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A new approach to jointly estimating the Lerner index and cost efficiency for multi-output banks under a stochastic meta-frontier framework

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ABSTRACT

This paper proposes the copula-based simultaneous stochastic frontier model, composed of a cost frontier and two output price frontiers, for the banking sector in order to measure cost efficiency and market power in the markets of loans and investments. The new Lerner indices are estimated by the simultaneous equations model, consisting of three frontier equations, thus avoiding obtaining negative measures of the Lerner index. We apply the stochastic meta-frontier model of Huang et al. (2014) to estimate and compare cost efficiency and market power across five European countries over the period 1998–2010. Our approach allows for calculating the technology gap ratio and evaluating the potential Lerner indices, which consist of the Lerner index and marginal cost gap ratio. Empirical results suggest that banks reallocate their output quantities toward the one with a higher measure of the potential Lerner index in order to promote profits. Adopting advanced technology and conducting merger and acquisitions are effective ways to achieve this goal.

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1. Introduction

Banks in the member countries of the European Union (EU) have faced dramatic systematic changes aiming at liberalization of financial markets over the past two decades. The implementation of the Single Banking Market for retail banking services on January 1, 1993 noticeably lowered barriers to competition among European banks, as mergers and acquisitions (M&As) decreased the number of banks. The number of foreign banks in each country increased due to the removal of restrictions to foreign bank entry. Whether these financial reforms intensified banking competition and improved banking performance in the EU has drawn much attention from researchers.

The conventional [Lerner \(1934\)](#) index (henceforth, the old Lerner index) is a popular indicator of market power, ranging

between 0 (perfect competition) and 1 (pure monopoly). There are two potential problems associated with its measurement in existing studies. First, it may take a negative value for some observations, which lacks economic implications. This arises mainly from the fact that its calculation requires using output price and marginal cost (MC), but those variables are derived from two separate sources. One first estimates the standard translog cost function to derive MC by taking the partial derivative of the estimated cost function with respect to output quantity. Output price is directly computed as the ratio of total revenues to the corresponding output measure. The so-derived MC may exceed output price for some banks. Second, the estimation of market power usually fails to consider potential cost inefficiency, which is likely to severely bias the parameter estimates of the cost function and the subsequent calculation of MC. See, for example, [Berg and Kim \(1998\)](#), [Delis and Tsionas \(2009\)](#), and [Koetter and Poghosyan \(2009\)](#).

To our knowledge, no existing works address the correlation between market power and cost inefficiency. This paper proposes the use of the copula-based simultaneous stochastic frontier model (CSSFM), which is composed of three equations, i.e., a cost frontier

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and two price frontiers that relate output prices to individual MCs, to jointly examine the issues of market power and cost inefficiency. This means that banks are assumed to produce two (multiple) outputs, loans and investments, instead of a single output like the related works do, thus escaping from the aggregation problem that arises from the single output model. Our model requires the joint estimation of a cost frontier with two output price frontiers, leading to consistent parameter estimates. The estimated cost frontier can then be used to assess the cost efficiency, and the estimated two price equations can be used to calculate the new Lerner indices of the two outputs for each bank. The measures of cost efficiency and the new Lerner indices are yielded simultaneously. The salient feature of this procedure is that the resultant Lerner index measures will be non-negative for each bank, since these measures are internally built into the simultaneous equations model and treated as if they are inefficiency terms. Note that the adoption of the joint estimation procedure is able to improve the efficiency of the parameter estimates.

This paper also generalizes the three equations model for a single country to the stochastic meta-frontier framework of Huang, Huang, and Liu (2014), which is suitable for comparisons of bank efficiency and market power across countries. We simultaneously estimate the stochastic meta-cost frontier and two meta-MC frontiers. The former enables us to evaluate technology gap ratios (TGRs), and the latter measures the MC gaps for each bank. This study also employs the mixed approach of Battese, Rao, and O'Donnell (2004) and O'Donnell, Rao, and Battese (2008) to assess TGRs for the purpose of a comparison. Note that the mixed approach is performed under the single equation (cost function) framework.

Since our meta-MC frontiers envelop group MC frontiers, we can gauge the MC gaps between them, which are analogous to TGR. The MC gap ratio (MCGR) of an output is thus defined as the ratio of the MC gap to the corresponding output price, which represents a bank's potential profitability. An efficient bank operating under a superior production technology has a smaller value of MCGR and is closer to the meta-MC frontier than a less efficient bank that has a larger value of MCGR and is farther apart from the meta-MC frontier.

The purpose of this paper is three-fold. First, we develop a three-equation model in the context of multiple outputs, which enables us to jointly estimate measures of technical efficiency and the Lerner indices. This appears to be a novel idea in the literature. Second, a joint estimation procedure of market power and cost efficiency is applied to yield the Lerner indices of various outputs for individual banks, thus solving the potential problem of a negative value in the Lerner index. Finally, we employ a new two-step SFA to simultaneously estimate the meta-cost frontier and two meta-MC frontiers, allowing us to compare bank efficiency, market power of different outputs, and profitability across countries, respectively.

The rest of the paper is organized as follows. Section 2 briefly reviews some relevant studies. Section 3 formulates the simultaneous equations suitable for estimating the cost and price frontiers, followed by deriving their joint probability density function (PDF) using the copula method. We also introduce the meta-cost frontier and MCGR. Section 4 briefly describes the data and variable definitions. Section 5 conducts the empirical study, while the last section concludes the paper.

2. Literature review

2.1. Market competition

There are two main approaches to measuring the market power of the banking industry in the literature: structure and non-structure. The structure approach is based on the Structure-Conduct-Performance (SCP) paradigm, which posits that market

structure affects a bank's behavior, which in turn determines its performance. Banks in a more concentrated market are inclined to be more collusive and thereby are less efficient. Several market concentration measures have been used to proxy for the measure of market competition, including market shares, concentration ratios for the largest firms (CR ratios), and the Herfindahl–Hirschman index (HHI). See, for example, Alegria and Schaeck (2008), Beck, Demirgüç-Kunt, and Levine (2006), and Berger, Demirgüç-Kunt, Levine, and Haubrich (2004). The structure approach has some disadvantages. For example, the CR ratio ignores the influences of smaller firms, and HHI is subject to the control of a few large firms. In addition, market concentration measures fail to consider the effect of regulation on a banking sector.

According to the new empirical industrial organization (NEIO) theory, the non-structure method relies on the direct observation of a firm's behavior and uses econometric models to estimate the degree of competition. Bresnahan (1982) and Lau (1982) examine banks' behavior on an aggregate level and estimate the average conjectural variation of banks, which lies between zero (perfect competition) and unity (monopoly). Panzar and Rosse (1987) are the first to develop the H-statistic (henceforth the PR model), based on the idea that market power can be gauged by the extent to which changes in input prices are reflected by the equilibrium revenues received by a specific firm. The H-statistic is equal to the sum of the elasticities of the reduced-form (log) gross revenues with respect to the (log) input prices. A negative H-statistic value corresponds to monopoly or perfect collusion, while a unitary value of it implies perfect competition. If its value ranges between zero and unity, then the market under study is either oligopoly or monopolistic competition. See, for example, Casu and Girardone (2006), Bikker and Haaf (2002), De Bandt and Davis (2000), Molyneux, Lloyd-Williams, and Thornton (1994), Molyneux, Thornton, and Lloyd-Williams (1996), and Turk-Ariss (2009). The PR model is also subject to two drawbacks: (1) one can only estimate a single H-statistic for the whole sample, rather than for each observation; (2) Bikker, Shaffer, and Spierdijk (2012) prove that the H-statistic fails to properly measure the degree of market competition in some circumstances.

Boone, van Ours, and van der Wiel (2007) develops the self-named Boone indicator, defined as the percentage fall in profits due to a percentage increase in marginal costs. The essential insight is that in a more competitive market, firms are punished more harshly (in terms of profits) for being inefficient. The larger the absolute value is of the Boone indicator, the stronger is the competition. This indicator is associated with the efficiency hypothesis (EH), which asserts that more efficient firms have better performance and gain larger market shares. See, for example, Boone et al. (2007) and Van Leuvensteijn, Bikker, van Rixtel, and Sorensen (2011), Van Leuvensteijn, Sorensen, Bikker, and van Rixtel (2013).

Ever since 2000, many researchers adopt the conventional Lerner index to explain the competition behavior among banks. This index reflects a bank's ability to set its output price over MC, which is positively related to the firm's market power. Many empirical researchers have applied the Lerner index to investigate the degree of competition, particularly in banking industries of various countries. The higher the Lerner index is, the larger the difference will be between output price and MC and hence a bank's stronger market power. Under the condition of perfect competition, profit maximization banks must set output price to be equal to MC, so that the Lerner index is equal to zero. Conversely, a monopolist can charge an output price over MC, and in the extreme case the Lerner index is equal to unity. If the value of the Lerner index lies between zero and unity, then the market is either oligopoly or monopolistic competition. Different from the H-statistic and Boone indicator, the merit of the Lerner index is that one can evaluate one value for each sample. See, for example, Angelini and Cetorelli (2003) for Italian banks, Berger, Klapper, and Turk-Ariss (2009) for the case of

23 different countries, Turk-Ariss (2010) for developing countries, Williams (2012) for Latin American banks, and Koetter, Kolari, and Spierdijk (2012) for U.S. banks.

Using the H statistic of the Panzar and Rosse (1987) approach, De Bandt and Davis (2000) confirm that right before the adoption of the Single Currency by the European Monetary Union the banking industries in the U.S., France, Germany, and Italy were operating under imperfect competition. Casu and Girardone (2006) conclude that the banking markets of the European Union can be characterized by monopolistic competition during 1997–2003. Schaeck, Cihak, and Wolfe (2009) employ the H statistic as a measure of competition in 45 countries and find that more competitive banking systems are less likely to undergo a systemic crisis after relying on the duration model. The empirical results of Huang and Liu (2014) support that, over the period 1994–2008, a majority of the banking markets in 17 Central and Eastern European countries experience rising H statistics and are operating under monopolistic competition.

Fernández de Guevara and Maudos (2007) find that the value of the Lerner index in Spain's banking system rises from 0.2 in 1986 to 0.25 in 2002, corresponding to monopolistic competition. Compiling banking data from 14 European countries over 1995–2001, Carbó, Humphrey, Maudos, and Molyneux (2009) obtain the mean value of the Lerner index ranging between 0.11 (Germany) and 0.22 (Denmark). Fernández de Guevara, Maudos, and Pérez (2005) examine the evolution of market power in the banking sector of five main European countries spanning the period 1992–1999. The average value of the Lerner index is found to be equal to 0.1 with a growing trend.

2.2. A meta-frontier model

There are two main approaches to measuring a firm's technical efficiency in the literature: parametric and non-parametric. Aigner, Lovell, and Schmidt (1977) as well as Meeusen and van den Broeck (1977) are the first to introduce the former, by measuring the deviation of a firm's actual output (cost or profit) level from that of the best-practice firm. Numerous researchers have popularly applied this method to evaluate banks' efficiency scores, e.g., Akhigbe and Stevenson (2010), Altunbas, Gardener, Molyneux, and Moore (2001), Berger et al. (2009), Fitzpatrick and McQuinn (2008), Huang (2000), Kasman and Yildirim (2006), and Koutsomanoli-Filippaki, Mamatzakis, and Staikouras (2009), to name a few. Charnes, Cooper, and Rhodes (1978) are the first to propose the latter approach, which involves mathematical programming techniques and assumes constant returns to scale (CRS). Banker, Charnes, and Cooper (1984) suggest an extension of the CRS DEA model to take variable returns to scale into account.

The previous studies on the comparisons of technical efficiency among different groups (or countries) do not take the differences in regulation, supervision, and technology adopted into account, which affect bank efficiency. To compare this efficiency across countries, Altunbas et al. (2001) and Vennet (2002) estimate a common frontier for all banks in different countries and compute efficiency scores against the common frontier. This procedure implicitly assumes that all sample banks from different countries undertake the same production technology. Such a strong assumption may result in undesirable consequences on parameter estimates and the measures of scale, scope, and technical efficiencies.

Battese et al. (2004) and O'Donnell et al. (2008) solve the foregoing problem by proposing a meta-frontier production function model (henceforth, the old meta-frontier), which is constructed on the basis that all firms have potential access to the same production technology, but each may choose a different process, relying on specific circumstances, such as regulation, various environments, production resources, and relative input prices. To find the

meta-frontier production function, they propose a mixed two-step procedure, in which SFA is first used to estimate the group-specific frontier and then the mathematical programming techniques are employed to estimate the meta-frontier that is used to compute TGR. See, for example, Bos and Schmiedel (2007), Chen and Yang (2011), and Huang, Chiang, and Chen (2011).

Bos and Schmiedel (2007) specifically collect a dataset of large commercial banks from 15 European countries over the period 1993–2004 to judge the existence of a single and integrated European banking market under the framework of the translog meta-frontiers. Evidence is found in favor of a single European banking market, as the average TGRs, measured against the cost and profit meta-frontiers, are close to unity in all the sample countries. Huang et al. (2011) compile banking data from nine European countries covering 1994–2003 and apply the Fourier flexible cost function to study differences in technical efficiency and TGRs across the sample banks in different countries. The mean technical efficiency scores for the sample nations lie between 0.73 and 0.98 and the mean TGRs range from 0.51 to 0.62, suggesting that many banks are operating off the meta-cost frontier. This result is inconsistent with that of Bos and Schmiedel (2007).

There are two potential disadvantages for estimating the meta-frontier model in the two-step mixed approach. The meta-frontier estimators have no statistical properties, as these results derive from the second-step estimation with mathematical programming techniques. Moreover, potential production environment conditions fail to be taken into account in the meta-frontier estimation. The difficulty is addressed by Huang et al. (2014), who propose a novel two-step SF approach to estimating the meta-frontier production function (henceforth, the new meta-frontier). The main difference between the new two-step SF approach and that of Battese et al. (2004) and O'Donnell et al. (2008) is that the former's second-step estimation of the meta-frontier is under the SF framework rather than depending on the mathematical programming technique. The new stochastic meta-frontier (SMF) regression has the following advantages. The estimated parameters of SMF using the conventional maximum likelihood (ML) method have the usual statistical properties. Moreover, TGR can be specified as a function of potential exogenous variables to capture group-specific environmental differences.

3. Methodology

3.1. Simultaneous equations model of the cost and price frontiers

We specify here a bank's cost frontier as the standard translog form:

$$\ln C = \alpha_0 + \sum_{k=1}^3 \alpha_k \ln Y_k + \sum_{m=1}^3 \beta_m \ln W_m + \frac{1}{2} \left(\sum_{k=1}^3 \sum_{h=1}^3 \delta_{kh} \ln Y_k \ln Y_h + \sum_{m=1}^3 \sum_{n=1}^3 \gamma_{mn} \ln W_m \ln W_n \right) + \sum_{k=1}^3 \sum_{m=1}^3 \rho_{km} \ln Y_k \ln W_m + \sum_{k=1}^3 \phi_k T \ln Y_k + \sum_{m=1}^3 \theta_m T \ln W_m + \varphi_1 T + \frac{1}{2} \varphi_2 T^2 + \varepsilon_3, \quad (1)$$

where C represents the bank's actual expenditures, $Y_k (k = 1, 2, 3)$ stands for the output quantities, including loans, investments, and non-interest income, and $W_m (m = 1, 2, 3)$ corresponds to the input prices of labor, physical capital, and borrowed funds, respec-

tively. Notation T represents the time trend, and $\varepsilon_3 = v_3 + u_3$ is the composite error term, in which random variable $v_3 \sim N(0, \sigma_{v_3}^2)$ is assumed to be statistically independent of the technical inefficiency term of $u_3 \sim N(0, \sigma_{u_3}^2) |$. We impose some restrictions, such as symmetry and homogeneity of degree one in input prices, on Eq. (1) before performing any estimation.

Once the unknown parameters of Eq. (1) are estimated, we can derive the implied MC function for the two outputs by taking the partial derivatives of Eq. (1) with respect to Y_1 and Y_2 , respectively.¹ We write the implied MC functions as:

$$MC_k = \frac{\partial \ln C}{\partial \ln Y_k} \frac{C}{Y_k}, \quad k = 1, 2. \quad (2)$$

The traditional Lerner index is defined as the ratio of the disparity between a firm's output price (P) and its MC to the output price, i.e., $L^{old} Y_k = (P_k - MC_k) / P_k, k = 1, 2$. The so-derived measures of the Lerner index are likely to be negative for some observations, indicating that these firms set their output prices below MC. This is inconsistent with the assumption of firms' profit maximization behavior.

In compliance with the principle of profit maximization, a profit maximizing firm decides to produce an output level at which the marginal revenue (MR) of selling the last unit of the output is equal to that unit's MC. Therefore, the inequality of $P \geq MR = MC$ must hold in equilibrium, which can be transformed into an equality by adding a composite error $\varepsilon_i = v_i + u_i$:

$$P_i = MC_i + \varepsilon_i, \quad i = 1, 2, \quad (3)$$

where $v_i \sim N(0, \sigma_{v_i}^2), i = 1, 2$, denotes the random disturbance, capturing the statistical noises uncontrollable by firms, and $u_i \sim |N(0, \sigma_{u_i}^2) |, i = 1, 2$, measures the gap between the output price and MC. Both v_i and u_i are mutually independent of each other. Variable $u_i, i = 1, 2$, can be treated like a firm's technical inefficiency term, and hence it can be estimated by taking the conditional expectation of $E(u_i | \varepsilon_i)$, which is similar to the computation of technical inefficiency. The larger the discrepancy is, the greater ability the firm has to exercise its market power to set the output price farther over MC, and the higher profit it can earn.

We propose to simultaneously estimate Eqs. (1) and (3) under the assumption that ε_i 's, $i = 1, 2, 3$, have a joint distribution, which is justified by the fact that bank managers usually make decisions on the employment of inputs together with output prices and quantities. Such an interrelationship can only be embodied under the framework of a simultaneous equations model. Since the composite error of ε_i is a skewed normal, it is difficult to deduce their joint PDF. Following Lai and Huang (2013), our paper suggests using copula methods to overcome the problem. See the next sub-section for details. Differing from the traditional Lerner index, our new Lerner index is calculated by $L^{new} = E(u | \varepsilon) / P \geq 0$, which must be non-negative since $u \geq 0$ by construction.

Compared with the conventional one, the new Lerner index has several advantages. First of all, the new Lerner index is certified to be non-negative since we impose the condition on the inequality $P \geq MC$ of Eq. (3). Second, we employ a joint estimation of market power and cost efficiency at the individual bank level by the ML method so that the estimated parameters are more efficient and at the same time the new Lerner index takes cost efficiency into account. Finally, the random shocks have less effect on the new Lerner index, which allows for the presence of v_i in separation from MC.

¹ Due to the lack of price information for non-interest income (Y_3), the corresponding Lerner index fails to be computed. Therefore, we do not derive the implied MC of Y_3 .

3.2. The copula-based joint PDF and the likelihood function

Eqs. (1) and (3) form a three equations seemingly unrelated stochastic frontier model. Let $\theta_j = (\beta_j^T, \sigma_{vj}, \sigma_{uj})^T, j = 1, 2, 3$, be a vector of parameters in the j^{th} regression equation, and $F_j(\varepsilon_j) = F(\varepsilon_j; \theta_j)$ is the marginal cumulative distribution function (CDF) of the composite error ε_j . There are two ways of deriving the approximate CDF of ε_j . One of them is proposed by Greene (2003, 2010), who uses the simulated ML to approximate the integration in computing $F_j(\varepsilon_j)$. Alternatively, the current paper derives a closed-form formula to approximate CDF of ε_j , based on Tsay et al. (2013) Tsay, Huang, Fu, and Ho (2013). According to Sklar's (1959) theorem, the joint CDF of the composite errors $\varepsilon = (\varepsilon_1, \varepsilon_2, \varepsilon_3)^T$ is expressed as: $F(\varepsilon_1, \varepsilon_2, \varepsilon_3) = C(F_1(\varepsilon_1), F_2(\varepsilon_2), F_3(\varepsilon_3) | \rho)$, where $C(\cdot)$ is a unique copula function if $F_1(\cdot)$ to $F_3(\cdot)$ are all continuous, and ρ is a vector of dependence parameters of the copula, which measures dependence between the marginal CDFs of $F_j(\cdot)$'s, $j = 1, 2, 3$.

We yield the joint PDF of ε by taking the partial derivatives of $F(\cdot)$ with respect to $(\varepsilon_1, \varepsilon_2, \varepsilon_3)$, i.e., $f(\varepsilon_1, \varepsilon_2, \varepsilon_3) = c(F_1(\varepsilon_1), F_2(\varepsilon_2), F_3(\varepsilon_3) | \rho) \times \prod_{j=1}^3 f_j(\varepsilon_j)$. Here, $c(\cdot)$ is the copula density function, and $f_j(\varepsilon_j), j = 1, 2, 3$, is the marginal probability density function (PDF). Following Lai and Huang (2013), this article selects the Gaussian copula to derive the 3-dimensional CDF, which takes the form:

$$\begin{aligned} C(F_1(\varepsilon_1), F_2(\varepsilon_2), F_3(\varepsilon_3) | \Omega) &= \Phi_3(\Phi^{-1}(F_1(\varepsilon_1)), \Phi^{-1}(F_2(\varepsilon_2)), \Phi^{-1}(F_3(\varepsilon_3)) | \Omega) \\ &= \int_{-\infty}^{\Phi^{-1}(F_1(\varepsilon_1))} \int_{-\infty}^{\Phi^{-1}(F_2(\varepsilon_2))} \int_{-\infty}^{\Phi^{-1}(F_3(\varepsilon_3))} \frac{1}{(2\pi)^{3/2} |\Omega|^{1/2}} \\ &\quad \exp\left[-\frac{1}{2} Z^T \rho^{-1} Z\right] dZ_1 dZ_2 dZ_3 \end{aligned} \quad (4)$$

Here, $\Phi^{-1}(\cdot)$ is the inverse of CDF of the standard normal distribution function, and Φ_3 is a 3-dimensional multivariate standard normal distribution function with the 3×3 correlation matrix Ω , whose diagonal elements (Ω_{jj}) are all equal to unity, and the off-diagonal elements (Ω_{jk}) are the correlation coefficients between the j^{th} and k^{th} variables. The corresponding Gaussian copula density function of Eq. (4) is written as:

$$c(F_1(\varepsilon_1), F_2(\varepsilon_2), F_3(\varepsilon_3) | \Omega) = \frac{1}{|\Omega|^{1/2}} e^{-\frac{1}{2} \xi^T (\Omega^{-1} - I_3) \xi}, \quad (5)$$

where $\xi = (\Phi^{-1}(F_1(\varepsilon_1)), \Phi^{-1}(F_2(\varepsilon_2)), \Phi^{-1}(F_3(\varepsilon_3)))^T$, and I_3 is a 3×3 identity matrix. This leads us to get the log-likelihood function of the simultaneous SFA model for a sample of N observations as:

$$\begin{aligned} \ln L(\theta) &= \sum_{i=1}^N \ln c[F_1(\varepsilon_{1i}), F_2(\varepsilon_{2i}), F_3(\varepsilon_{3i}) | \Omega] \\ &+ \sum_{i=1}^N \sum_{j=1}^3 \ln f_j(\varepsilon_{ji}) = -\frac{N}{2} \ln |\Omega| - \frac{1}{2} \sum_{i=1}^N \xi_i^T (\Omega^{-1} - I_3) \xi \\ &+ \sum_{i=1}^N \sum_{j=1}^3 \ln f_j(\varepsilon_{ji}) \end{aligned} \quad (6)$$

Here, $\theta = (\theta_1^T, \theta_2^T, \theta_3^T, \rho^T)^T$, and θ_j are the vectors of unknown parameters of the j^{th} SFA regression equation.

The ML estimation of Eq. (6) requires using $f_j(\varepsilon_{ji})$ and its CDF $F_j(\varepsilon_{ji})$. We already know PDF of $f_j(\varepsilon_{ji})$ as:

$$f_j(\varepsilon_{ji}) = \frac{2}{\sigma_j} \varphi\left(\frac{\varepsilon_{ji}}{\sigma_j}\right) \Phi\left(\frac{\varepsilon_{ji} \lambda_j}{\sigma_j}\right), \quad j = 1, 2, 3, \quad (7)$$

where $\lambda_j = \sigma_{uj}/\sigma_{vj}$ and $\sigma_j = \sqrt{\sigma_{vj}^2 + \sigma_{uj}^2}$. Since $f_j(\varepsilon_{ji})$ has no closed-form, its CDF of $F_j(\varepsilon_{ji})$ cannot be exactly deduced. We obtain an approximate closed-form formula for CDF of $F_j(\varepsilon_{ji})$ in line with Tsay et al. (2013). Here, CDF can be alternatively written as (ignore subscript j for the time being):

$$F(Q_i) = \int_{-\infty}^{Q_i} f(\varepsilon_i) d\varepsilon_i = \frac{2}{\sigma} \int_{-\infty}^{Q_i} \left[\int_{-\infty}^{a\varepsilon_i} \phi(\zeta) d\zeta \right] \phi(b\varepsilon_i) d\varepsilon_i = \frac{2}{\sigma} I(Q_i), \quad (8)$$

in which $a = \lambda/\sigma$ and $b = 1/\sigma$. The derivation of the approximate function to $I(Q_i)$, $I_{app}(Q_i)$, is more involved and tedious, which can be expressed as:

$$I_{app}(Q_i) = \frac{\operatorname{erf}\left(\frac{bQ_i}{\sqrt{2}}\right)}{2b} \frac{1 + \operatorname{sign}(Q_i)}{2} + \frac{1}{4\sqrt{b^2 - a^2c_2}} \exp\left(\frac{a^2c_1^2}{4(b^2 - a^2c_2)}\right) \left\{ 1 - \operatorname{erf}\left(\frac{-ac_1 + \sqrt{2}Q_i(b^2 - a^2c_2)\operatorname{sign}(Q_i)}{2\sqrt{b^2 - a^2c_2}}\right) \right\}, \quad (9)$$

where $\operatorname{erf}(z) = \frac{2}{\sqrt{\pi}} \int_0^z e^{-t^2} dt = 2 \int_0^{\sqrt{2}z} \phi(t) dt$, and the sign function takes the values of $\operatorname{sign}(Q_i) = 1, 0, \text{ or } -1$, as $Q_i >, =, \text{ or } < 0$.

Tsay et al. (2013) find the two constants $c_1 = -1.09500814703333$ and $c_2 = -0.75651138383854$ by simulation, which is able to ensure that the error function $\operatorname{erf}(z)$ can be precisely approximated by the function of $g(z) = 1 - \exp(c_1z + c_2z^2)$, for $z \geq 0$. When performing the empirical study, $I(Q_i)$ and $F(Q_i)$ are replaced by their respective approximation functions, i.e., $I_{app}(Q_i)$ and $F_{app}(Q_i)$, which is defined by $F_{app}(Q_i) = \frac{2}{\sigma} I_{app}(Q_i)$. Tsay et al. (2013) conduct Monte Carlo simulations and demonstrate that $F(Q_i)$ can be accurately approximated by $F_{app}(Q_i)$.

3.3. Meta-frontier cost function

The joint estimation of Eqs. (1) and (3) for each country allows one to calculate the country-specific cost efficiency and the new Lerner index, L^{new} . We now turn our attention to the meta-frontier and briefly introduce the mixed approach of Battese et al. (2004) and O'Donnell et al. (2008). They first use the ML estimation to estimate each country-specific frontier in Eq. (1), and then the meta-frontier function is obtained by solving the liner programming (LP) problem or the quadratic programming (QP) problem.²

Using mathematical programming techniques to compute the meta-frontier leads to two potential problems, as mentioned above. To disentangle these problems in the second step we extend the new meta-frontier model of Huang et al. (2014), which is a single equation framework, to the simultaneous equations SFA model containing three equations, rather than two equations like Lai and Huang (2013). We now briefly describe below the construction of the meta-frontier cost and the corresponding MC regression equations.

In the first step we estimate each country-specific frontier. Eq. (1) can be rewritten as:

$$\ln C = \ln f_j + \varepsilon_{3j} = \ln \hat{f}_j + \hat{\varepsilon}_{3j} \quad j = 1, \dots, 5, \quad (10)$$

where j denotes the j^{th} group, $\ln \hat{f}_j$ is the fitted values of $\ln f_j$, and $\hat{\varepsilon}_{3j}$ is the residual. Eq. (10) can be reformulated as:

$$\ln \hat{f}_j - \ln f_j = \varepsilon_{3j} - \hat{\varepsilon}_{3j} = V^M, \quad (11)$$

where $V^M \sim N(0, \sigma_v^{M2})$ is the estimated error. In the second step, the relation between country j 's frontier and the meta-frontier cost function is:

$$\ln f_j = \ln f^M + U^M, \quad (12)$$

where the non-negative component $U^M \sim |N(0, \sigma_u^{M2})|$ represents the gap between the country-specific frontier and the meta-frontier and is assumed to be a half-normal random variable. Plugging Eq. (11) into Eq. (12), we obtain:

$$\ln \hat{f}_j = \ln f^M + V^M + U^M. \quad (13)$$

Eq. (13) is similar to the conventional stochastic frontier model and hence is called the stochastic meta-frontier regression equation. The symmetric error V^M and U^M are assumed to be independent of each other.

We can deduce the corresponding meta-frontier MC function of output k , MC_k^M , by taking the partial derivative of the meta-frontier cost function, f^M , with respect to the k^{th} ($k = 1, 2$) output quantity. Note that MC_k^M should envelop all individual country-specific MC frontiers of the same product. Country j 's MC frontier of output k , MC_k^j , is associated with MC_k^M as follows:

$$MC_k^j = MC_k^M + U_k^M, \quad (14)$$

where $U_k^M \geq 0$ stands for the gap between country j 's MC frontier and MC_k^M . We re-write Eq. (3) by deleting the subscript i and adding the subscript k and superscript j as:

$$P_k^j = MC_k^j + \varepsilon_k^j = M\hat{C}_k^j + \hat{\varepsilon}_k^j, \quad (15)$$

where $M\hat{C}_k^j$ is the estimated MC of the j^{th} group in the first step. Eq. (15) implies that $M\hat{C}_k^j - MC_k^j = \varepsilon_k^j - \hat{\varepsilon}_k^j = V_k^M$, where V_k^M denotes the estimation error. Eq. (14) can then be reformulated as:

$$M\hat{C}_k^j = MC_k^M + U_k^M + V_k^M, \quad (16)$$

where U_k^M and V_k^M are assumed to be independent of each other and regarded as if they are a composed error term. Term U_k^M is the MC gap that will be used to compute the MC gap ratio (MCGR).

In the second step we simultaneously estimate the three stochastic frontiers of Eqs. (13) and (16) by ML. The estimation of the meta-frontier cost function enables one to compute the technology gap ratio (TGR). TGR evaluates the size of the technology gap for country j , whose currently available technology lags behind the potential technology available for all countries, as illustrated by the meta-frontier cost function. The larger the value of TGR is, the more advanced the technology is that the country has adopted. We define the overall technical efficiency, $\hat{C}\hat{E}^M$, against the meta-frontier cost function by the product of TGR and country-specific technical efficiency, $\hat{C}\hat{E}$:

$$\hat{C}\hat{E}^M = T\hat{G}\hat{R} \times \hat{C}\hat{E} = E\left(e^{-U^M} | \hat{U}^M + \hat{V}^M\right) \times E\left(e^{-u_3} | \hat{\varepsilon}_3\right). \quad (17)$$

Since the estimated TGR and CE are always less than or equal to unity, $\hat{C}\hat{E}^M$ must be less than or equal to unity.

² Readers can refer to Battese et al. (2004) and O'Donnell et al. (2008) for a more detailed description.

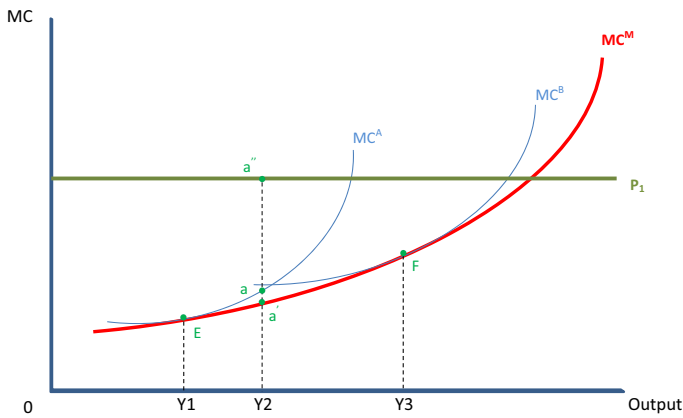


Fig. 1. Measuring the potential Lerner index.

The estimation of Eq. (16) enables one to measure MCGR by the ratio of the MC gap to the output price, which signifies a bank's potential profitability:

$$MCGR = \frac{E(U_k^M | \hat{V}_k^M + \hat{U}_k^M)}{P_k^j} \quad (18)$$

The potential Lerner index of output k for each bank, which is defined by $(P_k^j - MC_k^M) / P_k^j$, can be shown to be the sum of the new Lerner index and the MC gap ratio and written as follows:

$$Lerner_{k,j}^p = \frac{E(U_k^j | \hat{V}_k^j + \hat{U}_k^j)}{P_k^j} + \frac{E(U_k^M | \hat{V}_k^j + \hat{U}_k^j)}{P_k^j} = L_{k,j}^{new} + MCGR \quad (19)$$

Note that $L_{k,j}^{new}$ is empirically calculated in the first estimation step after simultaneously estimating Eqs. (1) and (3) for country j . An efficient bank adopting a superior production technology can reduce its production cost and MC more than a less efficient bank, thus earning more profit in a competitive market. The more advanced the technology a country adopts, the lower the country-specific MC is and the smaller the MCGR, and so the more potential profit a bank can make.

Fig. 1 illustrates Eq. (19) in the context of a single output, where two group MC curves are drawn, denoted by MC^A and MC^B , respectively, together with the meta-MC curve, denoted by MC^M , which envelops MC^A and MC^B . The current output price is P_1 . MC^A (MC^B) is assumed to be tangent to MC^M at point E (F), indicating that the bank located at E (F) producing output level Y_1 (Y_2) adopts the potential technology, whose MCGR is equal to zero and the potential Lerner index is the same as the new Lerner index. The potential Lerner index of bank a in group A is calculated as the sum of L^{New} (aa'' / P_1) and MCGR ($a'a / P_1$), i.e., $a'a'' / P_1$. The larger the MCGR is of a bank, the greater the possibility that it can increase market power and profit by adopting superior technology and producing on the meta-MC curve. We suggest that a comparison of market power between groups (countries) be conducted under the framework of the meta-MC curve, i.e., the potential Lerner index, $Lerner^p$, is the appropriate measure, instead of the group-specific new Lerner index, L^{New} . This is attributed to the fact that $Lerner^p$ of different banks from distinct groups is evaluated on the basis of the same MC^M , while L^{New} is evaluated on the basis of heterogeneous benchmarks, i.e., MC^A or MC^B .

4. Data description

We compile data mainly from the balance sheets and income statements of the Bankscope database for five west European countries: France, Germany, Italy, Luxembourg, and Switzerland. We exclude the UK and Spain due to their lack of complete output price information. All the accounting data are automatically transformed into nominal US dollars by the databank and are further deflated by the consumer price indices of the individual countries with base year 2005. The data consist of 725 commercial banks with a total of 4455 bank-year observations spanning from 1998 to 2010.

Following the intermediation approach, we identify three inputs and three outputs. The three inputs are labor, physical capital, and borrowed funds. The price of labor is calculated as the ratio of personnel expenses to total assets (TA).³ The price of physical capital is identified as the ratio of non-interest expenses minus personnel expenses to physical capital. The price of borrowed funds is defined as the ratio of interest expenses to all deposits and borrowed money. The total costs are the sum of expenditures on the three inputs, i.e., the total of personnel expenses, non-interest expenses minus personnel expenses, and interest expenses.

Total loans and investments are regarded as the conventional outputs. The ratios of their respective revenues to the corresponding outputs are defined as their prices. Interest income is the sum of loan income and investment income. We define non-interest income as the third output, as it represents a universal bank's degree of product diversification and becomes a critical source of revenue for modern commercial banks. Obviously, its price is unavailable. We also want to investigate the Lerner index of TA (a single output case), whereby the price of TA is defined as the ratio of total revenues (interest and non-interest income) to TA. Table 1 reports the descriptive statistics for all variables in the five sample countries, showing that there are considerable differences in the means and standard deviations and implying that the sample banks in the five countries are likely to adopt different production technologies to produce various outputs. It is thus invalid to directly compare the performance of those banks in different countries as they have distinct benchmarks. The meta-frontier model may be preferable.

5. Empirical results

This paper employs CSSFM, consisting of a cost frontier and two output price frontiers of loans and investments, in the first and second steps to estimate the individual group frontiers and the meta-frontiers for the commercial banks of the five EU states. The meta-frontier cost function model divides CE^M into CE and TGR and permits us to gain further insights on the sources of a bank's cost inefficiencies. This provides more regulatory and managerial implications to government authorities, business consultants, and bank managers. The meta-frontier price function can be similarly split into two parts: the Lerner index measure and MCGR, which reflects a bank's potential profitability.

5.1. Parameter estimates

We jointly estimate Eqs. (1) and (3) for each individual country to obtain the parameter estimates of the group frontiers with the results listed in Table 2. We also estimate the single cost frontier without jointly considering the price equation, presenting the results in Table 3. The number of parameter estimates of the cop-

³ Since the data on the number of employees are either missing or unavailable for many sample banks, the item of total assets is used as a proxy for the number of employees. Altunbas et al. (2001) and others utilize the same definition.

Table 1
 Descriptive statistics.

Variables	FRA	GER	ITA	LUX	SWI
Loans*	11052.8449 (43293.5013)	14320.4684 (60359.8403)	10294.6162 (29568.0407)	1748.1182 (3504.0127)	4292.1085 (29698.8148)
Investments*	18175.7162 (81581.7124)	17858.7505 (90047.6587)	8600.7110 (35852.4283)	5527.8754 (9888.0329)	5640.2340 (50364.0868)
Non-interest revenue*	268.0048 (997.9901)	294.3079 (1442.5626)	258.0840 (746.6936)	57.2079 (94.6002)	162.6026 (1307.9367)
Labor (TA)*	36029.1722 (160851.2775)	38585.2952 (198532.2096)	20263.7810 (64249.2606)	7595.4882 (13034.3419)	11428.0054 (92553.3368)
Physical capital*	79.5134 (311.2670)	71.9536 (262.8593)	132.5649 (394.9989)	21.2113 (52.4468)	57.6915 (381.9769)
Borrowed funds*	23386.7879 (98542.5932)	26441.5981 (122127.8204)	11915.3287 (33825.2851)	6314.1950 (10624.2919)	9337.8418 (75852.4448)
Price of labor	0.0164 (0.0124)	0.0148 (0.0149)	0.0144 (0.0091)	0.0069 (0.0082)	0.0208 (0.0223)
Price of physical capital	5.9739 (9.7181)	5.4659 (8.7270)	4.4915 (9.0339)	5.2759 (8.1748)	3.0691 (7.1345)
Price of borrowed funds	0.0456 (0.0524)	0.0394 (0.0346)	0.0342 (0.0437)	0.0529 (0.0595)	0.0232 (0.0203)
Price of loans	0.0669 (0.0471)	0.0412 (0.0245)	0.0541 (0.0250)	0.2749 (0.2190)	0.0733 (0.0969)
Price of investments	0.0857 (0.1851)	0.0190 (0.0152)	0.0451 (0.0501)	0.0155 (0.0169)	0.0136 (0.0105)
Price of total assets	0.0763 (0.0394)	0.0716 (0.0562)	0.0611 (0.0262)	0.0653 (0.0342)	0.0709 (0.0500)
Total costs*	1461.9805 (5327.7241)	1395.9295 (5795.9485)	803.5323 (2441.4952)	442.8657 (912.9426)	503.1359 (4674.8493)
Number of banks	163	132	166	101	163
Number of observations	966	1013	648	552	1276

Note: 1. * means measured by millions of real US Dollars with base year 2005.
 2. Numbers in parentheses are standard deviations.

ula method in Table 2 attaining at least the 10% significance level exceeds that of the single cost frontier in Table 3. This arises mainly from the fact that the coefficient estimates are more efficiently estimated by the copula method than the single equation, since more information, such as the potential dependence among equations, is used in estimation. It is worth emphasizing that most of the dependence parameters ρ are significant in these countries, indicating that the dependence between the production cost and output prices indeed exists, confirming that the simultaneous equations models of Eqs. (1) and (3) are preferable to the single equation model. As noted before, the exclusion of ρ may cause inconsistent estimated parameters, and the subsequent measures of technical efficiency and the Lerner index are also misleading. Note that the parameter estimates are found to satisfy the regularity conditions, as required by the microeconomic theory on the cost function in Tables 2 and 3.⁴

We now turn to jointly estimate Eqs. (13) and (16) to derive the parameter estimates of the meta-frontiers with the results presented in Table 4. We also apply the mixed approach of the LP model of the single cost function, proposed by Battese et al. (2004) and O'Donnell et al. (2008), to get the meta-frontier. Table 4 shows the results. The standard errors of the mathematical programming estimators are obtained through bootstrapping methods with

⁴ We simultaneously estimate Eqs. (1) and (3), assuming a single output (total assets) for each country, and estimate the single cost frontier without considering the price equation. The results are not shown to save space, but are available upon request from the authors. It is found that most of the parameter estimates of the copula method attain the 10% level of significance, while more estimates fail to be significant in the single cost frontier. The efficiency gain from using the copula method, stemming from the simultaneous estimation procedure, is confirmed. It is crucial to note that all the dependence parameters ρ in these countries are significant at least at the 10% level, whereby France, Italy, and Switzerland have negative values and Germany and Luxembourg have positive values, signifying that the simultaneous equation model is preferable to the single equation model. The omission of ρ may lead to inconsistent parameter estimates, and thereby the subsequent technical efficiency and the Lerner index measures may be misleading.

1000 replications. The estimated standard error of a meta-frontier parameter is the standard deviation of the 1000 replications. There are substantial differences between the coefficients of our proposed model and those of the LP model. In addition, most of the standard errors of the proposed model are relatively small versus those of the LP model.⁵

5.2. Various efficiency scores

We use the foregoing coefficient estimates to calculate various efficiency scores, including CE, TGR, CE^M , the Lerner index, and MCGR. Table 5 shows the results from CSSFM and LP under the assumption that each bank produces three outputs. The overall mean value of CE from CSSFM is equal to 0.6891. The mean CE values of the five countries range from 0.4402 for Germany to 0.8376 for France, indicating that on average the potential cost savings are around 56% and 17% of their actual costs, respectively. German banks have the highest cost inefficiency, which may result from the highest Lerner index in the markets for loans and investments, as noted below. Since German banks are found to have higher market power with less technical efficiency, the “quiet life hypothesis” may be applied.⁶ Banks in France, Italy, Luxembourg, and Switzerland have higher country-specific mean CE scores than the overall average. Note that the mean value of CE from LP is equal to 0.7978, which is not far from the results found by Bos and Schmiedel (2007), in which Luxembourg banks attain the lowest mean CE score.⁷ Bos and

⁵ We jointly estimate a cost meta-frontier and a meta-frontier MC function in the context of a single output. Both the new and the old meta-frontiers are estimated, and these parameter estimates are not shown to save space, but are available upon request from the authors. Similarly, all the standard errors of the new meta-frontier are smaller than those of the old meta-frontier.

⁶ The quiet life hypothesis asserts that a firm with market power has the luxury of being inefficient, ceteris paribus.

⁷ Since the results from QP are similar to those of LP, we choose not to show them to save space.

Table 2
 Parameter estimates of the Copula method for multiple outputs.

Variables	FRA	GER	ITA	LUX	SWI
Constant	3.4579*** (0.0300)	7.4594*** (0.0362)	5.8336*** (0.0240)	2.3742*** (0.0226)	6.2849*** (0.0234)
ln y ₁	0.3908*** (0.0200)	0.0638*** (0.0086)	0.1110*** (0.0291)	0.4850*** (0.0658)	0.3181*** (0.0132)
ln y ₂	0.6256*** (0.0299)	0.0546*** (0.0094)	0.0728*** (0.0226)	0.2389*** (0.0671)	0.0091 (0.0059)
ln y ₃	-0.1786*** (0.0520)	-0.055 (0.0719)	0.4599*** (0.0715)	0.2148*** (0.0888)	0.0701* (0.0419)
ln w ₂	-0.1015 (0.0639)	0.3649*** (0.1269)	0.0883 (0.0993)	0.1340 (0.0873)	-0.0939 (0.0692)
ln w ₃	0.2153*** (0.0680)	1.2428*** (0.1591)	1.1959*** (0.1302)	0.5961*** (0.1197)	0.3874*** (0.0650)
ln y ₁ × ln y ₁	0.0723*** (0.0024)	0.0079*** (0.0009)	0.0120*** (0.0011)	0.0417*** (0.0063)	0.0596*** (0.0017)
ln y ₂ × ln y ₂	0.0410*** (0.0019)	0.0124*** (0.0013)	0.0460*** (0.0025)	0.1419*** (0.0076)	0.0078*** (0.0008)
ln y ₃ × ln y ₃	0.0417*** (0.0072)	0.0984*** (0.0074)	0.0165** (0.0079)	-0.0125 (0.0096)	0.0972*** (0.0041)
ln y ₁ × ln y ₂	-0.0785*** (0.0025)	-0.0100*** (0.0008)	-0.0327*** (0.0023)	-0.0945*** (0.0057)	-0.0048*** (0.0007)
ln y ₁ × ln y ₃	-0.0070** (0.0033)	-0.0005 (0.0009)	0.0222*** (0.0028)	0.0506*** (0.0069)	-0.0520*** (0.0023)
ln y ₂ × ln y ₃	0.0194*** (0.0042)	-0.0041*** (0.0014)	-0.0090*** (0.0016)	-0.0431*** (0.0062)	-0.0035*** (0.0005)
ln w ₂ × ln w ₂	0.0534*** (0.0097)	-0.0246 (0.0242)	0.0311** (0.0163)	-0.0090 (0.0125)	0.0318*** (0.0095)
ln w ₃ × ln w ₃	0.0671*** (0.0104)	0.0277 (0.0379)	0.0074 (0.0306)	0.0319** (0.0154)	0.1608*** (0.0121)
ln w ₂ × ln w ₃	-0.0155* (0.0090)	-0.0080 (0.0256)	-0.0166 (0.0173)	-0.0026 (0.0114)	0.0072 (0.0080)
ln y ₁ × ln w ₂	-0.0014 (0.0027)	-0.0009** (0.0004)	-0.0052** (0.0023)	0.0214*** (0.0054)	-0.0259*** (0.0022)
ln y ₁ × ln w ₃	0.0238*** (0.0024)	0.0041*** (0.0010)	0.0118*** (0.0021)	0.0632*** (0.0072)	0.0028 (0.0024)
ln y ₂ × ln w ₂	-0.0013 (0.0021)	-0.0015 (0.0010)	-0.0019** (0.0008)	-0.0194*** (0.0052)	0.0043*** (0.0006)
ln y ₂ × ln w ₃	0.0576*** (0.0032)	0.0123*** (0.0018)	0.0289*** (0.0031)	-0.0354*** (0.0073)	0.0089*** (0.0007)
ln y ₃ × ln w ₂	-0.0051 (0.0051)	-0.0212** (0.0103)	-0.0125** (0.0062)	-0.0064 (0.0075)	0.0344*** (0.0059)
ln y ₃ × ln w ₃	-0.0696*** (0.0067)	-0.0130 (0.0142)	-0.1016*** (0.0119)	-0.0085 (0.0094)	0.0145** (0.0064)
t × ln y ₁	0.0047*** (0.0009)	0.0002 (0.0002)	0.0046*** (0.0009)	-0.0048** (0.0022)	0.0020** (0.0010)
t × ln y ₂	-0.0055*** (0.0008)	0.0005* (0.0003)	0.0032*** (0.0004)	0.0043** (0.0020)	-0.0011*** (0.0001)
t × ln y ₃	0.0011 (0.0018)	-0.0060** (0.0030)	-0.0085*** (0.0025)	0.0030 (0.0033)	-0.0023 (0.0017)
t × ln w ₂	-0.0056*** (0.0023)	0.0040 (0.0050)	0.0098** (0.0043)	0.0071** (0.0032)	-0.0006 (0.0027)
t × ln w ₃	0.0073*** (0.0028)	-0.0138* (0.0072)	0.0104 (0.0068)	-0.0165*** (0.0043)	-0.0085*** (0.0029)
t	0.0574*** (0.0221)	0.0788** (0.0381)	-0.0876*** (0.0348)	-0.0304 (0.0363)	0.0542*** (0.0224)
t × t	-0.0040** (0.0017)	0.0016 (0.0035)	0.0069** (0.0031)	0.0002 (0.0023)	0.0005 (0.0018)
ρ ₁₂	-0.0398 (0.0352)	0.0722 (0.0449)	0.1598*** (0.0357)	0.3507*** (0.0521)	-0.1920*** (0.0279)
ρ ₁₃	-0.0596* (0.0323)	0.0784*** (0.0325)	-0.0197 (0.0341)	0.1185 (0.0842)	0.1157*** (0.0272)
ρ ₂₃	-0.2300*** (0.0324)	-0.2865*** (0.0278)	-0.0609 (0.0483)	-0.5046*** (0.0401)	-0.1628*** (0.0277)
λ ₁	0.8066*** (0.1638)	1.9263*** (0.0937)	0.9798 (0.0685)	2.7567*** (0.2843)	1.3648*** (0.1463)
λ ₂	0.4462*** (0.0658)	3.8369*** (0.3032)	3.2940*** (0.2201)	0.7383** (0.1139)	0.1561*** (0.0184)
λ ₃	0.0233*** (0.0008)	1.5078*** (0.0046)	0.3457*** (0.0736)	0.0004*** (0.0011)	1.7816*** (0.0930)
σ ₁	0.3482*** (0.0168)	1.1449*** (0.0229)	0.4230*** (0.0136)	0.5471*** (0.0325)	0.49768*** (0.0178)
σ ₂	0.0542*** (0.0012)	0.0367*** (0.0007)	0.0504*** (0.0014)	0.1513*** (0.0039)	0.0723*** (0.0015)
σ ₃	0.1363*** (0.0002)	0.0180*** (0.0002)	0.0392*** (0.0011)	0.0246*** (0.0007)	0.0114*** (0.0002)
log L	1946.87	4117.38	2124.61	1585.15	5383.46

Note: 1. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

2. Numbers in parentheses are standard errors.

3. W₁ is arbitrarily selected as the numeraire to satisfy the homogeneity restriction in input prices. Therefore, input prices of w₂ and w₃ are already divided by w₁.

4. λ_j = σ_{u_j}/σ_{v_j} and σ_j = √(σ_{v_j}² + σ_{u_j}²), where j = 1, 2, 3.

Table 3
 Parameter estimates of a single equation for multiple outputs.

Variables	FRA	GER	ITA	LUX	SWI
Constant	1.4928*** (0.3698)	0.7626*** (0.3295)	0.6842 (0.4499)	0.0606 (1.0111)	1.0082*** (0.2632)
ln y ₁	0.4475*** (0.0641)	0.8392*** (0.0457)	0.5318*** (0.0693)	1.0305*** (0.1336)	0.6723*** (0.0439)
ln y ₂	0.6083*** (0.0583)	0.4559*** (0.0755)	0.4133*** (0.0665)	0.1597 (0.1787)	0.5192*** (0.0588)
ln y ₃	-0.0525 (0.0707)	-0.2368*** (0.0758)	0.1795*** (0.0818)	0.0878 (0.1203)	-0.1344*** (0.0616)
ln w ₂	0.1581*** (0.0085)	0.1706*** (0.0067)	0.1615*** (0.0065)	0.1441*** (0.0182)	0.1522*** (0.0051)
ln w ₃	0.1234*** (0.0061)	0.2100*** (0.0101)	0.1868*** (0.0094)	0.2045*** (0.0314)	0.1228*** (0.0093)
ln y ₁ × ln y ₁	0.0084 (0.0103)	-0.0162 (0.0111)	0.0229* (0.0133)	-0.0230 (0.0168)	0.0035 (0.0081)
ln y ₂ × ln y ₂	-0.1435*** (0.0057)	-0.2178*** (0.0067)	-0.1635*** (0.0071)	-0.1807*** (0.0170)	-0.1431*** (0.0046)
ln y ₃ × ln y ₃	-0.0084 (0.0077)	0.0216*** (0.0061)	0.0014 (0.0081)	-0.0218 (0.0126)	-0.0216*** (0.0052)
ln y ₁ × ln y ₂	0.0081 (0.0083)	0.0147 (0.0099)	-0.0286*** (0.0093)	0.0210 (0.0189)	0.0250*** (0.0087)
ln y ₁ × ln y ₃	0.0022 (0.0545)	0.0434 (0.0623)	0.1422*** (0.0557)	0.1288 (0.0961)	0.0272 (0.0438)
ln y ₂ × ln y ₃	0.2165*** (0.0629)	-0.1875 (0.1007)	-0.2066*** (0.0917)	-0.0538 (0.2019)	-0.0199 (0.0638)
ln w ₂ × ln w ₂	0.0310*** (0.0062)	0.0300*** (0.0088)	0.0025 (0.0079)	0.0004 (0.0113)	0.0205*** (0.0040)
ln w ₃ × ln w ₃	0.1041*** (0.0097)	-0.0260 (0.0280)	-0.0210 (0.0168)	-0.0546*** (0.0233)	0.1155*** (0.0082)
ln w ₂ × ln w ₃	-0.0079 (0.0070)	-0.0213* (0.0118)	0.0023 (0.0093)	0.0151 (0.0144)	0.0074 (0.0048)
ln y ₁ × ln w ₂	-0.0228*** (0.0053)	0.0001 (0.0050)	-0.0172*** (0.0052)	0.0030 (0.0094)	-0.0118*** (0.0037)
ln y ₁ × ln w ₃	0.0169*** (0.0066)	0.0542*** (0.0083)	0.0804*** (0.0072)	0.0704*** (0.0164)	0.0154*** (0.0060)
ln y ₂ × ln w ₂	0.0009 (0.0040)	-0.0135*** (0.0062)	0.0122*** (0.0055)	-0.0243* (0.0129)	-0.0095*** (0.0048)
ln y ₂ × ln w ₃	0.0329*** (0.0064)	0.0817*** (0.0143)	0.0199*** (0.0097)	-0.0043 (0.0243)	0.0194*** (0.0074)
ln y ₃ × ln w ₂	0.0206*** (0.0058)	0.0073 (0.0068)	0.0056 (0.0073)	0.0164 (0.0112)	0.0154*** (0.0047)
ln y ₃ × ln w ₃	-0.0466*** (0.0089)	-0.1048*** (0.0137)	-0.0851*** (0.0123)	-0.0032 (0.0130)	-0.0100 (0.0075)
t × ln y ₁	0.0061*** (0.0020)	0.0048*** (0.0020)	-0.0008 (0.0023)	0.0071 (0.0043)	-0.0008 (0.0014)
t × ln y ₂	-0.0002*** (0.0018)	0.0008 (0.0022)	-0.0006 (0.0023)	-0.0043 (0.0059)	-0.0013 (0.0017)
t × ln y ₃	-0.0057*** (0.0025)	-0.0063*** (0.0026)	0.0005 (0.0030)	0.0002 (0.0051)	0.0025 (0.0017)
t × ln w ₂	-0.0040*** (0.0017)	-0.0083*** (0.0019)	-0.0068*** (0.0021)	0.0035 (0.0036)	0.0013 (0.0012)
t × ln w ₃	0.0009 (0.0023)	0.0013 (0.0040)	0.0072*** (0.0034)	-0.0173*** (0.0069)	0.0009 (0.0020)
t	0.0260 (0.0187)	0.0216 (0.0187)	0.0133 (0.0227)	-0.0427 (0.0394)	-0.0155 (0.0132)
t × t	-0.0051*** (0.0012)	0.0006 (0.0014)	0.0018 (0.0014)	0.0014 (0.0024)	0.0021*** (0.0009)
γ	0.8144*** (0.0258)	0.9396*** (0.0108)	0.7648*** (0.0668)	0.9937*** (0.0033)	0.9214*** (0.0122)
σ ²	0.0829*** (0.0054)	0.2008*** (0.0109)	0.0677*** (0.0078)	0.3502*** (0.0239)	0.0645*** (0.0033)
log L	214.7036	-92.1569	179.4791	-140.8698	576.5571

Note: 1. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

2. Numbers in parentheses are standard errors.

3. W₁ is arbitrarily selected as the numeraire to satisfy the homogeneity restriction in input prices. Therefore, input prices of w₂ and w₃ are already divided by w₁.

4. $\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$ and $\sigma^2 = \sigma_u^2 + \sigma_v^2$.

Schmiedel (2007) claim that even in a coordinated single European banking market, banks' CE substantially fluctuates across markets due to country-specific conditions, i.e. regulation, competition, etc. This supports the use of the meta-frontier model to compare bank performance across nations.

Weill (2004) compiles data for 688 banks from five European countries, i.e., France, Germany, Italy, Spain, and Switzerland, span-

ning 1992–1998, which is immediately before our sample period of 1998–2010. Their average efficiency estimates from SFA range between 0.6652 (Switzerland) and 0.8418 (Italy) and those from DEA range between 0.4016 (France) and 0.7777 (Spain). Allen and Rai (1996) use 1988–1992 data for banks from 15 countries, and their average efficiency scores for the same five countries as Weill (2004) lie between 0.73 (France and Italy) and 0.88 (Germany) for

Table 4
 Parameter estimates of the meta-frontier cost function for multiple outputs.

Variables	Copula stochastic metafrontier method		Single LP metafrontier method	
	Parameter estimates	Standard errors	Parameter estimates	Bootstrapped standard errors
Constant	6.0478***	0.1235	0.2594	0.4489
ln y ₁	0.1334***	0.0105	0.7483	0.0923
ln y ₂	0.1669***	0.0120	0.4941	0.0726
ln y ₃	0.1752***	0.0181	-0.1347	0.0931
ln w ₂	0.0382	0.0237	0.1314	0.0107
ln w ₃	0.8345***	0.0266	0.1244	0.0120
ln y ₁ × ln y ₁	0.0432***	0.0007	-0.0553	0.0228
ln y ₂ × ln y ₂	0.0294***	0.0007	-0.1609	0.0089
ln y ₃ × ln y ₃	0.0517***	0.0025	0.0233	0.0133
ln y ₁ × ln y ₂	-0.0299***	0.0011	0.0328	0.0139
ln y ₁ × ln y ₃	-0.0073***	0.0013	0.2266	0.0834
ln y ₂ × ln y ₃	-0.0043***	0.0012	-0.3177	0.1238
ln w ₂ × ln w ₂	0.0003	0.0038	-0.0459	0.0120
ln w ₃ × ln w ₃	0.0920***	0.0041	-0.1110	0.0217
ln w ₂ × ln w ₃	-0.0257***	0.0032	0.0584	0.0126
ln y ₁ × ln w ₂	0.0013	0.0010	-0.0254	0.0087
ln y ₁ × ln w ₃	0.0045***	0.0007	0.0666	0.0112
ln y ₂ × ln w ₂	0.0083***	0.0007	0.0201	0.0096
ln y ₂ × ln w ₃	0.0338***	0.0013	0.0416	0.0137
ln y ₃ × ln w ₂	-0.0061***	0.0018	0.0029	0.0114
ln y ₃ × ln w ₃	-0.0450***	0.0025	-0.0789	0.0156
t × ln y ₁	0.0024***	0.0003	0.0068	0.0028
t × ln y ₂	-0.0027***	0.0002	-0.0004	0.0023
t × ln y ₃	-0.0042***	0.0006	-0.0055	0.0030
t × ln w ₂	0.0002	0.0008	0.0051	0.0024
t × ln w ₃	-0.0048***	0.0010	-0.0141	0.0038
t	0.0653***	0.0078	-0.0419	0.0213
t × t	0.0008	0.0006	-0.0018	0.0013
ρ	0.4541***	0.0077		
λ ₁	0.9616***	0.0012		
λ ₂	0.8451***	0.0003		
σ ₁	0.1332***	0.0019		
σ ₂	0.1094***	0.0001		
log L	7384.34			

Note: 1. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

2. W₁ is arbitrarily selected as the numeraire to satisfy the homogeneity restriction in input prices. Therefore, input prices of w₂ and w₃ are already divided by w₁.

3. $\lambda_j = \sigma_{w_j} / \sigma_{v_j}$ and $\sigma_j = \sqrt{\sigma_{v_j}^2 + \sigma_{w_j}^2}$, where $j = 1, 2$.

Table 5
 Various efficiency estimates for multiple outputs.

	CSSFM					LP			
	Mean	Min.	Max.	SD		Mean	Min.	Max.	SD
FRA					FRA				
CE	0.8376	0.4624	0.8730	0.0431	CE	0.8265	0.1461	0.9786	0.0874
TGR	0.9649	0.9046	0.9927	0.0108	TGR	0.7368	0.1084	1.0000	0.1564
CE ^M	0.8082	0.4347	0.8665	0.0430	CE ^M	0.6112	0.0507	0.8657	0.1454
GER					GER				
CE	0.4402	0.0878	0.6882	0.1394	CE	0.7491	0.1476	0.9775	0.1571
TGR	0.9600	0.8681	0.9938	0.0172	TGR	0.7846	0.2398	0.7711	0.1371
CE ^M	0.4207	0.0872	0.6617	0.1275	CE ^M	0.5896	0.1065	0.8718	0.1660
ITA					ITA				
CE	0.7576	0.1917	0.8447	0.0825	CE	0.8389	0.3448	0.9704	0.0825
TGR	0.9773	0.9282	0.9961	0.0092	TGR	0.8318	0.1362	1.0000	0.1387
CE ^M	0.7402	0.1905	0.8414	0.0793	CE ^M	0.6995	0.0931	0.9670	0.1362
LUX					LUX				
CE	0.7060	0.3131	0.8694	0.1234	CE	0.6915	0.1168	0.9868	0.2169
TGR	0.9760	0.9057	0.9934	0.0111	TGR	0.6023	0.0812	1.0000	0.1554
CE ^M	0.6890	0.3073	0.8637	0.1204	CE ^M	0.4219	0.0625	0.8646	0.1811
SWI					SWI				
CE	0.7321	0.1744	0.8275	0.0952	CE	0.8397	0.1333	0.9832	0.1018
TGR	0.9741	0.9167	0.9926	0.0088	TGR	0.7250	0.1489	1.0000	0.1589
CE ^M	0.7132	0.1727	0.8194	0.0935	CE ^M	0.6122	0.0496	0.9815	0.1591
Overall					Overall				
CE	0.6891	0.0878	0.8730	0.1744	CE	0.7978	0.1168	0.9868	0.1411
TGR	0.9696	0.8681	0.9961	0.0137	TGR	0.7414	0.0812	1.0000	0.1633
CE ^M	0.6682	0.0872	0.8665	0.1699	CE ^M	0.5960	0.0496	0.9815	0.1741

small banks. Our average efficiency of 0.44 from CSSFM for German banks is roughly half of the above two papers (0.84 and 0.88, respectively). This may be ascribable to three facts. First, the current paper identifies three outputs, while the foregoing works define two outputs, ignoring the output of non-interest revenue that is able to reflect the importance of banks' non-traditional activities. Second, the previous two papers cover the sample periods ahead of ours, during which market competition, environmental conditions, and the speed of technology adjustment among banks and across countries are likely to differ considerably. Third, our efficiency measures are calculated using the parameter estimates from the copula-based simultaneous stochastic frontier model, while those two papers yield their efficiency scores on the basis of the conventional SFA, which is a single equation model.

The overall mean TGR measure is as high as 0.9696 with a very small standard deviation (0.0137), implying that banks in our sample countries tend to adopt quite similar and advanced production technology in order to provide financial services to their customers in the highly integrated European banking market. The mean TGR measures of the five countries lie in a narrow range, i.e., between 0.96 and 0.9773. Among them, Italian banks adopt the most advanced production technology, because their country frontier is the closest to the meta-frontier, followed by Luxembourg, Switzerland, France, and Germany.⁸

A representative Italian bank can save merely 2.27% of its production costs, provided it undertakes the potential advanced technology. Having the lowest mean TGR value, German banks can shave 4% off their costs by exploiting the most advanced production technology available to all countries. The mean value of TGR is close to one, verifying that differences between country-specific frontiers and a meta-frontier are rather small for the single European banking market. Our results are similar to Bos and Schmiedel (2007), who employ the mixed approach of Battese et al. (2004) and O'Donnell et al. (2008). However, the average TGR of the LP approach for the five countries ranges widely from 0.6023 to 0.8318 with an overall mean value of 0.7414 and a standard deviation of 0.1633. This low mean value of TGR differs from that of Bos and Schmiedel (2007), and this larger value of standard deviation than that of CSSFM is as expected.

French banks reach the highest mean meta-cost efficiency score (CE^M), followed by Italy, Switzerland, Luxembourg, and Germany. The component CE is on average less than the component TGR in each country, meaning that the main source of input-oriented production inefficiency comes from managerial inabilities, rather than adopting inferior technology. It is thus suggested that the sample banks reduce their input mix for a given output bundle in such a way as to improve their cost efficiency scores.

Table 6 shows the average efficiency measures of CE, TGR, and CE^M from CSSFM for each country over two sub-periods: 1998–2006 (pre-subprime crisis period) and 2007–2010 (during and post-subprime crisis period). Generally speaking, those measures vary smoothly over the two sub-periods with small standard deviations. It is seen from the table that the mean CE values improve slightly over time, except for Luxembourg. Although the average TGR values are quite high and close to unity in all countries, they deteriorate a little over time, except for France and Italy. The average value of overall technical efficiency, CE^M , has the same trend as CE in each country, i.e., it gets better over time, except for Luxembourg. One may conclude that the aftermath of the subprime crisis mainly stimulated banks' managerial abilities (CE), instead of technology promotion (TGR).

⁸ The null hypothesis that Italy and Luxembourg have equal average TGR values is rejected by t-test statistics.

Following the convention of a single output bank, we re-estimate the CSSFM and LP models and present results in Table 7. The table shows that the mean CE value of CSSFM is equal to 0.8270 and ranges between 0.7070 for Germany and 0.8883 for Switzerland. The mean CE value of the LP model is equal to 0.8038 and varies from 0.6820 for Luxembourg to 0.8791 for Switzerland. Comparing to Table 5, we see that the mean CE score derived from the case of multiple outputs tends to be lower than that from the single output case. This implies that the aggregation of multiple outputs is likely to distort the estimates of cost efficiency.

The overall average TGRs of CSSFM and LP equal 0.9527 and 0.6837, respectively, which are both lower than those in Table 5. Aggregating outputs here is inclined to underestimate the average TGR. CSSFM still gives quite similar average TGRs among the five countries, while LP suggests that banks in the sample countries adopt quite different technologies. The standard deviation of CSSFM is smaller than that of LP for each country, as expected. The TGR component of CSSFM is on average larger than that of CE, but the reverse is true for LP.

5.3. Lerner index

Table 8 reports the summary statistics of the Lerner indices for the outputs of loans and investments and for the single output case across countries estimated by CSSFM and conventional models. As far as the loans market is concerned, the Swiss banking market is the most competitive among the five sample countries, as its average L^{New} is the lowest, followed by France, Luxembourg, Italy, and Germany.^{9,10} German and Italian banks appear to enjoy stronger market power than the remaining three nations. The average L^{Old} gives the same ordering, as shown in the last 5 columns of the table, but their magnitudes differ. Among them, the average L^{New} of German and Italian banks are found to be relatively close to their respective average L^{Old} . However, the remaining three countries have much higher average L^{New} measures than their respective average L^{Old} measures, due partially to the fact that some banks have negative L^{Old} estimates. One may conclude that our L^{New} measure, derived from CSSFM, is preferable to the conventional measure of L^{Old} , as the latter tends to underestimate the index and hence exaggerates the degree of market competition.

With regard to the investment market, the financial markets of Luxembourg and France are nearly perfectly competitive, as their average values of L^{New} fall short of 0.08.¹¹ The remaining three markets may be characterized as monopolistic competition. Again, the new Lerner index measures are all higher than the conventional ones across our sample countries. This time, three out of the five countries have negative average values of the L^{Old} measure, arising from large negative estimates that may result due to adverse random shocks. Conversely, our L^{New} measure is able to avoid such a problem, as it is internally built into the simultaneous equations model. A similar conclusion to the loans market is reached in that the L^{New} measure is more advantageous to use than the conventional one.

Table 9 presents the descriptive statistics of the new Lerner indices across countries from CSSFM over the two sub-periods. Banks in four out of the five countries enjoy increasing market power for both outputs. The degree of market competition falls

⁹ The pairwise differences in the average new Lerner index among these countries are all significant at the 1% level, except for the difference between Germany and Switzerland in the investment market and the difference between Germany and Luxembourg in the single output case.

¹⁰ This may be ascribable to the fact that Switzerland is essentially an offshore financial center with many international banks competing with one another.

¹¹ Similar to Switzerland, Luxembourg is also an offshore financial center with many international banks.

Table 6
 CSSFM efficiency estimates for multiple outputs over time.

	$EFF^{CSSFM}_{1998-2006}$					$EFF^{CSSFM}_{2007-2010}$			
	Mean	Min.	Max.	SD		Mean	Min.	Max.	SD
FRA					FRA				
CE	0.8374	0.4624	0.8730	0.0452	CE	0.8382	0.7002	0.8730	0.0356
TGR	0.9639	0.9046	0.9927	0.0117	TGR	0.9681	0.9379	0.9843	0.0066
CE^M	0.8072	0.4347	0.8665	0.0452	CE^M	0.8115	0.6806	0.8586	0.0352
GER					GER				
CE	0.4366	0.0878	0.6882	0.1395	CE	0.4514	0.1278	0.6882	0.1391
TGR	0.9604	0.8681	0.9931	0.0175	TGR	0.9586	0.8938	0.9938	0.0164
CE^M	0.4173	0.0872	0.6617	0.1272	CE^M	0.4310	0.1263	0.6577	0.1281
ITA					ITA				
CE	0.7548	0.1917	0.8447	0.0911	CE	0.7605	0.4112	0.8447	0.0727
TGR	0.9772	0.9407	0.9961	0.0092	TGR	0.9774	0.9282	0.9944	0.0093
CE^M	0.7373	0.1905	0.8414	0.0878	CE^M	0.7432	0.4082	0.8291	0.0695
LUX					LUX				
CE	0.7066	0.3131	0.8694	0.1245	CE	0.7035	0.4140	0.8694	0.1191
TGR	0.9773	0.9403	0.9934	0.0096	TGR	0.9697	0.9057	0.9934	0.0148
CE^M	0.6905	0.3073	0.8637	0.1213	CE^M	0.6822	0.4089	0.8630	0.1170
SWI					SWI				
CE	0.7299	0.1744	0.8275	0.0958	CE	0.7388	0.2583	0.8275	0.0932
TGR	0.9755	0.9167	0.9926	0.0080	TGR	0.9697	0.9255	0.9899	0.0095
CE^M	0.7121	0.1727	0.8194	0.0941	CE^M	0.7166	0.2514	0.8153	0.0918
Overall					Overall				
CE	0.6843	0.0878	0.8730	0.1781	CE	0.7020	0.1278	0.8730	0.1633
TGR	0.9698	0.8681	0.9961	0.0140	TGR	0.9692	0.8938	0.9944	0.0129
CE^M	0.6636	0.0872	0.8665	0.1733	CE^M	0.6806	0.1263	0.8630	0.1599

Table 7
 Various Efficiency Scores for a Single Output.

	CSSFM					LP			
	Mean	Min.	Max.	SD		Mean	Min.	Max.	SD
FRA					FRA				
CE	0.8463	0.2166	0.9058	0.0633	CE	0.8391	0.1783	0.9807	0.0725
TGR	0.9543	0.8234	0.9614	0.0102	TGR	0.6709	0.0481	0.9557	0.1663
CE^M	0.8077	0.1910	0.8708	0.0603	CE^M	0.5645	0.0364	0.8614	0.1493
GER					GER				
CE	0.7070	0.3225	0.8740	0.0719	CE	0.7420	0.2079	0.9817	0.1502
TGR	0.9501	0.8975	0.9614	0.0083	TGR	0.7380	0.0675	0.9498	0.1020
CE^M	0.6717	0.3079	0.8403	0.0686	CE^M	0.5485	0.0324	0.7981	0.1377
ITA					ITA				
CE	0.8613	0.5302	0.9050	0.0512	CE	0.8035	0.1972	0.9794	0.1220
TGR	0.9588	0.8534	0.9614	0.0073	TGR	0.8194	0.2730	1.0000	0.2122
CE^M	0.8259	0.5097	0.8701	0.0497	CE^M	0.6591	0.1625	0.9363	0.1389
LUX					LUX				
CE	0.8317	0.5023	0.9205	0.0661	CE	0.6820	0.1780	0.9744	0.2025
TGR	0.9450	0.8903	0.9614	0.0123	TGR	0.5873	0.0388	1.0000	0.2320
CE^M	0.7859	0.4741	0.8850	0.0633	CE^M	0.4117	0.0145	0.9428	0.2146
SWI					SWI				
CE	0.8883	0.4329	0.9349	0.0529	CE	0.8791	0.3525	0.9828	0.0664
TGR	0.9537	0.8980	0.9614	0.0064	TGR	0.6231	0.0177	0.8809	0.2134
CE^M	0.8472	0.4110	0.8989	0.0506	CE^M	0.5481	0.0160	0.8228	0.1929
Overall					Overall				
CE	0.8270	0.2166	0.9349	0.0915	CE	0.8038	0.1780	0.9828	0.1391
TGR	0.9527	0.8234	0.9614	0.0096	TGR	0.6837	0.0177	1.0000	0.1883
CE^M	0.7880	0.1910	0.8989	0.0884	CE^M	0.5510	0.0145	0.9428	0.1801

somewhat during the after-subprime crisis period due possibly to mergers and acquisitions. As far as the old Lerner indices (L^{Old}) are concerned, Table 10 draws a substantially different picture. Only two out of the five countries, i.e., France and Luxembourg, have increasing mean values of L^{Old} for output loans across periods, while output investment has decreasing mean values of L^{Old} and negative mean values in France, Luxembourg, and Italy.

In the context of the single output case, the largest value of the new Lerner index is Switzerland (0.2549), followed by France,

Italy, Germany, and Luxembourg. The new Lerner index is on average larger than the conventional Lerner index with the exception of Italy. Therefore, the conventional Lerner index is still apt to overstate the degree of market competition. The market for investments in the sample nations can be characterized as monopolistic competition. Our estimates of L^{Old} are close to Carbó et al. (2009). Retrieving data for 8235 banks in 23 developed nations, Berger et al. (2009) obtain an average value of the Lerner index that is 0.22 with a minimum value of -0.55. The implication is that their conventional

Table 8
 Summary statistics of the Lerner index measure.

Market	Mean of L^{New}					Mean of L^{Old}				
	FRA	GER	ITA	LUX	SWI	FRA	GER	ITA	LUX	SWI
Loan	0.3309 (0.1450)	0.8205 (0.1031)	0.7842 (0.1088)	0.4322 (0.2587)	0.1954 (0.0920)	0.2010 (1.1650)	0.8909 (0.7518)	0.7724 (0.6646)	0.2422 (2.4106)	0.1010 (1.0057)
Invest	0.0755 (0.0883)	0.6802 (0.1915)	0.3528 (0.2170)	0.0014 (0.0015)	0.6738 (0.2452)	-1.0396 (6.2813)	0.3063 (1.0056)	-0.1933 (1.5849)	-4.0624 (5.3883)	0.5202 (0.9505)
Total assets	0.1936 (0.0837)	0.1673 (0.0730)	0.1806 (0.0547)	0.1665 (0.0678)	0.2549 (0.0848)	0.1494 (0.4106)	0.1437 (0.1718)	0.1955 (0.1854)	0.1433 (0.1570)	0.2113 (0.1853)
Number of banks	163	132	166	101	163	163	132	166	101	163
Number of observations	966	1013	648	552	1276	966	1013	648	552	1276

Table 9
 Summary statistics of the new Lerner index measure over time.

Market	Mean of $L^{New}_{1998-2006}$					Mean of $L^{New}_{2007-2010}$				
	FRA	GER	ITA	LUX	SWI	FRA	GER	ITA	LUX	SWI
Loan	0.3133 (0.1381)	0.8166 (0.1006)	0.7903 (0.1096)	0.4056 (0.2391)	0.1845 (0.0849)	0.3863 (0.1527)	0.8327 (0.1101)	0.7778 (0.1079)	0.5553 (0.3081)	0.2290 (0.1044)
Invest	0.0657 (0.0678)	0.6740 (0.1881)	0.3169 (0.1912)	0.0015 (0.0016)	0.6583 (0.2518)	0.1064 (0.1291)	0.6995 (0.2011)	0.3902 (0.2354)	0.0012 (0.0014)	0.7219 (0.2172)
Number of observations	732	765	330	454	963	234	248	318	98	313

Table 10
 Summary Statistics of the old Lerner Index Measure over Time.

Market	Mean of $L^{Old}_{1998-2006}$					Mean of $L^{Old}_{2007-2010}$				
	FRA	GER	ITA	LUX	SWI	FRA	GER	ITA	LUX	SWI
Loan	0.1879 (1.2518)	0.8985 (0.7443)	0.8028 (0.3940)	0.2416 (2.6347)	0.1290 (0.7233)	0.2419 (0.8385)	0.8674 (0.7753)	0.7410 (0.8593)	0.2449 (0.7686)	0.0149 (1.5847)
Invest	-1.0388 (6.6128)	0.3381 (0.8189)	0.0426 (1.4227)	-4.2609 (5.4333)	0.5231 (0.8143)	-1.0421 (5.1201)	0.2079 (1.4341)	-0.4381 (1.7054)	-3.1433 (5.1011)	0.5114 (1.2834)
Number of observations	732	765	330	454	963	234	248	318	98	313

Lerner index suffers from negative estimates for some observations, which is a common problem faced by some previous research studies, e.g., [Coccorese \(2014\)](#), [Fonseca and González \(2010\)](#), [Jiménez, Lopez, and Saurina \(2013\)](#), and [Maudos and Fernández de Guevara \(2007\)](#), to mention a few.¹²

Table 11 shows that the overall mean value of MCGR is equal to 0.3848 for the loans market in the five countries as a whole. The same measure varies among the sample countries from 0.0857 for Luxembourg to 0.6835 for Switzerland, indicating that the potential increase in market power for banks in the two countries is 8.57% and 68.35%, respectively, provided they adopt the most advanced technology in the production of loans, which should boost their profits accordingly. The average value of MCGR is equal to 0.5338 for the entire investment market, lying in the range between 0.3127 for Germany and 0.9866 for Luxembourg. Banks in Germany and Switzerland can seize additional market power of up to 31.27% and 98.66%, respectively, when adopting the potential advanced technology in the production of investments. Our results imply that banks should first allocate scarce resources to promote their production technology in investments, since the potential market power and profitability from investments are larger than that of loans. Improving the production technology of investments is capable of raising higher marginal profits relative to enhancing the production technology of loans.

¹² For example, [Koetter et al. \(2012\)](#) report an average value (standard deviation) of their adjusted Lerner index of 0.411 (0.224), based on a sample of 342,856 bank-year observations from the U.S. Since the standard deviation is relatively large versus the mean value, some observations are anticipated to have negative values for the index.

Under the single output case, the mean value of MCGR is merely 0.0335 for the asset market. Italian banks have the highest value of 0.0620, followed by Luxembourg (0.0605), Germany (0.0490), France (0.0119), and Switzerland (0.0111). These numbers are substantially lower than the multiple output case, implying that the single output case is apt to underestimate the measure of MCGR.

Recall from Eq. (19) that the sum of L^{New} and MCGR is referred to as the potential Lerner index. In the loans market, German, Italian, and Luxembourg banks can substantially increase their profit by setting higher lending rates over their MCs, as their L^{New} measures exceed MCGRs, while it is suggested that banks in France and Switzerland lower their country-specific MCs as close as possible to the meta-frontier MCs, as their MCGRs are larger than the L^{New} measures. In the investments market, German and Switzerland banks can effectively increase their profits by setting a higher price of investments, but banks in the remaining three countries should reduce their MC in order to largely improve profits. In the single output case, all banks in the sample countries are recommended to exert their market power by raising the output price, rather than by reducing their MC, as the L^{New} measures are all larger than MCGRs.

6. Conclusion

This paper proposes a joint estimation procedure to investigate market power and cost efficiency at the individual bank level under the framework of CSSFM, which is composed of a cost frontier and two output price frontiers. The cost frontier allows us to estimate cost efficiency, and the two price frontiers allow for estimating the degrees of competition in the markets for loans and investments. In this manner, the new Lerner indices for products of loans and investments can be estimated by relying on the simultaneous equations model, which avoids obtaining negative measures of

Table 11
Estimates of the potential Lerner index.

Loan	FRA	GER	ITA	LUX	SWI	TOTAL
L^{New}	0.3309 (0.1450)	0.8205 (0.1031)	0.7842 (0.1088)	0.4322 (0.2587)	0.1954 (0.0920)	0.4819 (0.2958)
MCGR	0.5592 (0.1417)	0.1479 (0.1397)	0.1618 (0.1632)	0.0857 (0.0625)	0.6835 (0.1450)	0.3848 (0.2870)
$Lerner^P$	0.8901 (0.1668)	0.9684 (0.0949)	0.9460 (0.1155)	0.5179 (0.2077)	0.8789 (0.2062)	0.8667 (0.2145)
Invest						
L^{New}	0.0755 (0.0883)	0.6802 (0.1915)	0.3528 (0.2170)	0.0014 (0.0015)	0.6738 (0.2452)	0.4155 (0.3406)
MCGR	0.7638 (0.2106)	0.3127 (0.1947)	0.5630 (0.1978)	0.9866 (0.0615)	0.3245 (0.2447)	0.5338 (0.3197)
$Lerner^P$	0.8393 (0.2305)	0.9929 (0.0527)	0.9158 (0.1728)	0.9880 (0.0617)	0.9983 (0.0159)	0.9493 (0.1453)
Total assets						
L^{New}	0.1936 (0.0837)	0.1673 (0.0730)	0.1806 (0.0547)	0.1665 (0.0678)	0.2549 (0.0848)	0.1999 (0.0843)
MCGR	0.0119 (0.0094)	0.0490 (0.0453)	0.0620 (0.0307)	0.0605 (0.0239)	0.0111 (0.0227)	0.0335 (0.0368)
$Lerner^P$	0.2055 (0.0894)	0.2163 (0.0808)	0.2426 (0.0740)	0.2270 (0.0875)	0.2660 (0.0902)	0.2334 (0.0886)

Note: Numbers in parentheses are standard deviations.

the Lerner index, since the relationship between output price and MC is automatically built into the model. On the contrary, the conventional Lerner index suffers from getting negative values in the Lerner index for some observations.

The empirical results show that the mean values of the new Lerner index in all selected countries are larger than those of the conventional model, together with smaller standard deviations. This implies that the conventional model is inclined to exaggerate the degree of market competition. Our CSSFM model confirms that the loans markets in the five countries and the investment markets in 3 out of the five countries are running under monopolistic competition. The two investment markets of Luxembourg and France are characterized as being in perfect competition.

This paper further employs the new meta-frontier model, first introduced by Huang et al. (2014), to estimate and compare bank efficiency and market power across five countries over the period 1998–2010. The mean TGR of CSSFM is close to unity, indicating that all of the country-specific cost frontiers are quite close to the meta-cost frontier. The sample banks employ analogous, advanced production technology in the highly integrated European market, which is consistent with the finding of Bos and Schmiedel (2007). The component of CE falls short of the component of TGR, implying that the sample banks should enhance their managerial abilities by adjusting the three inputs for a given output mix to improve their cost efficiency scores. Evidence is found that all average TGR measures from the new meta-frontier model exceed those from the LP model with smaller standard deviations.

The potential Lerner index measure can be split into two parts: the Lerner index and MCGR. Some implications can be drawn from the empirical results. It is suggested that our sample banks reallocate their output quantities toward the one with a higher potential Lerner index in order to promote profits. Those banks can either increase their output prices to enlarge L^{New} and $Lerner^P$, or improve their production technology to reduce marginal costs and MCGR, holding $Lerner^P$ constant. However, it is difficult for banks to raise their output prices, due possibly to the risk of potential entrants, which complies with the feature of a contestable market. Therefore, banks need to reduce their marginal costs to maintain their higher market power by the following ways. First, bank managers should adopt the advanced technologies to efficiently produce various financial products or adopt financial innovation swiftly in order to serve their clients at a lower cost, thereby earning higher prof-

its. Second, banks are encouraged to expand the market share of the output with a higher measure of the new Lerner index relative to MCGR. This can be done through, e.g., mergers and acquisitions, leading to economies of scale and scope, as well as risk and product diversification.

There are two things worth mentioning. First, it is quite difficult for the likelihood function of CSSFM to converge during the estimation process since the simultaneous equations of (1) and (3), which are composed of error terms, are highly non-linear. Researchers must try many different sets of starting values for the unknown parameters, thus requiring a lot of time. Second, u_1 and u_2 in Eq. (3), which are the gaps between the two output prices and the corresponding MCs, and u_3 in Eq. (1), which is the technical inefficiency term, are implicitly assumed to be independent over time. However, allowing for such time-dependency would require another copula and would be computationally difficult. See, for example, Amsler, Prokhorov, and Schmidt (2014) for details. As for future research directions, it is suggested that environmental variables be related to u_1 , u_2 , and u_3 . This enables one to examine the determinants of those u 's. Allocative efficiency and productivity changes are also interesting topics that can be incorporated into CSSFM.

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