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Productivity changes in pre-crisis Western European banks: Does scale effect really matter?

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ABSTRACT

Insofar as the completion of the Single Market for Financial Services, it has presented new challenges for European Banking industries. In this study, we use a recently developed generalized metafrontier Malmquist productivity index (gMMPI) to provide insights on productivity growth. We extend the gMMPI to broaden the index's capacity by decomposing various sources of productivity change in the metafrontier context. The sample contains commercial banks from 12 Western European countries prior to the recent financial crisis. A key advantage of our extension is that it introduces the role of scale effects. The empirical results show that an average bank's productivity growth arises mainly from technical changes and scale effects. Moreover, smaller and larger banks grow faster than medium ones. In addition, conservative banks tend to grow faster. These findings suggest that a more competitive and integrated financial market induced by financial deregulation is indeed able to improve banks' productivity.

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1. Introduction

Western European banking industries have experienced fundamental changes in their regulatory and competitive environments ever since the completion of the Single Market for Financial Services

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in 1993. This regulation largely reduces or eliminates trade and entry barriers to the financial markets in the European Union (EU). Goldberg and Johnson (1990) find a positive relation between economic integration and the entry of foreign banks into developed countries. Subsequently, EU banks are facing an increasingly competitive environment not only from domestic markets, but also from abroad. Bank managers must adopt the best technologies and attempt to diversify their financial products in order to earn profits. Under this trend of international economic integration, the efficiencies and productivity changes of EU banks play pivotal roles in the keen race for survival. These ideas are the initial motivation for this study, where we investigate the productivity growth in Western European banking industries.

Many previous studies have carried out international comparisons between banks. These studies estimate a common frontier for banks of different countries by pooling all observations together. This approach implicitly assumes that banks from different countries have access to the same technology. This assumption appears to be strong, as each country has its own cultural traditions, resource endowments, and political and legal systems. These characteristics affect the behavior and willingness of banks to undertake new innovations. Different regulatory environments, for example, lead to either universal banking countries or separated banking countries. Universal banking countries permit commercial banks to engage in nontraditional activities such as investment, trading, real estate, and insurance, while separated banking countries do not. Barth, Caprio, and Levine (2004) describe some of the background information on regulatory and supervisory differences.

An alternative approach to these studies is to obtain individual production frontiers for each country to measure the country-specific technical efficiency scores. This method avoids making the assumption that all of the countries under consideration share the same technology. However, the efficiency scores are not comparable due to the fact that they are evaluated against different country-specific frontiers, rather than a common frontier. This dilemma motivated Battese, Rao, and O'Donnell (2004) and O'Donnell, Rao, and Battese (2008) to propose a metafrontier production function estimated in two steps that makes a comparison of the technical efficiency of banks in different countries possible.

As far as the specific context of the banking industry productivity are concerned, the Malmquist productivity index is the most commonly used measure of productivity change (Chortareas, Garza-García, & Girardone, 2011). Since the conventional Malmquist productivity index (MPI) is defined in the context of a single group production frontier, it is necessary to extend the MPI to the framework of a metafrontier production function. To this end, Rao (2006) defines a metafrontier and discusses how to derive the metafrontier Malmquist productivity index (MMPI). Rao implicitly assumes a constant return to scale (CRS) technology that excludes the existence of the scale effect. The MMPI can be used to compare the changes in technical efficiency, technology, and metatechnology ratio (TGR) among various countries. Although Rao's MMPI measure is innovative, it requires more elaboration to gain further insights into its sources and to get rid of the presumption of the CRS.

Recently, Chen and Yang (2011) have introduced the effect of scale efficiency change into the MMPI formula and the resulting index is called the generalized MMPI (gMMPI). Following this vein, our study uses three steps to decompose productivity change into a variety of sources under the framework of the metafrontier in an attempt to render more information. First, following Orea's (2002) development of a parametric approach that decomposes a generalized MPI while accounting for scale economies, we establish a measure of gMMPI in the context of a metadistance function. Second, Rao (2006) provides a catch-up item that is split into two terms: catch-up in technology (CUT) and potential technological change (PTC). These two terms give a better description of the relative adjustment speed of the technology undertaken by a country to that of the potential metafrontier. Third, recent empirical works, such as Chaffai, Dietsch, and Lozano-Vivas (2001), Cavallo and Rossi (2002), and Chronopoulos, Girardone, and Nankervis (2011), recommend that controlling for environmental variables is crucial for assessing efficiency scores and productivity changes. We use an output-oriented country-specific distance function that allows for multiple inputs and multiple outputs to estimate the technical efficiency of each bank. Our function comprises environmental variables like the function proposed by Battese and Coelli (1995). In this manner, the variance of the one-sided error term, representing the technical inefficiency of a bank, is heteroscedastic as pointed out by Kumbhakar and Lovell (2000). By doing so, we can examine the importance of various elements underlying the gMMPI and legitimately compare the productivity changes among different countries. This new approach gives insight into the

composition of the gMMPI and provides more information about the sources of productivity changes for the countries of interest.

Therefore, the main purpose of this paper is to illustrate a procedure that assesses the dynamics of total factor productivity. Further, the procedure takes the effect of scale economies into account with the variable return to scale (VRS) technology and in the context of a metafrontier to re-examine productivity change and its components. In this process, we provide new estimates of productivity change in Western European banks after the creation of a single market in 1993 by using this parametric technique. In particular, the gMMPI is capable of detecting the effect of the change in scale efficiency that contributes to the productivity growth during this sample period.

Our sample set does not cover the period of the financial crisis starting from the late of 2007, since banks experience marked structural changes in, e.g., prices of marketed funding and some quantitative constraints, leading to sample heterogeneity. In addition, these constraints may limit banks' capability of optimizing behaviors (Boucinha, Ribeiro, & Weyman-Jones, 2013). By limiting the sample period to the years prior to the recent financial crisis, this study attempts to quantify the ex ante productive justification for the completion of the Single Market for Financial Services. Therefore, the attempt to account for recent financial crisis would require a different research methodology and a tailored dataset that is not feasible in this study.

The rest of the paper is organized as follows. Section 2 gives an overview of the literature on productivity changes and reviews several empirical studies specific to banks' productivity changes in Western European countries. Section 3 shows how to formulate and decompose the new measure of gMMPI in the context of the metafrontier function. Section 4 illustrates the econometric specifications and outlines the data and variables. Section 5 performs an empirical application by using the panel data of commercial banks from 12 Western European countries, while Section 6 concludes the paper.

2. Productivity changes in Western European banking

The structure of European banking markets has experienced rapid changes during and after the 1990s, making it particularly suitable for not only comparing efficiency changes among European banks, but also for understanding the determinants of productivity change. Different frontier approaches based on either parametric or nonparametric techniques have been carried out in order to evaluate banks' technical efficiencies and productivity changes in the Western Europe and other areas. Berger and Humphrey (1997), Goddard, Molyneux, and Wilson (2001), and Berger and Mester (2003) offer excellent reviews on this matter.

Many earlier works have already performed cross-country comparisons for the technical efficiency of the commercial banks in European countries, for example, Allen and Rai (1996), Dietsch and Lozano-Vivas (2000), Altunbaş, Gardener, Molyneux, and Moore (2001), and Weill (2004). Differing from these, Bos and Schmiedel (2007) and Huang, Chiang, and Chen (2011a) estimate comparable efficiency measures for European banks under the framework of the translog and the Fourier flexible metacost functions, respectively. Although the issue of technical efficiency is pivotal, it is in essence static. That is, technical efficiency provides no information on whether efficiency is time-invariant during a sample period. Conversely, a productivity measurement is dynamic and provides additional information on whether efficiency and technology have experienced considerable changes during a sample period.

The MPI has been widely applied to conduct cross-country comparisons as pioneered by Berg, Førsund, and Jansen (1992). The existing works have recourse to estimate either a common frontier or individual production frontiers against which the efficiency measures can be computed and used for calculating the MPI. Berg, Førsund, Hjalmarsson, and Suominen (1993) and Murillo-Melchor, Pastor, and Tortosa-Ausina (2010) adopt nonparametric techniques to estimate a common distance function and assess the productivity changes of banking industries across European countries. Berg et al. use data envelopment analysis (DEA) to explore the differences in banking efficiency and productivity between Norway, Sweden and Finland. Their evidence shows that the banks in Sweden tend to be the most efficient and have the highest productivity, followed by the banks in Norway and Finland. Most of the difference in productivity can be attributed to the efficiency component. Murillo-Melchor et al. analyze the differences in banks' productivity growth across 14 major European countries for the

post-deregulation period, namely 1995 to 2001. Their empirical results show that productivity growth, which involves technical progress and efficiency losses, exists for the post-deregulation period.

Another strand of contemporary literature compares the productivity changes of banks across European nations by estimating individual production frontiers for each nation. Chaffai et al. (2001) nonetheless use the stochastic frontier approach to estimate and compare the productivity differences between banks in France, Germany, Italy, and Spain from 1993 to 1997, where the productivity difference is divided into purely technological and environmental effects. Their results show that environmental conditions are relevant in explaining the productivity gaps between the banks in these countries. Casu, Girardone, and Molyneux (2004) adopts both nonparametric and parametric techniques to conduct cross-country comparisons of the productivity changes in banks from France, Germany, Italy, Spain, and the United Kingdom with data covering 1994 to 2000. Their evidence shows that technical progress was the primary source that drove productivity growth during the sample period, rather than change in the technical efficiency. Casu and Girardone (2005) also reach similar results based on a nonparametric analysis.

All of the aforementioned papers, involving cross-country comparisons of productivity change, count on either estimating a common frontier or individual production frontiers. The common frontier approach requires the imposition of homogeneous technology adopted by banks from different countries, while the individual frontiers approach suffers from the problem of incomparability due to heterogeneous technologies undertaken by banks from different countries. Cross-country comparisons of productivity change within the frame of a metafrontier are able to overcome the above difficulties, but this approach seems to have not drawn much attention from empirical researchers, which is a motivation for this study.

3. Methodology

3.1. Decomposition of the MMPI

In the context of the metafrontier, the MPI can be illustrated with the framework of an output distance function and so can the MMPI. According to Färe, Grosskopf, Norris, and Zhang (1994), the traditional MPI with respect to country k between t and $t+1$ is written as:

$$\begin{aligned}\mathrm{MPI}^k_{t,t+1}(x_t, y_t, x_{t+1}, y_{t+1}) &= \left[\frac{D^k_t(x_{t+1}, y_{t+1})}{D^k_t(x_t, y_t)} \times \frac{D^k_{t+1}(x_{t+1}, y_{t+1})}{D^k_{t+1}(x_t, y_t)}\right]^{1/2} \\ &= \frac{D^k_{t+1}(x_{t+1}, y_{t+1})}{D^k_t(x_t, y_t)}\left[\frac{D^k_t(x_t, y_t)}{D^k_{t+1}(x_t, y_t)} \times \frac{D^k_t(x_{t+1}, y_{t+1})}{D^k_{t+1}(x_{t+1}, y_{t+1})}\right]^{1/2} \\ &= \mathrm{TEC}^k_{t,t+1} \times \mathrm{TC}^k_{t,t+1}.\end{aligned} \tag{1}$$

Therefore, the MPI is composed of the technical efficiency change, $\mathrm{TEC}^k_{t,t+1}$, and the technical change, $\mathrm{TC}^k_{t,t+1}$. Following this vein, the MMPI between t and $t+1$ can be similarly formulated as:

$$\begin{aligned}\mathrm{MMPI}_{t,t+1}(x_t, y_t, x_{t+1}, y_{t+1}) &= \left[\frac{D^*_t(x_{t+1}, y_{t+1})}{D^*_t(x_t, y_t)} \times \frac{D^*_{t+1}(x_{t+1}, y_{t+1})}{D^*_{t+1}(x_t, y_t)}\right]^{1/2} \\ &= \frac{D^*_{t+1}(x_{t+1}, y_{t+1})}{D^*_t(x_t, y_t)}\left[\frac{D^*_t(x_t, y_t)}{D^*_{t+1}(x_t, y_t)} \times \frac{D^*_t(x_{t+1}, y_{t+1})}{D^*_{t+1}(x_{t+1}, y_{t+1})}\right]^{1/2} \\ &= \mathrm{TEC}^*_{t,t+1} \times \mathrm{TC}^*_{t,t+1}.\end{aligned} \tag{2}$$

The first component can be interpreted as the rate at which a firm's observed output moves to or from the metafrontier, which itself might be shifting across time, and the second component measures

the rate of technical change that shifts the metafrontier up or down between the two periods. Rao (2006) derives a link between MMPI and MPI. From Eq. (2), the MMPI can be re-expressed as:

$$\begin{aligned}
\mathrm{MMPI}_{t,t+1} &= \frac{D^k_{t+1}(x_{t+1},y_{t+1})\left(D^*_{t+1}(x_{t+1},y_{t+1})/D^k_{t+1}(x_{t+1},y_{t+1})\right)}{D^k_t(x_t,y_t)\left(D^*_t(x_t,y_t)/D^k_t(x_t,y_t)\right)} \\
&\quad\times\left[\frac{D^k_t(x_t,y_t)\left(D^*_t(x_t,y_t)/D^k_t(x_t,y_t)\right)}{D^k_{t+1}(x_t,y_t)\left(D^*_{t+1}(x_t,y_t)/D^k_{t+1}(x_t,y_t)\right)}\times\frac{D^k_t(x_{t+1},y_{t+1})\left(D^*_t(x_{t+1},y_{t+1})/D^k_t(x_{t+1},y_{t+1})\right)}{D^k_{t+1}(x_{t+1},y_{t+1})\left(D^*_{t+1}(x_{t+1},y_{t+1})/D^k_{t+1}(x_{t+1},y_{t+1})\right)}\right]^{1/2} \\
&= \mathrm{TEC}^k_{t,t+1}\times\mathrm{TC}^k_{t,t+1}\times\left[\frac{\left(D^*_t(x_{t+1},y_{t+1})/D^k_t(x_{t+1},y_{t+1})\right)}{\left(D^*_t(x_t,y_t)/D^k_t(x_t,y_t)\right)}\times\frac{\left(D^*_{t+1}(x_{t+1},y_{t+1})/D^k_{t+1}(x_{t+1},y_{t+1})\right)}{\left(D^*_{t+1}(x_t,y_t)/D^k_{t+1}(x_t,y_t)\right)}\right]^{1/2} \\
&= \mathrm{TEC}^k_{t,t+1}\times\mathrm{TC}^k_{t,t+1}\times\mathrm{TGRC}^k_{t,t+1} \\
&= \mathrm{MPI}^k_{t,t+1}\times\mathrm{TGRC}^k_{t,t+1}.
\end{aligned} \tag{3}$$

The term TGRC can be equivalently written as:

$$\mathrm{TGRC}^k_{t,t+1} = \left[\frac{\mathrm{TGR}^k_t(x_{t+1},y_{t+1})}{\mathrm{TGR}^k_t(x_t,y_t)}\times\frac{\mathrm{TGR}^k_{t+1}(x_{t+1},y_{t+1})}{\mathrm{TGR}^k_{t+1}(x_t,y_t)}\right]^{1/2} \tag{4}$$

that is the geometric mean of the index of the metatechnology ratio between the two periods. Rao (2006) refers to the inverse of $\mathrm{TGRC}^k_{t,t+1}$ as the catch-up effect. A value of $\mathrm{TGRC}^k_{t,t+1}$ greater than unity indicates that country k's frontier catches up with the metafrontier over time, while a value below unity indicates that country k's frontier deviates away from the metafrontier. Of important note is that this term can be split into two terms, that is, the catch-up in technology (CUT) and the potential technological change (PTC):

$$\begin{aligned}
\mathrm{TGRC}^k_{t,t+1} &= \frac{\mathrm{TGR}^k_{t+1}(x_{t+1},y_{t+1})}{\mathrm{TGR}^k_t(x_t,y_t)}\left[\frac{\mathrm{TGR}^k_t(x_t,y_t)}{\mathrm{TGR}^k_{t+1}(x_t,y_t)}\times\frac{\mathrm{TGR}^k_t(x_{t+1},y_{t+1})}{\mathrm{TGR}^k_{t+1}(x_{t+1},y_{t+1})}\right]^{1/2} \\
&= \frac{\mathrm{TGR}^k_{t+1}(x_{t+1},y_{t+1})}{\mathrm{TGR}^k_t(x_t,y_t)}\left[\frac{\left(D^*_t(x_t,y_t)/D^k_t(x_t,y_t)\right)}{\left(D^*_{t+1}(x_t,y_t)/D^k_{t+1}(x_t,y_t)\right)}\times\frac{\left(D^*_t(x_{t+1},y_{t+1})/D^k_t(x_{t+1},y_{t+1})\right)}{\left(D^*_{t+1}(x_{t+1},y_{t+1})/D^k_{t+1}(x_{t+1},y_{t+1})\right)}\right]^{1/2} \\
&= \frac{\mathrm{TGR}^k_{t+1}(x_{t+1},y_{t+1})}{\mathrm{TGR}^k_t(x_t,y_t)}\times\frac{\mathrm{TC}^*_{t,t+1}}{\mathrm{TC}^k_{t,t+1}} \\
&= \frac{\mathrm{TGR}^k_{t+1}(x_{t+1},y_{t+1})}{\mathrm{TGR}^k_t(x_t,y_t)}\times\left[\frac{\mathrm{TC}^k_{t,t+1}}{\mathrm{TC}^*_{t,t+1}}\right]^{-1} \\
&= \mathrm{CUT}^k_{t,t+1}\times\mathrm{PTC}^k_{t,t+1}.
\end{aligned} \tag{5}$$

The first term on the right-hand side gauges the relative change of the metatechnology to country k's frontier between t and $t+1$. The gap between the metafrontier and country k's frontier shrinks over time, if CUT exceeds unity, while the reverse is true if CUT falls short of unity. Put differently, the first term explains the change in the relative technical efficiency of the metafrontier to that of the country frontier between periods t and $t+1$. A value of CUT greater than one discloses that the country frontier catches up with the potential frontier. The second term on the right-hand side is the ratio of the technical change of the metafrontier to that of country k's frontier. If the value of $\mathrm{PTC}^k_{t,t+1}$ is greater than unity, then the metatechnology improves at a faster rate than country k's frontier, which leads to a positive contribution to the MMPI. Thus, the MMPI can be expressed as:

$$\mathrm{MMPI}_{t,t+1} = \mathrm{TEC}^k_{t,t+1}\times\mathrm{TC}^k_{t,t+1}\times\mathrm{CUT}^k_{t,t+1}\times\mathrm{PTC}^k_{t,t+1}. \tag{6}$$

3.2. The generalized MMPI

The above decomposition of the MMPI is based on CRS technology that ignores entirely the possibility of scale effects. However, if the production technology exhibits non-constant returns to scale, this

index might not provide an appropriate measure of the productivity change due to overlooking the potential impact of the scale efficiency change (SEC). To overcome this difficulty, Orea (2002) develops a novel parametric approach that is able to add scale efficiency change into the conventional MPI. We generalize that Orea's approach is suitable for the metafrontier. If the technology can be described by the transcendental logarithmic (translog) output-oriented distance function, then the (log) index of the total factor productivity (TFP) change is formulated as:

$$\begin{aligned}\ln \mathrm{MMPI}_{t,t+1} &= \frac{1}{2}\sum_{m=1}^{M}\left[\frac{\partial \ln D^*_{t+1}(y_{t+1},x_{t+1},t+1)}{\partial \ln y^m_{t+1}} + \frac{\partial \ln D^*_t(y_t,x_t,t)}{\partial \ln y^m_t}\right]\times \ln\left(\frac{y^m_{t+1}}{y^m_t}\right)\\ &\quad -\frac{1}{2}\sum_{n=1}^{N}\left[\frac{-\partial \ln D^*_{t+1}(y_{t+1},x_{t+1},t+1)}{\partial \ln x^n_{t+1}} + \frac{-\partial \ln D^*_t(y_t,x_t,t)}{\partial \ln x^n_t}\right]\times \ln\left(\frac{x^n_{t+1}}{x^n_t}\right)\\ &= \frac{1}{2}\sum_{m=1}^{M}\left[\varepsilon^{*m}_{t+1}+\varepsilon^{*m}_t\right]\times \ln\left(\frac{y^m_{t+1}}{y^m_t}\right) - \frac{1}{2}\sum_{n=1}^{N}\left[-\varepsilon^{*n}_{t+1}-\varepsilon^{*n}_t\right]\times \ln\left(\frac{x^n_{t+1}}{x^n_t}\right)\end{aligned} \tag{7}$$

where $\varepsilon^{*m}_t = \partial \ln D^*_t(y_t,x_t,t)/\partial \ln y^m$ and $\varepsilon^{*n}_t = \partial \ln D^*_t(y_t,x_t,t)/\partial \ln x^n$ are output and input distance elasticities, respectively. Because the translog output distance function belongs to a quadratic function in $\ln x^n_t$, $\ln y^m_t$, and t, Diewert's (1976) quadratic identity lemma is applicable for:

$$\begin{aligned}\ln D^*_{t+1}(y_{t+1},x_{t+1},t+1) - \ln D^*_t(y_t,x_t,t) &= \frac{1}{2}\sum_{m=1}^{M}\left[\frac{\partial \ln D^*_{t+1}(y_{t+1},x_{t+1},t+1)}{\partial \ln y^m_{t+1}} + \frac{\partial \ln D^*_t(y_t,x_t,t)}{\partial \ln y^m_t}\right]\times \ln\left(\frac{y^m_{t+1}}{y^m_t}\right)\\ &+\frac{1}{2}\sum_{n=1}^{N}\left[\frac{\partial \ln D^*_{t+1}(y_{t+1},x_{t+1},t+1)}{\partial \ln x^n_{t+1}} + \frac{\partial \ln D^*_t(y_t,x_t,t)}{\partial \ln x^n_t}\right]\times \ln\left(\frac{x^n_{t+1}}{x^n_t}\right)\\ &+\frac{1}{2}\left[\frac{\partial \ln D^*_{t+1}(y_{t+1},x_{t+1},t+1)}{\partial t} + \frac{\partial \ln D^*_t(y_t,x_t,t)}{\partial t}\right].\end{aligned} \tag{8}$$

Substituting Eq. (8) into Eq. (6), we obtain:

$$\begin{aligned}\ln \mathrm{MMPI}_{t,t+1} &= \left[\ln D^*_{t+1}(y_{t+1},x_{t+1},t+1) - \ln D^*_t(y_t,x_t,t)\right]\\ &-\frac{1}{2}\left[\frac{\partial \ln D^*_{t+1}(y_{t+1},x_{t+1},t+1)}{\partial t} + \frac{\partial \ln D^*_t(y_t,x_t,t)}{\partial t}\right].\end{aligned} \tag{9}$$

The first term on the right-hand side measures exactly the change in the output-oriented measure of the Farrell technical efficiency between t and $t+1$, $\mathrm{TEC}^*_{t,t+1}$, and the second term is a measure of technical change, $\mathrm{TC}^*_{t,t+1}$.

A TFP index should usually have four desirable properties: identity, monotonicity, separability, and proportionality. Although the ln MMPI in Eq. (9) satisfies the first three properties, the proportionality property that requires a homogeneous condition of +1 in outputs and −1 in inputs might not be fulfilled because the input weights do not necessarily sum up to unity (see, e.g., Balk, 2001; Orea, 2002). This lack of unity means that, unless in the case of the CRS technology, this index is invalid as a measure of productivity change. Drawing on ideas recommended by Denny, Fuss, and Waverman (1981), Orea (2002) aggregates the growth in inputs by using distance elasticity shares in place of distance elasticities as weights, which warrants the proportionality property.

A (log) generalized output-oriented MMPI, ln gMMPI, can be defined as:

$$\begin{aligned}\ln gMMPI_{t,t+1} &= \frac{1}{2}\sum_{m=1}^{M}\left[\varepsilon^{*m}_{t+1}+\varepsilon^{*m}_t\right]\times \ln\left(\frac{y^m_{t+1}}{y^m_t}\right)\\ &\quad -\frac{1}{2}\sum_{n=1}^{N}\left[\frac{-\varepsilon^{*n}_{t+1}}{\sum_{n=1}^{N}-\varepsilon^{*n}_{t+1}} + \frac{-\varepsilon^{*n}_t}{\sum_{n=1}^{N}-\varepsilon^{*n}_{t+1}}\right]\times \ln\left(\frac{x^n_{t+1}}{x^n_t}\right)\end{aligned} \tag{10}$$

where $-\sum_{n=1}^{N}\varepsilon_t^{*n}$ provides a measure of returns to scale that characterizes the output distance function in which a value of the function is greater than (less than or equal to) unity according to increasing (decreasing or constant) returns to scale. The ln gMMPI gauges the growth in outputs net of the growth in inputs and is now a valid TFP index, because it has the four desirable properties. Using Eqs. (8) and (10) are composed of ln MMPI and the contribution of the scale effects, that is:

$$\begin{aligned}\ln \mathrm{gMMPI}_{t,t+1} &= \left[\ln D_{t+1}^{*}(y_{t+1},x_{t+1},t+1)-\ln D_t^{*}(y_t,x_t,t)\right]-\frac{1}{2}\left[\frac{\partial \ln D_{t+1}^{*}(y_{t+1},x_{t+1},t+1)}{\partial t}+\frac{\partial \ln D_t^{*}(y_t,x_t,t)}{\partial t}\right]\\ &+\frac{1}{2}\sum_{n=1}^{N}\left[\left(-\sum_{n=1}^{N}\varepsilon_{t+1}^{*n}-1\right)\times\frac{\varepsilon_{t+1}^{*n}}{\sum_{n=1}^{N}\varepsilon_{t+1}^{*n}}+\left(-\sum_{n=1}^{N}\varepsilon_{t}^{*n}-1\right)\times\frac{\varepsilon_{t}^{*n}}{\sum_{n=1}^{N}\varepsilon_{t}^{*n}}\right]\times\ln\left(\frac{x_{t+1}^{n}}{x_t^{n}}\right).\end{aligned} \tag{11}$$

The third term on the right-hand side is the element of the scale efficiency change ($\mathrm{SEC}_{t,t+1}^{*}$) that reflects the scale effect under VRS technology and vanishes when the CRS technology prevails, such that ln gMMPI = ln MMPI. Therefore:

$$\mathrm{gMMPI}_{t,t+1}=\mathrm{TEC}_{t,t+1}^{*}\times\mathrm{TC}_{t,t+1}^{*}\times\mathrm{SEC}_{t,t+1}^{*}. \tag{12}$$

Non-constant returns to scale make a positive contribution to ln gMMPI if the scale elasticity $-\sum_{n=1}^{N}\varepsilon_t^{*n}>1$ corresponds to increasing returns to scale; and input use expands ($\ln\left(x_{t+1}^{n}/x_t^{n}\right)>0$), or if $-\sum_{n=1}^{N}\varepsilon_t^{*n}<1$, corresponds to decreasing returns to scale, and the input's use contracts ($\ln\left(x_{t+1}^{n}/x_t^{n}\right)<0$). Both cases cause $\mathrm{SEC}_{t,t+1}^{*}$ to be greater than unity. This value indicates that the production scale of the bank is moving toward the optimal size and is enjoying the cost savings from a lower long-run average cost. However, the reverse is true when both prompt $\mathrm{SEC}_{t,t+1}^{*}$ to be less than unity. This value incurs cost wastes in terms of a greater long-run average cost.

We now substitute Eq. (5) into Eq. (11) to obtain:

$$\begin{aligned}\ln \mathrm{gMMPI}_{t,t+1} &= \left[\ln D_{t+1}^{k}(y_{t+1},x_{t+1},t+1)-\ln D_t^{k}(y_t,x_t,t)\right]-\frac{1}{2}\left[\frac{\partial \ln D_{t+1}^{k}(y_{t+1},x_{t+1},t+1)}{\partial t}+\frac{\partial \ln D_t^{k}(y_t,x_t,t)}{\partial t}\right]\\ &+\left[\ln \mathrm{TGR}_{t+1}^{k}(y_{t+1},x_{t+1},t+1)-\ln \mathrm{TGR}_{t}^{k}(y_t,x_t,t)\right]-\frac{1}{2}\left[\frac{\left(\partial \ln D_{t+1}^{*}(y_{t+1},x_{t+1},t+1)/\partial t\right)+\left(\partial \ln D_t^{*}(y_t,x_t,t)/\partial t\right)}{\left(\partial \ln D_{t+1}^{k}(y_{t+1},x_{t+1},t+1)/\partial t\right)+\left(\partial \ln D_t^{k}(y_t,x_t,t)/\partial t\right)}\right]\\ &+\frac{1}{2}\sum_{n=1}^{N}\left[\left(-\sum_{n=1}^{N}\varepsilon_{t+1}^{*n}-1\right)\times\frac{\varepsilon_{t+1}^{*n}}{\sum_{n=1}^{N}\varepsilon_{t+1}^{*n}}+\left(-\sum_{n=1}^{N}\varepsilon_{t}^{*n}-1\right)\times\frac{\varepsilon_{t}^{*n}}{\sum_{n=1}^{N}\varepsilon_{t}^{*n}}\right]\times\ln\left(\frac{x_{t+1}^{n}}{x_t^{n}}\right).\end{aligned} \tag{13}$$

After taking an exponent from both sides, Eq. (13) can be transformed into:

$$\mathrm{gMMPI}_{t,t+1}=\mathrm{TEC}_{t,t+1}^{k}\times\mathrm{TC}_{t,t+1}^{k}\times\mathrm{CUT}_{t,t+1}^{k}\times\mathrm{PTC}_{t,t+1}^{k}\times\mathrm{SEC}_{t,t+1}^{k}\times\frac{\mathrm{SEC}_{t,t+1}^{*}}{\mathrm{SEC}_{t,t+1}^{k}} \tag{14}$$

where the last term on the right-hand side measures the ratio of the scale efficiency change of the metafrontier to that of the country frontier between two periods (henceforth, RSEC). This ratio can also be referred to as a catch-up in scale. A value for the ratio that exceeds one implies that the production scale measured on the country frontiers is correcting toward the CRS faster than that measured on the metafrontier.

4. Econometric specifications and data description

4.1. Econometric specification

For the purpose of estimation, country k's output distance function for firm i (=1, . . ., I) at time t (=1, . . ., T) can be specified as a standard translog form with a time trend to deal with technical change, namely:

$$\begin{aligned}\ln D_O^k &= a_0 + \sum_{n=1}^{N} a_n \ln(x_n) + \sum_{m=1}^{M} b_m \ln(y_m) + \frac{1}{2}\sum_{j=1}^{N}\sum_{n=1}^{N} a_{jk} \ln\left(x_j\right) \ln(x_n) \\ &+ \frac{1}{2}\sum_{m=1}^{M}\sum_{l=1}^{M} b_{ml} \ln(y_m)\ln(y_l) + \sum_{n=1}^{N}\sum_{m=1}^{M} g_{nm} \ln(x_n)\ln(y_m) + j_0 t + \frac{1}{2} j_{00} t^2 \\ &+ \sum_{n=1}^{N} \gamma_{nt} t \ln(x_n) + \sum_{m=1}^{M} \theta_{mt} t \ln(y_m).\end{aligned} \tag{15}$$

To estimate the parameters we have to impose the linear homogeneity constraint on the outputs. This constraint leads to the normalization of the distance function by using any one of the M outputs, such as y_1, as the numeraire. After letting $-u = \ln D_O^k$ and appending a statistical noise, $v \sim N\left(0, \sigma_v^2\right)$, the resulting output distance function is written as:

$$\begin{aligned}-\ln y_1 &= a_0 + \sum_{n=1}^{N} a_n \ln(x_n) + \sum_{m=2}^{M} b_m \ln\left(\frac{y_m}{y_1}\right) + \frac{1}{2}\sum_{j=1}^{N}\sum_{n=1}^{N} a_{jn} \ln\left(x_j\right) \ln(x_n) \\ &+ \frac{1}{2}\sum_{m=2}^{M}\sum_{l=2}^{M} b_{ml} \ln\left(\frac{y_m}{y_1}\right) \ln\left(y_l/y_1\right) + \sum_{n=1}^{N}\sum_{m=2}^{M} g_{nm} \ln(x_n) \ln\left(y_m/y_1\right) + j_0 t + \frac{1}{2} j_{00} t^2 \\ &+ \sum_{n=1}^{N} \gamma_{nt} t \ln(x_n) + \sum_{m=2}^{M} \theta_{mt} t \ln\left(\frac{y_m}{y_1}\right) + v + u\end{aligned} \tag{16}$$

where term u is a non-negative random variable signifying technical inefficiency and is independent of v. Following Battese and Coelli (1995), the inefficiency term is allowed to be variant with an array of environmental variables, z, that is:

$$u = z\delta + W \geq 0 \tag{17}$$

where δ is a vector of parameters corresponding to z, and W is a normal variate with a mean of zero and a constant variance of σ^2. Country k's stochastic frontier model (16) together with Eq. (17) are estimated by the maximum likelihood.

Next, the parameters of the output metadistance function can be estimated by using linear programming (LP) and quadratic programming (QP) techniques. Battese et al. (2004) propose these techniques and suggest applying either simulations or bootstrapping to obtain the standard errors for the parameter estimates. Measures TE_t^* and TGR_t^k can be calculated based on these coefficient estimates.

4.2. Data description

This paper compiles unconsolidated accounting statements from the BankScope database of BVD-IBCA. The sample contains 1824 commercial banks from 12 Western European countries spanning 1993 to 2006, 10 of which belong to the Eurozone: Austria, Belgium, Finland, France, Germany, Italy, Netherlands, Portugal, Spain, and Sweden. Although Denmark and the United Kingdom are the member states of the EU, they have opt-outs from joining the Eurozone by reasons of economic sovereignty. A number of banks reporting extreme values on the variables of interest are removed. The unbalanced

Table 1
Descriptive statistics.

	AUS	BEL	DNK	FIN	FRA	DEU	ITA	NLD	PRT	ESP	SWE	GBR
Number of banks	146	77	97	11	280	876	106	22	17	49	101	42
Number of observations	1235	632	1132	81	2496	9640	690	121	109	342	609	269
Labor (total assets net of fixed assets)	2613	14,068	2652	12,975	13,494	4934	7689	1629	8406	7294	6845	1783
	(8788)	(48,850)	(16,737)	(16,059)	(64,075)	(39,664)	(17,619)	(2076)	(12,102)	(18,369)	(22,281)	(2580)
Physical capital	21	69	22	91	51	31	124	4	135	131	32	13
	(43)	(195)	(97)	(150)	(243)	(97)	(272)	(9)	(189)	(356)	(175)	(34)
Borrowed funds	2430	12,707	2216	11,556	11,070	4504	6620	1460	7643	6550	5655	1366
	(8192)	(43,001)	(13,600)	(14,398)	(48,257)	(33,413)	(15,209)	(1859)	(10,890)	(16,553)	(18,257)	(1884)
Loans	2080	8706	1234	8763	8880	3459	5605	1038	6244	5245	4635	1238
	(7022)	(30,089)	(6944)	(11,540)	(37,557)	(24,202)	(13,200)	(1063)	(8919)	(12,680)	(14,783)	(1675)
Investments	441	4429	1182	3109	3112	1175	1503	481	1377	1582	1589	328
	(1642)	(14,601)	(7975)	(3648)	(17,383)	(10,396)	(3235)	(1425)	(1997)	(4673)	(5721)	(813)
Non-interest revenue	16	47	18	83	76	29	74	6	48	58	54	41
	(43)	(145)	(91)	(119)	(321)	(229)	(157)	(14)	(90)	(145)	(162)	(106)
Equity over total asset	8.42	6.23	13.67	5.69	8.23	6.08	12.69	9.10	8.37	9.81	12.64	15.30
	(9.67)	(5.20)	(5.31)	(3.31)	(10.47)	(7.09)	(12.22)	(6.73)	(4.96)	(10.70)	(6.26)	(10.33)
Return on assets	0.54	0.49	1.40	0.34	0.32	0.31	0.36	0.46	0.67	-0.15	1.02	0.51
	(0.27)	(0.35)	(0.44)	(0.52)	(0.50)	(0.09)	(0.47)	(0.27)	(0.50)	(1.50)	(0.37)	(0.66)
Per capita income	3.16	3.07	3.36	3.09	3.07	3.11	2.91	3.12	2.30	2.57	3.34	3.19
	(0.07)	(0.08)	(0.07)	(0.13)	(0.07)	(0.06)	(0.05)	(0.09)	(0.09)	(0.09)	(0.08)	(0.10)
Population density	4.57	5.82	4.82	2.73	4.67	5.44	5.24	5.94	4.70	4.37	2.99	5.49
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)	(0.00)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Deposit density	7.74	8.93	7.77	5.32	7.51	8.53	7.65	9.14	7.04	6.77	5.66	8.79
	(0.17)	(0.22)	(0.20)	(0.18)	(0.18)	(0.25)	(0.14)	(0.28)	(0.11)	(0.22)	(0.25)	(0.46)

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

Table 2
Construction of regulatory variables.

Variables and definitions
Bank activity regulatory (BAR)
It is proxied by overall restrictions on banking activities that measures the extent to which a bank can both engage in securities, insurance, and real estate activities and own non-financial firms. The overall index is constructed by calculating the average value over the four categories. Higher values indicate more strictive
Capital regulatory (CR)
It is proxied by capital regulatory index that measure the amount of capital banks must hold and the stringency of regulations on the nature and source of regulatory capital. Higher values indicate greater stringency
Market structure indicators (MSI)
The extent to which the banking system's assets are foreign-owned (in percentage terms).

Notes: see Barth et al. (2013) for more detailed.

panel data contain 17,356 bank-year observations after excluding all missing observations. Table 1 summarizes the detailed distribution of banks across each sample country.

Following Dietsch and Lozano-Vivas (2000), Lozano-Vivas, Pastor, and Hasan (2001, 2002), we consider two micro-level variables consisting of the equity to total assets ratio (ETA) and the average return on assets (ROA), as well as three macro-variables that comprise per capita income (PCI), population density (PD), and deposit density (DD) as the environmental variables that might affect a bank's technical inefficiency. In addition, recent studies suggest that regulatory and institutional differences play a crucial role in explaining bank performance. See, e.g., Pasiouras (2008), Delis, Molineux, and Pasiouras (2011), Barth, Caprio, and Levine (2013), Chortareas, Girardone, and Ventouri (2013), Curi, Guarda, Lozano-Vivas, and Zelenyuk (2013). We also control factors that comprise bank activity regulation (BAR) proxied by overall restrictions on banking activities, capital regulation (CR) proxied by capital regulatory index, and market structure indicators (MSI) proxied by foreign-owned banks as environmental variables. Variables relating to regulatory difference measures are taken from Barth et al. (2013). Table 2 reports those descriptive statistics. The variables PCI and PD come from the World Development Indicator (WDI) and the DD from the International Financial Statistics (IFS). Our application for Western European banking is fruitful because of the abundance of quality data available on banks in Western European.

Based on the intermediation approach, banks are assumed to use three inputs – labor (x_1), physical capital (x_2), and borrowed funds (x_3) – to produce three outputs: loans (y_1), investments (y_2), and non-interest revenue (y_3).[1] Because there are quite a bit of missing data on the number of employees, we select the total assets net of fixed assets as the proxy for input labor. This proxy is the same as the proxy in Altunbaş et al. (2001) and Weill (2004). The input of physical capital is measured by the amount of fixed assets, while input of borrowed funds consist of all deposits and borrowed money. As to the output variables, loans comprise short-term and long-term loans. Investments aggregate government bonds, corporate securities, and other investments. The output of non-interest revenue is used in an attempt to reflect a bank's degree of product diversification. This revenue constitutes a crucial source of income for modern universal banks. All of the inputs and outputs are expressed in millions of real US dollars deflated by the consumer price index of individual countries by using 2000 as the base year.

Table 1 also presents the descriptive statistics for the aforementioned variables by countries. These statistics show that substantial variation exists between countries in the operational characteristics for each sample of banks. Banks in different countries might have different qualities of inputs that produce heterogeneous outputs under dissimilar production techniques. Such variations justify the use of the metafrontier model for the study of international comparison.

[1] Another line of research introduce a directional distance function to model joint production of goods and bads simultaneously, which try to provide a practical managerial meaning about efficiency. It is an important direction for future research, especially for the purpose of making the empirical model more realistic.

5. Empirical results and analysis

The first section analyzes the outcomes of estimated efficiency scores from Eq. (16) with Eq. (17) being imposed on the scores. Section 2 discusses the various components of the productivity change measures that might shed some light on the policy implications and the research issues regarding the banks under consideration.

5.1. Efficiency estimates

FRONTIER 4.1 software yields the parameter estimates for the country frontier of Eq. (16) for each of the 12 countries (see Coelli, 1996). These estimates are not shown to save space, but are available on request from the authors. In summary, more than half of the parameter estimates for each country reach statistical significance at least at the 10% level and most of the observations are in line with the regularity conditions imposed by microeconomic theory. We, thus, claim that these estimates are valid to represent the sample banks' production technologies.

Because the partial elasticities of the output distance function with respect to inputs and outputs have been computed, the scale economies can be investigated. Following Färe and Primont (1995), the scale elasticity equals the negative of the sum of the input elasticities. The measures range from 0.977 in Portugal to 1.016 in the Netherlands and the overall mean value attains 0.999, implying that the representative bank is operating nearly at the optimal scale.

As far as the environmental conditions are concerned, the results show that most of their parameter estimates are significant in the sample countries, but their signs are mixed. We therefore focus our attention only on those estimates that attain statistical significance. The directions of these environmental factors on technical inefficiencies are not the same in the sample countries, depending on the country-specific situations. For the first two micro-level variables, it is expected that the higher the capital to assets ratio (ETA) is, the lower is the insolvency risk. Moreover, banks with higher levels of ETA are able to provide more financial outputs and hence earn more interest revenues, which promote efficiency. With the only exception of Netherlands, the impact of ETA on technical inefficiency is negative. This outcome implies that the higher the ETA is, the more efficient is the bank. This result is congruent with many previous studies, such as Hughes and Mester (1998), Dietsch and Lozano-Vivas (2000), Kumbhakar and Wang (2007), and Huang, Shen, Chen, and Tseng (2011b), to mention a few. As to the ROA, the relationship between the profitability ratio and efficiency is expected to be positive. Except for France, Portugal, and Spain, the coefficient of ROA is found to be significantly negative, showing that high profitability prompts banks' technical efficiency in these countries. This finding is consistent with Cavallo and Rossi (2002) and Casu and Molyneux (2003).

In the cases of three macro-variables, As noted by Dietsch and Lozano-Vivas (2000), Lozano-Vivas et al. (2001, 2002), and Huang et al. (2011b), per capita income (PCI) is an overall indicator and affects both demand for and supply of banking services, such as deposit and loans. Therefore, the sign of PCI is mixed. Evidence is found that significantly negative effects of PCI on technical inefficiency are obtained in Belgium, France, Portugal, and Sweden, while Demark, Germany, Finland, Italy, Netherlands, and Spain, show significantly positive effects. The variable of population density (PD) is found to have negative effect on technical inefficiency in Demark, Germany, Finland, Netherlands, and the United Kingdom. Lozano-Vivas et al. (2002) claim that high levels of PD should make retail distribution of banking activities less expensive, hence prompting bank efficiency. This variable also exerts positive effect on technical inefficiency in Austria, Belgium, France, Italy, Portugal, and Sweden, indicating that high PD tends to entail higher operation costs, worsening technical inefficiency. The variable of deposit density (DD) is expected to have positive impacts on technical inefficiency. As claimed by Huang et al. (2011b), banks operating in a market of high DD are facing keen competition and have to employ more and high quality inputs to provide high quality of services to their customers, but still charge competitive prices. As a result, DD should be positively correlated with inefficiency. With the only exception of France, we confirm this positive relationship.

Since banks are one of the heavily regulated sectors in an economy, cross-country comparisons of bank efficiency should consider the influence of different regulatory environments

(Curi et al., 2013). Regulatory and institutional differences are suggested to be modelled in estimating and comparing technical efficiencies across countries. From a theoretical point of view, there are conflicting predictions about the impact of regulatory policies and market structures on bank performance (e.g., Barth et al., 2004, 2013). Some empirical studies support that higher restrictions improve efficiency (e.g., Pasiouras, 2008; Barth et al., 2013), while others do not (e.g., Fernandez & Gonzalez, 2005, Barth et al., 2004; Beck, Demirguc-Kunt, & Levine, 2006). Our empirical results show that bank activity regulation (BAR) is found to have positive effect on technical inefficiency in Belgium, Demark, Germany, Finland, Spain, and the United Kingdom. This means that higher activity restrictions may result in lower efficiency levels. For capital regulation (CR), it exerts positive effect on technical inefficiency, except for Belgium and Spain, indicating that the increase in capital requirement adversely affects banks' managerial abilities. As for the market structure indicators (MSI), it has significantly negative effects on technical inefficiency in Belgium, Germany, Finland, France, Portugal, and Spain, while the reverse is true in Austria, Demark, Italy, Sweden, and the United Kingdom.

Before estimating the metafrontier, it is important to test whether the banks from different countries have access to the same technology. If the null hypothesis (H_0) of the presence of a common frontier is accepted by the data that implies that all banks share the same technology, then the estimation of the metafrontier is no longer needed. A likelihood ratio (LR) test statistic can be used to fulfill the test, which has a chi-squared distribution. It is defined by

$$\lambda = -2\left\{\ln\left[L(H_0)\right] - \ln\left[L(H_1)\right]\right\} \sim x^2(m) \tag{18}$$

whre $L(H_0)$ is the value of the log-likelihood functions for a common frontier estimated by pooling the data of all countries, and $L(H_1)$ is the sum of the values of the log-likelihood function over the 12 individual frontiers. The degrees of freedom m for the chi-square distribution are 429, which is the difference between the number of parameters estimated under H_1 and H_0. The value of the test statistics equal 3339, leading to a rejection of the null hypothesis. Therefore, we conclude that the banks from different countries are indeed operating under different technologies. This finding validates the construction of the metafrontier.

Table 3 summarizes the parameter estimates of the stochastic frontier model obtained by pooling all of the banks in the 12 countries, which implicitly assumes that banks from different countries adopt homogeneous technology. The table also presents the parameter estimates of the metafrontier in the context of the linear and quadratic programming. A bootstrapping technique with 1000 replications is used to get the sampling variabilities of the metafrontier estimates. The coefficient estimates of the stochastic frontier model deviate substantially from the ones obtained by the programming techniques, whereas the estimates of LP and QP are relatively close to each other. As noted by Battese et al. (2004) and O'Donnell et al. (2008), both the LP and the QP are feasible ways of estimating the metafrontier in that they produce very similar TGR and TE^* estimates. Therefore, we concentrate our attention on the QP estimates from now on.

The relevant efficiency scores can be calculated using the parameter estimates derived in the first stage. Table 4 shows summary statistics of the TE, TGR, and the TE^* for all countries. The average values of TE vary from roughly 0.77 (France) to 0.98 (Demark), which imply that a representative bank in France (Demark) is producing 77% (98%) of the potential output level. The average TGRs range from roughly 0.61 (Sweden) to 0.82 (France). These values indicate that the technology adopted by an average Swedish bank deviates far from the potential technology such that its frontier output reaches merely 61% of the potential output for a given input mix. Conversely, an average bank in France undertakes quite advanced technology, because its frontier output attains about 82% of the potential output.

Noteworthy is the question of whether the country-specific frontiers are at least partially tangent to the metafrontier. Table 4 shows that the country-specific stochastic frontiers of Austria, France, Germany, Netherlands, and Sweden are tangent to the metafrontier, since they all have estimated values of TGR equaling unity. This unity confirms that the metafrontier is a smooth function and not a segmented envelope of the stochastic frontier functions for different technologies.

Table 3
ML estimates of the stochastic output distance frontier for Western European banks and estimates of the metafrontier output distance function.

Independent variables	Stochastic frontier			Metafrontier (QP)			Metafrontier (LP)		
	Coefficient		S.E.	Coefficient		S.E.	Coefficient		S.E.
Constant	0.887	***	0.036	−0.426		0.328	−1.277	*	0.662
$\ln(x_1)$	−1.215	***	0.026	−1.378	***	0.223	−0.617	*	0.352
$\ln(x_2)$	−0.025	***	0.005	0.074	**	0.033	0.107	**	0.049
$\ln(x_3)$	0.224	***	0.025	0.467	**	0.216	−0.178		0.310
$\ln(y_2/y_1)$	0.349	***	0.004	0.097		0.079	0.010		0.111
$\ln(y_3/y_1)$	0.053	***	0.005	0.114	**	0.046	0.149	*	0.083
$0.5 \times \ln(x_1)^2$	−0.024	***	0.006	0.106		0.066	−0.025		0.079
$0.5 \times \ln(x_2)^2$	0.008	***	0.001	0.009		0.009	0.003		0.014
$0.5 \times \ln(x_3)^2$	−0.089	***	0.004	−0.012		0.033	−0.143	***	0.051
$\ln(x_1) \times \ln(x_2)$	−0.013	***	0.002	−0.045	*	0.024	−0.085	***	0.032
$\ln(x_1) \times \ln(x_3)$	0.060	***	0.005	−0.044		0.044	0.080		0.057
$\ln(x_2) \times \ln(x_3)$	0.006	***	0.002	0.029		0.021	0.073	**	0.032
$0.5 \times \ln(y_2/y_1)^2$	0.085	***	2.70E − 04	0.032	***	0.006	0.033	***	0.007
$\ln(y_2/y_1) \times \ln(y_3/y_1)$	0.011	***	2.89E − 04	0.021	**	0.010	0.026		0.016
$0.5 \times \ln(y_3/y_1)^2$	0.010	***	0.001	−0.007		0.006	−0.018	**	0.008
$\ln(x_1) \times \ln(y_2/y_1)$	0.060	***	0.001	0.064	***	0.020	0.072	**	0.030
$\ln(x_2) \times \ln(y_2/y_1)$	−0.010	***	2.49E − 04	−0.002		0.004	−0.002		0.006
$\ln(x_3) \times \ln(y_2/y_1)$	−0.048	***	0.001	−0.044	*	0.026	−0.043		0.041
$\ln(x_1) \times \ln(y_3/y_1)$	−0.005	***	0.002	0.049	**	0.023	0.094	***	0.034
$\ln(x_2) \times \ln(y_3/y_1)$	−0.003	***	0.001	−0.012	*	0.006	−0.006		0.013
$\ln(x_3) \times \ln(y_3/y_1)$	0.009	***	0.002	−0.048	**	0.023	−0.105	***	0.032
t	−0.006	***	0.002	0.076	***	0.010	0.054	***	0.013
$0.5 \times t^2$	2.11E − 04	***	8.24E − 05	−0.013	***	0.001	−0.013	***	0.001
$t \times \ln(x_1)$	0.007	***	0.001	0.003		0.007	−0.008		0.009
$t \times \ln(x_2)$	0.001	***	1.45E − 04	0.001		0.001	0.001		0.001
$t \times \ln(x_3)$	−0.008	***	0.001	−0.005		0.007	0.008		0.009
$t \times \ln(y_2/y_1)$	−0.001	***	1.05E − 04	−0.001		0.001	−0.003	*	0.001
$t \times \ln(y_3/y_1)$	−2.18E − 04		1.78 E − 04	2.02 E − 04		0.001	0.002		0.002

Notes: The standard errors of the metafrontier estimators are obtained using a bootstrapping method with 1000 replications. The ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

5.2. Estimated productivity change using the generalized MMPI

This study decomposes the gMMPI into a set of components related to productivity change by using Eqs. (12) and (14). We now turn our attention to the sources of productivity growth. Recall that a value of these components greater than one indicates a productivity gain, while a value less than one indicates a productivity loss. As far as the metafrontier is concerned, the left part of Table 5 presents the rates of change in gMMPI and its individual components per annum. The average rate of gMMPI is equal to 0.25% per year, which is consistent with the findings of Casu et al. (2004) and Casu and Girardone (2005) over the period of 1994 to 2000, Murillo-Melchor et al. (2010) over the period of 1995 to 2001, as well as Barros, Peypoch, and Williams (2010) over the period of 1996 to 2003. This measure of productivity growth consists of technical efficiency losses (3.04%), technical progress (3.60%), and the effect of scale improvement (0.07%) toward constant returns to scale.

An interesting issue associated with institutional alteration concerns whether the integration policy is really helpful in promoting bank productivity. We divide the entire sample period into four sub-periods, i.e., 1993–1996, 1996–1999, 1999–2002, and 2002–2006. Evidence exists that Western European banks have experienced a faster positive productivity growth during 1993 to 1999, immediately after the establishment of the single market for European financial services that leads to an economic integration in this area, than the latter two sub-periods. This evidence shows that a single, competitive market for financial services can improve banking productivities within the member countries. This result is further confirmed by an increasing positive scale effect that contributes to productivity growth during the entire sample period. Sample banks can increase their productivity by changing their operational scales toward the optimal scale of production.

Table 4
Summary statistics of TEs, TGRs, and TE*.

Country	Mean	Min	Max	S.D.	Country	Mean	Min	Max	S.D.
Austria					Italy				
TE	0.950	0.290	1.000	0.055	TE	0.708	0.039	0.863	0.111
TGR	0.700	0.087	1.000	0.146	TGR	0.943	0.265	1.000	0.071
TE*	0.667	0.086	0.918	0.150	TE*	0.670	0.039	0.840	0.124
Belgium					Netherlands				
TE	0.919	0.458	1.000	0.072	TE	0.944	0.458	0.991	0.064
TGR	0.675	0.044	0.977	0.163	TGR	0.653	0.107	1.000	0.179
TE*	0.622	0.042	0.911	0.159	TE*	0.617	0.106	0.829	0.170
Demark					Portugal				
TE	0.982	0.845	1.000	0.017	TE	0.951	0.782	1.000	0.057
TGR	0.650	0.037	0.990	0.136	TGR	0.704	0.401	0.946	0.127
TE*	0.639	0.037	0.950	0.137	TE*	0.665	0.401	0.896	0.100
Finland					Spain				
TE	0.973	0.927	1.000	0.024	TE	0.960	0.493	0.992	0.055
TGR	0.669	0.306	0.861	0.128	TGR	0.724	0.185	0.866	0.107
TE*	0.650	0.304	0.849	0.121	TE*	0.697	0.172	0.848	0.115
France					Sweden				
TE	0.771	0.251	0.984	0.172	TE	0.961	0.415	0.992	0.067
TGR	0.817	0.066	1.000	0.133	TGR	0.612	0.159	1.000	0.129
TE*	0.621	0.047	0.869	0.136	TE*	0.583	0.145	0.867	0.104
Germany					United Kingdom				
TE	0.945	0.249	1.000	0.076	TE	0.939	0.597	0.988	0.051
TGR	0.738	0.190	1.000	0.119	TGR	0.637	0.232	0.867	0.135
TE*	0.699	0.118	0.952	0.134	TE*	0.600	0.166	0.828	0.136
Total									
TE	0.922	0.249	1.000	0.111					
TGR	0.730	0.037	1.000	0.136					
TE*	0.671	0.037	0.952	0.140					

Note: The quadratic programming estimates of the metafrontier are used to make the relevant calculations.

Table 5
Summary statistics of the various gMMPI components over time.

Period	gMMPI	TEC*	TC*	SEC*	MMPI	TEC	TC	SEC	RSEC	TGRC	CUT	PTC
1994	1.0068	1.0523	0.9566	1.0002	1.0067	1.0084	0.9970	1.0000	1.0002	1.0019	1.0443	0.9595
1995	1.0040	1.0350	0.9697	1.0005	1.0037	1.0035	0.9994	1.0000	1.0005	1.0011	1.0318	0.9703
1996	1.0029	1.0210	0.9829	0.9993	1.0035	1.0003	1.0018	0.9999	0.9995	1.0022	1.0215	0.9813
1997	1.0052	1.0099	0.9961	0.9993	1.0060	0.9998	1.0038	0.9993	1.0012	1.0050	1.0126	0.9926
1998	1.0011	0.9906	1.0096	1.0012	1.0001	0.9949	1.0059	1.0004	1.0009	1.0012	0.9974	1.0039
1999	1.0055	0.9824	1.0232	1.0002	1.0053	0.9925	1.0080	1.0003	0.9999	1.0058	0.9909	1.0155
2000	1.0000	0.9642	1.0369	1.0003	0.9997	0.9908	1.0106	0.9998	1.0005	1.0002	0.9747	1.0264
2001	0.9969	0.9487	1.0510	0.9998	0.9971	0.9841	1.0137	1.0001	0.9997	1.0027	0.9671	1.0374
2002	1.0023	0.9393	1.0650	1.0021	1.0004	0.9861	1.0152	1.0002	1.0019	1.0018	0.9550	1.0499
2003	1.0002	0.9243	1.0796	1.0025	0.9978	0.9871	1.0178	1.0001	1.0025	0.9953	0.9381	1.0617
2004	1.0047	0.9165	1.0943	1.0018	1.0030	0.9835	1.0188	1.0000	1.0020	1.0037	0.9342	1.0754
2005	0.9996	0.9022	1.1092	0.9989	1.0007	0.9800	1.0221	1.0001	0.9988	1.0023	0.9233	1.0866
2006	1.0035	0.8896	1.1244	1.0033	1.0003	0.9770	1.0242	1.0000	1.0034	1.0045	0.9150	1.0994
93–96	1.0045	1.0354	0.9703	1.0000	1.0046	1.0039	0.9995	1.0000	1.0000	1.0017	1.0320	0.9709
96–99	1.0039	0.9943	1.0096	1.0002	1.0037	0.9957	1.0059	1.0000	1.0007	1.0040	1.0003	1.0039
99–02	0.9998	0.9508	1.0509	1.0007	0.9991	0.9871	1.0131	1.0000	1.0007	1.0015	0.9656	1.0378
02–06	1.0020	0.9087	1.1012	1.0016	1.0004	0.9821	1.0206	1.0001	1.0016	1.0013	0.9280	1.0802
Average	1.0025	0.9696	1.0360	1.0007	1.0019	0.9917	1.0102	1.0000	1.0008	1.0021	0.9792	1.0257

The gMMPI is further decomposed into the technical efficiency change, technical change, and the scale efficiency change based on the country frontiers. The results are listed in the middle of Table 5, while various catch-up effects are on the right side of the table. Recall that $\mathrm{MMPI}_{t,t+1} = \mathrm{TEC}^k_{t,t+1} \times \mathrm{TC}^k_{t,t+1} \times \mathrm{CUT}^k_{t,t+1} \times \mathrm{PTC}^k_{t,t+1}$ differs from the gMMPI due to the omission of scale effect, that is, term SEC^*. Because the average rate of productivity growth for MMPI is 0.19% per year, this omission leads to an underestimation, as compared with the 0.25% of the gMMPI. Among the four sources, the TC and PTC play the most important role, and the remaining two sources curb productivity.

As mentioned earlier, neglecting scale efficiency change can lead to inaccurate results for the productivity change. On the basis of the country frontiers, the scale effect is essential not only for capturing scale efficiency change, but also for helping shed light on the effect of catch-up in scale. The ratio of the scale efficiency change of the metafrontier to that of the country frontiers exceeds one that suggests there is catch-up in the scale. That is, the production scale measured on the country frontiers is adjusting toward the CRS faster than the scale measured on the metafrontier. Finally, before the advent of European Economic and Monetary Union (EMU) in 1999, the TGRC shows an increasingly positive effect and then exerts a decreasingly positive effect thereafter, mainly due to the regress of the CUT. This finding discloses that the stimulation effect of the EMU on the banking productivity appears to last for a short period.

Of more interest is to know the sources of productivity change for each country. Table 6 reports the mean values of these measures in a descending order according to the gMMPI. Banks in 9 out of the 12 countries have positive measures of the gMMPI, indicating that their productivities grow over time when assessed against the metafrontier. Banks in the remaining countries undergo a productivity decline. Banks in United Kingdom have the highest productivity growth (1.48%), followed by Sweden (1.35%) and Finland (1.21%). A common feature of these three countries is that they are modern, very open, and well-developed market economies. Conversely, the lowest rate of growth occurs in Spain (−0.74%), followed by Italy (−0.35%), and Portugal (−0.27%). This may be attributed to the fact that these three countries have the lowest levels of income per capita (see Table 1). Banks in these countries are difficult to perform banking business (Lozano-Vivas et al., 2002). Our findings are similar to Pastor, Pérez, and Quesada (1997), Kondeas, Caudill, Gropper, and Raymond (2008), and Murillo-Melchor et al. (2010), without relying on the metafrontier framework. Taking a closer look at the three elements, most countries show a gain in scale efficiency and technical progress, while all countries have losses in technical efficiency.

The measures TEC, TC, and SEC in Table 6 are not comparable between countries, because they are computed against distinct country frontiers. The evidence found in the previous paragraph is attributed to the trend toward consolidation in response to the intensified competition between banks within the EMU. According to Goddard et al. (2001), all Western European countries, apart from Portugal, have undergone a decline in the number of banks since 1989. Faced with this new atmosphere, a bank must manage to enhance its competitiveness by lowering production costs by means of, for example, merger and acquisition activities to expand the production scale and by adopting innovations to stimulate technical progress instantly.

After the completion of a consolidation, some time is needed for the managers of the firm to rearrange the workforce and the capital of the merged firm, which is apt to cause an adverse efficiency change. Mergers and acquisitions can incur extra costs from adapting to the new environment and reconsidering business strategies, the disappearance of traditional revenues, and any other unfinished banking reforms. Another explanation related to the economic environment stresses that the lower the level of economic conditions, the harder it is to engage in banking activities, as noted by Lozano-Vivas et al. (2001, 2002). Our finding confirms this argument in that Spain and Portugal have the lowest levels of per capita income among the sample states, which lead to losses in technical efficiency.

To gain further insights into the impact of a bank's size and risk attitude on productivity change, we respectively classify the entire sample into eight countries based on total assets and the ratio of equity to total assets. Table 7 presents the outcomes. According to Panel A of Table 7, smaller and larger banks appear to grow faster than medium-sized banks do. The evidence supports the establishment of large

Table 6
Summary statistics of the various gMMPI components across country.

Rank	Country	gMMPI	TEC*	TC*	SEC*	MMPI	TEC	TC	SEC	RSEC	TGRC	CUT	PTC
1	United Kingdom	1.0148	0.9708	1.0478	1.0001	1.0147	1.0004	1.0062	1.0006	1.0001	1.0091	0.9719	1.0414
2	Sweden	1.0135	0.9415	1.0780	1.0005	1.0132	1.0051	0.9994	1.0000	1.0006	1.0116	0.9376	1.0790
3	Finland	1.0121	0.9811	1.0321	1.0024	1.0098	1.0023	0.9918	0.9979	1.0045	1.0169	0.9799	1.0412
4	Belgium	1.0095	0.9808	1.0328	0.9993	1.0105	0.9981	1.0063	1.0002	0.9991	1.0094	0.9852	1.0262
5	Demark	1.0088	0.9748	1.0385	0.9987	1.0100	0.9993	1.0016	1.0003	0.9985	1.0097	0.9758	1.0367
6	Netherlands	1.0051	0.9764	1.0336	0.9982	1.0076	1.0123	0.9999	0.9966	1.0032	1.0083	0.9770	1.0338
7	Austria	1.0025	0.9568	1.0494	1.0005	1.0020	0.9989	1.0053	0.9998	1.0007	1.0047	0.9646	1.0440
8	Germany	1.0017	0.9696	1.0351	1.0007	1.0011	0.9990	1.0017	1.0000	1.0007	1.0005	0.9704	1.0331
9	France	1.0000	0.9706	1.0313	1.0020	0.9981	0.9473	1.0594	1.0005	1.0015	0.9984	1.0264	0.9730
10	Portugal	0.9973	0.9809	1.0134	1.0051	0.9930	1.0197	0.9910	0.9987	1.0069	0.9849	0.9632	1.0225
11	Italy	0.9965	0.9815	1.0172	1.0001	0.9965	0.9881	1.0045	0.9994	1.0034	1.0107	0.9997	1.0126
12	Spain	0.9926	0.9835	1.0087	1.0023	0.9906	1.0014	1.0005	1.0001	1.0022	0.9896	0.9832	1.0082
Average		1.0025	0.9696	1.0360	1.0007	1.0019	0.9917	1.0102	1.0000	1.0008	1.0021	0.9792	1.0257

Table 7
Summary statistics of the various gMMPI components by asset sizes and the ratio of equity to total assets.

Class		Obs.	gMMPI	TEC*	TC*	SEC*	MMPI	TEC	TC	SEC	RSEC	TGRC	CUT	PTC
Panel A. Total assets														
Size1	Below 100	975	1.0066	0.9694	1.0419	0.9987	1.0080	0.9924	1.0096	1.0005	0.9983	1.0114	0.9818	1.0323
Size2	100–200	1195	1.0038	0.9703	1.0371	0.9998	1.0042	0.9940	1.0103	1.0002	0.9996	1.0006	0.9765	1.0268
S ize3	200–400	1879	1.0019	0.9744	1.0310	0.9995	1.0024	0.9917	1.0094	1.0001	0.9994	1.0027	0.9835	1.0215
S ize4	400–1000	3753	1.0018	0.9726	1.0325	1.0000	1.0018	0.9939	1.0070	1.0000	1.0005	1.0036	0.9807	1.0255
S ize5	1000–3000	4378	1.0008	0.9678	1.0360	1.0009	1.0000	0.9937	1.0071	1.0000	1.0009	1.0010	0.9752	1.0288
S ize6	3000–5000	1147	1.0033	0.9658	1.0403	1.0014	1.0020	0.9912	1.0133	0.9998	1.0016	0.9988	0.9750	1.0270
S ize7	5000–10,000	1053	1.0047	0.9671	1.0389	1.0026	1.0021	0.9847	1.0202	1.0002	1.0025	1.0014	0.9850	1.0189
S ize8	Above 10,000	1115	1.0051	0.9633	1.0422	1.0043	1.0010	0.9814	1.0233	0.9996	1.0047	0.9982	0.9818	1.0191
Panel B. ETA (%)														
S ETA1	Below 3	1017	1.0074	0.9887	1.0208	1.0011	1.0065	0.9890	1.0165	1.0000	1.0012	1.0035	1.0008	1.0045
S ETA2	3–4	2624	1.0024	0.9855	1.0183	1.0009	1.0015	0.9973	1.0065	1.0000	1.0009	0.9988	0.9888	1.0118
S ETA3	4–5	3740	1.0015	0.9711	1.0330	1.0008	1.0007	0.9947	1.0060	0.9999	1.0009	1.0011	0.9769	1.0269
S ETA4	5–7	3366	1.0006	0.9554	1.0489	1.0011	0.9995	0.9897	1.0105	1.0000	1.0011	1.0008	0.9662	1.0382
S ETA5	7–12	2450	1.0031	0.9673	1.0392	1.0007	1.0025	0.9870	1.0146	1.0000	1.0007	1.0038	0.9821	1.0246
S ETA6	12–15	846	1.0058	0.9689	1.0409	0.9995	1.0063	0.9919	1.0110	1.0001	0.9995	1.0065	0.9793	1.0299
S ETA7	15–20	774	1.0075	0.9639	1.0489	0.9989	1.0086	0.9918	1.0093	1.0000	0.9990	1.0087	0.9719	1.0400
S ETA8	Above 20	678	0.9991	0.9566	1.0469	0.9999	0.9996	0.9850	1.0226	1.0007	1.0017	1.0063	0.9841	1.0249

Notes: The values of total assets are measured in millions of US dollars to save space.

banks as this form exhibits the swift rates of growth in the TC^* and the SEC^*, resulting possibly from mergers and acquisitions. Yang and Chen (2009) adopt two approaches, i.e., switching regression of the stochastic frontier model and stochastic metafrontier model, to investigate the difference between the small and medium-sized firms (SMEs) and large enterprises. They estimate separate frontiers for each of the two groups and argue that the production technologies undertaken by the two groups of firms are different from each other. Large banks can acquire advanced technology and enjoy the advantage of scale economies, because they are able to employ highly specialized inputs and coordinate their resources better. In contrast, small banks enjoy a gain in technical change and a gradually increased technical efficiency, because they have flexible, non-hierarchical structures.

Panel B of Table 7 shows the productivity differences for banks with diverse attitudes toward risk. Because equity capital provides a buffer against portfolio losses, the expectation is that the higher the capital to assets ratio, the less likely a bank will be involved in insolvency, and vice versa. Interestingly, with the exception of ETA1 and EAT8, the highest three classes of banks correspond to the quickest productivity growth, mainly because they have the highest average values of the TC^*. Conservative banks tend to grow at a rapid rate. However, the TEC^* worsens with the ETA. The outcomes appear to be quite reasonable, because there is incentive for a risk-averse bank manager to engage in monitoring, supervising activities, and making circumspect decisions thereby losing efficiency.

6. Conclusion

This paper successfully extends the insightful metafrontier Malmquist productivity index (MMPI) developed by Rao (2006). The extension adds the scale effect without assuming constant returns to scale by using the technique proposed by Orea (2002). The new model allows for conducting international comparisons of efficiency scores and productivity changes for banks that operate under different technologies. We find that the omission of the scale effect on average leads to an underestimation of the productivity growth.

Using the newly developed formulas, this paper aims to gain further insights on the productivity growth of Western European banks during the period of 1993 to 2006 and to broaden our capacity for identifying various components of the productivity growth. Most importantly, these components can provide useful information to managers, industry consultants, and regulators to assess performance, to adjust business strategies, and to enforce new regulation policy. The empirical application discloses that a representative bank in Western Europe sustains positive productivity growth after the financial markets become more competitive and integrated due to the creation of a single market in 1993. The productivity gains are stimulated by technical changes and scale efficiency change that justifies the significance of the scale effect in the evaluation of a bank's change in productivity. Overlooking the role played by the scale effect is likely to result in an underestimation for the measure of productivity change. Furthermore, there exists a strong catch-up in scale and Rao's catch-up effect in productivity growth.

The banks in 9 out of the 12 countries are confronted with productivity growth and scale efficiency gains and technical progress prevail in the vast majority of the sample states. However, the data fail to identify the prevalence of a positive change in technical efficiency in most of the countries under consideration. Larger banks seem to grow faster than smaller ones due to technology advancements and the enhancements in the scale of production, rather than a change in efficiency. Finally, a bank with a higher value of ETA is inclined to grow faster than a bank with a lower value of ETA. This result might be ascribable to the fact that risk-averse bank managers are frequently engaged in monitoring and supervising activities that help reduce the exposure of risks.

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References

Allen, L., & Rai, A. (1996). Operational efficiency in banking: An international comparison. *Journal of Banking and Finance*, *20*(4), 655–672.

Altunbaş, Y., Gardener, E. P. M., Molyneux, P., & Moore, B. (2001). Efficiency in European banking. *European Economic Review*, *45*(10), 1931–1955.

Balk, B. M. (2001). Scale efficiency and productivity change. *Journal of Productivity Analysis*, *15*(3), 159–183.

Barros, C. P., Peypoch, N., & Williams, J. (2010). A note on productivity change in European cooperative banks: The Luenberger indicator approach. *International Review of Applied Economics*, *24*(2), 137–147.

Barth, J. R., Caprio, G., Jr., & Levine, R. (2004). Bank regulation and supervision: What works best? *Journal of Financial Intermediation*, *13*(2), 205–248.

Barth, J. R., Caprio, G., Jr., & Levine, R. (2013). Bank regulation and supervision in 180 countries from 1999 to 2011? *Journal of Financial Economic Policy*, *5*(2), 119–219.

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, *20*(2), 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. *Journal of Productivity Analysis*, *21*(1), 91–103.

Beck, T., Demirguc-Kunt, A., & Levine, R. (2006). Bank supervision and corruption in lending. *Journal of Monetary Economics*, *53*(8), 2131–2163.

Berger, A. N., & Humphrey, D. B. (1997). Efficiency of financial institutions: International survey and directions for future research. *European Journal of Operational Research*, *98*(2), 175–212.

Berger, A. N., & Mester, L. J. (2003). Explaining the dramatic changes in performance of US banks: Technological change, deregulation, and dynamic changes in competition. *Journal of Financial Intermediation*, *12*(1), 57–95.

Berg, S. A., Førsund, F. R., & Jansen, E. S. (1992). Malmquist indices of productivity growth during the deregulation of Norwegian banking, 1980–89. *Scandinavian Journal of Economics*, *94*, 211–228.

Berg, S. A., Førsund, F. R., Hjalmarsson, L., & Suominen, M. (1993). Banking efficiency in the Nordic countries. *Journal of Banking and Finance*, *17*(2–3), 371–388.

Bos, J. W. B., & Schmiedel, H. (2007). Is there a single frontier in a single European banking market. *Journal of Banking and Finance*, *31*(7), 2081–2102.

Boucinha, M., Ribeiro, N., & Weyman-Jones, T. (2013). An assessment of Portuguese banks' efficiency and productivity towards euro area participation. *Journal of Productivity Analysis*, *39*(2), 177–190.

Casu, B., & Girardone, C. (2005). An analysis of the relevance of off-balance sheet items in explaining productivity change in European banking. *Applied Financial Economics*, *15*(15), 1053–1061.

Casu, B., & Molyneux, P. (2003). A comparative study of efficiency in European banking. *Applied Economics*, *35*(17), 1865–1876.

Casu, B., Girardone, C., & Molyneux, P. (2004). Productivity change in banking: A comparison of parametric and non-parametric approaches. *Journal of Banking and Finance*, *28*(10), 2521–2540.

Cavallo, L., & Rossi, S. P. S. (2002). Do environmental variables affect the performance and technical efficiency of the European banking systems? A parametric analysis using the stochastic frontier approach. *European Journal of Finance*, *8*(1), 123–146.

Chaffai, M. E., Dietsch, M., & Lozano-Vivas, A. (2001). Technological and environmental differences in the European banking industries. *Journal of Financial Services Research*, *19*(2–3), 147–162.

Chen, K. M., & Yang, H. Y. (2011). A cross-country comparison of productivity growth using the generalised metafrontier Malmquist productivity index: With application to banking industries in Taiwan and China. *Journal of Productivity Analysis*, *35*(3), 197–212.

Chortareas, G. E., Girardone, C., & Ventouri, A. (2013). Financial freedom and bank efficiency: Evidence from the European Union. *Journal of Banking and Finance*, *37*(4), 1223–1231.

Chortareas, G. E., Garza-García, J. G., & Girardone, C. (2011). Financial deepening and bank productivity in Latin America. *European Journal of Finance*, *17*(9–10), 811–827.

Chronopoulos, D. K., Girardone, C., & Nankervis, J. C. (2011). Are there any cost and profit efficiency gains in financial conglomeration? Evidence from the accession countries. *European Journal of Finance*, *17*(8), 603–621.

Coelli, T. J. (1996). A guide to FRONTIER version 4.1: A computer program for stochastic frontier production and cost function estimation. In *CEPA working papers no. 7/96*. Armidale: School of Economics, University of New England.

Curi, C., Guarda, P., Lozano-Vivas, A., & Zelenyuk, V. (2013). Is foreign-bank efficiency in financial centers driven by home or host country characteristics? *Journal of Productivity Analysis*, *40*(3), 367–385.

Delis, M. D., Molineux, P., & Pasiouras, F. (2011). Regulations and productivity growth in banking: Evidence from transition economies. *Journal of Money, Credit and Banking*, *43*(4), 735–764.

Denny, M., Fuss, M., & Waverman, L. (1981). The measurement and interpretation of total factor productivity in regulated industries with an application to Canadian telecommunications. In T. G. Cowing, & R. E. Stevenson (Eds.), *Productivity measurement in regulated industries* (pp. 179–218). New York, NY: Academic Press.

Dietsch, M., & Lozano-Vivas, A. (2000). How the environment determines banking efficiency: A comparison between French and Spanish industries. *Journal of Banking and Finance*, *24*(6), 985–1004.

Diewert, W. E. (1976). Exact and superlative index numbers. *Journal of Econometrics*, *4*(2), 115–145.

Färe, R., & Primont, D. (1995). *Multi-output production and duality: Theory and applications*. Boston, MA: Kluwer Academic.

Färe, R., Grosskopf, S., Norris, M., & Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *American Economic Review*, *84*(1), 66–83.

Fernandez, A. I., & Gonzalez, F. (2005). How accounting and auditing systems can counteract risk-shifting of safety-nets in banking: Some international evidence. *Journal of Financial Stability*, *1*(1), 466–500.

Goddard, J. A., Molyneux, P., & Wilson, J. O. S. (2001). *European banking: Efficiency, technology and growth*. Chichester: John Wiley and Sons.

Goldberg, L., & Johnson, D. (1990). The determinants of US banking activity abroad. *Journal of International Money and Finance*, *9*(2), 123–137.

Huang, T. H., Chiang, L. C., & Chen, K. C. (2011). An empirical study of bank efficiencies and technology gaps in European banking. *Manchester School*, *79*(4), 839–860.
Huang, T. H., Shen, C. H., Chen, K. C., & Tseng, S. J. (2011). Measuring technical and allocative efficiencies for banks in the transition countries using the Fourier flexible cost function. *Journal of Productivity Analysis*, *35*(2), 143–157.
Hughes, J. P., & Mester, L. J. (1998). Bank capitalization and cost: Evidence of scale economies in risk management and signaling. *Review of Economics and Statistics*, *80*(2), 314–325.
Kondeas, A. G., Caudill, S. B., Gropper, D. M., & Raymond, J. E. (2008). Deregulation and productivity changes in banking: Evidence from European unification. *Applied Financial Economics Letters*, *4*(3), 193–197.
Kumbhakar, S. C., & Lovell, C. A. K. (2000). *Stochastic frontier analysis*. Cambridge: Cambridge University Press.
Kumbhakar, S. C., & Wang, D. (2007). Economic reforms, efficiency and productivity in Chinese banking. *Journal of Regulatory Economics*, *32*(2), 105–129.
Lozano-Vivas, A., Pastor, J. T., & Hasan, I. (2001). European bank performance beyond country borders: What really matters? *European Finance Review*, *5*(1–2), 141–165.
Lozano-Vivas, A., Pastor, J. T., & Pastor, J. M. (2002). An efficiency comparison of European banking systems operating under different environmental conditions. *Journal of Productivity Analysis*, *18*(1), 59–77.
Murillo-Melchor, C., Pastor, J. M., & Tortosa-Ausina, E. (2010). A bootstrap approach to analyse productivity growth in European banking. *Journal of the Operational Research Society*, *61*(12), 1729–1745.
O'Donnell, C. J., Rao, D. S. P., & Battese, G. E. (2008). Metafrontier frameworks for the study of firm-level efficiencies and technology ratio. *Empirical Economics*, *34*(2), 231–255.
Orea, L. (2002). Parametric decomposition of a generalized Malmquist productivity index. *Journal of Productivity Analysis*, *18*(1), 5–22.
Pasiouras, F. (2008). International evidence on the impact of regulation and supervision on banks' technical efficiency: An application of two-stage data envelopment analysis. *Review of Quantitative Finance and Accounting*, *30*(2), 187–223.
Pastor, J. M., Pérez, F., & Quesada, J. (1997). Efficiency analysis in banking firms: An international comparison. *European Journal of Operational Research*, *98*(2), 395–407.
Rao, D. S. P. (2006). Metafrontier frameworks for the study of firm-level efficiencies and technology gaps. In *2006 Productivity and Efficiency Seminar*, March 10, Taipei.
Weill, L. (2004). Measuring cost efficiency in European banking: A comparison of frontier techniques. *Journal of Productivity Analysis*, *21*(2), 133–152.
Yang, C. H., & Chen, K. H. (2009). Are small firms less efficient. *Small Business Economics*, *32*(4), 375–395.