Economic Modelling 44 (2015) 188–199

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.elsevier.com/locate/ecmod

Applying the New Metafrontier Directional Distance Function to Compare Banking Efficiencies in Central and Eastern European Countries

Tai-Hsin Huang, Dien-Lin Chiang, Chao-Min Tsai

Department of Money and Banking, National Chengchi University

ARTICLE INFO

Article history:
Accepted 9 October 2014
Available online 6 November 2014

JEL classification:
D24
G21
P34

Keywords:
metafrontier directional distance function
technical efficiencies
environmental variables
undesirable output

ABSTRACT

This paper establishes a new metafrontier directional technology distance function (MDDF) under a stochastic framework, rather than a deterministic setting like the one proposed by Battese et al. (2004). The new MDDF allows for calculating comparable technical efficiencies for banks under different technologies relative to the potential technology available to the industry across nations. The inefficiency term of the new MDDF is further associated with relevant environmental variables of the form proposed by Battese and Coelli (1995). The new MDDF is then applied to examine and compare bank efficiencies of 17 Central and Eastern European countries. Non-performing loans (NPLs) are regarded as an undesirable, jointly produced with various loans, and the omission of them tends to underestimate technical inefficiency scores. Evidence is found that the estimated technology gap dominates technical efficiencies. Bank managers are suggested to swiftly adopt new financial innovations with an eye to shift the group frontier closer to the metafrontier.

1. Introduction

Commercial banking is a very important service industry in a nation. A country having a healthy financial system is able to establish a stable, sound financial market, to deepen its financial development, and to avoid suffering from financial distress. Scarce loanable funds can thus be efficiently allocated to the most productive projects that prompt a nation's economic development. The presence of financial crises, such as the Asian financial crisis that occurred in 1997 and the global financial crisis starting in early 2007 when the sub-prime mortgage crisis erupted in the U.S., usually severely hurt the well-being of multiple countries, such as decreases in income and jobs. European banking has undergone fundamental changes over the last two decades. After the disintegration of the former Soviet Union in the 1990s, Central and Eastern European (CEE) countries have committed themselves to conducting various forms of financial reform, including privatization and the entry of foreign banks and investments, in an attempt to enhance the efficiency and productivity of their financial sectors, to promote corporate governance and the effectiveness of supervision, and to speed up a country's financial development and economic growth. Most CEE countries intended to restructure their banking systems by initiating large scale privatization programs in the mid-1990s in an attempt to encourage competition and efficiency of banks by increasing foreign and private domestic participation. Therefore, the managerial ability of financial institutions is an important issue worth a further investigation, given the promotion of competition from the presence of foreign banks in the CEE area and the improvement in the institutional, regulatory, and supervisory structure.

Most previous studies on the issues of bank efficiency and productivity change apply either the data envelopment analysis (DEA) or the stochastic frontier approach (SFA) to find the production or cost frontier. Recently, the directional technology distance function (DDF), proposed by Färe et al. (1997), has drawn much attention of empirical researchers. Almost all works, except for Koutsomanoli-Filippaki et al. (2009), adopt the DEA to investigate the efficiency and productivity of firms, and though DEA has several strengths such as being free from specifying a functional form, it is unable to separate the effect of random shocks on the estimated efficiency scores. Conversely, the SFA assumes composed errors that distinguish statistical noise from the technical inefficiency term, while it requires specifying a particular functional form.

Following Koutsomanoli-Filippaki et al. (2009), this paper applies the stochastic frontier DDF to investigate bank efficiencies in 17 CEE countries. The advantages of using this DDF are as follows. First, it characterizes the joint production of desirable outputs with undesirable outputs and allows for a bank to increase desirable outputs and concurrently decrease inputs and undesirables. This differs from either the input- or the output-oriented distance function that permits either input savings or output expansion, but not both, and is incapable of handling undesirable outputs. Second, the DDF is specified as if the translog form without the need to take the natural logarithm. This flexible functional form can lessen the potential error of functional specification and

E-mail addresses: thuang@nccu.edu.tw (T.-H. Huang), a0958920058@hotmail.com (D.-L. Chiang), 98352003@nccu.edu.tw (C.-M. Tsai).

http://dx.doi.org/10.1016/j.econmod.2014.10.029
0264-9993/

the sample with variables taking a zero value can hold. Finally, the inefficiency term can be linked with a set of environmental variables that influence a bank's production effeciency.

In the banking industry, non-performing loans may be viewed as an undesirable, by-product jointly produced with various loans. According to Färe and Grosskopf (2005), desirable outputs are said to be null-joint with undesirable outputs, if there are no bad outputs produced, then only zero good output can be produced. Furthermore, undesirables are assumed to be weakly disposed, i.e., the disposal of them needs to consume resources and is not costless. Consequently, the exclusion of undesirables from the model is apt to overestimate the technical efficiency score. For example, suppose that banks A and B are producing the same level of outputs, but bank A employs less number of workers than bank B to screen out its applicants for loans. This would result in the amount of bank A's non-performing loans to exceed bank B's. Taking an intput-oriented distance function as an example, it is very likely that bank A's efficiency score is greater than bank B's, since the former hires less labor than the latter to yield the same output quantities. If the bad output, satisfying the foregoing properties of null jointness and weak disposability, is explicitly taken into account, then the rank of the efficiency scores of the two banks may be reversed. This is because bank A has to consume some resources to deal with the bad output, lowering the output oriented technical efficiency measure.

The metafrontier, dated back to Hayami (1969) and Hayami and Ruttan (1970, 1971), is established on the basis that all firms in different production groups have access to the same, potential technology, but each may choose to operate on a different part of it. This may be attributed to the fact that each group (or country) has its own cultural and economic traditions, resource endowments, market structure characteristics, regulation, and political and law systems (Bolt and Humphrey, 2010; O'Donnell et al., 2008). These conditions hinder firms in different countries from selecting from the full set of technologically optimal input–output mixes in the potential technology set. Therefore, banking industries, for example, of different countries adopt heterogeneous, sub-technologies. In this context, their performance cannot be compared directly on the ground of group-specific frontiers. Another source of technological heterogeneity may be due to bank-specific features linked with, e.g., expenditures on R&D, the capacity to learn new knowledge, and the core competences (Cohen and Levinthal, 1989; Kontolaimou and Tsekouras, 2010).

To validly conduct a cross-country comparison, a researcher has to design a procedure that takes care of heterogeneous technologies, on the one hand, and that the performance of banks should be assessed on the same benchmark for different countries, on the other. This requires the use of the newly developed metafrontier model by Battese et al. (2004) and O'Donnell et al. (2008), which proceeds in a two-step procedure. In the first step, the stochastic frontier of each country (or group) is estimated to yield technical efficiency scores for all banks within the individual countries. In the second step, one estimates the metafrontier to obtain the technology gap ratios (TGRs) between the (deterministic) metafrontier and the group frontiers for each bank, using the linear or quadratic programming technique that allows for easily imposing the tangency restriction between the metafrontier and the group frontiers. Bos and Schmiedel (2007) apply this model to examine banking efficiency in 15 Western European countries accounting for potential differentials among country-specific banking technologies.

We extend the stochastic frontier DDF of Koutsomanoli-Filippaki et al. (2009) to the new metafrontier DDF (MDDF), which allows for estimating and comparing bank efficiency across 17 CEE countries. The idea of the new MDDF is first proposed by Huang et al. (2014) exemplified by a production function. It differs considerably from Battese et al. (2004) and O'Donnell et al. (2008) mainly in the second step, aiming at establishing the (stochastic) metafrontier. Our new MDDF is constructed under the stochastic frontier framework, instead of relying on mathematical programming techniques. The primary difficulties of programming techniques are that they are deterministic, similar to the DEA, such that the estimation results are easily confounded with random shocks, and that no statistical inferences can be made, because the statistical properties of the estimates are unknown. Both difficulties can be disentangled by the employment of the new MDDF, to be thoroughly discussed in Section 3.

The purpose of this paper is three-fold. First, we attempt to build a new MDDF under the stochastic frontier framework. The new MDDF is recommended and possibly preferable, because the resulting estimates of TGRs are free from the influence of random shocks. Second, the TGRs can be further specified as a function of an array of exogenous variables characterizing the environments in which production takes place. This approach is akin to Battese and Coelli (1995). In this manner, one is able to study the determinants of the TGRs and, more importantly, banks from different countries can be compared under similar condisitons. Third and finally, the new MDDF is applied to estimate and compare bank efficiencies of 17 CEE countries, as banks in these transition nations tend to adopt heterogeneous technologies due to systematic, cultural, regulatory, and endowment differences, and the financial systems in these countries have experienced various series of financial reforms during the past two decades.

The rest of this paper is organized as follows. Section 2 briefly reviews relevant literature on the DDF and MDDF. Section 3 establishes the new MDDF. Section 4 describes the data. Section 5 analyzes the empirical results, while the last section concludes the paper.

2. Literature review

2.1. Applications of the directional distance function

Färe et al. (1993) derive a formula suitable for calculating shadow prices of undesirables, which can be empirically estimated by linear programming.[1] Most existing works estimating technical efficiency, on the basis of the directional distance function (DDF), require solving a linear programming problem. Chung et al. (1997) study the Malmquist-Luenberger productivity index (MLPI) of 39 Swedish pulp and paper firms over the period 1986–1990 and find that the main source of their productivity gains comes from technological progress. To highlight the importance of undesirable outputs, Färe et al. (2001) estimate the MLPI of the manufacturing sector of the U.S. covering 1974–1986, confirming that the MLPI is seriously underestimated if the model ignores undesirable outputs.

Yu (2004) consider both undesirables and environmental factors in his directional output distance function to measure the physical efficiency of Taiwan's airports. Comparing to the conventional output-oriented DEA method, his model leads to a large increase in the estimated efficiency scores for the sample airports, echoing the results of Färe et al. (1989). This may be attributed to the fact that firms (airports) must reallocate inputs not only to execute pollution control activities, but also to maintain desirable outputs' production activities in response to the imposition of a weak disposability constraint on undesirables. As a result, the efficiency measures obtained from the DDF are likely to reflect true production efficiency of the sample firms.

Watanabe and Tanaka (2004) employ a directional output distance function to evaluate the efficiency of the Chinese industry at the provincial level spanning from 1994 to 2002 under the framework of the DEA.

[1] In general, there are no market trading undesirable outputs, and hence their market prices are unobserved. However, their implied prices can be theoretically established from economic models and are referred to as shadow prices. The shadow price is useful to assess the effectiveness of existing regulatory measures and helps managers decide whether to buy pollution rights or not.

They find evidence that efficiency levels are biased if the model excludes undesirables. Both Picazo-Tadeo et al. (2005) and McMullen and Noh (2007) confirm the importance of undesirable outputs in evaluating technical efficiencies of Spanish producers of ceramic pavement and single-mode U.S. bus transit agencies, respectively. Using the DDF and the MLPI, Kaneko and Managi (2007) investigate a Chinese province-level economy wide dataset over 1987–2001 and stress the significance of efficiently utilizing pollution abatement technologies in gauging productivity gains.

Fukuyama and Weber (2008) view problem loans, jointly produced with the loan production process, as an undesirable output of the Japanese banking industry and assess this industry's inefficiency and the shadow price of problem loans. They estimate the directional output distance function of Färe et al. (2005) using the DEA and a parametric linear programming technique. Their results verify that NPLs for Japanese banks in 2002 to 2004 are like polluting by-products of manufacturing firms or power generation.[2] Treating non-performing loans as an undesirable by-product of South Korean banks, Park and Weber (2006) examine these banks' inefficiency and productivity change for the period 1992–2002. They find positive productivity growth due to the excess of technical progress over efficiency declines. Tsang et al. (2014) propose a range-adjusted measure model to estimate dynamic productivity in the presence of negative data and undesirable outputs for 36 Taiwan's commercial banks spanning 2007–2009. Using the similar data to the previous work, Yang (2012) characterizes the production process of commercial banks as three components in the context of the network DEA and DDF.

Unlike the foregoing studies, Koutsomanoli-Filippaki et al. (2009) formulate a stochastic DDF with composed errors, which is used to measure technical efficiency and productivity change in terms of the Luenberger productivity indicators and their components for banks across 10 CEE countries covering 1998–2003. Unfortunately, their DDF precludes undesirable outputs so that the advantage of a DDF is not fully utilized. They detect strong relationships of competition and concentration with bank efficiency. Furthermore, efficiency and productivity gains of foreign banks are found to be superior to domestic private and state-owned banks.

2.2. Metafrontier functions

Battese et al. (2004) first propose a two-step approach to construct a metafrontier function suitable for estimating and comparing the technical efficiency of firms belonging to various technology groups. In the second step, they suggest using either a linear programming or quadratic programming technique, which permits the imposition of inequality constraints and forces the group frontier to be below (or above) the metafrontier, in order to compute the technology gap ratio for each firm in different groups. Following the same procedure, O'Donnell et al. (2008) compare the technical efficiency of agricultural production across 97 countries spanning 1986 to 1990. Huang et al. (2011a) extend the above model to the metafrontier Fourier flexible cost function and compare technical efficiencies for banks in 16 Western European countries. A relatively technically efficient bank is found to be possibly technologically efficient and vice versa.

Huang et al. (2014) initiate a new metafrontier to estimate technical efficiency (TE) scores for firms in different groups. Their approach diverges from Battese et al. (2004) and O'Donnell et al. (2008) mainly in the second step, where a stochastic frontier model is formulated and estimated by the maximum likelihood to obtain the parameter estimates of the metafrontier, instead of relying on programming techniques. In this manner, the so-derived estimators have the desirable statistical properties and enable some relevant statistical inferences to be drawn.

The use of a metafrontier is preferable in that it allows researchers to assess the TGR for firms from different groups with respect to the common metafrontier. Therefore, these TGRs are comparable among firms of different groups, which are the salient features under the metafrontier framework. This present article intends to exploit such advantages and to explore banks' performance among CEE countries. It is noteworthy that a study on cross-country efficiency measure comparisons in transition countries' banking industry has largely increased recently without relying on the metafrontier. See, for example, Allen and Rai (1996), Altunbas et al. (2001), and Weill (2004), Bonin et al. (2005), Fries and Taci (2005), Yildirim and Philippatos (2007), and Huang et al. (2011a, 2011b), to mention a few.

However, Bos and Schmiedel (2007) and Huang et al. (2011a) perform the cross-country comparisons in the context of the metafrontier, proposed by Battese et al. (2004).

3. New metafrontier directional distance function

3.1. Directional technology distance function

Input quantities are denoted by $x = (x_1, \ldots, x_N)' \in R_+^N$, output quantities are denoted by $y = (y_1, \ldots, y_M)' \in R_+^M$, and the undesirable vector is signified by $b = (b_1, \ldots, b_J)' \in R_+^J$. Following O'Donnell et al. (2008), the kth ($k = 1,\ldots, K$) group's technology set is defined as:

$$T^k = \{(x, y, u) : x \text{ can be used by firms in group } k \text{ to produce } (y, b)\}.$$

A directional vector is expressed as $g = (g_x', g_y', g_u')'$, in which $g_x \in R_+^N$, $g_y \in R_+^M$, and $g_b \in R_+^J$.

We now define the directional technology distance function (DDF) for group k as:

$$\overline{D}_T^k(x, y, b; g) = \sup\left\{\beta : \left(x - \beta g_x, y + \beta g_y, b - \beta g_b\right) \in T^k\right\} \tag{1}$$

It expands outputs in the direction g_y and contracts inputs and undesirables in the directions g_x and g_b, respectively, in order to be able to produce on the group frontier. The DDF translates the (x, y, b) vector in the direction g onto the boundary of the technology.

Since (x, y, b) is usually interior to technology T^k, the value of the distance function is non-negative. A firm having a value of $\overline{D}_T^k(x, y, b; g) = 0$ implies that it is already producing at the frontier, while a value of $\overline{D}_T^k(x, y, b; g) > 0$ reveals that the firm's actual (x, y, b) locates underneath the frontier. Following Koutsomanoli-Filippaki et al. (2009), the directional vector herein is specified as $g = (1,1,1)$, which means that a firm can produce at the efficient frontier if it simultaneously reduces its input quantities and undesirables by β units and increases outputs by β units along with the direction (1,1,1).

The DDF is commonly expressed as a flexible quadratic functional form allowing for a non-neutral technical change. It can be shown that the DDF has the translation property, i.e.,

$$\overline{D}_T^k\left(x - \xi g_x, y + \xi g_y, b - \xi g_b; g_x, g_y, g_b\right) = \overline{D}_T^k\left(x, y, b; g_x, g_y, g_b\right) - \xi.$$

This property means that if we translate the vector (x, y, b) into $(x - \xi g_x, y + \xi g_y, b - \xi g_b)$, then the value of the distance function is reduced by the scalar ξ. The translation property is used to transform the DDF into an estimable regression equation. See, for example, Färe and

[2] Note that the linear programming method allows the authors to estimate the shadow price of non-performing loans for 99% of the sample banks, while the DEA can estimate shadow prices for only 13% of the banks.

Grosskopf (2005). We arbitrarily choose $\xi = x_1$ to translate the quadratic DDF into:

$$\begin{aligned}
-x_1 &= \vec{D}_T^{k*}(x-x_1, y+x_1, b-x_1; 1,1,1,t,\theta) + v - u \\
&= \alpha_0 + \sum_{n=2}^{N}\alpha_n(x_n-x_1) + \sum_{m=1}^{M}\beta_m(y_m+x_1) + \sum_{j=1}^{J}\lambda_j(b_j-x_1) \\
&\quad + \frac{1}{2}\sum_{n=2}^{N}\sum_{n'=2}^{N}\alpha_{nn'}(x_n-x_1)(x_{n'}-x_1) \\
&\quad + \frac{1}{2}\sum_{m=1}^{M}\sum_{m'=1}^{M}\beta_{mm'}(y_m+x_1)(y_{m'}+x_1) + \frac{1}{2}\sum_{j=1}^{J}\sum_{j'=1}^{J}\lambda_{jj'}\left(b_j-x_1\right)\left(b_{j'}-x_1\right) \\
&\quad + \sum_{n=2}^{N}\sum_{m=1}^{M}\gamma_{mn}(y_m+x_1)(x_n-x_1) + \sum_{n=2}^{N}\sum_{j=1}^{J}a_{jn}\left(b_j-x_1\right)(x_n-x_1) \\
&\quad + \sum_{m=1}^{M}\sum_{j=1}^{J}c_{jm}\left(b_j-x_1\right)(y_m+x_1) \\
&\quad + \delta_1 t + \frac{1}{2}\delta_2 t^2 + \sum_{n=2}^{N}\psi_n t(x_n-x_1) + \sum_{m=1}^{M}\mu_m t(y_m+x_1) + \sum_{j=1}^{J}c_j t\left(b_j-x_1\right) + \varepsilon
\end{aligned} \tag{2}$$

where $\theta = (\alpha, \beta, \lambda, \gamma, a, c, \delta, \psi, \mu, c)$ is a vector of parameters to be estimated and $\varepsilon = v - u$ is the composed error term. Here and henceforth, $\vec{D}^{*}(\cdot)$ signifies the translated DDF that will be estimated later in our empirical study. In addition, $u = \vec{D}_T^{*}(x, y, b; 1, 1, 1, t, \theta)$ is treated as a non-negative random variable, reflecting technical inefficiency of the firm under consideration, and v is a two-sided, normally distributed error with a mean of zero and a constant variance σ_v^2, which is traditionally assumed to be independent of u. The DDF of (2) must also satisfy the symmetrical conditions, i.e.,$\alpha_{nn'} = \alpha_{n'n}$, $\beta_{mm'} = \beta_{m'm}$ and $\lambda_{jj'} = \lambda_{j'j}$.[3]

Similar to Battese and Coelli (1995) and Koutsomanoli-Filippaki et al. (2009), inefficiency term u is further specified as:

$$u = \alpha' z + w \geq 0 \tag{3}$$

Here, z is a set of environmental variables, α is the corresponding unknown parameters, and w is assumed to be $w \sim N(0, \sigma_w^2)$. A set of bank-level factors will be selected as the environmental variables to describe banks' technical inefficiency. Eq. (3) implies that $w \geq -\alpha' z$. Eq. (2) can be estimated by the maximum likelihood (ML). After obtaining all of the parameter estimates, one is able to compute the conditional expectation that serves as a point estimator for u, representing technical inefficiency, i.e.:

$$E(u|\varepsilon) = \alpha' z + \mu_* + \sigma_* \frac{\phi\left(\frac{-\alpha' z - \mu_*}{\sigma_*}\right)}{1 - \Phi\left(\frac{-\alpha' z - \mu_*}{\sigma_*}\right)}, \tag{4}$$

where $\mu_* = -\varepsilon\sigma_w^2/\sigma^2$, $\sigma_*^2 = \sigma_v^2\sigma_w^2/\sigma^2$, $\sigma^2 = \sigma_v^2 + \sigma_w^2$, and $\varepsilon = v - w$.[4] The conditional expectation of (4) is non-negative by construction. The higher the value of $E(u|\varepsilon)$ is, the less technically efficient the firm is.

[3] A DDF must also satisfy the following three properties (the superscript k is dropped for simplicity):

(i) If $x' \geq x$, then $\vec{D}_T(x', y, b; g) \geq \vec{D}_T(x, y, b; g)$.
(ii) If $y' \geq y$, then $\vec{D}_T(x, y', b; g) \leq \vec{D}_T(x, y, b; g)$.
(iii) If $b' \geq b$, then $\vec{D}_T(x, y, b'; g) \geq \vec{D}_T(x, y, b; g)$.

[4] It can readily be shown that the conditional distribution of $w|\varepsilon$ is a truncated normal distribution at zero from below with a mean of μ_* and a variance of σ_*^2.

3.2. Metafrontier directional distance function (MDDF)

A metafrontier technology set is defined by:

$$T^m = \{(x, y, b) : x \geq 0, y \geq 0, b \geq 0,\ x \text{ can produce } (y,\ b) \text{ for all firms under study}\}.$$

The MDDF is then expressed as:

$$\begin{aligned}
&\vec{D}^m\left(x, y, u; g_x, g_y, g_u\right) \\
&= \sup\left\{\beta^m : \left(x - \beta^m g_x, y + \beta^m g_y, u - \beta^m g_u\right) \in T^m\right\}
\end{aligned} \tag{5}$$

This has similar implications to (1), but the reference set of T^k has to be replaced by T^m. O'Donnell et al. (2008) show that there exist four properties between group frontiers and the metafrontier, in which $\vec{D}^{k*}(x-x_1, y+x_1, b-x_1; g) \leq \vec{D}^{m*}(x-x_1, y+x_1, b-x_1; g)$, for all $k = 1, \ldots, K$, requires that the translated metafrontier envelops translated group frontiers. Hence, the value of group k's DDF has to be less than or equal to that of the metafrontier DDF along the prespecified direction vector g.[5] Based on this property, we refer their difference to the technology gap difference (TGD), i.e.:

$$\vec{D}^m(x, y, b; g) = \vec{D}_T^k(x, y, b; g) + TGD, \tag{6}$$

which shows that the overall inefficiency $\vec{D}^m(x, y, b; g)$, i.e., the firm's production technical inefficiency with respect to the metafrontier production technology, is equal to the sum of the firm's production technical inefficiency with respect to the group-k production technology and TGD. Term TGD displays the gap between the translated metafrontier and translated group-k frontier and is non-negative by construction. It depends on the accessibility and extent of adoption of the available potential production technology. The larger the value of TGD is, the less advanced the technology is adopted by firms of group k, and vice versa. It is crucial to note that since the overall inefficiency measures of firms are evaluated against the metafrontier, common to all firms in different groups, they are comparable for firms operating under different technologies.

Battese et al. (2004), Bos and Schmiedel (2007), and O'Donnell et al. (2008) utilize linear and/or quadratic programming techniques to calculate the unknown parameters of the metafrontier. Even though simulation or bootstrapping methods are recommended to obtain the standard errors of the calculated parametes, their statistical properties are still not known such that no inferences can be made. As the so-derived metafrontier is deterministic in essence, it is unable to escape from the influences of the random shocks. In other words, the parameter estimates are apt to be confounded by shocks. In addition, the environmental variables that affect the TGD cannot be included (see below), which is likely to incur biased estimation results.

Due to the foregoing drawbacks, we are now attempting to establish a new, stochastic metafrontier based on the stochastic frontier approach (SFA), which avoids the aforementioned problems and has the desired statistical properties. Recall that the new metafrontier of Huang et al. (2014) is developed for a production function. Their model has to be modified to adapt for the case of the DDF. Using the translation property, Eq. (6) can be reformulated as:

$$\vec{D}^{k*}(x-x_1, y+x_1, b-x_1; g) = \vec{D}^{m*}(x-x_1, y+x_1, b-x_1; g) - TGD. \tag{7}$$

[5] The other theee properties are: (i) if $(x, y, b) \in T^k$ for any k, then $(x, y, b) \in T^m$; (ii) if $(x, y, b) \in T^m$, then $(x, y, b) \in T^k$ for some k; (iii) $T^m = \{T^1 \cup T^2 \cup \ldots \cup T^k\}$.

Although the true group-k frontier of $\vec{D}^{k*}(\cdot)$ is unknown, its fitted value of $\hat{\vec{D}}^{k*}(\cdot)$ can be obtained after estimating (2) by the ML, which leads to:

$$\vec{D}^{k*}(x-x_1, y+x_1, b-x_1; g) = \hat{\vec{D}}^{k*}(x-x_1, y+x_1, b-x_1; g) + \tilde{V}^m, \tag{8}$$

where $\tilde{V}^m = \hat{\varepsilon} - \varepsilon$ denotes a random error arising from the estimation error of the translated group frontier from (2), which can be shown to have a mean of zero with a non-constant variance.[6] This arises from the fact that the residual $\hat{\varepsilon}$ is affected by the set of variables in the group frontiers.

Substituting (8) into (7) we yield the following estimable stochastic metafrontier:

$$\hat{\vec{D}}^{k*}(x-x_1, y+x_1, b-x_1; g) = \vec{D}^{m*}(x-x_1, y+x_1, b-x_1; g) + V^m - U^m, \tag{9}$$

where $V^m = -\tilde{V}^m$, $V^m - U^m$ forms the composed errors, and U^m is nothing but the TGD that is treated as if it is the inefficiency term. The presence of V^m is important, since it makes (9) in a stochastic, rather than a deterministic, context. According to the previous paragraph, V^m (or $\tilde{V}^m$) is not independently and identically distributed (i.i.d.) and is obviously correlated with ε of the group frontier. The presence of heteroscedasticity does not influence consistency property of the ML estimators, but biases the estimated covariance matrix of the coefficients. The method developed by White (1982) should be applied to correct for the estimated covariance matrix and the so-derived estimates are referred to as quasi-maximum likelihood estimates in the literature. Also see, for example, Johnston and DiNardo (1992), page 428–430. We will show both original and corrected standard errors of the parameter estimates of the metafrontier in Section 5.

Note that U^m can also be linked with a set of environmental variables like (3), which is infeasible if the programming technique is adopted as suggested by Battese et al. (2004) and O'Donnell et al. (2008). To appropriately characterize the differences of the TGR among countries, we will choose country-level factors as the environmental variables, as opposed to bank-level factors relating to u's of group frontiers. This implicitly assumes that U^m of the metafrontier is unrelated with u of the group frontier. The assumption appears to be reasonable due to the fact that the two measures have distinct attribute. Recall that U^m represents the gap between the metafrontier, fromed by all groups, and group frontiers, while u evaluates managerial incapabilities of banks of a particular group.

The functional form of the translated MDDF $\left(\vec{D}^{m*}\right)$ in (9) is analogously specified to (2) and the TGD is estimated by formula (4). It is interesting to note that our approach permits the estimated group frontier to exceed the metafrontier, i.e.: $\hat{\vec{D}}^{k*}(x-x_1, y+x_1, b-x_1; g) \geq \vec{D}^{m*}(x-x_1, y+x_1, b-x_1; g)$, due to the presence of the error (V^m) from estimating $\vec{D}^{k*}(x-x_1, y+x_1, b-x_1; g)$. However, the metafrontier must always exceed the true group frontier, i.e., $\vec{D}^{k*}(x-x_1, y+x_1, b-x_1; g) \leq \vec{D}^{m*}(x-x_1, y+x_1, b-x_1; g)$.

[6] On the ground of (2), the following relationship must be true:

$$-x_1 = \vec{D}^{k*}(\cdot) + \varepsilon = \hat{\vec{D}}^{k*}(\cdot) + \hat{\varepsilon}$$

where a "^" on the top of a variable denotes the estimated value by the ML. It follows that

$$\vec{D}^{k*}(\cdot) = \hat{\vec{D}}^{k*}(\cdot) + \hat{\varepsilon} - \varepsilon$$

and $\hat{\varepsilon} - \varepsilon$ vanishes as the sample size goes to infinity.

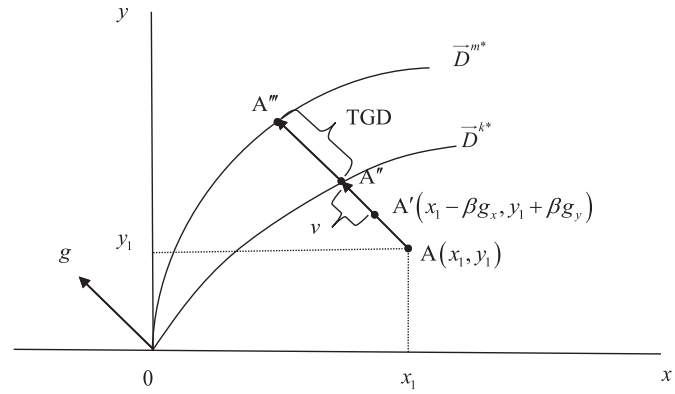

Fig. 1. Metafrontier directional distance function.

Fig. 1 illustrates the MDDF model. At given input and output levels, say, x_1 and y_1, the observed point A relative to the projected metafrontier point A‴ consists of three components: the technology gap difference, $TGD = \vec{D}^{m*}(\cdot) - \vec{D}^{k*}(\cdot)$, the firm's technical inefficiency between points A and A′, estimated by $E(u|\varepsilon)$ of (4), and the random noise component v of (2) between points A′ and A″, i.e.:

$$A = A''' - TGD - v - u, \tag{10}$$

or equivalently:

$$A''' - A = TGD + u + v. \tag{11}$$

It should be emphasized that, although both the technology gap difference TGD and the firm's production inefficiency are non-negative, the translated metafrontier $\vec{D}^{m*}$ does not necessarily envelop all firms' observed production at point A. The unrestricted difference in (11) distinguishes the metafrontier model using the SFA from the DEA due to the presence of the random noise component v.

We summarize the estimation procedure for the stochastic MDDF in the following three steps.

Step 1 Estimate (2) by the ML to get the parameter estimates for each group and then calculate the fitted value $\hat{\vec{D}}^{k*}(x-x_1, y+x_1, b-x_1; g)$ for each firm in the group. The parameter estimates of each group are also used to measure group-specific technical inefficiency scores for firms in the group according to (4).

Step 2 Estimate (9) by the ML again to obtain the parameter estimates of the MDDF. The resulting inefficiency measures from (9) using formula (4) again for all firms represent the measure of TGDs.

Step 3 The sum of the above two inefficiency measures constitutes the overall inefficiency estimate of (6), which enables us to make comparisons across different technology groups.

4. Data description

4.1. Data sources

We compile unbalanced panel data covering 1995–2008 from 17 CEE countries from the accounting statements of the Bankscope database.[7] The sample contains 1466 banks with a total of 6770 bank-year observations. All variables are measured in millions of US dollars and deflated by the individual consumer price indices of the sample countries with base year 2005.

[7] We exclude three countries, i.e., Albania, Belarus, and Montenegro, due to severe data unavailability.

According to the intermediation approach, we identify three inputs and three outputs. The input categories consist of labor (x_1), physical capital (x_2), and borrowed funds (x_3).[8] Total loans (y_1) and other earning assets (y_2) are regarded as the conventional outputs. Non-interest revenue (y_3) is considered as an additional output, reflecting a bank's degree of product diversification and constituting a crutial source of revenue for modern universal banks. The inclusion of y_3 enables us to correctly describe a bank's production process and its capability at diversifying the output spectrum. Furthermore, the item of non-performing loans is defined as the single undesirable, mainly because this item co-exists with various loans granted, which meet the property of null jointness. Appendix 1 gives detailed variable definitions together with some environmental variables.

This paper classifies the environmental variables into micro- and macro-environmental variables to reflect the different atmospheres confronted by banks. The former variables are used to explain technical inefficiencies for the group frontiers and the latter to explain technology gap differences. Following Berger et al. (1993), Mester (1993), Allen and Rai (1996), Lozano-Vivas et al. (2002), and Huang et al. (2011b), Huang et al. (2014), we identify four micro-level variables: the ratio of equity to total assets (ETA), average ROA per year (AROA), ownership dummies, and an unlisted dummy. Three macro-level variables are defined: real GDP per capita (RGDP), population density (PD), and the Herfindahl-Hirschman Index (HHI).[9]

The variable ETA shows the regulatory conditions of a country's banking industry, as well as bank managers' attitudes toward risk. Some earlier works, e.g., Hughes and Mester (1993), Mester (1996), Berger and Mester (1997), and Huang (2000), consider the variable as a fixed netput in either a cost or a profit function in order to control for regulation and a bank's risk preferences. A risk-averse manager prefers to maintain a higher level of equity capital than a risk-neutral manager so as to lower possible insolvency risk, at the expense of lowering loanable funds that can be granted to promising projects earning high interest revenues. As each country's regulatory conditions change over time and bank managers' preferences differ, the expected sign of ETA on inefficiency is unclear. Mester (1993), Lozano-Vivas et al. (2002), and Huang et al. (2011b), support that ETA negatively affects technical inefficiency, i.e., the higher the ETA is, the more efficient the bank will be.

The variable ROA is used as an indicator of profitability, which is intimately correlated with competitiveness in the financial sector. To escape from any possible endogeneity of the variable, we apply the average value of the ROA over a country's entire banks for each year. Therefore, it varies only with time in a country. A positive relationship between the average ROA and efficiency is expected in competitive surroundings. See, for example, Berger et al. (1993), Mester (1993), Allen and Rai (1996), Lozano-Vivas et al. (2002), and Huang et al. (2011b), for banking and savings and loan industries. The sample banks are divided into three classes, i.e., foreign-, domestic private-, and state-owned banks, with the first one arbitrarily selected as the normalization. In addition, we classify the sample banks into listed and unlisted ones to the stock markets.

The variables real GDP per capita (RGDP) and population density (PD) are taken from the World Development Indicators data bank. The former variable is measured in thousands of US dollars and the latter is calculated by the ratio of population to the area of the country (square kilometer). RGDP is used to represent the overall economic condition that influences both demand and supply sides of various banking activities. An increase in RGDP helps the development of a country's financial sector, which usually stimulates bank efficiency. It thus is expected that the variable is positively associated with technical efficiency, as confirmed by Lozano-Vivas et al. (2002) and Huang et al. (2011b). Lozano-Vivas et al. (2002) assert that a higher level of population density should make retail distribution of banking activities less expensive, enhancing bank efficiency.

We finally consider the market concentration index - the Herfindall-Hirschman index (HHI) - as a determinant of technical efficiency. In a highly condensed market, a bank is apt to be inefficient due to a lack of competition - the quiet life hypothesis. However, Fries and Taci (2005) claim that if the high market concentration arises from consolidation through the survival of more efficient banks and the market is contestable, then market concentration is with higher efficiency. Therefore, the sign of HHI's coefficient is ambiguous, emphasizing the importance of conducting an empirical study on this topic.

Table 1 shows the number of observations and ownership structure across nations. The sample states have at least 80 observations, in which the number of foreign banks leads the other two types of banks and the number of state-owned banks makes up the least in most of the states, except for Russia whose private banks outnumber the other two types of banks. Moreover, the number of unlisted banks exceeds that of listed banks in most countries, while the reverse is true in Croatia, Moldova, Macedonia, and Serbia. Note that Estonia has no listed banks.

Table 2 summarizes the sample statistics for inputs and outputs of all countries. The average amounts of loans, investments, and non-interest revenue in the CEE countries are equal to 439, 297, and 50 million US dollars, respectively. Average total assets net of fixed assets, the proxy of labor, are equal to 821 million US dollars. The remaining two inputs, i.e., fixed assets and borrowed funds, have the mean values of 22 and 631 million US dollars, respectively. Finally, the mean of the undesirable, the NPL, is equal to 27 million US dollars.

Table 3 reveals that the average loans, non-interest revenue, labor, and borrowed funds of foreign banks are greater than those of private and state-owned banks, while state-owned banks produce the highest undesirable (10.68% of total loans), indicating that political intervention is likely to be serious and the quality of granted loans by state-owned banks needs improvement. This further shows that loan quality may play a certain role in a bank's decision-making process. As for the environmental variables, private banks have higher average ETA and ROA than the other two types of banks.

Sample statistics across countries are not shown to save space. Generally speaking, banks in different countries are inclined to hire quite different amounts of inputs to produce various output quantities under heterogeneous environments. The assumption that these banks adopt the same technology to provide an array of financial products seems to be unrealistic. The construction of the new metafrontier introduced in Subsection 3.2 solves this difficulty, which enables researchers to estimate and compare banks' technical efficiencies on the basis of a common metafrontier, while at the same time those banks are operating under dissimilar technologies.

5. Empirical results

5.1. Coefficient estimates of group frontiers

To validate the use of MDDF, it is crucial to test the null hypothesis that the banking systems among countries undertake the same technology. If the hypothesis is not rejected, then researchers can simply pool the data from different countries and estimate a common frontier. There is no need to establish a MDDF.

Following Battese et al. (2004), the likelihood-ratio (LR) test statistic $L = -2\{\ln(L_1) - \ln(L_2)\}$ is computed, where $\ln(L_1) = -30120$ is the value of the likelihood function for the stochastic DDF estimated by pooling the data for all groups, and $\ln(L_2) = -22664$ is the sum of the

[8] The entry for the number of employees is missing for many sample banks. Although the item of personnel expense is available, it is missing entirely in Bosnia and Bulgaria for 1995–1997, in Serbia for 1995–1999, and in Poland for 1995–1996. In addition, some countries have merely a few (less than three) observations on this variable for several years. The item of total assets net of fixed assets is instead used as a proxy for the number of employees. Altunbas et al. (2000, 2001), Weill (2004), and Fries and Taci (2005), to mention a few, utilize the same definition for labor.

[9] The variable of density of demand for deposits is used by several previous works. Unfortunately, this variable is not available in Serbia and hence is overlooked here.

Table 1
Number of observations and ownership structure.

Country	Number of Banks	Number of Obs.	State-owned (%)	Domestic Private-owned (%)	Foreign-owned (%)	Unlisted (%)	Listed (%)
Bosnia (BA)	26	174	12.07	25.29	62.64	59.77	40.23
Bulgaria (BG)	22	165	12.73	18.18	69.09	92.12	7.88
Czech (CZ)	30	180	6.67	35.00	58.33	93.33	6.67
Estonia (EE)	11	71	15.49	21.17	63.38	100	0.00
Croatia (HR)	54	374	5.88	37.70	56.42	47.86	52.14
Hungary (HU)	20	87	13.79	27.59	58.62	79.31	20.69
Lithuania (LT)	13	118	19.49	12.71	67.80	58.48	41.52
Latvia (LV)	29	259	9.27	17.76	72.97	89.58	10.42
Moldova (MD)	17	81	11.11	40.74	48.15	49.38	50.62
Macedonia (MK)	16	98	3.06	30.61	66.33	12.24	87.76
Poland (PL)	45	126	7.93	29.37	62.70	60.31	39.68
Romania (RO)	29	179	5.59	14.53	79.89	94.42	5.59
Serbia (RS)	36	179	10.06	32.96	56.98	44.13	55.87
Russia (RU)	1,030	4,242	1.25	82.13	16.62	91.61	8.39
Slovenia (SI)	15	99	26.26	23.23	50.51	81.82	18.18
Slovakia (SK)	22	93	2.15	30.11	67.74	74.19	25.81
Ukraine (UA)	51	245	2.86	32.24	64.90	70.2	29.80
Total	1,466	6,770	4.19	61.70	34.11	83.13	16.87

Table 2
Descriptive statistics for all countries.

Variable	Mean	Standard Deviation
Loans (y_1)	439.930	2,273.688
Investments (y_2)	297.619	1,463.854
Non-interest revenue (y_3)	50.900	462.341
Labor (x_1)	821.277	4,088.618
Capital (x_2)	22.425	143.046
Funds (x_3)	631.803	3,314.271
Undesirable (b)	27.962	251.935

Note: All items are measured in millions of US dollars and deflated by the CPI of each country with base year 2005.

values of the likelihood functions for the 17 country frontiers. The value of the LR statistic is equal to 14912 and the hypothesis is decisively rejected at the 1% level of significance with 706 degrees of freedom. Banks of different countries are indeed operating under heterogenous technologies.

The parameter estimates of each country are not shown to save space, but their results are summarized as follows. More than half of the estimates of the DDF attain statistical significance at least at the 10% level and the test for the hypothesis that technical change is neutral is decisively rejected at the 1% significance level for each country, impling that nonneutral technical change occurs in the sample countries.[10] With regard to environmental variables, the ETA of Romania has a significantly positive effect on inefficiency, which implies that a bank in Romania with a higher ETA has lower technical efficiency on average. The remaining countries have significantly negative parameter estimates for ETA, except for Latvia, Poland, and Serbia. The higher the value of ETA is, the more technically efficient are the banks in these nations, consistent with Mester (1993), Huang et al. (2011b), and Lozano-Vivas et al. (2002). The average ROA is found to have a significantly negative effect on technical inefficiency in eight nations, i.e., Czech Republic, Estonia, Latvia, Poland, Russia, Slovenia, Slovakia and Ukraine, indicating that profitability is positively correlated with efficiency. This is congruent with, e.g., Allen and Rai (1996), Mester (1993), Berger et al. (1993), Lozano-Vivas et al. (2002), and Huang et al. (2011b). However, profitability has no significant impact in the remaining countries.

For the ownership dummies, the class of foreign banks is arbitrarily selected as the normalization. There is, in fact, no consensus in the literature about which type of bank is more efficient than the other types. Our results confirm this claim as evidence from Bulgaria, Czech Republic, Croatia, Latvia, and Serbia supports the hypothesis of home field advantage, i.e., private banks are found to be more efficient than the remaining two forms of banks. However, six countries, i.e., Lithuania, Macedonia, Russia, Slovenia, Slovakia, and Ukraine, support the hypothesis of global advantage and/or cherry-picking strategies,[11] since foreign banks are the most technically efficient in these countries, while state-owned banks in Estonia, Poland, and Romania outperform the other two forms of banks. Ownership dummies in the remaining three countries are insignificant.

Unlisted banks in Latvia, Moldova, Macedonia, and Poland are more efficient than listed banks, while the reverse is true in seven countries: Bosnia, Bulgaria, Czech Republic, Serbia, Russia, Slovenia, and Ukraine, where the market discipline hypothesis is supported.[12] The foregoing indicates whether or not being listed in the stock market has advantages, as well as disadvantages. This outcome is consistent with Mamatzakis et al. (2008).

Following Färe et al. (2005), we test the condition of null-jointness for all sample countries, using the coefficient estimates of group frontiers. We evaluate $\vec{D}_T^k(x, y, 0; g)$ for $y > 0$ and $g = 1$. Vast majority of our sample countries have more than 95% of observations with $\vec{D}_T^k(x, y, 0; g) < 0$, except for Croatia (87%) and Russia (85%). Viewed from this angle, our parameter estimates are satisfactory.

5.2. Group-specific technical inefficiency

Table 4 presents average inefficiency scores for each country over time, and mean inefficiency scores are in the last column. These measures tell us how many units of outputs and inputs (undesirables), on average, should be increased and reduced, respectively, in order to be able to produce on the efficient group frontier. A higher inefficiency score of a bank implies that the observed input–output mix of the bank deviates farther away from the group-specific frontier and that the bank is less technically efficient. It is worth mentioning that these average inefficiency scores across countries are not comparable since they are gauged against heterogeneous frontiers.

[10] The same applies to the MDDF.

[11] Foreign investors could follow "cherry-picking" strategies, meaning that foreign banks acquire the most efficient banks, or foreign banks transfer knowledge and managing experience to their subsidiaries banking.

[12] The hypothesis asserts that banks whose shares are publicly traded would be more efficient, other things being equal, to the extent that stock-holders of the bank can exert discipline over the management. See, for example, Isik and Hassan (2003). Shareholders have incentives to monitor management performance as it contains risks correlated with agency problems.

Table 3
Descriptive statistics by ownership structure.

	State-owned		Domestic Private-owned		Foreign-owned	
Variable Name	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Loans (y_1)*	667.004	1,496.583	224.093	2,471.936	802.451	1,899.736
Investments (y_2)*	699.160	2,307.773	130.097	1,171.541	551.281	1,735.885
Non-interest revenue (y_3)*	80.988	469.234	31.508	374.005	82.278	587.412
Labor (x_1)*	1,482.169	3,973.177	406.739	4,241.116	1,489.891	3,706.081
Capital (x_2)*	39.750	116.905	13.142	142.604	37.089	145.372
Funds (x_3)*	1,061.563	2,765.472	309.600	3,481.500	1,161.812	2,975.760
Undesirable (b)*	71.211	252.440	17.160	294.249	42.185	145.037
Equity to asset ratio (%)	17.255	13.816	21.335	15.682	16.996	13.591
ROA (%)	1.326	1.290	1.777	0.605	1.341	0.947
Sample Size	284		4,177		2,309	

Note: *: Measured in millions of US dollars and deflated by the CPI of each country with base year 2005.

Table 4
Average group-specific technical inefficiency over time.

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Mean
Bosnia (BA)	NA	1.50	0.74	1.28	1.10	1.16	1.23	0.90	1.31	1.47	1.43	1.48	1.25	1.21	***1.24***
Bulgaria (BG)	0.95	0.86	2.07	1.30	1.37	1.66	1.52	0.91	0.61	1.99	1.73	2.03	1.62	1.59	***1.53***
Czech (CZ)	1.39	10.04	1.97	6.25	5.77	2.97	1.97	2.88	3.17	1.80	1.70	1.31	1.05	1.68	***2.90***
Estonia (EE)	0.96	1.48	0.82	1.01	0.70	1.01	0.47	0.71	1.28	0.37	1.03	0.75	0.12	2.79	***0.97***
Croatia (HR)	2.44	1.57	1.27	1.27	2.32	2.03	1.98	1.93	1.52	1.84	2.62	3.08	1.98	2.23	***1.98***
Hungary (HU)	3.75	2.71	2.21	1.94	1.53	1.41	1.08	0.70	1.20	1.20	2.32	4.91	1.75	0	***2.13***
Lithuania (LT)	0.83	1.60	1.12	1.22	1.40	0.80	1.01	0.80	0.81	1.00	0.95	1.14	0.91	1.95	***1.09***
Latvia (LV)	1.73	1.24	0.89	2.41	2.20	1.27	1.35	1.41	1.47	1.46	0.98	0.86	1.69	3.84	***1.61***
Moldova (MD)	2.71	2.82	2.58	2.83	2.54	2.61	2.49	2.75	2.45	2.63	2.54	2.54	2.59	2.56	***2.58***
Macedonia (MK)	0.58	0.26	0.15	0.34	0.31	0.35	0.44	0.27	0.88	0.33	0.30	0.27	0.36	0.53	***0.38***
Poland (PL)	1.57	1.06	2.79	2.98	3.39	3.83	8.44	18.00	8.33	5.64	5.58	1.67	2.88	4.63	***4.11***
Romania (RO)	29.08	11.37	0.51	0.96	9.48	2.79	5.17	4.38	4.40	3.61	7.18	9.04	11.10	5.49	***5.94***
Serbia (RS)	1.28	1.92	2.21	1.43	3.02	2.54	2.99	2.30	3.23	2.48	2.48	2.09	2.67	3.97	***2.68***
Russia (RU)	19.36	15.01	18.63	10.46	5.49	6.33	5.19	4.61	4.74	3.13	2.72	2.99	3.51	3.80	***3.66***
Slovenia (SI)	5.04	2.46	2.54	1.95	2.38	3.04	9.64	5.04	5.41	7.71	3.18	3.43	3.07	3.77	***3.82***
Slovakia (SK)	1.03	3.98	2.70	3.01	0.83	0.67	2.89	1.18	0.61	1.45	1.94	1.26	1.30	1.35	***1.79***
Ukraine (UA)	0.88	0.90	0.45	0.48	0.48	1.84	1.47	1.27	1.24	1.73	2.40	2.22	2.21	4.36	***2.03***

Average technical inefficiency scores range from 0.38 (Macedonia) to 5.94 (Romania). Macedonian banks should simultaneously decrease 0.38 units (millions of US dollars) of both inputs and the undesirable and increase 0.38 units of outputs in order to attain the efficient frontier. The measure of 5.94 for Romanian banks can be analogously explained.

The determinants of a bank's efficiency can be attributed to both external and internal factors. The former is related to a nation's institutional and macroeconomic conditions, to which we are trying to capture using the environmental variables. The latter depends on a bank's managerial capabilities and how well it deals with the undesirables. We draw the mean inefficiency scores for each sample country over the sample period.[13] Generally speaking, shocks, such as the Russian and the global financial crises respectively in 1998 and 2008 did stimulate technical inefficiency.[14] In addition, eight of our sample countries, i.e., Poland, Czech Republic, Hungary, Slovakia, Slovenia, Estonia, Latvia, and Lithuania, joined the European Union (EU) on May 1, 2004, followed by another two countries, i.e., Romania and Bulgaria, on January 1, 2007. Since the EU is highly integrated especially its financial market, banks' managerial abilities are very likely impacted. Finally, the technical inefficiency measure is found to be positively associated with the level of the undesirable due possibly to the fact that a bank must consume resources to disentangle its undesirables and/or from the imposition of weak disposability of outputs on the technology. The weak disposability simply says that if the economic bads of a firm are to be reduced, then the economic goods of the same firm must also be reduced, keeping the input mix constant. This consequently worsens the firm's producton efficiency. We shall come back to this point in Subsection 5.4.

Viewed from the angles of sample statistics, inefficiency scores, and the likelihood ratio testing result, we may conclude that banks of different countries adopt heterogenous technologies to offer financial products, as pointed out by Staikouras et al. (2008) and Mamatzakis et al. (2008). If this is the case, then the MDDF can play a pivotal role in the cross-country comparisons of technical efficiency, because it renders a common standpoint on which banks' performance in different nations can be correctly evaluated and compared.

5.3. Empirical results of the MDDF

Table 5 presents the parameter estimates of the MDDF, in which more than one half of the parameters are significantly estimated at least at the 10% level, based on uncorrected standard errors.[15] Only one of the three macro-environmental variables, i.e., HHI, is significantly estimated. Its negative coefficient estimate reflects that banks in more

[13] We do not show these diagrams to save space, but they are available upon request from the authors.

[14] The Russian financial crisis was, in fact, infected from the Asian financial crisis in 1997. The Russian Ruble at that time sharply depreciated. This adverse event also devalued the currencies of its neighboring countries and heavily injuried their banking systems and economic growth.

[15] There are merely 15 estimates attain statistical significance on the ground of corrected standard errors. This confirms that the composed error is indeed heteroskedastic, which causes the original standard errors to be underestimated and then the t-statistics tend to lie in the critical region.

Table 5
Parameter estimates of the MDDF.

Variables	Parameter Estimates	Variables	Parameter Estimates	Variables	Parameter Estimates	Variables	Parameter Estimates
Intercept	1.78E-01 (1.00E+00) [1.81E-1]	x_2^2	−1.94E-05 (6.05E-06)*** [1.73E-05]	y_3x_2	4.36E-05 (1.84E-05)** [6.05E-05]	ty_2	1.73E-02 (4.89E-04)*** [3.21E-03]***
y_1	−3.90E-01 (8.08E-03)*** [4.66E-01]	x_3^2	3.04E-05 (6.40E-06)*** [3.03E-04]	y_3x_3	−1.12E-05 (1.46E-06)*** [3.60E-06]***	ty_3	−6.04E-04 (2.25E-03) [6.54E-03]
y_2	−3.85E-01 (2.68E-03)*** [2.23E-02]***	b^2	3.16E-05 (1.03E-06)*** [6.51E-05]	x_2x_3	1.14E-05 (7.02E-06)* [5.16E-05]	tx_2	2.25E-02 (1.07E-03)*** [1.10E-02]**
y_3	−2.39E-02 (8.75E-04)*** [6.42E-02]	y_1y_2	−2.37E-05 (4.61E-06)*** [9.71E-06]**	y_1b	−2.18E-05 (9.86E-07)*** [4.27E-05]	tx_3	−6.39E-03 (8.04E-04)*** [1.41E-02]
x_2	−1.74E-01 (2.04E-02)*** [1.03E-01]*	y_1y_3	8.65E-06 (8.76E-07)*** [2.32E-06]***	y_2b	1.88E-05 (4.24E-06)*** [5.97E-06]***	tb	2.59E-02 (1.09E-03)*** [1.24E-02]**
x_3	9.64E-02 (2.97E-02)*** [3.99E-01]	y_2y_3	1.90E-05 (5.86E-07)*** [7.77E-06]**	y_3b	2.17E-06 (1.50E-05) [5.05E-05]	Intercept	−3.50E+02 (1.00E+00)*** [3.12E-02]***
b	2.47E-05 (3.53E-06)*** [3.29E-05]	y_1x_2	−4.61E-05 (1.18E-05)*** [3.22E-05]	x_2b	−4.85E-05 (1.02E-05)*** [3.56E-05]	RGDP	−2.16E-01 (9.98E-01) [7.75E-01]
y_1^2	−2.66E-05 (3.40E-06)*** [1.23E-05]**	y_1x_3	9.44E-06 (8.67E-06) [3.45E-05]	x_3b	1.39E-05 (9.73E-06)* [2.70E-05]	PD	1.72E-04 (2.03E-04) [2.18E-04]
y_2^2	2.00E-06 (7.03E-06) [1.68E-05]	y_2x_2	−3.58E-05 (1.01E-05)*** [2.54E-05]	t	6.43E-01 (9.04E-01) [2.62E+00]	HHI	−2.46E-02 (1.91E-03)*** [1.57E-02]
y_3^2	7.26E-07 (1.31E-06) [7.76E-06]	y_2x_3	2.08E-05 (1.07E-06)*** [2.65E-05]	t^2	−2.76E-02 (1.29E-03)*** [3.58E-03]***	σ^2	2.36E+03 (1.00E+00)*** [3.64E+02]***
likelihood	−0.3292E+05			ty_1	1.55E-02 (8.68E-04)*** [1.59E-02]	gamma	9.73E-01 (1.33E-02)*** [4.28E-02]***

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
Numbers in brackets are corrected standard errors suggested by White (1982).

concentrated markets are more technically efficient. Koutsomanoli-Filippaki et al. (2009) yield similar evidence. This result can be justified using the contestable theory, proposed by Baumol (1982). When those markets under consideration become more concentrated, incumbent banks behave competitively to discourage entry; otherwise higher prices and profits will induce potential competitors to enter and to share the market. A number of works investigating transition countries, such as Mamatzakis et al. (2008), Fries and Taci (2005), and Yildirim and Philippatos (2007) reach similar findings.

We next use the parameter estimates to compute the conditional mean of U^m in (10), which is exactly the TGD estimate. Table 6 presents the average TGD measures over time and various mean inefficiency measures for each sample country. Moreover, Fig. 2 draws the trend of these average TGD measures. The measure falls from 1996 to 1998 and then rises until 2003, or the year before some of the sample countries joined the EU. The measure goes down in the first two years after entering the EU, followed by three years of slight increases. Generally speaking, a representative bank's TGD measure in the CEE countries slightly worsens during the sample period, and enrollment in the EU prompts an increase in an average bank's technology somewhat.

The average TGD measure is equal to 5.32, which gauges the difference between the metafrontier and the group-specific frontier. An average bank is able to produce 5.32 million US dollars of more desirables and less undesirable, respectively, and to employ 5.32 million US dollars of fewer inputs, if it adopts the potential technology to provide financial products. Latvia has the lowest mean TGD (2.68), followed by Slovenia (2.79) and Moldova (3.00), while Czech Republic (17.77), Serbia (13.91), and Romania (10.47) are at the other end of the spectrum. It is noticeable that most of the countries have higher average TGDs than their average technical inefficiency measures, with the exception of Slovenia. This implies that the main source of inefficiency comes from the failure of our sample banks to undertake the potential technology, instead of managerial inabilities. Bank managers are suggested to adopt new innovations swiftly to enhance their production technology in such a way as to be able to produce on the metafrontier. By doing so, their outputs can be largely increased, accompanied by a decrease in both inputs and the undesirable output.

Fig. 3 depicts the scatter diagram for each country with the horizontal and vertical axes being the mean values of the group-specific technical inefficiency score and TGD, respectively. Countries located at the lower-left quadrant reflect that their banks outperform those of the

Table 6
Average TGD over time and various inefficiency estimates across countries.

年	Year	TGD	Country	TGD	Group-specific Ineff.	Overall Ineff.
1995	1995	4.87	BA	7.58	1.24	8.82
1996	1996	5.89	BG	5.65	1.53	7.18
1997	1997	4.75	CZ	17.77	2.9	20.67
1998	1998	3.21	EE	5.22	0.86	6.08
1999	1999	3.77	HR	5.12	1.98	7.10
2000	2000	4.44	HU	5.30	2.13	7.43
2001	2001	5.06	LT	6.76	1.09	7.85
2002	2002	4.56	LV	2.68	1.61	4.29
2003	2003	6.43	MD	3.00	2.58	5.58
2004	2004	5.45	MK	6.16	0.38	6.54
2005	2005	4.92	PL	8.44	4.11	12.55
2006	2006	5.29	RO	10.47	5.94	16.41
2007	2007	5.64	RS	13.91	2.68	16.59
2008	2008	6.09	RU	4.34	3.66	8.00
平均	Average	5.32	SI	2.79	3.82	6.61
			SK	5.70	1.79	7.49
			UA	5.90	2.03	7.93

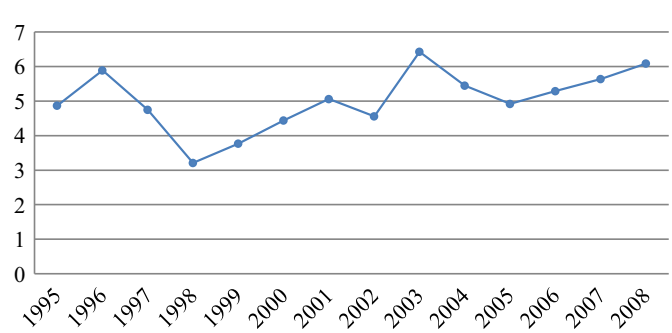

Fig. 2. The trend of average TGD measures.

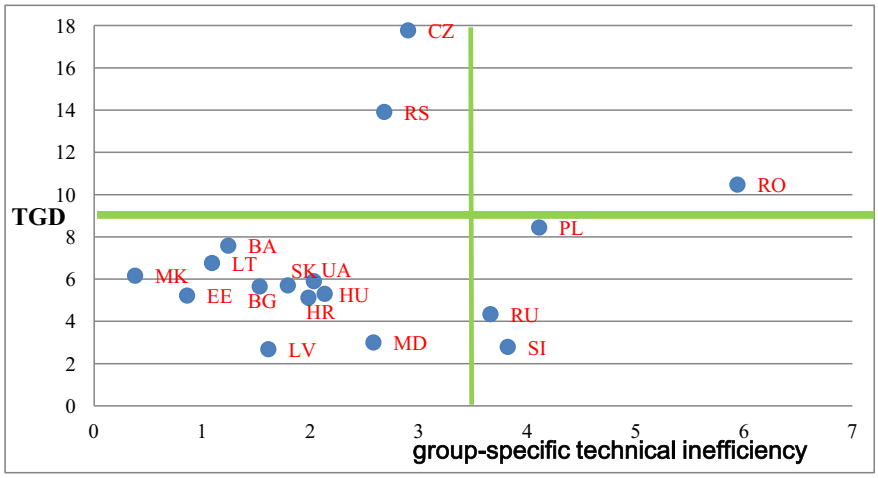

Fig. 3. Scatter diagram.

remaining countries in the other three quadrants on average, because the former have a smaller average inefficiency score and a narrower average technology gap. In this regard, banks in Latvia, Bosnia, Bulgaria, Estonia, Croatia, Hungary, Lithuania, Moldova, Macedonia, Slovakia, and Ukraine perform relatively well.

The average technical inefficiency of Romania's banks stands the highest, along with the third highest average TGD, indicating that their managerial abilities and production technology have large room for improvement. Banks in Poland, Russia, and Slovenia have worse technical efficiency measures, but adopt advanced production technology, while the reverse is true for banks in Czech Republic and Serbia. The two countries' banks have better managerial abilities, but undertake less sophisticated technology.

5.4. Effects on inefficiency measures from excluding undesirables

If undesirables are removed from the DDF, then the parameter estimates of such a simplified model are expected to be biased due to the incapability of the model in correctly describing the true production process. The subsequent estimated technical inefficiency measure is also biased as its calculation requires the use of the biased parameter estimates. In addition, the simplified model tends to find more banks producing at the metafrontier, since the omission of undesirables decreases capabilities of the model to distinguish performance among banks.

Table 7 shows the average inefficiency scores for each group, which are consistent with our expectation. The average technical inefficiencies that are derived from the model precluding undesirables are much less than those derived from the one incorporating undesirables in all sample countries. The simplified model also reveals that there are more banks producing on their group frontiers than the maintained model projects. Finally, as the standard likelihood ratio test statistics for the null hypothesis - that all of the coefficients of the terms involving undesirables are jointly zero - are not accepted, the simplified model is not recommended by the data.

6. Concluding remarks

The current paper has applied the MDDF to compute and compare production efficiencies of banks in 17 CEE countries, in which the banking industry of each country is assumed to have potential access to the same technology, but each bank chooses to operate on a different part of technology frontier. The directional distance function appears to be a better choice for estimating banking efficiency, since it allows for gauging a bank's efficiency from the orientations of inputs, outputs, and undesirables at the same time. As the undesirables are jointly produced with some desirables - various loans - and the disposal of the undesirables requires the use of resources and adversely affects the production of desirables, it is suggested that researchers include

Table 7
Comparisons between models with and without undesirables.

	With Undesirables			Without Undesirables			
	Mean Tech. Ineff.	Number of Banks Producing on the Group-frontier	Likelihood Value	Mean Tech. Ineff.	Number of Banks Producing on the Group-frontier	Likelihood Value	Likelihood Ratio Test
BA	1.24	7	−2.60E+02	0.88	79	−3.13E+02	*105.96*
BG	1.53	8	−2.96E+02	0.40	147	−4.07E+02	*223.29*
CZ	2.90	74	−6.38E+02	1.57	172	−7.45E+02	*215.07*
EE	0.86	4	−8.76E+01	0.32	51	−2.42E+02	*308.42*
HR	1.98	31	−8.31E+02	0.22	356	−1.30E+03	*948.61*
HU	2.13	23	−2.30E+02	0.09	86	−3.03E+02	*145.96*
LT	1.09	12	−2.20E+02	0.95	112	−2.57E+02	*73.57*
LV	1.61	15	−5.03E+02	1.23	90	−5.96E+02	*186.91*
MD	2.58	0	7.71E+00	0.92	0	−3.32E+01	*81.92*
MK	0.38	19	−4.86E+01	0	98	−1.00E+02	*103.42*
PL	4.11	41	−4.83E+02	0.30	119	−4.86E+02	*5.25*
RO	5.94	30	−1.34E+03	0.62	164	−1.44E+03	*199.01*
RS	2.68	72	−5.78E+02	2.55	136	−6.02E+02	*47.63*
RU	3.66	206	−1.60E+04	3.45	1770	−1.68E+04	*1575.23*
SI	3.82	7	−2.76E+02	2.05	65	−2.89E+02	*26.08*
SK	1.79	23	−2.14E+02	0.08	86	−2.31E+02	*33.30*
UA	2.03	34	−6.42E+02	0.30	217	−6.96E+02	*108.73*

the undesirables in their econometric models in order to appropriately characterize a bank's production process, as well as to correctly measure its technical efficiency. Moreover, the employment of the MDDF enables the technology gap to be evaluated for banks under different technologies relative to the potential technology available to the industry as a whole in the framework of the stochastic frontier approach, as opposed to the programming technique proposed by Battese et al. (2004). One of the advantages of our MDDF is that the technology gap can be further related to a group of environmental variables, which is infeasible in the context of programming techniques.

Evidence is found to verify that the banking industries of the 17 CEE countries do indeed adopt different technologies. This justifies the validity of the MDDF in the comparison of technical efficiencies among groups. Some of the environmental variables are found to have significant impacts on the group frontiers and the metafrontier, confirming the usefulness of the stochastic metafrontier model.

Our empirical study shows that the average TGDs substantially vary across countries and exceed average technical inefficiency scores in most countries, while those mean TGDs present no clear trend during the sample period. Bank managers should promote their production technology by quickly responding to financial innovations in such a way as to shift their group frontiers closer to the metafrontier. As the average technical inefficiency score is relatively small to the average TGD of the same country, managerial inability appears to be less of an issue.

The production of undesirables is almost inevitable in many industries, such as manufacturing and banking sectors, and it requires the disposing of consuming resources. The exclusion of undesirables from the model is apt to mislead the subsequent results. Therefore, using the directional distance function by the current paper is more preferable. This is confirmed in Subsection 5.4, where the model ignoring the undesirables tends to underestimate the technical inefficiency scores.

For future research studies, our MDDF can be extended to measure and compare productivity change for banks in different countries under the framework of the Luenberger productivity indicator. Since these indicators of different groups are evaluated relative to the same metafrontier, they are comparable and able to provide insightful information, or more specifically, whether productivity change is driven by technical efficiency change or technological change has different implications to managers, business consultants, and regulatory authorities.

Appendix 1. Variable definitions

Variable Name	Definition
Total loans (y_1)	Short-term and long-term loans
Other earning assets (y_2)	Other earning assets, including government bonds, corporate securities, and other investments
Non-interest revenue (y_3)	Fee and commission income and other income
Labor (x_1)	Proxied by total assets net of fixed assets
Capital (x_2)	Total fixed assets
Borrowed funds (x_3)	Deposits, other borrowed money, and money market fund
Undesirable (b)	Non-performing Loans
Environmental variables	
Equity to asset ratio (ETA)	The ratio of equity capital to total assets of a bank
Average return on assets per year (ROA, %)	Average ROA across all banks of a country per annum
Ownership	State = 1 for state-owned banks and 0 otherwise; private = 1 for private banks and 0 otherwise; foreign banks are the normalization.
Unlisted	1 if the bank has not been listed on the stock market and 0 otherwise
Real GDP per capita (RGDP)	Thousands of the US dollars with the base year 2000
Population Density (PD)	Number of persons per square kilometer
HHI	The Herfindall-Hirschman index

References

Allen, L., Rai, A., 1996. Operational efficiency in banking: an international comparison. J. Bank. Financ. 20, 655–672.

Altunbas, Y., Gardener, E.P.M., Molyneux, P., Moore, B., 2001. Efficiency in European Banking. Eur. Econ. Rev. 45, 1931–1955.

Battese, G.E., Coelli, T.J., 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empir. Econ. 20, 325–332.

Battese, G.E., Rao, D.S.P., O'Donnell, C.J., 2004. A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. J. Prod. Anal. 21, 91–103.

Baumol, W.J., 1982. Contestable Markets: An Uprising in the Theory of Industry Structure. Am. Econ. Rev. 72, 1–15.

Berger, A.N., Mester, L.J., 1997. Inside the black box: what explains the differences in the efficiencies of financial institutions? Journal of Banking and Finance 21, 895–947.

Berger, A.N., Hancock, G.A., Humphrey, D.B., 1993. Bank efficiency derived from the profit function. J. Bank. Financ. 17, 317–347.

Bolt, W., Humphrey, D., 2010. Bank competition efficiency in Europe: A frontier approach. J. Bank. Financ. 34, 1808–1817.

Bonin, J., Hassan, I., Wachtel, P., 2005. Bank performance, efficiency and ownership in transition countries. J. Bank. Financ. 29, 31–53.

Bos, J.W.B., Schmiedel, H., 2007. Is there a single frontier in a single European banking market? J. Bank. Financ. 31, 2081–2102.

Chung, Y.H., Färe, R., Grosskopf, S., 1997. Productivity and undesirable outputs: A directional distance function approach. J. Environ. Manag. 51, 229–240.

Cohen, W.M., Levinthal, D.A., 1989. Innovation and learning: The two faces of R&D. Econ. J. 99, 569–596.

Färe, R., Grosskopf, S., 2005. New directions: efficiency and productivity. Kluwer Academic Publishers, Boston, U.S.A.

Färe, R., Grosskopf, S., Lovell, C.A.K., Yaisawarng, S., 1993. Derivation of shadow prices for undesirable outputs: A distance function approach. Rev. Econ. Stat. 75 (2), 374–380.

Färe, R., Grosskopf, S., Lovell, C.A.K., Pasurka, C., 1989. Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. Review of Economics and Statistics 71, 90–98.

Färe, R., Grosskopf, S., Weber, W., 1997. The effect of risk-based capital requirements on profit efficiency in banking. Discussion paper series No. 97–12. Department of Economics, Southern Illinois University at Carbondale.

Färe, R., Grosskopf, S., Pasurka Jr., Carl A., 2001. Accounting for air pollution emissions in measures of state manufacturing productivity growth. J. Reg. Sci. 41 (3), 381–409.

Färe, R., Grosskopf, S., Noh, D., Weber, W., 2005. Characteristics of a polluting technology. J. Econ. 126, 469–492.

Fries, S., Taci, A., 2005. Cost efficiency of banks in transition: Evidence from 289 banks in 15 post-communist countries. J. Bank. Financ. 29, 55–81.

Fukuyama, H., Weber, W.L., 2008. Japanese banking inefficiency and shadow pricing. Math. Comput. Model. 48, 1854–1867.

Hayami, Y., 1969. Sources of agricultural productivity gap among selected countries. Am. J. Agric. Econ. 51, 564–575.

Hayami, Y., Ruttan, V.W., 1970. Agricultural productivity differences among countries. Am. Econ. Rev. 60, 895–911.

Hayami, Y., Ruttan, V.W., 1971. Agricultural Development: An International Perspective. Johns Hopkins University Press, Baltimore.

Huang, C.J., Huang, T.H., Liu, N.H., 2014. A New Approach to Estimating the Metafrontier Production Function Based on a Stochastic Frontier Framework. Journal of Productivity Analysis 42, 241–254.

Huang, T.H., Chiang, L.C., Chen, K.C., 2011a. An Empirical Study of Bank Efficiencies and Technology Gaps in European Banking. Manch. Sch. 79, 839–860.

Huang, T.H., Shen, C.H., Chen, K.C., Tseng, S.J., 2011b. Measuring Technical and Allocative Efficiencies for Banks in the Transition Countries Using the Fourier Flexible Cost Function. J. Prod. Anal. 35, 143–157.

Huang, T.H., 2000. Estimating X-efficiency in Taiwanese banking using a translog shadow profit function. Journal of Productivity Analysis 14, 225–245.

Hughes, J., Mester, L.J., 1993. A quality and risk-adjusted cst function for banks: evidence on the too-big-to fail doctrine. Journal of Productivity Analysis 4, 293–315.

Isik, I., Hassan, M., 2003. Efficiency, ownership and market structure, corporate control and governance in the Turkish banking industry. J. Bus. Finan. Acc. 30, 1363–1421.

Johnston, J., DiNardo, J., 1992. Econometric Methods, fourth edition. McGraw-Hill companies, Inc., New York.

Kaneko, S., Managi, S., 2007. Environmental productivity in China. Econ. Bull. 17, 1–10.

Kontolaimou, A., Tsekouras, K., 2010. Are cooperatives the weakest link in European banking? A non-parametric metafrontier approach. J. Bank. Financ. 34, 1046–1057.

Koutsomanoli-Filippaki, A., Margaritis, D., Staikouras, C., 2009. Efficiency and productivity growth in the banking industry of Central and Eastern Europe. J. Bank. Financ. 33, 557–567.

Lozano-Vivas, A., Pastor, J.T., Pastor, J.M., 2002. An efficiency comparison of European banking systems operating under different environmental conditions. J. Prod. Anal. 18, 59–77.

Mamatzakis, E., Staikouras, C., Koutsomanoli-Filippaki, A., 2008. Bank efficiency in the new European Union member states: Is there convergence? Int. Rev. Financ. Anal. 17, 1156–1172.

McMullen, B.S., Noh, D.W., 2007. Accounting for emissions in the measurement of transit agency efficiency: A directional distance function approach. Transp. Res. D 12, 1–9.

Mester, L.J., 1996. A study of bank efficiency taking into account risk-preferences. Journal of Banking and Finance 20, 1025–1045.

Mester, L.J., 1993. Efficiency in the savings and loan industry. J. Bank. Financ. 17, 267–286.
O'Donnell, C.J., Rao, D.S.P., Battese, G.E., 2008. Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. Empir. Econ. 34, 231–255.
Park, K.H., Weber, W.L., 2006. A note on efficiency and productivity growth in the Korean Banking Industry, 1992–2002. J. Bank. Financ. 30, 2371–2386.
Picazo-Tadeo, A.J., Reig-Martínez, E., Hernández-Sancho, F., 2005. Directional distance functions and environmental regulation. Resour. Energy Econ. 27, 131–142.
Staikouras, C., Mamatzakis, E., Koutsomanoli-Filippaki, A., 2008. Cost efficiency of the banking industry in the South Eastern European region. J. Int. Financ. Mark. Inst. Money 18, 483–497.
Tsang, S.S., Chen, Y.F., Lu, Y.H., Chiu, C. Ren, 2014. Assessing productivity in the presence of negative data and undesirable outputs. The Service Industries Journal 34, 162–174.
Watanabe, M., Tanaka, K., 2004. Efficiency analysis of Chinese industry: A directional distance function approach. Energy Policy 35, 6323–6331.
Weill, L., 2004. Measuring cost efficiency in European banking: A comparison of frontier techniques. J. Prod. Anal. 21, 133–152.
White, H., 1982. Maximum likelihood estimation of misspecified models. Econometrica 50, 1–16.
Yang, C.C., 2012. Service, investment, and risk management performance in commercial banks. Serv. Ind. J. 32, 2005–2025.
Yildirim, S., Philippatos, G., 2007. Efficiency of banks: Recent evidence from the transition economies of Europe, 1993–2000. Eur. J. Financ. 13, 123–143.
Yu, M.M., 2004. Measuring physical efficiency of domestic airports in Taiwan with undesirable outputs and environmental factors. J. Air Transp. Manag. 10, 295–303.