\&A}$ reports a 5 % rise, which of course is closer to what would be expected given the wave of consolidation and financial innovation in the European banking system during the sample period (see ECB, 2002). Allocative inefficiency stands at almost 25% for the whole period, with the trend since 1996 being noticeably downward (16% in 2003). The results clearly suggest that inefficiencies are more important than scale economies for European banks. Country-wise the lowest efficiency scores were found to be those of Ireland, Portugal and Sweden, countries that, interestingly enough, report comparatively high technical efficiency scores when allocative inefficiency is not being modeled. The best-practice countries are Germany, Austria and the UK, with average technical and allocative efficiency scores close to 80%.

Comparison with previous studies in terms of efficiency scores cannot be made directly since we utilize data from 1997 onwards, the endpoint of the datasets in most of the recent literature. However, our findings regarding the most efficient banking sectors are similar to those in Altunbas *et al.* (2001), Bikker (2002) and Casu and Molyneux (2003), with the exception of Belgium whose banking system seems to operate at a significantly improved efficiency level. It also seems that at the beginning of our data period (1996) the average efficiency level of our dataset is higher than that of Altunbas *et al.* (2001) when we do not incorporate allocative efficiency, but lower when we do.

A clearer picture is obtained by the diagrammatic representation of the results discussed above. Fig. 1 presents kernel density functions of technical efficiency for models with TE and T&AE. There is an apparent parallel shift to the left when the model includes allocative inefficiency. Results from the model with technical inefficiency show that efficiency scores below 70% are highly improbable, whereas this occurs at around 60% when we include allocative inefficiency. The scatterplot of the ranking of banks' TE obtained from the SUR_T model against that obtained from the $SUR_{T\&A}$ model is provided in Fig. 2. The correlation between these rankings is fairly high, although there exist some outliers. Yet, if the focus is on individual bank efficiency, a choice between models cannot be made, given the high degree of correlation of efficiency rankings between the two models.

Fig. 3 illustrates the kernel density function of the allocative efficiency estimates, showing that the range of the allocative efficiency scores is wider than those of technical efficiency. Therefore, there exists a broader array of firms that are allocative inefficient. One could then identify which set of inputs is the major source of this inefficiency by looking at the kernel density functions of the ξs and ηs. The density functions of allocative inefficiency parameters (price distortion ξ_j) are reported in Fig. 4. These density functions, even though centered around zero (which means that banks on average do not seem to have significant relative price distortions), differ in terms of spread and overall shape. For loanable funds (input 1), relative price distortions (ξ_1) can be as large as 4% with a peak at around –1%, whereas for labor (input 2) the spread is much lower and the peak is very close to zero. This reflects the fact that for loanable funds banks seem to misperceive prices, while they seem to manage labor costs efficiently. Finally, the fact that the density function of ξ_1 is not particularly tight means that banks are quite heterogeneous in terms of allocative inefficiency.

Fig. 5 presents the country-specific temporal variation of overall efficiency (calculated as the average of each country's individual bank efficiencies).[19] Banks in Austria, Germany, Ireland and Luxembourg considerably improved their efficiency. These results are not surprising: In Austria, the five largest banks have seen fundamental changes in their ownership structure, including mergers. In Germany, even though concentration remains low, the number of credit institutions decreased by 540 only between 1998 and 2000 (see ECB, 2002). Finally, Irish banks have become more efficient possibly due to significant improvement in their operating expenses

[18] The reported values are averages of the bank-specific estimates across countries (Table 4a) and across years (Table 4b). Technical efficiency is calculated using eq. 17 and allocative efficiency as described in the rest of Section 4.

[19] A graph for Sweden is not reported, since it shows quite a bit of volatility due to the small number of banks included in the sample.

management coupled with the strong economic growth of the period.[20] On the other hand, the Spanish banking system was the only one to see a slight decline in its efficiency.

Finally, in Table 5 we report the average technical change across countries (again calculated as the average of the bank-specific estimates across countries), measured by the derivative of the estimated cost function with respect to the time trend. The main finding is that technical change positively contributed to the annual cost of banks, especially in Denmark, Ireland and Italy. However, we should treat these estimates with great caution, given the problems associated with the use of a time trend as a proxy for technical change (Hunter and Timme, 1991).

Policy implications are straightforward. Banks should focus on reducing managerial and other inefficiencies rather than trying to exploit economies of scale in the rather competitive European banking framework, and estimates show that this has recently been their main policy objective. Apparently, deregulation, liberalization and ongoing financial integration have increased the need for better quality management and forced banks to operate more rationally. In this context, banks' policy objective should be twofold, although this tends to be overlooked by the literature. The first objective reflects their ability to maximize output from a given set of inputs (TE), while the second involves their ability to optimize the amount of inputs to be used, given prices (AE). Banks, on average, stand to gain an additional 18% improvement from output maximization and a 16% improvement from a better allocation of their inputs (see last row of Table 4b). Yet, we should note that this study examined the efficiency of commercial banks only, which are on average characterized by higher inefficiencies.

6. Conclusions

The world of European banking is in a constant state of flux, as bankers, governments and the European Commission react to the pressures produced by new competition, new technology and growing globalization. As the level of sophistication

[20] Luxembourg is a unique case, not easily comparable with other EU banking systems, mainly due to the fact that few of the banks operating in Luxembourg are active in the domestic market and other legal reasons. Cost efficiencies are achieved by offering a broad range of products or services to a very large customer base (which could originate e.g. from the large fixed costs incurred in gathering an information data base to be used for providing a large set of services).

in the operation of the banking sector improves, there is evidently less gain to be exploited from economies of scale, while there is still considerable room for improvement stemming from higher levels of efficiency.

We contend that overall economic efficiency of banks should be modeled along the proposition of Farrell (1957), who decomposed it into its technical and allocative components. In the present paper, we exploited the relationship derived in Kumbhakar (1997) to overcome the problems associated with estimation of both technical and allocative inefficiency using flexible functional forms, known in the literature as the Greene problem. Next we described the empirical implementation of this model on a panel dataset of commercial banks of 13 EU countries.

The findings suggest that both the technical and allocative components significantly contribute to overall inefficiency, while exclusion of the latter from the model biases TE and, therefore, the overall efficiency level. The most technically efficient banking sectors were found to be those of Austria, Germany and the UK, the same sectors also recording the lower allocative inefficiency scores. In contrast, the banking sectors of Ireland, Portugal and Italy have much more to gain from improving their efficiency level. The high allocative inefficiency and its degree of differentiation in terms of the efficiency scores among the countries examined suggest that much is to be done regarding the optimization of banking inputs' usage and management. Since the efficient use of individual inputs in banking is substantially underinvestigated, this is a desideratum for future research.

Appendix

The task is to find the first derivatives of the cost function and share equations with respect to the ξ's, and evaluate them at $\xi = 0_{M-1}$. Omitting observation subscripts and error terms for simplicity, the cost function is

$$\ln C^{a} = \ln C^{0} + \ln C^{AL}$$

$$\ln C^{AL} = \ln G + \sum_{j} \alpha_{j} \xi_{j} + \sum_{j} \gamma_{jy} \xi_{j} \ln y + \sum_{j} \sum_{k} \beta_{jk} \xi_{j} \ln w_{k} + \tfrac{1}{2} \sum_{j} \sum_{k} \beta_{jk} \xi_{j} \xi_{k}$$

and $\ln C^{0}$ is the usual translog cost function. Clearly, assuming all restrictions implied by the theory in place, we get

$$\frac{\partial \ln C^{AL}}{\partial \xi_{j}} = \frac{\partial \ln G}{\partial \xi_{j}} + \alpha_{j} + \gamma_{jy} \ln y + \sum_{k} \beta_{jk} \ln w_{k} + \sum_{k} \beta_{jk} \xi_{k}$$

Since

$$G = \sum_{l} S_{l}^{*} \exp(-\xi_{l}), \text{ where } S_{l}^{*} = \alpha_{l} + \sum_{k} \beta_{lk} (\ln w_{k} + \xi_{k}) + \gamma_{ly} \ln y$$

we obtain

$$\frac{\partial \ln G}{\partial \xi_{j}} = G^{-1} \left\{ \sum_{l} \beta_{lj} \exp(-\xi_{l}) - \exp(-\xi_{j}) S_{j}^{*} \right\}$$

Therefore, $\left. \frac{\partial \ln C^{AL}}{\partial \xi_{j}} \right|_{\xi=0} = 0$. Since $\left. \ln C^{AL} \right|_{\xi=0} = 0$, the cost function contributes nothing to the conditional posterior of ξ up to a first order of approximation. This is particularly important because the cost function is the most complicated function of the system, and omitting the cost function from further consideration results in computational gain. Next, we consider the share equations. These are given by

$$S_{m}^{a} = S_{m}^{0} + \eta_{m}$$

$$\eta_{m} = \frac{S_{m}^{0} \{ 1 - G \exp(\xi_{m}) \} + \sum_{k} \beta_{mk} \xi_{k}}{G \exp(\xi_{m})} \qquad \text{for } m = 1,..,M-1.$$

Clearly, $\left. \eta_{l} \right|_{\xi=0} = 0$, and $\left. G \right|_{\xi=0} = \sum_{k} \left. S_{k}^{*} \right|_{\xi=0} = 1$. Moreover, it is easy to show that

$$\left.\frac{\partial[G\exp(\xi_m)]}{\partial\xi_j}\right|_{\xi=0} = \left(S_j^0\right)^2 + \beta_{jj} \text{ if } m = j \text{, and } S_m^0\left(1+S_j^0\right)+\beta_{mj} \text{, if } m \neq j .$$

After some algebra, the derivatives of the allocative inefficiency term with respect to ξ 's are

$$\left.\frac{\partial\eta_m}{\partial\xi_j}\right|_{\xi=0} = -S_j^0\left(1-S_j^0\right)+\beta_{jj} \text{ if } m = j \text{, and } S_m^0 S_j^0 + \beta_{mj} \text{, if } m \neq j .$$

These partial derivatives are simple functions of the data and β , and can be computed easily at no cost conditional on the $\beta' s$.

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Table 1
Descriptive statistics of the variables

Variable	Definition	Mean	Std Dev
TC	Total operating and financial cost	119621	361552
y_1	The value of total aggregate loans	871028	3126397
y_2	The value of transaction deposits	1300930	3843171
y_3	The value of total other earning assets	779460	2368579
w_1	Price of funds (interest paid on total funds/total funds)	0.0348	0.0210
w_2	Price of labor (total personnel expenses/total assets)	0.0152	0.0112
w_3	Price of physical capital (total depreciation and other capital expenses/total assets)	0.0188	0.0160
T	A trend variable (calculated as the deviation from year 1996)		
E	Capital ratio (total equity/total assets)	0.0888	0.0545

Number of observations: 3935
The figures have been deflated using country-specific CPI indices with 1995 as a base year.
To define the price of labor and the price of physical capital we use total assets instead of the number of employees and the value of fixed assets respectively, since the BankScope database does not include comprehensive information on these measures.

Table 2
Estimation results

	OLS[1]		SUR[2]		SUR_T[3]		ML_{NM}[4]	$SUR_{T\&A}$[5]	
Variables	Coef.	S.E	Coef.	S.E	Coef.	S.E		Coef.	S.E
Constant	3.1460	0.1792	3.2048	0.0094	3.0770	0.0338	3.0720	2.9748	0.0377
w_1	0.5226	0.0238	0.3708	0.0059	0.3760	0.0054	0.2858	0.2789	0.0062
w_2	0.1725	0.0379	0.3070	0.0064	0.3029	0.0053	0.3064	0.3486	0.0063
y_1	0.6190	0.0224	0.5601	0.0165	0.6007	0.0159	0.6048	0.6119	0.0200
y_2	-0.3470	0.0425	-0.3177	0.0315	-0.3850	0.0163	-0.3769	-0.3972	0.0172
y_3	0.5458	0.0224	0.5883	0.0207	0.6129	0.0182	0.6163	0.6490	0.0150
T	-0.0009	0.0106	-0.0170	0.0101	-0.0031	0.0076	-0.0408	-0.0506	0.0064
E	-1.9688	0.5584	-1.9326	0.0081	-1.9755	0.0139	-1.7247	-1.7650	0.0122
$w_1 w_1/2$	0.2236	0.0031	0.1982	0.0007	0.1984	0.0006	0.1064	0.0874	0.0062
$w_1 w_2$	-0.1026	0.0037	-0.0884	0.0006	-0.0883	0.0006	-0.0395	-0.0342	0.0023
$w_1 y_1$	0.0279	0.0019	0.0017	0.0006	0.0023	0.0006	0.0033	-0.0085	0.0034
$w_1 y_2$	-0.0718	0.0041	-0.0062	0.0011	-0.0078	0.0011	-0.0058	-0.0007	0.0021
$w_1 y_3$	0.0314	0.0024	0.0037	0.0007	0.0043	0.0006	0.0095	0.0175	0.0014
w_1 T	0.0039	0.0010	-0.0006	0.0003	-0.0006	0.0003	0.0034	-0.0005	0.0011
w_1 E	-0.1810	0.0406	-0.0447	0.0116	-0.0482	0.0076	0.0987	0.1693	0.0222
$w_2 w_2/2$	0.1596	0.0057	0.1427	0.0010	0.1424	0.0009	0.2286	0.2016	0.0052
$w_2 y_1$	-0.0351	0.0028	0.0019	0.0006	0.0018	0.0006	0.0113	0.0035	0.0008
$w_2 y_2$	0.0618	0.0055	-0.0005	0.0012	0.0003	0.0011	-0.0183	0.0023	0.0012
$w_2 y_3$	-0.0189	0.0031	-0.0008	0.0007	-0.0013	0.0006	0.0071	-0.0094	0.0017
w_2 T	-0.0018	0.0015	0.0002	0.0003	0.0002	0.0003	0.0010	0.0010	0.0003
w_2 E	0.2480	0.0677	0.0032	0.0120	0.0070	0.0074	0.0975	-0.0562	0.0219
$y_1 y_1/2$	0.1031	0.0015	0.1062	0.0015	0.0862	0.0015	0.0858	0.0841	0.0014
$y_1 y_2$	0.0384	0.0035	0.0331	0.0027	0.0532	0.0038	0.0530	0.0775	0.0021
$y_1 y_3$	-0.1626	0.0038	-0.1501	0.0030	-0.1540	0.0035	-0.1544	-0.1746	0.0023
y_1 T	0.0082	0.0009	0.0058	0.0009	0.0035	0.0009	0.0031	-0.0025	0.0012
y_1 E	-0.0916	0.0417	-0.2783	0.0247	-0.4346	0.0353	-0.4252	-0.5100	0.0451
$y_2 y_2/2$	-0.0215	0.0059	-0.0105	0.0045	-0.0499	0.0080	-0.0489	-0.0915	0.0053
$y_2 y_3$	0.0278	0.0040	0.0076	0.0030	0.0352	0.0045	0.0355	0.0492	0.0041
y_2 T	-0.0111	0.0017	-0.0070	0.0017	-0.0041	0.0016	-0.0047	0.0029	0.0020
y_2 E	0.3301	0.0865	0.7490	0.0660	1.0054	0.0650	0.9546	1.1372	0.0949
$y_3 y_3/2$	0.1236	0.0023	0.1336	0.0022	0.1059	0.0027	0.1039	0.1117	0.0040
y_3 T	0.0039	0.0009	0.0040	0.0010	0.0022	0.0010	0.0034	0.0023	0.0012
y_3 E	-0.1189	0.0536	-0.3952	0.0465	-0.4964	0.0455	-0.5490	-0.6761	0.0597
TT/2	0.0028	0.0009	0.0019	0.0009	0.0008	0.0008	0.0112	0.0063	0.0010
TE	0.0005	0.0188	0.0106	0.0168	0.0078	0.0132	-0.0389	0.0930	0.0289
EE/2	4.3675	1.1507	4.3705	0.0056	4.3527	0.0080	4.4962	4.5011	0.0130
					0.0527	0.0033	0.1811	0.1350	0.0088
σ_u					0.1802	0.0045	0.3878	0.3393	0.0208

Notes:

1. Simple OLS estimation of cost function.
2. SUR estimation of translog cost share system.
3. SUR estimation of translog cost share system with technical inefficiency.
4. Approximate system with technical inefficiency (the ML estimate is obtained from Nelder-Mead simplex).
5. Estimation of approximate translog cost share system with technical and allocative inefficiency.

Table 3
Temporal variation of scale economies of European banks

	OLS	SUR	SUR_T	$SUR_{T\&A}$
1996	0.9968	0.9886	0.9945	0.9922
1997	0.9991	0.9919	0.9969	0.9942
1998	1.0017	0.9955	0.9994	0.9956
1999	1.0077	1.0004	1.0036	0.9985
2000	1.0072	1.0035	1.0055	1.0014
2001	1.0099	1.0068	1.0080	1.0030
2002	1.0144	1.0104	1.0107	1.0045
2003	1.0194	1.0149	1.0143	1.0065
Overall	1.0065	1.0009	1.0037	0.9992

Table 4
(a) Average efficiency levels of European banks by country

Country	TE (SUR_T)	TE ($SUR_{T\&A}$)	ξ_1	ξ_2	η_1	η_2	$1-\ln C^{AL}$
Austria	0.8736	0.8032	-0.3699	-0.0081	0.0356	-0.0107	0.792
Belgium	0.8888	0.7998	-0.2883	-0.1914	0.0156	-0.0478	0.784
Denmark	0.8453	0.7679	-0.3983	-0.0181	0.0398	0.0107	0.713
France	0.8948	0.7976	-0.1776	-0.0475	0.0171	-0.0230	0.782
Germany	0.8983	0.8047	-0.2321	-0.1302	0.0112	-0.0255	0.794
Ireland	0.8887	0.7281	-1.2091	0.0854	0.1462	-0.0686	0.631
Italy	0.8460	0.7553	-0.6572	0.0613	0.0878	-0.0564	0.687
Luxembourg	0.8758	0.7623	-0.9090	-0.0166	0.1120	-0.0894	0.705
Netherlands	0.8896	0.7583	-0.6339	-0.0151	0.0773	-0.0546	0.693
Portugal	0.8544	0.7442	-1.0118	0.0784	0.1449	-0.0849	0.663
Spain	0.8599	0.7937	-0.4032	-0.0145	0.0434	-0.0261	0.769
Sweden	0.9043	0.7587	-0.7775	0.0200	0.0965	-0.0623	0.699
UK	0.9011	0.8022	-0.3157	-0.0301	0.0306	-0.0326	0.791
Overall	0.8784	0.7852	-0.4263	-0.0360	0.0464	-0.0362	0.753

(b) Temporal variation of average efficiency levels

Years	TE (SUR_T)	TE ($SUR_{T\&A}$)	ξ_1	ξ_2	η_1	η_2	$1-\ln C^{AL}$
1996	0.8842	0.7728	-0.7268	-0.0826	0.0884	-0.0826	0.723
1997	0.8814	0.7691	-0.6427	-0.0637	0.0757	-0.0632	0.717
1998	0.8851	0.7694	-0.5621	-0.0531	0.0652	-0.0440	0.717
1999	0.8839	0.7790	-0.3647	-0.0674	0.0355	-0.0285	0.738
2000	0.8774	0.7793	-0.4401	-0.0370	0.0474	-0.0377	0.739
2001	0.8744	0.7903	-0.3731	-0.0108	0.0397	-0.0217	0.765
2002	0.8694	0.8080	-0.1858	0.0149	0.0133	-0.0071	0.805
2003	0.8686	0.8236	0.0089	0.0309	-0.0109	0.0098	0.840

Note:
TE (SUR_T): Technical efficiency estimated from the model with technical efficiency only; TE ($SUR_{T\&A}$): Technical efficiency estimated from the model with technical and allocative efficiency.

Table 5
Technical change in European banks 1996-2003

	OLS	SUR	SUR_T	$SUR_{T\&A}$
Austria	0.020	0.022	0.019	0.027
Belgium	0.019	0.021	0.018	0.025
Denmark	0.025	0.028	0.022	0.034
France	0.016	0.018	0.017	0.023
Germany	0.016	0.018	0.017	0.022
Ireland	0.026	0.026	0.021	0.036
Italy	0.018	0.019	0.017	0.032
Luxembourg	0.016	0.017	0.016	0.027
Netherlands	0.017	0.018	0.017	0.015
Portugal	0.014	0.015	0.015	0.018
Spain	0.021	0.023	0.020	0.027
Sweden	0.016	0.016	0.016	0.018
UK	0.017	0.020	0.018	0.017
Overall	0.018	0.020	0.018	0.025

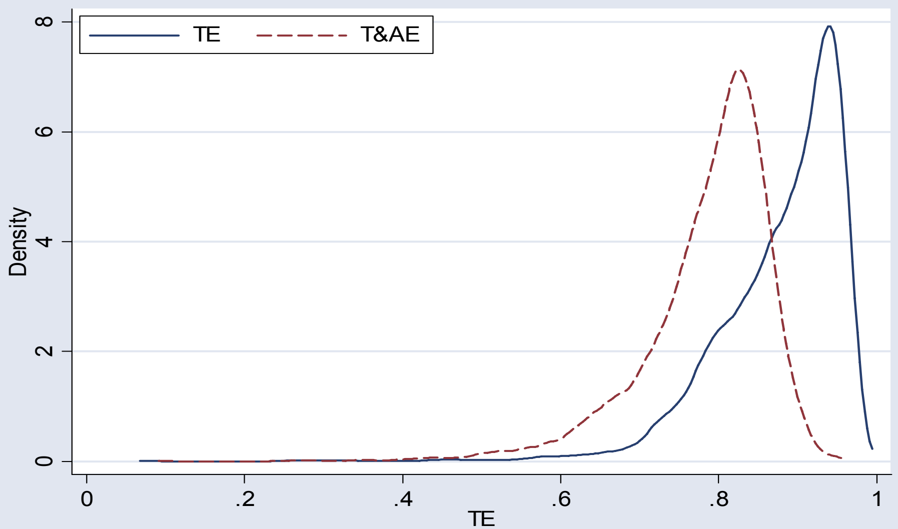

Figure 1. Technical effiicency distribution from models with TE and T&AE

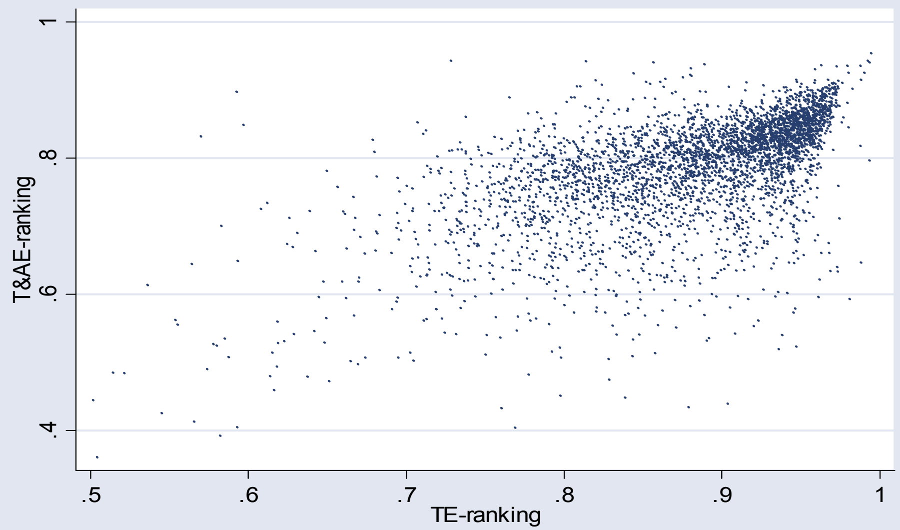

Figure 2. Comparison of efficiency rankings

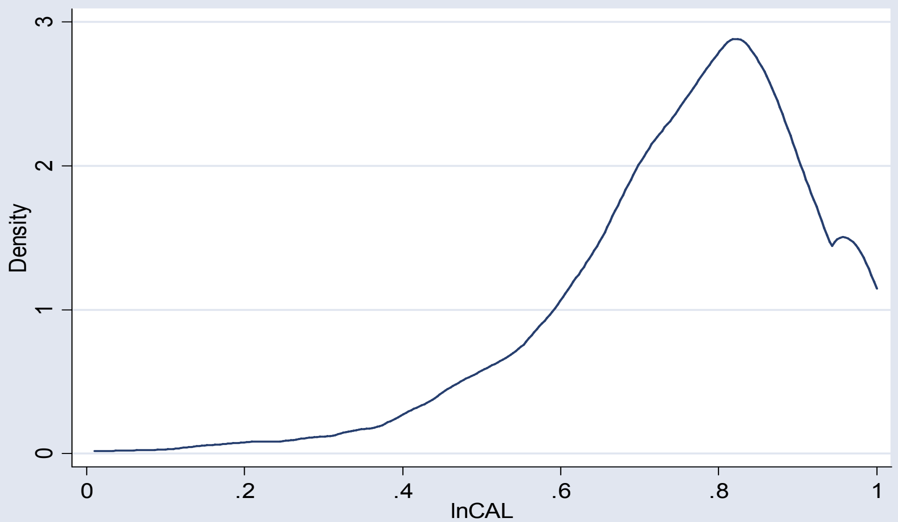

Figure 3. Distribution of cost of allocative efficiency

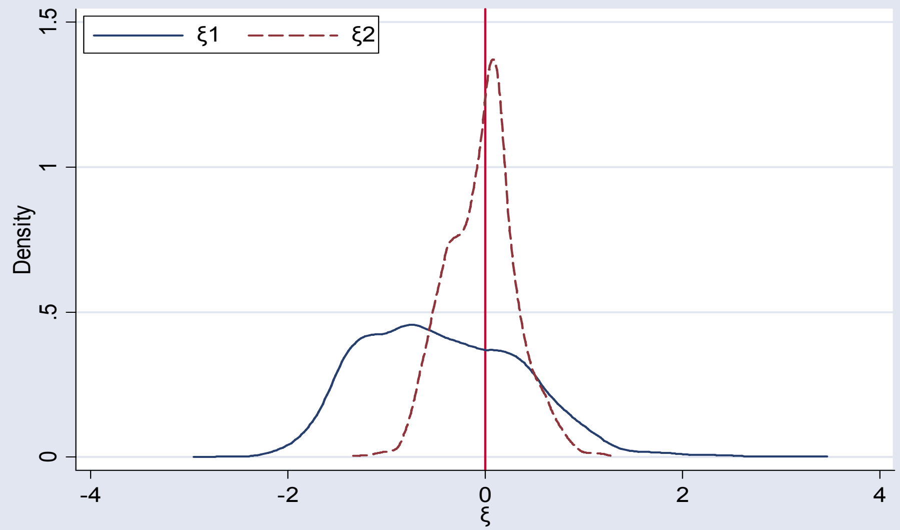

Figure 4. Distribution of price distortions

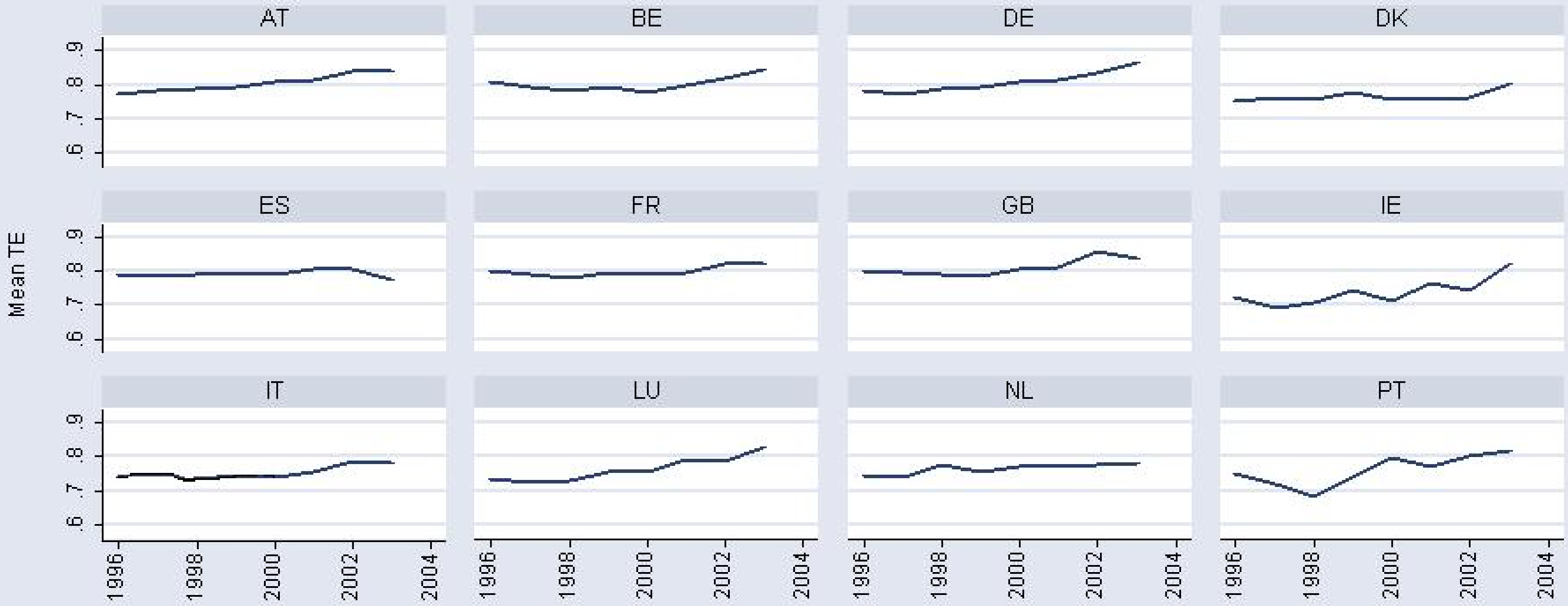

Figure 5.Temporal variation of overall efficiency by country

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